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Knowledge inheritance and performance of spinouts

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Abstract

We investigate the impact of knowledge inheritance by vertical spinouts originating from user and supplier industries on performance. We test whether spinouts from a supplier or user industry perform better than focal industry spinouts and de novo entrants. Using longitudinal micro data for the Portuguese molds and plastics industries we find that vertical user and supplier spinouts perform better in terms of survival (but not in terms of early sales) than focal industry spinouts, and all types of spinouts perform better than de novo entrants. The results suggest that vertical spinouts possess specific knowledge that might be more valuable than that of focal industry spinouts, while spinouts originating from suppliers underperform those originating from users.

Keywords Vertical spinouts · Focal spinouts · User industry · Supplier industry · Pre-entry knowledge · Clusters

JEL Classification $~J62 \cdot L22 \cdot L26 \cdot L61 \cdot R12$

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1 Introduction

Extensive research has shown that firm- and industry-specific knowledge inherited by founders of independent spinouts¹ from their previous employers contributes to enhancing the performance of these kinds of entrants (Agarwal et al., 2004; Chatterji, 2009; Klepper, 2009).

Spinouts often take place across related industries. For example, some of the first firms to enter the automotive industry in the US were founded by entrepreneurs with experience in related industries, such as bicycles, engines, carriages, and wagons (Klepper, 2002). In a series of works, Adams et al. (2016, 2017, 2019, 2022) examine 'vertical spinouts'—defined as new ventures founded by the ex-employees of established firms in either an upstream (supplier) or a downstream (user) industry. They find that these kinds of spinouts represent a significant share of all start-ups, and their founders carry specific knowledge acquired in their previous user or supplier work experience (Adams et al., 2019).

The present study examines the performance of spinouts from supplier (upstream) industries and from user (downstream) industries, and from the user to the supplier, contrasting it with the performance of focal industry spinouts² as well as de novo entrants (i.e., new ventures started by founders originating from unrelated industries). We focus on two vertically related industries in Portugal: molds for plastic injection and plastics (i.e., users of molds).

A large proportion of both molds and plastics industries is densely clustered outside the main metropolitan centers, in the Marinha Grande and Oliveira de Azeméis municipalities and surrounding areas. Knowledge inheritance by spinouts is found to play a significant role in the emergence of industrial clusters: local spinouts are more likely to succeed than other start-ups, therefore contributing to geographical agglomeration (Buenstorf & Klepper, 2010; Dahl et al., 2010; Klepper, 2011). Conducting the study in a context in which the two vertically related industries are co-located allows us to control for the effects of agglomeration on performance highlighted by, among others: Diodato et al. (2018); Ellison et al. (2010); Krugman (1991); Marshall (1890).

Agglomeration benefits are sometimes associated with pools of specialized workers and easy access to knowledge spillovers (Baptista & Swann, 1998). An important conduit for knowledge transfer is provided when a spinout 'inherits' firm-, industry- and region-specific knowledge acquired by its founders while working for incumbents (Buenstorf & Klepper, 2009, 2010; Klepper, 2009, 2011; Phillips, 2002). Our analysis seeks to identify benefits imparted to firms resulting from the inheritance of knowledge resources and capabilities occurring

¹ In line with Agarwal et al. (2004) and Franco and Filson (2006), we use the term "spinouts" to designate entrepreneurial ventures by former employees of incumbents in the same or a closely related industry to that of the start-up. This is roughly equivalent to Klepper's definition of spinoffs as entrants founded by former employees of incumbent firms (Klepper, 2007; 2009; 2011).

 $^{^2}$ In line with Adams et al., (2016; 2017; 2019; 2022) we use the term 'focal' to designate the industry where the spinout is founded. Thus, spinouts founded by former employees of incumbents in the same industry as the start-up are designated as 'focal industry spinouts.'

in the context of spinouts, which should be distinct from agglomeration economies arising in the context of clusters. The latter are more likely to benefit all firms equally, regardless of their origin.

In what constitutes a novel contribution to the literature, we aim to discern the effects of knowledge inheritance on the performance of spinouts originating from user industries from those on spinouts from suppliers. Research on vertical spinouts has either focused solely on spinouts from downstream (user) industries (Adams et al., 2016, 2017, 2022) or addressed spinouts from user and supplier industries as equivalent (Adams et al., 2019; Diodato et al., 2018). However, work by Delgado et al. (2016), as well as the arguments put forward by Adams et al., (2016, 2017, 2022), suggest that the intrinsic advantages of knowledge inheritance should vary across types of spinouts.

Our analysis uses detailed longitudinal linked employer-employee data for Portugal that provides detailed information for the universe of firms, workers, and business owners, enabling us to observe new firm founders' employment and location backgrounds. It is then possible to identify user and supplier spinouts located both inside and outside a cluster, distinguishing them from other startups and comparing their performances. Therefore, we can distinguish between heritage-related performance effects from user and supplier origin while controlling for agglomeration effects.

Our results suggest a strong influence of knowledge inheritance in driving spinout performance, even after controlling for other factors known to influence new venture performance. Notably, we find that vertical spinouts perform better than focal industry spinouts, while spinouts from users appear to capture more substantial benefits than spinouts from suppliers.

The present study makes several contributions. First, we examine the performance of local cross-industry spinouts, whereas most extant studies of clusters focus on intra-industry spinouts. Second, our estimations distinguish between effects imparted on user spinouts from those imparted on supplier spinouts. Third, we differentiate between effects on local start-up performance that may be attributed to specific knowledge inheritance by spinout founders from those that can only be attributed to agglomeration (i.e., effects imparted on all local startups – both spinouts and de novo entrants). This kind of analysis is novel for geographically clustered cross-industry spinouts. Finally, we contribute to the literature on industrial districts (e.g., Brusco, 1982; Camagni, 1991; Piore & Sabel, 1984) by examining an industrial context composed predominantly of small and medium-sized firms where clustering benefits manifest primarily through learning and vertical relationships across local networks of small businesses.

The remainder of the paper is organized as follows. The next section discusses the mechanisms driving geographical clustering and spinout performance, paying specific attention to the budding literature on vertical spinouts. In the third section, we describe the empirical setting, including data and methodology. The fourth section presents the results. In the final section, we discuss our findings and present our conclusions.

2 Literature background

2.1 Spinouts and pre-entry knowledge

When entering the market, a firm's resources and capabilities depend on its' prehistory. Based on evolutionary theories, Helfat and Lieberman (2002) argue that the greater the similarity between pre-entry organizational knowledge and the kind of knowledge required by an industry, the greater the likelihood that a firm will enter that industry and the greater the likelihood that the firm will survive and grow. Pre-entry knowledge may be acquired through transfer to the new firm of routines and experience from the previous employers of founders (Phillips, 2002). Founder knowledge and resources are critical to the success of start-ups (Baptista et al., 2014; Klepper, 2007, 2008). Agarwal et al. (2004) and Klepper (2008) argue that the success of new organizations is fundamentally shaped by knowledge inherited from incumbents. This knowledge includes routines, technology, organization processes, and access to suppliers and intermediate services.

