

**Let's Get Away from Big Daddy: How Human Capital and Parent Size Influence the  
Destination Industry of Spinouts**

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September 2017

**ABSTRACT**

We develop and test a unified framework of how spinout founders' human capital and parent size relate to the founders' propensity to stay in the same industry as their parent firms or to go outside. High human capital individuals face a higher performance penalty if they form spinouts outside the parent industry, but they also face greater competitive threat from large parents if they stay in that industry. Using matched employer-employee data on spinout founders and their co-workers, we find that the propensity to form spinouts within the parent industry increases with human capital but declines for high human capital individuals at large parents. In contrast, the propensity to form spinouts in related industries though less positively associated with human capital exhibits no such decline.

**Keywords:** Spinouts, new firm formation, new firm performance, human capital, competitive threat

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This research uses data from the Census Bureau's Longitudinal Employer Household Dynamics Program, which was partially supported by the following National Science Foundation Grants SES-9978093, SES-0339191 and ITR-0427889; National Institute on Aging Grant AG018854; and grants from the Alfred P. Sloan Foundation. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. All results have been reviewed to ensure that no confidential information is disclosed. We would like to thank Rajshree Agarwal, Marvin Lieberman, Sonali Shah and participants and reviewers at the annual meetings of the Academy of Management and Strategic Management Society, and the Census Bureau 2017 Research Data Center Conference for helpful comments. We gratefully acknowledge the financial support of the Kauffman Foundation, the Harold Price Center for Entrepreneurial Studies at UCLA Anderson School of Management and the Academic Senate of the University of California, Los Angeles.

## INTRODUCTION

New firm formation is an important economic process of particular interest to strategic management scholars. New firms often bring new products, technologies and ideas to the market, displace poorly performing incumbents, and alter patterns of economic value creation and distribution in their industries. Our study aims to improve our understanding of this critical process of new firm formation. We focus on spinouts—new firms founded by employees of established firms—and study the interplay among individual human capital, parent firm attributes, and the distance between parent and spinout industries on the formation and performance of spinouts.

Spinouts have received a lot of attention from researchers in management, economics and finance (Agarwal, Echambadi, Franco, and Sarkar, 2004; Gompers *et al.*, 2005; Klepper 2007), partly because many industry studies (e.g., Agarwal *et al.*, 2004; Klepper and Sleeper, 2005; Klepper, 2007) find that spinouts perform better than other types of new ventures. This superior performance is often attributed to the founders' being able to exploit their industry-specific human capital they developed during their employment at their parent firms (Agarwal *et al.*, 2004; Klepper 2009; Chatterji, 2009).

In this line of studies, parent firms are naturally regarded as sources of knowledge, either technological or organizational, and founders act as the channels that transfer that knowledge from the parents to spinouts. Consistent with this view, past studies find that large parents generate more spinouts (Agarwal *et al.* 2004) and that spinouts of larger parent firms perform better (Hvide, 2009). However, parent firms can also be threats to spinouts, and can critically influence the formation and performance of spinouts (Walter, Heinrichs, and Walter, 2013; Starr, Balasubramanian, and Sakakibara, 2017). For example, if spinouts are formed in the parent firm's industry (hereinafter within-industry spinouts or WSOs), parent firms are direct

competitors to these spinouts. In such cases, parents can engage in competitive tactics that hurt the post-entry performance of the spinout. Alternatively, parents may dissuade potential founders from forming the spinout by compensating them well, by providing them better career opportunities within their firm or using other means to reduce the attractiveness of the entrepreneurial opportunity. Furthermore, it is reasonable to expect that the magnitude of this threat varies by the level of individual human capital. For instance, firms may be more motivated to retain higher human capital individuals or dissuade spinout formation by such individuals since those spinouts may be more harmful to the parent (Starr *et al.*, 2017). This issue of potential competitive threat by parents has not received much attention in studies of spinout performance with the notable exception of Walter *et al.* (2013), who find from a survey of 144 German spinouts that spinouts suffer negative consequences from perceived parent hostility.<sup>1</sup>

Though spinout studies implicitly emphasize WSOs because of their focus on a specific industry (Agarwal *et al.*, 2004; Franco and Filson, 2006; Chatterji, 2009), potential spinout founders can develop knowledge at their parents which is applicable outside of the parent firm's industry (parent industry). For example, Henry Ford gained knowledge of portable steam engines while working at his family farm and then as a serviceman for Westinghouse, which he then used to start developing gasoline engines and automobiles while he was with the Edison Illuminating Company (Watts, 2009). Zillow (an online real-estate database company) was formed by ex-employees of Microsoft and Expedia (an online travel company that was formed within Microsoft) by utilizing their knowledge of text-based internet services. Examining broader

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<sup>1</sup> The effect of parent size on new firm formation in general has been studied, and many studies find that small firms spawn new firms more than large firms (e.g., Elfenbein, Hamilton, and Zenger, 2010). This literature argues that potential founders sort (by ability or preference) to work for small parents because small firms provide autonomy and tighter pay-for-performance, or working for small firms provides experience that will be useful for entrepreneurship.

patterns of employee mobility also suggest that individual knowledge may be more widely applicable. Indeed, a majority of people who switch jobs switch industries. Golan *et al.* (2007) find about half of the people who switched jobs went to different SIC 2-digit industries. Recognizing the possibility of spinouts formed outside the parent industry (out-of-industry spinouts or OSOs), a few recent studies have expanded their analysis of spinouts to include such spinouts (Eriksson and Kuhn, 2006; Andersson and Klepper, 2013; Yeganegi *et al.*, 2016; Agarwal and Shah, 2014).

Though the knowledge gained in one industry may be applicable beyond that industry, prior studies from other literatures at the firm level also suggest that the relevance of such knowledge is likely to diminish outside the industry (Helfat and Lieberman, 2002; Carroll, Bigelow, Seidel, and Tsai, 1996). For instance, distance to the destination market has been found to have negative performance implications in international business (where distance includes geographic, economic, cultural and other dimensions as well as industry relatedness; see, e.g., Ghemawat, 2001), and in diversification (e.g. Rumelt, 1974). Similar evidence has been found at the individual level too. Neal (1995) and Hyatt and McEntarfer (2012) find people who switched industries typically earned less in the destination industry. Furthermore, these earning losses appear to be higher for high human capital individuals as measured by skill and tenure (Neal, 1995; Dustmann and Meghir, 2005). Within the literature on spinouts though, the effect of how the distance of spinouts from parent industry affects their formation and performance, and how the level of individual human capital relates to the distance has received limited attention.

Addressing these gaps is important for at least two reasons. First, from a strategy perspective, much like any fundamental discussion of competition in an industry pays particular attention to firms entering from other industries (diversifying firms), it is important to consider

new firms that are formed by founders from other industries (Carroll *et al.*, 1996) and study what factors affect the formation of such firms. Second, from a policy perspective, we want highly capable entrepreneurs to start new firms where they can best utilize their capabilities. However, if parent firms can potentially impede entrepreneurial activities in their industry and influence the destination industry of entrepreneurs, then relevant policy measures may be called for. This is likely to be particularly important when these impediments arise from market imperfections (e.g., market power of large firms) or policies (e.g., competition policy).

The main contribution of our study is to address these critical gaps identified above by developing and testing a unified theoretical framework of the interactions among founder human capital, parent firm size and industry distance in the formation and performance of spinouts. In the extant literature, there are studies about (i) how the level of human capital affects the formation of WSOs (Campbell, Ganco, Franco and Agarwal, 2012; Ganco, 2012) and the performance of WSOs (Chatterji, 2009), (ii) how the size and other characteristics of parent firms affect the formation of spinouts (Eriksson and Kuhn, 2006) or WSOs (Agarwal *et al.*, 2004; Franco and Filson, 2006) and the performance of spinouts (Hvide, 2009; Walter *et al.*, 2013; Eriksson and Kuhn, 2006) or WSOs (Agarwal *et al.*, 2004; Franco and Filson, 2006; Campbell *et al.*, 2012), and (iii) how the knowledge relatedness between spinouts and parents affects the performance of spinouts (Sapienza *et al.*, 2004; Clarysse *et al.*, 2011). These studies typically examine separate pieces of how founder human capital, parents and industry distance affect the formation and performance of spinouts. However, a full understanding of what drives the formation and performance of spinouts requires the examination of these factors together. After all, the founding decisions of potential founders are affected by how their parents would respond to their actions. In turn, the parents' responses are influenced by the extent of their own

resources and their perception of the potential competitive strength of the spinouts, which is a function of the founders' human capital and how close the spinouts are in competitive space.

We develop our theoretical framework in two stages. First, we focus on WSOs and build on some of the seminal studies in the spinout literature (e.g., Agarwal *et al.*, 2004; Campbell *et al.*, 2012). We incorporate parent competitive threat, broadly defined, in the framework through parent size, and examine how parent size interacts with individual human capital to influence the propensity of those individuals to form WSOs. We argue that this effect is likely to be higher for high human capital individuals given their greater value to the firm or greater potential competition to the firm, should they form a spinout. This effect should also be stronger for large parents because they have more resources to provide the necessary incentives and threats, and better competitive capability to compete with the spinouts. Therefore, we expect that high human capital individuals who work for large parents are relatively more discouraged to form WSOs.

We then extend the theoretical framework to OSOs by incorporating the “distance effect,” that is the decreasing relevance of industry-specific knowledge inherited by the founders as the distance between the spinout and parent industry increases. We argue that high human capital individuals are more likely to develop industry-specific human capital because they face higher opportunity costs of abandoning their industry expertise. Besides reducing the relevance of knowledge, industry distance also alleviates the competitive threat imposed by parents because parents will perceive lower competitive threats from spinouts outside their industry. Together these arguments suggest that high human capital individuals are less likely to form their new firms in industries very far from the parent industry.

We test our theoretical framework using matched employer-employee data covering 30 U.S. states from 1990 to 2010. Our data comprise 4.2 million individual-quarter observations on

individuals who formed spinouts, matched to their coworkers at parent establishments in the quarter those individuals leave the parent to form the spinout. By limiting the comparison to spinout founders and their co-workers, rather than comparing all founders to all workers, we control for differences across parents including potential sorting of employees into parents. We focus primarily on spinouts formed in manufacturing and information technology (NAICS 31, 32, 33 and 51) to make it computationally tractable, and because these industries have been the focus of most prior research on spinouts. We classify spinouts into WSOs, OSOs in industries related to the parent industry (OSO-R) and OSOs formed in unrelated industries (OSO-U) depending on how far the spinout industry is from the parent industry.

