The Effect of High-Performer Migration and Entrepreneurship on Parent Firm Performance

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Abstract

We investigate the effect on parent firm performance from high-performer migration to same-industry start-ups. We propose two set of mechanism to explain this effect. 1) high-performer migration to same-industry start-ups enables competition by transferring human and complementary assets from the parent firm to a competitor and 2) it induces a loss of human assets. In support of the latter, we find that performance effects of same-industry start-ups are comparable to other types of high-performer migration including noncompetitive destinations. These findings demonstrate that competitive migration might not be more harmful than other types of high-performer migration.

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Introduction

The ability to recruit and retain human assets is a key ingredient for the success of firms. Firms invest vast resources in training key employees, and these employees build competencies and social relations that are vital for the stability of employers. When high-performing employees depart, the human asset perspective predicts a detrimental loss of human and social capital to the previous employer (the parent firm) (Coff, 1997; Somaya, Williamson, and Lorinkova, 2008; Campbell et al., 2012). High-performer migration might also disrupt organizational routines (McKendrick, Wade, and Jaffee, 2009; Briscoe and Rogan, 2016) or increase competitive threats through the recreation or transfer of complementary assets and clients from the parent firm to a competitor (Campbell et al., 2012; Raffiee, 2017). The expectation of such negative effects on parent firm performance makes high-performer migration important to strategic human resource management.

Specifically, the departure of high performers to engage in entrepreneurship seems a focal point in firms' retention strategies. When they leave, high-performing employees are more likely to found competitive startups in the same industry and they have greater abilities to transfer complementary assets from their parent firm to the new firm (Campbell et al., 2012). The phenomenon of employees leaving incumbent firms to found their own firms in the same industry has been labeled spin-off, spin-out, spawn, and progeny (we call these firms *spin-offs*.) Spin-offs are remarkably more likely to succeed compared with *de novo* entrants (Agarwal et al., 2004; Klepper, 2007; Dahl and Reichstein, 2007; Chatterji, 2009; Dahl and Sorenson, 2012). However, while spin-offs are found to accrue greater and more long-lasting welfare effects (Klepper, 2009; Gjerløv-Juel and Dahl, 2012), expectations of a negative effect on parent firm performance might lead parent firms to try to prevent spin-offs (Carnahan, Agarwal, and Campbell, 2012), particularly spin-offs by high-performing employees.

Although increasing attention has been paid to spin-offs, we have little evidence on the effects that spin-offs have on parent firms (Klepper, 2009) or on the mechanisms driving their potential effects. We suggest a detrimental performance effect of high-performer migration to spin-offs, and we propose two sets of mechanisms to explain this effect. First, high-performer migration to spin-off entrepreneurship might enable competition and value appropriation at the expense of parent firms. This impact depends on the employee's ability to transfer or recreate human and complementary assets from the parent firm to a competitor (Campbell et al., 2012; Raffiee, 2017). Second, a high performer's departure also implies a loss of human assets, potentially destabilizing organizational routines (Gjerløv-Juel, 2019).

To separate these mechanisms and their impacts, we investigate the effects of high-performer migration to five different destinations: spin-offs, rival incumbent firms, nonrival startups, nonrival incumbent firms, and other noncompetitive destinations (e.g., retirement). Within these different types of high-performer migration, we compare the adverse impacts of local and distant migration. An adverse impact on parent firm performance from non-competitive and distant migration suggests that a loss of human assets play a significant role in explaining this effect. Moreover, greater impacts on parent firm performance from high-performer migration to spin-offs and incumbent rivals and a greater impact from local migration than from distant migration would indicate that increased competition is a significant driver of this detrimental effect. In addition, we investigate how these effects differ within selected industries with one of three characteristics: 1) the transferability of complementary and human assets is low, 2) the market's geographic expansion varies and a nearby location is critical, or 3) clients are easily transferred.

Though few studies have focused on parent firm effects of employee entrepreneurship, an exception is the seminal paper of Damon Phillips (2002). Using data on Silicon Valley law firms, Phillips (2002) shows that the hazard of exit of parent firms initially rises when a highly ranked employee leaves to found her own law firm, a spin-off. More recently, this result has been found in studies of Dutch accounting firms (Wezel, Cattani, and Pennings, 2006) and U.S. law firms (Campbell et al., 2012) and for technological performance in the U.S. hard drive industry (McKendrick et al., 2009). Across these four studies, parent firms have lower performance when employees found spin-offs, at least initially. Much of this literature has adopted a Schumpeterian creative destruction view to explain how innovative entrants thrive at the expense of incumbent firms. Adverse impacts are explained by the transfer of complementary assets from the parent to a competitor (Wezel et al., 2006; Campbell et al., 2012).

While these studies are innovative and valuable contributions, we do see some limitations. To assess the effect of spin-offs on parent firms, it would be interesting to compare and control for the general migration of employees. Is the effect the same, better or worse when high-performing employees depart for incumbent competitors? Is it also harmful when they depart for noncompetitive destinations, for example, firms in other industries? Campbell et al. (2012) partly accounts for this by comparing migration to spin-offs and rival incumbent firms. Due to limitations in their data, they do not control for noncompetitive migration. We find that noncompetitive migration accounts for 3/4 of high-performer migration. These studies thus leave the major source of high-performer migration unaccounted for. This limitation also makes it difficult to assess the mechanisms empirically. Finally, it is an open question whether these studies are generalizable to other industries or countries.

We address these limitations and study whether spin-offs are more or less harmful to the parent firm than other types of high-performer migration, specifically rival incumbent firms and three types of nonrival migration. We use a unique dataset to study the effects of high-performer migration on the survival and sales growth of 30,911 parent firms from 2000 to 2013. First, we investigate the average effects across all private-sector industries in Denmark. Second, we conduct a series of industry analyses that not only allow for more direct tests of our hypotheses but also allow for comparability with existing industry studies. High-performing employees are defined as those ranked in the top 25% of wage earners in the parent firm prior to departure.

As with similar empirical studies, we are concerned about endogeneity in the form of selection bias and/or omitted variable bias. In our case, we expect that the decision of a high-performing employee to leave the parent firm could be explained by expectations about the parent firm's future performance. Another concern is that parent firms with spin-offs are different than other parent firms in our analysis. If so, any difference in ex post performance could be driven by these differences rather than by the spin-offs. Ideally, we would study these issues in a randomized experiment that randomly assigns departures from random parent firms to different destinations. While this design is not feasible in a real-world setting, we have attempted to address these concerns in as much detail as possible given the data at hand, including matching the parent firms to one another based on their observable characteristics and performance history. This design enabled us to study the effect of high-performer migration in a more conservative setting in which there is less concern about selection bias and omitted variable bias.

We find that the departure of high-performing employees to spin-offs has an adverse impact on the performance of parent firms. This evidence shows that the negative effects found in the four specific studies are also found in general across all industries. In addition, we find detrimental effects of noncompetitive migration and migration to distant spin-offs. These findings extend prior work by demonstrating that, in addition to increased competition, we should explain parent effects of spin-offs also (and in some cases only) as a depletion of the parent firm's human asset stock. In some specifications, departures to spin-off entrepreneurship do have larger negative effects compared to departures to (some) noncompetitive destinations and rival incumbent firms. However, these differences are small and not robust to different specifications and robustness tests.

We contribute to the entrepreneurship literature from both a macro- and microeconomic perspective. We explicitly capture the value destruction of parent firms and investigate how much of this loss stems from the competitive transfer of human and complementary assets versus the loss of human assets. This evidence contributes to a macro-level understanding of creative destruction. In addition, we offer important insights relevant to the discussion of the effects of spin-offs on parents firms. Our evidence complements prior studies by demonstrating significant affects from the loss of human assets and that not all spin-offs build on the complementary assets of parent firms, compete for the same clients and resources, and appropriate value at the expense of the parent firms.

Our research also contributes to the strategic human resource management, compensation and retention literature by developing our understanding of knowledge transfer through employee mobility. Our results call into question the extent to which employee mobility enables direct competition. This has several implications. First, it challenges the apparent greater resistance to competitive departures such as spin-off entrepreneurship and the distribution of noncompete covenants, which have been shown to decrease interfirm mobility and entry into entrepreneurship (Stuart and Sorenson, 2003; Marx, Strumsky, and Fleming, 2009). Moreover, it has implications for employee bargaining power in wage negotiations. In a wide range of settings, we show that employee mobility poses little risk of a competitive transfer of parent firm complementary and human assets or the appropriation of parent firm value. This result is independent of the apparent value, transferability and type of parent firm complementary assets.

High-performer migration and parent firms

Several theories may explain the potentially harmful effects of high-performer migration on a parent firm. It is however a common theoretical view to see employees as resources or assets for firms. Building on Teece (1986), Campbell et al. (2012) argue that human assets in combination with complementary assets are essential parts of value creation and appropriation. Previous studies have largely applied this theoretical framework to explain how complementary assets affect the appropriation of technological innovations (see, e.g., Tripsas (1997)). We adopt the Campbell et al. (2012) view of complementary assets to frame our analysis of why the migration of high performers to spin-off entrepreneurship could have an adverse impact on parent firm performance. As we will subsequently discuss, there are complementary and alternative explanations to the one we present below, all of which have implications for strategic management.

In combination, human and complementary assets are sources of sustainable advantage for a firm, depending on how easily these unique resources are imitated (Coff, 1997). Some assets are tacit, while others are more readily codified. Some assets are contractually governed, while others are not. Contractual assets are exceptions rather than the norm (Teece, 1986), leaving considerable opportunities for competitive firms (incumbents or new entrants) to replicate the complementary assets of the parent firm. High performers' mobility enables competitive transfer or recreation, with adverse effects on parent firm performance as a potential result (Campbell et al., 2012).

Complementary assets are embodied in the firm and its employees. Complementary assets traditionally refer to the different organizational functions (from manufacturing to marketing) needed to commercialize (technical) innovations (Yeganegi et al., 2016). While embodied in the firm or groups of employees, complementary assets can survive the migration of individual high performers. Campbell et al. (2012) categorize complementary assets into organizational knowledge (e.g., intellectual property, codified knowledge embodied in products or routines and processes), nonhuman complementary assets (e.g., brand equity and physical capital such as machines and buildings), and human complementary assets (i.e., tacit and noncodified knowledge such as organizational routines, processes and culture embodied in other employees).