Spinouts should inherit knowledge and routines that are more likely to be valuable in the market they enter and are therefore expected to perform better than de novo entrants (Agarwal et al., 2004; Andersson et al., 2012; Klepper, 2009). The mobility of key employees of incumbents towards the creation of start-ups is a prime conduit for knowledge transfer and has been shown to impact new firm success (Franco & Filson, 2006) as well as incumbents' strategies and incentives for R&D investment (Colombo et al., 2017). Furlan and Grandinetti (2016) add that spinouts also acquire critical social capital through learning-by-doing, on-the-job training, and interpersonal exchanges, both from within and outside the parent firm. Therefore, it is likely that knowledge inherited by new entrants through the conduit provided by their founders will be more relevant and useful if these founders worked for incumbents in the focal or related industries (customers and suppliers).

2.2 Spinouts, agglomeration, and clusters

The fact that firms benefit from close proximity to other firms with which they can exchange inputs, skilled labor, or know-how helps explain why many geographical clusters are so successful. Evidence for agglomeration having a positive effect on a variety of measures of firm success (including growth and innovativeness) is found in several studies (e.g., Baptista & Swann, 1998; Wennberg & Lindqvist, 2010), although diseconomies of agglomeration play an increasingly important role as clusters evolve and grow (Folta et al., 2006).

Various types of economies of agglomeration are identified in the literature, including input–output linkages, labor market pooling, knowledge spillovers, sophisticated local demand, specialized institutions, and the organizational structure of the business and social networks (e.g., Baptista, 1998; Duranton & Puga, 2004; Krugman, 1991; Markusen, 1996; Porter, 1990, 1998). However, since agglomeration economies should accrue fairly equally to all firms co-located in a cluster, their existence does not fully explain a key mechanism found in many successful clusters:

employees leaving established incumbents to create their own firms or shape new entrants in their industry (Klepper, 2008, 2011).

The prevalence of spinouts in geographical clusters has been chronicled in more than a few industries (e.g., Buenstorf & Klepper, 2009, 2010; Cheyre et al., 2015; Klepper, 2002, 2007). Klepper (2007, 2008, 2011) argues that the advantages conferred to spinouts by the knowledge acquired by their founders are a major driver of industry agglomeration and cluster formation because successful spinouts will locate close to their founders' previous employers. Buenstorf and Klepper (2009, 2010) and Klepper (2007, 2010) find that the growth of successful clusters is often triggered by the spinouts of a successful pioneer firm.

Spinout founders (and start-up founders in general) prefer to locate in their 'home' region, i.e., near their previous employer (the 'parent' firm) (Figueiredo et al. (2002). Michelacci and Silva (2007) and Dahl and Sorenson (2009) suggest that this choice results from advantages accrued from local networking and relationships. Agarwal et al. (2016) propose that entrepreneurs have greater knowledge about local prospective hires based on their prior work experience, while Buenstorf and Costa (2018) find that spinouts are often able to hire more and better experienced early workers. Finally, Carias et al. (2022) find that spinout founders located in their home region hire workers from their parent firm and other firms in the same region and industry, employ them longer and perform better (i.e., survive longer) than other new firms.

The quality of the parent firm may also affect spinout performance as more successful incumbents spawn more spinouts that tend to survive longer (Agarwal et al., 2004; Buenstorf & Klepper, 2009, 2010; Klepper, 2007, 2010). The agglomeration of high-performing spinouts next to their successful parent firms facilitates the emergence of successful clusters.

2.3 Cross-industry spinouts and the agglomeration of related industries

Arguably, spinouts originating from closely related industries also inherit unique combinations of knowledge that will influence their choices at entry and their ability to survive in the focal industry (Adams et al., 2016; Klepper, 2002). Knowledge inherited from related industries confers an advantage to new entrants in a focal industry, as found by Klepper and Simons (2000) when studying the entry of prior radio producers in the US television receiver industry. Exploring agglomeration economies in US cities, Ellison et al. (2010) find evidence of input–output dependencies and labor pooling benefits. However, Glaeser and Kerr (2009) find only modest support for the effect of linkages to customers and suppliers on the patterns of industry entry in US regions.

Studying the co-location of related industries, Diodato et al. (2018) find that while value chain linkages explain much of the co-location patterns in manufacturing, the co-location of services is driven more by similarities in industries' skill requirements. Their results suggest that while manufacturing firms seek benefits from co-location with users and suppliers, service firms value proximity due to skill-sharing advantages. In the case of manufacturing, which applies to the present

paper, proximity to upstream and downstream industries appears to confer benefits that may be associated with the inheritance of relevant knowledge by spinouts, or may simply be due to various types of agglomeration externalities. In the case of spinouts, such benefits might have different intensities depending on the direction in which the founder moves in the value chain.

The dynamics and effects of cross-industry knowledge flows-including those occurring in the context of spinouts-are complex. Dosi et al. (2021) propose that the nature of knowledge flowing upstream from user industries differs from that of knowledge flowing downstream from supplier industries. While knowledge flowing from users is mostly disembodied, leading to labor-friendly innovation effects, knowledge flowing from suppliers is mostly embodied, leading to labor-saving productivity gains. This outcome suggests that spinouts occurring from the user/ demand side benefit mainly from product differentiation and strategic advantages. In contrast, those occurring from the supply side would primarily benefit from costbased advantages. We suggest that this may have significant implications when examining the potential impact of founder-related knowledge on spinout performance. While user industry spinouts are likely to benefit significantly from product differentiation and other strategic advantages arising from market-related knowledge, supplier industry spinouts may be less able to benefit from embodied, laborsaving knowledge due to smaller size and investment constraints (Gimenez-Fernandez et al., 2020; Lefebvre, 2022).

Previous research lends support to the significant positive effects of knowledge flows from parent companies in user/upstream spinouts. Fontana and Malerba (2010) argue that spinouts from the demand side are better performers because they bring along knowledge and experience about applications and end markets. They find that user spinouts are even superior performers to focal industry spinouts because they possess unique and tacit knowledge and experience about applications and end markets, particularly when demand is not homogeneous.

Using the same data (from the US semiconductor industry between 1997 and 2007), Adams et al., (2016, 2017) reiterate the advantages of spinouts originating from user industries, arguing that the specific nature of their knowledge influences which product markets they choose to enter (Adams et al., 2016), as well as their choice of entry location (Adams et al., 2017). However, both studies focus only on comparing user and focal industry spinouts (with users including computers and office equipment, consumer electronics, communication equipment, and automobiles) and do not address spinouts from supplier industries.

In a subsequent study, Adams et al. (2019) compare the performance of vertical spinouts with both focal industry spinouts and de novo entrants in semiconductors, telecommunications equipment, and telecommunications networks/connectivity, finding that vertical spinouts (originating in both user and supplier industries) outperform (i.e., survive longer) not only de novo start-ups, bus also focal industry spinouts. The authors argue that these findings are consistent with Helfat and Lieberman's (2002) proposition that the better the match between the pre-entry resources of a start-up and the requirements of the market entered, the greater the likelihood that the new venture will survive. In the case of user- and supplier-industry spinouts, the resources inherited from downstream and upstream industries seem to provide a good match with the resources required to enter and compete in a new, vertically related industry. Such a match is found to be generally superior to the match between industry requirements and knowledge inherited from the industry entered.