Consistent with our predictions, we find that high human capital individuals tend to stay in the parent industry, and that when they form spinouts in other industries, they tend to be in related industries. In particular, the propensity to form WSOs is increasing in human capital but consistent with a negative parent size effect, declines modestly for the highest human capital individuals. Furthermore, we find that parent size discourages high human capital individuals disproportionately more from forming WSOs than low human capital individuals. Consistent with a distance effect, relative to the propensity to form WSOs, the propensity to form OSOs is decreasing in human capital with the propensity to form OSO-U's decreasing faster. Our results on observed performance are broadly consistent with these results on propensity.

## **THEORY AND HYPOTHESIS DEVELOPMENT**

We start our discussion by focusing on WSOs, the most commonly studied type of spinouts. We then incorporate the distance effect and expand our discussion to include OSOs. Broadly, our framework models the propensity to form a spinout as being influenced by the expected performance of the spinout, which in turn is determined by the relevance of the individual's

inherited knowledge and competitive threat from the parent, both of which are functions of distance from the parent industry. Because expected performance drives spinout formation in our framework, there is a natural correspondence between the propensity to form spinouts and the observed performance. Hence, we focus our hypothesis development primarily on the formation of spinouts and briefly discuss observed performance later.

### **Spinouts and knowledge inheritance**

Spinout founders inherit knowledge from parent firms, which improves the survival and post-entry performance of these new firms (Helfat and Lieberman, 2002; Agarwal *et al.*, 2004; Klepper and Sleeper, 2005; Chatterji, 2009; Dencker, Gruber, and Shah, 2009; Sorensen and Fassiott, 2011; Ganco, 2012; Argyres and Mostafa, 2016; Agarwal *et al.* 2016). Economic theory suggests that inherited knowledge should also influence the founders' entry decisions since that decision is contingent on the expected post-entry performance of the new firm and the associated returns to the founders (Hamilton, 2000). Consistent with this, recent studies have found that the level and type of pre-entry knowledge influences the decision to be an entrepreneur (e.g., Campbell *et al.* 2012; Ganco, 2012).

The inherited knowledge is often related to technological aspects (e.g., Agarwal *et al.*, 2004; Klepper and Sleeper, 2005; Clarysse *et al.*, 2011; Ganco, 2012), but founders also inherit broader nontechnical knowledge such as knowledge about dealing with novel organizational challenges (Klepper, 2002), regulatory strategy and marketing (Chatterji, 2009) or organizational routines and practices (Phillips, 2002, 2005).

### **Individual human capital and spinout formation**

Individuals, including spinout founders, vary widely in their human capital. At its broadest, human capital can be defined as the result of any investment in “activities that influence future

real income [of people] through the imbedding of resources in people” (Becker, 1962: 9). For our purposes, such resources could be any individually resident knowledge or skill that is likely to create value for the firm where the individual is employed (Campbell *et al.*, 2012). Some relevant individual human capital includes innate ability, on-the-job training, problem-solving capabilities, opportunity-identification abilities, environmental and managerial knowledge, and networks. Not surprisingly, numerous studies have found that founder human capital has a positive effect on post-entry performance (e.g., Klepper, 2002; Phillips, 2002; Colombo and Gili, 2005; Campbell *et al.*, 2012).

Human capital influences the propensity to form spinouts through both its effect on expected post-entry performance of the new firm and its effect on the opportunity cost to the individual. This creates an interesting theoretical trade-off: though potential profits from forming the spinout is higher for individuals with higher human capital, they are also likely to be paid more as employees, and hence likely to have a higher opportunity cost of forming a spinout. Empirically, the coefficients in Table 3 of Campbell *et al.* (2012) imply that higher human capital individuals are more likely to form spinouts. If we interpret patenting productivity and tenure as indicators of human capital, Ganco (2012) reaches a similar conclusion. These findings are consistent with the thesis that equity and other considerations at firms make it difficult to completely reward the capabilities of high human capital individuals. For instance, high wage inequality in a team may create frictions in the team or the firm may not be able to customize compensation to every individual. Profits being the residual flow entirely to the potential founder, and hence, do not face the same constraint. This is also consistent with the evidence that entrepreneurial earnings have a higher variance and skew than wages (e.g., Hamilton, 2000) and that high-earning individuals are more likely to start new firms (e.g., Åstebro *et al.*, 2011;

Poschke, 2013). Thus, all else being equal, the propensity to form spinouts is likely to be increasing in human capital.

### **Competitive effect of parents**

A less-studied effect of the parent on the spinout is the competitive threat, broadly defined, from the parent. Parent firms may be hostile to the spinout (Walter *et al.*, 2013) or may offer incentives or environments that dissuade spinout formation (Campbell *et al.*, 2012). Focusing on the latter, given the cost of replacing productive employees, employers provide incentives to stay by offering higher pay, better work conditions, etc. to the workers they want to retain. Since high human capital individuals are likely to contribute more to the parent, it is reasonable to expect that the parent will provide more incentives for such individuals to stay (Zenger, 1992).

Consistent with this, Campbell *et al.* (2012) find that high human capital individuals are less likely to leave their employer. This effect is also likely to be higher for larger firms since such firms typically have greater resources and hence, are likely to provide more such incentives or offer alternative opportunities (Kacperczyk and Marx, 2016). This will increase the founder's opportunity cost of leaving employment at a larger firm, and reduce the propensity to form a spinout for employees at larger firms. Evidence consistent with this is found in prior studies (e.g., Wagner, 2004; Dobrev and Barnett, 2005; Elfenbein *et al.*, 2010).

The parent may also pose a more direct competitive threat to the spinout if both firms are in the same industry (Klepper and Sleeper, 2005). For instance, parent firms can retaliate with lower prices or offer a product that is similar to the spinout's products, or engage in other competitive tactics that reduce the spinout's profits. This direct competitive effect is also likely to be higher for high human capital individuals, and for employees at larger parents. High human capital individuals are likely to have better ideas that have the potential to cause more damage to

a parent firm's performance (Starr *et al.*, 2017), and hence, parent firms may respond aggressively to such spinouts. Furthermore, given their greater resources, larger firms are more likely to be able to engage in direct competitive actions against the spinouts. From now on, we term this direct competitive threat from parents and the provision of incentives or opportunities to their employees to stay as the "parent effect" or "competitive effect of parents".

### **WSO formation**

Our previous arguments imply that the propensity to form WSOs will be generally increasing in human capital, but that high human capital individuals will suffer a stronger parent effect, which will diminish their propensity to form WSOs (Fig. 1a). Combining these, we get:

*Hypothesis 1: Parent size is associated with a reduced propensity of high human capital individuals to form a WSO.*

*Hypothesis 2: Controlling for parent size, the propensity of an individual to form a WSO is increasing in human capital.*

### **Industry distance, individual human capital and knowledge relevance**

Though we have discussed only WSOs so far, spinouts can be formed anywhere in relation to the parent industry. A majority of employees who switch jobs move to jobs outside their industries (Golan *et al.*, 2007) suggesting that knowledge gained at parent firms can be applied to contexts beyond the parent industry. Similarly, many types of knowledge inherited by spinout founders (e.g., knowledge about marketing (Chatterji, 2009) or organizational routines and practices (Phillips, 2002, 2005)) can be transferred to new firms outside the parent industry. Even technological knowledge can often be applied more broadly. Indeed, this assumption underlies many models of employee start-ups (e.g., Anton and Yao, 1995; Cassiman and Ueda, 2006).

Though useful, the relevance of inherited knowledge to the performance of the spinout is

likely to decrease with distance from the parent industry. This is because a large part of the founders' knowledge is often acquired in the context of a specific industry, which though applicable to "nearby" industries is not very useful in "distant" industries. For instance, while knowledge of organizational routines and practices in law firms (Phillips, 2002) may be beneficial to a new law firm and perhaps to a new professional firm, it is less likely to apply to a new process-manufacturing firm. Neal (1995) offers empirical evidence for this argument. He finds that although pre-displacement tenure in an industry was positively correlated with post-displacement wages for all displaced workers, the correlation was much stronger for industry-stayers than industry-switchers. This indicates that even though workers were able to leverage their knowledge of the old industry in the new industry, such knowledge was less relevant.

We now go beyond existing theory, and posit that high human capital individuals are more likely to have such industry-specific knowledge than low human capital individuals. First, knowledge building is an accretive and cumulative process, in which acquiring new knowledge relies on a base of existing related knowledge (Argote and Miron-Spektor, 2011). Since high human capital individuals are likely to learn at a faster rate than low human capital individuals, they are likely to have a greater base of accumulated knowledge, which in turn makes it easier for them to acquire new related knowledge. This, in turn, increases their incentive to build their knowledge in an area that is in the same or closely related area as their current knowledge base. Thus, high human capital individuals are likely to learn and earn more from staying in an industry. In line with this, Dustmann and Meghir (2005) find that the returns to tenure in an industry, as measured by earnings, are higher for skilled workers than unskilled workers.

The same process of knowledge acquisition also implies that the opportunity cost of leaving the industry for a completely unrelated industry is higher for high human capital

individuals than for low human capital individuals.<sup>2</sup> This is because high human capital individuals have to forgo the benefits of acquiring a much larger quantity of knowledge in their current industry. Consistent with this argument, Brown, Haltiwanger, and Lane (2006) find that workers in higher-wage, particularly high-tech industries, tend to gain by staying within that industry. Similarly, Neal (1995) finds significant wage losses for displaced workers switching to new industries, which are greater for higher human capital workers (as measured by experience and tenure). Together, these arguments imply that higher human capital individuals are likely to suffer a greater loss of knowledge relevance as they move farther from their parent industry.

### **Industry distance and competitive effect of parents**

Industry distance also has an impact on the competitive threat from parents. In particular, as the industry distance between the parent and the spinout increases, the parent is less likely to find the spinout to be a competitive threat, and accordingly less likely to engage in competitive behavior against the spinout. For instance, Starr *et al.* (2017) focuses on non-compete agreements as one specific threat that a parent can impose, and present a model where the probability of non-compete enforcement decreases as the distance of the spinout from the parent increases. Consistent with this rationale, Walter *et al.* (2013) find that product differentiation reduces the impact of parent hostility on spinout performance, and Clarysse, Wright and Van de Velde (2011) find that corporate spinouts grow most if “they start with a specific narrow-focused technology sufficiently distinct from the technical knowledge base of the parent” (p.1420).