Campbell et al. (2012) refer to human assets as 'core assets'. Similar to the economic term 'human capital', human assets refer to skills and knowledge, as well as personal (noncontractual) relations and social processes (Coff, 1997). Human assets, as opposed to complementary assets, are embodied in individual employees. Therefore, human assets are lost when employees leave, resulting in adverse impacts on parent firms. For both complementary and human assets, there is an additional threat in the potential transfer or recreation and appropriation of the parent firm's assets when employees leave to found spin-off firms.

High-performer migration transfers human and complementary assets from parent firms to competitors

The complementary assets of incumbent firms are argued to shield them from the creative destruction of new entrants by providing a comparative advantage in commercializing technological innovations while impeding imitation (e.g., Teece (1986) and Stieglitz and Heine (2007)). However, complementary assets might not provide protection from entrants that are spawned by the parent firms themselves, i.e., from spin-off entrepreneurship.

High-performer migration to spin-off entrepreneurship affects value creation along two dimensions. The adverse impact on parent firm performance depends on 1) the *loss* of human assets and 2) the employee's ability to *transfer* or *recreate* the parent firm's complementary assets (and human assets) at a low cost. Previous empirical studies that address this question rely on the latter explanation by adopting a Schumpeterian creative destruction approach to explain the negative impact on parent firm performance (Wezel et al., 2006; Campbell et al., 2012). This explanation suggests that innovative entrants (spin-offs) thrive at the expense of incumbent firms.

Spin-offs have often been highlighted as a particularly successful type of entrant in specific industry studies (Agarwal et al., 2004; Klepper and Sleeper, 2005) and in general (Dahl and Sorenson, 2012; 2014). Studies of spin-off success typically argue that founders transfer human and complementary assets from parent firms to spin-offs. Founders accumulate organizational and firm-specific knowledge at parent firms that enables them to outperform other entrants and overcome the liability of newness (Stinchcombe, 1965). This firm-specific knowledge could include knowledge about products, production, technologies and organizational practices; it may also include knowledge regarding strategy and markets (Sørensen, 1999; Klepper, 2001; Helfat and Lieberman, 2002; Phillips, 2002; Wezel et al., 2006; Feldman, Ozcan, and Reichstein, 2018) that might not directly conflict with the intellectual property of parent firms (Cooper, 1985; Roberts, 1991; Shane, 2003). Additionally, such knowledge may include network relationships (Corredoira and Rosenkopf, 2010), for example, when high performers sustain customer relations upon departure. These assets are particularly helpful if the new firm is established in the same industry. While the transfer or recreation of such assets and experience gives the entrepreneur a head-start compared with her peers (Agarwal et al., 2004), it may also increase the spin-off's similarity to the parent firm in terms of products, technologies and markets and strategies. By definition, spin-offs are established in the same industry as the parent firm, implying that they potentially compete directly. The departure of an employee to a spin-off might thus increase the hazard of failure for parent firms. This hazard might increase in proportion to the overlap in products and markets between the parent firm and the spin-off (Phillips, 2002; Wezel et al., 2006). In addition, Campbell et al. (2012) argue that employees with high value-generating abilities (e.g., high performers) are better able to transfer to or recreate within their startup the human and complementary assets of the parent firm.

In contrast to this Schumpeterian perspective, Cassiman and Ueda (2006) and Hellmann (2007) suggest that spin-offs often exploit opportunities that have been rejected by parent firms. Moreover, Yeganegi et al. (2016) show that employees who are engaged with the core technologies of the parent firm are *less* likely to found spin-offs, potentially because of intellectual property rights. As a result, the overlap is likely to be small (Chatterji, 2009). This finding suggests that spin-offs often do not engage in direct competition with parent firms. Rather, this condition may open the door to synergy and mutually beneficial cooperation or knowledge sharing between parent firms and spin-offs (Kim and Steensma, 2017) and, more importantly in this context, reduce the harmful effects of departures, if harmful effects are otherwise associated with increased competition.

If we turn to the effect of a high-performing employee's departure to a spin-off, the empirical evidence favors a negative effect (Phillips, 2002; Wezel et al., 2006; McKendrick et al., 2009; Campbell et al., 2012). Here, the main explanation is that the adverse impact on parent firm performance is due the formation of a competitor and the transfer of human and complementary assets, as described above. This allows for spin-offs to appropriate value at the expense of the parent firm, making spin-off entrepreneurship more harmful than migration to noncompetitive destinations (e.g., employment in remote industries). However, if competitive transfer or replication of the parent firm's human and complementary assets impedes its value creation, it is clear that high-performer migration to *incumbent* rivals poses a similar threat to parent firm performance (Somaya et al., 2008; Bermiss and Murmann, 2015).

In addition, more productive complementary assets might even provide incumbent firms an advantage in value appropriation over new firms. Rival incumbent firms have greater abilities and more resources to utilize the human and complementary assets obtained from the parent firm. This competitive transfer or recreation of higher-order routines intensifies competition with adverse effects on parent firm performance (Aime et al., 2010; Bermiss and Murmann, 2015). Moreover, the ability to commercialize human assets from the parent firm might depend on specialized complementary assets not available at new and smaller firms (Teece, 1986; Tripsas, 1997). On the other hand, incumbent firms already have established organizational designs that are not readily altered or influenced by a new employee (Schein, 1983; Wezel et al., 2006). Such inertia could make it difficult for high performers to transfer and implement parent firm complementary assets, particularly when doing so involves altering existing organizational practices. New firms, on the other hand, are not yet locked into an organizational structure or specific set of routines. No pre-existing patterns restrain them from adapting or replicating parent firms' complementary assets (Wezel et al., 2006; Campbell, Kryscynski, and Olson, 2017). Feldman et al. (2018) find empirical evidence that founders transfer a wide range of organizational practices from parent firms to spin-offs. Overlap with parent firm activities makes the replication of the parent's organizational practices a low-risk, low-search strategy. This strategy could increase the competitive impact of migration to spin-offs relative to incumbent rivals (Wezel et al., 2006; Campbell et al., 2012).

In summary, *if* the negative effect on parent firm performance of spin-off entrepreneurship results from the competitive transfer of assets from the parent firm, this suggests similar detrimental effects on parent firm performance of the migration of high-performing employees to either spin-offs or rival incumbent firms. Similarly, while the parent firm risks losing personnel to spin-offs, a departing employee's ties to former colleagues might also encourage other employees to leave and lead to further migration to an incumbent rival (Marx and Timmermans, 2017). In empirical work, only Campbell et al. (2012) have accounted for migration to incumbent rivals.

High-performer migration and parent firm losses of human assets

The above arguments suggest that high-performer migration transfers human and complementary assets from parent firms to competitors (i.e., spin-offs and incumbent rivals), allowing for them to appropriate value at the expense of the parent firms. On the other hand, complementary assets, by definition, involve synergies between complementary activities such that the total value to the firm exceeds the sum of the individual activities (Stieglitz and Heine, 2007). This idiosyncratic nature of complementary assets suggests that the transfer or replication of single assets might produce less commercial appropriation in a different setting, i.e., at a different firm. In addition, human assets might also be highly firm-specific, involving tacit, complex knowledge and social relationships, which are difficult to imitate (Coff, 1997). While essential to value creation in the focal firm, high performers' human assets might be less valuable in the absence of the parent firm's complementary assets (Campbell et al., 2017). Thus, while the loss of human assets from high-performer migration impedes parent firm performance, it might not equally enhance the value creation of the receiving firm or allow for it to appropriate value at the expense of the parent firm. Put somewhat differently, high-performer migration might not be a zero-sum game where spin-offs and other rivals appropriate value at the expense of the parent firm.

Regardless of whether the previous argument is a plausible explanation for the negative effect on parent firm performance of spin-off entrepreneurship, it is not the only explanation. Recent studies show that employees with more education, higher job performance and higher wages are more likely to enter and succeed in entrepreneurship (Braguinsky, Klepper, and Ohyama, 2012; Groysberg, Nanda, and Prats, 2009; Elfenbein, Hamilton, and Zenger, 2010; Carnahan et al., 2012). Carnahan et al. (2012) hypothesize that, conditional on mobility, high-performing employees are more likely to enter entrepreneurship because entrepreneurship offers a direct link between individual performance and pay, attracting high performers seeking to improve their earnings (Carnahan et al., 2012; Elfenbein et al., 2010). While the employee mobility literature recognizes that a *loss* of human assets does not necessarily imply a competitive *transfer* of human assets (see e.g., Briscoe and Rogan (2016)), such dual focus has not yet been adopted in the entrepreneurship literature. However, if spin-offs are founded by high performers with stronger human assets, the loss of human assets could be a significant explanation of their departure's adverse impact on parent firm performance.

By definition, a high-performing employee possesses a large stock of firm-specific human capital, making her important, or even indispensable, to her employer. For that reason, losing a high-performing employee to a spin-off implies a decrease in human assets and, potentially, a negative performance effect. From a social network perspective, this drop in the parent firm's stock of human assets might also entail a detrimental loss of social relations. This loss of social capital depletes the parent firm's organizational capabilities and reduces performance (Shaw, Duffy, and Johnson, 2005).

High-performer migration affects not only external network relationships but also within-firm relationships (Corredoira and Rosenkopf, 2010). The latter implies a loss of instrumental relationships and reduced organizational efficiency (Cao, Maruping, and Takeuchi, 2006). High-performers, executives in particular, have a disruptive effect on the internal functioning of the organization as coordinators of activities and knowledge networks and hence their departure disrupts organizational routines (Briscoe and Rogan, 2016). When an employee leaves the parent firm to engage in entrepreneurship, her departure and subsequent replacement might trigger organizational restructuring within the parent firm, potentially destabilizing the organization and resulting in missed opportunities (Hannan and Freeman, 1977, 1984; McKendrick et al., 2009). This result is more likely when the employee is high ranking and when she is more important to the parent firm (McKendrick et al., 2009). If spin-offs are generally initiated by high-performing employees, departures might further increase the need for organizational restructuring, leading to a decline in parent firm performance and greater losses of human assets that are costly to replace.

In summary, the potential loss of human assets (including human capital and social capital) and/or organizational adjustments following high-performer migration to spin-off entrepreneurship could also drive the negative performance effects associated with high-performing employees leaving for spin-off entrepreneurship. This explanation thereby offers a supplement to the prevailing hypothesis in the entrepreneurship literature that the negative performance effects of high performers' spin-off migration is due to Schumpeterian creative destruction.

