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ORIGINAL PAPER

Familiar but also radical? The moderating role of regional clusters for family firms in the emergence of radical innovation

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Abstract Family firms are widely acknowledged to be the most predominant form of organization and hold a great relevance in most economies. Nevertheless, despite their popularity, research has thus far yielded inconsistent findings with regard to their innovative performance. This paper aims to address this research gap by focussing on a specific form of innovation: radical innovation. It seeks to determine the propensity of family firms to generate such innovations. Furthermore, by considering the heterogeneity between regions and firms, this paper also investigates the potential moderating effects of being located in a regional cluster and firm size. Based on various data sources, it is empirically shown that family firms are on average less capable of producing radical innovation than non-family firms. However, the corresponding regional context matters in this regard. By being located within regional clusters, family firms can reap the benefits of localization externalities, leading to produce more radical innovations than being located outside regional clusters.

Keywords Radical innovation · Recombinant novelty · Family firms · Regional clusters · Agglomeration · Firm size

1 Introduction

It is widely acknowledged that family firms are the most predominant form of organization and that they have a great relevance in most economies (Basco and

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Bartkevičiūtė 2016; Bjuggren et al. 2011; Cappelli et al. 2021). They account for the dominant proportion of companies (between 65 to 80% of all European companies) and a large proportion (on average between 40 and 50% of all jobs) of European private employment (European Family Businesses 2021). As a result, the phenomenon of family firm has not only captured the attention of researchers, but also emerged as a subject of considerable interest among policymakers. For instance, in her initial speech as the President-elect Ursula von der Leyen highlighted that: "We should never forget that competitive sustainability has always been at the heart of our social market economy. We just called it differently. Think of the family-owned businesses all across our Union. They were not built solely on shareholder value or the next bonuses. They were built to last, to pass down generations, to provide a fair living to employees. They were built on passion for quality, tradition and innovation." (Speech by President-elect von der Leyen in the European Parliament Plenary, 2019).[1]

Despite their popularity and economic relevance, when it comes to innovation, one of the key factors for economic development (e.g. Verspagen, 2005), research on family firms has so far only found rather inconsistent results (Calabrò et al., 2019). To further resolve the inconsistencies in the results, recent research has highlighted the need to distinguish between different types of innovation and to study radical innovation in particular (Calabrò et al. 2019; Hu and Hughes 2020). In contrast to incremental innovations, radical innovations arise from the synthesis of previously unconnected knowledge pieces (Fleming 2001; Nerkar 2003; Weitzman 1998).[2] The atypical combination processes also make radical innovations more expensive and more likely to fail than incremental innovations (Ayres 1988; Fleming 2007). Nonetheless, in the event of success, they can establish a completely new technological approach that leads to further incremental follow-up innovations and thereby provide enormous economic benefits (Ahuja and Lampert 2001; Arthur 2007). For this reason, radical innovations have attracted increasing interest from policy makers (e.g. SprinD[3]) and academics (e.g. Shkolnykova and Kudic 2021), who, given the distinctive characteristics of radical innovations, have recently highlighted differences between different types of firms, such as SMEs and large firms, in their ability to generate these innovations (e.g. Grashof and Kopka 2023). However, despite recent calls (e.g. Hu and Hughes 2020) and some important exceptions (e.g. Nieto et al. 2015; Schäfer et al. 2017), there has been limited research on radical innovation in the specific firm type of family firms—especially from a quantitative empirical perspective. In a first step, this paper therefore aims to contribute to the ongoing discussion about the relationship between family firms and innovation by

[1] The speech is also accessible under: https://multimedia.europarl.europa.eu/en/presentation-by-the-commission-president-elect-of-the-college-of-commissioners-and-their-programme-statement-by-ursula-von-der-leyen-president-elect-of-the-ec_I180740-V_v.

[2] These combinations are sometimes also called 'atypical combinations' (e.g. Uzzi et al. 2013).

[3] In 2019, the German government founded the national agency "Agentur für Sprunginnovationen" (SprinD). For more information, please see BMBF (2020).

empirically investigating the extent to which family firms are more likely to create radical innovations[4] than non-family firms.

Beyond examining firm-specific differences (family vs. non-family firms) in the emergence of radical innovation, the specific context might also play a role. Following Basco et al. (2021a), it is argued that contextual factors of heterogeneity are often overlooked when examining the innovative performance of family firms. Not considering these contextual influences, however, can lead to potential misinterpretations (De Massis et al. 2012). In a second step, it is therefore empirically investigated under which conditions family firms can actually generate radical innovation. Based on recent efforts to link family businesses with the regional context (e.g. Basco 2015; Basco et al. 2021b) and the current discussion about the role of regional clusters for the emergence of radical innovation (e.g. Grashof et al. 2019), the potential moderating role of regional clusters is considered. In addition to the regional context, following the concept of the resource-based view (e.g. Barney 1991) and the suggestions of De Massis et al. (2012), differences in terms of firm size are also examined as a potential moderating variable.

To empirically investigate these two research gaps, several data sources are combined, particularly firm-level information from the ORBIS database and information on inventions from the PATSTAT database. The resulting database includes 10,596 patent-active companies in Germany between 2012 and 2020. Due to data limitations (regarding the identification of clusters and family firms), the final data set is pooled and a cross-sectional analysis is performed. Since the corresponding dependent variable is a count variable, suffering from over-dispersion, a zero-inflated negative binomial regression approach with robust standard errors is applied.

By investigating the two underlying research questions in a quantitative way, this article extends previous research in regional and innovation studies with respect to a better understanding of heterogenous economic actors (in this case family firms) in the context of regional clusters and radical innovation, as well as in family business studies with regard to the relevance of the regional context in studying the (innovative) performance of family firms. Besides these scientific contributions, this paper also offers practical insights for (regional) policy makers to fully understand the heterogeneity of family firms and thus harness the potential of family firms in creating radical innovations.

The remainder of this paper is structured as follows: The subsequent section introduces the theoretical background on family firms, radical innovations, regional clusters and firm size, thereby deducting three hypotheses. In the third section, the methodological approach, the database and the corresponding variables are described in detail. Thereafter, in the fourth section, the main findings are presented and discussed. The paper will end with concluding remarks, including limitations and promising future research endeavours.

[4] Similar to Castaldi et al. (2015), the terms "innovation" and "invention" are used interchangeably here, because the theoretical framework of recombinant innovation also uses the term "innovation". But, it is highlighted that this study focuses on technological achievements rather than successful commercialization.

2 Theoretical background

2.1 Family firms and radical innovations

Innovation is generally understood to be the result of (re)combining existing knowledge in a unique way to create something new (Arthur 2007; Basalla 1988, Castaldi et al. 2015). This common understanding of innovation has its roots in Schumpeter's idea of "Neue Kombinationen" (Schumpeter 1934) and the related work by Weitzman (1998) introducing the concept of "recombinant innovation", which is defined as "(...) the way that old ideas can be reconfigured in new ways to make new ideas." (Weitzman 1998, p. 333). Nevertheless, the corresponding degree of novelty can thereby be quite different (e.g. Suwala 2017). On the one hand, incremental innovations can be characterized by a reuse and refinement of existing combinations, referring to exploitative search processes (March 1991; Mewes 2019). They develop along well-defined trajectories and are therefore the norm (Dosi 1982; Schoenmakers and Duysters 2010; Verhoeven et al. 2016). On the other hand, radical innovations rely on an explorative search for and development of completely new combinations of knowledge pieces that have not been put together before (Fleming 2001; March 1991; Mewes 2019). Since the exploration of these new and previously unknown combinations is accompanied by higher costs and higher risks for failure (in technological as well as commercial terms) than incremental innovations (Ayres 1988; Fleming 2007), they are relatively rare (Fleming 2001; Hesse and Fornahl 2020). Nevertheless, if successful, radical innovations can establish a completely new technological approach (Arthur 2007; Verhoeven et al. 2016) leading to strong competitive advantages (e.g. Castaldi et al. 2015) as well as to the creation of entire new markets and industries (e.g. Grillitsch et al. 2018; Henderson and Clark 1990; Tushman and Anderson 1986).

