Family firms, Regional Competitiveness and Productivity: A Multilevel Approach

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Abstract. As not all firms benefit to the same extent from regional competitiveness, this article investigates the influence of the regional context on the productivity of a sample of family and non-family manufacturing firms in Spain. Using a multilevel approach to account for the nested structure of the data, and a composite indicator of regional competitiveness, to capture the spatial endowment of tangible and intangible resources, we found family firms to be more sensitive to the regional context than non-family businesses. Cross-level interactions show that family firms achieve higher productivity gains from their location in more competitive regions than their non-family counterparts. This result is in line with our theoretical arguments postulating the unique social capital of family firms which allows them to benefit most from location advantages. Implications for regional and family business studies, as well as policymakers, are discussed.

Keywords: Family firms, Regional competitiveness, Productivity, Social capital, Multilevel analysis, Spain

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1. Introduction

Regional scholars have shown a growing interest in studying the influence of the regional context on firms' productivity (Agostino, Di Tommaso, Nifo, Rubini, & Trivieri, 2020). While there is evidence that spatial externalities[1] affect firms' productivity (van Oort, Burger, Knoben, & Raspe, 2012), the influence is uneven (Hervas-Oliver, Sempere-Ripoll, Rojas Alvarado, & Estelles-Miguel, 2018). Indeed, some firm-specific characteristics (such as size) make firms more or less productive in specific contexts (van Oort et al., 2012). Against this background, a largely disregarded firm-specific characteristic in investigating the regional determinants of productivity is family status, i.e., family involvement in the management of the firm. We explore this research gap from the regional competitiveness perspective, encompassing a diverse set of features and conditions affecting the productivity of firms located in a given region (Bristow, 2005). Hence, our study is driven by the following research questions: *does regional competitiveness matter for firm productivity? Who between family and non-family firms benefits the most from regional competitiveness?*

To address the question mentioned above, we link arguments from regional competitiveness studies and social capital theory to hypothesize that family firms are better positioned for rent appropriation, by exploiting business opportunities and external resources, which flourish in highly competitive regions (Budd & Hirmis, 2004). While any organization can leverage its competitive advantage by using social capital – understood as the goodwill engendered by the set of relationships that can be mobilized to facilitate action and create value (Adler & Kwon, 2002)[2] – family firms are endowed with a unique type of social capital (Sorenson, Goodpaster, Hedberg, & Yu, 2009) encompassing both the bonding and bridging

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[1] Externalities are regarded as geographically-bounded resources or locational factors that reside outside firms that might lead to static (e.g., increasing return to scale) – and dynamic (e.g., higher innovativeness) advantages compared to firms elsewhere (Bellmann, Evers, & Hujer, 2018; Kitson et al., 2004).

[2] Adler & Kwon (2002) define social capital as "the goodwill available to individuals or groups. Its source lies in the structure and content of the actor's social relations. Its effects flow from the information, influence, and solidarity it makes available to the actor" (p. 23).

dimension (Chang, Memili, Chrisman, Kellermanns, & Chua, 2009; Debellis, Torchia, Quarato, & Calabrò, 2022). Bonding social capital is the result of trustworthiness, feeling of closeness, and interpersonal solidarity within the organizational boundaries (Herrero, 2018). The moral infrastructure – which provides the basis for family values, obligations, and expectations – is at the roots of the bonding social capital (Danes et al., 2009; Sorenson & Bierman, 2009), leading to collective actions, shared vision, and emotional support toward the business, ultimately improving the exploitation of the resources (Salvato & Melin, 2008). Bridging social capital cuts across organizational boundaries (Herrero, Hughes, & Larrañeta, 2022; Sirmon & Hitt, 2003), molding the relationships with the region where the family firm operates, and improving the drawing of external resources and business opportunities (Estrada-Robles, Williams, & Vorley, 2021; Randerson, Frank, Dibrell, & Memili, 2021). Family firms may combine bridging and bonding social capital to leverage and exploit spatially-bounded resources and business opportunities (Salvato & Melin, 2008), thus achieving productivity advantages vis-à-vis non-family businesses (Martikainen, Nikkinen, & Vähämaa, 2009).

To test our conjecture, this study relies on a longitudinal dataset of Spanish manufacturing firms for the period 2002-2015. Spain represents a fascinating setting for our research. From a regional perspective, Spain is characterized by widespread and long-lasting territorial imbalances regarding well-being, knowledge and human capital (McGowan & San Millán, 2019). Additionally, family firms represent the backbone of the Spanish economy accounting for nearly 90% of total non-financial companies (IEF, 2017). In testing our hypothesis, we resorted to multilevel modeling, which allows us to link micro (the firm) and macro (regional context) levels simultaneously (van Oort et al., 2012) and addresses potential ecological measurement fallacies (Raspe & van Oort, 2011). Our findings show that the family status of the firm *per se* is not related to productivity whereas, as expected, regional competitiveness is positively associated with firm productivity. However, this effect varies depending on the family status of the firm. Specifically, cross-level interactions display productivity differentials between family vis-à-vis non-family firms, with family firms achieving higher productivity gains as regional competitiveness heightens.

This study makes several contributions. First, it advances the existing research at the intersection of family business and regional studies (Basco, 2015) and the current debate on the firm-level heterogeneity to explain the unequal effect of regional context on firm behavior and performance (López-Bazo & Motellón, 2018; van Oort et al., 2012). Due to the firm's ability to exploit the benefits of the regional context, the firm-level heterogeneity line of research discloses new opportunities for a greater understanding of how different types of firms perform within the regional boundaries. In the same vein, our contribution lies in showing that family firms, as a unique type of regional economic actor, are better positioned to exploit the advantages of being located in competitive regions. Stemming from the social capital theory and proxying the idiosyncratic, tacit in nature, and hard-to-imitate social capital of family firms, by considering the family's involvement in the firm, we found that family firms benefit the most from location in highly competitive regions. Therefore, following the call for connecting family business and regional studies (Stough, Welter, Block, Wennberg, & Basco, 2015), our research explores the uneven influence of context on the productivity of family and non-family firms.

Second, more specifically to family business studies, we contribute to the existing productivity debate (Creemers, Peeters, Quiroz Castillo, Vancauteren, & Voordeckers, 2022) and address the research gap related to the lack of explantion for the mixed evidence regarding the productivity difference of family firms *vis-à-vis* non-family firms (Barbera & Moores, 2013). Our research highlights the role of the regional context in explaining productivity differentials between family and non-family firms. In so doing, this line of research allows us to unravel unresolved questions, specifically related to productivity, by considering the regional dimension. Omitting context – which represents a largely neglected/overlooked variable in the investigation of the family firm phenomenon (Amato, Basco, & Lattanzi, 2021) – might lead to an overestimation (upward bias) or underestimation (downward bias) in the empirical analysis leading to erroneous conclusions on productivity.

Regarding policy implications, while there is common agreement that policy interventions should be geared toward correcting territorial imbalances (Pike, Rodríguez-Pose, & Tomaney, 2016) and enhancing the overall regional business environment (Rodríguez-Pose & Hardy, 2017), we found that family firms benefit the most. Therefore, the enhanced competitiveness of a region would result in an additional effect on family firms, ultimately fostering – through its indirect impact on productivity – regional economic growth (van Oort et al., 2012).

2. Review of the literature

2.1. Regional competitiveness and firm's productivity

Regional development literature emphasizes the importance of spatially-bounded resources (e.g., the endowment of physical resources and knowledge) and conditions (e.g., intangible factors, such as the institutional and regulatory framework) in enabling firms to thrive (Pike et al., 2016; Rodríguez-Pose, 2013). At the regional level, many empirical contributions have investigated the determinants of productivity and economic growth and analyzed the role of human capital endowment (Ascari & Cosmo, 2005; Gennaioli, La Porta, Lopez-de-Silanes, & Shleifer, 2013), regional innovation (Capello & Lenzi, 2016), physical infrastructure (Crescenzi & Rodríguez-Pose, 2012; Destefanis & Sena, 2005) and the quality of regional institutions (Ketterer & Rodríguez-Pose, 2018; Tabellini, 2010).

All these factors may also play a role in explaining productivity at firm level. As echoed by Huggins et al. (2013), "as traditional forms of advantage become nullified, competitive advantage lying outside companies – i.e., in the business environment in which they are located – increased in importance" (p. 159). From this perspective, the regional *milieu* of the firm is crucial to the way businesses allocate resources internally (Abdel Fattah, Arcuri, Garsaa, & Levratto, 2020), exploit localized knowledge and regional resources in general (Tojeiro-Rivero & Moreno, 2019) and business opportunities (Acs, Audretsch, & Lehmann, 2013), leading ultimately to higher levels of efficiency and competitive advantage (European Commission, 1999; Kitson, Martin, & Tyler, 2004).

Early interest about the regional determinants of firms' productivity focused on the agglomeration economies as stemming from either the geographical concentration of firms belonging to the same sector (i.e., MAR externalities or localization economies) or the economic diversity of the regional *milieu* (i.e., Jacobinian externalities or urbanization economies) (Fazio & Maltese, 2015; Parr, 2002). It has been found that localization in densely populated (Raspe & van Oort, 2011) and industrialized areas (Amara & Thabet, 2019; Lu, Ruan, & Reve, 2016) promotes firm productivity gains through regional externalities. As geographical concentration was deemed to foster knowledge spillovers conducive for a firm's performance (Schmutzler & Lorenz, 2018), the focus shifted to the physical, and socio-economic, and softer dimensions at regional level accounting for productivity differentials (Kitson et al., 2004; Turok, 2004).

The regional-specific characteristics include tangible and intangible factor endowment (Kitson et al., 2004) in terms of regional knowledge from human capital (Manzocchi, Quintieri, & Santoni, 2017; Raspe & van Oort, 2011), innovation and research (Aiello, Pupo, & Ricotta, 2015; Raspe & van Oort, 2011; Tojeiro-Rivero & Moreno, 2019) and the physical infrastructure (Aiello, Pupo, & Ricotta, 2014; Manzocchi et al., 2017; Ricotta, 2019). Taken together, the endowment of the aforementioned spatially-bounded resources portrays the competitiveness of a given region (Huggins et al., 2013) ensuring, on average, firms in a given region higher productivity levels than would otherwise be the case (Kitson et al 2004). Regional competitiveness, therefore, can be seen as a multidimensional construct where varied regional factors operate simultaneously (Boschma, 2004; Bristow, 2005) explaining firms' productivity differentials (Fazio & Maltese, 2015)[3]. For instance, Fazio and Piacentino (2010) use an indicator that synthesizes many socio-economic features of the Italian provinces (NUTS 3) and show that better socio-economic conditions of the regional business environment positively affect firm productivity. Hence, we formulate the following hypothesis:

Hypothesis 1: Firm's productivity is positively related to the degree of regional competitiveness.

Having said that, previous research also shows that the influence of the regional business environment on firm outcomes is unevenly distributed across firms in the same region (Hervas-Oliver et al., 2018). This implies that the regional effect is contingent on certain firm-specific characteristics (Raspe & van Oort, 2011; van Oort et al., 2012). In other words, not all firms may be equally affected by the competitiveness of their region (López-Bazo & Motellón, 2018), and some attributes may enable specific types of firms to better capitalize on the advantages of the location in a highly competitive region. One of these specific characteristics is the family status of the firm, stemming from the involvement of a family in the business.