However, this last study does not distinguish between user and supplier vertical spinouts. There seems, therefore, to be an opportunity to contribute by comparing the performance of user and supplier vertical spinouts, contrasting them with focal industry spinouts and de novo entrants. If the nature of knowledge flows associated with supplier/downstream spinouts is indeed different, it is expected that their performance patterns will differ from those of user/upstream spinouts.

2.4 Hypotheses

The theoretical and empirical literature lends support to the proposition that firms in a variety of industries are generally likely to perform better when co-locating with other firms in their own (focal) industry. While there are noticeably fewer empirical studies focusing specifically on co-location with firms in related industries, the evidence also points to positive effects. In the case of manufacturing, which is the focus of our study, co-location is primarily associated with relatedness through the value chain (i.e., with upstream and downstream industries) (Diodato et al., 2018). In studies for the semiconductor industry, Adams et al., (2016, 2017) find that user industry spinouts (i.e., start-ups by former employees in downstream industries) make different location choices and perform better than spinouts founded by former employees in the same (focal) industry). In addition, Adams et al. (2019) find that vertical spinouts (both from user/downstream and supplier/upstream industries) are more likely to survive than de novo entrants.

Informed by the theoretical and empirical bodies of literature on agglomeration externalities and inheritance of knowledge by spinouts originating in the focal industry and in related industries, we formulate four hypotheses. First, because focal industry spinouts benefit from positive effects from their founders' heritage of focal industry-specific knowledge, which are independent of all-purpose agglomeration economies, we predict that:

Hypothesis H1 The performance of focal industry spinouts is superior to that of de novo start-ups.

Second, because vertical spinouts benefit from their founders' heritage of vertical industry-specific knowledge, which are independent of all-purpose agglomeration economies, we predict that:

Hypothesis H2 The performance of vertical industry spinouts originating in both user (downstream) and supplier (upstream) industries is superior to that of de novo start-ups.

Third, because the market-related knowledge inherited from user firms facilitates strategic differentiation, leading to products that fit the requirements of the market better than knowledge inherited from parent firms in the same (focal) industry:

Hypothesis H3 The performance of vertical industry spinouts originating in user (downstream) industries is superior to that of focal industry spinouts.

Finally, because knowledge flowing to downstream spinouts from supplier industries is more likely to be embodied and associated with cost advantages which are likely to benefit new firms less due to liabilities of smallness initially:

Hypothesis H4 The performance of vertical industry spinouts originating in supplier (upstream) industries is superior to that of focal industry spinouts, but inferior to that of vertical industry spinouts originating in user (downstream) industries.

When testing these four hypotheses, the analysis takes special care in controlling for agglomeration economies associated with a strong geographical concentration of firms in the focal and vertically related industries.

3 Empirical setting

3.1 The Portuguese plastics and molds for plastic injection industries

The Portuguese industry of molds for plastic injection (i.e., the 'molds industry') is densely agglomerated outside the main metropolitan centers in the Marinha Grande municipality and surrounding areas (hereafter referred to as 'Marinha') and, to a somewhat lesser extent, in Oliveira de Azeméis (hereafter referred to as 'Oliveira'). A disproportionate number of plastics firms are also located in the Marinha region, close to their suppliers from the molds industry. The emergence of the Portuguese molds industry was contemporary with that of plastics, and their histories are closely interlinked. The Portuguese molds industry reflects an empirical setting dominated by vertically disintegrated networks of small firms where scale economies are not prevalent, as each mold order represents a fundamentally new product. In such a context, a major role is played by tacit knowledge and local networks—in a way similar to Italian textiles and ceramic clusters in Emilia Romagna (Brusco, 1982; Porter, 1998). While displaying a larger firm size, the Portuguese plastics industry has, over time, concentrated close to molds, and employee mobility through spinouts within and between the two industries is a recurrent phenomenon (Callapez, 2000).

Costa and Baptista (2015) provide an account of the emergence of the molds and plastics industries in Marinha in the 1930s and 1940s, originating from the local presence of a precursor industry—glass—in that same region. The first few firms played a fundamental role in developing both industries by becoming worker training and networking centers. Since plastic molds are highly specialized products developed based on unique customer specifications, economies of scale are of little relevance for the organization of the industry. Moreover, the specialized nature of the custom-fit products also means that new firms could emerge without entering into direct competition with incumbents, so there was little scope for non-compete agreements or other practices constraining competition from new entrants and the mobility of technical workers (see Marx et al., 2009). Local networks allowed firms receiving complex orders to identify and subcontract other local firms or identify workers with the specialized knowledge required to fulfill those orders. From the 1970s, the increased demand for plastic-based inputs from the IT and automobile industries created a growth spurt. Consequently, it established the international

reputation of Marinha as source of low-cost, high-quality products. The Oliveira region followed suit and benefited from the reputation effect.

The supplier-customer link between the molds and the plastics industries is by far the most substantial vertical relationship within Portuguese territory for the plastics industry.³ While the downstream relationship with plastics is dominant for the molds industry, a large proportion of its output (most often over 80%) is exported. Geographical concentration (in the aforementioned Marinha region) is far more intense in the molds industry than in plastics, although a large number of plastics firms locate in the molds cluster. The different levels of geographical concentration for the two industries provide an interesting setting for our analysis.

3.2 Data and methodology

3.2.1 Data source and empirical strategy

The present study uses a dataset extracted from the 'Quadros de Pessoal' (QP) micro-data. QP is a Portuguese longitudinal matched employer-employee database collected annually since 1985 by the Ministry of Labor, Solidarity, and Social Security. Data submission by firms is mandatory, so the data contain detailed information on all private firms with at least one wage earner, linking it with information on individuals (workers and business owners). Data for firms include size (number of employees), sales, and location of each establishment). Information on individuals covers age, education, employment, job assignment, and wages. We focus on the molds and plastics industries, collecting information on all new firms and incumbents, workers, and entrepreneurs (i.e., owners who are also managers of their firms) for the period 1987–2009⁴ in continental Portugal (firm location is collected at the municipality level).

The detailed nature of this archival data allows for the identification of spinouts and their parent firms, as well as their respective geographical locations. It is also possible to distinguish between start-ups with different industries of origin, thus identifying supplier, user, and focal industry spinouts, as well as de novo entrants. Considering that we aim to examine spinouts in the context of an industry cluster, where agglomeration externalities are deemed to impact firm performance, our empirical strategy requires that we are able to distinguish between effects on performance that are associated with agglomeration (which differentiate between firms located inside and outside the cluster) and effects associated with heritage (which differentiate between spinouts and de novo entrants). By examining linked

 $^{^3}$ While there are other industries with significant vertical relationships with plastics and molds – such as petrochemicals and metal/iron-based alloys, most essential inputs are imported, and none of these industries fits the context of co-location/geographical clustering that would allow us to control for agglomeration effects when examining the impact of knowledge inheritance on the performance of spinouts. Thus, we have chosen to focus exclusively on the relationship between molds and plastics.