However, the ability to generate radical innovation may differ between different types of firms (e.g. Grashof and Kopka 2023). While research on the relationship between firm size and innovation in general has a long history (e.g. Cohen 2010), particularly in recent years there has been a growing interest in the specific case of family firms and their innovativeness (Calabrò et al. 2019; Urbinati et al. 2017). The economic relevance of family firms has led researchers to pay attention to the ways in which family firms behave differently from those of non-family firms, and to the way in which family-specific attributes contribute to family firms' greater profitability and productivity (Cappelli et al. 2021; Sraer and Thesmar 2007) as well as their innovativeness (Nieto et al. 2015; Zybura et al. 2021). In fact, scholars have ascribed some characteristics to family firms that positively affect innovation, such as their long-term orientation (particularly because their family's fortune, reputation and future are at stake), the rather informal knowledge sharing as well as stewardship behaviour (Miller et al. 2008; Zahra 2012, Zellweger 2007).[5] But, at the same time, scholars have also ascribed some characteristics to family firms that negatively affect innovation (Aiello et al. 2020; Hu and Hughes 2020). For example, these include

[5] Although, these characteristics may contribute in different degrees to the emergence of incremental and radical innovations (Nieto et al., 2015).

the frequently observed risk aversion of family firms due to concerns about wealth preservation, parental altruism, which may favour the hiring of family members resulting potentially in a shortage of qualified managers, and the overall rather low innovation capabilities (De Massis et al. 2014; Gómez-Mejía et al. 2007; Sciascia et al. 2015; Sirmon and Hitt 2003).

Despite this variety of arguments (going in both directions), in the case of radical innovations, family firms are here assumed to be less likely to achieve them. In line with the argumentation by Nieto et al. (2015), it is reasonable to assume that particularly the risk aversion and the desire to preserve socio-emotional wealth hinder the engagement in explorative search processes. Regarding the latter aspect, contrary to non-family firms, family firms are confronted with the tension between economic and non-economic goals. These non-economic goals encompass among other aspects the wealth preservation for future generations, constant control over the company, a strong family identity and intrafamily succession, as well as the preservation of binding social ties to clients and suppliers (Filser et al. 2018; Gómez-Mejía et al. 2007; Nieto et al. 2015). Since radical innovations rely on the pioneering recombination of former unconnected knowledge pieces, which is accompanied by uncertainty and risk (Fleming 2001; Nerkar 2003) as well as potential disruption to previous social ties (Nieto et al. 2015), it is likely that family firms are relatively reluctant to introducing radical innovations. Thus, the following hypothesis is proposed:

Hypothesis 1: Family firms are less likely to develop radical innovations than non-family firms.

2.2 Regional clusters and radical innovations in family firms

While the geographical concentration of economic activities and the possible economic effects have fascinated researchers from multiples disciplines (Grashof 2020), at least since Marshall (1920), in the case of family business research the regional context has often been neglected (Basco 2015). Recently, however, there have been efforts to link family businesses with the regional context (e.g. Basco et al. 2021b; Basco and Suwala 2020). In this context, based on the notion of the regional familiness approach[6] (Basco 2015), it has been argued that the relatively high local embeddedness of family firms allows them to better exploit the proximity dimensions of the corresponding regional context (Basco et al. 2021a, Boschma 2005).[7] This goes in line with previous research showing that the sole location in regional clusters is not sufficient to actually benefit from potential localization externalities,

[6] Regional familiness is originally definied as (...) the embeddedness of family businesses in social, economic, and productive structures within the spatial context and the type of connections that emerge and interact with regional factors (i.e., tangible and intangible factors) and regional processes (e.g., spillovers, information exchange, learning processes, social interactions, competition dynamics, and institutional dynamics) through regional proximity dimensions (i.e., relational, institutional, organizational, social, and cognitive proximity) (Basco 2015, p. 260).

[7] As described by Basco and Suwala (2021), there is a research tradition to address family firms in regional studies in the case of Industrial districts, which has only recently been taking up again (e.g Cucculelli and Storai 2015; Pittino et al. 2021).

such as knowledge spillovers (Grashof 2021; Hervas-Oliver et al. 2018). Through their strong regional ties and engagement, family firms are more strongly embedded in the corresponding regional innovation system than non-family firms (Basco et al. 2021a; Block and Spiegel 2013; Déniz and Suárez 2005), making them more likely to benefit from localization externalities, particularly from the supply-side ones (McCann and Folta 2008). As a result of their long-standing regional presence and their social relationships (Basco et al. 2021a), family firms can create a certain (regional) reputation in terms of trustworthiness, security and stability making them more likely to attract local talents from the specialised labour pool (Hauswald et al. 2016). Having such an access to the specialized labour pool can potentially lead to radically new ideas, as the expertise of local human resources can challenge conventional processes and mindsets (Bekkers and Freitas 2008; Grashof et al. 2019; Zucker et al. 2002).[8] Moreover, the high degree of regional embeddedness and long-term orientation have both the potential to reduce the transaction and coordination costs for cooperation, e.g. with (local) suppliers, leading ultimately to more (trustful) relationships and more knowledge exchange (Block and Spiegel 2013). The access to these knowledge spillovers can be used to enrich in-house knowledge and thereby create rather radical new knowledge (Dong et al. 2017; Faems et al. 2005). This holds particularly true, since the pronounced social proximity may additionally allow to overcome the challenges associated with cooperating with cognitive distant partners (Adjei et al. 2019; Boschma 2005). Furthermore, due to the rather close, trustful and long-term oriented relationships of family firms (Block and Spiegel 2013; Miller et al. 2008) it is also likely that particular tacit knowledge is exchanged (Adjei et al. 2019), which is relevant for the creation of radical innovations (Audretsch 1998; Mascitelli 2000).

However, it has also been suggested that, over time, firms located within clusters may face (cognitive) inertia with respect to market and technological change, which hampers radical innovation (Hassink 2007; Pouder and St John 1996; Schamp 2005). Furthermore, when local networks heavily depend on local face-to-face contacts and tacit knowledge, they become more susceptible to lock-in situations, thereby perpetuating the inertia of firms situated within clusters (Boschma 2005; Martin and Sunley 2003). Moreover, in the case of industrial districts it has recently been shown that the potential locational advantages do not necessarily match well with the firm-specific advantages of family firms due to redundancies, but instead may even decrease the financial performance of family firms (Cucculelli and Storai 2015; Pittino et al. 2021).

Nevertheless, it is important to note that industrial districts represent a special form of a regional cluster, with a particular emphasis on the social dimension, thereby making redundancies with the firm-specific advantages of family firms more likely (Grashof and Fornahl 2021; Pittino et al. 2021). Additionally, this study focuses on innovation rather than financial performance, unlike Cucculelli and Storai (2015) as well as Pittino et al. (2021), which are not necessarily intertwined (Grashof

[8] However, it has also been highlighted that family firms tend to hire employees with a similar cognitive background, which would of course limit or even offset the benefits from the incorporated knowledge of new employees (Brinkerink 2018).

and Fornahl 2021). For the concrete research context of this study, it is therefore reasonable to assume that family firms, which are more locally embedded than non-family firms, are better capable to exploit the localization externalities within regional clusters (Basco 2015; Basco et al. 2021a), which have been shown to rather promote the emergence of radical innovations (e.g. Grashof et al. 2019). Thus, the following hypothesis is proposed:

Hypothesis 2: Being located in a regional cluster increases the likelihood for family firms to create radical innovations (compared to family firms located outside regional clusters).

2.3 Firm size and radical innovations in family firms

However, family firms are of course not a homogenous group (Corbetta and Salvato 2004; Filser et al. 2018). In line with the resource-based view[9] (RBV), they differ in terms of their resources[10] and capabilities (Barney 1991; Werner et al. 2018). One prominent aspect that has been frequently considered in this context is the size of firms (Nieto et al., 2015). Prior research has shown that firm size is a crucial factor in driving overall innovation in firms (e.g. Cohen and Klepper 1996).