2.2. Regional competitiveness and firm productivity. The contingent role of the family status of the firm.

A large body of research shows that family involvement in the firm implies a specific type of ownership and management regime making family firms different from their non-family counterparts (Carney, 2005). The interaction of the family members and the non-family stakeholders results in a unique bundle of resources and capabilities (Habbershon & Williams, 1999), which accounts for the family effect influencing firm productivity (Barbera

[3] Similarly, the European Commission (1999, p. 75) states that "[the concept of regional competitiveness] should capture the notion that, despite the fact that there are strongly competitive and uncompetitive firms in every region, there are common features within a region which affect the competitiveness of all firms located there".

& Moores, 2013; Martikainen et al., 2009). One of these specific resources is the family firm's social capital as idiosyncratic, tacit in nature, and a difficult asset for competitors to imitate (Pearson, Carr, & Shaw, 2008). Family business social capital consists of a double-layered intangible resource. First, bonding social capital, which encompasses the fabric of family relationships within the firm (Arregle, Hitt, Sirmon, & Very, 2007; Danes et al., 2009). Second, bridging social capital, which accounts for the bonds between the family firm and the immediate regional context where the family and the firm are located (Salvato & Melin, 2008).

The bonding social capital is the result of recurrent interactions among family members (Carr, Cole, Ring, & Blettner, 2011), which are framed by the shared history, beliefs and assimilated norms portraying the "moral infrastructure" of the family (Sorenson & Bierman, 2009; Sorenson et al., 2009). At the base of bonding social capital lies the trust and commitment of family members (Salvato & Melin, 2008) along with the exclusive identity (Pearson et al., 2008). Built up over time as relationships intensify, trust is a crucial element of family cooperation and individual commitment toward the business (Pearson et al., 2008). Reciprocity and mutual obligations among family members develop a supportive culture and collectivistic orientations (Arregle et al., 2007; Azizi, Salmani Bidgoli, Maley, & Dabić, 2022). The unique identity originating from the interconnections between the family and firm values and beliefs systems (Zellweger, Eddleston, & Kellermanns, 2010), sets defined boundaries distinguishing members from the outside (Herrero, 2018). While close-knit relationships also extend to non-family members who become an extension of the family (Amato, Patuelli, Basco, & Lattanzi, 2021), the family social capital engenders the development of the firm's organizational social capital (Arregle et al., 2007; Herrero et al., 2022).

The second layer of social capital configuration in family firms is the bridging social capital stemming from family firm interactions with economic and social actors beyond the organizational boundaries (Debellis et al., 2022; Salvato & Melin, 2008). Built on the bonding social capital, the bridging one is source of several benefits, including the increased ability to gather information, gain power or better placement within the network, or recognize new opportunities in the regional context (Adler & Kwon, 2002; Randerson et al., 2021). Bridging social capital may be especially valuable for family firms because they are highly dependent upon their immediate surroundings (Backman & Palmberg, 2015). Family firms are, indeed, intrinsically spatial, that is more responsive to the geographical distance and unevenness of key resources than non-family counterparts (Amato, Backman, & Peltonen, 2020). Family firms are also inherently territorial (Pallares-Barbera, Tulla, & Vera, 2004), that is heavily reliant on their regional context in conducting business operations (Amato et al., 2021).

Two main attributes of family firms' bridging social capital may explain their distinctive ability to appropriate the location advantages. First, while family members may mobilize their social and professional networks for the benefit of the firm (Uhlaner, Matser, Berent-Braun, & Flören, 2015), the centrality of family members in these networks eases access to valuable resources (Chang et al., 2009; Salvato & Melin, 2008). The second attribute is related to the network closure of family firms (Salvato & Melin, 2008). Network closure is the extent to which actors in a regional network have relationships with one another (Malecki, 2012) or, economically speaking, the degree to which a firm's economic activity is "embedded in concrete, ongoing systems of social relations" (Granovetter, 1985, p. 487). Family firms are strongly embedded in the regional social, economic, and productive networks (Basco, 2015; Bird & Wennberg, 2014), which eases access to and allocation of regional resources (Baù, Chirico, Pittino, Backman, & Klaesson, 2018). Family firm embeddedness is deepened by a strong sense of regional belonging based on shared social and cultural values, and common language (Amato et al., 2020), which molds the localized networks into trust-based and reciprocal bonds (Córcoles-Muñoz, Parra-Requena, García-Villaverde, & Ruiz-Ortega, 2020). These, in turn, reduce uncertainty and facilitate cooperation with economic agents (Boschma, 2005), thereby ensuring the acquisition of tangible and intangible resources and the identification of valuable business opportunities (Cucculelli & Storai, 2015; Randerson et al., 2021).

While the bridging social capital assists family firms in discovering and accessing regional resources and business opportunities (i.e., exploration), the bonding dimension helps family firms make use of them (i.e., exploitation) (Salvato & Melin, 2008). From this perspective, strategic flexibility allows family firms to make quick adjustments to their strategic plans in line with the changes occurring in their immediate surroundings (Grant, 2003). In this vein, Zahra et al. (2008) point out that strategic flexibility is particularly beneficial in highly competitive regions where "it helps firms maintain competitiveness in the face of rapid spillovers of new knowledge, continuous innovation, or frequent technological discontinuities" (2008, p. 1037). Specifically, family firms' decision-making usually occurs in impromptu, informal meetings, and collaborative dialogue (Casillas, Moreno, & Barbero, 2011; Sorenson et al., 2009) within a highly centralized, non-hierarchical structure (Craig, Dibrell, & Garrett, 2014). The sense of unity among family members and convergence towards the business goals (Zahra et al., 2008), may result in a greater internal orchestration (Craig et al., 2014), resource mobilization (Estrada-Robles et al., 2021), and the potential to exploit spatially-bounded assets and fast-growing business opportunities, mainly when located in highly-competitive regional environments (Casillas, Moreno, & Barbero, 2010).

Based on the arguments above, though all firms may benefit from location in competitive regional environments, family firms are better equipped to capitalize on the spatial benefits these regions offer, thus achieving higher productivity levels than non-family counterparts. This leads to the formulation of our second hypothesis:

Hypothesis 2: The positive influence of regional competitiveness on firm productivity is higher for family firms than for non-family counterparts.

3. Data, variables and econometric approach

3.1. Data

This study relies on longitudinal microdata from a sample of Spanish manufacturing firms. Spain represents a suitable setting for the purpose of our study for several reasons. First, because of wide and persistent disparities across Spanish regions in a number of areas aside from income, such as well-being, education, labor markets, innovation and infrastructure (McGowan & San Millán, 2019). Second, because family firms represent the backbone of the Spanish economy, accounting for almost 90% of the private firms and contributing to nearly 67% of employment and 57% of Spain's GDP (IEF, 2017). Finally, the incidence of family firms is particularly notable in the manufacturing sector, where they account for 83% of total businesses (IEF, 2017)[4].

In particular, we use Spanish micro-level data from the Survey on Business Strategies (ESEE) carried out by the SEPI foundation[5] in agreement with the Ministry of Industry, Trade and Tourism. ESEE is oriented towards capturing fine-grained yearly information on a representative sample of manufacturing firms[6]. In doing so, ESEE combines exhaustiveness and random sample criteria. Specifically, while all firms with more than 200 employees are surveyed, those up to 200 employees are selected by means of a stratified, proportional and systematic sampling procedure with random seed. The initial sample consists of 77,924 firm-year observations distributed across 5,556 firms for the period 2002-2015. After removing observations with missing data[7], we obtain a final sample consisting of 3,771 firms across 20

[4] The Instituto de la Empresa Familiar (IEF) is a non-profit organization owned by a hundred Spanish family firms, leaders in their respective sectors. Since its foundation in 1992, IEF is the main representative of family firms in Spain. For more information about the IEF, please refer to: www.iefamiliar.com.
[5] For more information on SEPI foundation, please refer to: https://www.sepi.es/en.
[6] Since ESEE is based on self-reported data, concerns related to response bias may potentially arise. However, the fact that survey participation takes place in strict anonymity and confidentiality mitigates considerably the risks associated with mis-reporting.
[7] Since our focus is on the regional context, we have removed all the observations without a regional code. Few missing values have emerged in creating the other variables (all the percentages are less than 1%, except for debt on liabilities with a percentage of missing values equal to 3.8%).

industries at NACE Rev. 2 two-digit[8] and 17 Spanish autonomous communities for the period 2002-2015, thus resulting in 23,662 firm-year observations.

Regional information is drawn from publicly available databases of Eurostat and OECD at NUTS 2 level[9]. This territorial administrative unit represents the main geographical scope for public policy intervention programs (Capello & Perucca, 2018) and has been largely employed in previous studies investigating the relationship between firms and regional contexts (López-Bazo & Motellón, 2018; Tojeiro-Rivero & Moreno, 2019).

3.2. Variables

3.2.1. Dependent variable. As an indicator of a firm's performance, we adopt labor productivity as expressed by the log value added per employee[10] that been widely used to investigate the regional influence on firm growth (Fazio & Piacentino, 2010; Raspe & van Oort, 2011). Additionally, labor productivity is preferred to other measures of performance (e.g., employment and sales growth) particularly when it comes to manufacturing industries consisting of firms investing in labor-saving innovations (van Oort et al., 2012).

3.2.2. Independent variables

3.2.2.1. Family firm. We base the definition of the family firm on the so-called demographic approach (Basco, 2013), which considers the family's involvement as a sufficient condition

[8] NACE is the abbreviation for "Nomenclature statistique des activités économiques dans la Communauté européenne" and represents the European standard classification of productive economic activities. Particularly, ESEE adopts the NACE Rev. 2 classification implemented in 2006. For more information on NACE classification, please refer to: https://ec.europa.eu/eurostat/web/nace-rev2.

[9] NUTS stands for 'Nomenclature of Territorial Units for Statistics' and represents the level of territorial divisionfor statistical purposes. The Spanish territory is divided in the following levels: NUTS 1 consists of seven groups of autonomous communities (Agrupación de comunidades autónomas); NUTS 2 comprises 19 autonomous communities and cities (Comunidades y ciudades autónomas); NUTS 3 is made up of 59 provinces and islands (Provincias, Islas). However, the ESEE excludes the autonomous cities of Ceuta and Melilla, thus leaving 17 autonomous communities. For more information on NUTS classification, please refer to: https://ec.europa.eu/eurostat/web/nuts/background.

