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Parental endowments versus business acumen: Assessing the fate of low-tech, service-sector spinouts

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Abstract

***Research Summary*:** In recent years, scholarship on intra-industry entrepreneurial spinouts has coalesced around a heredity-focused perspective, propounding the notion that spinouts from high-quality parent-firms outperform those emanating from low-quality parent-firms. This view has found strong support in high-tech sectors, but it is unclear whether parental lineage is a determinant of performance and survival in sectors exhibiting low-technological dynamism, especially when the locus of value creation stems from generalist rather than technical-specialist knowledge. Applying the knowledge spillover theory of entrepreneurship and jack-of-all-trades framework, we assess the fate of a complete population of 678 service-sector firms for the entire 32-year history of an industry. Our study offers explanatory mechanisms that more fully account for the non-hereditary success factors driving performance heterogeneity among entrepreneurial spinouts.

***Managerial Summary*:** In many industries, half or more of the firms are founded by former employees of existing companies (i.e., “entrepreneurial spinouts”). In high-tech sectors, these “spinouts” often appear to perform better than entrants without prior industry experience. Moreover, spinouts spawned by high-performing parent-firms tend to outperform spinouts from low-performing parents, suggesting that spinouts benefit from advantageous parental knowledge and capabilities. However, this does not seem to be the case among spinouts in industries characterized by low-technological dynamism. Our findings indicate that when technological dynamism is low, general business acumen eclipses parental lineage in determining spinout performance. In these cases, spinout founders with primarily technical experience would be well-served by partnering with individuals possessing experience in marketing, sales, and day-to-day business management.

KEYWORDS

entrepreneurship, knowledge spillovers, market entry, service sector, spinouts

1 | INTRODUCTION

In 1996, 31 new firms entered the Colorado asbestos abatement industry, a sector devoted to the controlled removal and disposal of asbestos-containing material from existing structures slated for renovation or demotion. Six of these firms were de novo entrants, newly created firms without any prior experience in the asbestos industry. The remaining 25 entrants that year were spawned entities, comprised of intraindustry entrepreneurial spinouts founded by ex-employees of incumbent abatement firms. By 1999, only seven firms from the 1996 cohort were still operational, including four of the six de novo firms and just three of the 25 spinouts. Attrition for the spinouts approached 90 % in the first 1,000 days.

New ventures are often spawned from existing organizations, (Klepper, 2009; Stinchcombe, 1965) and entrepreneurial market entrants of all sorts frequently fail, often in large numbers (Shane, 2008). Still, the failure rate illustrated by the 1996 cohort prompts several questions: How do we explain such a high attrition rate, especially among the spinouts; firms that are definitionally founded and operated by industry veterans? Was the wave of failures a rarified occurrence, or is it indicative of generalizable challenges confronting service sector spinouts?

Prevailing theories of organizational knowledge transfer (Agarwal, Audretsch, & Sarkar, 2010; Connor & Prahalad, 1996; Franco & Filson, 2006; Kogut & Zander, 1992) and extensive empirical evidence (Agarwal, Echambadi, Franco, & Sarkar, 2004; Chatterji, 2008; Dick, Hussinger, Blumberg, & Hagedoorn, 2013; Dyck, 1997; Eriksson & Kuhn, 2006; Franco & Filson, 2006; Gompers, Lerner, & Scharfstein, 2005; Klepper, 2007, 2009; Klepper & Sleeper, 2005) support the notion that spinout founders benefit from parent-firm endowments, consisting of advantageous knowledge that confers improved prospects of survival for the spawned entity. Moreover, good parenting appears to be important. “Better-performing firms have better-performing intra-industry spinouts,” noted Klepper and Thompson (2010, p. 5).

Given the tightly linked conception of inter-generational coupling in the existing literature (e.g., Agarwal et al., 2004; Klepper, 2009), the dismal performance of the illustrative 1996 cohort raises important questions for extant theory. In this industry context, spawned entities dramatically under-performed even the de novo entrants, firms that definitionally had no parental endowments nor any prior industry experience. The question is: Why did so many experienced industry insiders fail to survive? Is it possible that heredity is less relevant to entrepreneurial survival in some sectors than it is in others? If so, why?

Using novel data from the complete population of all 678 firms ever to enter the Colorado asbestos abatement industry, we develop and test a new framework for the consideration of intervening factors that appear to impact knowledge transfer, parental endowments, and spinout survival in service-related industries characterized by low-technological dynamism. At more than 80% of the U.S. economy, service sector businesses are numerically and economically important (Cleveland, 2012), but relatively unstudied with respect to spinouts. Our central thesis builds on Lazear's jack-of-all-trades approach to entrepreneurial outcomes (2004), which argues that the multi-faceted demands of entrepreneurial action favors founders who possess varied skills and adaptive capabilities. We connect these arguments to extant research grounded in the knowledge spillover theory of entrepreneurship (Acs, Audretsch, & Lehmann, 2013; Agarwal et al., 2010) to explore the boundary conditions within which transferrable knowledge derived from a parent-firm's technological prowess determines spinout success or failure (Agarwal et al., 2010; Brown & Campbell, 2001, 2002; Yeganegi, Laplume, Dass, & Huynh, 2016). Bridging these theories enables us to identify the circumstances under which hereditary factors may play less of a role, especially when knowledge spillovers are modest, or even non-existent. Leveraging the industry insight and experience of one co-author who owned and operated a firm in the hazardous waste industry for 8 years, we take material steps towards completing the unfinished portrait of spinouts by delving into service sector dynamics. Our approach lends veridicality to spinout theory, while opening new lines of inquiry.

In the following section, we discuss extant spinout theory, highlighting both the strong empirical support emanating from technologically dynamic contexts and the relative quietude in assessing spinout performance outcomes among service-sector firms operating under conditions of low-technological dynamism. We develop four testable hypotheses that form the basis of our empirical findings and conceptual refinements. In concluding, we reflect upon the implications for spinout theory development and the opportunities for future study.

2 | THEORY AND HYPOTHESES

The inter-generational features of entrepreneurial spinouts offer a fruitful domain for scholars to test theories related to the transfer of advantageous knowledge and capabilities (e.g., Agarwal et al., 2004; Klepper & Sleeper, 2005). Scholars have exploited the spinout phenomenon to undergird seminal management theories, including evolutionary theory (Nelson & Winter, 1982), organizational learning (Cyert & March, 1963; Fiol & Lyles, 1985; Levitt & March, 1988), tacit and explicit knowledge transfer (Franco & Filson, 2006; Kogut & Zander, 1992), and a variety of economic-based (Geroski, 1995) and sociology-based (Aldrich & Fiol, 1994; Hannan & Freeman, 1989) explanations for market entry. It is common for scholars studying spinouts to invoke the language of procreation and heredity as an explanatory framework for spinout births, survival, and operational performance. An expanding set of studies supporting a progeny model (Phillips, 2002) variously refer to the parent-child ties (Klepper, 2001) as "spawning" (Chatterji, 2008; Gompers et al., 2005), "inheritance" (e.g., Agarwal et al., 2004), "organizational births," "children" and "offspring" (Dyck, 1997), "parenting" (Klepper & Sleeper, 2005), "heritage" (Cheyre, Kowalski, & Veloso, 2015), and "heredity" (Dick et al., 2013).

The use of proto-biological speak closely parallels the accumulating empirical support for a widening set of "stylized facts" (Klepper, 2009) that together form the theoretical foundation for the study of entrepreneurial spinouts, namely: that spinout founders learn lessons from their parents that are advantageously deployed towards an improved likelihood of survival and the achievement of superior performance. Most existing evidence supports the notion that high-performing parent-firms serve as a wellspring for high-performing spinouts (Elfenbein, Hamilton, & Zenger, 2010; Eriksson & Kuhn, 2006; Gompers et al., 2005; Klepper, 2009). "Firms can be thought of as giving birth to spinouts," argued Klepper and Sleeper, "so that spinouts have parents from whom they inherit specific traits" (2005, p. 1303). Through this, better-performing parents are expected to spawn better-performing spinouts (Klepper & Thompson, 2010).

High-tech firms, operating in knowledge-intensive environments such as lasers (Klepper & Sleeper, 2005), hard disk drives (Agarwal et al., 2004), automobiles (Klepper, 2002, 2007), medical devices (Chatterji, 2008), biotechnology (Stuart & Sorenson, 2003), and internet services (Landoni, 2018) exhibit the favorable impact of these parent-progeny linkages. Existing empirical work suggests that a high degree of technological dynamism increases the performance of spawned entities. This appears to even be true in service sectors when employees are able to leverage a high degree of specialized technical knowledge (Klepper & Thompson, 2010; Yeganegi et al., 2016), such as intellectual-property lawyers and consultants, (Carnahan, Agarwal, & Campbell, 2012; Phillips, 2002). However, existing scholarship has not examined parent-progeny linkages in the absence of technological dynamism and indifferentiable knowledge stocks, including important sectors such as traditional retail, transportation, construction, distribution, restaurants, education, tourism, and specialty trades (Triplett & Bosworth, 2004).

2.1 | Spinout performance heterogeneity

If the transfer of advantageous knowledge is an essential characteristic of parent-progeny resemblance, what happens to that resemblance when knowledge and technologies diminish in importance? Agarwal et al. (2010) argued that while, "[a]n organizational context rich in scientific knowledge would be expected to generate a high degree of knowledge spillover entrepreneurship….an organizational context low in knowledge would not be expected to generate significant knowledge spillover" (2010, p. 275). Extending the premise of Agarwal et al. to industry contexts that lack these spillovers, parent-spinout resemblance should be less frequent and less pronounced. Figure 1 captures this in a framework based on two key factors: technological dynamism and locus of value creation.

Consistent with a plethora of empirical findings across a wide range of technology-driven sectors (Capone, Malerba, & Orsenigo, 2019; Klepper, 2009; Klepper & Sleeper, 2005), a high degree of technological dynamism, when coupled with value-creating specialized knowledge (Yeganegi et al., 2016), typically generates strong, patterned resemblance between spinouts and their parents (Agarwal et al., 2010). Also, consistent with findings related to parent-progeny spillovers, high-achieving parents will generally be associated with high-performing spinouts when the advantageous knowledge is specialized, meaning that it is directly related to a firm's ability to create and capture value in a sustainable fashion (Klepper, 2009; Phillips, 2002).