Again, these explanations are not unique to spin-off migration. If the adverse impact on parent firm performance depends on the loss of human assets, we should expect similar effects when high performers migrate to rival incumbent firms and when they leave for noncompetitive destinations such as nonrival firms or retirement. In any case, we expect spin-offs to have a negative effect on parent firm performance. However, questions remain as to whether this negative effect is mainly driven by the competitive transfer and recreation of parent firm human and complementary assets *or* by the loss of human assets and the subsequent organizational disruption and weakening of complementary assets. We address this question empirically. In the following section, we first discuss the contexts in which high-performer migration increases competition. We build on this discussion to present four hypotheses that, in combination with industry analyses, empirically address the focal question by separating and testing the adverse effects of our two explanations.

Hypotheses

The above arguments suggest that high-performer migration to spin-off entrepreneurship (as well as other types of high-performer migration) negatively affects parent firm value creation. We provide two explanations for this negative performance effect: 1) a detrimental loss of human assets and 2) a detrimental transfer or recreation of the parent firm's complementary and human assets. All else being equal, the first mechanism negatively affects parent firm performance independent of the destination of high performers.

H1a: High-performer migration has an adverse impact on parent firm performance independent of the destination.

Hypothesis 1a allows us to establish a baseline effect of high-performer migration to different destinations. In addition, it provides a first test of which mechanisms drive the negative effect of high-performer migration. An adverse impact from noncompetitive migration suggests that the loss of human assets and the subsequent disruption of routines play a significant role.

The second mechanism relies on the destination being competitive, i.e., a spin-off or an incumbent rival. A high performer who retires or takes a job in a remote industry will not induce value appropriation at the expense of the parent firm. Therefore, the adverse impact of high-performer migration should be significantly greater when high performers migrate to spin-offs or incumbent rivals, *provided* that this effect is (at least partly) driven by the detrimental transfer of human and complementary assets from the parent firm to a competitor.

H1b: The adverse impact on parent firm performance of high-performer migration is greater for migration to spin-offs and rival incumbent firms than for migration to noncompetitive destinations.

A greater effect from competitive migration suggests that high performers' mobility enables competition. Moreover, a comparison of the effects of high-performer migration to spin-offs and incumbent rivals will indicate whether one type of competitive migration is more able and likely to appropriate the complementary and human assets of parent firms.

The average effects of different types of high-performer migration we address in the the above hypotheses might vary greatly across industries and contexts. Among other things, the adverse competitive effect depends on the extent to which employee mobility enables competition. For spin-offs (or rival incumbent firms) to appropriate value at the expense of the parent firm, operations must occur in the same market with competition over the same customer base and resources. Thus, in industries where competition is local, the entry of local, but not distant, spin-offs will cannibalize the parent firm's market. In addition, local migration is more likely to encourage additional migration by former co-workers to the spin-off or rival incumbent firm, worsening adverse competition and human asset losses. However, provided that the main mechanism driving the adverse impact is a loss of human assets then distance does not play a role and we would expect that also distant high-performer migration negatively affects parent firm performance.

H2a: Distant high-performer migration has an adverse impact on parent firm performance independent on the destination.

On the other hand, if competition is a significant driver of the adverse impact of high-performer migration on parent firm performance, we should expect a greater negative effect from migration to spin-offs or incumbent rivals that are active in the same local market as the parent firm.

H2b: The adverse impact on parent firm performance of high-performer migration to local spin-offs and rival incumbent firms is greater than that of high-performer migration to distant spin-offs and rival incumbent firms.

Finally, we recognize that the adverse impact, as well as the significance of local and distant migration, differs across industries. Among other things, the transferability of human and complementary assets depends on the type of asset and therefore varies across industries. The parent firm's geographic expanse and, hence, reaction to local versus distant migration is another example of industry variation. We utilize such industry differences to test our competing explanations in a more direct way, supplementing the above with a series of industry analyses. We introduce these analyses in a later section.

Methods and data

Sample

We analyze the effects of spin-offs and other types of high-performer migration on incumbent firms' performance using linked employer-employee registries from Denmark. These labor market registries (formerly referred to by their Danish acronym, IDA) contain information on all firms and employees from 1980 to 2013 and are maintained by Statistics Denmark. Social security numbers enable the collection of large government registries, which are carefully maintained due to the extensive welfare system, which ensures that all firms and employees can be followed over time.

We do not expect the departures of all types of employees to have equal effects on the performance of firms. Blue-collar workers might not have measurable impacts on firms when they resign, and sorting by lower-level workers might even increase firm performance (Carnahan et al., 2012). Lower-level workers are more easily replaced and are not likely to be unique holders of firm-specific knowledge. Along these lines, Campbell et al. (2012) find that the migration of lower income employees to spin-offs and rival incumbent firms have no and positive impacts, respectively, on parent firm performance. Consequently, we only examine high-performer migration. In their study of employee migration within the U.S. legal services industry, Campbell et al. (2012) define three pay classes based on absolute compensation levels, the highest pay class (i.e., high performers) being employees with compensation levels greater than $300,000. We do not follow this definition of high performers because compensation levels vary significantly across industries. A similar categorization of employee performance based on absolute wage levels is thus not suitable for this study of all private sector industries. Instead, we follow Elfenbein et al. (2010) and Carnahan et al. (2012) and define high-performing employees based on their earnings relative to other employees at the parent firm. More precisely, we define high-performing employees as full-time employees (with a minimum of 30 days of tenure with the parent firm) with a salary equal to or above the 75th percentile of full-time salaries in each firm.[1]

For our sample of incumbent firms, we start with the population of firms in the private sector from 2000 to 2013. Organizations in the public sector, nonprofits, and foundations are excluded, since other factors affect firm performance in those sectors. The firm registry, which we rely on for information on entry year and for annual firm data, only includes firms that meet an industry-specific minimum requirement for either sales or employment, i.e.,

[1]Similarly, Elfenbein et al. (2010) define high- and low-performing employees as the top and bottom 20 percent, respectively, of the firm's pay distribution. We have tested the robustness of our results to the 75th percentile threshold and estimated the central models of our analysis (Models 2, 5, 7 and 10 in Tables 2 and 3) using the 90th percentile as a threshold. In addition, we tested a definition of high-performing employees based on their occupational codes: employer, CEO, and top management (following, e.g., Dahl, Dezső, and Ross (2012)). Our results are robust to these alternative definitions. These estimations are presented in an online appendix.

0.5 full-time equivalent employees. This requirement automatically excludes inactive firms. If a firm does not appear in the firm database for two consecutive years, we consider the firm closed. We allow for a single year with low activity. We do not allow for reentry. Subsequent observations are dropped, providing a conservative dataset of 654,579 incumbent firms for the analyses. The number of reentering firms that are at risk of being excluded is so small that they are essentially irrelevant here. The literature on spin-offs focuses on larger firms, which exceed these minimum requirements. Excluding inactive microfirms does not lead to selection bias because firms without full-time employees do not allow for meaningful comparison of different types of high-performer migration.

Parent firms are incumbent firms that lost one or more high performers during the period under investigation. The argument above implies that only high-performing employees can affect parent firm performance with their departure. In smaller firms, however, all employees might cause such effects, independent of their salary and rank. While the latter is an interesting question for small firms, it is not the objective of our study. Parent firms are, therefore, restricted to those that employ a minimum of 10 full-time equivalents at the time of resignation. In order for firms in the dataset to be comparable, we only include firms with at least 10 full-time equivalents in at least one of two years from 2000 to 2013, reducing our sample to 32,753 firms. Finally, in our models, we exclude observations from 2013, as we could not identify whether a firm exited this year (i.e., the firm is not observed in the dataset in 2014 and 2015). This method leaves us with a final sample of 30,911 firms with more than 10 employees in any year between 2000 and 2012.

Depending on their postdeparture employment, we divide the departing high-performing employees into five categories: (i) spin-off entrepreneurs, (ii) nonrival entrepreneurs, (iii) movers to rival incumbent firms, (iv) movers to nonrival incumbent firms or (v) movers to other destinations. The latter category includes entrepreneurs in unknown industries without employees, retirees, students and unemployment. These five categories cover all types of high-performer departures and are mutually exclusive. A **spin-off entrepreneur** is a founder of a new business in an industry closely related to the industry of the parent firm, i.e., one with the same four-digit SIC code. A **nonrival entrepreneur** is a founder of a new business in a remote industry. The entry year is the year following migration. We use the firm database to identify startups and obtain information on the entry year. We do not allow for reentry.[2] For startups with less than 20 employees at entry, we define the founder(s) as all employees in the first year. This definition follows, for example, Burton, Dahl, and Sorenson (2017), who define all first-year employees as members of the founding team. If there are more than 20 employees in the startup year, we use Statistics Denmark's information on individual occupation to identify all founders. A departure to a **rival incumbent firm** is a departure to an existing firm within the same four-digit SIC code as the parent firm. Similarly, a **nonrival incumbent firm** is an existing firm in a remote industry. Incumbent firms include firms of all ages, except new firms. In practice, this implies that an employee who departs to a new rival firm in the year it is founded is a spin-off entrepreneur, while an employee leaving for the same firm in the year after it was founded is moving to a rival incumbent firm.[3]

Estimation methodology

We use two performance measures, firm failure and sales growth, to study the effects of high-performer migration on parent firm performance. We estimate the effect on parent firm survival using an exponential survival model, accelerated failure time (AFT) form.[4] One advantage of AFT is an intuitive interpretation, with estimates predicting how high-performer migration affects parent firms' expected time to failure. In other words, we estimate time to failure (t_i) by assuming that the baseline hazard, $\tau_i = e^{(-\beta_1 x_{1i,t} + \ldots + \beta_k x_{ki,t})t_i}$, follows an exponential distribution (Cleves, Gould, and Gutierrez, 2004):

$$ln(t_i) = \beta_1 x_{1i,t} + ... + \beta_k x_{ki,t} + \epsilon_{i,t} \tag{1}$$

[2] A few startups reappear in the firm database with the same identification number but a different entry year. We drop these subsequent observations from the dataset.

[3] There is no overlap between the two categories. A departure to a spin-off in the startup year by a nonfounder is categorized as departure to a rival incumbent firm. The previous criteria identify the founders.

[4] To test the robustness of our results to various model specifications, we also estimated a Gompertz survival model (AFT), a Weibull survival model (AFT), a Probit model, and a Cox proportional hazards model. We comment on the estimation results in a later section.

We measure sales growth as a percentage from year t to $t+1$ relative to average sales in year t and $t+1$. The advantages of this measure are that the distribution is symmetric for positive and negative growth rates and has a limited range of -200 to 200, thus lowering the standard deviation. We estimate firm fixed effects models with clustered standard errors.