⁴ While there are data available for later years, we chose to exclude the years of the Great Recession, since the effects on the Portuguese economy were substantial, introducing a factor that affected both new firm entry and firms' chances of survival significantly.

employer-employee data covering all incumbents and start-ups in an industry, we can identify founders' professional backgrounds in terms of employment and geographical location, thus distinguishing between new firms located inside and outside the cluster, as well as between new firms located in the same region of their parent firm and those whose founders move to the clustered region. These distinctions guide our empirical strategy.

3.2.2 Data description and variables

For our analysis, we identify firms in the plastics industry as firms that mainly use plastic injection technology to produce plastic products. Molds firms are producers of molds for plastic injection. We use two measures to examine the performance of new entrants according to their location and backgrounds (focal industry, supplier industry and user industry spinouts; and de novo start-ups). First, we look at the likelihood of survival of new firms in molds and plastics and how it is influenced by the founders' background, controlling for regional agglomeration (measured by worker density) and parent quality (proxied by parent size). Second, we examine the impact of the same variables on the likelihood that surviving molds and plastics entrants will become top one-third sellers by their third year of activity, an empirical measure similar to the one employed by Coad and Timmermans (2014).

We identify 1,146 molds firms entering the industry in the period of analysis, including spinouts from the focal industry and spinouts from the user (plastics) industry. For the plastics industry, we identify 1,170 new entrants during the same period, including focal industry spinouts and spinouts from the supplier (molds) industry. The total number of firms in the market in both industries peaked in 2005 when there were 914 firms in the plastics industry and 681 in the molds industry.

In addition to Marinha, the molds industry also registers some agglomeration in the region of Oliveira de Azeméis. The plastics industry is less agglomerated than molds but also has a high proportion of firms located in the Marinha region, with no significant concentration in Oliveira. Figure 1 shows that about 21.6% of the plastics firms are located in Marinha and Oliveira. The remaining firms are scattered around 140 other municipalities (14.4% are located in the main metropolitan centers of Lisbon and Porto). Molds firms are strongly clustered, with about 47.6% located in the Marinha and Oliveira regions (39.2% in the Marinha region alone).

The Portuguese plastics industry developed a close relationship with its local molds suppliers throughout its emergence. However, from the mid-1950s, the molds industry started exporting intensely, and soon the local plastics customers represented only a small part of the market for Portuguese molds (the molds industry consistently exported about 80–90% of its production during the period of analysis). Still, the local molds suppliers continued to be important for the plastics industry, as Portuguese plastics firms bought nearly half of their molds from domestic suppliers.

For each entrant in the molds and plastics industries, we identify the founder(s). Tracing back their professional histories, we look for each founder's occupations in the previous five years of available data, allowing us to identify focal industry spinouts, vertical spinouts, and de novo entrants (Fig. 2). Focal-industry spinouts are new entrants founded by at least one person with a prior job in the focal industry,

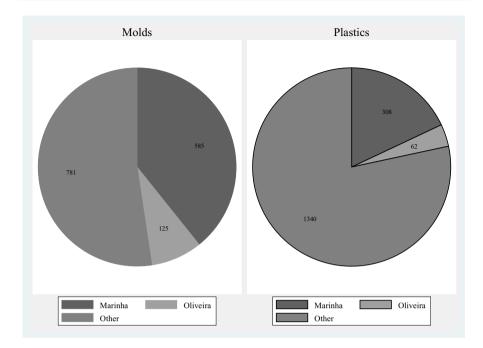


Fig. 1 Location of the molds and plastics firms

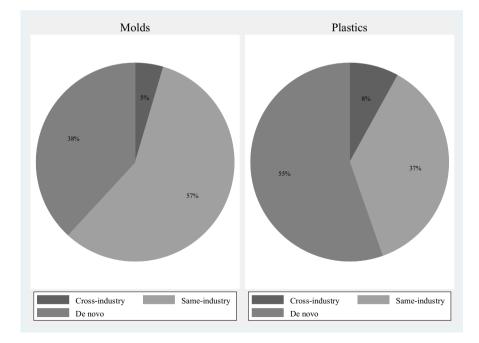


Fig. 2 Types of molds and plastics entrants

with no known connection (legal or otherwise) to the parent firm. Vertical industry spinouts are new entrants founded by at least one person with a prior job in a vertically-related industry (molds or plastics, respectively), also with no known connection to the parent firm. These will be user spinouts if started in molds by someone coming from plastics, and supplier spinouts if started in molds by someone coming from plastics. De novo entrants are independent new entrants whose founders did not have a prior job in the focal or a related industry, but may have had jobs in other industries, which are deemed unrelated for the purpose of the present study.

Focal industry spinouts represent the majority of identified entrants in both industries (about 57% in molds and 55% in plastics). Vertical industry spinoffs are appreciably less numerous (about 4% in molds and 5% in plastics) but still represent a significant number of entrants in the period of analysis.

There are also entrants with unknown backgrounds, for whom it was not possible to identify the previous jobs of the entrepreneurs for at least five years prior to startup.⁵ These new entrants are significantly less likely to survive than de novo entrants and spinouts. In our analysis, we consider that a firm has an "unknown" background in those cases where it is not possible to identify the background of the founder(s) in the five years prior to start-up. This includes several possible instances: (1) the founder might have been unemployed in the years prior to start-up; (2) the founder might not have been part of the workforce in the years prior to start-up (i.e., not actively looking for work); (3) the founder might have been working for the public (administrative) sector (i.e., as a civil servant) in the years prior to start-up; iv) the founder might have been working for a firm that did not report social security data in the years prior to start-up.

Let us address each case in turn. Founders coming from long-term unemployment (over 5 years) may be deemed a kind of "necessity-based" entrepreneur. Baptista et al. (2014) report that, for necessity-based (i.e., previously unemployed), specific forms of entrepreneurial human capital (such as industry-specific experience) tend to have insignificant effects on the performance (survival) of new businesses. Also, research in labor economics suggests that interrupted careers translate into the depreciation of knowledge stocks, making workers less likely to retain relevant knowledge that can be used in their future occupations, including business ownership (Mincer & Ofek, 1982). Founders who were not part of the workforce prior to start-up are unlikely to have acquired any firm- or industry-specific experience or training. In some cases, they may be new to the workforce and business ownership is their first professional experience. In other cases, they may have been away from the workforce for a while, having undergone skill depreciation in a way analogous to the one reported above for the long-term unemployed. Given the high job security and benefits associated with public sector careers, mobility to the private sector is relatively rare. Also, given the nature of tasks, the kind of specific knowledge acquired in public administration is unlikely to have a significant impact on the performance of most private sector start-ups. The last case is very rare and usually associated with micro-firms (fewer than five employees) that do not survive in the

⁵ Unknown entrants represent a significant proportion (over 30%) of total entry in both industries.

market longer than one or two years, meaning that founders are unlikely to bring significant specific knowledge to their start-ups. Therefore, we believe that in all cases of entrants with unknown backgrounds, any kind of inherited knowledge will have a lower value than in those where we can positively identify independent start-ups and focal, supplier, and user industry spinouts. Thus, we will use unknown entrants as the baseline for our analysis.