### **Industry distance and OSO formation**

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<sup>2</sup> This is likely to be generally true even if high human capital individuals can learn faster in the new industry. For instance, this would be true if for an individual with human capital  $\theta$ , knowledge acquired (K) in period  $t$  follows  $K_t = \theta K_{t-1}^\alpha$ ,  $0 < \alpha < 1$ , a knowledge production function often used in the literature.

We examine how human capital influences the relationship between industry distance and spinout formation. The arguments above would suggest that, since high human capital individuals suffer more from loss of knowledge relevance than low human capital individuals do, high human capital individuals will have a lower propensity to form OSOs relative to forming WSOs, especially far from the parent industry, and this difference will be greater than for low human capital individuals (Fig. 1b).

However, the prediction is more ambiguous when we also consider the parent effect because the direction of the parent effect is opposite to that of the distance effect. In distant industries, the threat from the parent decreases, which increases the propensity of high human capital individuals to form OSOs in such industries. If the parent effect dissipates more with distance than the distance effect does, so that the reduction in the threat (or parent effect) offsets the loss of knowledge relevance (or distance effect), then we may observe higher human capital individuals to have a higher propensity to form OSOs, relative to forming WSOs. However, we posit that this is unlikely to be the case and that the parent effect is unlikely to completely offset the distance effect even for OSOs close to parent industry. A vast majority of firms compete in narrow industries, and often in only one (e.g., Jarmin, Klimek and Miranda (2004) find that 94% of the firms in the U.S retail sector were single-industry firms, and the average number of 4-digit SIC industries for multi-unit firms was only about 1.3). Compared to this, individual knowledge about technology and industry can be applied more broadly as seen by the significant movement of workers across 2-digit SIC industries (Golan *et al.* 2007). Hence, firms are less likely to be concerned about spinouts in industries that do not directly compete with them but where the founders' knowledge still has relevance. These arguments imply the following hypothesis:

*Hypothesis 3: Industry distance is associated with a reduced propensity of high human capital*

*individuals to form spinouts.*

Finally, because the parent competitive threat is higher for larger parents, parent size will not inhibit OSO formation as much as WSO formation by high human capital individuals, especially for OSOs far from the parent industry (Fig. 1c). So, we hypothesize:

*Hypothesis 4: The negative effect of parent size on the propensity of high human capital individuals to form spinouts decreases with industry distance.*

Turning to the implications for *observed* performance, there is a natural, but not a one-to-one, correspondence between expected performance and observed performance. We need to make several additional assumptions about how the selection process works, especially about the distribution of human capital, to make predictions about observed performance. A full discussion of this subject is beyond the scope of this paper. Instead, one of the key assumptions of our framework is that human capital determines expected performance. If this is accurate, then we should expect that conditional on human capital of the founders, the predicted patterns of performance differences would be similar to those for propensity differences. Hence, we state:

*Hypothesis 5: Conditional on founder human capital, the effects of parent size and industry destination on the observed performance of spinouts will be similar to their effects on the propensity to form spinouts.*

## **DATA AND EMPIRICS**

The primary data for the study come from the “Longitudinal Employer Household Dynamics” (LEHD), a matched employer-employee dataset of the U.S. Census Bureau. It provides the employment history and wages for all employees in 30 states and quarterly information on employment and payroll for all employers in those states. Our study was based on thirty states (AR, CA, CO, FL, GA, HI, IA, ID, IL, IN, LA, MD, ME, MT, NC, NJ, NM, NV, OK, OR, RI, SC,

TN, TX, UT, VA, VT, WA, WI, and WV). 1991 is the first year the LEHD data are available for at least 3 states, the minimum required for public disclosure of results, 2008 is the last year.

### **Identification of spinouts**

For our empirical analysis, we divide spinouts into WSOs, related OSOs or OSO-Rs (those at a close “distance” to the parent industry) and unrelated OSOs or OSO-Us (those at a larger distance). Compared with a continuous measure of industry distance, this classification, particularly of OSOs, makes it easier to interpret our results and allows for non-linearity in the effects of industry distance.

Because the LEHD does not directly identify spinouts, we used employee-movement data from the LEHD to identify them. In this regard, our approach follows Starr *et al.* (2017), which in turn draws on Benedetto *et al.* (2005) about identifying various firm events from these data. Broadly, the approach uses knowledge inheritance from the parent through employee mobility, and the relative importance of that knowledge to a new firm to identify spinouts. Thus, conceptually this is similar to Andersson and Klepper (2013) who define spinouts as new firms that have a majority of their founders who were employees at the same parent firm. We began by identifying “founding clusters” of one to twenty employees moving from one establishment (“the predecessor establishment”) to a new firm as identified by its first appearance (“the successor establishment”) within the same state during a one-year period (there were very few inter-state clusters). From these clusters, we excluded clusters where the predecessor establishment was too small relative to cluster size (cluster size more than 50% of employment at the predecessor establishment). This ensures that simple identifier changes do not result in being classified as a spinout (Benedetto *et al.*, 2005). We also excluded clusters where the successor establishment was too large relative to cluster size (cluster size less than 75% of employment at the successor

establishment). This cutoff ensures that the founding cluster accounts for a majority of the individual-resident knowledge at the spinout. Broadly, then, these clusters represent groups of employees moving from an existing firm to join a new firm. Employees in this cluster were classified as founders of the new firm<sup>3</sup>. The predecessor establishment was defined as the parent.

We identified WSOs as those that have the same four-digit NAICS code as their parent. Those that had a different code were classified as out-of-industry spinouts (OSO). We then classified OSOs into two types—related (OSO-R) and unrelated (OSO-U)—based on the distance between the industry of the parent and the industry of the spinout. This was based on a dissimilarity measure computed using the entire universe of establishments (LBD) for 2002 and the baseline NAICS 2002 4-digit industry definition. In particular, the distance from industry A to B was computed as the negative (log) ratio of the number of firms that had establishments in both industries to the total number of firms in either of these industries. If there were no firms that had establishments in both industries, which occurred in a small proportion of instances in our data, we set the distance to be the maximum available distance based on other industry pairs. OSOs with a distance less than the median distance were classified as OSO-R while those with a larger distance were classified as OSO-U (results using alternative cutoffs were consistent with expectations). WSOs were uniformly assigned a zero distance. Thus, at the end, we had three types of spinouts: WSOs (24%), OSO-Rs (38%) and OSO-Us (38%).

To create our sample for analysis, we appended to the list of spinout founders for each spinout, all their co-workers in the quarter they left the parent to form the spinout. If there were

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<sup>3</sup> Since the LEHD is a state-level dataset, we also used a national-level dataset of establishments (Longitudinal Business Database) to exclude firms that appear to be new in a state but actually belong to a firm that has establishments in multiple states.

more than 100 coworkers, we chose a random sample of 100 coworkers for our analysis, along with the appropriate sampling weight. This results in a matched sample of founders and their coworkers at the time of the founders' leaving the parent, which allows us to examine the propensity to form different types of spinouts after controlling for various parent effects. Finally, because most prior studies of spinouts have in the technology and manufacturing sectors, as well as to keep the data analysis manageable, we limited a majority of our analyses to spinouts formed in manufacturing and information (NAICS 31, 32, 33 and 51). Together, this resulted in about 4.2 million observations comprising about 180,000 founders of 83,000 spinouts, and 4.0 million coworkers at their *parents*. Descriptive statistics are provided in Table I. Throughout, all numbers have been rounded to meet U.S. Census Bureau disclosure requirements

### **Propensity to form spinouts**

Our first interest is in studying how the propensity to form spinouts varies by human capital and spinout type. Since we have detailed data, we use human capital deciles (as measured by earnings) in a semi-parametric specification. In contrast to linear or quadratic specifications, which impose a pre-determined pattern of correlation on the data, this approach allows the coefficients on human capital to vary by decile and thus, allows us to paint a very rich picture of the role of human capital and uncover any potential non-linearities. We use two specifications to examine propensity. The first is a baseline regression of the following form:

$$F_{ikpt} = \sum_{k=1}^{k=10} \alpha_k HQ_{ik} + \sum_{k=1}^{k=10} \beta_k D_{OSOR}HQ_{ik} + \sum_{k=1}^{k=10} \gamma_k D_{OSOU}HQ_{ik} + \mathbf{Z}_{i[t]} + \omega_{pt} + \epsilon_{ikpt} \quad (1)$$

Where  $F_{ikpt}$  is a binary variable that is 1 if individual  $i$  belonging to parent  $p$  at time  $t$  and in human capital decile  $k$  founded a spinout at time (year-quarter)  $t$ , and 0 otherwise,  $HQ_{ik}$  denotes the human capital decile of an individual constructed based on the (log) individual's real earnings (in 2008 dollars) in the quarter they left the parent to form the spinout,  $D_{OSOU}$  is 1 if the spinout is an OSO-

U and 0 otherwise,  $D_{OSOR}$  is 1 if the spinout is an OSO-R and 0 otherwise,  $\mathbf{Z}$  is a set of time-varying and time-invariant individual-level controls discussed below, and  $\omega_{pt}$  are joint parent-year-quarter fixed effects. In addition, we allow the intercept to vary by type of spinout. Included in  $\mathbf{Z}$  are XPIND, the individual's (log) experience in the industry of the parent, XPAR, the (log) experience at the parent, XNIND, the (log) number of industries the individual has worked in, XSIND, the (log) experience in the spinout industry, AGE is the (log) age, EDU is the (log) years of education as imputed by the US Census Bureau, ALIEN, a dummy indicating whether the founder is an alien in the US, and GENDER, an indicator of the founder's gender. All these controls except ALIEN and GENDER are measured in the year-quarter that the founder leaves the parent to form the spinout. Of these variables, due to Census Bureau disclosure restrictions, we do not present coefficients on ALIEN and GENDER, but dropping them from the regression did not make any significant difference to the results. Throughout, we cluster standard errors at the parent level to allow for arbitrary correlation of errors within a parent.

Our main coefficients of interest in this specification are  $\alpha_k$ ,  $\beta_k$ , and  $\gamma_k$ . We set the lowest decile as the baseline omitted category, and hence, we have 9 coefficients in each set corresponding to the other nine deciles. Broadly,  $\alpha_k$  measures the average propensity of individuals in human capital decile  $k$  to form WSOs relative to those in the lowest decile, after controlling for individual characteristics and time-varying parent characteristics (see below). We focus on relative propensities rather on absolute propensities, since the latter is a function of the absolute number of ideas for each type of spinout (e.g., there may be many more OSO-U ideas than OSO-R ideas simply because there are many more destination industries) and is unknown.  $\beta_k$  and  $\gamma_k$  are quasi difference-in-difference coefficients that measure propensities to form OSOs relative to WSOs, and thus reflect the distance effect after controlling for any factors common to the formation of

OSOs and WSOs. In particular,  $\beta_k$  denotes the difference between (i) the average propensity of individuals in human capital decile  $k$  to form OSO-Rs relative to those in the lowest decile and (ii) the average propensity of individuals in human capital decile  $k$  to form WSOs relative to those in the lowest decile. Analogously,  $\gamma_k$  refer to the relative propensities to form OSO-U.s.