Ratios of high-performer migration

We count the number of high-performing employees that depart to become spin-off entrepreneurs in the following year. In line with Campbell et al. (2012), we investigate lagged departures. We include lagged departures from year $t-3$ to $t-1$. For each of these three years, we calculate the share of high-performing employees that depart to spin-off entrepreneurship relative to the total number of high-performing employees in each firm. We account for the effect of high-performer migration to competitive (spin-offs and rival incumbent firms) and noncompeting (nonrival entrepreneurship, nonrival incumbent firms, and other) destinations. We include the lagged ratios of high-performer migration to each of these five destinations.

We expect an initial negative effect on performance captured by our lagged high-performance departure ratios. We expect the effect of high-performer migration on parent firm performance to diminish over time. Eventually, incumbent firms should recover from their loss, which will be indicated by a smaller or insignificant estimate for the most distant years. If the adverse impact on parent firm performance is primarily driven by the depletion of human assets, then high-performer migration has detrimental effects on parent firm performance independent of the destination. If, on the other hand, departures to spin-off entrepreneurship or rival incumbent firms are more harmful than noncompetitive migration, this indicates that the detrimental transfer or recreation of parent firm human and complementary assets (also) drives the effect. The differences in the effects of the five destinations thereby provide evidence regarding different potential mechanisms, even though our data do not provide information to directly test these.

Control variables

We hypothesize on the adverse impact from local versus distant high-performer migration. We define **local migration** as migration to a startup or incumbent firm within 100 km of the parent firm. Similarly, **distant migration** is migration to a startup or incumbent firm that is located more than 100 km from the parent firm. We only observe the municipalities where firms are located, not their exact addresses. Therefore, we measure the distance between two firms as the distance between their respective municipalities. We measure the distance from the center of the municipality. This approach is similar to that of Dahl and Sorenson (2009). If two firms are located in the same municipality, the distance is zero. Denmark is a geographically small country, which historically had 271 municipalities.[5] These municipalities are similar in size to U.S. counties or parishes, covering an average of 156 km^2 (Dahl and Sorenson, 2009). It is unlikely that neighboring municipalities are farther than 100 km apart (from center to center); thus, it is unlikely that migration between firms in neighboring municipalities is categorized as distant.

Carnahan et al. (2012) hypothesize that, conditional on mobility, high-performing employees are more likely to enter entrepreneurship. To capture the additional adverse impacts of spin-offs and nonrival entrepreneurs driven by the loss of above-average human capital, we controlled for the departing employee's salary rank. We assign high-performing employees a wage score between zero and ten based on their relative salary. If more than one high-performing employee departs in a given year, this variable is the average rank of all departing high performers. We include these lagged wage scores of departing high performers for each year from t-1 to t-3.

In general, entry rates are higher in entrepreneurial regimes where entry barriers are low (Klepper, 1996; Agarwal, Sakar, and Echambadi, 2002). If motivated by the prospect of improved earnings, high-performing employees might depart for spin-offs when market concentration is low and economic profits exist. Departing to spin-offs might be less harmful to parent firms in these environments than in more competitive environments. Moreover,

[5]Today, there are only 98 municipalities in Denmark. The number was reduced following a reform in 2007. We use the historical 271 municipalities for a more fine-grained analysis.

market concentration is likely to affect firm performance independently of high-performer migration. We control for industry concentration and other differences using industry-year dummies.

In addition to the covariates described above, we include controls for number of high-performing employees, legal form (dummy for unlimited liability), wage level (the average gross wage level of top managers, white collar, and blue collar workers (all logged))[6], industries (11 dummies), year dummies, and labor market regions (12 dummies). The sales growth models also include firm age (logged).

Results

Table 1 provides descriptive statistics for the entire sample of 30,911 unique incumbent firms. On average, firms experience 1.65 departures each year, corresponding to an average high-performer turnover ratio of 13.22 percent. The wage rank in Table 1 indicates differences in human capital among our five categories of high performers. For example, the average wage rank of high performers departing for spin-off entrepreneurship is 6.23 but only 5.69 for high performers departing for a rival incumbent firm. Table 1 and Table 2 in the online appendix provide additional descriptive statistics and correlations, respectively. Additionally, these tables show that our dataset includes 397,450 high-performer departures, including 8,299 departures to spin-offs. In the online appendix, we also provide kernel density plots of the high-performer departure ratios for all destinations.[7]

— Insert Table 1 here —

Hypotheses 1a and 1b

We use exponential survival models and fixed effects models of sales growth to investigate the impact on parent firm performance following high-performer migration to spin-offs, rival

[6]Real wages using the GDP deflator with 2010 as the index year. Missing values (not all firms have employees in all categories) were replaced with the industry average.

[7]These plots do not reveal major problems with distribution skewness (see Figures 1 to 6 in the online appendix). We return to and control for the robustness of our results to distribution skewness in a later section.

incumbent firms, and three different nonrival destinations. Table 2 and Table 3 present the results. Model 2 in Table 2 estimates the impact on parent firm survival of total high-performer migration from year $t-1$ to $t-3$. These results show the general effect of high-performer migration on parent firm performance independent of the destination. We find negative effects on firm survival of the high-performer departure ratios for the past three years ($t-1$ to $t-3$, $p = 0.000$). The effect is strongest for recent departures (i.e., $t-1$). A one-percentage-point increase in the last year's high-performer departure ratio decreases the expected time to failure by 3.06% ($p = 0.000$). An increase of one standard deviation in last year's departure ratio thus decreases the expected time to failure by 68%. This result shows that there is generally a negative effect of losing high-performing employees, independent of their destination.

— Insert Table 2 here —

In models 3 to 5, Table 2, we examine the impact of high-performing employees who depart for spin-off entrepreneurship and rival incumbent firms, controlling for other types of (noncompetitive) high-performer departures. In model 5, we include all controls, including lagged wage scores for high performers who leave. We included this variable to account for differences in departing employees' wage ranks. In particular, we wish to ensure that the negative impact of spin-offs is not driven by the loss of above-average human capital from this group of employees (Carnahan et al., 2012). In support of Hypothesis 1a, we find a negative effect of the loss of high-performing employees in the last year to spin-offs, rival incumbent firms, and the three noncompetitive destinations ($p = 0.000$). As seen for high-performing employees in general (model 2), this impact is greater for recent departures, although it is also significant ($p = 0.000$) for more distant migrations.[8]

When comparing the negative survival effects of the previous year's migration, we find few differences across the five destinations. First, the impacts of high-performer migration to spin-off entrepreneurship and rival incumbent firms in year $t-1$ are not significantly different

[8]In Table 3 of the online appendix, we include the five categories in the model one at a time. Supporting Hypothesis 1a, all models find a negative effect from the lagged departure ratio at time $t-1$ ($p = 0.000$).

from each other (95% confidence interval, [-0.046; -0.041] and 95% confidence interval, [-0.044; -0.039] for spin-offs and rival incumbents, respectively). Moreover, these effects do not differ significantly from migration to nonrival entrepreneurship (95% confidence interval, [-0.046; -0.040]) and nonrival incumbent firms (95% confidence interval, [-0.043; -0.038]). On the other hand, the negative survival effects of the previous year's migration to spin-off entrepreneurship and rival incumbent firms are significantly greater than the negative survival effect from migration to 'other destinations' (95% confidence interval, [-0.039; -0.034]), but the differences in the size effects are small. Overall, the survival analysis provides little support for Hypothesis 1b and the notion that Schumpeterian creative destruction and competition drive the adverse impact on parent firm performance of high-performer migration to spin-offs. Moreover, a negative survival effect from high performers who leave for other destinations such as retirement, unemployment or education indicates that a significant depletion of parent firm human assets and the potentially harmful destabilization of the organization drive the effect.[9]

Table 3 presents results from the fixed effects panel regressions estimating the adverse impact on sales growth from spin-offs and other types of high-performer migration. We follow the order of the survival analysis and first estimate the impact on parent firm sales growth from total high-performer migration and then the impact of five types of high-performer migration, gradually adding controls.

— Insert Table 3 here —

While model 10, Table 3, confirms a negative effect on parent firm performance from high-performer migration independent of the destination (t and $t-1$, $p = 0.000$), the

[9]To test the robustness of our results to different model specifications, we re-estimated model 5 in Table 2 using a Gompertz survival model (AFT), a Weibull survival model (AFT), a Probit model, and a Cox proportional hazards model. Overall, these estimation results do not alter the above conclusions. In all models, we confirm a negative impact on parent firm performance of high-performer migration, independent of the destination (t-1 to t-3, $p = 0.000$). In all but the Weibull survival model, we find that the impact of migration to spin-offs and rival incumbent firms is significantly greater (on a 95% confidence interval) than departures for other reasons. However, as in model 5, Table 2, the differences in the size effects are small. Furthermore, in the Probit model we find that the impact of migration to spin-offs is significantly greater (on a 95% confidence interval) than departures for rival incumbent firms. Again, the difference in the size effects is small.

size effects vary significantly across the five destinations. A one-percentage-point increase in the ratio of high-performing employees who depart to spin-off entrepreneurship, nonrival entrepreneurship, rival incumbent firms, nonrival incumbent firms, and other destinations reduces parent firm sales growth in the next year ($p = 0.000$) by 0.92, 0.83, 0.79, 0.67, and 0.43 percentage points, respectively, controlling for wage rank (model 10).

In model 10, we find that the effect on parent firm sales is significantly larger when high-performing employees leave to become spin-off entrepreneurs (t, 95% confidence interval, [-0.968; -0.877]) compared to high-performing employees who leave to work for rival incumbent firms (t, 95% confidence interval, [-0.819; -0.768]). However, this adverse impact from spin-off migration is not significantly greater than migration to nonrival entrepreneurship (t, 95% confidence interval, [-0.884; -0.768]). The negative effects of high-performer migration to rival incumbent firms, spin-off entrepreneurship and nonrival entrepreneurship are all significantly larger than high-performer departures to nonrival incumbent firms (t, 95% confidence interval, [-0.690; -0.645]) and other destinations (t, 95% confidence interval, [-0.460; -0.398]).