We use the location quotient to assess the level of industry agglomeration across regions. The location quotient is the ratio of two shares: the employment share of a particular industry in a region and the employment share of that industry in the country. This quotient has long been applied to estimate the strength of regional economic activities (see, for example, Isserman, 1977). Following the standard procedure in the literature, we weigh the industry shares using the number of employees to attribute more importance to the location decision of larger plants.

Building on the dartboard approach developed by Ellison and Glaeser (1997), which removes the effect of agglomeration driven by random independent location decisions, Guimarães et al. (2009) developed significance tests for the location quotient, which we apply here as well. It is usually assumed that the industry is concentrated in the region if the quotient is above one. Using the significance tests introduced by Guimarães et al. (2009), we can verify whether the location quotients show evidence of geographic concentration in excess of what would be expected to happen randomly.

QP data assign firms and establishments to municipalities.⁶ We use this information to estimate location quotients for the molds and plastics industries and also a joint location quotient. Results show that the molds industry is concentrated in fewer municipalities, while the plastics industry has a strong presence in a large number of municipalities (see Fig. 3).

The average location quotient across municipalities is 0.58 for the molds industry and 1.26 for the plastics industry. As expected, the highest location quotient for the molds industry is for Marinha (27.46). Nearby municipalities like Leiria, Alcobaça, and Batalha also rank high. Oliveira also has a strong presence of molds further north. The highest location quotient for the plastics industry is for the municipalities of Constância (25.22) and Ponte de Sôr (23.16). For Marinha (7.09) and nearby Leiria (7.52), agglomeration is still high and well above average. It is noteworthy that if we weigh industry shares using the number of firms, rather than employment, agglomeration levels for the plastic industry in Marinha and Leiria would rank higher, suggesting that these municipalities have a large number of small firms located in the large molds cluster. The high plastics location quotient for Constância is due mainly to the presence of a large Tupperware plastic injection plant. Similarly, Ponte de Sôr hosts a large Delphi plant producing plastic components for the automotive industry. While these two regions host the largest share of employment in the plastics industry, Marinha and Leiria host large numbers of small plastics firms.

Considering that the average employment in the molds industry for the period is 8.599 employees per year, while for the plastics industry it is 18.233 employees, the

⁶ There are 278 municipalities in continental Portugal.

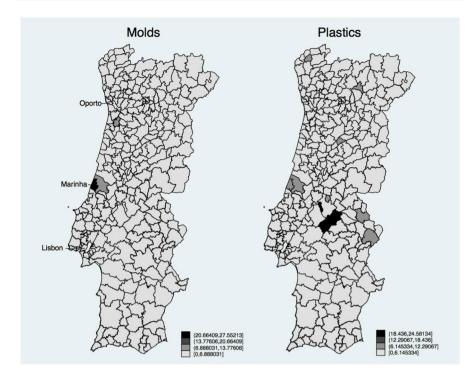


Fig. 3 Municipalities with significant concentration in the molds and plastics industries (1986–2009)

joint location quotient is, unsurprisingly, dominated by the regions where the plastics industry has a more substantial presence. We use the location quotient estimates to proxy for the agglomeration of these industries across municipalities. Specifically, we use the value of the quotient when the estimate is significant and replace it with zero when the test does not confirm that localization is significantly greater than what we expect to find randomly. Table 1 presents descriptive statistics for our variables and a correlation matrix.

Entrants are classified as focal-industry spinouts (at least one founder with experience in the same industry as the start-up), vertical (user and supplier) spinouts (at least one founder with experience in the downstream—plastics—or upstream molds—industry), and de novo *entrants* (independent entrants whose background is not in plastics or molds). The omitted baseline category is unknown entrants.

3.2.3 Model estimation

We estimate models for the two variables measuring performance. Model I focuses on the probability of survival, while Model II looks at sales ranking (i.e., the probability of placing in the top one-third of sellers by the third year of activity). The survival analysis examines the probability of firm survival in plastics and molds as a function of the firm's background (i.e., whether it is a focal-industry spinout or a vertical spinout). We control for industry agglomeration by using the location

Table 1 Descriptive statistics													
Variables	Mean	SD	Min	Max	1	5	3	4	5	9	7	~	6
Molds					-			-					
1. Survival	8.469	5.930	1	23	1								
2. Size at entry (log)	5.914	11.914	1	194	0.023	1							
3. Size of spinout's parent (log)	1.108	1.738	0	10.298	0.186	0.051	1						
4. Focal industry spinout	0.328	0.470	0	1	0.113	0.004	0.788	1					
5. Vertical spinout	0.026	0.160	0	1	0.082	0.041	0.262	-0.115	1				
6. De novo	0.219	0.413	0	1	0.063	0.055	-0.337	-0.370	- 0.087	1			
7. Unknown background	0.427	0.495	0	1	-0.186	- 0.063	-0.551	-0.603	-0.142	- 0.456	1		
8. Location Quotient Molds and Plastics	5.273	5.095	0	15.331	0.127	- 0.092	0.176	0.197	- 0.005	-0.138	- 0.070	1	
9. Location Quotient Plastics	3.376	2.990	0	12.316	0.169	- 0.089	0.188	0.206	0.007	-0.131	- 0.089	0.867	1
Plastics													
1. Survival	9.956	6.501	1	23	1								
2. Size at entry (log)	7.850	17.710	0	272	0.100	1							
3. Size of spinout's parent (log)	0.663	1.404	0	7.458	0.117	0.121	1						
4. Focal industry spinout	0.183	0.387	0	1	0.090	0.081	0.772	1					
5. Vertical spinout	0.040	0.196	0	1	0.041	-0.025	0.349	- 0.097	1				
6. De novo	0.277	0.447	0	1	0.043	0.043	-0.292	- 0.293	-0.126	1			
7. Unknown background	0.500	0.500	0	1	-0.125	- 0.092	-0.473	-0.474	-0.205	-0.619	1		
8. Location Quotient Molds and Plastics	2.553	3.811	0	15.331	0.057	0.032	0.165	0.078	0.160	-0.124	-0.012	1	
9. Location Quotient Molds	3.487	7.412	0	35.227	0.020	-0.007	0.144	0.048	0.186	-0.102	-0.019	0.915	1
Molds and plastics													
1. Survival	9.184	6.278	1	23	1								
2. Size at entry (log)	6.934	15.304	1	272	0.079	1							
3. Size of spinout's parent (log)	0.872	1.586	0	10.299	0.131	0.077	1						
4. Focal industry spinout	0.257	0.437	0	1	0.084	0.033	0.797	1					
5. Vertical spinout	0.027	0.163	0	1	0.045	0.003	0.276	- 0.099	1				