Focusing on the parent-time fixed effects in Equation (1), it is well known that parent characteristics have an influence on the propensity of employees to form spinouts. For instance, a parent may be very entrepreneurially oriented, which will make it more likely that employees at that parent are more likely to form spinouts. Other factors such as the innovativeness of the parent, its performance and perhaps even something specific to the parent's market conditions may influence the propensity of employees to form spinouts. There are also temporal variations in spinout formation (e.g., firm entry declines during recessions). By including parent-time fixed effects, we mitigate the confounding influence of these factors.

To test our hypotheses on the role of industry distance and parent size, we modify Equation (1) by interacting the human capital terms with parent size as follows:

$$F_{ikpt} = \sum_{k=1}^{k=10} \alpha'_k HQ_{ik} + \sum_{k=1}^{k=10} \beta'_k D_{OSOR} HQ_{ik} + \sum_{k=1}^{k=10} \gamma'_k D_{OSOU} HQ_{ik} + \sum_{k=1}^{k=10} a_k S_{pt} HQ_{ik} + \sum_{k=1}^{k=10} b_k D_{OSOR} S_{pt} HQ_{ik} + \sum_{k=1}^{k=10} c_k D_{OSOU} S_{pt} HQ_{ik} + \mathbf{Z}_{i[t]} + \omega_{pt} + \epsilon_{ikpt} \quad (2)$$

where  $S_{pt}$  is size of parent  $p$  at time  $t$ , measured as the (log) number of employees at the parent establishment. Thus, the coefficients  $a_k$ ,  $b_k$ , and  $c_k$  reflect what happens to the various propensities as parent size increases. In particular, if some  $a_k$  is negative, that will indicate that parent size reduces the propensity of individuals in decile  $k$  (relative to those in the lowest decile, as always) to form spinouts.

### **Earnings as a measure of individual human capital**

We now briefly discuss the use of earnings as a measure of human capital. As we define it, human

capital is individual-level capital that creates value for the firm. This construct is highly correlated with earnings (Campbell *et al.*, 2012). Indeed, individual earnings either directly, or as wage residuals, have been extensively used as a measure of human capital both in the strategic management and economics literatures (Campbell *et al.*, 2012; Carnahan, Agarwal and Campbell, 2012; Neal, 1995), and are the most commonly-used measure of individual human capital in large-data studies (e.g., Hamilton, 2000). Furthermore, studies such as Abowd, Kramarz and Margolis (1999) find that person-specific effects are the most important determinant of earnings suggesting that earnings are a good proxy for individual human capital. The other important component of earnings relates to employer effects, which we eliminate by including parent-year-quarter fixed effects in our specifications. We also include several individual-level variables such as age, gender, and alien status, all of which may influence wages but not reflect human capital. Thus, our specification uses differences in earnings across individuals after controlling for these various other drivers of earnings as proxy for differences in their human capital, and is conceptually very similar to the wage residual used in Carnahan *et al.*, (2012) to identify high and low performers. As we show later, there is also a strong correlation between earnings and spinout performance, justifying its relation with human capital. A potential concern is that earnings is a reflection of wealth and that our results are primarily driven by wealth constraints rather than human capital. However, it is not clear why pure wealth constraints may affect WSOs and OSOs differently.

### **Performance differences among spinouts**

We broadly follow the same approach used above to assess performance differences. However, because performance is at the firm level, and not at the individual level, the sample size is considerably smaller. This makes using human capital deciles and the inclusion of joint parent-year-quarter fixed effects infeasible. Hence, we use the same type of specification as in Equation

(2) with spinout performance (as measured by employment at ages 0 and 3) as the dependent variable regressed on spinout type and a full set of its interactions with parent size and founder human capital (as measured by the earnings of the highest-earning founder) along with industry-year fixed effects. As a robustness check, we use a sample of spinouts from all industries (rather than just the four industries examined here) and re-estimate our specifications after including joint parent-year-quarter effects, and show that the inferences are identical.

## **RESULTS AND THEIR ECONOMIC SIGNIFICANCE**

Focusing first on simple cross tabulations, Table II shows the relative frequency of founders by spinout type and human capital, as measured by prior earnings decile. Panel A shows the distribution of founder human capital for each type of spinout. Overall, middle and higher human capital founders comprise the majority of all WSO and OSO-R founders with OSO-R founders dominating at the highest deciles. In contrast, OSO-U founders tend to be predominantly in the lower human capital deciles. Panel B presents the share of each type of spinouts for each level of human capital. It shows that the share of WSOs increases with the level of human capital from 25% in the first decile to about 36% in the 5th decile, and then declines slowly to 31% in the highest decile. Among OSOs, the share of OSO-R relative to OSO-U increases monotonically as human capital increases; indeed, the share of OSO-R is monotonically increasing while that of OSO-U is monotonically decreasing. These patterns are broadly consistent with our hypotheses.

Turning to the regression results, we first estimate Equation (1) that provides a view of how the propensity to form different types of spinouts changes with human capital without considering the parent size effect (Table III). Note that the lowest decile is the omitted category and hence, these coefficients indicate the propensity of individuals in a certain decile to form spinouts relative to individuals in the lowest decile. It is clear from the table that the propensity

to form WSOs (Column WSO) increases with human capital up to the 7<sup>th</sup> decile, and then declines slowly. Compared to individuals in the second decile, the probability of someone in the 7<sup>th</sup> and last deciles forming a WSO are higher by about 0.0046 and 0.0032, respectively. These differences are economically significant compared to the weighted average propensity to form WSOs (0.0066).

The other two columns in Table III present the coefficients on the interaction of OSO-R and OSO-U with human capital for each of the human capital deciles. From Hypothesis 3, we expect that the propensity to form OSO-Rs (relative to the propensity to form WSOs) will be increasingly negative in human capital. In line with this, we find that relative to WSOs, the propensity to form OSO-Rs has a broad declining trend, consistent with a higher distance penalty for higher human capital individuals. The coefficients on OSO-U have a similar pattern as the OSO-R but are more negative. Figure 2b plots the difference of the coefficients between the two OSO-human capital interaction terms and associated 95% confidence intervals. It shows that the difference between the propensity to form OSO-R relative to OSO-U increases with the level of human capital, consistent with higher human capital individuals being able to utilize their knowledge in related industries.

The overall relationships between human capital and the propensity to form the different types of spinouts are presented in Figure 2a. The figure plots the coefficients on the human capital deciles from Equation (1) for WSOs, and the sum of the direct WSO terms and the OSO-R/OSO-U interaction terms. The pattern for WSOs is very different from that of the OSO-Rs. In particular, unlike the pattern for WSOs, we do not observe a decline in propensity to form OSO-Rs among higher human capital individuals. Rather, human capital and the propensity to form OSO-Rs are positively correlated throughout, with the difference between the second and last

deciles being about 53% of the weighted average propensity to form OSO-Rs. Finally, in contrast to both WSOs and OSO-Rs, there is no discernible relation between human capital and the propensity to form OSO-U. This strongly suggests that individual human capital plays a much larger role in WSO and OSO-R founding decisions than in OSO-U founding decisions. This is consistent with our arguments that high human capital individuals tend to have more industry-specific knowledge, which they apply to their spinouts. Furthermore, the “flatter” profile with respect to human capital for the propensity to form OSOs (relative to WSOs, which has a peak in the middle) is consistent with Carnahan *et al.* (2016) who find that OSO performance has a higher variance than WSO performance.

Our basic control variables are generally in line with expectations. Consistent with being useful for WSOs, parent industry experience is associated with a higher propensity to form WSOs, and lower propensity to form OSOs relative to WSOs. Parent experience is positively associated with the propensity to form spinouts, but no difference between the different types of spinouts. The length of education is positively associated with the propensity to form WSOs. There is no additional effect on OSO-Rs, while there is a negative effect on the propensity to form OSO-U. Since education is also a rough proxy for general human capital, these results are consistent with WSOs and OSO-Rs being more human capital intensive. The number of industries an individual has worked in, not unexpectedly, has a negative effect on the propensity to form WSOs, but a positive effect on the propensity to form OSOs, both relative to WSOs and in absolute terms. Experience in the spinout industry is negative correlated with the propensity to form WSOs and relative to that, positively correlated with the propensity to form OSOs.

Table IV presents the results of estimating Equation (2), which incorporates the parent size effect. For brevity, the coefficients on the controls, which are similar to those in the previous

table, are not presented. Focusing on the WSO-related direct terms first (Column WSO), the coefficients increase with the level of human capital up to the 8<sup>th</sup> decile, then declines, but the decline is much smaller than what is seen in Figure 2a. This supports Hypothesis 2, and is consistent with what one would expect in smaller parents. The interaction of WSO with parent size broadly decreases with human capital, which supports Hypothesis 1 (parent size reduces the propensity of high human capital individuals to form WSOs).

Another interesting result is that though the magnitude of the negative parent effect is much higher for high human capital individuals, it flattens out or even weakly decreases at the highest deciles. For instance, the coefficient on the 5<sup>th</sup> decile is nearly three times that on the 3<sup>rd</sup> decile but the coefficient on the 10<sup>th</sup> decile is only about 20% higher than that on the 5<sup>th</sup> decile. This less-than-proportionate effect at the higher deciles suggests that a greater proportion of the highest human capital individuals have expected returns high enough to overcome the potential parent effect so that they form WSOs at about the same rate as middle human capital individuals.

Turning to the differential effect of the parent size effect, from Hypothesis 4, we expect that as parent size increases, the propensity of high human capital individuals to form OSO-Rs relative to the propensity to form WSOs increases, and this differential is higher for OSO-U. This is indeed what we find. The coefficients on the triple interactions with OSO-R in Table IV (Column OSO-R) shows that relative to WSOs, the propensity to form OSO-Rs is increasing with human capital as parent size increases. The corresponding triple interactions for OSO-U are larger. Together, these strongly suggest that negative parent size effect on high human capital individuals declines as they move farther from the parent industry (Hypothesis 4).