On the one hand, these results support Hypothesis 1b, indicating an increase in competitive pressure from departures to both spin-offs and incumbent rivals, but the greatest increase occurs when high-performing employees leave to found spin-offs. The difference between spin-offs and migration to rivals is significant but not large. On the other hand, we also find support for Hypothesis 1a and the supplementary explanation that the parent firm suffers a loss of human assets when high-performing employees leave. We thus find a significant adverse effect on parent firm sales growth independent of the destination. Moreover, we do not find a significant difference in the impacts of departures to spin-offs and nonrival entrepreneurship. One explanation is that entrepreneurship (both spin-off and nonrival) attracts high performers with greater human assets, imposing a greater loss on the parent firm than other types of high-performer migration. This explanation is supported by Table 1, and we investigate it in more detail in a later section.[10]

[10] In Appendix Tables 7, 8, 9, 10, and 11, we supplement the above analyses with a matching approach, directly comparing the impacts of five different destinations while accounting for the potentially unequal likelihood that parent firms lose high performers. While this analysis (Table 9) finds adverse impacts from all five types of departures, it also finds some variation among the five categories (Table 10). Table 10 shows a greater impact on parent firm sales (logged) when high performers migrate to spin-offs compared to all other

Overall, the sales growth analysis also finds support for the previous result that the effects of high-performer migration on parent firm performance are not solely driven by an increase in competitive pressure but also by, for example, the loss of human assets. We would expect that sales growth is more sensitive than survival to the departure of high-performing employees, but this sensitivity also means faster recovery.[11]

Hypotheses 2a and 2b

To investigate Hypotheses 2a and 2b, we split our four main categories of high-performers migration (i.e., spin-offs, nonrival entrepreneurship, rival incumbent, and nonrival incumbent) into local and distant migration. Local migration is departure to a destination within 100 km of the parent firm, and distant migration is farther than 100 km from the parent firm. The last category, 'other', includes retirement and other destinations with no location. Hence, we do not divide this category into local and distant, but we keep this category as a control. In total, this approach leaves nine different destinations for high performers who migrate. We follow the above structure and estimate the adverse impacts of these nine categories on parent firm survival and sales growth in turn.

destinations. Similarly, departures for rival incumbents show greater impact on parent firm sales than the three types of noncompetitive migration. However, the evidence is weak when we investigate the impact on parent firm sales growth and survival. Moreover, high-performer migration to nonrival entrepreneurship appears less harmful for this subsample of smaller parent firms than for the full sample of parent firms (Tables 2 and 3). Generally, we find some evidence supporting a greater impact of competitive migration within this subsample of smaller parent firms, but the evidence is not conclusive. See the Appendix for a detailed description of our approach and results.

[11] We present Kernel density plots for high-performer departure ratios in the online appendix, Figures 1 to 6. To ensure that our results are not driven by a few parent firms with large departure ratios, we dropped observations with departure ratios (including lagged departure ratios) >60 percent and re-estimated our survival and sales growth models in Table 2 and Table 3, respectively. In our re-estimation of model 5 (Table 2), we find that a one-percentage-point increase in last year's high-performer departure ratio to spin-offs, nonrival entrepreneurship, rival incumbent firms, nonrival incumbent firms and other reduces the expected time to failure by 4.7%, 3.3%, 2.2%, 2.2%, and 1.9%, respectively ($p = 0.000$). While the adverse impact of high-performer migration to spin-offs is significantly greater than the four other types of high-performer migration (95% confidence interval), we find negative effects from all types of departures. Moreover, the difference between spin-offs and nonrival entrepreneurship is barely significant, while there is no significant difference between departures to rival and nonrival incumbent firms. In our re-estimation of model 10 (Table 3), we find that a one-percentage-point increase in the high-performer departure ratio reduces parent firm sales growth by 0.35, 0.34, 0.28, 0.27, and 0.18 percentage points for departures to spin-offs, nonrival entrepreneurship, rival incumbent firms, nonrival incumbent firms and other, respectively. Contrary to model 10, we find no significant differences for the four first destinations, while they are all significantly more harmful than high-performer migration for other reasons. Overall, these tests support the paper's general conclusions.

— Insert Table 4 here —

Model 11 in Table 4 estimates the survival effect of total high-performer migration for local and distant migration. In support of Hypothesis 2a, the model finds a negative effect of both local and distant migration ($p = 0.000$), with size effects that are comparable to those of model 2, Table 2. In model 12, we present the joint survival model, controlling for wage rank. To test Hypothesis 2b, we first compare the estimates of high-performer migration to local and distant spin-offs. A one-percentage-point increase in last year's ratio of high-performer departures to spin-offs decreases the expected time to failure by 4.39% ($p = 0.000$) and 3.91% ($p = 0.000$) for local and distant spin-offs, respectively. However, this difference is not significant (95% confidence intervals: Local, [-0.046; -0.041] and Distant, [-0.048; -0.031]). Similarly, we compare the estimated effects of local and distant migration to rival incumbent firms. Again, we do not find a significant difference in the effects of local and distant migration (95% confidence intervals: Local, [-0.044; -0.039] and Distant [-0.046; -0.041]).

We also test Hypotheses 2a and 2b by estimating the effects of local and distant migration on parent firm sales growth. Table 4 summarizes the results. Model 14, Table 4, shows the joint model, controlling for wage rank. We do not find a significant difference in high-performer departures to local and distant spin-offs (95% confidence intervals: Local, [-0.969; -0.876] and Distant [-1.250; -0.587]). Similarly, we do not find a significant difference in migration to local and distant rival incumbent firms (95% confidence intervals: Local_{t-1}, [-0.818; -0.765] and Distant_{t-1} [-0.912; -0.727]). Our analyses find no support for Hypothesis 2b and the explanation that the transfer of complementary and human assets increases competition and appropriates parent firm value creation. On the contrary, these results indicate that the loss of human assets drives the adverse impact on parent firm performance. Overall, we confirm Hypothesis 2a and we reject Hypothesis 2b.

Industry analyses

Our hypotheses suggest that an adverse impact on parent firm performance from competitive migration depends, among other things, on the transferability and value appropriation of parent firm human and complementary assets. We utilize industry differences along these two dimensions to provide a more direct test of what drives the adverse impact on parent firm performance.

First, not all human and complementary assets are easily transferred and thus at real risk of appropriation by spin-offs or rival incumbents. For example, this might not be the case in industries where value creation is the result of nonhuman capital assets (such as physical capital) that are either nontransferable or only available to market entrants at a high cost. Manufacturing is an example of an industry that is expected to rely on nonhuman tangible assets such as production machinery. Manufacturing therefore provides an example of an industry where the transferability of complementary assets should be low. Thus, if competitive transfer or recreation drives the adverse impact of high-performer migration, we should expect a smaller impact from competitive migration within this industry. This argument applies especially for migration to new firms in which financial capital for the recreation of such complementary assets is likely not available.

Second, even in industries where complementary assets are easily transferred or recreated, the competitive migration of high performers might not always enable competition. As we argued in a previous section, this requires competing in the same market over the same customers and resources. In industries such as hotels, restaurants, retails, and some services, the geographic reach of the parent firm is limited. When a nearby location is critical for competition, we should expect a greater effect from local than distant migration to spin-offs and incumbent rivals, provided that this effect is driven by increased competition.

Finally, for some parent firms, the loss of social relations may help explain the adverse impact of high-performer (local) migration. These network effects, however, do not apply equally to all industries. We expect that this effect is especially strong within certain consultancy industries, for example, accounting firms (studied by Wezel et al. (2006)) or law firms (as studied by Phillips (2002) and Campbell et al. (2012)). These are industries in which decisions about business relations are more closely related to particular individuals than to whole companies. Therefore, provided that increased competition drives the adverse impact on parent firm performance, we should expect a greater impact in client-based industries, such and law and accounting, where high-performer local migration to spin-offs or rival incumbents might involve the direct transfer of clients and business relationships from the parent firm.

We test our hypotheses separately for three industry categories: manufacturing, local competition and client-based industries. In Table 5, we re-estimate our survival model for each of these three industries. Overall, the estimations are comparable to those of model 5, Table 2. For all industries, the adverse impact on parent firm performance from last year's high-performer migration to spin-offs and incumbent rivals do not differ significantly (95% confidence intervals) from the estimates of model 5. This result adds further support to Hypothesis 1a.

— Insert Table 5 here —

Next, we re-estimate our main sales growth model, model 10 of Table 3, separately for these three industries. Table 5 summarizes the results. For manufacturing, one type of migration differs from the earlier results. The effect of high-performer migration to incumbent rivals is greater than the general impact of high-performer migration to rival incumbent firms found in model 10, Table 3 (95% confidence intervals: manufacturing, lagged [-1.034; -0.868] and all industries (model 10), lagged [-0.819; -0.768]). One explanation for this finding is that complementary, tangible assets are particular important within this industry and necessary for appropriating complementary assets from the parent firm. Moreover, these (fixed capital) assets are more likely to be present in incumbent firms than in startups. For two industries, local competition and client-based industries, the adverse impacts on parent firm performance from last year's high-performer migration are comparable to the estimates of model 10 for all types of high-performer migration.

— Insert Table 6 here —

Finally, we test Hypotheses 2a and 2b and compare local and distant migration to spin-off entrepreneurship for each of these three industries. Similarly, we compare local and distant migration to rival incumbent firms for each of these three industries. Table 6 summarizes the results. If the loss of human assets drives the adverse impact on parent firm performance from high-performer migration, we would expect an effect from both distant and local migration independent of the destination. If the competitive transfer of the parent firm's human and complementary assets explains the adverse impact, we would expect greater effects from local migration than from distant migration, particularly within industries where markets and competition are geographical bounded or rely on client relationships. We do not find significant differences in the effects of local and distant migration (lagged departure ratios) for any of these industries, including local market industries. This evidence strongly rejects Hypothesis 2b while supporting Hypothesis 2a and the argument that the loss of human assets is the main mechanism behind the adverse impact of high-performer migration to spin-offs and incumbent rivals on parent firm performance.

In our online appendix, we present additional industry-level analyses for industries for which we expect that competition takes place locally and where client relationships play a significant role (see Tables 8 and 9 in the online appendix). The latter includes industries that are comparable with those of previous industry studies (see Phillips (2002); Wezel et al. (2006); Campbell et al. (2012)).

Additional analyses and robustness checks

Carnahan et al. (2012) hypothesize that, conditional on mobility, high-performing employees are more likely to enter entrepreneurship, because entrepreneurship offers a direct link between individual performance and pay, attracting high performers seeking to improve their earnings (Carnahan et al., 2012; Elfenbein et al., 2010). External firms, on the other hand, cannot observe outside employees human capital and might underestimate their value (Campbell et al., 2017). This finding is interesting for at least two reasons. First, if spin-offs are founded by high performers with stronger human capital, this would help explain the negative performance effect of their departure on parent firm performance. Second, if employees departing for spin-off entrepreneurship are generally smarter and more skilled employees, this would contribute to our understanding of why spin-offs outperform other startups. We therefore tested this hypothesis by estimating the relationship between high-performer migration and their relative salaries (see Table 14 in the online appendix). We find a positive effect on the wage score from high-performer migration in general. This shows a positive relationship between the relative salary and the likelihood of departure. Conditional on mobility, we find that high-performing employees departing for spin-offs or noncompetitive entrepreneurship have higher wage scores than high performers departing for noncompetitive incumbents (the omitted category in model 3). High-performing employees who depart for rival incumbent firms, on the other hand, have relatively low wage scores. This result supports the idea of entrepreneurs as high-performing employees. Moreover, this result supports Hypothesis 1a by suggesting that a significant loss of human assets (and not increased competition) drives the negative impact of spin-off entrepreneurship on parent firm performance.