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Table 1 (continued)													
Variables	Mean	SD	Min Max	Max	1	2	3	4	5	6	7	8	6
6. De novo	0.250	0.433	0	1	0.061	0.050	- 0.318	- 0.340	- 0.097	1			
7. Unknown background	0.465	0.499	0	1	-0.142	-0.073	-0.513	- 0.549	-0.157	- 0.538	1		
8. Location Quotient Molds and Plastics	3.850	4.679	0	15.331	0.054	-0.040	0.206	0.197	0.043	-0.143	-0.063	1	
9. Location Quotient Molds	6.309	9.794	0	35.226	0.012	- 0.057	0.182	0.174	0.045	-0.127	- 0.058	0.943	1

quotient of the region where the firm locates. The analysis also controls for the parent firm's quality (measured by its size), as better parents should influence the innate ability of entrants to compete. Finally, we control for the entrant's initial size. We use mixed Frailty models with the following specification:

$$h(t \mid \alpha) = \alpha \left\{ \exp \left[\beta_1 \log(entry \ size) + \beta_2 \log(parent \ size) + \beta_3 focal + \beta_4 vertical + \beta_5 denovo + \beta_6 LQ \right] \right\}$$

Frailty models are random effects models for time variables, where the random effect (the frailty) has a multiplicative effect on the hazard. Using a frailty model allows us to introduce unobserved heterogeneity into the proportional hazards model, thus accounting for the influence of unobserved covariates (Hougaard, 1995).

The sales ranking analysis looks at the probability that entrants will be positioned in the top one-third of sellers by their third year of activity. We estimate Logit models using the same variables of interest and controls and adding year dummies to control for the business cycles. The specification for the Logit models is the following:

$$P(TopSeller = 1|x) == \Lambda[\beta_1 \log(entry \ size) + \beta_2 \log(parent \ size) + \beta_3 focal + \beta_4 vertical + \beta_5 denovo + \beta_6 LQ + \beta_7 year]$$

4 Results

4.1 Survival

Table 2 displays the results of Model I, the frailty survival model using a Gompertz distribution with Gamma heterogeneity. By accounting for unobserved firm heterogeneity, we expect more accurate results than with Cox proportional hazards models. The Gompertz specification with Gamma heterogeneity provided the better fit for the data when compared with alternative specifications.⁷

The coefficients in Table 2 are hazard ratios. Hazard ratios compare the effect of the variable on the likelihood of exit with its effect on the likelihood of exit for the baseline group (start-ups where the founders' origin is unknown, most often because of long periods of unemployment). For a discrete explanatory variable identifying a type of entrant, this will be the ratio between the hazard of exit for that type of entrant and the hazard of exit for the baseline group. Thus, if the hazard ratio for focal industry spinouts is 0.5, that means that focal industry spinouts are 50% as likely to exit as the baseline entrants; a hazard ratio of 0.4 for vertical industry spinouts would mean they are only 40% as likely to exit as start-ups out of unemployment, meaning their hazard of exit is lower than for focal industry spinouts.

⁷ The Gamma/Gompertz model was compared with the Gamma/Weibull specification as well as with the inverse Gaussian specification.

ny)—nazard ratios						
Variables	(1) Molds and j	plastics	(2) Molds entra	ints	(3) Plastics entr	rants
Size at entry (log)	0.914*	0.917*	0.985	0.983	0.883*	0.880*
	(0.043)	(0.043)	(0.069)	(0.070)	(0.060)	(0.059)
Size of spinout's	0.968	0.963	0.976	0.974	0.976	0.971
parent (log)	(0.058)	(0.058)	(0.075)	(0.076)	(0.100)	(0.100)
Focal industry	0.448***	0.446***	0.382***	0.389***	0.449**	0.453**
Spinouts	(0.101)	(0.101)	(0.110)	(0.114)	(0.170)	(0.171)
Vertical	0.406**	0.408**	0.236***	0.234***	0.412*	0.413*
Spinouts	(0.147)	(0.148)	(0.130)	(0.131)	(0.199)	(0.200)
De novo	0.493***	0.499***	0.558***	0.553***	0.420***	0.424***
	(0.063)	(0.064)	(0.094)	(0.095)	(0.082)	(0.083)
Location quotient	0.978**		0.952***		0.982	
molds and plastics	(0.010)		(0.013)		(0.017)	
Location		0.995				0.994
quotient molds		(0.005)				(0.009)
Location				0.905***		
quotient plastics				(0.022)		
Constant	0.106***	0.101***	0.141***	0.151***	0.084***	0.082***
	(0.011)	(0.010)	(0.021)	(0.023)	(0.012)	(0.011)
Observations	2,152	2,152	1,066	1,066	1,121	1,121
Log-likelihood	- 2,544.0	- 2,545.8	- 1,289.1	- 1,286.2	- 1,262.4	- 1,262.7

 Table 2
 Model I: estimates of the survival frailty model, Gompertz distribution (Gamma heterogeneity)—hazard ratios

Standard errors in parentheses

Lh ratio test $\theta = 0$

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

0.000

0.001

Looking at entrants in both plastics and molds industries (first column in Table 1), after controlling for agglomeration effects the hazard ratios associated with all types of entrants are positive, meaning that vertical and focal industry spinouts, as well as de novo entrants, have greater survival probabilities than the baseline type of entrant (entrants of unknown origin). Hazard ratios for user industry spinouts are smaller (closer to zero) than for focal industry spinouts, and these are smaller than for de novo entrants, although the differences are relatively small. Still, these results suggest that the positive effect of vertical user spinout background on start-ups' chances of survival is stronger than that of focal industry background, while the latter is stronger than the effect of being a de novo entrant. Vertical industry spinouts perform better than de novo entrants). Vertical supplier industry spinouts underperform their user industry counterparts.

0.002

0.001

0.003

0.003

The joint location quotient for both industries has a positive effect on the probability of survival, while the location quotient for molds only has no significant effect. These results suggest that agglomeration economies are associated with the presence of vertically related industries rather than a single industry, confirming the findings of Diodato et al. (2018) for manufacturing.

A similar pattern emerges when only molds entrants are examined (second column). The chances of start-up survival are most enhanced by the founder's background in the user industry (lower hazard ratios for user spinouts than for focal-industry spinouts and de novo entrants, with greater differences between coefficients). In particular, the results corroborate the findings by Adams et al., (2016, 2017) for user spinouts. Also, by examining performance in the context of geographical agglomeration and location choices of start-ups, our results lend special support to those obtained by Adams et al. (2019). Findings are similar for the plastics entrants (third column), although the coefficients for supplier spinouts are only significant at the 10% level. Also, the differences between the hazard ratios for the three types of backgrounds are quite small. These results suggest that, in this particular context, the advantages of supplier industry spinouts over focal industry spinouts and de novo startups are less substantial than those of user industry spinouts. All in all, hypotheses H1–H4 are supported, although vertical supplier industry spinouts do not always perform significantly better than either de novo entrants or focal industry spinouts.