[10] Given the wide time-span of our data and, hence, to consider inflation, value added and all the monetary variables have been deflated using the production price index, retrieved from the Instituto Nacional de Estadística (INE), for each industry at the NUTS 2 level.

to capture its effect on the organization[11]. To each firm participating in the survey is asked how many family members hold managerial positions. Following previous studies (Amato et al., 2021; Nieto, Santamaria, & Fernandez, 2015), we created a dummy variable coded "1", if one or more members of the owner family are involved in managerial positions, "0" otherwise;

3.2.2.2. Indicator of Regional Competitiveness (IRC). In the vein of Fazio & Piacentino (2010), we create a synthetic indicator of regional competitiveness, which accounts for the ability of a given territory to offer the best contextual conditions – based on a set of social, economic and technological dimensions – to prosper for firms and economic actors located therein (Budd & Hirmis, 2004). Specifically, we started with 12 regional statistics retrieved from publicly accessible databases for 2002-2015 and listed in table 1. These capture the regional endowment in terms of knowledge base (employment in technological and knowledge-intense sectors, intramural R&D expenditure, patent applications, R&D personnel and researchers), human capital (persons with tertiary education employed in science and technology, population by educational attainment, the participation rate in education and training), socio-economic conditions (regional GVA per worker, unemployment rate, percentage of NEET and infant mortality rate[12]) and physical connectivity (i.e., infrastructure) across the 17 Spanish autonomous communities. They represent the bases of the regional competitiveness identified by Kitson et al. (2004).

[INSERT TABLE 1 AROUND HERE]

[11] Grounded on the behavioural perspective and the resource-based view of the firm, the essence approach complements the demographic approach. For an in-depth analysis of the two aforementioned approaches, please refer to Basco (2013).

[12] By accounting for regional disparities in living conditions (Van Raalte, Klüsener, Oksuzyan, & Grigoriev, 2021), the regional mortality rate in general and the infant one in particular signal persistent spatial imbalances (Kibele, Klüsener, & Scholz, 2015), especially in terms of the well-being of a given community and its environmental development (Fantini, Stivanello, Dallolio, Loghi, & Savoia, 2006). The infant mortality rate usually displays noteable sub-national geographical variations (Rosicova et al., 2011). For these reasons, we considered information on the infant mortality rate in building our synthetic indicator of regional competitiveness.

Then, a principal component analysis (PCA) was carried out to collapse this set of variables into a single composite indicator of regional competitiveness (IRC), which will be entered into the models as additional regressor in addition to firm-level explanatory variables (Fazio & Piacentino, 2010; Srholec, 2010). PCA is a multivariate statistical method used to reduce the dimensionality of the data while minimizing information loss (Jollife & Cadima, 2016). The smaller number of variables – the principal components – are given by the uncorrelated linear combinations of the original ones. Eigenvalue and eigenvector of the PCA by year are reported in Table 2. Following similar studies (Gumbau Albert, 2017; Rodríguez-Pose & Crescenzi, 2008), we retained only the first component, which accounts for the largest possible variance in the data set. As shown in Table 2, the first principal component accounts for more than 50% of the total variance present in the 12 original variables across the period 2002-2015 with an eigenvalue consistently above 6 in the same period[13]. The eigenvector displays a certain similarity of the coefficients over time. The Kaiser-Meyer-Olkin (KMO) test score is above the minimum threshold of 0.50 in the years in question (Hair, Black, Babin, & Anderson, 2019), which suggests our analysis meets the criteria of sampling adequacy[14]. Bartlett's test of sphericity is significant ($p<0.05$) (Hair et al., 2019), indicating that sufficient correlations exist among the variables. Thus, overall, the data are suitable for a dimension-reduction technique such as the PCA.

[INSERT TABLE 2 AROUND HERE]

[13] With a value of 56.06% in 2002-2015, we may consider the percentage of total variance explained by the first component as satisfactorily. Indeed, it is in line with previous studies such as Fernández-Serrano, Martínez-Román, & Romero (2019) (56.15%) and Gumbau Albert (2017) (54.22%) or even higher. For instance, in Rodríguez-Pose & Crescenzi (2008) and Coshall, Charlesworth, & Page (2015), the first component explains only 43.1% and 29.39% of the total variance, respectively.

[14] The KMO test value is similar to that found in previous studies dealing with regional statistics. For instance, in (Rizzi, Graziano, & Dallara, 2018) the KMO test score ranges from 0.60 to 0.71. Galluzzo (2021) reported a KMO test value equal to 0.64, while in Dallara & Rizzi (2012) the score is even lower than the threshold of 0.5, amounting to 0.475.

The synthetic indicator obtained from the PCA is such that higher (positive) values signify a better regional business environment and vice versa. Finally, the indicator's value was rescaled to be in the range 0-1, thereby ensuring both regional and temporal comparability.[15]

3.2.3 Control variables. We control for a set of firm-specific characteristics potentially affecting labor productivity. We use the ratio of the firm's R&D expenditure to sales (*R&D intensity*) to capture the absorptive capacity. To account for the firm's innovative outcomes, we include a dummy variable which takes value "1" if the firm has introduced product (process) innovation, "0" otherwise (*Product* and *Process innovation*). The log of total employees and the percentage of external funding on total funds account for size (*Size*) and indebtedness (*Leverage*), respectively. We control for the firm's age by computing the number of years from its foundation (*Age*). We control for investment in human capital as weighted percentage of training expenses on total labor cost (*Employee T&D*). To capture the firm's involvement in international trade, we include the weighted percentage of both export and import on total sales (*Export intensity* and *Import intensity*). We include a dummy variable coded "1" if the firm is part of a corporate group and "0" otherwise (*Group*). We control for the firm's listing by including a dummy variable equal to "1" if it is publicly-traded, "0" otherwise (*Listed*). We control for foreign shareholding proxied by the percentage of the firm's equity held by foreign investors (*Foreign*). To account for firm anchorage in the territorial setting, we include a dummy variable coded "1" if the local area represents the main market for the firm and "0" otherwise (*Territorial embeddedness*). Finally, we check whether the firm's labor productivity is affected by time-invariant unobserved heterogeneity across

[15] The European Commission in the EU Regional Competitiveness publishes the Regional Competitiveness Index (RCI) measuring, with more than 70 comparable indicators, the major factors of competitiveness for all the NUTS-2 level regions across the European Union. The latest report is the fourth edition and refers to 2019. The previous editions refer to 2010, 2013 and 2016. Therefore, our indicator differs in a minor number of indicators and on the covered period. Considering the values of 2013, we have compared the two indicators with the Spearman rank correlation and we obtained a value equal to 0.91, demonstrating that our indicator and the RCI are highly correlated.

industries. For this, we include the industry dummies aggregated according to the taxonomy proposed by Eurostat, namely low-tech, medium-low, medium-high, and high-technology[16]. Table 3 summarizes the variables employed in the study.

[INSERT TABLE 3 AROUND HERE]

3.3. Econometric approach

Our aim is to analyze how firm-level characteristics and the regional context may influence labor productivity and, in particular, whether and to what extent the competitiveness of the regional business environment differs for the performance of family and non-family firms. Due to the hierarchical structure of the data – with firms that are clustered in regions – the proper technique is to use a multilevel approach. In a multilevel model, variables at different levels are not simply add-ons to the same single-level equation, but linked together in ways that make the simultaneous existence of distinct level-one and level-two equations explicit. Hence, level-two variables are used to explain not only the variability in a level-one dependent variable, but also the variability in random intercepts and random slopes (Bickel, 2007). Multilevel modeling, therefore, allows us to control for spatial dependence and overcome the ecological and atomistic fallacies (Raspe & van Oort, 2011).[17] For these reasons, multilevel modeling represents a unique estimation to show how "contextual effects

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[16] Eurostat bases the level of technological intensity on the R&D expenditure/Value added ratio. In doing so, the following groups of manufacturing activities at 2-digit level of NACE Rev. 2 classification are identified: i) *High-technology*, consisting of Manufacture of basic pharmaceutical products and pharmaceutical preparations (21) and Manufacture of computer, electronic and optical products (26); ii) *Medium-high technology*, which consists of Manufacture of chemicals and chemical products (20) and Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c.; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment (27 to 30); iii) *Medium-low technology*, which comprises Manufacture of coke and refined petroleum products (19), Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products; Manufacture of basic metals; Manufacture of fabricated metals products, excepts machinery and equipment (22 to 25) and repair and installation of machinery and equipment (33); iv) *Low-technology*, consisting of Manufacture of food products, Manufacture of beverages, Manufacture of tobacco products, Manufacture of textile, Manufacture of apparel, Manufacture of leather and related products, Manufacture of wood and wooden products, Manufacture of paper and paper products, Printing and reproduction of recorded media (10 to 18) and Manufacture of furniture and Other manufacturing (31 to 32).

[17] Ecological fallacy occurs when a result obtained at an aggregate level is not confirmed after replicating the analysis on an individual basis. In this sense, micro-founded analysis is preferable since it controls for any potential aggregation bias. The atomistic fallacy represents the opposite problem: working with micro-data may lead to the absence of any link between individual-level and group-level relationships (Raspe & van Oort, 2011; van Oort et al., 2012).

translate into individual behavior" (Amara & Thabet, 2019, p. 26) and, therefore, to link micro and macro-level (van Oort et al., 2012). In hierarchically structured data, firms operating in a given region are likely to be more alike than firms in different regions due to cluster-specific factors. Thus, the assumption of independence of errors is violated. This violation translates into an inflated significance of level-two coefficients because tests are made on the number of level-one observations and not on the number of level-two groups.[18]

Moreover, since ESEE dataset is longitudinal, time must be considered. We rely on the so-called growth curve model, in which time is treated as a level 1 explanatory variable.[19] The data, therefore, have a three-level structure with occasions or years (*t*) at level 1, nested with firms (*i*) at level 2 clustered in regions (*j*) at level 3.[20]

[18] One way to overcome this problem is to estimate clustered ordinary least squares (OLS), by relaxing the assumption of independence and adjusting the error term to accommodate the lack of independence of firms within regions. However, clustered OLS leaves both the noise associated with difference between firms and noise associated ,with differences between regions in the error term. On the contrary, the multilevel model goes further by allowing these two error components to be separated.

[19] The basic two-level growth model, with measurement occasions at level one nested within individuals at level two, involves fitting a curve through each firm's productivity (*LP*) to summarize the change in *LP* over the observation period. In this simplest case, a straight line is fitted, and the intercepts of the firm-specific lines are allowed to vary about the average line (Steele, 2014).

[20] In the multilevel approach, the sample size at any level of analysis is a key issue since the requirements of precise measurement of between-group variance impose a 'sufficient' number of clusters. However, there is no clear indication since some authors suggest that 20 is a sufficient number of groups (Rabe-Hesketh & Skrondal, 2006), others 30 (Hox, Moerbeek, & van de Schoot, 2017) or 50 (Maas & Hox, 2004). Stegmueller (2016) in a Monte Carlo experiment shows that as long as more than 15 or 20 groups are available, maximum likelihood estimates and confidence interval coverage of estimated individual and macro effects are only biased to a limited extent, while cross-level interactions tend to be biased downward (p. 758).