Selection bias

When we investigate the effect of high-performer migration on firm sales, our estimates may be subject to selection bias, as firms exit the population. In particular, we cannot observe exiting firms that would have been among the lowest performing firms in the population, potentially due to the migration of high-performing employees. Selection-corrected growth models can control for this potential selection bias. In our sample, the likelihood of observing a given firm in the sample is equivalent to the likelihood of that firm surviving. Building on Hall (1987), ln(sales) might be an appropriate instrument[12], and we re-estimate model 10 (Table 3) using a Heckman selection model with sales (logged) as our instrumental variable. These results support the above conclusions. Note, however, that we expect positive selection bias because selection is associated with higher performance. This potential positive selection bias

[12]While this variable is significant in explaining selection ($p = 0.000$), it is also significant in the sales growth models ($p = 0.000$). The latter indicates that this instrument is correlated with the error term in the explanatory equation, violating one of the requirements of instrumental variable methods and potentially resulting in inconsistent estimates of the selection models. For that reason, we do not report the selection-corrected models. They are, however, available upon request.

suggests that high-performer migration (of all types) could be even more harmful to parent firm performance than our models in Table 3 predict.

The sinking ship hypothesis

Our results illustrate a negative effect of losing high-performing employees to spin-offs, rival incumbent firms, and other noncompeting destinations. An alternative explanation for these findings is that parent firms differ from other firms. For example, it might be that these employees leave declining firms or firms with dark futures, a phenomenon coined *the sinking ship hypothesis*. For spin-offs, however, this hypothesis goes against the majority of the literature, which typically finds that the most successful parent firms also have the largest number of spin-offs (Klepper, 2007; McKendrick et al., 2009). Employees at successful firms are more exposed to unexploited (or underexploited) opportunities (Agarwal et al., 2004), and working at a successful firm might be a stamp of approval that enables spin-off entrepreneurs to raise capital and attract the most talented employees (Dahl and Reichstein, 2007; Dahl and Klepper, 2015). Franco and Filson (2006) even suggest that potential entrepreneurs might accept lower wages for *apprenticeships* at successful parent firms, pointing to more spin-offs from firms with higher growth rates in the past years.

Parent firm performance might also be positively correlated with other types of high-performer migration. For example, high firm growth might increase the need for organizational restructuring. If organizational changes alter an organization's blueprint, they might increase employee turnover (Baron, Hannan, and Burton, 2001). High-performing employees might be in a more favorable position to find alternative employment (or receive more job offers) when employed by more successful firms, suggesting that parent firm performance is associated with higher rates of high-performer migration in general. On the other hand, economic theory suggests that wage differences allocate labor among firms. More productive firms can pay higher salaries and thus attract the most talented employees. If parent firms are more successful, we would expect them to compensate high-performing employees financially to prevent their departures. Nevertheless, other studies on Denmark have found a strong positive effect of changing employers on employees' salary (Dahl and Klepper, 2015), indicating that employees (in Denmark) are more likely to experience salary increases when switching employers (Bingley and Westergaard-Nielsen, 2003). We test this alternative explanation below and investigate the relation between parent firm performance and high-performer migration.

First, we estimate negative binomial regressions for the number of high-performing employees departing in each of the five categories (see Table 10 in the online appendix). Among other things, we control for the employment growth in the past three periods before the departure of high-performing employees. We find that growing firms experience more migration of high-performing employees to spin-offs, noncompetitive startups, rival incumbent firms, noncompetitive incumbent firms, and other destinations. For example, a one-standard-deviation (40.09) increase in employment growth one year prior to departure increases the number of high-performing employees departing to spin-offs and incumbent rivals by 0.16 ($p = 0.000$) and 0.04 ($p = 0.004$), respectively. Overall, our results show a positive relationship between parent firm performance and high-performer migration, and we do not find support for *the sinking ship hypothesis*.

Discussion and conclusion

We find that high-performer migration has negative effects on parent firm performance independent of the destination, including distant startups and employers. The results are robust across industries. These results show that the negative performance effects of high-performer migration are not restricted or unique to competitive departures, such as migration to spin-offs and rival incumbents. This result indicates that transfers of human and complementary assets from parent firms to competitors play a smaller role in explaining the adverse impact on parent firm performance from high-performer migration. On the contrary, this result suggests that the loss of human capital, social relations, and potential destabilization of parent firm routines are significant drivers of the negative performance effects following all types of high-performer migration.

We used different methods to account for the endogeneity associated with different probabilities that parent firms lose high-performing employees. Whether or not the endogeneity problem is associated with the sinking ship hypothesis, it constitutes a potential risk that can never be completely eliminated. One method used to account for different probabilities of losing high-performing employees was propensity score matching within a subsample of smaller parent firms. This matching analysis confirmed the negative effects on parent firm performance following all but one type of high-performer migration. Migration to 'other' destinations (e.g., retirement) did not have a negative effect on parent firm performance within this subsample. Nevertheless, these results support the above conclusion that the adverse impact on parent firm performance is mainly driven by noncompetitive mechanisms.

It is clear that the effects we observe are the net effects of a complex process wherein parent firms likely have some, though not perfect, indication of the net loss. Thus, we cannot (and do not intend to) capture the effects of migration that is not taking place, potentially because parent firms avert departures through additional wage increases, promotions, etc. However, this does raise a number of relevant questions. For example, are such averting gestures by the parent firm equally effective for different destinations? Similarly, do parent firms (and departing employees) have asymmetric information or lack information about the net value loss from different types of departures? Regarding the latter, it might be more difficult to predict the net loss of departures to new firms than that of departures to incumbent firms. Two reasons for this are that 1) the parent firm cannot predict how a spin-off will affect competition, as they do not know the new firm yet, including its products and strategy, among other things, and 2) a new firm has a higher exit risk than incumbent firms, increasing the difficulty of assessing this threat and, hence, the net value loss from departures to new firms. In addition, it might be easier to avert departures to incumbent firms, potentially due to the aforementioned asymmetric information between parent firm and employee entrepreneur (the employee has better information than the parent regarding, e.g., similarities in products and strategies). Moreover, Nielsen (2014) shows that entrepreneurs are motivated by intrinsic work values rather than extrinsic values. Similarly, Schumpeter argued that entrepreneurs are motivated by '*the joy of creating*' and the '*will to conquer*', while '*the financial result is secondary consideration*' (Schumpeter, 1934, p. 93). Thus, a higher income from the parent firm might be less attractive than the autonomy offered by entrepreneurship.

While we show negative net effects of high-performer migration, the departure of high-performing employees might also induce positive effects on the parent firms. Tan and Rider (2017) suggest that it might send a positive signal to the labor market that the parent firm is a stepping stone to career advancement or entrepreneurship. Moreover, if departing employees are replaced, these new employees imply potential inflows of new knowledge and social relations (Corredoira and Rosenkopf, 2010; Kaiser, Kongsted, and Rønde, 2015). We expect that stronger and healthier firms are less sensitive to negative impacts, such as human capital losses and organizational disruptions, and should quickly rebound and regain strength. Though the replacement of human assets might be difficult and long lasting, we assume that the negative effects on parent firm performance of high-performer migration are only temporary, and parent firms with productive complementary assets eventually bounce back (McKendrick et al., 2009).

In this study, we demonstrate that endogeneity is likely associated with positive effects on firm performance because better firms apparently have more spin-offs and more migration among top-level employees. This result scales down the overall economic implications of high-performing employee entry into, for example, spin-off entrepreneurship.

We do not assess whether the value created by spin-offs offsets the negative impact on parent firm performance. However, when the loss of human capital, rather than appropriation from the parent firm or cannibalization of market, drives the negative performance effect of high-performer migration, this suggests that the overall economic benefit is positive. Complementary assets are embodied in the firm and rarely rely on single employees, allowing for the parent firm to sustain its competitive advantage from complementary assets despite high-performer migration. Indeed, several studies argue that employees generally found spin-offs on the periphery of parent firms' activities (e.g., Cassiman and Ueda (2006) and Chatterji

(2009)). In a recent study, Yeganegi et al. (2016) show that employees with experience that is unrelated to the core technology of the parent firm are more likely to found spin-offs. While intellectual property plays a role in this as well, support for the overall conclusion of this study remains. These considerations suggest an overall positive welfare effect of spin-off entrepreneurship.

We have illustrated that high-performer migration is associated with lower parent firm performance, and we partly explain this finding as a loss of human capital. This negative performance effect might discourage firms from investing in the human capital of their high-performing employees, especially if they expect high employee turnover. Moreover, we expect that idiosyncratic human capital will increase with the length of high-performing employees' tenure, indicating a larger effect on parent firm performance when employees leave after a longer period of employment.

In summary, our findings support the apparent resistance of incumbent firms to the general departure of high-performing employees. However, while parent firm postmigration performance differs among the five groups of high-performing employees, these effect differences are often marginal and not robust to various methods and measures of parent firm performance. Thus, our findings do not unequivocally support greater resistance to departures to competitive firms. Similarly, though we found relatively large negative effects on parent firm sales growth from migration to spin-off entrepreneurship, the effect differences are small, and our findings do not support greater resistance to spin-offs. Incumbent firms should focus on general retention strategies for all high-performing employees and not specifically on preventing spin-off entrepreneurship.

Finally, in many ways, the Danish labor market resembles that of the U.S. Compared with many other European countries, the Danish labor market is less restrictive. The employer costs of firing employees are low, and annual rates of job creation and turnover resemble the labor market of the U.S. (Sørensen and Sorenson, 2007; Dahl and Klepper, 2015; Burton et al., 2017), which suggests that the effects on parent firm performance of high-performer turnover might be larger in other European countries but similar in the U.S.