De novo entrants perform remarkably well in the plastics industry. Indeed, they tend to survive longer than entrants with a background in the focal industry. This is possibly associated with the presence of manufacturing branches of multinational companies such as the previously mentioned Tupperware and Delphi plants. In the case of molds entrants, the performance advantage of vertical (user) spinouts is substantial, suggesting that, in an industry where each new order represents a fundamentally new product and firms need to work according to the specifications of the customer, prior knowledge of the user industry plays a key role. This conclusion is consistent with Adams et al. (2017), who find that user industry spinouts make different strategic choices than focal industry ones.

In the plastics industry, the (good) performance of de novo entrants suggests that prior knowledge is not as important as elements such as learning-by-doing and economies of scale. The results seem to show that the nature of knowledge in these industries is not comparable, and thus knowledge inheritance mechanisms play a less important role in the plastics industry than in molds. However, we must note that this de novo categorization may not correspond entirely to the classification usually found in the literature. Our sample of entrants with an unknown background may contain entrants who are also de novo entrants (or other types of entrants), but we are unable to confirm that in the data.

Our controls for the agglomeration economies are significant for the molds entrants, but in lower magnitudes than the variables accounting for spinouts. The control for the size of the entrants is significant for the joint sample, as well as for the plastics entrants. However, there is no significant effect on the molds entrants. This is consistent with our expectations about the importance of scale economies in each of these industries.

Entry size has only a barely significant effect on survival in the joint sample. This effect is likely driven by plastics firms (where entry size is also barely significant)

$\begin{array}{c} (0.010) & (0.010) & (0.010) \\ (0.010) & (0.010) & (0.010) \\ (0.012) & (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) & (0.012) \\ (0.012) & (0.012) & (0.012) & (0.012) \\ (0.046) & (0.046) & (0.046) & (0.046) & (0.046) \\ (0.046) & (0.046) & (0.046) & (0.046) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.024) & (0.024) & (0.024) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) & (0.014) & (0.014) & (0.014) & (0.014) & (0.014) & (0.014) \\ (0.014) &$	0.176*** (0.015)	0.177*** (0.014)	0.158***	0.159***
Size of spinout's -0.003 -0.003 -0.003 parent (log) (0.012) (0.012) (0 Focal industry 0.161^{***} 0.162^{***} (0 spinouts (0.046) (0.046) (0 Vertical 0.161^{**} 0.161^{**} (0 spinouts (0.077) (0.077) (0 De novo 0.081^{***} 0.079^{***} (0 (0.024) (0.024) (0 (0	· /	(0, 014)		0.159
parent (log) (0.012) (0.012) (0 Focal industry 0.161*** 0.162*** (0 spinouts (0.046) (0.046) (0 Vertical 0.161** 0.161** (0 spinouts (0.077) (0.077) (0 De novo 0.081*** 0.079*** (0 (0.024) (0.024) (0 (0	0.001	(0.014)	(0.014)	(0.014)
Focal industry 0.161*** 0.162*** 0 spinouts (0.046) (0.046) (0 Vertical 0.161** 0.161** 0 spinouts (0.077) (0.077) (0 De novo 0.081*** 0.079*** 0 (0.024) (0.024) (0.024) (0	- 0.001	- 0.001	- 0.006	- 0.005
spinouts (0.046) (0.046) (0 Vertical 0.161** 0.161** 0 spinouts (0.077) (0.077) (0 De novo 0.081*** 0.079*** (0 (0.024) (0.024) (0 (0	(0.014)	(0.014)	(0.020)	(0.020)
Vertical 0.161** 0.161** 0 spinouts (0.077) (0.077) (0 De novo 0.081*** 0.079*** (0 (0.024) (0.024) (0 (0	0.146**	0.143**	0.159**	0.158**
spinouts (0.077) <	(0.057)	(0.057)	(0.071)	(0.071)
De novo 0.081*** 0.079*** ((0.024) (0.024) (0.156	0.152	0.164	0.167
(0.024) (0.024) ((0.119)	(0.119)	(0.103)	(0.103)
	0.039	0.039	0.118***	0.116***
Location quotient 0.002	(0.036)	(0.036)	(0.032)	(0.032)
Location quotient 0.003 0	0.003		0.002	
molds and plastics (0.002) ((0.003)		(0.004)	
Location quotient 0.001				-0.000
molds (0.001)				(0.002)
Location quotient		0.008*		
plastics		(0.005)		
Observations 2091 2091 1	1039	1039	1087	1087
Log-pseudo likelihood - 1,117.5 - 1,118.2 -	- 528.3	- 527.6	- 595.6	- 595.7
Pseudo R^2 0.1676 0.1670 0	0.2082	0.2091	0.1480	0.1478
Wald test 0.0000 0.0000 0	0.0000	0.0000	0.0000	0.0000

Table 3 Model II: estimates of the logit models for top sales in the third year-marginal effects

Robust standard errors in parentheses

Year dummies omitted

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

since the effect for molds entrants is not significant. The parent firm's quality (proxied by its size) does not play a significant role in the survival in either industry, contrary to previous studies (Agarwal et al., 2004; Buenstorf & Klepper, 2009, 2010; Klepper, 2007, 2010). This is unsurprising in the case of molds, where the large majority of businesses are small or micro firms and specialized workers are likely to start as apprentices, learning through practice. In the case of plastics, where micro firms are mixed with large plants, size may not effectively capture the quality of the parent firm due to the large variability.

4.2 Sales ranking

Table 3 presents the estimates from Model II, the Logit model, showing the marginal effects for the likelihood of becoming a top one-third seller by the third year in the market. For a discrete explanatory variable, the marginal effect is the change in the dependent variable when the explanatory variable is incremented by one unit. We again look at the entrepreneur's background and use the same controls for industry density and quality of the firm and parent. In addition, entry-year dummies are included as controls for business cycles.

Looking at the estimates from the sample that joins molds and plastics entrants (first column), we see that focal-industry and vertical spinouts are significantly more likely to become top sellers. While there is a substantial difference in performance between spinouts and de novo entrants, the marginal effects for vertical and focal industry spinouts are quite similar. Spinout firms seem to have a much higher likelihood of becoming top performers, confirming the impact of knowledge inheritance. Still, the effects are even for focal industry and vertical spinouts.

However, the vertical spinout effect is no longer significant when we look at the separate samples for molds and plastics (second and third columns). For both the molds and plastics industries (columns 2 and 3), entrants with a background in the focal industry have a significantly higher likelihood of becoming top sellers early on. Still, vertical spinouts do not, which is particularly surprising for user industry spinouts since they would be expected to have specific knowledge of the markets faced by the new entrant. Thus, while hypotheses H1–H2 are supported, hypotheses H3–H4 are not confirmed for sales.

Unlike for survival models, the location quotient is also not significant (except for molds, where it is barely significant), suggesting that all-purpose agglomeration economies do not impact the chances of becoming a top seller early on. This is unsurprising since plastics is a less geographically concentrated industry than molds.

Also different from survival models, in this setting we find significant positive effects of entrant size. This suggests that firms enter these two industries with different strategies and perspectives: while firms that enter with large sizes have a product design ready and clear target market—thus becoming top sellers quickly—firms that start small may still be learning about the market and need time to develop a successful product. However, this does not seem to preclude them from surviving for a long time. Finally, for parent quality, the results are similar to the survival models, with no significant effects.