In our specification we consider two random intercepts, one for the firm and one for the region[21]; we also allow the slope for the family firm status (FF) to vary across firms and regions.[22]

The reduced form specification of our full model is as follows:

$$y_{tij} = \gamma_{000} + \beta_{100} T + \gamma_{200} FF_{tij} + \gamma_{001} \overline{IRC_j} + \gamma_{202} FF_{tij} * \overline{IRC_j} + \sum_{f=1}^{k} \lambda_f X_{ftij} + \sum_{s=1}^{p} \mu_s S_{si} +$$

$$+ \sum_{f=1}^{k} \varphi_f \bar{X}_{ij} + (u_{00j} + u_{0ij} + u_{20j} FF_{tij} + u_{2ij} FF_{tij} + e_{tij}) \qquad [1]$$

where the dependent variable y_{tij} refers to the value of labor productivity (*LP*) of the *i-th* firm from the *j-th* region in time *t*. *T* is the time indicator[23], thus, β_{100} represents the growth rate that is assumed to be the same for all firms. *FF* represents the family firm status, $\overline{IRC_j}$ the average over 2002-2015 for each region of the regional competitiveness indicator[24], and $FF*\overline{IRC}$ the interaction between these two variables. This represents a cross level interaction and appears in the model by modeling the varying slope of the firm-level variable FF with the regional-level variable $\overline{IRC_j}$ (see Appendix A4)

Moreover, we control for a set of firm characteristics (X_{tij}) and sectorial dummies (*S*). To mitigate the possibility of simultaneity problems, we considered, for all firm level controls,

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[21] Considering the so-called "empty" model, that is a model without covariates, it is possible to calculate the variance partition coefficient (VPC), also known as the intra-class correlation (ICC), which represents the proportion of firms' LP variance explained by each level and is a standardized measure of the similarity between higher-level units (Bell and Jones, 2015), that is:

$$\mathrm{VPC(l)} = \frac{\sigma_l^2}{\sigma_i^2 + \sigma_j^2 + \sigma_e^2}$$

where index l represents either *i*, *j* or *e*. It is worth noting, however, that while for a two-level structure where individuals are nested in groups, the exchangeability assumption, that is the correlation between a pair of responses is the same for any randomly selected pair of individuals from the same group, is plausible, on the contrary, to assume equal correlation when responses have a temporal structure is less realistic as it is probable that outcomes at consecutive times will be more highly correlated than measures that are further apart in time (Steele, 2014). For example, we would expect the correlation to be higher for two consecutive years than for the first and the last year.

[22] More details about the empirical specification are provided in Appendix A4 in the supplemental data online.

[23] T has been recorded to 0, 1, 2....15, calculated as the difference between each year and the first one, 2002.

[24] In a multilevel framework, the variables of the higher levels cannot vary at the lower levels: "By definition, a cluster-level variable must be constant within clusters" (Schmidt-Catran, Fairbrother, & Andreß, 2019, p. 113). In our case, in order to be a regional-level variable, the IRC value has to be the same for all firms located in a given region. Following Tojeiro-Rivero and Moreno (2019), this can be done by averaging over time our regional variable IRC. The use of the average also has the advantage of eliminating fluctuations.

the previous period values compared with labour productivity. The average of firm-level variables ($\bar{X}_{ij}$) is inserted in order to remove the possibility of correlation between the lower level predictor variables and higher-level error terms, a procedure known as the Mundlak (1978) correction.

The random part of the model is in parenthesis. The first two elements are the random effects on intercept (one for region and the other one for firm), $u_{20j}FF_{tij}$ and $u_{2ij}FF_{tij}$ are the random components related to the FF variable and the error term e_{tij} captures randomness due to time (see Appendix A4 for further details).

4. Empirical results

4.1. Descriptive analysis

Table 4 displays the descriptive statistics. Looking at the Panel 4A, nearly half of the firms in our sample are family firms with an average 28.65 years in business. While almost 20% of firms introduced product innovations, those engaged in process innovations account for over one-third of the sample. More than 20% of sales originate from export activity, and 35% are part of a business group. Panel 4B shows sample differences between family and non-family firms. Family firms are less productive and innovative-oriented, as reflected in the lower R&D intensity and propensity to engage in both product and process innovation, than their non-family counterparts. Additionally, family firms are smaller and less internationalized. Tables A1 and A2 in the Appendix show the sample distribution by size and technological intensity across firm type, family and non-family firms, respectively. Additionally, 70% of family firms are concentrated in the small class (up to 49 employees), and 52% are low-tech.

[INSERT TABLE 4 PANEL 4A-4B AROUND HERE]

The average IRC is around 0.534, given the range 0-1. Figures 1a and 1b display Spanish regions colored according to the indicator value in 2002 and 2015. They highlight the spatial imbalance between the more (darker colors) and less competitive (lighter colors) regions. From a visual inspection there seems to emerge a certain persistence in the gap in competitiveness across Spanish regions with Catalonia, the Basque Country, Navarra, and the Community of Madrid displaying the highest level of the indicator across time. Conversely, the overall improvement of Cantabria, La Rioja, and the Valencian Community stand out against the territorial decline of Castilla-La Mancha and the Canary Islands.

[INSERT FIGURE 1A and 1B AROUND HERE]

Finally, Figure A1 in the Appendix displays the regional density of family firms, found in detail in Table A3. In the Spanish context, family firms represent a ubiquitous phenomenon, for example up to 65% in the Region of Murcia and 68% in Balearic Islands, respectively.

In Table 5, we report the correlations between our regression variables. While the family status of the firm is negatively correlated with productivity, higher level of regional competitiveness is associated with higher level of productivity. Inspection of the variance inflation factors (VIFs) rules out multicollinearity concerns in our data because all VIF coefficients are well below the commonly accepted threshold of 10 signaling multicollinearity distortion (Michael & Abiodun, 2014).

[INSERT TABLE 5 AROUND HERE]

4.2. Regression results

The regression results are displayed in Table 6[25]. The estimates are differentiated between the fixed and the random part of the model. Models 1-2 refer to empty models – that is, without covariates – that allow us to evaluate how much of the variation in labor productivity might be attributable to unobserved factors operating at each level, time, firm, and region in our case (see footnote 20). In Model 1, we consider random effects only at the

[25] It is worth noting that the lagging of all control variables by one year – to mitigate endogeneity concerns – results in the loss of 3,543 firm-year observations. Hence, the sample used in the regression analysis consists of 20,119 firm-year observations distributed across 3,060 unique firms from 2002 to 2015.

firm level. The likelihood-ratio test, which compares this model with the standard linear regression, is highly significant and supports multilevel modeling. In this case, as shown by the VPC at firm level, more than 63% of firm productivity can be attributed to firm-specific characteristics, while nearly 36% to the years. In Model 2, the three levels of nesting are considered together. The likelihood-ratio test, which is highly significant, indicates that the intercepts related to the different groups should be considered as a group-on-group variant coefficient. The LR test comparing Model 2 with Model 1 indicates that the former offers a significantly better data fit[26]. Model 2 shows that the regional context accounts for 6.6% of the variation in firm productivity. This result is consistent with that of Fazio & Piacentino (2010) and Aiello et al. (2014) carried out in the Italian context, Aiello and Ricotta (2016) for European countries, Guevara-Rosero (2021) for Latin America SMEs and Amara & Thabet (2019) for Tunisian firms. Instead, Raspe and Van Oort (2011) found a smaller proportion for manufacturing and business services firms in the case of the Netherlands (2.5%).

Hence, location matters for firm productivity, but regions exert a much less significant role than the firm-specific characteristics. In Model 3, variable *Time* is included in the model. The coefficient is negative and statistically significant (β = -0.015; $p<0.01$) which suggests a downward path in productivity across time. In Model 4, industry dummy variables are entered in the regression, resulting in a reduction in the proportion of variance ascribable to regions. Firms belonging to high-tech industries show higher level of labor productivity than low-tech firms.[27]

Models 5-7 display the independent variables at both firm and regional levels.[28] In particular, in Model 5, the family firm status is entered in the regression. The coefficient of

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[26] The likelihood ratio test is a statistical test of the goodness-of-fit between two models. A relatively more complex model is compared to a simpler model to see if it fits a particular dataset significantly better.
[27] For space reasons, the coefficients for sector dummies are not reported in the table. Results are available upon request.
[28] The Wald test for the means of firm variables shows that all of them are jointly significant in all models.

Family firm is negative but not statistically significant, which suggests that family firms do not differ in terms of productivity from non-family firms. A look at the control variables reveals that firm size (*Size*) is significant and positively related – due to the economies of scale – to productivity. In addition to the size, process innovation (*Process innovation*) and the degree of internationalization (*Export intensity*) positively affect productivity. In Model 6, the IRC is introduced in the regression to assess whether and to what extent regional competitiveness affects firm productivity. As expected, the coefficient of our composite index is strongly positive and statistically significant (β = 0.235; p<0.01), meaning that more competitive regional contexts lead to higher firm-level productivity. This result is in line with the study of Fazio & Piacentino (2010) carried out on Italian SMEs.

To ascertain the existence of a different impact, across family and non-family firms, of regional competitiveness, in Model 7 we introduce a cross-level interaction between *Family firm* and *IRC*[29]. The interaction term coefficient is positive and statistically significant (β = 0.109; p<0.05), which suggests that, localization in more competitive regions has a greater effect on the productivity of family firms than non-family counterparts. We can, thus, conclude that the regional competitiveness matters for the productivity of all firms, but even more for family ones.

[INSERT TABLE 6 AROUND HERE]

For a more straightforward interpretation of this result, we plot the two-way interaction in Figure 2. The figure shows that, as the degree of regional competitiveness heightens, the labor productivity of family firms increases to a greater extent. However, beyond a certain threshold of the indicator of regional competitiveness (i.e., 0.54) family firms outperform non-family firms.

[29] As suggested by Raspe & van Oort (2011), it may that the relationship between regional-level variables and firm productivity is different for certain types of firms. This heterogenous effect can be detected through interactions between variables measured at different levels of hierarchically structured data.

[INSERT FIGURE 2 AROUND HERE]

4.3. Robustness check

To validate the robustness of our results, we carried out additional analysis displayed in Table 7. First, given that the results may be affected by the uneven representation of some groups, we investigated to what extent our findings are influenced by group size (Fazio & Piacentino, 2010; van Oort et al., 2012). Hence, we ran separate regressions where groups with either the smallest (i.e., La Rioja) or largest firm-year observations (i.e., Cataluña) have been dropped from the sample as shown in Model 1 and Model 2, respectively. Second, we removed from the sample large firms with more than 1,000 employees (Model 3). Third, in Model 4, instead of using the dichotomous variable *Family firm*, we used the continuous variable counting the number of family members in a managerial position (*Family management*). Fourth, we resorted to a single-level model with random effects at the firm level to estimate the coefficients, as shown in Model 5[30]. Fifth, we also estimated a model in which for sectors we use a set of dummies grouping firms according to the two-digit NACE classification instead of the technological one[31,32]. Finally, to compare more balanced groups, we used the Coarsened Exact Matching (CEM) algorithm (Blackwell, Iacua, King, & Porro, 2010). The goal of this procedure is to prune observations from the data so that the remaining part has a better balance between the treated (i.e., family firms) and the control (i.e., non-family firms) groups, meaning that the empirical distributions of the covariates in the groups are more similar (Blackwell et al., 2010). We have estimated a pooled cross-section model on

[30] Due to the presence of a number of firms with less than three observations (30%) we do not use fixed-effects approach as the estimated group-effect is unreliable for small-sized groups while for random-effects models only the clusters must be sized with at least two observations.
[31] Results are available on request.
[32] We also performed a sub-sample analysis based on the family firm status. The results reveal the magnitude of the IRC coefficient is much greater for the family firm-related sample than for non-family firms ($\beta = 0.528$; $p < 0.001$ vs. $\beta = 0.161$; $p < 0.1$). Results are available on request.

matched units (results are available on request)[33]. The findings of the additional analysis are consistent with those obtained in the main analysis, thus confirming our results.