Nevertheless, when it comes to radical innovations, there are rather few findings and these are generally inconsistent (Chandy and Tellis 2000). For example, in their recent study about the influence of AI knowledge on the emergence of radical innovations in firms, Grashof and Kopka (2023) found different results with respect to the role of firm size depending on the underlying features of AI technologies (AI applications vs. AI techniques). In general, there exist arguments in favour and against a positive influence of firm size on the emergence of radical innovations. While large firms have, on the one hand, more (financial) resources and (technical) capabilities to actually develop this type of innovation, on the other hand, they are more likely to face inertia due their complex internal structure, making them rather inflexible to new (rather radical) ideas (Chandy and Tellis 2000; Colombo et al. 2015).

In the case of family firms, firm size has also been shown to matter for firm performance in general (e.g. Cucculelli and Storai 2015) and firm innovativeness in particular (e.g. Werner et al. 2018). However, as described in section 2.1., family firms have some unique characteristics that could enhance or mitigate the firm size effect compared to non-family firms. Recent empirical studies for instance show that small family firms are more innovative than small non-family firms, while

[9] The Resource-Based View (RBV) assumes that resources are unequally distributed among firms and are immobile, resulting in varying resource endowments and their persistence over time. As a result of this imbalance, firms can potentially achieve a resource-based competitive advantage by leveraging their internal resource base. Therefore, the central concept of the RBV focuses on how firms can utilize their resources to gain a competitive advantage (Barney 1991; Grashof and Kopka 2023; Newbert 2007).

[10] Following the widely used definition by Barney (1991), resources are here defined as "(...) all assets, capabilities, organizational processes, firm attributes, information, knowledge, etc. controlled by a firm that enable the firm to conceive of and implement strategies that improve its efficiency and effectiveness." (Barney 1991, p. 101).

the opposite holds true for larger firms (Werner et al. 2018). Whether this also applies to radical innovations is still unclear. In general, it has been argued that the tendency of family firms to keep the control of the business in family hands (Aiello et al. 2020; Sirmon and Hitt 2003), might imply relatively high agency costs (e.g. implementation of an incentive system) when they are large. Contrary, smaller family firms do not face these agency costs, as influential management positions can be filled with family members, thereby providing them with more financial resources that can be invested in innovative activities (Werner et al. 2018). Moreover, in light of the relatively high level of ownership concentration within family firms it is also likely that a relatively large and complex internal structure will slow down decision making processes, thereby enforcing the inertia and rigidity of large family firms (Aiello et al. 2020; Werner et al. 2018). In addition, as family firms are less likely to use risky financial capital to avoid losing control, they may have more problems than (large) non-family firms in financing their growth and related innovation activities (Aiello et al. 2022; Gómez-Mejía et al. 2007; Kets de Vries 1993).

Despite the potential advantages in terms of more (financial) resources and (technical) capabilities, in the specific case of family firms it is therefore reasonable to assume that the potential disadvantages in terms of inflexibility outweigh, so that smaller family firms are better able to introduce radical innovations than non-family firms, while large family firms are less able to do so. Thus, the following hypothesis is proposed:

Hypothesis 3: Firm size inhibits the creation of radical innovations in family firms more than in the case of non-family firms.

3 Empirical background

3.1 Data

The sample for the empirical analysis is constructed by using several data sources. In particular, similar to previous approaches (e.g. Grashof et al. 2020), this study combines firm-level information (e.g. ownership information) from the ORBIS database, offered by Bureau van Dijk (BvD), and information on inventive activities (e.g. technology classes) from the PATSTAT database.[11] The resulting data set contains detailed information about 10,596 actively patenting (i.e. at least one patent filed) organisations in Germany between 2012 and 2020, of which 8.75% actually filed radical patents.[12] In particular, non-family firms are relatively well represented, with almost twice as many non-family firms (604) filing radical patents as family firms (323).

[11] To match the patent data with the firm-level data from ORBIS, a unique patent identifier is created based on information from PATSTAT.

[12] Table 3 in the appendix reports the distribution across industries.

3.2 Operationalisation

Despite some well-discussed drawbacks[13], most recent studies rely on patent-based indicators for capturing radical innovations (Grashof and Brenner 2021; Hesse and Fornahl 2020). In light of the underlying concept of recombinant innovation (Weitzman 1998), acknowledging that innovation results from the (re)combination of existing knowledge pieces in a new way (Arthur 2007; Basalla 1988, Castaldi et al. 2015), this study considers the combination of technology classes listed on patents (Grashof et al. 2019; Hesse and Fornahl 2020). As highlighted in the theoretical section, radical innovations rely on an explorative search for and development of completely new combinations of knowledge pieces that have not been linked before (Fleming 2001; March 1991; Mewes 2019). In line with recent studies (e.g. Arant et al. 2019; Verhoeven et al. 2016), this study therefore measures radical innovations by the pioneering combination of technology classes listed on patents. For this, a procedure from previous articles was used (e.g. Grashof and Kopka 2023), which first identifies all four-digit codes[14] of the Cooperative Patent Classification (CPC) that appear on patent filings between 2012 and 2020, and then compares them to a sample of all CPC combinations in Germany between 1981 and the preceding year. In other words, a CPC combination that is completely new to Germany (since 1981) is deemed radical (Hesse 2020; Hesse and Fornahl 2020). After merging this information with the firm-level data from ORBIS, the dependent variable is constructed by adding all the patents with new combinations of each firm based on the DOCDB patent family ids (*rad_count*). Hence, patents belonging to the same patent family are not counted twice per firm. When a radical patent is filed by multiple companies, the knowledge contained therein is assumed to be non-exclusive and consequently a full patent is assigned to each of the filing companies (Grashof and Kopka 2023).

The firm-level data from ORBIS is also used to identify family firms. For the identification of family firms, this article takes the so-called "demographic approach", which regards the participation of a family member in a firm, e.g. shown in its ownership, as a sufficient condition for recording the family's influence on the business (Basco 2013; Basco et al. 2021a). In line with previous research (e.g. Cucculelli and Storai 2015) that makes use of the ORBIS data, the information about the "Global Ultimate Owner" (GUO) is used.[15] In this regard, family firms are those with GUO equal to "one or more named individuals or families". Consequently, a dummy variable (*family_dummy*) has been created that indicates whether a company is a family firm (equal to one) or not (Cucculelli and Storai 2015).

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[13] For a comprehensive discussion on the imperfections of patent data, please see Griliches (1990).

[14] In line with previous studies (e.g. Mewes and Broekel 2020; Hesse and Fornahl 2020), the aggregation on the four-digit CPC level is argued to be the most appropriate option, as it offers a maximum number of technologies while also ensuring a sufficiently large number of patents.

[15] BvD determines a company's "Global Ultimate Owner" by looking at its shareholding structure, seeking the shareholder with the biggest percentage stake or direct ownership. Whenever this shareholder is independent, it is defined as the Ultimate Owner of the respective company. However, if this shareholder is not independent, then BvD repeats this process until it identifies the "Global Ultimate Owner" (Cucculelli and Storai 2015).

Furthermore, this article additionally considers the potential moderating role of firm-specific characteristics. In this context, especially differences between firm size classes have been highlighted to be a crucial factor (e.g. Cohen and Klepper 1996). Following previous studies (e.g. Nieto et al. 2015), the number of employees is used to measure the size of companies. To avoid a potential measurement error due to year-to-year variability inherited to micro-level data (Grashof 2021; Rigby and Brown 2015) and to minimize problems due to missing data, the average number of employees between 2012 and 2020 is calculated.[16] Since the underlying distribution is skewed, the logged average number of employees is used (*log_size_mean*).[17]

For the identification of all relevant regional clusters in Germany, the method of Brenner (2017) is applied, following previous studies (e.g. Grashof 2021). Based on official IAB employment data from 2012 in three-digit NACE Rev. 2 industries, a cluster index is calculated for each firm on the municipality level ("Gemeindeebene"). Such an actor-based cluster identification approach offers two main advantages compared with more traditional indicators. First, the index is border-free, meaning that is independent from specific territorial units, thereby avoiding the Modifiable Area Unit Problem. Second, by additionally using a distance decay function based on travel times, the index also considers the geographical proximity and thereby avoids a potential overvaluation of very large, but geographical isolated, companies (Brenner 2017; Grashof 2021). However, the approach requires different and quite detailed information about a set of locations (L), their geographical distances (D), the level of activity at each location (v_l), a set of actors (A) and their locations (l_a). Based on this information, it is possible to calculate the cluster index for each actor a in the following form:

$$C_a = \sum_{l \in L} \left(v_l f\left(d_{l,l_a}\right)\right), \tag{1}$$

where *f(d)* must be a function that decreases with d. Put differently, this distance decay function indicates how the relevance of activity v (location quotient based on employment data) decreases with the geographical distance from the actor. While several alternative definitions of the distance decay function f(d) exist, the log-logistic decay function and the radius decay function have been widely supported in the literature (Brenner 2017). Since the log-logistic decay function is the most flexible one (Brenner 2017), this function is applied in line with previous studies (e.g. De Vries et al. 2009; Duschl et al. 2015). The log-logistic decay function of travel time d can be expressed as follows:

$$\mathrm{f}(\mathrm{d}) = \frac{1}{1 + \exp(\mathrm{s} * \log(\mathrm{d}/\mathrm{r}))} = \frac{1}{1 + \left(\frac{\mathrm{d}}{\mathrm{r}}\right)^{-\mathrm{s}}} \tag{2}$$

[16] In addition, the data limitations described in section 3.3 require that the average is used here.