Our empirical analysis investigated how much of an adverse effect on parent firm performance is accounted for by the detrimental loss of human assets versus the competitive transfer or recreation of human and complementary assets. However, different types of migration might rely on different explanations. For example, spin-offs are more likely to replicate parent firm organizational practices, as they are not yet locked into existing organizational structures. On the other hand, incumbent rivals are more likely to have the necessary complementary assets to appropriate the parent firm's human assets. Similarly, while our analysis controlled for differences in the wage scores of departing employees, we did not measure knowledge, social relations and other human assets directly. Thus, we cannot know which factors have the largest impact and whether the effects vary across our five destinations. In other words, a direct test of the mechanisms that drive the negative effect on parent firm performance is left for future research.

Another limitation is that we do not distinguish between individual and collective migration. The transfer or recreation of parent firm complementary assets, for example, organizational routines, is more likely to succeed and thereby pose a threat to the parent firm when the organization's members leave as a group (Wezel et al., 2006). Messersmith et al. (2014) argue that increased rates of high-performer migration lead to a detrimental depletion of the parent firm's resources. While individual migration also implies a loss of human and social capital, collective migration further erodes performance as shared experience and knowledge is lost. Furthermore, collective migration is more likely to disrupt social structures and trigger organizational change in the parent firm compared with the departure of a single employee (Messersmith et al., 2014). Future research should address how the departure of teams and groups of employees to same destination might multiply these effects.

When we investigate the effects on parent firm performance of high-performer migration, we distinguish among departures to spin-offs, rival incumbent firms, and three noncompetitive destinations. We further distinguish between local and distant migration. However, we do not investigate how other characteristics or the performance of the receiving firms (the firms to which high-performing employees depart) affect the parent firm's performance. We expect that greater similarity between the parent and the receiver will increase the competitive fallout. In addition to the geographical dimension that we accounted for, other factors such as similarity in the institutional, socioeconomic and historical environment might increase the likelihood of competition for the same resources (Sørensen, 1999; Wezel et al., 2006). Greater similarity might also increase the receiving firm's absorptive capacity (Corredoira and Rosenkopf, 2010). This result suggests that future studies should undertake a more exhaustive analysis and investigate the circumstances under which high-performer migration is most harmful to parent firms.

In contrast to previous studies of spin-offs and high-performer migration, which limit themselves to an industry or geographical area, we have investigated the phenomenon more generally. In addition, we have showed that our findings apply to a number of different industries. We have focused on industries that rely to varying degrees on social relations, local markets, and the intensity of tangible, nonhuman capital assets. Future research should strive to outline in more detail the industries and circumstances under which spin-offs contribute significantly to parent firm performance. For example, in knowledge- and technology-intensive industries, the transferability and appropriation of the parent firm's human assets might rely heavily on existing productive complementary assets. Such industries could provide rival incumbent firms with an advantage over spin-offs. Similarly, venture capital-backed startups might have the necessary resources to compete in markets that require significant investments in complementary tangible assets (Yeganegi et al., 2016). Future studies should also focus on spin-offs founded by lower ranked employees and investigate small firms (i.e., those with fewer than ten employees).

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Tables

Table 1
Descriptive statistics (2000-2012)

	All		**Conditional on departure**	
No. of observations (firm year)	241.271		104,683	
No. of firms	30,911		28,087	
No. of firm failures	12,736		11,762	
Legal form (personal liability, pct.)	12.39		10.42	
	Mean	Std. Dev.	Mean	Std. Dev.
Sales growth, pct.	-0.36	47.21	-7.35	45.55
Age, years	16.54	14.76	17.74	16.04
Salary, blue collar, logged	12.72	0.23	12.73	0.23
Salary, white collar, logged	12.84	0.24	12.86	0.25
Salary, TMT, logged	13.02	0.36	13.08	0.37
No. of high-performing employees (per year)	11.26	58.13	20.86	86.86
No. of high-performer departures (per year)	1.65	10.42	3.80	15.56
No. of high performers to spin-offs (per year)	0.03	0.29	0.08	0.44
No. of high performers to nonrival entrepreneurship (per year)	0.06	0.39	0.13	0.59
No. of high performers to rival incumbents (per year)	0.35	5.77	0.81	8.73
No. of high performers to nonrival incumbents (per year)	0.92	5.79	2.11	8.64
No. of high performers to other (per year)	0.29	2.01	0.66	3.00
Ratio in pct. (0 to 100), high-performer departures (total)	13.22	22.35	30.47	25.03
Ratio in pct. (0 to 100), high-performer departures to spin-offs	0.63	5.93	1.44	8.94
Ratio in pct. (0 to 100), high-performer departures to nonrival startups	0.60	4.56	1.38	6.85
Ratio in pct. (0 to 100), high-performer departures to rival incumbents	3.14	11.72	7.24	16.93
Ratio in pct. (0 to 100), high-performer departures to nonrival incumbents	6.51	14.28	15.00	18.51
Ratio in pct. (0 to 100), high-performer departures to other	2.35	8.04	5.41	11.50
Wage score (0 to 10), high-performer departures			5.73	2.27
Wage score (0 to 10), departures to spin-offs			6.23	2.43
Wage score (0 to 10), departures to nonrival ent			5.97	2.71
Wage score (0 to 10), departures to rival incumbents			5.69	2.47
Wage score (0 to 10), departures to nonrival incumbents			5.55	2.40
Wage score (0 to 10), departures to other			5.77	2.75

The category 'conditional on departure' only includes firm-year observations if one or more high performers depart that year. Wage score statistics only include high performers in the focal category.

Table 2
Exponential survival model (AFT)

	(1)	(2)	P-values	(3)	(4)	P-values	(5)	P-values
Ratio, h-p departures, t-1	-0.036	-0.031	0.000					
	(0.000)	(0.001)						
Ratio, h-p departures, t-2	-0.007	-0.007	0.000					
	(0.000)	(0.000)						
Ratio, h-p departures, t-3	-0.003	-0.004	0.000					
	(0.000)	(0.000)						
Ratio, h-p to spin-offs, t-1				-0.039	-0.034	0.000	-0.044	0.000
				(0.000)	(0.001)		(0.001)	
Ratio, h-p to spin-offs, t-2				-0.014	-0.012	0.000	-0.016	0.000
				(0.002)	(0.002)		(0.002)	
Ratio, h-p to spin-offs, t-3				-0.010	-0.010	0.000	-0.012	0.000
				(0.002)	(0.002)		(0.002)	
Ratio, h-p to nonrival ent, t-1				-0.038	-0.033	0.000	-0.043	0.000
				(0.000)	(0.001)		(0.001)	
Ratio, h-p to nonrival ent, t-2				-0.009	-0.008	0.000	-0.013	0.000
				(0.002)	(0.002)		(0.002)	
Ratio, h-p to nonrival ent, t-3				-0.009	-0.009	0.000	-0.011	0.000
				(0.002)	(0.002)		(0.002)	
Ratio, h-p to rival incumbent, t-1				-0.037	-0.032	0.000	-0.042	0.000
				(0.000)	(0.001)		(0.001)	
Ratio, h-p to rival incumbent, t-2				-0.010	-0.010	0.000	-0.014	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to rival incumbent, t-3				-0.002	-0.002	0.018	-0.005	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to nonrival inc, t-1				-0.034	-0.030	0.000	-0.040	0.000
				(0.000)	(0.001)		(0.001)	
Ratio, h-p to nonrival inc, t-2				-0.006	-0.007	0.000	-0.011	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to nonrival inc, t-3				-0.003	-0.004	0.000	-0.007	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to other, t-1				-0.029	-0.024	0.000	-0.036	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to other, t-2				-0.004	-0.004	0.000	-0.009	0.000
				(0.001)	(0.001)		(0.001)	
Ratio, h-p to other, t-3				-0.001	-0.001	0.205	-0.004	0.000
				(0.001)	(0.001)		(0.001)	
Wage score (0-10), t-1							0.165	0.000
							(0.011)	
Wage score (0-10), t-2							0.034	0.000
							(0.005)	
Wage score (0-10), t-3							0.017	0.000
							(0.004)	
No. of high performers		0.067	0.000		0.064	0.000	0.035	0.021
		(0.019)			(0.018)		(0.015)	
Personal liability: yes		-0.259	0.000		-0.231	0.000	-0.263	0.000
		(0.021)			(0.021)		(0.021)	
Ln(wage blue collar)		-0.400	0.000		-0.407	0.000	-0.370	0.000
		(0.041)			(0.041)		(0.041)	
Ln(wage white collar)		-0.401	0.000		-0.390	0.000	-0.371	0.000
		(0.043)			(0.044)		(0.046)	
Ln(wage TM)		0.478	0.000		0.484	0.000	0.524	0.000
		(0.055)			(0.056)		(0.052)	
Constant	4.292	8.110	0.000	4.237	7.940	0.000	6.611	0.000
	(0.285)	(0.726)		(0.281)	(0.739)		(0.756)	
Industry (11 dummies)	yes	yes		yes	yes		yes	
Year (13 dummies)	yes	yes		yes	yes		yes	
Industry year (143 dummies)	yes	yes		yes	yes		yes	
Labor market region (12 dummies)	yes	yes		yes	yes		yes	
Log pseudolikelihood	-8486	-7571		-8275	-7414		-6856	
Observations	241271	241271		241271	241271		241271	

Clustered standard errors in parentheses. P-values to the right.