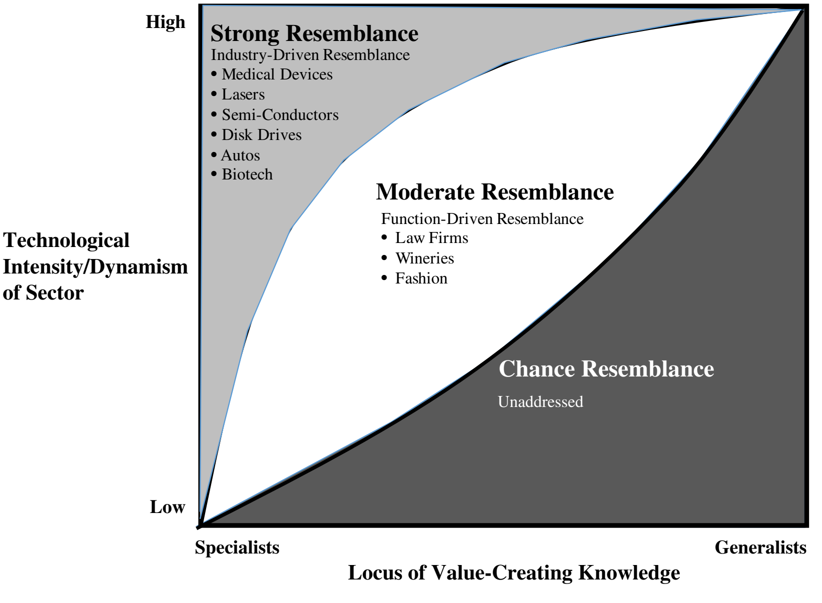

FIGURE 1 Effects of technological intensity/dynamism on spinout-parent resemblance

Thus, we have designated two primary dimensions that form the basis of a generalizable theory of spinout performance. The first dimension accounts for the magnitude of technological dynamism. Consistent with existing literature, the *y*-axis in Figure 1 captures the role of technology and the importance of a parent's technological prowess as key determinants of spinout performance (Agarwal et al., 2004; Agarwal et al., 2010; Brown & Campbell, 2001, 2002; Yeganegi et al., 2016). The second dimension, situated along the *x*-axis, accounts for individual skills and capabilities in the context of industry-specific value creation. Felin and Hesterly (2007, p. 196) make the case that the locus of value creation begins with individual-level, capability-based factors, asserting that "…a coherent theory of new value creation must start with a consideration of the individuals who make up the organization." Extending this perspective, we develop a generalizable landscape for the locus of value creation among spinouts based on a capabilities-based continuum, ranging from technical-specialists who possess primarily industry-specific knowledge, to management-generalists who possess general business acumen related to marketing, sales, customer service, and day-to-day business management (Lazear, 2004).

When technological dynamism is low and when the locus of value creation is not principally tied to the knowledge of technical specialists, then any resemblance between parent-firms and spinouts is expected to arise as a consequence of chance. Under these conditions, the long-term success of the spinout is likely to be more directly related to general market acumen than specialized technical knowledge. Figure 1 illustrates this darkened region, labeled "chance resemblance." As numerous scholars, including Garvin (1983), Klepper (2009), and Capone et al. (2019) have noted, extant literature on spinouts has given scant attention to these firms.

The asymmetry between the three resemblance states in Figure 1 is intentional, reflecting two well-proven impediments to spinout success: (i) the imperfect processes associated with knowledge spillovers, particularly the differentiating role of individual founder factors, such as prior experience (Agarwal et al., 2010); and, (ii) the tendency of incumbent firms to under-innovate when technological changes necessitate departing from profitable existing lines (Benner & Tushman, 2003; Christensen, 2013; Hunt & Ortiz-Hunt, 2017), a phenomenon that often leads to firm-specific employee departures (Hunt, Townsend, Asgari, & Lerner, 2018; Klepper & Thompson, 2010). In the "chance resemblance" sector, spin-outs are more likely to arise when employees seek to obtain market-based repricing of their respective skills and capabilities (Brown & Campbell, 2001, 2002; Campbell, Ganco, Franco, & Agarwal, 2012), a phenomenon that will be explored in the following section.

Prior studies have largely attributed heterogeneity of performance among entrepreneurial spinouts to hereditary linkages between parent-firms and their respective spawn, such that good parents produce "good kids" and bad parents produce "bad kids." "Spinouts will have the same expected profits and survival prospects as their parents, thus more innovative and long-lived parents will have more innovative and long-lived spinouts" (Klepper, 2001, p. 646; Franco & Filson, 2006; Garrett, Miao, Qian, & Bae, 2017). The essence of this parent-progeny clustering is depicted in Figure 2a. Among parent-firms in technologically dynamic sectors, most evidence suggests that there is clustering of spinouts around their respective parents. High-performing spinouts tend to emanate from good parents, while low-performing spinouts appear to have low-performing parents. However, when knowledge spillovers—defined as "the external benefits from the creation of knowledge that accrue to parties other than the creator" (Agarwal et al., 2010)—play a small or even non-existent role in determining the fates of spinouts, then a parent-firm's cohort of spinouts is more likely to be dispersed, evidenced by little or no clustering (Figure 2b).

As the two scenarios imply, if the performance variance is greater within the cohort of spinouts for a given parent-firm than for the overall industry population, then high-performing spinouts may routinely have low-performing parents and vice versa. Thus, under these conditions, spinout performance heterogeneity occurs as a consequence of factors that are unrelated to parent-progeny linkages. This, in turn, means that the heterogeneity of performance within spinout cohort groups (i.e., spinouts emanating from the same parent-firm) should be similar to or greater than the performance differences exhibited by the entire population of spinouts in a given industry; most notably, those that are service-related and with few knowledge spillovers, such as retail, distribution, restaurants, education, tourism, and public service (Triplett & Bosworth, 2004). There is no test that is more directly germane to

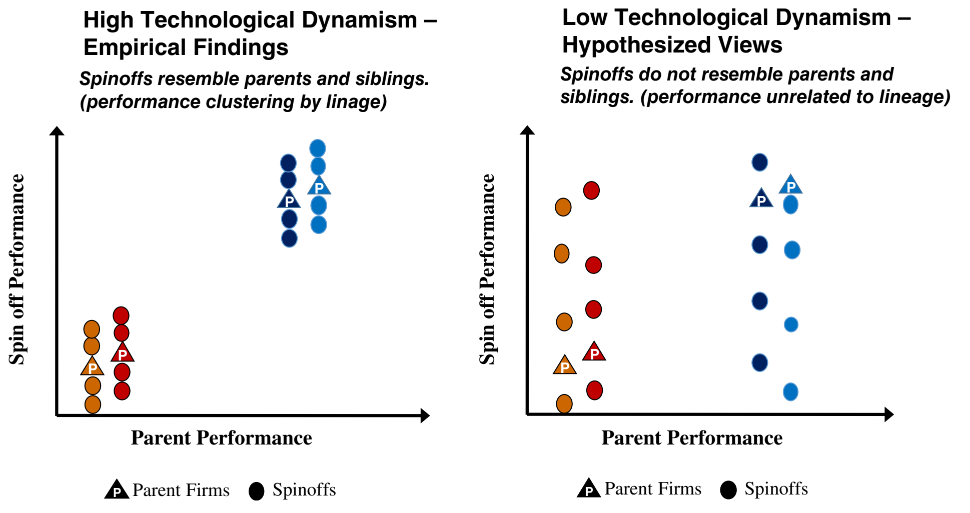

FIGURE 2 Models of spinout performance—hereditary clustering and non-clustering

hereditary endowments than to scrutinize the effects of parental influence across a cohort of spinout siblings. As we elaborate later, our discovery of data on numerous, materially large spinout cohorts is critical since it provides the basis to determine if there is at least some resemblance between parents and offspring.

To this precise point, Agarwal et al. noted that "past authors have assumed an underlying process of knowledge inheritance without explicitly testing whether inheritance from an incumbent parent actually occurs" (2004, p. 502). More recently, cross-industry analysis undertaken by Capone et al. (2019)—which includes the asbestos industry context developed by Hunt (2013, 2015), and Hunt and Lerner (2012)—reveals key differences in sector-to-sector spinout performance. Capone et al. (2019) speculate that lower levels of parent-progeny resemblance may be attributable to customer homogeneity as well as factors related technology or parental knowledge stocks, which can vary across industries. Cognizant of these calls for explicit empirical testing of inheritance (Agarwal et al., 2004), and consistent with the knowledge spillover theory of entrepreneurship (Acs et al., 2013; Agarwal et al., 2010), we posit that hereditary linkages are not present in sectors with low-technological dynamism. Rather than witnessing the clustering of parent-progeny performance suggested by hereditary linkages, we expect that clustering of parent-firms and their spinouts will be virtually non-existent. In other words, dispersion in performance among siblings should be equal to or greater (per central tendency) than the dispersion in performance displayed by the overall industry population.

> **Hypothesis (H1):** *Within sectors with low technological dynamism, the variation in performance within a parent-firm's cohort of spinouts will, on average, equal or exceed the variation in performance for the population of all spinouts, regardless of parent-firm quality.*

The substance of H1 is denoted in Figure 3 by the triangular region.[1] The line H_0 represents no performance variance between parents and progeny. The area below the line is what would be expected by hereditary theory (i.e., some clustering among siblings in a cohort). That is, given at least some inherited resemblance, sibling performance will vary less than the overall population. Conversely, support for H_1 would indicate that both low- and high-performing parents consistently produce both low- and high-performing spinouts, making high-low mismatches commonplace. Siblings would resemble their respective parents and one another *with no greater frequency than they do any other firm.* This, in turn, would support the view that in some industries hereditary endowments play little or no role in determining spinout performance.