[17] As a robustness check and in line with Grashof and Kopka (2023), the 'Company size categories' provided by Bureau van Dijk are used, which not only consider the number of employees but also operating revenue and total assets (Bureau van Dijk 2011). The corresponding results remain robust and can be provided upon request.

where *r* is a parameter for the distance at which the decay function has reached a value of ½, and *s* indicates the shape of the function. Following previous studies (e.g. Brenner 2017; Scholl and Brenner 2016), it was decided that *r* equals 45 min. Based on the results of Duschl et al. (2015) showing that most values are at the upper bound (*s* is equal to 20) but those that are not at the upper bound have a value between 5 and 10, it was decided that setting *s* to 7 is a good compromise in this context (Grashof 2021).[18] In line with the procedure of the European Cluster Observatory, a cluster threshold is set at a value of two (European Cluster Observatory 2018, European Commission 2008). Based on this, a *cluster_dummy* is created that has a value of 1 if a firm is located within a regional cluster and 0 otherwise.

Moreover, several control variables from the firm- and regional-level have been additionally considered. First, to account for firm-specific factors, as has been done in previous research (e.g. Grashof 2021), both the average age (*age_mean*) of the firm (years since foundation) and its corporate structure, where independent or part of a corporate structure is represented by a value of 1 or 0 respectively (*independence_dummy*), were included. This information was obtained from the ORBIS database. Furthermore, based on the NACE codes provided by Gehrke et al. (2013), a dummy variable is created that takes the value of 1 if the corresponding firm is active in a research-intensive industry and 0 otherwise (*researchintensiveindustry*). Finally, to control for regional effects, such as urbanization effects (e.g. Basco et al. 2021a) and the absorptive capacity of regions (e.g. Hesse and Fornahl 2020), the mean of the population density in German NUTS-3 regions (*popdens_mean*) as well as the average share of persons with tertiary education (ISCED) and/or with S&T occupation in the total population in German NUTS-2 regions is considered (*share_academics_mean*). The underlying data come from Eurostat. The descriptive statistics of the above-mentioned variables are reported in Table 1.[19]

In line with previous findings (e.g. Fleming 2001; Hesse and Fornahl 2020), radical innovations appear to be the exception rather than the rule. During the whole study period (2012–2020) firms have on average only 0.327 radical patents, although we can also observe a relatively large standard deviation in this context. Moreover, the majority of firms in the sample are family firms (almost 55%). Although one might expect this number to be higher (e.g. European Family Businesses 2021), it has to be considered that the study sample consists of patenting firms. To get a first impression about potential differences between family and non-family firms in generating radical innovations, their activities are descriptively analysed. Figure 1 shows the average number of radical patents of family and non-family firms for each year (from 2012 to 2020). As already indicated, in general it can be seen that in both groups radical patents are rather the exception than the norm. However, we can additionally observe interesting development patterns over time.

[18] While other specifications are not further tested, thus leaving room for future research, the chosen specifications closely resemble those examined in recent studies by Brenner (2017), Ebert et al. (2019) and Grashof (2021), and are argued to be appropriate for the purpose of this study.

[19] Since one firm in the sample was founded in the year 2018, the minimum of the variable *age_mean* has a negative value. However, the exclusion of this company has no influence on the results. The corresponding results can be made available upon request.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Rad_count	10,596	0.327	4.697	0	338
Family_dummy	10,596	0.549	0.498	0	1
Cluster_dummy	10,596	0.107	0.310	0	1
Log_size_mean	10,456	3.872	1.909	0.693	13.286
Age_mean	10,550	30.421	32.626	–2	685
Independence_dummy	10,596	0.024	0.152	0	1
researchintensiveindustry	10,596	0.253	0.435	0	1
popdens_mean	10,476	820.896	967.388	36.525	4627.862
share_academics_mean	10,596	37.178	4.142	31	46.256

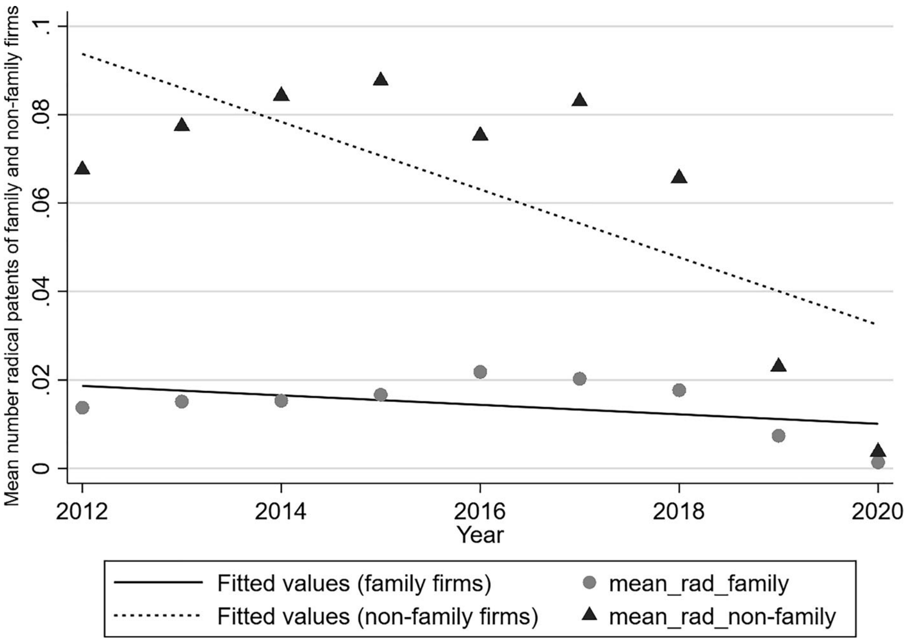

Fig. 1 Average number of radical patents (new to Germany) of family and non-family firms (2012–2020)

Firstly, in line with previous findings (e.g. Agrawal et al. 2019; Jones 2009; Park et al. 2023), the overall trend for both groups is negative, meaning that it seems that it becomes harder for firms to develop completely new combinations of knowledge pieces that have not been linked before.[20] Secondly, while throughout the whole time period non-family firms have on average a higher number of radical patents than family firms, based on the fitted trend it can be seen that this number significantly

[20] Another explanation for the relatively sharp decline in 2020 could be the Covid-19 crisis, which led to a decline in the total number of patent applications (see https://www.epo.org/about-us/annual-reports-statistics/statistics/2020.html), as well as the technical limitation that the most recent years of patent data are not yet fully updated and therefore contain less data (Grashof and Kopka 2023).

decreased from almost 0.1 in the year 2012 to about 0.03 in 2020. For the same time period, the fitted trend for family firms shows that they experienced only a slightly decrease in their relatively low average number of radical patents. This indicates a convergence pattern on a low level. In other words, while on average non-family firms still appear to be more capable of generating radical patents than family firms, the relatively large difference between both groups in generating radical patents has narrowed considerably.