Finally, Table V presents the performance results. Broadly, these results are consistent with the propensity results (Hypothesis 5). Consistent with prior studies, our results show a

negative coefficient on the OSO-R dummy, and an even larger negative coefficient on OSO-U (Columns 1 and 4). When the full set of interactions are included (Columns 3 and 6), the coefficient on founder human capital is always strongly positive, and the interaction of founder human capital and spinout type is negative for the OSOs, consistent with a negative distance effect on OSOs for high human capital individuals. Also, consistent with a parent competitive threat on WSOs formed by high human capital individuals, the coefficient on the interaction of founder human capital and parent size is negative. The three-way interaction terms are positive for both OSO-Rs and OSO-Us, consistent with a smaller threat from (large) parents for high human capital individuals who form OSOs.

### **Robustness checks**

We performed a number of checks to assess the robustness of our results to alternative specifications and measures. These results are included in the Online Appendix. First, we repeated our two baseline specifications without using weights. The results are similar to the weighted regressions (Figures A1a-A1c) with changes one would expect if larger firms were under-weighted. For instance, we do not observe the decline in the propensity to form WSOs at the higher end of the human capital distribution. Classifying spinouts into two types (WSOs and OSOs) instead of three did not make any difference to our inferences (Tables A1a-A1b). Using alternative measures of industry experience (Tables A2a-A3b) or adding interactions for industry capital intensity and R&D intensity (Tables A4) did not change the results significantly. Similarly, using a continuous measure of distance rather than the trichotomous classification did not make any major changes to our key inferences (Tables A5a-A5b). Using the number of establishments as a measure of parent size yielded qualitatively similar results as did a specification that included parent wage as an additional interaction variable (Tables A6a-A7b).

Finally, we repeated our performance analysis on the sample of spinouts in all industries (rather than those in just the four industries studied here) and included parent-year-quarter results (Table A8). The inferences are similar to those from the baseline results.

## **DISCUSSION AND CONCLUSION**

### **Distance effect**

Our results highlight the economic importance of “where” in the entrepreneurial process. Many studies have examined “why” founders choose to found new firms but detailed studies of entrepreneurial destination are, to our knowledge, rare. Indeed, though most studies of spinouts examine new firms formed in the same industry as their parents, WSOs comprised only 24% of spinouts in our sample; the vast majority of spinouts in our sample were not in their parent industries. Thus, by incorporating both WSOs and OSOs, our study extends the literature on how the level of human capital affects the formation and performance of spinouts (e.g., Chatterji, 2009; Campbell, Ganco, Franco and Agarwal, 2012; Ganco, 2012) that has largely focused on WSOs as well as studies such as Sapienza *et. al* (2004) and Clarysse *et al.* (2011) that examine how knowledge relatedness between spinouts and parents affects the performance of spinouts.

More specifically, our results strongly suggest that how far from parent industry entrepreneurs go is affected by both their human capital and parent size. Focusing on the distance-human capital relation first, the OSO-R and OSO-U interaction terms in Table III show a broad decreasing trend with human capital. Since these are relative to WSOs, they are consistent with our arguments that the applicability of founder human capital diminishes with distance from the parent industry, especially for high human capital individuals. Similar distance effects have been found in the international business and corporate diversification literatures but to our knowledge, this is the first study to show such an effect in entrepreneurship (we discuss

related performance implications later).

Our theoretical arguments and results regarding the distance effect also broadly parallel and are consistent with arguments in the literature that high and low human capital entrepreneurs have different motives and orientation to enter entrepreneurship. Specifically, individuals with low ability might become entrepreneurs out of necessity because they face low wages and therefore, have a low opportunity cost of starting a new firm (or they might also perceive their current job to be poor fit with their ability). On the other hand, the workers with high ability may start their business out of opportunity: they recognize business ideas whose potential return exceeds their current wage level (Poschke 2013). Our results strongly suggest that these two groups of entrepreneurs also differ considerably in where they are likely to form a new firm.

### **Parent effect**

The other major contribution of our results is to provide direct evidence for the existence of a negative parent effect on the propensity to form spinouts, particularly WSOs. This negative effect for high human capital individuals can be seen in Figure 2c, which presents the predicted propensity (relative to individuals in the first decile) for the three spinout types at two parent sizes (0.5 standard deviations above and below the weighted average parent size). The propensity to form WSOs increases monotonically with human capital in the smaller parent but drops sharply with human capital in the larger parent. The effect is much less pronounced for OSOs.

Prior studies have generally focused on the knowledge and resource benefits of being at large firms or on the competitive effect of the spinout on the parent (e.g., Eriksson and Kuhn, 2006; Agarwal *et al.*, 2004; Franco and Filson, 2006; Walter *et al.*, 2014; Campbell *et al.*, 2012). While founders of a spinout do derive knowledge and resource benefits from large parents (consistent with the large positive coefficient on parent size in Table V), these parents can also

take actions to dissuade the formation of the spinout or compete intensely with the spinout once it is formed, especially if the spinout is a WSO. Our data do not allow us to fully disentangle whether this dissuasive parent effect is in the form of higher wages for potential WSO founders or in the form of actual competitive threat. As a rough check, we re-estimated our baseline specifications including average wage at the parent as an additional interaction variable (Tables A6a-A6b in the Online Appendix). We find that though the coefficients on parent wage are negative they are much smaller than the coefficients on size, suggesting that higher wages may not be the only way parents dissuade spinout formation.

### **Performance implications**

In addition to providing a more unified view, our theoretical framework also sheds new light on another understudied topic—the performance difference between WSOs and OSOs. A notable exception is Dahl and Sorenson (2013), who argue that OSO founders have different motivation to form new firms compared to WSO founders. OSO founders perceive low expected returns to staying in the same industry because of the lack of abilities or attributes to succeed in the industry, or have a poor fit with the industry. They find that the difference in motivations explains some of performance differences between WSOs and OSOs. We build upon their arguments, and show that the distance effect and parent effect also influence the formation and performance of different types of spinouts. More importantly, our results provide a new explanation for findings in past spinout studies (of WSOs) that WSOs perform better: WSOs perform better partly because higher human capital individuals are more likely to form WSOs.

A key implication of the distance effect in our framework is that the positive relationship between human capital and spinout performance is highest for WSOs because human capital of WSO founders are most directly relevant to the performance. This is exactly what we find. With

regard to parent size effect, our framework implies that the competitive threat of large parents on OSO-Rs and OSO-Us should be less than that on WSOs. Hence, parent size should exhibit a negative association with WSO performance for high human capital individuals. This effect should be less for OSO-Rs, and even lower for OSO-Us. These implications are also supported.

### **Alternative explanations**

We now discuss some potential alternative explanations based on past studies.

#### *A. High human capital individuals learn more from large parents.*

Several studies have shown the benefits spinout founder receive from being at large parents (Agarwal *et al.*, 2004; Klepper, 2009; Chatterji, 2009). It is plausible that high human capital individuals benefit more from the parent (e.g., they may learn more), and hence, we may observe an increasing propensity to form spinouts (especially WSOs) with human capital. However, if this were the main driver of our results, we would expect individuals at larger parents to benefit from their parents and hence, be more likely to form spinouts. In our case, the parent size effect is in the opposite direction. Furthermore, we find that the negative parent effect is stronger for WSOs than for OSOs; a knowledge-based explanation would suggest that WSOs should have benefitted the most, making them most likely to occur in larger parents.

#### *B. Sorting into parents*

Elfenbein *et al.* (2010) examine the small firm effect on entrepreneurship in general and discuss three additional explanations (beyond the opportunity cost explanation implicit in this study) for why propensity to form new firms may be linked to parent size. We discuss them below. Broadly, they relate to why some types of individuals may choose small parents. (a) *Preference sorting*. Small firms attract people with preferences that are common among those likely to form spinouts. (b) *Ability sorting*. High-ability employees select into small firms

because they offer tighter pay for performance, which allows them to earn more or because high ability in small firms translates to high ability in entrepreneurship. (c) *Learn about entrepreneurship*. Small firms provide skills and environment valuable for entrepreneurship.

All these explanations imply that individuals at small firms are more likely to form spinouts, and thus explain the negative parent size effect. In particular, we find the parent effect to be most negative for WSOs. For (a) to explain this finding, it must be that individuals with preferences associated with being a WSO founder sort disproportionately more into small parents than large parents. It is not clear why this would be true since preferences such as those for autonomy and risk are unlikely to be correlated with distance from the parent industry. A similar argument suggests that (b) and (c) are unlikely to explain our results (e.g., the benefits for tighter pay for performance and entrepreneurial skills are likely to be similar for both WSO and OSO founders). However, we cannot completely rule a variant of (b) and (c). If high ability or learning in small firms were more relevant for the success of WSOs than OSOs, then we would observe a greater negative parent effect for WSOs. This appears less likely since larger firms are more likely to offer founders greater access to industry-specific knowledge and resources (e.g., supplier or buyer relationships, technological knowledge etc.). Therefore, the small firm effect alone does not seem to explain our results, and distinguishing different types of spinouts provides us a richer understanding of parent size effects.

*C. Distance is a proxy for the founder's misfit or unhappiness with industry*

It has been argued that some individuals become entrepreneurs because they don't fit their current job or they lack abilities or attributes to succeed in the industry (Astebro *et al.*, 2011; Dahl and Sorenson, 2013). This implies that misfits are more likely to form OSOs, and greater misfits are more likely to form OSO-U's. (Note that misfits with the parent but not the

industry will not likely move outside the parent industry.) If the misfit is because the founder's skills do not match industry requirements, then if the individual moves to the new industry where his or her skills are more applicable, there should be no performance penalty for OSOs relative to WSOs. However, this does not appear to be true; we find that WSOs tend to be significantly larger than OSOs. If the misfit is one of preferences (e.g., the founder does not like the working conditions in an industry), then individuals may be willing to sacrifice performance in order to be in an industry closer to their preference. This will explain the performance penalty for OSOs, and the greater penalty for OSO-U.s. However, in this case it is not clear why the degree of such a preference misfit may vary systematically with human capital or even with parent size, which our results suggest. Therefore, misfit alone cannot explain the distance effect.

### **Implications for research**

Our study has several implications for the study of strategic management and entrepreneurship. First, our study suggests that working at large parents may be a double-edged sword for potential spinout founders; though the founders can gain from the parents' knowledge and resources, they may also face a greater threat from such parents. Hence, future studies of spinout formation may benefit from extending the traditional view of parents as providers of pre-entry knowledge. Second, as discussed in the strategic management and industrial organization literatures, industry has an important effect on a new firm's performance. This study highlights the importance of the relation between the parent and destination industries and how that relation affects the formation and performance of spinouts. Recent studies have begun to move beyond spinouts in parent industries, but our study suggests that deeper examinations of such spinouts may be fruitful. Finally, our study adopts a unified view of formation and performance that helps develop a fuller picture of the phenomenon. However, this is only a small first step towards a complete

understanding of the complex web of relationships that drive spinout formation and performance. Moving further in this direction and fully integrating formation and performance is likely to be valuable. We hope our study inspires future researchers to address these challenges.