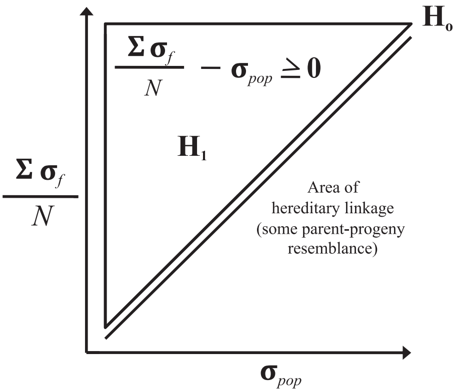

FIGURE 3 Hypothesized spinout performance variance within low-tech sectors Hypothesis 1 (i.e., the triangular region denoted as H_1) predicts that the average performance variance for the cohort of spinouts spawned *by the same parent* will exceed the performance variance for the entire population of abatement firms. Line H_0, the null hypothesis, involves no difference in variance. A result of H_1 =/> H_0, functionally indicates that both low- and high-performing parents produce both low- and high-performing spinouts

2.2 | Founder-specific experience

If parental lineage proves to be less important among spinouts in sectors with low levels of technological dynamism, then to what can scholars attribute spinout performance heterogeneity? Returning to the *x*-axis of Figure 1, our framework predicts that industries characterized by the dominating influence of value-creating generalists will exhibit nothing more than a chance resemblance between parent and progeny. This argument is consistent with key assertions in the knowledge spillover theory of entrepreneurship, which posits that sectors characterized by low-technological dynamism will tend to drift towards a commoditization of the skills and capabilities (Agarwal et al., 2010; Audretsch & Lehmann, 2006). Under these conditions, managers leading spin-outs who possess technical-specialist knowledge are less likely to obtain any form of enhanced, market-based repricing of their skills (Brown & Campbell, 2001, 2002; Campbell et al., 2012; Capone et al., 2019; Hartog, et al., 2010). Conversely, employees possessing a generalizable command of business operations and a battle-tested sense of market acumen may find more fertile ground in launching a business.

This notion of a high-functioning entrepreneur with generalist knowledge hearkens to the work of Lazear (2004, 2005) and Wagner (2003), who identified the value-generating capacity of well-rounded, "jack-of-all-trades" entrepreneurs. This "skill balancing," as envisioned by Lazear, has been empirically tested (Åstebro & Thompson, 2011; Bublitz & Noseleit, 2014; Stuetzer, Goethner, & Cantner, 2012; Wagner, 2006). For example, Bublitz and Noseleit (2014) found that skill scope is an important determinant of entrepreneurial outcomes. Firm founders possessing a wider range of capabilities outperform those who have fewer capabilities grounded in more specialized knowledge (Åstebro & Thompson, 2011; Lazear, 2004). Generalist entrepreneurs possess "the ability to perform many tasks without necessarily excelling at any of them" (Minniti & Lévesque, 2008, p. 604). Fern, Cardinal, and O'Neill (2012) found that a diversity of prior experience better equips founders with the range of capabilities required to manage a competitive enterprise. This is especially true in contexts for which specialized knowledge is not a material source of competitive differentiation among firms (Brown & Campbell, 2001; Koster & Andersson, 2018), such as low-tech, service sectors characterized by commoditized technologies and routines. Top achievers will be those who are able to flourish in a commoditized context, where general business acumen is critical to operational success (Hurst & Pugsley, 2011). Koster and Andersson (2018) argue that the ability to play varied roles is pivotal to successful self-employment. Lazear (2004) found support for this in the fact that more than one-third of self-employed individuals have prior experience in executive, administrative, or managerial roles, a level that is far above the overall proportion of these roles economy-wide.

Founders vary in their respective abilities to read market signals, identify mission critical resources, and deploy resources in a successful fashion (Alvarez & Barney, 2002; Colombo & Grilli, 2005; Lee, Lee, & Penning, 2001; Winter, 1987). In this vein, Chatterji (2008) tested the bifurcation between technical specialists and management generalists among spinout founders, finding that generalists displayed superior acumen in obtaining key resources, particularly venture financing. In this sense, his argument that founder-specific differences play a role in driving spinout performance heterogeneity is likely to be even more potent among generalists in a low-tech sector, where knowledge spillovers are less likely to occur and where founders are significantly less likely to harvest benefits from parental lineage (Agarwal et al., 2010).

As noted by Hayward, Shepherd, and Griffin (2006, p. 166), "different market segments have different task environments with different contingencies that require different skills," which drives a stratification of the matching process that occurs between the operational and competitive context and a founder's skill set. Therefore, in extending the jack-of-all-trades premise developed by Lazear (2004, 2005) and Wagner (2003), and the founder-centric findings of Chatterji's study (2008), we explore the set of circumstances in which technical-specialist may find themselves at a disadvantage to generalists in seeking to pursue an entrepreneurial spinout.

> **Hypothesis (H2):** *Within sectors with low levels of technological dynamism, spinouts created by founders with primarily technical-specialist knowledge will exhibit lower survival rates and performance levels than spinouts led by founders with primarily non-technical (general) business knowledge.*

3 | SPINOUTS VERSUS DE NOVO ENTRANTS

As noted in the introductory anecdote, the 1996 entry cohort faced extraordinarily high attrition. Interestingly though, de novo firms—entrants with no prior experience in hazardous material abatement—fared much better than spinouts: evidenced by a 33% attrition rate for de novo entrants versus a 90% attrition rate for spinouts. Even after accounting for the effects of operating within an industry with low-technological dynamism and the low-value nature of specialized technical knowledge illustrated in Figure 1, it is difficult to conceive of why spinouts—companies with personnel possessing significant experience in abatement operations—would under-perform newcomers by such a wide margin. However, the explanation may reside in the differential effects of technical-specialist versus generalist knowledge.

Empirical findings are near-universal in asserting that spinouts outperform de novo entrants in high-tech and moderate-tech sectors, including the fashion industry (Wenting, 2008), medical devices (Chatterji, 2008), autos (Klepper, 2007), hard drives (Agarwal et al., 2004) and lasers (Klepper, 2001). Moreover, broad, cross-locational, and cross-industrial studies reveal similar results (Eriksson & Kuhn, 2006). Figure 1 incorporates these findings, but then extends beyond them since prior studies did not involve sectors characterized by low-technological dynamism and occupational contexts favoring jack-of-all-trades founders (Lazear, 2004, 2005).

If general business acumen and strong, capable attentiveness to the market are the leading determinants of success or failure among spinouts operating amidst commoditized technologies and processes, then experienced spinout-generalists are likely to closely resemble de novo founders in terms of their respective backgrounds and skill sets (Hunt, 2013, 2015). Both generalist spinouts and de novo founders can recruit technical specialists at approximately the same rate that specialists receive from any other employer because the technologies and processes are commoditized throughout the sector (Hunt & Hayward, 2018). The differentiating capabilities instead hinge on marketing, sales, and operational execution. As one generalist spinout founder put it, "To be successful, you need to know how to make the phone ring. You need to know how to help customers find you and then how to serve them in flawless fashion." Another said, "It's really just Business 101. Either you know how to line up profitable jobs, or you don't. Supervisors [the technical specialists] have no idea how to bring in the jobs, but they are often the ones starting new companies."

These perspectives are reflected in anecdotal evidence from the 1996 cohort of firms we highlighted at the outset as an illustrative example. Notably, 20 of the 25 spinouts in the cohort were founded by technicians and five by generalists, who worked as estimators, marketers, or office managers. While all 20 of the technician-founded firms failed within 3 years, three of the five generalist-founded firms survived more than 10 years each. Interestingly, the 60% survival rate for generalist-founders is almost exactly the same survival rate for de novo firms (67%). For both groups, the key differentiator was the same: general business acumen.

Consistent with the jack-of-all trades literature (Hurst & Pugsley, 2011; Koster & Andersson, 2018; Lazear, 2004; Wagner, 2003), the skills of generalist spinouts and de novo entrants similarly exude operational breadth rather than technical depth. Furthermore, each of these two classes of entrants face similar employment-related opportunity costs (Brown & Campbell, 2002). Despite the fact that one group consists of industry insiders (generalists) and the other group consists of outsiders (de novo firms), both groups possess skills and perspectives that are more broadly applicable than the technical demands of asbestos abatement. Thus, rather than conceptually and empirically linking the spinout story primarily to technological know-how (Agarwal et al., 2004) and parent-knowledge spillovers (Eriksson & Kuhn, 2006; Klepper & Thompson, 2010; Anton & Yao, 1995)—as would be apropos for sectors with high technological dynamism—service-oriented sectors with low-technological dynamism may be more aptly managed by jack-of-all-trades, generalist-founders, who resemble de novo firms more so than their respective parent-firms. In this regard, we pose the following:

> **Hypothesis (H3a):** *Spinouts founded by technical experts in service sector industries with low technological dynamism will, on average, underperform de novo entrants.*

> **Hypothesis (H3b):** *Spinouts founded by generalists in service sector industries with low technological dynamism will, on average, perform as well or better than de novo entrants.*

4 | THE ASBESTOS ABATEMENT CONTEXT

4.1 | Industry purpose and history

4.2 | Asbestos health concerns

Asbestos is a naturally occurring mineral with microscopic crystalline structures. It was used in 5,500 different building materials due its ease of use and unusual confluence of beneficial physical properties that lent durability and resilience to materials designed for insulation, flooring, fire proofing, sound proofing, water proofing and strengthening (EPA, 2011). However, when disturbed, asbestos-containing materials (ACM) release microscopic fibers that are capable of migrating past human respiratory defense systems. Sustained exposure to a high quantity of fibers can result in penetration to the lungs, potentially causing three deadly diseases: asbestosis, lung cancer and mesothelioma.

4.3 | Regulatory history

Until the mid-1980s, concern regarding human exposure to asbestos in existing buildings evolved slowly, given the long latency periods for asbestos-related illnesses and the absence of definitive studies connecting low-level asbestos exposure to potential health risks. The general concern regarding the handling of ACM in existing building materials was loosely conveyed in a number of air quality and worker safety provisions, but there was no clear commitment to a comprehensive policy involving the controlled removal and disposal of asbestos until the passage of the Asbestos Hazards Emergency Response Act (AHERA) in 1985. Though specifically focused on asbestos in schools, the Act formally established standards requiring the professional abatement of asbestos in existing structures. Functionally, the enforcement of AHERA was delegated to state-level agencies.