5 Discussion and conclusions

This study has sought to examine the impact of knowledge inheritance by user and supplier spinouts on firm performance in the context of vertically related industries and geographical agglomeration. The molds industry in Portugal is an example of a successful cluster that emerged over seven decades ago and is still prevalent. Presently, Portugal is the eighth-largest plastic injection molds producer in the world and the third in Europe (ISTMA, 2022), exporting about 85% of its total production (CEFAMOL, 2021). The primary market, representing 71% of sales in 2021, is precision molds for the automotive industry in Europe (CEFAMOL, 2021). By studying the interaction of molds with its primary customer industry—plastics—we aim to shed some light on the vertical spinout dynamics in the context of geographical clustering, adding to the still sparse literature (e.g., Adams et al., 2017).

Our examination of the performance of new firms in the Portuguese molds and plastics industries shows that spinouts, both associated with vertical and focal industries, have a significant advantage in terms of performance (in particular, survival) over de novo entrants. This suggests that the knowledge inheritance by spinouts plays a significant role in driving firm performance, regardless of agglomeration economies resulting from clustering. The results support the findings by Klepper (2007, 2009, 2011) and Buenstorf and Klepper (2009, 2010).

Importantly, these effects appear to be significant for both spinouts originating in the focal industry and spinouts originating from a vertically related industry (supplier or user). In the case of survival, vertical industry spinouts perform better than focal industry ones, suggesting that their vertical industry-specific knowledge (e.g., information about downstream and upstream markets and technologies) matters more than focal industry-specific knowledge (e.g., organizational routines and focal industry technologies). These results support the findings of Adams et al. (2019), who found that vertical spinouts are more likely to survive than de novo entrants. However, the present study goes further by comparing vertical and focal industry spinouts and by differentiating between user and supplier spinouts.

These effects stand after controlling for the impact of geographical concentration (i.e., agglomeration benefits that touch all types of cluster entrants equally). In the case of survival, these positive effects are quite significant, hinting that superior firm performance in clusters results from the intersection and interaction of agglomeration economies and knowledge inheritance by spinouts, as found by Golman and Klepper (2016).

When examining early (third-year) sales rather than survival, we find that knowledge associated with spinouts becomes less important, particularly in the case of vertical spinouts. While this is an unexpected result, it is noteworthy that initial size acquires a significant and substantial effect that was not recorded for survival. A possible explanation for this is that there are two kinds of start-ups entering these industries with different strategies and perspectives: while firms that enter with large size have a product design ready and clear target market—thus becoming top sellers quickly—firms that start small may still be learning about the market and need time to develop a successful product. However, this does not seem to preclude survival.

Vertical and focal industry-specific knowledge seems to play a more significant role in the molds industry than in the plastic industry. Molds firms are significantly smaller than plastics firms, and each order represents a substantially new product. The transmission of knowledge through spinouts and local networks of small firms (including users and suppliers) is more critical for molds than for plastics, where economies of scale in manufacturing likely play a more prominent role. The pervasiveness of spinouts in molds—resulting from a tradition of mobility of experienced workers towards entrepreneurship—is likely to enhance the impact of knowledge inheritance.

Our results also suggest that the impact of knowledge inheritance on the dynamics of firm performance varies according to origin (focal vs. user vs. supplier). Cross-industry knowledge flows have different impacts on spinout performance according to their upstream or downstream origin. As found by Dosi et al. (2021), knowledge flowing upstream from user industries is mostly disembodied,

leading to product innovation and differentiation strategies that benefit spinout performance. This positive effect is borne out by our results, confirming previous work by Fontana and Malerba (2010) and Adams et al., (2016, 2017). Knowledge flowing from suppliers is mostly embodied, leading to labor-saving productivity gains (Dosi et al., 2021), bringing about cost-based advantages that are likely to be less beneficial to new firms due to liabilities of smallness and investment constraints. The hypothesis that supplier industry spinoffs underperform user industry spinoffs is confirmed by our study, providing the literature with original evidence.

While our data does not allow for a finely-grained distinction between product/ market strategies across spinout firms, as in Adams et al., (2016, 2017, 2019), our study offers evidence in a different context, both in terms of focal industries and in accounting for the impact of geographical agglomeration. The main focus of analysis in Adams et al., (2016, 2017) is the semiconductor industry, which is composed mainly of large firms where scale economies and intellectual property protection and commercialization are prevalent (Adams et al., 2016, 2017, 2019). The contrast with the Portuguese molds industry is very significant. Portuguese molds (and, by osmosis, plastics) represent an organic network of small and medium-sized firms where the transmission of knowledge across firm boundaries arguably plays a critical role. This pattern is reminiscent of the regional industry settings of Italian textiles and ceramic clusters that were the subject of early studies of industrial districts and geographical clustering (e.g., Brusco, 1982; Piore & Sabel, 1984; Porter, 1990). Our findings suggest that knowledge inheritance by spinouts is likely to have played a pervasive role in developing those industrial districts.

The present study has several limitations. First, regarding the econometric study, tracing the backgrounds of entrepreneurs is not always possible when dealing with the data, although a sizable and representative sample of molds and plastics startups entering over 24 years was assembled. While using data for entrants of unknown origin provides a useful baseline for analysis, it is likely that a lot of de novo entrants (many entering from unemployment) are on the baseline. While this is unlikely to affect the results for spinouts (which are at the center of this study and where founders can more easily be identified), it is possible that the performance of de novo entrants is overestimated.

Also, the unavailability of firm-specific data other than size (employment) limits our ability to control for firm heterogeneity, as size is not a critical variable accounting for firm quality in the Portuguese molds industry, where economies of scale are absent. Also, the study could benefit from identifying other industries in the molds value-chain through additional analyses of input–output, data that was not accessible. Finally, while the plastics industry is molds' biggest customer by far, our analysis is constrained to look at all plastics firms as homogeneous in their use of molds for plastic injection, rather than recognizing that manufacturing of plastics for different customers (e.g., the automobile and beverage industries) involves different technologies and customer relations.

Our findings offer practical implications as well as insights for policymakers. While there is significant research arguing that geographical clusters of industries are breathing grounds for entrepreneurs (e.g., Delgado et al., 2010; Glaeser & Kerr, 2009; Glaeser et al., 2010), it should be acknowledged that the supply of entrepreneurs in any region is likely populated by a majority of spinout founders. A steady stream of both vertical and focal industry spinouts is a key mechanism for industrial and regional development. Therefore, policies restricting non-compete agreements (Marx et al., 2009) and facilitating the mobility of workers towards entrepreneurship in focal and related industries may be more effective than indiscriminate incentives for regional entry.

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Data availability The microdata sets used in this study are available from Statistics Portugal upon request by researchers. Statistical microdata are subject to both the personal data protection framework and statistical confidentiality framework as defined by Eurostat (https://ec.europa.eu/eurostat/web/microdata/statistical-confidentiality-and-personal-data-protection).

Declarations

Conflict of interest The authors do not have any association that might pose a conflict of interest/competing interest.

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