## REFERENCES

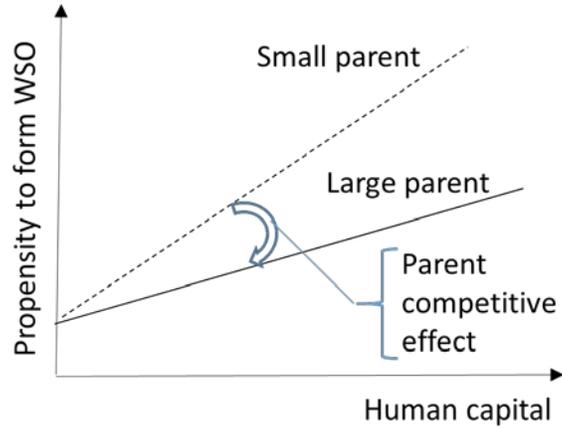
- Anton, J.J. and Yao, D.A. 1995. Start-ups, Spin-offs, and Internal Projects. *Journal of Law, Economics, and Organization*, 11(2): 362–378.
- Abowd, J. M., Kramarz, F., and Margolis, D. N. 1999. High wage workers and high wage firms. *Econometrica*, 67(2): 251–333.
- Agarwal, R., Echambadi, R., Franco, A. M., and Sarkar, M. B. 2004. Knowledge transfer through inheritance: Spin-out generation, development, and survival. *Academy of Management Journal*, 47(4): 501–522.
- Agarwal, R, Campbell, B.A., Franco, A.M., and Ganco, M. 2016. What Do I Take With Me? The Mediating Effect of Spin-out Team Size and Tenure on the Founder–Firm Performance Relationship. *Academy of Management Journal*, 59(3): 1060–1087.
- Agarwal, R. and Shah, S., 2014. Knowledge sources of entrepreneurship: Firm formation by academic, user and employee innovators. *Research Policy*, 43(7); 1109–1133.
- Andersson, M. and Klepper, S. 2013. Characteristics and performance of new firms and spinoffs in Sweden. *Industrial and Corporate Change*, 22(1): 245–280.
- Argote, L. and Miron-Spektor, E. 2011. Organizational Learning: From Experience to Knowledge. *Organization Science*, 22(5): 1123–1137.
- Argyres, N. and Mostafa, R. 2016. Knowledge Inheritance, Vertical Integration, and Entrant Survival in the Early U.S. Auto Industry. *Academy of Management Journal*, 59(4): 1474–1492.
- Astebro, T., Chen, J., and Thompson, P. 2011. Stars and misfits: Self-employment and labor market frictions. *Management Science*. 57(11): 1999–2017.
- Becker, G. 1964. *Human capital*. New York: Columbia University Press.
- Benedetto, G., Haltiwanger, J., Lane, J., and McKinney, K., L. 2005. *Using worker flows in the analysis of the firm*. US Census Bureau, LEHD Technical Paper No. TP-2003-09.
- Brown, C., Haltiwanger, J., and Lane, J. 2006. *Economic turbulence: The impact on workers, firms and inequality*. Chicago: University of Chicago Press.
- Campbell, B.A., Ganco, M., Franco, A.M., and Agarwal, R. 2012. Who leaves, where to, and why worry? employee mobility, entrepreneurship and effects on source firm performance. *Strategic Management Journal*, 33(1): 65–87.
- Carnahan, S. Agarwal, R., and Campbell, B.A. 2012. Heterogeneity in turnover: The effect of relative compensation dispersion of firms on the mobility and entrepreneurship of extreme performers. *Strategic Management Journal*, 33(12): 1411–1430.
- Carnahan, S. Agarwal, R., Campbell, B.A., and Choi, J. 2016. All in the Tails? Pre-Entry Knowledge and the Distribution of Startup Performance. *Working Paper*.

- Carroll, G. R., Bigelow, L. S., Seidel, M.-D. L., and Tsai, L. B. 1996. The fates of de novo and de alio producers in the American automobile industry 1885–1981. *Strategic Management Journal*, 17: 117–137.
- Cassiman, B. and Ueda, M. 2006. Optimal Project Rejection and New Firm Start-ups. *Management Science*, 52(2): 262–275.
- Chatterji A. K. 2009. Spawned with a silver spoon? Entrepreneurial performance and innovation in the medical device industry. *Strategic Management Journal*, 30(2): 185–206.
- Clarysse, B., Wright, M., and Van de Velde, E. 2011. Entrepreneurial origin, technological knowledge, and the growth of spin-off companies. *Journal of Management Studies*, 48(6): 1420–1442.
- Colombo, M.G. and Grilli, L. 2005. Founders' human capital and the growth of new technology-based firms: A competence-based view. *Research Policy*, 34(6): 795–816.
- Dahl, M. S., and Sorenson, O. 2014 The who, why, and how of spinoffs. *Industrial and Corporate Change*. 23 (3): 661–688.
- Dencker, J. C., Gruber, M., and Shah, S. K. 2009. Pre-entry knowledge, learning, and the survival of new firms. *Organization Science*, 20(3): 516–537
- Dobrev, S. D., and Barnett, W. P. 2005. Organizational roles and transition to entrepreneurship. *Academy of Management Journal*, 48(3): 433–449.
- Dustmann, C. and Meghir, C. 2005. Wages, Experience and Seniority. *Review of Economic Studies*, 72(1): 77–108.
- Elfenbein, D. W., Hamilton, B. H., and Zenger, T. R. 2010. The small firm effect and the entrepreneurial spawning of scientists and engineers. *Management Science*, 56(4): 659–681.
- Eriksson, E. and Kuhn, J.M. 2006. Firm spin-offs in Denmark 1981–2000 — patterns of entry and exit. *International Journal of Industrial Organization*, 24(5): 1021–1040.
- Franco, A.M. and Filson, D. 2006. Spin-outs: knowledge diffusion through employee mobility. *Rand Journal of Economics*, 37(4): 841–860.
- Ganco, M. 2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. *Strategic Management Journal*, 34(6): 666–686.
- Ghemawat, P. 2001. Distance still matters. *Harvard Business Review*, 79(8): 137–147.
- Golan, A., Lane, J., and McEntarfer, E., 2007. The Dynamics of Worker Reallocation within and across Industries. *Economica* 74: 1–20
- Gompers, P., Lerner, J. and Scharfstein, D. 2005. Public corporations and the genesis of new ventures: 1986 to 1999. *Journal of Finance*, 60(2): 577–614.
- Hamilton, B. H. 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, 108(3): 604–631.
- Helfat, C. E., and Lieberman, M. B. 2002. The birth of capabilities: Market entry and the importance of pre-history. *Industrial and Corporate Change*, 11(4): 725–760.
- Hvide, H.K. 2009. The Quality of Entrepreneurs. *Economic Journal*, 119: 1010–1035
- Hyatt, H. and McEntarfer, E., 2012. Job-to-Job Flows and the Business Cycle. *CES Working Paper*

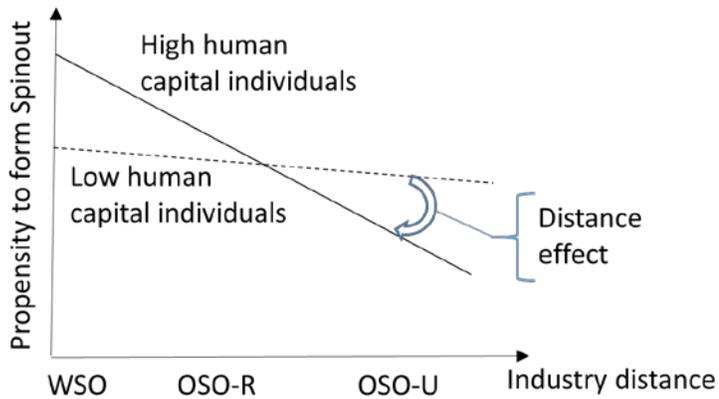
(CES 12-04)

- Jarmin, R.S., Klimek, S.D., and Miranda, J. 2004. Firm entry and exit in the U.S. Retail sector: 1977–1997. *CES Working Paper* (CES 04-17).
- Kacperczyk, A., and Marx, M. 2016. Revisiting the small-firm effect on entrepreneurship: Evidence from firm dissolutions. *Organization Science*, 27(4): 893–910.
- Klepper, S. 2002. The capabilities of new firms and the evolution of the US automobile industry. *Industrial and Corporate Change*, 11(4): 645–666
- Klepper S. 2007. Disagreements, spinoffs, and the evolution of Detroit as the capital of the U.S. automobile industry. *Management Science*. 53:616–631
- Klepper, S. 2009. Spinouts: A review and synthesis. *European Management Review*, 6(3): 159–171.
- Klepper, S., and Sleeper, S. 2005. Entry by spinoffs. *Management Science*, 51(8): 1291–1306.
- Neal, D. 1995. Industry-Specific Human Capital: Evidence from Displaced Workers. *Journal of Labor Economics*, 13(4): 653–677.
- Phillips, D.J. 2002. A Genealogical Approach to Organizational Life Chances: The Parent-Progeny Transfer among Silicon Valley Law Firms, 1946–1996. *Administrative Science Quarterly*, 47: 474–506.
- Phillips, D.J. 2005. Organizational Genealogies and the Persistence of Gender Inequality: The Case of Silicon Valley Law Firms. *Administrative Science Quarterly*, 50: 440–472.
- Poschke, M. 2013. Who becomes an entrepreneur? Labor market prospects and occupational choice. *Journal of Economic Dynamics and Control*, 37(3): 693–710.
- Rumelt, R. P. 1974. *Strategy, structure, and economic performance*. Cambridge, MA: Harvard University Press.
- Sapienza, H.J., Parhankangas, A., and Autio, E. 2004. Knowledge relatedness and post-spin-off growth. *Journal of Business Venturing*, 19(6): 809–829.
- Sorensen, J. B. and Fassiotto M.A. 2011. Organizations as Fonts of Entrepreneurship. *Organization Science*, 22(5): 1322–1331
- Starr, E., Balasubramanian, N., and Sakakibara, M. 2017. Screening spinouts? How noncomplete enforceability affects the creation, growth, and survival of new firms. *Management Science*, Articles in Advance.
- Wagner, J. 2004. Are young and small firms hothouses for nascent entrepreneurs? Evidence from German micro data. *Applied Economics Quarterly*, 50(989): 379–391.
- Walter, S.G., Heinrichs, S. and Walter A. 2013. Parent hostility and spin-out performance. *Strategic Management Journal*, 35(13): 2031–2042.
- Watts, S. 2009. *The People's Tycoon: Henry Ford and the American Century*. Vintage Books.
- Yeganegi, S., Laplume, A.O., Dass, P., and Huynh, C. 2016. Where do spinouts come from? The role of technology relatedness and institutional context. Working Paper.
- Zenger, T.R. 1992. Why Do Employers Only Reward Extreme Performance? Examining the Relationships Among Performance, Pay, and Turnover. *Administrative Science Quarterly*, 37(2): 198–219.