4.4 | State-level enforcement

Many states chose to administer federal enforcement of the new asbestos regulations in a minimalist fashion. However, some states implemented regulations that were stricter than federal law and that placed the power of enforcement in the hands of newly formed regulatory divisions devoted to monitoring compliance. Colorado was one of these “high-enforcement” states. In the wake of AHERA, the Colorado legislature commissioned in 1986, an Asbestos Enforcement Group through the Air Quality Division of the Colorado Department of Public Health and Environment (CDPH&E, 2019), whereby regulations were adopted that required professional certifications, company licenses and project permitting that were specific to Colorado. In the absence of any reciprocity with other states (i.e., Colorado neither recognizes nor honors licenses obtained in other states), closed-system of regulatory compliance was created in Colorado. For our purposes, this regulatory ardor resulted in well-structured data of a complete population of firms for its entire history (Hunt, 2013; Hunt & Lerner, 2012).

5 | ASBESTOS ABATEMENT

Asbestos-containing building materials can be separated into two broad categories: friable and non-friable. Regulations define friable ACM as that which can be pulverized with hand pressure, while non-friable has a tight, crystalline structure that makes pulverization by hand impossible. Friable ACM is found in surfacing and texturing materials, spray-applied sound proofing (i.e., “popcorn ceilings”), fire-proofing and thermal insulation for ducts and pipes. These types of ACM are highly prone to significant fiber release if they are disturbed, thereby creating the need for sophisticated removal techniques, including a fully enclosed workspace that is kept under continuous negative air pressure. These engineering controls are costly to construct and maintain and require experienced supervisory oversight to design and implement. Non-friable ACM is found in resilient flooring, cementitious siding and various asphalts. Though still tightly regulated in Colorado, non-friable abatement requires somewhat less sophisticated, and considerably less costly, engineering controls than those associated with the abatement of friable ACM.

5.1 | Abatement personnel

All personnel associated with asbestos abatement must hold a state license that is annually renewed after successfully passing a federal and state exam. Actual abatement is performed by licensed supervisors and workers, who don protective clothing and breathing equipment while working in a containment set under continual negative air pressure. Thus, supervisors are the technical experts in the industry, though every facet of the engineering controls and removal process is detailed in strictly enforced government regulations. Meanwhile, other personnel associated with the abatement business consist of the industry generalists; individuals not directly involved with engineering controls, ACM removal and disposal. Generalist roles include: estimation, supply management, customer relations, sales, government relations, and office management. More than half worked in other industries for five or more years prior to moving into abatement.

5.2 | Industry characteristics

Technically, asbestos abatement is highly specialized, with relatively few profitable cross-applications to other commercial domains. Abatement primarily involves the methodical demolition of pre-existing structures under highly prescribed conditions; the control associated with asbestos abatement is extensive and the monitoring by the regulatory authorities is intense. In other words, abatement work is far from simple, requiring considerable knowledge and 'engineering control, including containment of the workspace, establishment of negative pressure and extensive protection of workers and occupants' (Hunt, 2015). Thus, the skills necessary to operate and perform abatement are relatively unique. Comparatively few market entrants involved diversifying entry on the part of incumbents who were migrating from other industries, such as general contracting, specialty trades or environmental waste handlers. Rather, the abatement industry was formed through an initial group of de novo entrants and, soon after, spinouts from existing firms, which quickly predominated as the principal form of market entry, as indicated in Table 1 below.

From the inception of the Colorado asbestos abatement industry in 1986, 678 firms have entered the market, and 112 parent-firms have spawned 495 spinouts. Among these, 39 parent-firms produced 5 or more spinouts, and 16 of those firms produced 10 or more spinouts. The industry has witnessed a steady stream of spinouts-begetting-spinouts in successive fashion. An example of this phenomenon is illustrated in Figure 4, showing the genealogy of a prolific parent-firm, Dominion Services.

TABLE 1 Industry participants—By entry mode

Entry mode	# Firms	% Firms
De novo	122	18
De alio	61	9
Spinouts	495	73
Total entrants	678	100

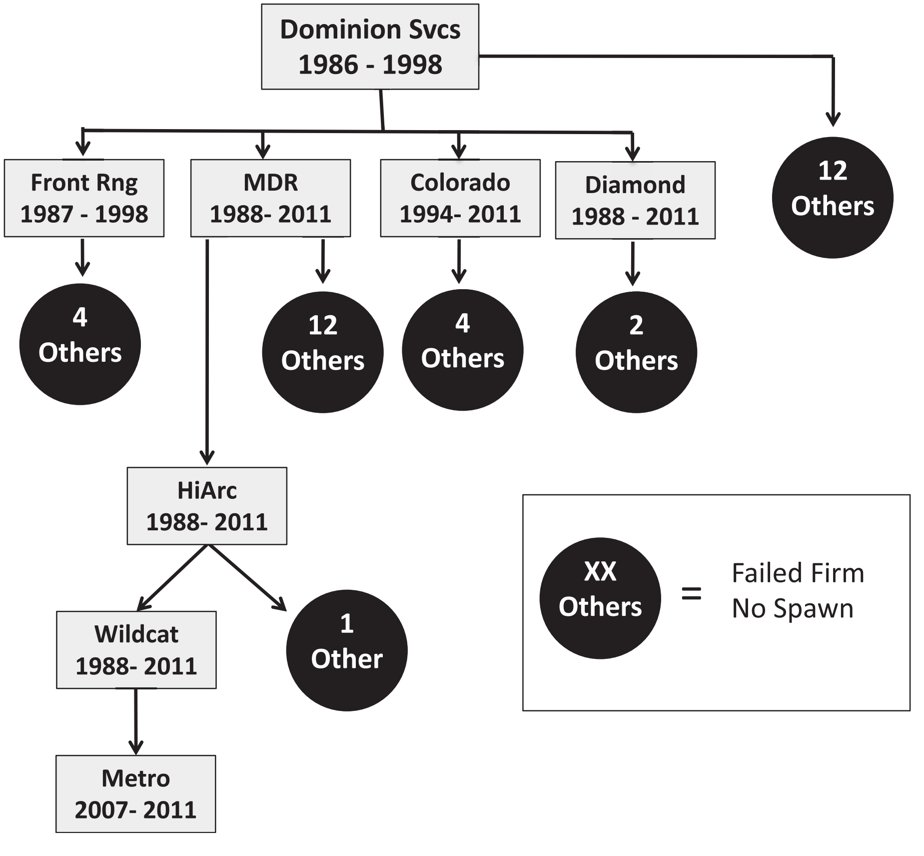

FIGURE 4 Dominion services family tree

Dominion was one of the most successful firms in the history of the industry, ranking #8 (out of 678 total firms) in age-adjusted projects completed (i.e., projects per firm-year); it was also the fifth most prolific parent, spawning 16 spinouts. Though Dominion itself closed operations in 1998, its progeny continued to spawn. By 2013, the Dominion family tree spanned five generations and 43 separate spinouts, virtually all of which failed. Only six firms from the Dominion tree were operational in 2011, representing 13% of the extended family. The average lifespan in the Dominion family is 3.4 years and the average number of projects per firm-year is 8.8. There is little to distinguish Dominion's spawn. Most were abject failures that died young without achieving a substantive commercial presence. Of the firms comprising the Dominion Services family tree, 19 firms (43%) had no operational activity whatsoever. Yet, in the context of this complete population and given the highly compressed nature of successive generations, the extensiveness of public records, and the presence of highly prolific parents, the Dominion example represents a microcosm of the entire industry (Hunt, 2013; Hunt & Lerner, 2012).

6 | DATA AND METHODS

As we illustrated at the outset, anecdotal evidence drawn from the 1996 spinout cohort—in which more than 90% of the firms failed in less than 3 years—poses a mystery for extant theory on knowledge spillovers, parent-progeny linkages, and the fate of spin-out ventures: Is this an anomalous set of circumstances, or is this a generalizable effect endemic to service sector spinouts? To answer this question and to test the theoretical framework presented in Figure 1, our analysis examines the complete history and entire population of firms comprising this industry.

6.1 | Data

Our empirical analysis involves a quantitative research design based on archival data comprised of the complete, non-truncated population of firms and founders having ever entered or exited the market. The methodology employed in this study is an event-history analysis (Delacroix & Carroll, 1983; Tuma, Hannan, & Groeneveld, 1979) of a comprehensive database constructed from records at the CDPH&E, covering the industry from its inception in 1986 through 2017. This 32-year period witnessed the entry of 678 firms, objectively documented through licensing data. At the project level, 71,818 permits were issued towards for the removal of 400 million square feet of asbestos-containing material, for revenue exceeding $2.5 billion.

The use of registration data as the indicator of market entry warrants discussion. Yang and Aldrich (2012) proffer several important caveats related to the use of registration data in the study of new ventures. However, the stringent regulatory regime governing the asbestos abatement industry substantively mitigates these concerns. First, an Act of Congress created the entire industry. As an exogenous event, the creation of the industry and all subsequent operational activity can be traced to a precise time, with well-understood founding conditions. Second, as a consequence of the strict monitoring and reporting requirements associated with the removal and disposal of ACM in Colorado, an unusual level of detail is obtained by governmental agencies, which is closely tracked and exhaustively made available to the public. By law, companies must obtain (and annually renew) a State-issued license prior to commencing any work. This allows for comprehensive tracking of every firm into and out of the industry. It also allows the unusual ability to capture the existence of those firms that fail to complete even one project or that fail to survive beyond even their first annual license. This marks perhaps the first time that a dataset includes a complete accounting of organizational forms that fail prior to becoming substantively operational.

Finally, the asbestos abatement data set is markedly different from other attempts to use registration data by virtue of the specific requirements implemented by the State. As a state that adopted a comprehensive regulatory regime, Colorado situated itself as a domain in which every abatement-related "footprint" was clearly recorded. In the wake of AHERA, the Colorado legislature commissioned in 1986 an Asbestos Enforcement Group through the

Air Quality Division of the CDPH&E, whereby regulations were adopted that required State-level certifications, company licenses, specialized training, annual exams and project permitting.