5. Discussion

In a bid to outline the local conditions that enable firms to thrive in their chosen market, the concept of regional competitiveness has attracted growing interest among academics and policymakers (Annoni & Kozovska, 2010; Budd & Hirmis, 2004). Existing research shows the influence of the regional environment on a firm's economic performance (López-Bazo & Motellón, 2018; van Oort et al., 2012), yet firms may not benefit equally from the regional externalities due to several firm-specific characteristics (Hervas-Oliver et al., 2018; Raspe & van Oort, 2011). Our aim, therefore, was to extend this line of research by considering the family status of the firm – that is the involvement of a family in the firm's management– as a unique firm-specific characteristic that may play a contingent role in the regional competitiveness-firm productivity link. Stemming from social capital theory, we conjectured that due to their unique social capital, family firms are better positioned to capitalize on the spatial advantages of being located in highly competitive regions.

To this end, we studied a sample of Spanish manufacturing firms for the period 2002-2015. Multilevel modeling was employed to link the firm and regional level simultaneously, thereby exploiting the nested structure of the data to estimate the extent to which firm productivity is related to unobserved factors operating at each level, time, firm, and region. Indeed, variance decomposition reveals that even though most of the variability in productivity can be attributed to firm-specific characteristics, location still matters, given that regional location explains 6.6% of labor productivity variability.

This study brought three main empricial findings. First, we found that the family firm status is not associated with productivity *per se*. Family involvement in the firm alone does

[33] We performed the CEM procedure with the command "cem" on Stata and matched on five variables, namely *Age*, *Size*, *Industry, Listed*, and *Foreign*.

not result in higher productivity levels than in non-family firms. Second, the sign and magnitude of the indicator of regional competitiveness – stemming from distilling a pool of regional variables into a composite index – shows that locational advantages can turn into higher productivity gains. Hence, this result provides evidence that, aside from internal attributes, a regional effect accounts for firms' productivity gains. However, and this is our third finding, cross-level interaction reveals that the influence of regional competitiveness on productivity is stronger for family firms than their non-family counterparts. In other words, regional competitiveness is a source of spatial advantages for indigenous firms, but more so for family firms than for non-family counterparts.

Family firms benefit to a greater extent from their location in highly competitive regions. Specifically, beyond a certain threshold of the regional competitiveness index (i.e., 0.54), family firms are able to turn a better regional business environment into productivity differentials vis-à-vis non-family firms. In such contexts, in line with the social capital theory (Arregle et al., 2007; Sorenson & Bierman, 2009), the fabric of relationships inside and outside the organizational boundaries allows family firms to reap the localization benefits, positively affecting firm performance (Herrero et al., 2022; Sorenson et al., 2009). Family members may mobilize their professional and personal networks to discover and access regional resources and business opportunities (Salvato & Melin, 2008). Network mobilization is engendered by the collective action stemming from trust-based and reciprocal ties between family and non-family members (Estrada-Robles et al., 2021; Uhlaner et al., 2015). The embeddedness of family firms in the regional networks (Bird & Wennberg, 2014), thus eases the recognition of the resources and opportunities available in highly competitive regional environments (Randerson et al., 2021). Together, the social capital of family firms results in strategic flexibility that, backed by adaptable and informal decision-making practices (Chirico & Bau, 2014), collaborative dialogue (Sorenson & Bierman, 2009; Sorenson et al., 2009), convergence towards the business goals (Zahra et al., 2008), and a common language

(Herrero, 2018) furthers the exploitation of such locational advantages, thus resulting in higher productivity levels.

6. Contributions

This study makes several contributions. First, by addressing the call for research to connect family business and regional development (Basco, 2015; Basco et al. 2021), this study contributes to the current debate on firm-level heterogeneity in regional studies (López-Bazo & Motellón, 2018; van Oort et al., 2012), questioning what types of firms profit the most from the location in highly competitive regions. Regional externalities positively affect the productivity of local firms, yet heterogenous firms may reap the most from their location (Kitson et al., 2004). In this perspective, our study shows that family firms are better positioned to turn such locational advantages (when located in highly-competitive regions) into higher productivity levels. This finding sheds new light on the uneven consequences of regional externalities on firms' productivity. While previous studies have shown that productivity differentials among co-located firms depend on some firm characteristics such as size (van Oort et al., 2012), capital intensity (Fazio & Piacentino, 2010), and age (Amara & Thabet, 2019) among others, our research reveals that the family nature of the firm is also a crucial element in the uneven consequences of regional externalities on firms' productivity. Our explanation is that a unique multilayered social capital – involving the social relationships both within and outside the organizational boundaries – allows family firms to benefit the most from regional competitiveness. As such, social capital becomes a key asset in understanding the uneven influence of location between family and non-family firms.

Second, this study contributes to family business research by providing new evidence on the unresolved issue of family business productivity. The current empirical evidence is inconclusive on whether family firms are more (Martikainen et al., 2009) or less (Neckebrouck, Schulze, & Zellweger, 2018) productive than non-family firms. One explanation of this contradiction could be that the discussion to date has largely neglected the influence of the regional context in accounting for productivity differentials of family *vis-à-vis* non-family firms. Put differently, the investigation of family firms' productivity has been context-less. By challenging this research gap and making this strand of research context-sensitive (Amato et al., 2021), our study reveals new facets of the family firm-productivity link. Along with firm-level dimensions, context matters for explaining productivity differentials between family and non-family businesses. In other words, omitting contextual dimensions in the investigation of family and non-family firm's productivity may bias the empirical analysis leading to erroneous conclusions.

Finally, one policy implication of this study is that, besides internal-specific characteristics, productivity is strongly affected by a set of features and conditions within a region as a source of increasing returns for all firms located therein (Kitson et al., 2004; Rodríguez-Pose & Hardy, 2017). Hence public policy interventions should aim at enhancing regional competitiveness acting upon the regional knowledge base, human capital endowment, socio-economic conditions, and physical connectivity that, together, "reflect the capability of a region to attract and keep firms with stable or increasing market shares in an activity, while maintaining stable or increasing standards of living for those who participate in it" (Bristow, 2005, p. 289). However, the authorities should also pay attention to the type of firms since family firms – because of their unique social capital – benefit the most from location in competitive regions. That implies that the same policy intervention may produce different effects depending on the territorial composition given by the prevalence of family firms. Since regional externalities foster regional economic growth indirectly through their effect on productivity (van Oort et al., 2012), enhancing regional competitiveness would further support such localized growth, depending on the prevalence of family firms.

7. Future research avenues

Given the limitations of this paper, we suggest areas for further research. First, our study relies on a demographic approach to define family firms. Future research should investigate the regional influence on productivity using multiple definitions of family firms, such as those integrating the essence approach accounting for soft factors such as the family's vision and intentions (Basco, 2013). Second, the cross-level interaction between family firms and regional variables is worth further investigation because of their heterogeneity (Chua, Chrisman, Steier, & Rau, 2012). Indeed, not all family firms but only specific ones – depending, for instance, on the generation in charge of the business – may profit from the degree of regional competitiveness. Third, we did not measure the firms' bonding and bridging dimensions of social capital (Carr et al., 2011; Debellis et al., 2022). This could open the way for future studies – based on primary data – to empirically test the interplay of social capital and regional competitiveness and the influence on the productivity of family and non-family firms. Fourth, the current multilevel analysis does not fully account for the spatial dependence present in the data. Indeed, firm productivity may be influenced by productive spillovers arising from geographical proximity to other firms. Failure to fully account for spillover effects may underestimate the importance of space when investigating firm performance (van Oort et al., 2012). Hence, future studies should combine hierarchical with spatial econometrics models to account for spatial heterogeneity in the data (Lacombe & McIntyre, 2016). Fifth, since our study relies on productivity, there is room in future work for investigating the regional influence on outcomes by employing non-financial measures such as innovativeness (Srholec, 2010), survival (Ferragina & Mazzotta, 2015) and new venture creation (Bird & Wennberg, 2014), among others. Sixth, since our sample consists of firms located in a developed country such as Spain, future research could also consider the family firm-territory "nexus" in emerging countries (Schmutzler & Lorenz, 2018) or transition economies, which are characterized by wide regional disparities (Fan, Kanbur, & Zhang, 2011). Finally, by shifting from "regions" to "territory," future research should explore the interplay between the territorial capital – as theorized by Camagni & Capello (2013) – and the locational advantages of family and non-family firms.

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Table 1. Regional variables

n.	Variable	Description	Unit	Source	Obs.	Mean	Std. dev.
1	Employment_T&K	Employment in technology and knowledge-intense sectors by manufacturing	Percentage	Eurostat	238	15.40	6.32
2	Pop_S&T	Persons with tertiary education employed in science and technology	Percentage	Eurostat	238	16.50	3.96
3	GERD	Intramural R&D expenditures on Gross Domestic Product (GDP)	Percentage	Eurostat	238	1.00	0.46
4	Patent	Patent application	Per million inhabitants	OECD	238	28.45	22.79
5	R&D personnel	R&D personnel and researchers by sector	Percentage	Eurostat	238	0.92	0.44
6	Pop_Edu	Population aged 25-64 by educational attainment level	Percentage	Eurostat	238	29.98	6.83
7	E&T	Participation rate in education and training	Percentage	Eurostat	238	9.50	2.90
8	Value Added	Regional GVA per worker	Euro (current prices)	OECD	238	7716.90	7779.23
9	Unemployment	Unemployment rate	Percentage	Eurostat	238	15.20	7.54
10	NEET	Young people neither in employment nor in education and training	Percentage	Eurostat	238	14.10	3.97
11	Infrastructure	Road, rail and navigable inland waterways networks	Kilometres per thousand square kilometres	Eurostat	238	34.81	20.02
12	Mortality	Infant mortality rates	Percentage	Eurostat	238	3.32	0.93

Note: Variables are standardized before entering the PCA.