3.3 Method

Nevertheless, based on the previous descriptive analysis it is of course difficult to draw statistically robust conclusions about the relationship between family firms and radical innovations. Therefore, this section describes the econometric approach followed in this study. While the patent data and most firm-level data are available for several years (2012–2020), due to data limitations the ownership information (used to identify family firms) and the actor-based cluster index are both time-invariant variables, where the underlying data comes from 2012. Based on the robust Hausman test (e.g. Schaffer and Stillman 2010; Wooldridge 2002), a random effects panel regression would however not preferable to a fixed effects model. As a result of this and since the focus lies anyway more on the differences between firms, it was decided to pool the data and apply a cross-sectional analysis. This, of course, does not allow for robust statements about cause and effect, which is why in line with previous studies (e.g. Hervas-Oliver et al. 2018) correlation can only be claimed. Nevertheless, given the described data limitations, it is argued that such a cross-sectional approach is still appropriate to provide initial insights into the relationship between radical innovations and family businesses.

The dependent variable (*rad_count*)[21] is a nonnegative count variable, which suffers from over-dispersion, i.e. the variance is greater than the mean. The variance of *rad_count* is more than fourteen times larger than the mean. Consequently, in line with previous studies using count data (e.g. Fleming 2001; Hesse 2020), negative binomial regression models are fitted to test the previously proposed hypotheses. Additionally, the likelihood ratio test also suggests the use of a negative binomial regression approach. In light of the excessive number of zeros (9669 observations had not a radical patent), zero-inflated negative binomial regression models are fitted to test the proposed hypotheses (see for instance: Greene 1994).[22] We expect that the

[21] As a further robustness check, instead of the overall number of radical patents, the mean number of radical patents is also tested. The corresponding results remain stable (see Table 5 in the appendix).

[22] As further robustness checks, all models are also tested with a standard negative binomial regression approach (see Table 7 in the appendix) and (although not suggested by the likelihood ratio test) zero-inflated poisson approach (see Table 8 in the appendix). The corresponding results remain thereby stable, despite the variable *family_dummy* which becomes insignificant (p-value = 0.199) when using a zero-inflated poisson approach. However, in the model with the interaction term (see Model 3 in Table 8 in the appendix) the variable is again significant and negative, indicating that family firms that are not located in a regional cluster file significantly fewer radical patents than non-family firms.

number of patents per organisation between 2012 and 2020 (*pat_count*)[23] can predict the excess number of zeros and thus is negatively associated with the possibility of not combining unconnected knowledge pieces. In other words, firms with higher patent activities in general are assumed to have a lower probability of having no radical innovation ("always zero" group). To control for heteroscedasticity, robust standard errors are calculated.

Moreover, in order to minimize a bias through idiosyncratic sampling (Fleming 2001), as a further robustness check the longitudinal nature of the dependent variable is exploited by conducting the empirical analysis for two different five-year time periods (t_1: 2012–2016; t_2: 2016–2020). In this way, the robustness of the empirical results over different time periods is verified, at least to some extent. The corresponding results remain relatively robust[24] and are presented in Table 6 in the appendix.

As can be seen in Table 4 in the appendix, the explanatory variables correlate only slightly with each other. Therefore, multicollinearity is considered less of a concern. However, in line with previous studies (e.g. Lee et al. 2001), when examining possible interaction effects, the corresponding interaction terms are included individually to avoid serious multicollinearity problems.

4 Empirical results and discussion

In this section, the results of the empirical analysis will be presented and discussed (see Table 2). Model 1 illustrates the baseline model. In general, the control variables are mostly stable throughout the models. In line with previous research (e.g. Grashof et al. 2020), the results of the control variables indicate for instance that on average older firms are more capable of generating radical innovations. Hence, their advantages in terms of resource and knowledge accumulation (Herriott et al. 1985; Levitt and March 1988) providing more opportunities to recombine knowledge pieces seem to outweigh organizational inertia issues which may restrict their capacity to change (e.g. Majumdar 1997). Moreover, throughout all models a significant positive influence of the *independence_dummy* is found, indicating that an independent ownership structure is beneficial for the emergence of radical innovations. The research-intensive industry dummy is however only slightly significant in the baseline model. Thus, the research intensity of the relevant industry in which the firm operates is not a significant determinant of the occurrence of radical innovation, which is consistent with previous findings (e.g. Hesse 2020). With regard to the regional context in which the companies are located, it can be stated that

[23] As a further robustness check, instead of the overall number of patents, the mean number of patents is also tested. The corresponding results remain stable (see Table 5 in the appendix).

[24] In the second time period, the *family_dummy* becomes slightly insignificant. However, in the model with the interaction term (see Model 3 in Table 6b in the appendix), it stays significant negative, indicating that family firms that are not located in a regional cluster remain significantly less capable of creating radical patents than non-family firms.

Table 2 Regression results: Family firms and radical innovation

	Dependent variable			
	rad_count	rad_count	rad_count	rad_count
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–0.521***	–0.746***	0.264
	–	(0.158)	(0.134)	(0.358)
Cluster_dummy	–	–	0.535**	–
	–	–	(0.254)	–
Family_dummy* cluster_dummy	–	–	0.757*	–
	–	–	(0.436)	–
Log_size_mean	–	–	–	0.392***
	–	–	–	(0.044)
Family_dummy* log_size_mean	–	–	–	–0.066
	–	–	–	(0.057)
Age_mean	0.012***	0.012***	0.009***	0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Independence_dummy	1.075***	0.923***	0.986***	0.437**
	(0.295)	(0.298)	(0.305)	(0.209)
researchintensiveindustry	0.282*	0.251	0.181	–0.034
	(0.151)	(0.154)	(0.130)	(0.099)
Popdens_mean	0.0002**	0.0001*	0.0001	0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.054**	0.048**	0.055***	0.022
	(0.022)	(0.020)	(0.019)	(0.016)
Constant	–2.536***	–2.113***	–2.272***	–2.983***
	(0.811)	(0.741)	(0.723)	(0.848)
Inflate: pat_count	–0.249***	–0.024***	–0.231***	–0.212***
	(0.032)	(0.033)	(0.032)	(0.039)
Constant	2.864***	2.779***	2.748***	2.540***
	(0.094)	(0.098)	(0.096)	(0.105)
N	10,431	10,431	10,431	10,293
McFadden's Adj R2	0.184	0.186	0.191	0.225
Log-likelihood	–3854.557	–3840.852	–3813.604	–3621.056
Akaike Inf. Crit.*N	7727	7702	7661	7270

Robust standard errors in parentheses

* $p<0.10$, ** $p<0.05$, *** $p<0.01$

locating in highly urbanized regions (at least in Model 1 and 2) is advantageous for the creation of radical innovation by companies.

This can eventually be explained by the large diversity of different actors and knowledge within these regions which offers a rather large potential for knowledge recombination (Hesse and Fornahl 2020). In addition, the proportion of average share of persons with tertiary education and/or with S&T occupation in the region, proxying the regional absorptive capacity, seem to matter for the emergence of radical innovation, which is line with previous studies (e.g. Hesse 2020).

Model 2 introduces the family firm dummy variable (*family_dummy*). As assumed (see Hypothesis 1), a significant negative influence is found. Family firms are therefore on average less capable of creating radical innovations than non-family firms. This can be explained by the risk aversion and the desire to preserve socio-emotional wealth which both hinder the engagement in explorative search processes and thereby the creation of radical innovations (Nieto et al. 2015). Hence, Hypothesis 1 cannot be rejected.

By following an "interactionist approach" (Beugelsdijk 2007), the potential moderating role of the regional context is additionally investigated in Model 3, where a dummy variable for firms' location in a regional cluster is introduced. As indicated by the significant positive interaction term ($\beta = 0.757$; $p = 0.082$), being located in a cluster increases the likelihood for family firms to create radical innovations.[25] Due to their active participation and close connections within their region, family firms are more strongly embedded in the regional innovation system compared to non-family firms (Basco et al. 2021a; Block and Spiegel 2013; Déniz and Suárez 2005). As a result, they are more likely to reap the benefits of localization externalities within regional clusters (Basco 2015; Basco et al. 2021a), which have been shown to foster the emergence of radical innovation (e.g. Grashof et al. 2019). Consequently, it can be resumed that Hypothesis 2 cannot be rejected.