6.2 | Dependent variables

Three separate dependent variables were used to test the efficacy of our proposed framework: *Operational performance, lifespan, and performance variance.* The first two measures—operational performance and lifespan—each provide a useful portal to conditions and outcomes. Although operational performance is positively correlated with lifespan, "survival is not strictly a function of performance" (Gimeno, Folta, Cooper, & Woo, 1997, p. 750). In order to insure a comprehensive assessment, both outcomes are modeled.

Lifespan refers to the total duration of operational existence measured in years.

Operational performance refers to the total number of projects a firm has completed, adjusted by firm-age. In other words, this measure is the average number of projects completed per firm-year for each market entrant. For instance, a firm completing 1,300 projects in 25 years of operation would have completed 52 projects per firm-year. A firm completing just six projects in 3 years would have completed two projects per firm-year. This metric creates a standardized basis for comparison regardless of how long a firm has been in business, thereby solving common challenges arising from right-side censoring (Hunt & Lerner, 2017). Logically, projects vary in complexity and size, so that no two projects are precisely the same. To account for these differences, firm-level controls were used to capture the mean duration and size of each year's projects. These controls allow the average number of annual projects completed to serve as a prudent, easily interpretable metric of performance, across firms of different ages and sizes.

Population performance variance is the measure used to address performance heterogeneity. It refers to the spinout population performance standard deviation, recalculated for the exclusion of each parent-firm's finite population of spinouts. We then compare this value with variance calculated for each of the parent-firm spinout cohorts.

6.3 | Independent variables

Parent performance is the number of projects completed per firm-year. For the cohort analysis an average is calculated for the annual projects completed in order to assess relative quality among the parent-firms and among the spinouts as they relate to parent performance.

Parent longevity is measured as years of operation.

Founder experience is a categorical variable that identifies whether a firm founder is a technical-specialist, a generalist, both, or neither (in the case of de novo founders). This was possible to determine from the comprehensive regulatory regime, and associated public records, requiring different types of licensing for individuals in the industry. A technical-specialist in abatement is a person who holds state licensing to serve as the site supervisor for asbestos abatement projects. Such a person has sole legal and operational responsibility for the installation and maintenance of full engineering controls related to occupant and worker protection during the removal and disposal of asbestos-containing material. A generalist in the abatement industry serves in a business development capacity, estimating projects to be bid, handling customer inquiries, completing project contracts, and managing the firm's office operations.

Parent-firm spinout cohort performance variance is the variance in the performance of spinouts emanating from the same parent. This is represented by the standard deviation of cohort performance and is calculated separately for each parent-firm with five or more spinouts. Parent-firms with fewer than five spawned firms were excluded since the standard deviations are not meaningful for such small cohorts.

Differences in variation is the difference between the standard deviation in the performance of all abatement firms and the standard deviation in performance of each parent-firm's cohort of spinouts.

6.4 | Controls

To rule out alternative explanations, our regression models include controls for key covariates. To rule out the impact of founding conditions on firm survival and performance, we control for entry cohort size, entry cohort as a percentage of the industry population, entry cohort mean lifespan, and the industry population at entry (Hannan & Carroll, 1992). Additionally, since our population of firms spans 32+ years, we rule out the effects of temporal changes in the macroeconomic, industry, and operating environments of each firm, using vectors we developed for macroeconomic, industry-specific and firm-specific time-series variables. Consistent with prior use of instrumental vectors composed of lagged variables in a time series (e.g., Angrist & Pischke, 2008; Holtz-Eakin, Newey, & Rosen, 1988)—particularly those estimating vector autoregressions with panel data—we use R to calculate macro, industry, and firm-level vectors to parsimoniously and simultaneously account for multi-level time-series data. The macroeconomic vector contains growth measures for construction, unemployment, and economic activity. Industry-specific measures consist of total abatement projects permitted, total asbestos removed from buildings, total industry revenue, and statewide abatement personnel. The firm-specific vector consists of codes for specific years of business operation, the average duration and size of projects per-year, and the relative level of firm business activity as a percentage of the total industry activity. Since the spinouts emanating from each parent-cohort are non-independent, dummy variables were employed to control for shared lineage. Dummy codes were used also to control for unobservable year-specific effects.

6.5 | Model specifications

Our research design consists of a longitudinal model that extracts annual data for the complete population of firms for the entire history of the industry (Hunt & Lerner, 2012, 2017). As with all industries, new firms continually enter and existing firms continually exit the abatement sector. Thus, the firms do not constitute a single panel, per se, but are best thought of as a "pooled" cross-sectional design (Frees, 2004), for which we are uniquely able to gather the entire population of firms every year, due to state licensing requirements, allowing us to perform temporal analysis that isolates changes in performance and survival across the observation window (Frees, 2004). Since we obtain a snapshot of the complete population every year for 32 years, our pool combines cross-sectional features of N firms and the temporal features of T_f time periods (i.e., the duration of a firm's operational existence) to generate $N*T_f$ pooled firm-years, representing the entire industry history (Hunt, 2015). This design is ideally suited for a test of our four hypotheses.

Hypothesis 1 predicts that the average variance in spinout performance for each cohort of sibling firms spawned from the same parent will be similar to or greater than the total population variance (Figure 3). This is illustrated below, in contrast to what hereditary theory would predict:

$$\begin{aligned} &H_1 : \mathrm{VAR}_{\text{sibling-cohort}} \geq \mathrm{VAR}_{\text{pop}} \\ &H_{\text{heriditary-theory}} : \mathrm{VAR}_{\text{sibling-cohort}} < \mathrm{VAR}_{\text{pop}}. \end{aligned} \tag{1}$$

Mathematically, if the results demonstrate that the average performance variance among spinouts emanating from the same parent exceeds the performance variance for the entire population of spinouts, then the predictive power of hereditary factors, such as parent-firm performance (Klepper, 2009; Klepper & Sleeper, 2005) would be non-significant. Extending this notion, the parent-progeny linkage was tested in the context of a complete set of controls. The general model can be expressed as a regression of parent performance onto progeny performance:

$$\text{Spinout Performance} = \beta_0 + \beta_1 \mathrm{CONTROL}_{\text{industry}} + \beta_2 \mathrm{CONTROL}_{\text{macro}} + \beta_3 \mathrm{CONTROL}_{\text{firm}} + \beta_4 \text{Parent Performance}. \tag{2}$$

Hypothesis 2 predicts that Spinout Founder Experience is a predictor of heterogeneity in Firm Lifespan and Operational Performance. Both measures of fitness were tested since, as Gimeno et al. (1997) demonstrated, low-performing firms may persist for non-financial reasons related to each business owner's unique utility function. In order to insure a comprehensive assessment, both outcomes are modeled:

$$\text{Performance}_{\text{GeneralExperience}} > \text{Performance}_{\text{TechExperience}} \tag{3}$$

$$\text{Lifespan}_{\text{GeneralExperience}} > \text{Lifespan}_{\text{TechExperience}}. \tag{4}$$

Firm performance is assessed through a single degree-of-freedom regression analysis, the basic structure of which is represented by:

$$\text{Spinout Performance} = \beta_0 + \beta_1\text{CONTROL}_{\text{industry}} + \beta_2\text{CONTROL}_{\text{macro}} + \beta_3\text{CONTROL}_{\text{firm}} + \beta_4\text{Founder Experience}. \tag{5}$$

Our approach to survival analysis employs the classic hazard rate model (Cox, 1972), where no assumptions are made regarding normality in the distribution of surviving entities, which is ideal given the extremely high rate of early failures in abatement. Each variable is exponentiated to provide the hazard ratio for a one-unit increase in the predictor:

$$\text{h}(t) = \text{h}_0(t)\exp(\beta_1 \text{X} + \beta_0). \tag{6}$$

The equation states that the hazard of the focal event occurring at a future time *t* is the derivative of the probability that the event will occur in time *t*. Using SPSS and the R commander survival plug-in, coefficients were determined through the maximum likelihood function. Each survival function was then plotted using a Kaplan–Meier estimate.

Finally, we test Hypotheses 3a and 3b, related to spinout performance versus de novo entrant performance, reflecting the premises that generalist spinouts will resemble de novo firms, while technical-specialist spinouts will be discernably worse:

$$\text{Performance}_{\text{GeneralExperience}} \geq \text{Performance}_{\text{de novo}} \tag{7}$$

$$\text{Performance}_{\text{TechExperience}} < \text{Performance}_{\text{de novo}}. \tag{8}$$

7 | RESULTS

Of the 678 firms entering the industry at any point in its history 73% were entrepreneurial spinouts, thereby providing a significant population of foundings and outcomes. Bivariate correlations and descriptive statistics are provided in Tables 2 and 3. The directionality of the correlations is consistent with the hypothesized relationships.

Consistent with prior research (Garvin, 1983; Klepper, 2001), the spinout entrants in this study failed quickly and in large numbers. As Tables 4 and 5 reveal, there is ample evidence that the early failure of spinouts is a common occurrence, raising the general question of what, if any, parental benefits are ever accrued by spinouts in the sector. Of the 495 spinouts that entered the abatement industry, 201 exited by the end of their first year (Table 4) and 145 exited without ever performing a single project (Table 5).

7.1 | Performance heterogeneity

In the asbestos abatement industry, commoditization forces are, in a sense, taken to the extreme since virtually every facet of abatement techniques is legally prescribed in CDPH&E's Regulation 8. When key sources of technical differentiation are slight, then there is little or no advantageous knowledge to transfer from parent to progeny. To probe

TABLE 2 Descriptive statistics

	N	Minimum	Maximum	Mean	*SD*
Firm foundings (year)	678	1986	2017	1998	7.62
Firm failures (year)	550	1987	2017	2002	7.85
Currently operating (yes = 1)	678	0	1	0.18	0.39
Firm lifespan (years)	678	0	31	3.61	4.57
Entry mode (spinout = 1)	678	0	1	0.73	0.77
Total completed projects	678	0	3,215	84.21	266.04
Average annual projects	678	0	161	10.96	16.80
Spinout frequency by parent	112	1	22	4.39	4.45
Entry cohort size	678	14	41	24.70	7.28
Spinout cohort performance (average annual projects)	112	0	20.8	11.30	22.07
Population at entry	678	0	134	98	22.39
Entry cohort as % of population	678	12%	100%	31%	17%
Entry cohort average lifespan	678	1	14	3.72	3.15

the boundaries of knowledge spillover theories (e.g., Agarwal et al., 2010), Hypothesis 1 predicted that hereditary effects, and thus parent-progeny resemblance, are negligible; which, if correct, would result in high and low-achieving parents producing both high and low-achieving spinouts. Even though the technical-specialist knowledge is indispensable to operating in the asbestos abatement industry, it is not strategically decisive because there is no differentiation due to low-technological dynamism. As the regression results in Table 6 indicate, Hypothesis 1 finds strong support (Models 2 & 3). Parental performance is not a significant predictor of spinout performance. In fact, the coefficients for performance and lifespan are slightly negative, albeit not statistically significant.