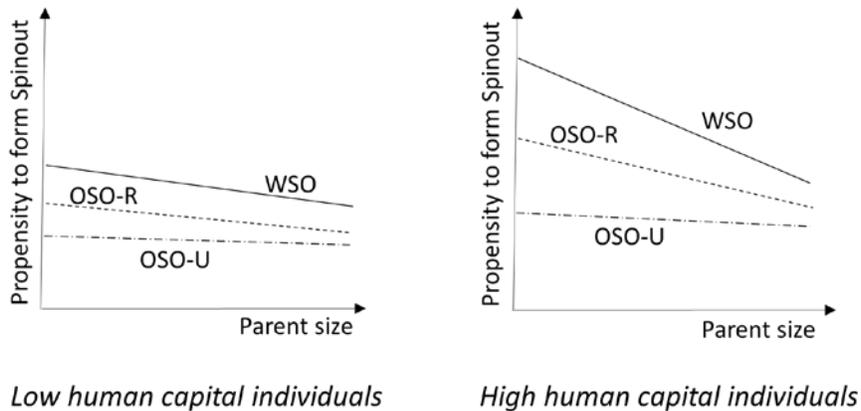
How human capital and parent size affect spinout destination industry



**1a: Competitive effect of parents**



**1b: Distance effect**

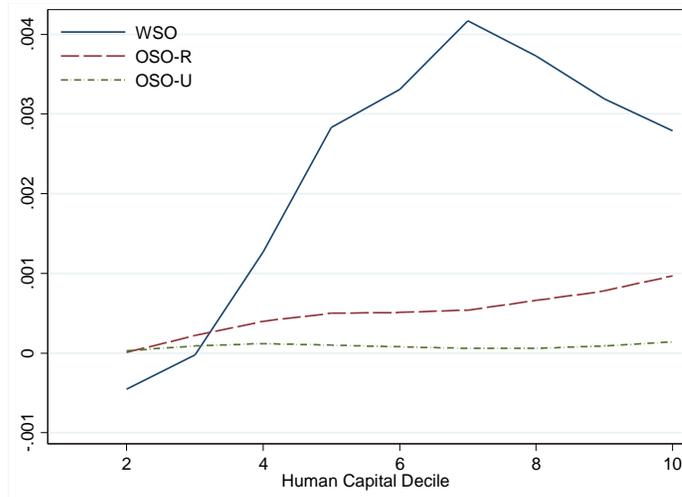


**1c: Industry distance and parent effect**

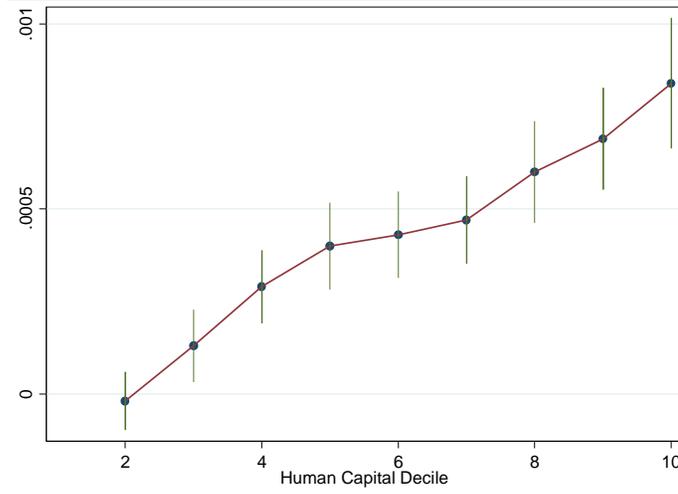
**Note:** WSO: Within-industry Spinout; OSO-R: Out-of-Industry Spinout in Related Industry; OSO-U: Out-of-Industry Spinout in Unrelated Industry

**Figure 1: Overview of our theoretical framework**

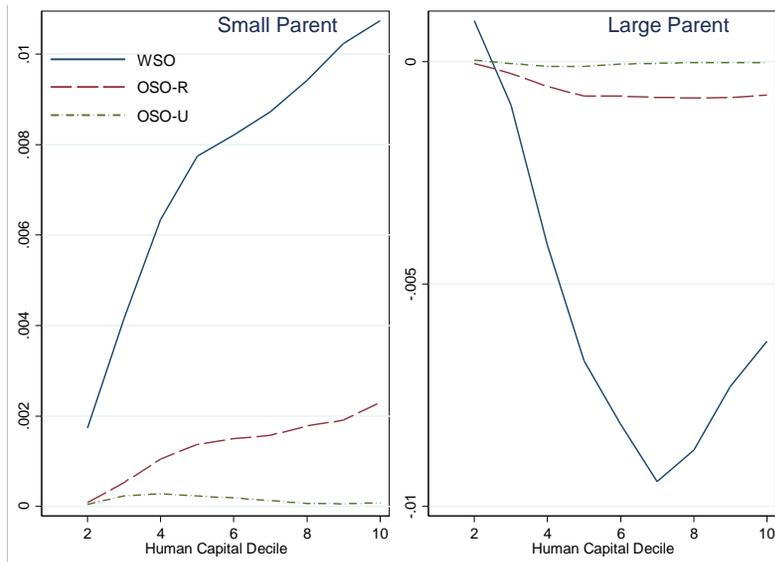
How human capital and parent size affect spinout destination industry



2a: Propensity to form spinouts



2b: Propensity to form OSO-R relative to OSO-U



2c: Parent size effect on propensity to form spinouts

Figure 2: Propensity to form spinouts and human capital

**Note:** Fig 2a plots Eq 1 coefficients on HC decile dummies for WSOs and total effects on HC decile dummies for OSO-R and OSO-U. Fig.2b presents difference between the coefficients on HC decile dummies for OSO-R and OSO-U from Eq.(1). Fig.2c presents estimated propensities to form spinouts by HC decile for two different parent sizes (0.5 s.d. below the mean, left, and 0.5 s.d. above the mean, right).

**Table I. Sample summary statistics (weighted)**

| Variable                        | Overall     |          | Founders |          | Co-workers  |          |
|---------------------------------|-------------|----------|----------|----------|-------------|----------|
|                                 | Mean        | Std. dev | Mean     | Std. dev | Mean        | Std. dev |
| Founder                         | 0.0015      | 0.0393   | 1        | 0        | 0           | 0        |
| Log earnings                    | 8.1361      | 1.7124   | 8.4281   | 1.3269   | 8.1357      | 1.7129   |
| Log parent size                 | 9.5649      | 1.5353   | 4.1298   | 2.3518   | 9.5733      | 1.5187   |
| Log parent industry experience  | 1.8890      | 1.1050   | 1.6199   | 0.9797   | 1.8894      | 1.1051   |
| Log parent experience           | 1.7176      | 1.1829   | 1.5609   | 1.0740   | 1.7179      | 1.1831   |
| Log # of industries worked      | 0.9980      | 0.7971   | 0.8979   | 0.7155   | 0.9981      | 0.7972   |
| Log spinout industry experience | 0.2880      | 0.9746   | 0.7115   | 1.0888   | 0.2874      | 0.9743   |
| Log age                         | 4.9577      | 0.3650   | 4.9368   | 0.3611   | 4.9577      | 0.3650   |
| Log education                   | 2.6403      | 0.3005   | 2.6214   | 0.2981   | 2.6403      | 0.3005   |
| N (Rounded)                     | 118,290,000 |          | 180,000  |          | 118,190,000 |          |

Note: Throughout, numbers have been rounded to meet U.S. Census Bureau disclosure requirements.

**Table II: Relative frequency of founders by human capital and spinout type***Panel A*

| Spinout type/<br>HC decile | 1    | 2     | 3     | 4     | 5     | 6     | 7     | 8     | 9     | 10    | Total  |
|----------------------------|------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|
| WSO                        | 3.29 | 7.39  | 10.03 | 11.97 | 13.09 | 13.02 | 12.88 | 11.42 | 8.66  | 8.25  | 100.00 |
| OSO-R                      | 3.63 | 6.88  | 8.50  | 9.73  | 11.62 | 12.51 | 12.63 | 12.43 | 10.64 | 11.43 | 100.00 |
| OSO-U                      | 6.83 | 11.23 | 12.15 | 11.89 | 11.78 | 11.34 | 10.64 | 9.51  | 7.59  | 7.04  | 100.00 |
| Overall                    | 4.42 | 8.28  | 10.05 | 11.1  | 12.16 | 12.35 | 12.15 | 11.26 | 9.11  | 9.12  | 100.00 |

*Panel B*

| Spinout type/<br>HC decile | 1      | 2      | 3      | 4      | 5      | 6      | 7      | 8      | 9      | 10     | Overall |
|----------------------------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|---------|
| WSO                        | 25.04  | 30.06  | 33.61  | 36.34  | 36.25  | 35.50  | 35.70  | 34.14  | 32.02  | 30.48  | 33.68   |
| OSO-R                      | 31.19  | 31.58  | 32.16  | 33.33  | 36.33  | 38.50  | 39.51  | 41.96  | 44.40  | 47.67  | 38.02   |
| OSO-U                      | 43.77  | 38.36  | 34.23  | 30.33  | 27.42  | 26.00  | 24.80  | 23.90  | 23.59  | 21.85  | 28.31   |
| Total                      | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00  |

Note: Panel A presents the relative frequency of founders by human capital for each type of spinout. Hence, the top cell in the first column indicates the proportion of all WSO founders in the first earnings decile. Panel B presents the relative frequency of each type of spinout by founder human capital decile. Hence, the top cell in the first column indicates the proportion of all founders in the first earnings decile who formed WSOs.