Since not all family firms belong to a homogenous group (e.g. Filser et al. 2018), in Model 4, the moderating influence of firm size is tested. While the influence of firm size takes the assumed negative direction, it is however insignificant. Firm size therefore does not significantly inhibit the creation of radical innovations in family firms more than in non-family firms.[26] Instead, in the case of non-family firms, we even find evidence for a significant positive influence of firm size, meaning that larger non-family firms are better capable of generating radical innovation. Indeed, in both cases a significant positive coefficient is found for firm size (see Fig. 3 in the Appendix). For non-family firms the average marginal effect (AME) is 0.107, while for family firms it is slightly lower (AME is 0.073), although still highly significant. Consequently, Hypothesis 3 has to be rejected.

Overall, the results show that, on average, family businesses are less likely to produce radical innovation than non-family businesses. However, the corresponding regional context matters in this context. Family firms that are located in regional clusters can create more radical innovation, since they can exploit the advantages of localization externalities through their strong regional embeddedness.

5 Conclusion

Despite the relatively extensive research on innovation in family firms (e.g. Calabrò et al. 2019), it remains unclear whether family firms have a greater likelihood to

[25] In general, 9.77% of all family firms in the sample (corresponding to 568 firms) are located in regional clusters. Of these family firms, 9.33% (corresponding to 53 family firms) created radical innovations, compared to 5.15% (corresponding to 270 family firms) in the case of non-clustered family firms.

[26] The corresponding predicted margins are illustrated in Fig. 2 in the Appendix.

generate radical innovation and to what extent contextual variables moderate this relationship. This paper addressed these two research gaps by combining several data sources to empirically examine the relationship between family firms and radical innovation as well as the moderating effects of regional clusters and firm size.

In summary, the study provides three main results. First, it shows that, on average, family firms create less radical innovation than non-family firms. Their risk aversion and desire to preserve socio-emotional wealth may act in this context as obstacles to engaging in exploratory search processes, which ultimately hinders the creation of radical innovation (Nieto et al. 2015). Second, the study shows that the specific context in regional clusters can moderate this relationship. On average, being located in a cluster favors the emergence of radical innovations in family businesses. Clusters therefore constitute a beneficial environment (e.g. through their localization externalities) for family firms. The potential substitution effect between the rather redundant conditions enhancing the advantages of industrial districts and family firms shown in recent studies (e.g. Cucculelli and Storai 2015; Pittino et al. 2021) can therefore not be confirmed for the more general context of regional clusters. Unlike in the case of industrial districts, regional clusters do not necessarily build on the social and cultural dimension (Grashof and Fornahl 2021). Hence, it seems promising for future research to further differentiate regional clusters according to their characteristics (e.g. size, share of SMEs, strength of social and cultural background). Third, the study shows that, unlike innovation in general (e.g. Werner et al. 2018), the size of firms does not significantly hinder the creation of radical innovations in family firms more than in non-family firms. Instead, it is revealed that in both cases larger firms are more likely to file new radical patents, which is consistent with previous research (e.g. Grashof and Kopka 2023) that explains this by the fact that larger firms can benefit from more internal R&D resources (Ortega-Argilés et al. 2009; Rammer and Schubert 2016).

Nevertheless, this study does not come without limitations, thereby offering additional opportunities for further research. First of all, the underlying data base for determining radical innovations and knowledge variety are patents, which have some drawbacks (e.g. Griliches 1990). Future research could therefore use alternative, non-patent-based data (e.g. Hervas-Oliver et al. 2019). Additionally, future research could also investigate alternative patent-based measures for the emergence of radical innovation, e.g. backward citations, and its impact and diffusion, e.g. forward citations (Dahlin and Behrens 2005; Trajtenberg et al. 1997). Moreover, due to data constraints (with respect to the identification of clusters and family firms), the corresponding empirical analysis is only based on pooled cross-sectional data, which raises potential concerns of endogeneity (e.g. Block and Spiegel 2013; Grashof et al. 2019). Future research may therefore use panel data in order to determine dynamic effects. In this context, it is also useful for future studies to additionally examine other types of regions (e.g. rural vs. urban regions) in order to further disentangle the cluster effect. Furthermore, similar to previous studies (e.g. Block and Spiegel 2013), due to data availability only information on family ownership is used to determine family firms. Future studies may consider the direct influence of family members in terms of firm management or supervisory board. In this context, it also seems interesting to additionally consider the influence of the individual characteristics of the owners, especially between different generations in leadership (De Massis et al. 2012). Lastly, the analysis is limited to the high-tech and polycentric country Germany. The consideration of further countries with different levels of economic development and regional structure could be taken up by future studies to control for potential country effects.

Nevertheless, despite these limitations all in all it can be resumed that the results about the relationship between family firms and radical innovations contribute to the family firm, regional and innovation economics literature. The article provides insights about the emergence of radical innovation on the firm-level by examining the corresponding role of family firms in Germany and the moderating role of regional clusters and firm size. In doing so, it extends recent studies in innovation economics that have examined radical innovation across different types of firms (e.g. Grashof and Kopka 2023). Furthermore, it contributes to the regional studies literature by showing that the cluster-specific benefits do not accrue to all types of firms, but rather to specific ones (such as family firms), which adds to previous studies that attempt to explain the heterogenous firm-specific performance effects of being located in regional clusters (e.g. Hervas-Oliver et al. 2018). At the same time, it also contributes to the family business studies literature by stressing the relevance of the regional context when examining the (innovative) performance of family firms, which supports recent efforts to consider contextual heterogeneity in family business research (e.g. Basco et al. 2021a). In addition to the scientific contribution, the results also offer relevant policy implications. The results on the lower average radical patent activities in family businesses require special attention in the form of policy measures that should primarily address the risk avoidance of family businesses, such as technical services and advice that can provide an external perspective and reduce the risk of potentially misleading investments (Jones and Grimshaw 2016; Shapira and Youtie 2016). Furthermore, by finding evidence for a moderating influence of the location of firms in a regional cluster, this study additionally shows that the relationship between family firms and radical innovation is far more complex than often assumed. Hence, there is a need for a more differentiated view on family firms that also reflects this heterogeneity (De Massis et al. 2012). By following such an approach, family firms can also successfully become more radical in their innovation process.

6 Appendix

Table 3 Industrial distribution of sample and share of dependent variable

NACE	Activity	No. of firms	Share of radical patents (in %)
1	Crop and animal production, hunting and related service activities	10	2.27
3	Fishing and aquaculture	1	0.00
5	Mining of coal and lignite	1	0.00
6	Extraction of crude petroleum and natural gas	1	0.00
7	Mining of metal ores	1	0.00
8	Other mining and quarrying	16	4.61
10	Manufacture of food products	92	3.48
11	Manufacture of beverages	6	1.49
12	Manufacture of tobacco products	1	12.50
13	Manufacture of textiles	102	2.58
14	Manufacture of wearing apparel	17	11.08
15	Manufacture of leather and related products	20	3.64
16	Manufacture of wood and of products of wood and cork. except furniture; manufacture of articles of straw and plaiting materials	77	2.86
17	Manufacture of paper and paper products	76	2.47
18	Printing and reproduction of recorded media	34	0.90
19	Manufacture of coke and refined petroleum products	8	8.62
20	Manufacture of chemicals and chemical products	248	2.01
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	107	1.35
22	Manufacture of rubber and plastic products	391	1.05
23	Manufacture of other non-metallic mineral products	157	3.66
24	Manufacture of basic metals	113	2.90
25	Manufacture of fabricated metal products. except machinery and equipment	741	2.61
26	Manufacture of computer. electronic and optical products	707	2.23
27	Manufacture of electrical equipment	389	1.66
28	Manufacture of machinery and equipment n.e.c.	1339	2.34
29	Manufacture of motor vehicles. trailers and semi-trailers	152	1.64
30	Manufacture of other transport equipment	79	4.60
31	Manufacture of furniture	83	1.01
32	Other manufacturing	385	2.10
33	Repair and installation of machinery and equipment	58	2.26
35	Electricity. gas. steam and air conditioning supply	59	5.43

Table 3 (Continued)