This means that, on average, in a service sector exhibiting relatively low-technological dynamism and low technician-centric value creation, parental performance is not a determinant of spinout performance. Importantly, this does not mean that parental performance is inversely related to the performance of its progeny, only that it is non-predictive. Unlike sectors characterized by high technological dynamism—such as hard disk drives, lasers, and biotechnology—or by conditions in which the locus of value creation resides with technical professionals, knowledge spillovers between parent-firms and spinouts in this industry appear to be inconsequential.

Although this examination of the grand mean of the relationship between the 495 spinouts and their respective parents is the same analytical approach employed in previous studies (e.g., Agarwal et al., 2004; Dick et al., 2013; Eriksson & Kuhn, 2006; Klepper & Sleeper, 2005), earlier empirical work offered no further optics into the relative clustering of each sibling cohort—a critical shortcoming that limits the conclusions one can draw regarding the true parent-progeny resemblance. However, as a consequence of the many sizable sibling cohorts and the comprehensive reporting of the abatement industry, we are able to gather the cohort-level data that is missing from prior studies. As a direct test regarding parent-progeny clustering in, we assess the degree of clustering for all cohorts of statistically reliable size (Table 7). If the average performance variance for spinout cohorts equals or exceeds the performance variance for the complete population of all spinouts, then siblings, on average, bear no resemblance to their respective parents, lending key support for the regression model findings.

As the data in Table 7 indicate, the standard deviation for performance by the entire population of abatement firms is 16.8. This is significantly lower than the weighted average standard deviation for all spinout cohorts, which is 22.0 ($t_{1,495}$ = 11.2, p < .001). The 16 parent-firms that spawned 10 or more spinouts are listed in Table 7, as well. The weighted average standard deviation for cohorts from this group of highly prolific parents is 25.3, also exceeding the population variance of 16.8 projects per firm-year ($t_{1,168}$ = 7.48, p < .001). Moreover, all of the parent-firms exhibited this outcome, meaning that every parent-sibling cohort (i.e., 16 of 16) exhibits greater performance

TABLE 3 Key correlations

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	Spinout avg. annual projects	-*-										
2	Spinout lifespan	*0.317*	-*-									
3	Parent performance (avg. annual projects)	−0.093	−0.016	-*-								
4	Parent longevity (years of operation)	−0.027	−0.007	*0.388*	-*-							
5	Founder experience—technical specialist	*−0.301*	*−0.275*	−0.049	0.004	-*-						
6	Founder experience—generalist	*0.235*	*0.174*	0.015	−0.013	0.008	-*-					
7	Entry cohort size	*−0.148*	−0.015	0.040	0.072	*0.363*	−0.014	-*-				
8	Entry cohort as % of population	−0.130	*−0.172*	0.031	−0.003	0.241	0.007	0.114	-*-			
9	Entry cohort average lifespan	*0.221*	*0.264*	0.027	0.122	−0.143	*0.181*	*−0.178*	−0.116	-*-		
10	Total completed projects	0.140	0.108	*0.213*	0.147	*−0.368*	*0.199*	*−0.197*	−0.135	*0.441*	-*-	
11	Industry population at entry	*−0.181*	*−0.228*	0.002	0.045	0.011	0.003	0.044	0.006	0.114	−0.132	-*-
12	Year effects	0.030	0.018	0.119	0.092	0.064	0.001	0.111	0.093	0.005	0.125	0.022

Note. Italicized correlations are significant at $p < .01$ level (2-tailed).

TABLE 4 Spinout longevity (lifespan in years)

Firm lifespan	Spinout firms: # of spinout firms	Spinout firms: % of spinout firms
Up to 1 year	201	40.6
2 years	105	21.2
3 years	77	15.6
4 years	25	5.1
5 years	18	3.6
6 to 10 years	40	8.1
11 to 15 years	23	4.7
16 years or greater	6	1.2
Total	*495*	*100*
Firms surviving 5 or fewer years	426	86.1
Firms surviving 6 or more years	69	13.9

TABLE 5 Spinout performance (lifetime projects completed)

Total projects completed	Spinout firms: # of spinout firms	Spinout firms: % of spinout firms
0	145	28.1
1	70	14.1
2	43	9.2
3	28	5.6
4	20	4.0
5	10	2.0
6–10	43	8.9
11–20	23	4.9
21–50	30	6.5
51–100	20	4.0
101–250	31	6.5
251–500	18	3.6
501–999	7	1.3
1,000+	7	1.3
Total	*495*	*100*
Firms completing 10 or fewer Total projects	359	72.5
Firms completing 11 or more Total projects	136	27.5

variance than the full population, reflecting the extremely low underlying probability of parent-progeny resemblance in this technologically stable industry. As would be expected by central-tendency in the absence of heritability, parental cohort variances exceed the population variance, meaning that there is no discernible clustering. Mathematically, the wide performance range for cohorts will drive higher standard deviations than the overall population due to the fact that cohorts have a smaller *N*, since each is a subset of the 495 total spinouts in the study. Clustering, if it existed, would be indicated by smaller variances.

TABLE 6 Parent-firm versus founder effects on spinout performance

	Models					
	1	2	3	4	5	6
Constant	38.2***	38.8***	39.4***	33.7***	35.4***	34.3***
	(18.5)	(17.7)	(17.1)	(12.9)	(13.0)	(10.7)
Macro-level controls	−3.8*	−3.4*	−3.0*	−2.8*	−2.7*	−2.6*
	(1.4)	(1.3)	(1.1)	(0.9)	(0.9)	(0.7)
Industry-level controls	−2.3*	−2.2*	−2.2*	−2.0*	−2.0*	−1.8*
	(0.7)	(0.7)	(0.7)	(0.5)	(0.5)	(0.3)
Firm-level controls	−7.3**	−6.7*	−6.9*	−3.9*	−3.1*	−2.9*
	(4.4)	(2.1)	(2.4)	(1.3)	(0.8)	(0.7)
Year effects	−8.3**	−9.4**	−8.5**	−5.8*	−5.4*	−5.3*
	(2.6)	(3.0)	(2.6)	(1.5)	(1.2)	(1.2)
Entry cohort size	−0.8	−0.6	−0.5	−0.4	−0.2	0.2
	(0.2)	(0.1)	(0.1)	(0.1)	(0.0)	(0.0)
Entry cohort as a % of industry population	−1.7*	−1.2	−1.3	−0.4	−0.3	0.2
	(0.4)	(0.2)	(0.2)	(0.1)	(0.0)	(0.0)
Entry cohort average lifespan	−0.9	1.1	0.9	0.6	0.8	−0.5
	(0.2)	(0.6)	(0.3)	(0.2)	(0.3)	(0.2)
Indus population at entry	−1.6*	−1.3	−0.8	−0.5	−0.6	0.1
	(0.5)	(0.4)	(0.2)	(0.2)	(0.2)	(0.0)
Parent performance (avg annual projects)		−1.0				
		(0.3)				
Parent-firm longevity (years of operation)			−1.5			
			(0.5)			
Founder experience (1 = Tech background)				−12.1***		
				(3.2)		
Founder experience (1 = GM background)					9.8***	
					(1.7)	
Founder experience (1 = de novo entrant)						11.5***
						(3.3)
Adj. R^2	0.394	0.402	0.430	0.597	0.588	0.609
ΔR^2 (versus controls)	-*-	0.008	0.036	0.203	0.194	0.215
F-value	30.7***	32.4***	33.1***	50.6***	50.6***	50.6***

Note. Dependent Variable is *Spinout Performance*, measured as projects completed per firm-year. Non-standardized coefficients. Standard errors in parentheses.
*p < .05, **p < .01, ***p < .001.

Given that a significant number of spinouts never become substantively operational, as shown in Tables 4 and 5, it is important to ask if perhaps clustering is discernible once these low-performing spinouts are excluded so that only those spinouts that achieve a material market presence are considered.[2] As a robustness check, we assessed this possibility by excluding all the firms with three or fewer years and five or fewer projects. Dropping the extreme low achievers reduced both the population and firm-specific standard deviations, which would be expected since the low-end of the performance range was expunged for each; however, the change did not affect the lack of discernible

TABLE 7 Heterogeneity of performance—cohort variance versus population variance

Parent name	# of spinouts in cohort	Parent performance (# projects per firm-year)	Average spawn performance (# projects per firm-year)	Spawn performance range (# projects per firm-year)	Cohort *SD*	Cohort std. dev. minus population *SD*[a]
American	22	109.3	14.5	0–89.4	26.4	9.6
RRI	20	92.7	16.8	0–116.9	35.2	18.4
LVI	17	162.5	15.2	0–97.9	25.6	8.8
Great Plains	17	5.4	11.2	0–77.2	21.0	4.2
Dominion	16	97.2	12.7	0–53.5	25.2	8.4
ACM Removal	14	88.3	9.9	0–58.7	19.1	2.3
Mac-Bestos	13	61.0	14.6	0–60.6	19.5	2.7
MDR	12	55.2	9.4	0–47.4	18.4	1.6
EAS	12	48.6	7.3	0–38.9	22.5	4.7
A.R.C.	11	14.4	13.6	0–52.8	17.9	1.1
Excel	11	83.1	9.5	0–33.0	20.7	3.9
Schauer	10	51.0	10.6	0–28.9	21.8	5.0
Asbestos Tech	10	16.5	10.1	0–86.5	26.9	10.1
Onyx	10	33.3	18.9	0–133.1	20.1	3.3
Misers	10	49.8	10.3	0–87.9	28.2	11.4
Cert. Insul.	10	47.9	7.2	0–93.3	31.4	14.6
16 Largest Cohorts	*215*	*63.7*	*11.4*	*0–133.1*	*25.3*[b]	*8.5*[b]
All 112 Spinout Cohorts	*495*	*28.5*	*11.3*	*0–133.1*	*22.0*[b]	*5.2*[b]

[a]The *SD* in projects completed per firm-year for all 495 spinouts is 16.8.
[b]Mean differences (average cohorts variance vs. population variance) were highly significant, $p < 0.001$.

clustering. The reason for this appears to be that all of the parent-firms still spawned both high- and low-achieving spinouts even after removing the extreme, low-achieving spinouts. Thus, the relative size of each performance range versus the population range remained proportionate even after the exclusion of the early failures.