**Table III. Propensity to form spinout by human capital level and spinout type**

|                                   | <i>Type of spinout</i>       |                              |                              |
|-----------------------------------|------------------------------|------------------------------|------------------------------|
|                                   | WSO                          | OSO-R                        | OSO-U                        |
| Human capital decile 2            | <b>-0.00045</b><br>(0.00013) | <b>0.00046</b><br>(0.00014)  | <b>0.00048</b><br>(0.00013)  |
| Human capital decile 3            | -0.00002<br>(0.00015)        | 0.00024<br>(0.00015)         | 0.00011<br>(0.00015)         |
| Human capital decile 4            | <b>0.00127</b><br>(0.00032)  | <b>-0.00087</b><br>(0.00030) | <b>-0.00115</b><br>(0.00032) |
| Human capital decile 5            | <b>0.00283</b><br>(0.00056)  | <b>-0.00233</b><br>(0.00054) | <b>-0.00273</b><br>(0.00056) |
| Human capital decile 6            | <b>0.00331</b><br>(0.00065)  | <b>-0.00280</b><br>(0.00064) | <b>-0.00323</b><br>(0.00066) |
| Human capital decile 7            | <b>0.00417</b><br>(0.00070)  | <b>-0.00363</b><br>(0.00068) | <b>-0.00411</b><br>(0.00070) |
| Human capital decile 8            | <b>0.00373</b><br>(0.00068)  | <b>-0.00307</b><br>(0.00066) | <b>-0.00367</b><br>(0.00069) |
| Human capital decile 9            | <b>0.00319</b><br>(0.00064)  | <b>-0.00241</b><br>(0.00062) | <b>-0.00310</b><br>(0.00064) |
| Human capital decile 10           | <b>0.00279</b><br>(0.00056)  | <b>-0.00182</b><br>(0.00053) | <b>-0.00265</b><br>(0.00056) |
| Log parent industry experience    | <b>0.02259</b><br>(0.00225)  | <b>-0.02274</b><br>(0.00225) | <b>-0.02281</b><br>(0.00225) |
| Log parent experience             | <b>0.00026</b><br>(0.00009)  | -0.00003<br>(0.00009)        | -0.00007<br>(0.00009)        |
| Log # of industries worked        | <b>-0.00037</b><br>(0.00008) | <b>0.00128</b><br>(0.00009)  | <b>0.00075</b><br>(0.00008)  |
| Log spinout industry experience   | <b>-0.02378</b><br>(0.00235) | <b>0.02360</b><br>(0.00233)  | <b>0.02454</b><br>(0.00235)  |
| Log age                           | 0.00017<br>(0.00016)         | -0.00014<br>(0.00016)        | -0.00022<br>(0.00016)        |
| Log education                     | <b>0.00030</b><br>(0.00012)  | -0.00016<br>(0.00012)        | <b>-0.00027</b><br>(0.00012) |
| # of observations                 |                              | 4,220,000                    |                              |
| R-squared                         |                              | 0.175                        |                              |
| Parent-year-quarter fixed effects |                              | Yes                          |                              |

Note: This table shows the result from one regression that estimates Equation (1). Standard errors clustered by parent in parentheses. The sample consists of spinout founders and their coworkers. Dependent variable: 1 if an individual is a founder, 0 otherwise. WSO and human capital decile 1 are omitted categories. WSO column shows the coefficients on the variables in the first column, and OSO-R and OSO-U columns show the coefficients on the interactions of those variables with each type of spinout. This regression was run with sampling weights to adjust for coworker sampling. The number of observations is rounded to nearest 10,000. Coefficients with p-value less than 0.01 are in bold. Coefficients on gender and alien status are not presented due to disclosure concerns.

**Table IV. Propensity to form spinout by human capital level and spinout type: parent effect**

|                                      | <i>Type of spinout</i>       |                              |                              |
|--------------------------------------|------------------------------|------------------------------|------------------------------|
|                                      | WSO                          | OSO-R                        | OSO-U                        |
| Human capital decile 2               | 0.00640<br>(0.00591)         | -0.00561<br>(0.00566)        | -0.00626<br>(0.00591)        |
| Human capital decile 3               | <b>0.03364</b><br>(0.00894)  | <b>-0.02853</b><br>(0.00847) | <b>-0.03182</b><br>(0.00894) |
| Human capital decile 4               | <b>0.06625</b><br>(0.01203)  | <b>-0.05596</b><br>(0.01147) | <b>-0.06377</b><br>(0.01203) |
| Human capital decile 5               | <b>0.09061</b><br>(0.01434)  | <b>-0.07692</b><br>(0.01373) | <b>-0.08844</b><br>(0.01433) |
| Human capital decile 6               | <b>0.1019</b><br>(0.01548)   | <b>-0.08738</b><br>(0.01487) | <b>-0.1003</b><br>(0.01548)  |
| Human capital decile 7               | <b>0.1128</b><br>(0.01636)   | <b>-0.09759</b><br>(0.01570) | <b>-0.1117</b><br>(0.01635)  |
| Human capital decile 8               | <b>0.1134</b><br>(0.01656)   | <b>-0.09675</b><br>(0.01586) | <b>-0.1128</b><br>(0.01655)  |
| Human capital decile 9               | <b>0.1107</b><br>(0.01724)   | <b>-0.09322</b><br>(0.01650) | <b>-0.1102</b><br>(0.01724)  |
| Human capital decile 10              | <b>0.1083</b><br>(0.01891)   | <b>-0.08849</b><br>(0.01803) | <b>-0.1076</b><br>(0.01890)  |
| Log parent employment x HC decile 2  | -0.00053<br>(0.00060)        | 0.00045<br>(0.00057)         | 0.00052<br>(0.00060)         |
| Log parent employment x HC decile 3  | <b>-0.00335</b><br>(0.00095) | <b>0.00283</b><br>(0.00089)  | <b>0.00317</b><br>(0.00095)  |
| Log parent employment x HC decile 4  | <b>-0.00681</b><br>(0.00135) | <b>0.00576</b><br>(0.00128)  | <b>0.00656</b><br>(0.00134)  |
| Log parent employment x HC decile 5  | <b>-0.00942</b><br>(0.00167) | <b>0.00802</b><br>(0.00159)  | <b>0.00920</b><br>(0.00167)  |
| Log parent employment x HC decile 6  | <b>-0.01065</b><br>(0.00183) | <b>0.00917</b><br>(0.00175)  | <b>0.01049</b><br>(0.00182)  |
| Log parent employment x HC decile 7  | <b>-0.01183</b><br>(0.00195) | <b>0.01028</b><br>(0.00186)  | <b>0.01172</b><br>(0.00194)  |
| Log parent employment x HC decile 8  | <b>-0.01182</b><br>(0.00194) | <b>0.01013</b><br>(0.00185)  | <b>0.01176</b><br>(0.00194)  |
| Log parent employment x HC decile 9  | <b>-0.01142</b><br>(0.00202) | <b>0.00965</b><br>(0.00192)  | <b>0.01137</b><br>(0.00201)  |
| Log parent employment x HC decile 10 | <b>-0.01109</b><br>(0.00219) | <b>0.00910</b><br>(0.00208)  | <b>0.01102</b><br>(0.00219)  |
| # of observations                    |                              | 4,220,000                    |                              |
| R-squared                            |                              | 0.177                        |                              |
| Parent-year-quarter fixed effects    |                              | Yes                          |                              |

Note: *This table shows the result from one regression that estimates Equation (2).* Coefficients on control variables not presented to conserve space, and are available on request. Standard errors clustered by parent in parentheses. Refer to notes under Table III for further details.

**Table V. Analysis of spinout performance**

|                                  | Age 0                       |                              |                              | Age 3                       |                              |                              |
|----------------------------------|-----------------------------|------------------------------|------------------------------|-----------------------------|------------------------------|------------------------------|
|                                  | (1)                         | (2)                          | (3)                          | (4)                         | (5)                          | (6)                          |
| OSO-R dummy                      | <b>-0.3110</b><br>(0.00956) | -0.09213<br>(0.1069)         | <b>1.0591</b><br>(0.1063)    | <b>-0.2052</b><br>(0.0137)  | -0.1493<br>(0.1258)          | <b>1.2066</b><br>(0.1561)    |
| OSO-U dummy                      | <b>-0.4813</b><br>(0.00929) | 0.1344<br>(0.1105)           | <b>1.4825</b><br>(0.1010)    | <b>-0.3949</b><br>(0.01350) | 0.09538<br>(0.1316)          | <b>1.4923</b><br>(0.1507)    |
| Founder HC                       |                             | <b>0.1718</b><br>(0.0136)    | <b>0.3527</b><br>(0.01036)   |                             | <b>0.1528</b><br>(0.01538)   | <b>0.3386</b><br>(0.01442)   |
| OSO-R x Founder HC               |                             | -0.01938<br>(0.01295)        | <b>-0.1373</b><br>(0.01257)  |                             | -0.00095<br>(0.01500)        | <b>-0.1400</b><br>(0.01798)  |
| OSO-U x Founder HC               |                             | <b>-0.05982</b><br>(0.01337) | <b>-0.1989</b><br>(0.01213)  |                             | <b>-0.04519</b><br>(0.01580) | <b>-0.1828</b><br>(0.01792)  |
| Parent size                      |                             |                              | <b>0.4525</b><br>(0.02064)   |                             |                              | <b>0.5096</b><br>(0.02916)   |
| OSO-R x Parent size              |                             |                              | <b>-0.3398</b><br>(0.02370)  |                             |                              | <b>-0.4100</b><br>(0.03447)  |
| OSO-U x Parent size              |                             |                              | <b>-0.3859</b><br>(0.02270)  |                             |                              | <b>-0.4279</b><br>(0.03309)  |
| Founder HC x Parent size         |                             |                              | <b>-0.04630</b><br>(0.00221) |                             |                              | <b>-0.04999</b><br>(0.00303) |
| Founder HC x OSO-R x Parent size |                             |                              | <b>0.03301</b><br>(0.00259)  |                             |                              | <b>0.03976</b><br>(0.00361)  |
| Founder HC x OSO-U x Parent size |                             |                              | <b>0.03808</b><br>(0.00249)  |                             |                              | <b>0.04038</b><br>(0.00359)  |
| N                                | 83,000                      | 83,000                       | 83,000                       | 48,000                      | 48,000                       | 48,000                       |
| R-squared                        | 0.136                       | 0.183                        | 0.192                        | 0.156                       | 0.187                        | 0.196                        |

Note: Standard errors clustered by parent in parentheses.