Table 2. Eigenvalue and eigenvectors by year

Component 1 (PCA)	2002	2003	2004	2005	2006	2007	2008
Eigenvalue (% of variance)	6.19938(0.5166)	6.0949(0.5079)	6.19554(0.5163)	6.77302(0.5644)	6.83664(0.5697)	6.48176(0.5401)	7.04364(0.5870)
Eigenvector							
Employment_T&K	0.2548	0.2831	0.2858	0.2307	0.2215	0.2599	0.2322
Pop S&T	0.3601	0.3436	0.3571	0.3514	0.3476	0.3540	0.3486
GERD	0.3640	0.3609	0.3641	0.3484	0.3413	0.3702	0.3575
Patent	0.3301	0.3314	0.3240	0.3178	0.3287	0.3177	0.3208
R&D personnel	0.3781	0.3812	0.3801	0.3645	0.3528	0.3773	0.3586
Pop Edu	0.3781	0.3716	0.3696	0.3627	0.3611	0.3714	0.3551
E&T	0.0621	0.0214	-0.0699	0.2908	0.2497	0.1980	0.2458
Value Added	0.2175	0.2033	0.2094	0.1873	0.1746	0.1642	0.1669
Unemployment	-0.2353	-0.2417	-0.2517	-0.2460	-0.2650	-0.2629	-0.2566
NEET	-0.2759	-0.2836	-0.2981	-0.2664	-0.3070	-0.2876	-0.2592
Infrastructure	0.2827	0.2615	0.2345	0.2381	0.2306	0.2468	0.2526
Mortality	-0.1371	-0.1711	-0.1278	-0.1542	-0.2004	-0.0997	-0.2325
Kaiser-Meyer-Olkin test	0.5571	0.5345	0.6804	0.6462	0.4888	0.6934	0.8039
Bartlett's sphericity test χ^2 (p-value)	166.677 (0.000)	184.211 (0.000)	176.009 (0.000)	195.389 (0.000)	201.458 (0.000)	169.390 (0.000)	185.708 (0.000)

continues

Component 1 (PCA)	2009	2010	2011	2012	2013	2014	2015
Eigenvalue (% of variance)	6.73343(0.5611)	7.12667(0.5939)	7.11301(0.5928)	7.06299(0.5886)	6.91606(0.5763)	6.67978(0.5566)	6.9259(0.5772)
Eigenvector							
Employment_T&K	0.2574	0.2688	0.2395	0.2422	0.2252	0.2312	0.2343
Pop_S&T	0.3606	0.3442	0.3398	0.3420	0.3504	0.3562	0.3570
GERD	0.3652	0.3430	0.3532	0.3501	0.3484	0.3586	0.3467
Patent	0.3333	0.3164	0.3078	0.3207	0.3159	0.2853	0.3039
R&D personnel	0.3669	0.3511	0.3603	0.3585	0.3616	0.3681	0.3576
Pop_Edu	0.3606	0.3537	0.3541	0.3584	0.3606	0.3695	0.3615
E&T	0.2172	0.2074	0.2411	0.2331	0.2386	0.2201	0.2358
Value Added	0.1627	0.1372	0.1537	0.1640	0.1820	0.1845	0.1847
Unemployment	-0.2831	-0.3018	-0.3004	-0.3044	-0.2974	-0.2960	-0.2918
NEET	-0.2562	-0.3052	-0.3035	-0.3135	-0.2939	-0.3052	-0.3097
Infrastructure	0.2590	0.2267	0.2556	0.2620	0.2825	0.2717	0.2598
Mortality	-0.0903	-0.2138	-0.1514	-0.0350	-0.0009	-0.0262	-0.0908
Kaiser-Meyer-Olkin test	0.6696	0.7747	0.6903	0.6395	0.8170	0.7711	0.6735
Bartlett's sphericity test χ^2 (p-value)	193.939 (0.000)	205.518 (0.000)	196.273 (0.000)	200.867 (0.000)	185.308 (0.000)	196.452 (0.000)	206.866 (0.000)

Figure 1a

IRC 2002

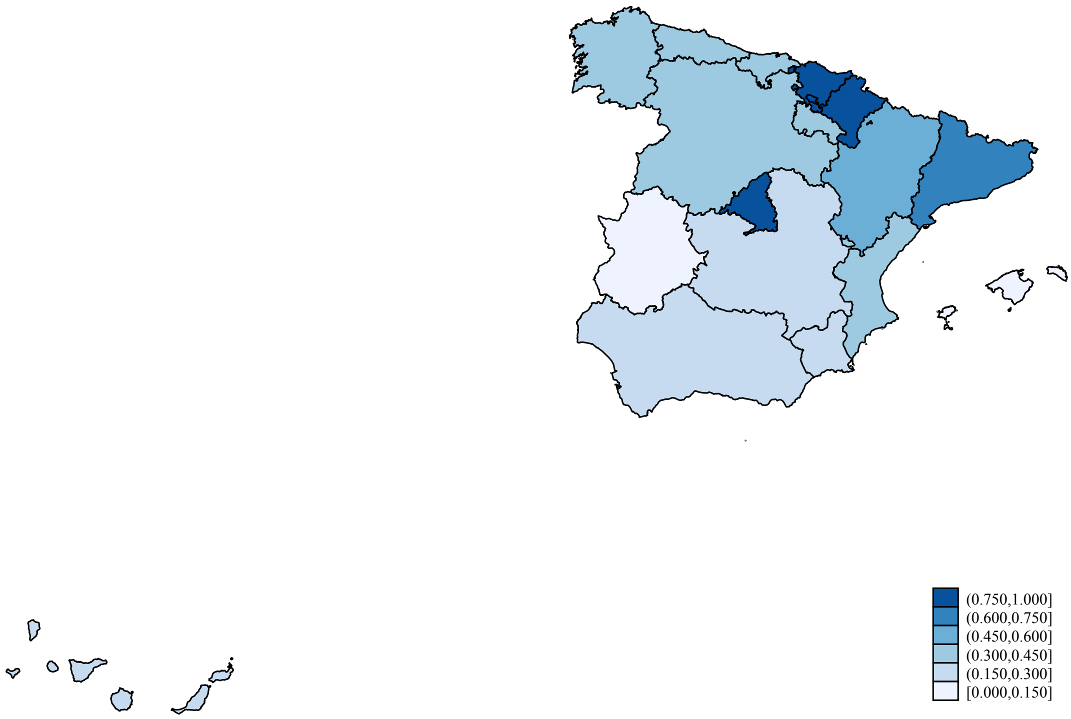


Figure 1b

IRC 2015

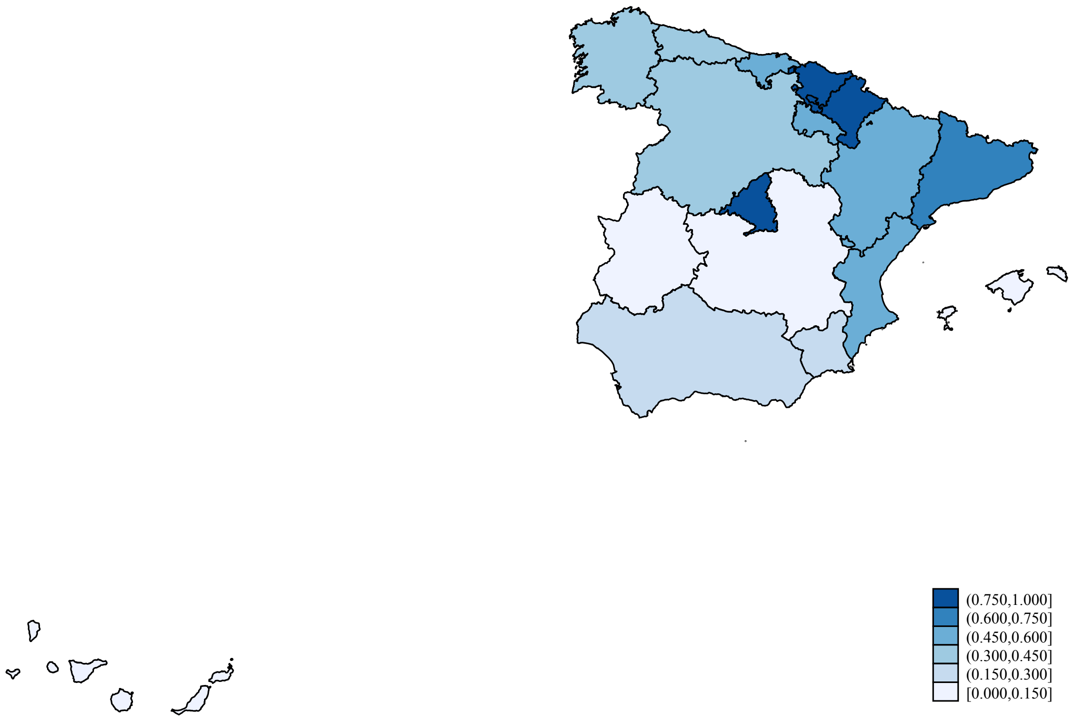


Table 3. Variable definition

Variable	Description
Dependent variable	
Productivity	Value added per employee taken in logarithm
Independent variable	
Family firm	Dummy variable coded "1" whether one or more family members of the owing family hold managerial positions, "0" otherwise
Indicator of Regional Competitiveness (IRC)	Composite indicator of regional competitiveness stemming from the PCA
Control variables	
R&D intensity	Ratio of firm's R&D expenditures to sales
Product innovation	Dummy variable coded "1" if the firm has introduced product innovation, "0" otherwise
Process innovation	Dummy variable coded "1" if the firm has introduced process innovation, "0" otherwise
Size	Number of total employees in logarithm
Age	Number of years since its establishment
Leverage	Percentage of external funds on total funding sources
Employee T&D	Ratio of training expenses to total labor cost
Export intensity	Ratio of firm's foreign sales to total sales
Import intensity	Ratio of firm's purchases to total sales
Group	Dummy variable coded "1" if the firm is part of a business group, "0" otherwise
Listed	Dummy variable coded "1" if the firm is publicly-listed, "0" otherwise
Foreign	Percentage of equity held by foreign investors

Territorial embeddedness	Dummy variable coded "1" if the local area represents the main market for company, "0" if the firm operates in other market (provincial, regional, national, abroad, national and abroad)
Industry	Dummies for each of 4 macro-aggregation according to the level of technological intensity and based on NACE Rev. 2 codes: 1) low-tech; 2) medium-low tech; 3) medium-high tech; 4) high-tech.
Year	Year dummies

Table 4. Descriptive statistics

Panel 4A: summary statistics for the whole sample

	Obs	Mean	St.Dev	Median	Min	Max
Productivity^{L}	*23,662*	3.551	0.657	3.554	-2.172	8.043
Family firm	*23,662*	0.496	0.5	0	0	1
IRC	*23,662*	0.534	0.261	0.459	0	1
R&D intensity	*23,662*	0.768	2.501	0	0	98.924
Product innovation	*23,662*	0.194	0.396	0	0	1
Process innovation	*23,662*	0.324	0.468	0	0	1
Size^{L}	*23,662*	4.150	1.442	3.912	0	9.575
Age	*23,662*	28.649	20.079	24	0	175
Leverage	*23,662*	54.319	23.646	55.65	0	100
Employee T&D	*23,662*	0.246	2.303	0	0	274.6
Export intensity	*23,662*	21.705	28.315	6.5	0	100
Import intensity	*23,662*	9.906	14.342	2.8	0	62.1
Group	*23,662*	0.358	0.479	0	0	1
Listed	*23,662*	0.019	0.138	0	0	1
Foreign	*23,662*	14.784	34.608	0	0	100
Territorial embeddedness	*23,662*	0.060	0.237	0	0	1

Note: ^{L}expressed in natural logarithm

Panel 4B: difference of means

Variable	Non-family firms	Family firms	Test for difference of means	
			Difference of means	t-statistics
Productivity[L]	3.708	3.391	0.317	38.26***
R&D intensity	0.926	0.607	0.318	9.821***
Product innovation	0.231	0.157	0.075	14.593***
Process innovation	0.364	0.284	0.08	13.191***
Size[L]	4.771	3.518	1.254	74.258***
Age	30.844	26.416	4.428	17.065***
Leverage	54.107	54.535	-0.428	-1.392
Employee T&D	0.309	0.182	0.126	4.209***
Export intensity	28.098	15.205	12.893	35.959***
Import intensity	13.574	6.175	7.4	-41.071***
Group	0.585	0.128	0.457	83.369***
Listed	0.033	0.005	0.028	-15.685***
Foreign	27.898	1.441	26.457	63.629***
Territorial embeddedness	0.054	0.066	-0.013	-4.191***
Observations	*11,932*	*11,730*		