In sum, rather than witnessing cohort-based clusters of spinouts performing at a level similar to that achieved by the parents, spinout performance appears to vary significantly, *irrespective of the parent's quality*. This finding provides additional support for H1 and the proposed boundary conditions presented in Figure 1 above, demonstrating that the transferability of knowledge or capabilities (Agarwal, Audretsch, & Sarkar, 2007) is significantly muted when parental knowledge spillovers are neutralized. This key difference shifts the explanatory bases of performance heterogeneity among low-tech, service-sector spinouts to individual-founder factors.

7.2 | Founder-level factors

Given the aforementioned finding that the performance variance within spinout cohorts is greater than the performance variance across the entire population, the question arises: What is driving this variance, if not the impact of differential, parentally-conferred endowments? Hypothesis 2 examined this question through the lens of founder-specific experience—specifically, the jack-of-all-trades perspective—while simultaneously testing for the influence of parental lineage. Mean comparisons indicate that spinouts founded by generalists have double the lifespan of spinouts founded by technical-specialists (Table 8).

TABLE 8 Spinout founder comparison—technical versus nontechnical knowledge

Founder type	Average lifespan	Average operating performance (projects/firm-year)
All spinouts	3.3	17.0
Technical-specialist spinouts	2.1	5.2
Generalist spinouts	5.6	34.8
De novo entrants	5.8	33.7

The mean difference of 3.5 years is highly significant ($t_{1,495}$ = 19.17, p < .001), as is the mean difference for firm performance, measured by completed projects per firm-year, which is nearly 400% higher for firms with non-technical founders ($t_{1,495}$ = 9.25, p < .001). These findings provide strong support for H2. The regression results in Models 4 and 5 (Table 6) reflect the same findings in the context of controls and other known predictors of operational performance and lifespan.

7.3 | Spinouts versus de novo entrants

It is also apparent from the results in Table 8 that de novo performance closely approximates that of generalist spinouts, while significantly exceeding the average performance of technical-specialist spinouts. The regression results in Table 6 (Models 5 and 6) further bear this out. Single d.f. tests of generalist spinouts (β_{GM} = 9.7, p < .001) and de novo firms ($\beta_{de\ novo}$ = 11.5, p < .001) show great similitude in their significant positive effects on firm performance. This finding provides support for Hypotheses 3a and 3b, which sought to explore the role of hereditary ties in the context of comparisons to new market entrants that had neither prior industry experience nor parental lineage. The central argument is that generalist spinouts and de novo firms will resemble one another due to jack-of-all-trade effects (Lazear, 2004) in which founders primarily bring general business acumen and operational knowledge to the market, while bearing similar opportunity costs in their respective decisions to become asbestos abatement firms.

Meanwhile, spinouts founded by technical specialists (Model 4, Table 6: β_{Spec} = −12.1, p < .001) languish in comparison. These spinouts, comprised of abatement supervisors seeking to monetize their knowledge in the technical aspects of asbestos abatement significantly underperform. The mean comparisons in Table 8 support this. While de novo firms had an average lifespan of 5.8 years and completed an average of 33.7 projects per firm-year, technical-specialist spinouts, on average, only survived 2.1 years and completed 5.2 projects. Taken together, the regression analysis and mean comparisons support Hypothesis 3a, predicting higher relative performance by de novo firms than spinouts by technical specialist. Conversely, de novo firms appear to hold no such edge over generalist spinouts. The comparative performance for both average lifespan and operational performance are statistically indistinguishable, consistent with Hypothesis 3b, predicting that positive jack-of-all-trade effects would be a characteristic of both de novo and generalist founders.

Analysis of the survival prospects for each of three founding states—generalist spinouts, technical spinouts, and de novo founders—tells a similar story, as detailed in the Cox Proportional Hazard (PH) Model (Table 9).

For each variable, the hazard rate indicates the relative likelihood of failure associated with a one-unit change in each variable. For example, each percentage point of economic growth reduces the hazard of failure by 1%, while each additional industry entrant above the mean-centered value increases the hazard of failure by 1%. Among these variables, the influence and statistical significance of entry mode is most pronounced. Industry entry as a technical-specialist spinout *increases* the hazard of instantaneous failure by 19%, while entry by a generalist spinout or de novo firm *reduces* the hazard by approximately 8 and 9%, respectively. The relationship between entry mode and survival probability is presented in Figure 5, a Kaplan–Meier estimate.

TABLE 9 Cox proportional Hazard model for firm failure

	Probability of firm failure		
	Hazard rate	*SD*	*p* value
Statewide economic growth rate (%)	0.99**	0.05	.01
Industry growth rate (%)	0.98*	0.05	.03
Spinout founder industry experience (years)	1.00*	0.15	.04
Entry cohort size (mean-centered)	1.01	0.12	.13
Entry cohort as a % of industry population	1.01	0.09	.07
Entry cohort mean lifespan (years)	0.98**	0.05	.01
Industry population at entry (mean-centered)	1.01	0.08	.10
Parent comparative performance (avg. annual projects above industry average)	1.00	0.34	.29
Parent comparative longevity (years of operation above industry average)	1.01	0.31	.27
Entry mode: technical-specialist spinout	1.19***	0.08	<.001
Entry mode: generalist spinout	0.92***	0.04	<.001
Entry mode: de novo entrant	0.91***	0.02	<.001
Degree of freedom	12		
N (firm-years)	2,447		
Modelχ^2	181.9		<.001
Log likelihood	−11,893.74		

**p < .05, ** p < .01, *** p < .001.*

The Kaplan–Meier plots provide support for our finding that the survival prospects of both generalist spinouts and de novo firms are similar, and are orders of magnitude better than those faced by technical-specialist spinouts. This confirms the prediction that general business acumen (Chatterji, 2008; Lazear, 2004, 2005; Wagner, 2003, 2006) plays an important role in determining spinout outcomes in the abatement industry. The results also underscore the extent to which industry-specific effects influence the degree to which spinouts do or do not have a performance advantage over de novo entrants. As the results reveal, de novo entrants have a distinct performance advantage over certain kinds of spinouts (i.e., technical-specialist founders) and are at parity with others

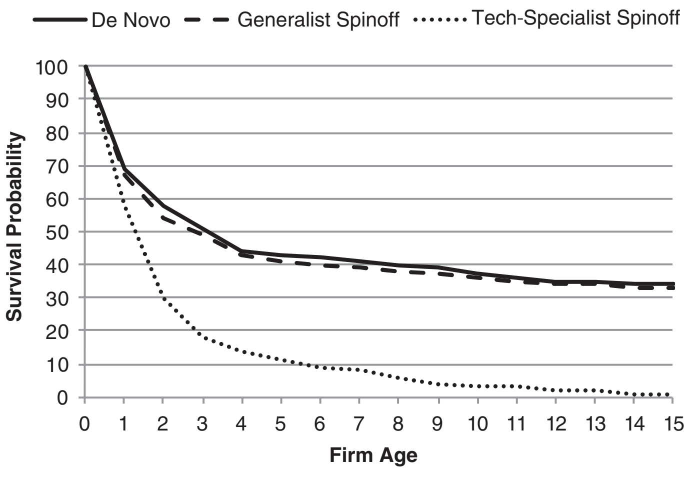

FIGURE 5 Kaplan–Meier plot—survival function for spinouts and de novo entrants

(i.e., generalist founders). In sum, the calculus of hereditary effects is markedly different for firms in the "chance resemblance" region of Figure 1. Hereditary effects, to the extent that they might exist in the service sector, are substantively eclipsed by founder-specific factors.

8 | DISCUSSION

We introduced this paper by recounting the story of the fate of a market entry cohort that challenged conventional notions of spinout performance. In 1996, 31 new firms—the great majority of which were intra-industry entrepreneurial spinouts—entered the Colorado asbestos abatement industry, joining 114 incumbents. Sixteen of the new ventures—all of them technical-specialist spinouts—failed within the first year, despite the booming U.S. and Colorado economies, explosive renovation growth, and a record number of asbestos projects. In the end, none of the spinouts that were founded by technically oriented supervisors survived, while three out of five generalist spinouts and four out of six de novo entrants survived longer than 3 years. Five of the seven long-term survivors are still operational today. In the words of one generalist spinout founder from the 1996 cohort: "Leaving [my old firm] was the best thing I could have ever done. [I] was lucky to make $65,000 per year lining up all the company's jobs. The first year on my own was rough, but I had great connections and figured out the game. By the fourth year on my own I was making more than $250,000 per year."

Meanwhile, the supervisors of the failed technical-specialist spinouts often returned to working as supervisor-employees, usually at the same firm they left to form a spinout. "I knew it wouldn't be easy," said the founder of one failed firm, "but I'd run crews on hundreds of jobs and everyone said I was crazy to just keep making money for the owners. I had no idea how hard it was to just get the jobs." Another pointed out the challenges of trying to leverage technical skills while running a company: "When I was in the hole [i.e., slang term for the asbestos abatement containment], I couldn't work the phones to get new jobs, so I had big gaps between projects and all my hands [i.e., abatement workers] left for steadier work. Just running the company was a full-time job, but that's not what I know how to do best."