NACE	Activity	No. of firms	Share of radical patents (in %)
36	Water collection. treatment and supply	4	0.00
37	Sewerage	7	8.33
38	Waste collection. treatment and disposal activities; materials recovery	35	2.08
39	Remediation activities and other waste management services	3	0.00
41	Construction of buildings	44	1.52
42	Civil engineering	37	1.02
43	Specialised construction activities	278	2.22
45	Wholesale and retail trade and repair of motor vehicles and motorcycles	82	1.99
46	Wholesale trade. except of motor vehicles and motorcycles	1269	1.57
47	Retail trade. except of motor vehicles and motorcycles	275	2.40
49	Land transport and transport via pipelines	29	3.92
50	Water transport	3	16.67
51	Air transport	1	0.00
52	Warehousing and support activities for transportation	37	4.08
53	Postal and courier activities	3	3.29
55	Accommodation	1	0.00
56	Food and beverage service activities	11	0.00
58	Publishing activities	7	0.00
59	Motion picture. video and television programme production. sound recording and music publishing activities	6	7.69
60	Programming and broadcasting activities	1	0.00
61	Telecommunications	14	0.27
62	Computer programming. consultancy and related activities	408	1.78
63	Information service activities	23	0.00
64	Financial service activities. except insurance and pension funding	232	2.05
66	Activities auxiliary to financial services and insurance activities	39	1.91
68	Real estate activities	157	2.47
69	Legal and accounting activities	9	1.64
70	Activities of head offices; management consultancy activities	481	2.16
71	Architectural and engineering activities; technical testing and analysis	583	3.03
72	Scientific research and development	420	2.08
73	Advertising and market research	26	0.00
74	Other professional. scientific and technical activities	94	3.13
75	Veterinary activities	2	0.00
77	Rental and leasing activities	48	3.73
78	Employment activities	8	0.00
79	Travel agency. tour operator and other reservation service and related activities	7	0.00

Table 3 (Continued)

NACE	Activity	No. of firms	Share of radical patents (in %)
80	Security and investigation activities	1	0.00
81	Services to buildings and landscape activities	34	3.33
82	Office administrative. office support and other business support activities	185	4.04
84	Public administration and defence; compulsory social security	4	0.00
85	Education	24	1.30
86	Human health activities	42	0.64
87	Residential care activities	3	0.00
88	Social work activities without accommodation	7	18.18
90	Creative. arts and entertainment activities	3	0.00
92	Gambling and betting activities	4	0.00
93	Sports activities and amusement and recreation activities	9	0.00
94	Activities of membership organisations	13	1.79
95	Repair of computers and personal and household goods	1	0.00
96	Other personal service activities	111	1.99

Table 4 Pairwise correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) rad_count	1.000	–	–	–	–	–	–	–	–
(2) family_dummy	–0.046***	1.000	–	–	–	–	–	–	–
(3) cluster_dummy	0.050***	–0.035***	1.000	–	–	–	–	–	–
(4) age_mean	0.090***	–0.098***	0.153***	1.000	–	–	–	–	–
(5) independence_dummy	0.099***	–0.171***	0.022**	0.150***	1.000	–	–	–	–
(6) researchintensiveindustry	0.045***	–0.096***	0.061***	0.071***	0.031***	1.000	–	–	–
(7) popdens_mean	0.018*	–0.095***	–0.098***	–0.045***	0.035***	–0.032***	1.000	–	–
(8) share_academics_mean	0.030***	–0.046***	–0.058***	–0.107***	0.020**	0.010	0.307***	1.000	–
(9) log_size_mean	0.169***	–0.381***	0.164***	0.383***	0.148***	0.181***	–0.019*	–0.068***	1.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 Regression results (with mean number of radical and non-radical patents)

	Dependent variable			
	rad_mean	rad_mean	rad_mean	rad_mean
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–0.988***	–1.278***	–0.088
	–	(0.205)	(0.147)	(0.383)
Cluster_dummy	–	–	0.858***	–
	–	–	(0.285)	–
Family_dummy* cluster_dummy	–	–	0.894**	–
	–	–	(0.447)	–
Log_size_mean	–	–	–	0.685***
	–	–	–	(0.042)
Family_dummy* log_size_mean	–	–	–	–0.006
	–	–	–	(0.068)
Age_mean	0.015***	0.014***	0.012***	0.001
	(0.003)	(0.003)	(0.002)	(0.001)
Independence_dummy	1.511***	1.165***	1.244***	0.363
	(0.336)	(0.339)	(0.002)	(0.225)
Researchintensiveindustry	0.886***	0.820***	0.743***	0.435***
	(0.182)	(0.179)	(0.166)	(0.141)
Popdens_mean	0.0002*	0.0001	0.0001*	0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.075***	0.074***	0.081***	0.049***
	(0.026)	(0.026)	(0.027)	(0.018)
Constant	–7.444***	–6.963***	–7.277***	–9.336***
	(0.966)	(0.977)	(1.005)	(0.773)
Inflate: pat_mean	0.0001	0.0002	0.0007	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	–24.907***	–23.219***	–23.475***	–26.534***
	(0.274)	(0.153)	(0.077)	(0.058)
N	10,431	10,431	10,431	10,293
McFadden's Adj R2	0.157	0.174	0.193	0.378
Log-likelihood	–1367.406	–1338.237	–1300.830	–992.307
Akaike Inf. Crit.**N*	2753	2697	2636	2013

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 Regression results (for t_1: 2012–2016; t_2: 2016–2020)

(a) Time period t_1: 2012–2016				
	Dependent variable			
	rad_count	rad_count	rad_count	rad_count
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–0.486***	–0.719***	0.097
	–	(0.167)	(0.138)	(0.513)
Cluster_dummy	–	–	0.520*	–
	–	–	(0.270)	–
Family_dummy* cluster_dummy	–	–	0.739*	–
	–	–	(0.442)	–
Log_size_mean	–	–	–	0.375***
	–	–	–	(0.063)
Family_dummy* log_size_mean	–	–	–	–0.035
	–	–	–	(0.074)
Age_mean	0.011***	0.012***	0.009***	–0.0002
	(0.002)	(0.002)	(0.002)	(0.001)
Independence_dummy	0.100***	0.859***	0.937***	0.408
	(0.300)	(0.304)	(0.320)	(0.262)
Researchintensiveindustry	0.245	0.216	0.148	–0.054
	(0.156)	(0.156)	(0.132)	(0.116)
Popdens_mean	0.0002**	0.0002*	0.0001	0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.062***	0.056***	0.064***	0.035*
	(0.022)	(0.021)	(0.020)	(0.020)
Constant	–2.978***	–2.609***	–2.796***	–3.489***
	(0.836)	(0.783)	(0.767)	(1.147)
Inflate: pat_count	–0.384***	–0.375***	–0.367***	–0.253***
	(0.059)	(0.060)	(0.061)	(0.069)
Constant	3.287***	3.204***	3.167***	2.809***
	(0.119)	(0.124)	(0.122)	(0.151)
N	10,431	10,431	10,431	6,812
McFadden's Adj R2	0.212	0.214	0.218	0.242
Log-likelihood	–2926.274	–2917.165	–2896.779	–2234.260
Akaike Inf. Crit.**N*	5871	5854	5828	4497

Table 6 (Continued)

(b) Time period t_2: 2016–2020

	Dependent variable			
	rad_count	rad_count	rad_count	rad_count
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–0.204	–0.440***	0.639*
	–	(0.176)	(0.158)	(0.360)
Cluster_dummy	–	–	0.537**	–
	–	–	(0.265)	–
Family_dummy* cluster_dummy	–	–	0.762*	–
	–	–	(0.458)	–
Log_size_mean	–	–	–	0.393***
	–	–	–	(0.042)
Family_dummy* log_size_mean	–	–	–	–0.080
	–	–	–	(0.058)
Age_mean	0.010***	0.010***	0.007***	–0.0002
	(0.002)	(0.002)	(0.002)	(0.001)
Independence_dummy	1.013***	0.953***	0.998***	0.382*
	(0.316)	(0.319)	(0.304)	(0.202)
Researchintensiveindustry	0.294*	0.279	0.215	0.015
	(0.168)	(0.171)	(0.151)	(0.117)
Popdens_mean	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.044**	0.042**	0.049**	0.019
	(0.021)	(0.020)	(0.020)	(0.014)
Constant	–2.484***	–2.326***	–2.512***	–3.505***
	(0.788)	(0.738)	(0.726)	(0.716)
Inflate: pat_count	–0.444***	–0.438***	–0.429***	–0.439***
	(0.067)	(0.069)	(0.068)	(0.105)
Constant	3.384***	3.349***	3.322***	3.067***
	(0.106)	(0.112)	(0.110)	(0.124)
N	10,431	10,431	10,431	10,184
McFadden's Adj R2	0.221	0.222	0.225	0.259
Log-likelihood	–2285.304	–2284.032	–2267.155	–2136.860
Akaike Inf. Crit.*N	4589	4588	4568	4302