Note: [L]expressed in natural logarithm. Level of significance **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table 5. Pearson correlation coefficients

	VIF	Productivity	Family firm	IRC	R&D intensity	Product innovation	Process innovation	Size	Age
Productivity	-	1							
Family firm	1.41	-0.232***	1						
IRC	1.10	0.187***	-0.101***	1					
R&D intensity	1.13	0.029***	-0.004	0.026***	1				
Product innovation	1.24	0.163***	-0.098***	0.068***	0.026***	1			
Process innovation	1.21	0.202***	-0.088***	0.040***	0.013**	0.354***	1		
Size	2.13	0.414***	-0.430***	0.102***	0.028***	0.287***	0.305***	1	
Age	1.18	0.215***	-0.109***	0.104***	0.019***	0.097***	0.075***	0.286***	1
Leverage	1.68	-0.144***	0.010*	-0.042***	0.010*	-0.001	0.017***	0.011*	-0.151***
Employee T&D	1.01	0.047***	-0.028***	0.017***	0.025***	0.040***	0.046***	0.046***	0.016**
Export intensity	1.32	0.267***	-0.225***	0.130***	0.013**	0.180***	0.175***	0.411***	0.169***
Import intensity	1.42	0.261***	-0.255***	0.102***	0.018***	0.131***	0.144***	0.397***	0.162***
Group	1.87	0.347***	-0.480***	0.095***	0.036***	0.171***	0.190***	0.596***	0.147***
Listed	1.04	0.088***	-0.106***	0.032***	0.008	0.033***	0.050***	0.179***	0.073***
Foreign	1.59	0.277***	-0.377***	0.141***	0.003	0.112***	0.128***	0.454***	0.154***
Territorial embeddedness	1.05	-0.117***	0.033***	-0.067***	-0.008	-0.096***	-0.090***	-0.165***	-0.060***

continues

	VIF	Leverage	Employee T&D	Export intensity	Import intensity	Group	Listed	Foreign	Territorial embeddedness
Leverage	-	1							
Employee T&D	-	0.007	1						
Export intensity	-	-0.039***	0.046***	1					
Import intensity	-	-0.015**	0.041***	0.339***	1				
Group	-	0.004	0.031***	0.324***	0.365***	1			
Listed	-	0.002	0.007	0.089***	0.088***	0.128***	1		
Foreign	-	-0.003	0.032***	0.303***	0.461***	0.459***	0.072***	1	
Territorial embeddedness	-	-0.031***	-0.015**	-0.160***	-0.118***	-0.075***	-0.018***	-0.080***	1

Note: Number of observations: *23,662*. Mean VIF = 1.32. Level of significance $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6 Regression results

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
Fixed part							
Time			-0.015***	-0.015***	-0.013***	-0.013***	-0.013***
			(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R&D intensity					-0.010***	-0.010***	-0.010***
					(0.002)	(0.002)	(0.002)
Product innovation					-0.010	-0.010	-0.010
					(0.011)	(0.011)	(0.011)
Process innovation					0.020**	0.020**	0.020**
					(0.009)	(0.009)	(0.009)
Size					0.039***	0.039***	0.039***
					(0.013)	(0.013)	(0.013)
Age					-0.001*	-0.001*	-0.001*
					(0.001)	(0.001)	(0.001)
Leverage					0.000	0.000	0.000
					(0.000)	(0.000)	(0.000)
Employee T&D					0.001	0.001	0.001
					(0.001)	(0.001)	(0.001)
Export intensity					0.001**	0.001**	0.001**
					(0.000)	(0.000)	(0.000)
Import intensity					0.001*	0.001*	0.001*
					(0.000)	(0.000)	(0.000)
Group					-0.019	-0.019	-0.019
					(0.017)	(0.017)	(0.017)
Listed					-0.112***	-0.112***	-0.112***
					(0.039)	(0.039)	(0.039)
Foreign					-0.000	-0.000	-0.000
					(0.000)	(0.000)	(0.000)
Territorial embeddedness					-0.001	-0.001	-0.001

					(0.022)	(0.022)	(0.022)
Family firm					-0.005	-0.005	-0.059**
					(0.016)	(0.016)	(0.028)
IRC						0.235***	0.187*
						(0.053)	(0.105)
Family firm*IRC							0.109**
							(0.048)
Constant	3.498***	3.462***	3.568***	3.454***	3.172***	3.067***	3.081***
	(0.010)	(0.045)	(0.045)	(0.039)	(0.049)	(0.053)	(0.055)
Random part							
Variance (family firm)	-	-	-	-	0.0014	0.0011	0.0007
Variance (region)	-	0.0305	0.0307	0.0210	0.0023	0.0014	0.0014
Variance (firm)	0.2900	0.2654	0.2697	0.2446	0.1636	0.1640	0.1635
Variance (year)	0.1673	0.1663	0.1638	0.1637	0.1632	0.1632	0.1632
VPC							
Region	-	0.066	0.066	0.049	-	-	-
ID	0.634	0.574	0.581	0.570	-	-	-
Log likelihood	-14152.6	-14062.27	-13949.9	-13810.4	-13247.54	-13243.03	-13238.94
LR test (a)	-	180.65***	224.69***	279.06***	1125.71***	12.42***	4.78*
LR test vs. linear model	12729.86***	12910.5***	13111.38***	11837.2***	7973.05***	7770.64***	7723.08***
Test Mean values (Mundlak)	-	-	-	-	347.08***	347.48***	348.37***
Sector	N	N	N	Y	Y	Y	Y
Firm	3,060	3,060	3,060	3,060	3,060	3,060	3,060
Region	17	17	17	17	17	17	17
Observations	*20,119*	*20,119*	*20,119*	*20,119*	*20,119*	*20,119*	*20,119*

Note: standard errors are reported in parentheses. Level of significance *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. (a) The LR test compares each model to the previous one.

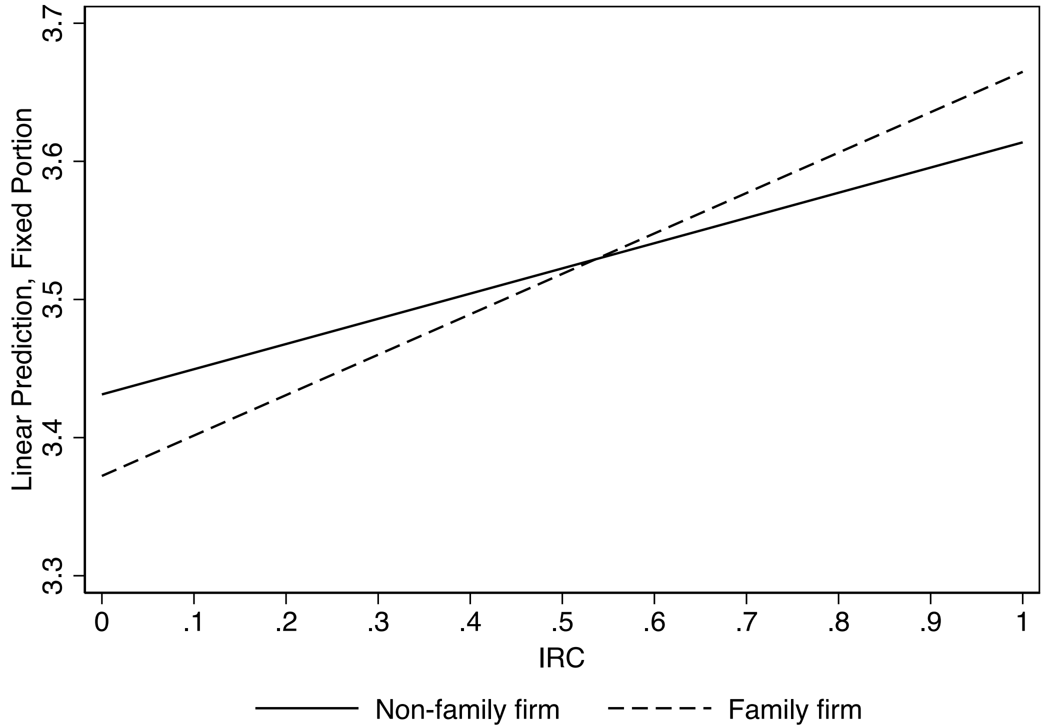
Table 7 Robustness check

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Fixed part					
Time	-0.014***	-0.014***	-0.014***	-0.014***	
	(0.001)	(0.001)	(0.001)	(0.001)	
R&D intensity	-0.010***	-0.010***	-0.010***	-0.010***	-0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Product innovation	-0.012	-0.011	-0.014	-0.011	-0.010
	(0.011)	(0.013)	(0.011)	(0.011)	(0.012)
Process innovation	0.020**	0.018*	0.020**	0.020**	0.023**
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
Size	0.037***	0.036**	0.041***	0.039***	0.028
	(0.013)	(0.015)	(0.013)	(0.013)	(0.025)
Age	-0.001*	-0.001*	-0.001*	-0.001*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employee T&D	0.000	0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Export intensity	0.001**	0.001***	0.001**	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Import intensity	0.001*	0.000	0.001	0.001*	0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Group	-0.016	-0.024	-0.018	-0.019	-0.022
	(0.017)	(0.019)	(0.017)	(0.017)	(0.022)
Listed	-0.112***	-0.092**	-0.118***	-0.111***	-0.129***
	(0.039)	(0.047)	(0.043)	(0.039)	(0.045)
Foreign	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Territorial embeddedness	-0.002	-0.016	-0.002	-0.000	-0.001

	(0.022)	(0.025)	(0.022)	(0.022)	(0.025)
Family firm	-0.055*	-0.060**	-0.055*	-	-0.063**
	(0.029)	(0.029)	(0.028)		(0.030)
Family management	-	-	-	-0.019	-
				(0.012)	
IRC	0.192*	0.190**	0.199*	0.232**	0.168**
	(0.103)	(0.093)	(0.105)	(0.110)	(0.067)
Family firm*IRC	0.106**	0.115**	0.101**	-	0.109**
	(0.051)	(0.052)	(0.049)		(0.046)
Family management*IRC	-	-	-	0.034*	-
				(0.021)	
Constant	3.087***	3.026***	3.086***	3.050***	3.072***
	(0.056)	(0.058)	(0.056)	(0.053)	(0.054)
Random part					
Variance (family firm)	0.0007	0.0008	0.0007	0.0000	-
Variance (region)	0.0013	0.0007	0.0014	0.0018	-
Variance (firm)	0.1641	0.1668	0.1646	0.1634	-
Variance (year)	0.1641	0.1707	0.1644	0.1632	-
Log likelihood	-12967.6	-10784.47	-12910.53	-13238.73	-
LR test vs. linear model	7565.01***	5844.53***	7456.95***	7731.07***	-
Test Mean values (Mundlak)	333.81***	290.68***	340.38***	356.64***	250.58***
Sector	Y	Y	Y	Y	Y
Years	-	-	-	-	Y
Firm	2,987	2,430	3,008	3,060	3,060
Region	15	16	17	17	17
Observations	*19,635*	*15,891*	*19,489*	*20,119*	*20,119*