The 1996 entry cohort was largest in the 32-year history of the Colorado abatement industry; but, as the foregoing results and our panoramic analysis of the complete industry history reveal, neither the attrition rate, nor the underlying dynamics are unique to 1996. Although the cornerstone of dominant spinout theory rests on the presumption that higher-quality parents spawn more and better spinouts than low-quality parents (Agarwal et al., 2004; Christensen, 1993; Klepper & Sleeper, 2005; Klepper & Thompson, 2010), the asbestos abatement context offers a radically different perspective as a consequence of two principal factors: the absence of technological dynamism that characterizes most of the sectors used in extant literature to study spinouts; and, the locus of value creation residing with generalists rather than technical-specialists.

8.1 | Implications and opportunities

While the asbestos abatement industry is not as economically and technologically transformational as the high-tech industries of prior studies (e.g., hard-disks, lasers, medical devices), it is representative of the vast milieu of technologically less-dynamic industries and organizations that comprise large portions of the service sector, which itself comprises more than 80% of the economies of Europe and the United States (Cleveland, 2012). Relatedly, it is considerably more representative of the mundane low-profile types of firms and industries that make up the bulk of business venturing (Aldrich & Ruef, 2018). Accordingly, the potential implications for theory and practice are broad. Although prior studies suggest parent-progeny ties explain much of the advantageous knowledge endowments and parent-cohort sibling clustering among high-tech spinouts, our results raise important questions about the applicability of these ties in the context of sectors characterized by low-technological dynamism wherein the locus of value creation resides principally with general business knowledge and skills. Interestingly, our findings offer evidence that the knowledge spillover theory of entrepreneurship not only explains clustering among high-tech spinouts (Agarwal et al., 2010), it also correctly predicts that in the absence of advantageous knowledge endowments, relatively little or no clustering will occur among spinouts in industries such as asbestos abatement. Our study takes the additional step in answering the “Why?” question for that important claim.

The evidence from this study shows that the operational performance of abatement spinouts is highly heterogeneous, even among spinouts emanating from the same parent-firm. In contrast to prior studies, we find that spinout performance heterogeneity is uncorrelated with parent-firm quality. If hereditary endowments were source of a performance advantage among service sector spinouts, then one would largely expect to see high-performing parents mainly spawning high-performing spinouts and low-performing parents mainly spawning low-performing spinouts. In fact, however, there is no discernible relationship. The performance variance among cohorts from shared parent-firms is significantly larger than the population variance (Table 7), indicating that variation within parent-cohorts is the norm for abatement spinouts. Therefore, individual-founder differences appear to be more important to spinout performance heterogeneity in the context of low-tech service sectors. In particular, generalists appear to rule the roost, supporting the jack-of-all trades perspective (Lazear, 2004, 2005; Wagner, 2003, 2006). The average lifespan for firms founded by technicians is less than half that of generalists, with average performance differences even greater (Table 8).

While it is beyond the scope of this study to explore in more detail why generalists outperform technical experts by such a wide margin, we believe that future research may discover fruitful answers in the startling similarities between generalist spinout founders and de novo founders. As noted above, it seems likely that these two groups of founders possess similar aptitudes and outlooks in two respects. First, the findings support the notion that generalist spinout founders and de novo founders may identify and interpret market opportunities (Heil & Robertson, 2006) in a similar fashion, partially evidenced by the relative immunity to the effects of impulse-driven or contagion-style entry (Greve, 1998; Hunt & Lerner, 2018; Lerner, Hunt, & Dimov, 2018) that is commonplace among technical spinout founders. As Table 3 shows, the entry-year cohort size is positively and significantly correlated (0.363) with founders possessing technical experience, suggesting that this group may be more prone to contagion entry patterns (Hunt, 2015) than are the generalist and de novo founders.

As the example of the 1996 cohort showed, large numbers of technical-specialist spinouts can materialize in the same year, while generalist spinouts and de novo entrants may take a more measured, studied approach to assessing the potential opportunity of market entry. Future research could find great interest in studying these contagion-style dynamics to examine differential behaviors based on professional experience and market sophistication. Second, generalist and de novo founders may possess similar marketing and sales acumen, particularly in the sourcing of new customers. Conversely, an accurate interpretation of market signals and successful implementation of marketing initiatives may prove to be elusive for technical founders who possess more of a project-engineering orientation. Future opportunities abound to assess and extend these findings by further scrutinizing the multi-level relationships between founder-specific attributes, entry mode, and firm performance.

From a policy perspective, small business support agencies may wish to insure technical-specialist founders have a more realistic sense of how to run a business by assisting them in developing key capabilities, such as sales, marketing, operations, and human resource management. Spinout founders not possessing general business acumen may also benefit from outsourcing arrangements for selected business activities such as accounting and finance. Still others may benefit by co-founding with individuals possessing business management experience.

8.2 | Limitations, alternative explanations, and future opportunities

As with all research designs, methodological decisions related to this study have limitations, some of which may foster concerns about robustness or elicit alternative explanations. A review of these potential issues will reinforce the central claims of this paper. First, the generalizability of asbestos abatement data might be questioned on the basis of the industry's relative anonymity. Despite its low-profile status, the industry represents a well-bounded, well-defined population, constituting a richly detailed data set that provides a full spectrum of organizational forms and near-perfect optics regarding not just entry and survival but also operational activity (Hunt & Lerner, 2017).

Generalizability might also be questioned due to the relatively modest technical demands associated with abatement compared to prior empirical studies which have focused on capital intensive, technologically complex manufacturing industries, such as autos, disk drives, lasers and medical devices. Intuitively, capital intensive, technologically complex products would seem to involve more knowledge that may be relevant to the survival and comparative performance of entrepreneurial spinouts. However, the sheer size and complexity of these industries create substantial challenges to observe and disentangle many potential causal factors, especially in the capture and analysis of nascent-stage events related to new ventures, industries and markets. Highly regulated service-sector industries with relatively low barriers to entry are more likely to provide access to more complete populations, including, as has been demonstrated here, early-stage events. In the end, generalizability is a function of the theory and research question under investigation. The central challenge in this inquiry was to investigate the efficacy of hereditary theory within the context of a complete industry population drawn from the service sector. Boundary conditions that specify high-tech manufacturing sectors (e.g., Klepper, 2009) and complex parental knowledge stocks may produce results that appear to be more supportive of hereditary transfers.

Another important characteristic of abatement industry data involves diversifying incumbents. Few incumbent firms have entered the abatement industry through diversifying market entry. The limited presence of *de alio* firms is likely to be less common in other industries. For the sake of this study, however, the limited presence of *de alio* firms provides an opportunity to focus on spinouts and to directly compare spinouts and de novo firms without the pervasive shadow dominant incumbents that often characterizes capital-intensive industries. Future studies can perhaps conduct similar analyses in the context of an industry that has more *de alio* activity.

Finally, concerns might be raised that the 145 spinout entrants failing to complete even one permitted project simply acquired an abatement firm license to create the option to become operational without possessing serious intent to compete. Several factors make this explanation implausible—especially for spinout founders. First, the issuance of the $2,000 license is a matter of public record. Every license holder is listed on the CDPH&E website. For a spinout founder still working for an employer, this constitutes a signal of direct competitive intent, especially because all project permits are also a matter of public record. Given that public and private entities seeking abatement services maintain rigorous, fully transparent requirements for adequate bonding, insurance, and prior experience, spinouts cannot be used by parent firms as part of a surreptitious bidding strategy for desirable projects. Even if "dummy bidding" were legal, which it is not, new entrants typically must be operational several years before they can obtain adequate hazardous material bonding and insurance to bid on large-scale projects. With more than 100 current firms, mandatory project permitting, and a limited array of marketing options, the Colorado abatement industry is, by any reasonable standard, a tightly knit universe. Second, abatement license issuance requires the submission of Federal and State tax identification numbers as well as the registration with Secretary of the State of Colorado as a formal operating entity. The latter stipulation involves incorporation, publication of by-laws, and annual reports to the State. Thus, the administrative burden is not a cursory matter.

8.3 | Conclusion

Why do firms emanating from virtually identical circumstances often meet with such different fates? Even firms that employ similar strategies may end up exhibiting vastly different operational performance and survival prospects. As the first exhaustive investigation of service sector spinouts through the lens of a complete industry population, this study broadens and strengthens the literature on intra-industry entrepreneurial spinouts. Extant literature has amply demonstrated that when technological dynamism is high and the locus of value creation has compelling technical-specialist qualities, then hereditary endowments may be decisive in determining the fate of entrepreneurial spinouts. However, in low-tech sectors, the influence of market savvy, jack-of-all-trades founders may present a drastically different conception of parent-progeny linkages.

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ENDNOTE

[1] Thanks to the insights of an anonymous reviewer, it is alternatively possible to mathematically derive the relationships that will indicate either presence or absence of clustering, which is the basis for specifying hereditary links. For hereditary effects to be present, spinouts must, on average, be more closely related to their respective parents than to the general population of firms. High-achieving parents should generally spawn high-achieving progeny and low-achieving parents should generally spawn low-achieving spinouts. An abbreviated summation of the argument can be expressed in the following fashion: *Assuming that spinout performance i from parent j can be specified as:* $y_{ij} = a_i + a_j + \varepsilon_i$, *where* a_i *is traits of spinout i,* a_j *is knowledge inherited from parent* j (which is fixed for all members of a given cohort) *and* ε_i *is a random error.*

- *The population variance is given by* $Var_{pop}(y_{ij}) = Var_{pop}(a_i) + Var_{pop}(a_j) + Var(\varepsilon_i) + 2cov(a_I, a_j)$
- *While the cohort variance is given by* $Var_{cohort}(y_{ij}) = Var_{cohort}(a_i) + Var(\varepsilon_i)$.
- *Thus, if hereditary linkages result in greater clustering of the cohort of spinouts, we should have* $Var_{pop}(y_{ij}) > Var_{cohort}(y_{ij})$.
- *Conversely, if* $Var_{pop}(y_{ij}) \leq Var_{cohort}(y_{ij})$, *then hereditary linkages and parent-progeny resemblance are by chance.*

[2] We wish to thank the Editor for bringing this concern to our attention. Prior studies typically exclude many of the substantively non-operational, early-stage failures due to left-side truncation (Hunt & Lerner, 2017). Our ability to capture these low-achievers is a unique facet of our data set, but it does raise the question whether our findings are driven solely by these early failures. The robustness checks we performed demonstrated that the absence of clustering persists even with the selective exclusion.

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