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 Regression results (based on negative binomial regression approach)

	Dependent variable			
	rad_count	rad_count	rad_count	rad_count
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–1.106***	–1.294***	–0.174
	–	(0.138)	(0.133)	(0.394)
Cluster_dummy	–	–	0.522**	–
	–	–	(0.228)	–
Family_dummy* cluster_dummy	–	–	0.830**	–
	–	–	(0.390)	–
Log_size_mean	–	–	–	0.516***
	–	–	–	(0.054)
Family_dummy* log_size_mean	–	–	–	–0.050
	–	–	–	(0.062)
Age_mean	0.017***	0.017***	0.013***	–0.0004
	(0.002)	(0.002)	(0.002)	(0.001)
Independence_dummy	1.667***	1.239***	1.256***	0.562***
	(0.308)	(0.308)	(0.298)	(0.213)
Researchintensiveindustry	0.540***	0.468***	0.391***	0.099
	(0.142)	(0.149)	(0.123)	(0.096)
Popdens_mean	0.0002**	0.0001*	0.0001*	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.050**	0.037**	0.044**	0.017
	(0.022)	(0.018)	(0.018)	(0.017)
Constant	–4.274***	–3.265***	–3.453***	–4.728***
	(0.815)	(0.679)	(0.660)	(0.945)
N	10,431	10,431	10,431	10,293
McFadden's Adj R2	0.045	0.059	0.064	0.120
Log-likelihood	–4511.791	–4443.722	–4413.324	–4116.528
Akaike Inf. Crit.**N*	9038	8903	8857	8257

Robust standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8 Regression results (based on zero-inflated poisson regression approach)

	Dependent variable			
	rad_count	rad_count	rad_count	rad_count
	(1.)	(2.)	(3.)	(4.)
Family_dummy	–	–0.335	–0.752***	0.432
	–	(0.261)	(0.189)	(0.399)
Cluster_dummy	–	–	0.619	–
	–	–	(0.383)	–
Family_dummy* cluster_dummy	–	–	1.035**	–
	–	–	(0.496)	–
Log_size_mean	–	–	–	0.504***
	–	–	–	(0.048)
Family_dummy* log_size_mean	–	–	–	–0.056
	–	–	–	(0.058)
Age_mean	0.011***	0.011***	0.009***	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)
Independence_dummy	0.880**	0.794**	0.894**	0.152
	(0.367)	(0.385)	(0.367)	(0.279)
Researchintensiveindustry	0.568**	0.558**	0.511**	0.278
	(0.226)	(0.229)	(0.123)	(0.169)
Popdens_mean	0.0001	0.0001	0.0001	–0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Share_academics_mean	0.094**	0.095**	0.102**	0.066***
	(0.042)	(0.043)	(0.043)	(0.024)
Constant	–3.471**	–3.357**	–3.683**	–5.277***
	(1.661)	(1.654)	(1.627)	(0.998)
Inflate: pat_count	–0.087***	–0.083***	–0.080***	–0.064***
	(0.008)	(0.009)	(0.007)	(0.006)
Constant	3.009***	2.960***	2.834***	2.288***
	(0.087)	(0.102)	(0.090)	(0.10)
N	10,431	10,431	10,431	10,293
McFadden's Adj R2	0.250	0.253	0.281	0.456
Log-likelihood	–6704.584	–6680.635	–6421.085	–4830.191
Akaike Inf. Crit.**N*	13425	13379	12874	9686

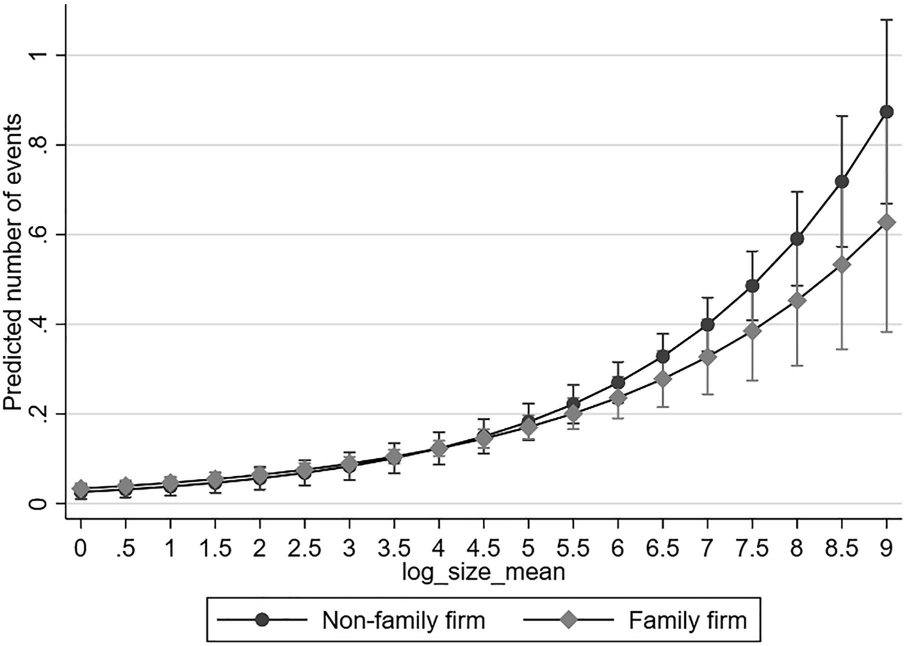

Fig. 2 Predictive margins of filling radical patents by firm ownership and size (with 95% CIs)

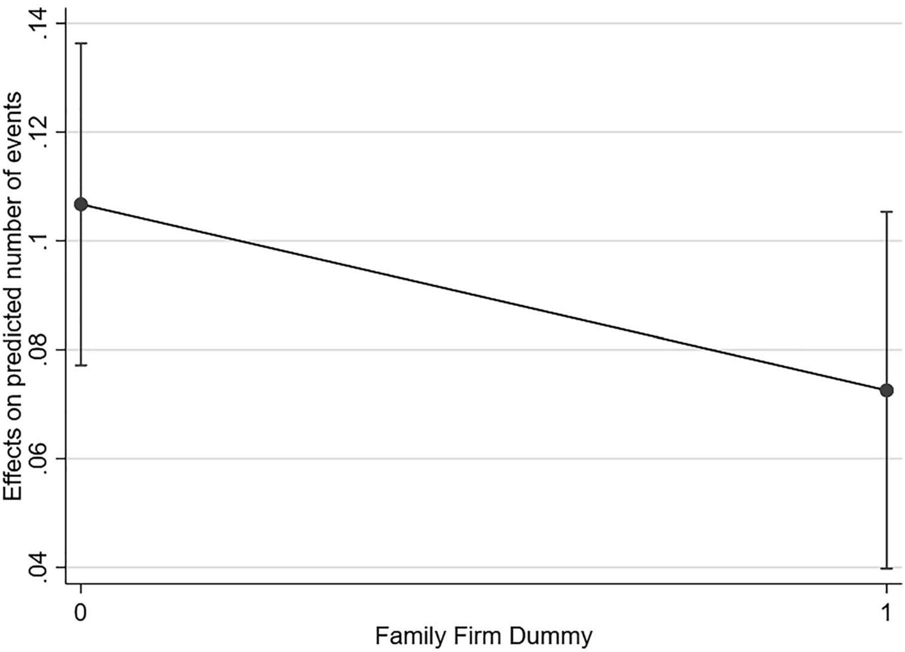

Fig. 3 Average marginal effects of firm size for family and non-family firms (with 95% CIs)

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