Note: standard errors are reported in parentheses. Level of significance *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Figure 2 Predictive margins of the two-way interaction *Family firm*IRC*



Appendix A

Table A1 *Distribution by size and firm's type*

Size	Freq.	Percent	Cum.	Type of firm	
				Family firm	Non-family firm
Small	11,821	49.96	49.96	*8,220*	*3,601*
Medium	7,257	30.67	80.63	*2,868*	*4,389*
Large	4,584	19.37	100.00	*642*	*3,942*
Total	*23,662*	100.00		*11,730*	*11,932*

Table A2 *Distribution by technological intensity and firm's type*

Tech	Freq.	Percent	Cum.	Type of firm	
				Family firm	Non-family firm
Low-tech	10,646	44.99	44.99	*6,087*	*4,559*
Medium-low	6,794	28.71	73.70	*3,362*	*3,432*
Medium-high	4,121	17.42	91.12	*1,558*	*2,563*
High-tech	2,101	8.88	100.00	*723*	*1,378*
Total	*23,662*	100.00		*11,730*	*11,932*

Figure A1 *Family firm's density by regions*

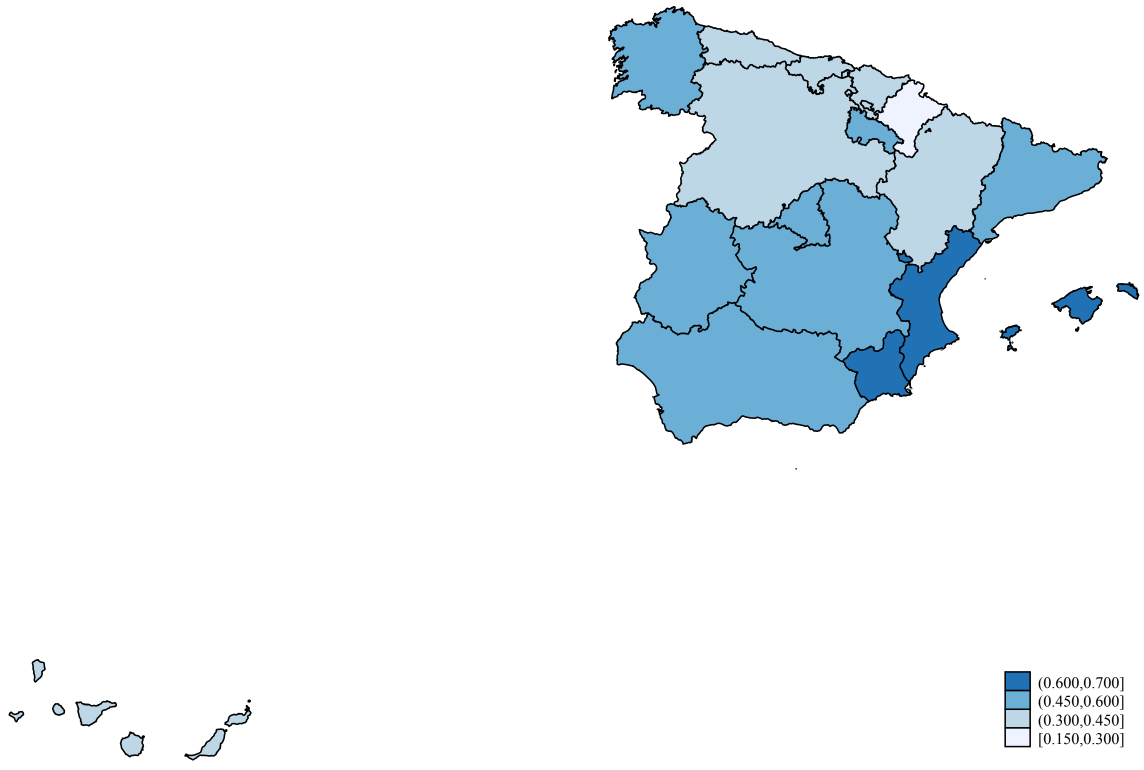


Table A3 *Family firm's density by regions (%)*

Region	**Family firm density (%)**
Andalucía	54.70
Aragon	41.26
Asturias	42.39
Balearic Islands	68.05
Canary Islands	38.76
Cantabria	33.56
Castilla-La Mancha	53.12
Castilla and León	40.67
Catalonia	47.90
Valencian Community	61.91
Extremadura	52.51
Galicia	52.11
Community of Madrid	50.28
Region of Murcia	64.87
Chartered Community of Navarre	28.78
Basque Country	31.29
La Rioja	46.97
Average	49.57

Appendix B *Empirical Specification: The Three-level Growth Model*

In presenting our three-level growth model, we begin with a simple model in which the firm's labor productivity depends linearly on time (*T*) and then, extending it, we consider that our data have a three-level hierarchical structure with measurement occasion *t* at level one nested within firms (*i*) at level two clustered in regions (*j*) at level three. Therefore, the level-1 equation is the following:

$$y_{tij} = \beta_{0ij} + \beta_{100} T + e_{tij} \qquad \text{[B1]}$$

with t = years, i = firms, j = regions and where the dependent variable y_{tij} refers to the value of labor productivity (*LP*) of the *i-th* firm from the *j-th* region in time *t.* In Eq. [B1] β_{100} represents the growth rate assumed to be the same for all firms while the regression parameters β_{0ij} is considered to vary across firms but also across regions (Curran, McGinley, Serrano, & Burfeind, 2012), that is:

$$\beta_{0ij} = \beta_{00j} + u_{0ij} \qquad \text{[B2]}$$

The group-specific intercept β_{00j} represent the mean of the intercepts of the growth trajectories for all the firms nested within group *j*. In our case, it represents the mean initial value of labor productivity for all the firms nested within a given region *j*.

Given the three-level structure of the data, the group-specific intercept β_{00j} varies randomly across region. The Level-3 equation is:

$$\beta_{00j} = \gamma_{000} + u_{00j} \qquad \text{[B3]}$$

Therefore,

$$\beta_{0ij} = \gamma_{000} + u_{00j} + u_{0ij} \qquad \text{[B4]}$$

Combining Eq. [B1] and Eq. [B4] yields:

$$y_{tij} = \gamma_{000} + \beta_{100} T + u_{0ij} + u_{00j} + e_{tij} \qquad \text{[B5]}$$

In Eq. [B5] the variable y_{tij} is modeled by the overall mean γ_{000}, together with a random departure u_{0ij} due to firm *i* capturing the effects on *LP* of unmeasured individual characteristics with values that are fixed over time, a random departure u_{00j} due to region j and a time-varying residual e_{tij} capturing the effects on LP of unmeasured time-varying characteristics with $e_{tij} \sim N(0, \sigma_e)$, $u_{0ij} \sim N(0, \sigma_i)$ and $u_{00j} \sim N(0, \sigma_j)$. The random effects and the residual term are assumed to be independent of each other and of covariates.

The model intercept is interpreted as the overall mean at year 2002 (the first year, coded 0). The variance of u_{0ij} (σ_i^2) represents the between-firm variance in y, the variance of u_{00j} (σ_j^2) is the between-region variance in y and the variance of e_{tij} (σ_e^2) is the within-firm variance in y after accounting for the linear effect of time.

In the three-level model, covariates can be included at any level of the analysis. We start by including the family firm status (FF). Our first-level equation is now:

$$y_{tij} = \beta_{0ij} + \beta_{100} T + \beta_{2ij} FF_{tij} + e_{tij} \qquad \text{[B6]}$$

the slope associated with FF is considered varying across firms and regions. The variation of the regression coefficients β_{0ij} and β_{2ij} is modeled using a regional-level regression model and depends on $\overline{IRC}$[34]:

$$\beta_{0ij} = \gamma_{00j} + \gamma_{001} \overline{IRC}_j + u_{0ij} \qquad \text{and} \qquad \gamma_{00j} = \gamma_{000} + u_{00j} \qquad \text{[B7]}$$

$$\beta_{2ij} = \gamma_{20j} + \gamma_{202} \overline{IRC}_j + u_{2ij} \qquad \text{and} \qquad \gamma_{20j} = \gamma_{200} + u_{20j} \qquad \text{[B8]}$$

The substitution and rearranging of terms give:

$$y_{tij} = \gamma_{000} + \beta_{100} T + \gamma_{200} FF_{tij} + \gamma_{001} \overline{\overline{IRC}}_j + \gamma_{202} FF_{tij} * \overline{IRC}_j + u_{00j} + u_{0ij}$$
$$+ u_{20j} FF_{tij} + u_{2ij} FF_{tij} + e_{tij} \qquad \text{[B9]}$$

The term $FF_{tij} * \overline{IRC}_j$ is an interaction term that appears in the model by modeling the varying slope β_{2ij} of the firm-level variable FF with the regional-level variable $\overline{IRC}_j$ (a cross level interaction). Moreover, we control for a set of firm characteristics (X_{tij}) and sectorial dummies (S). For all firm level controls, the previous period values compared with labour productivity are used to mitigate the possibility of simultaneity problems.

[34] See footnote 24.

$$y_{tij} = \gamma_{000} + \beta_{100} T + \gamma_{200} FF_{tij} + \gamma_{001} \overline{RCI}_j + \gamma_{202} FF_{tij} * \overline{IRC}_j + \sum_{f=1}^{k} \lambda_f X_{ftij} + \sum_{s=1}^{p} \mu_s S_{si} +$$

$$+ (u_{00j} + u_{0ij} + u_{20j} FF_{tij} + u_{2ij} FF_{tij} + e_{tij}) \qquad [B10]$$

In reality, in Eq. [B10] each firm level covariate contains two parts: one that is specific to the higher-level entity that does not vary between occasions (between effects) and one that represents the difference between occasions, within higher-level entities (within effects) (Bell & Jones, 2015, p. 137). If we use Eq. [B10], we assume that the within and between effects are equal. However, in general within-group coefficients differ from between-group coefficients (Snijders & Bosker, 2012, p. 60). If the between effect is omitted, the single coefficient attempts to account for both effects, within and between. This leads to a problem of endogeneity since the variance that is not accounted for will be absorbed into the error terms that, as a result, will be correlated with the covariate, violating the assumptions of the Random Effects model (Bell & Jones, 2015, p. 137). This is called heterogeneity bias (Bell & Jones, 2015; Li, 2011). A simple remedy to overcome this problem is to insert the group-level means of the lower level variables that accounts for the between effects as suggested by Mundlak (1978). Therefore, Eq. [B10] is augmented by the average of firm-level variables ($\bar{X}_{ij}$) and this is our full model (Eq. [1]):

$$y_{tij} = \gamma_{000} + \beta_{100} T + \gamma_{200} FF_{tij} + \gamma_{001} \overline{IRC}_j + \gamma_{202} FF_{tij} * \overline{IRC}_j + \sum_{f=1}^{k} \lambda_f X_{ftij} + \sum_{s=1}^{p} \mu_s S_{si} +$$

$$+ \sum_{f=1}^{k} \varphi_f \bar{X}_{ij} + (u_{00j} + u_{0ij} + u_{20j} FF_{tij} + u_{2ij} FF_{tij} + e_{tij})$$