Table 3
Fixed effects panel regression of sales growth

	(6)	(7)	P-values	(8)	(9)	P-values	(10)	P-values
Ratio, h-p departures, t	-0.598**	-0.567**	0.000					
	(0.007)	(0.007)						
Ratio, h-p departures, t-1	-0.384**	-0.339**	0.000					
	(0.009)	(0.009)						
Ratio, h-p departures, t-2	-0.128**	-0.078**	0.000					
	(0.008)	(0.008)						
Ratio, h-p to other, t				-0.307**	-0.269**	0.000	-0.429**	0.000
				(0.015)	(0.015)		(0.016)	
Ratio, h-p to other, t-1				-0.200**	-0.148**	0.000	-0.227**	0.000
				(0.015)	(0.014)		(0.016)	
Ratio, h-p to other, t-2				-0.102**	-0.046**	0.001	-0.068**	0.000
				(0.015)	(0.015)		(0.016)	
Ratio, h-p to spin-offs, t				-0.859**	-0.833**	0.000	-0.922**	0.000
				(0.023)	(0.023)		(0.023)	
Ratio, h-p to spin-offs, t-1				-0.753**	-0.716**	0.000	-0.767**	0.000
				(0.052)	(0.052)		(0.053)	
Ratio, h-p to spin-offs, t-2				-0.066	-0.028	0.547	-0.036	0.442
				(0.047)	(0.046)		(0.047)	
Ratio, h-p to nonrival ent, t				-0.745**	-0.702**	0.000	-0.826**	0.000
				(0.030)	(0.030)		(0.030)	
Ratio, h-p to nonrival ent, t-1				-0.483**	-0.430**	0.000	-0.498**	0.000
				(0.038)	(0.038)		(0.039)	
Ratio, h-p to nonrival ent, t-2				-0.190**	-0.136**	0.000	-0.150**	0.000
				(0.037)	(0.037)		(0.037)	
Ratio, h-p to rival incumbent, t				-0.712**	-0.689**	0.000	-0.793**	0.000
				(0.012)	(0.012)		(0.013)	
Ratio, h-p to rival incumbent, t-1				-0.508**	-0.472**	0.000	-0.532**	0.000
				(0.020)	(0.020)		(0.021)	
Ratio, h-p to rival incumbent, t-2				-0.106**	-0.064**	0.000	-0.076**	0.000
				(0.017)	(0.017)		(0.019)	
Ratio, h-p to nonrival inc, t				-0.565**	-0.530**	0.000	-0.667**	0.000
				(0.010)	(0.010)		(0.011)	
Ratio, h-p to nonrival inc, t-1				-0.356**	-0.308**	0.000	-0.382**	0.000
				(0.012)	(0.012)		(0.014)	
Ratio, h-p to nonrival inc, t-2				-0.140**	-0.087**	0.000	-0.105**	0.000
				(0.011)	(0.011)		(0.013)	
Wage score (0-10), t							1.339**	0.000
							(0.041)	
Wage score (0-10), t-1							0.637**	0.000
							(0.047)	
Wage score (0-10), t-2							0.179**	0.000
							(0.048)	
No. of high performers		-0.037**	0.000		-0.038**	0.000	-0.049**	0.000
		(0.007)			(0.007)		(0.009)	
Ln(firm age)		-22.705**	0.000		-22.914**	0.000	-23.805**	0.000
		(0.421)			(0.420)		(0.421)	
Personal liability: yes		14.159*	0.040		13.537†	0.054	13.554*	0.029
		(6.881)			(7.037)		(6.224)	
Ln(wage blue collar)		-3.581**	0.000		-3.661**	0.000	-3.658**	0.000
		(0.729)			(0.726)		(0.724)	
Ln(wage white collar)		-0.992†	0.083		-0.985†	0.084	-0.997†	0.079
		(0.572)			(0.569)		(0.568)	
Ln(wage TM)		-1.877**	0.000		-1.965**	0.000	-2.205**	0.000
		(0.455)			(0.453)		(0.451)	
Constant	23.870**	149.960**	0.000	23.192**	151.851**	0.000	155.941**	0.000
	(4.415)	(14.106)	(4.332)		(14.028)		(13.984)	
Industry (11 dummies)	yes	yes		yes	yes		yes	
Year (13 dummies)	yes	yes		yes	yes		yes	
Industry year (143 dummies)	yes	yes		yes	yes		yes	
Labor market region (12 dummies)	yes	yes		yes	yes		yes	
R^2	0.14	0.16		0.15	0.17		0.17	
Adjusted R^2	0.14	0.16		0.15	0.17		0.17	
Log-likelihood	-1280045	-1277392		-1279156	-1276433		-1275720	
Observations	250853	250853		250853	250853		250853	

Clustered standard errors in parentheses. P-values to the right.

Table 4
DV: survival and sales growth.

	Exponential survival model (AFT)				Fixed-effects panel regression of sales growth			
	(11)	P-values	**(12)**	P-values	**(13)**	P-values	**(14)**	P-values
Ratio, h-p to local, lagged	-0.030**	0.000			-0.565**	0.000		
	(0.001)				(0.007)			
Ratio, h-p to distant, lagged	-0.032**	0.000			-0.602**	0.000		
	(0.001)				(0.030)			
Ratio, local spin-off, lagged			-0.044**	0.000			-0.922**	0.000
			(0.001)				(0.023)	
Ratio, distant spin-off, lagged			-0.039**	0.000			-0.918**	0.000
			(0.004)				(0.169)	
Ratio, local nonrival ent, lagged			-0.043**	0.000			-0.837**	0.000
			(0.001)				(0.030)	
Ratio, distant nonrival ent, lagged			-0.045**	0.000			-0.384*	0.041
			(0.003)				(0.188)	
Ratio, local rival incumbent, lagged			-0.042**	0.000			-0.792**	0.000
			(0.001)				(0.013)	
Ratio, distant rival incumbent, lagged			-0.043**	0.000			-0.820**	0.000
			(0.001)				(0.047)	
Ratio, local nonrival inc, lagged			-0.040**	0.000			-0.666**	0.000
			(0.001)				(0.012)	
Ratio, distant nonrival inc, lagged			-0.041**	0.000			-0.686**	0.000
			(0.001)				(0.036)	
Ratio, h-p to other, lagged			-0.036**	0.000			-0.429**	0.000
			(0.001)				(0.016)	
Wage score (0-10), lagged			0.165**	0.000			1.339**	0.000
			(0.011)				(0.041)	
Constant	8.103**	0.000	6.577**	0.000	149.982**	0.000	156.001**	0.000
	(0.726)		(0.755)		(15.049)		(13.986)	
R^2					0.30		0.17	
Adjusted R^2					0.21		0.17	
Log-likelihood	-7569		-6850		-1277386		-1275709	
Observations	241271		241271		250853		250853	

DV of models 11 and 12: survival time at time t. Thus, lagged effects refer to time $t-1$. Local: <100 km and distant: >100 km.
DV of models 13 and 14: Sales growth from t to $t+1$. Thus, lagged effects refer to time t. Local: <100 km and distant: >100 km.
Full tables with second and third year effects are available in the online appendix. Clustered standard errors in parentheses. P-values to the right.
We include controls for the number of high-performing employees, legal form (dummy for unlimited liability), wage level (average gross wage level of top managers, white collar, and blue collar workers (all logged)), industries (10 dummies), year dummies, industry year (143 dummies), and labor market regions (12 dummies). The sales growth models also include firm age (logged).

Table 5

Exponential survival model (AFT) and FE panel regression of sales growth

	Exponential survival model (AFT)						FE panel regression of sales growth					
	Manufacturing	P-values	**Local competition**	P-values	**Client based**	P-values	**Manufacturing**	P-values	**Local competition**	P-values	**Client based**	P-values
Ratio, h-p to spin-offs, lagged	-0.047**	0.000	-0.047**	0.000	-0.046**	0.000	-0.999**	0.000	-0.937**	0.000	-0.957**	0.000
	(0.002)		(0.003)		(0.002)		(0.072)		(0.031)		(0.093)	
Ratio, h-p to nonrival ent, lagged	-0.047**	0.000	-0.047**	0.000	-0.046**	0.000	-0.880**	0.000	-0.823**	0.000	-0.986**	0.000
	(0.002)		(0.003)		(0.002)		(0.063)		(0.048)		(0.113)	
Ratio, h-p to rival incumbent, lagged	-0.046**	0.000	-0.045**	0.000	-0.044**	0.000	-0.951**	0.000	-0.773**	0.000	-0.869**	0.000
	(0.001)		(0.003)		(0.002)		(0.042)		(0.018)		(0.050)	
Ratio, h-p to nonrival inc, lagged	-0.046**	0.000	-0.043**	0.000	-0.042**	0.000	-0.691**	0.000	-0.653**	0.000	-0.755**	0.000
	(0.001)		(0.003)		(0.002)		(0.026)		(0.019)		(0.045)	
Ratio, h-p to other, lagged	-0.040**	0.000	-0.041**	0.000	-0.037**	0.000	-0.432**	0.000	-0.467**	0.000	-0.521**	0.000
	(0.002)		(0.003)		(0.002)		(0.042)		(0.024)		(0.068)	
Wage score (0-10), lagged	0.137**	0.000	0.183**	0.000	0.192**	0.000	1.109**	0.000	1.520**	0.000	1.445**	0.000
	(0.017)		(0.022)		(0.022)		(0.079)		(0.066)		(0.155)	
Constant	-1.813	0.417	9.636**	0.000	3.652†	0.095	164.637**	0.000	180.709**	0.000	88.026*	.032
	(2.234)		(2.072)		(2.188)		(33.388)		(24.186)		(40.974)	
R^2							0.20		0.21		0.19	
Adjusted R^2							0.20		0.20		0.19	
Log-likelihood	-436		-2761		-689		-218706		-448207		-103112	
Observations	42803		83162		19867		44453		89795		20125	

DV of models 1, 2 and 3: survival time at time t. Thus, lagged effects refer to time $t-1$. DV of models 4, 5, and 6: Sales growth from t to $t+1$. Thus, lagged effects refer to time t. P-values to the right. Full tables with second and third year effects are available in the online appendix. Clustered standard errors in parentheses. We include controls for the number of high-performing employees, legal form (dummy for unlimited liability), wage level (average gross wage level of top managers, white collar, and blue collar workers (all logged)), year dummies, and labor market regions (12 dummies). The sales growth models also include firm age (logged).

Table 6

Exponential survival model (AFT) and FE panel regression of sales growth

	Exponential survival model (AFT)						FE panel regression of sales growth					
	Manufacturing	P-values	**Local competition**	P-values	**Client based**	P-values	**Manufacturing**	P-values	**Local competition**	P-values	**Client based**	P-values
Ratio, local spin-off, lagged	-0.047**	0.000	-0.047**	0.000	-0.047**	0.000	-0.999**	0.000	-0.938**	0.000	-0.963**	0.000
	(0.002)		(0.003)		(0.002)		(0.073)		(0.031)		(0.094)	
Ratio, distant spin-off, lagged	-0.069	0.127	-0.042**	0.000	-0.052**	0.000	-1.153**	0.000	-0.831**	0.001	-0.730**	0.000
	(0.045)		(0.008)		(0.003)		(0.029)		(0.242)		(0.127)	
Ratio, local nonrival ent, lagged	-0.047**	0.000	-0.047**	0.000	-0.046**	0.000	-0.880**	0.000	-0.818**	0.000	-0.994**	0.000
	(0.002)		(0.003)		(0.002)		(0.063)		(0.049)		(0.113)	
Ratio, distant nonrival ent, lagged	-0.081**	0.000	-0.050**	0.000	-0.054**	0.000	-0.749*	0.039	-1.113**	0.000	-0.647	0.638
	(0.017)		(0.004)		(0.007)		(0.363)		(0.264)		(1.377)	
Ratio, local rival incumbent, lagged	-0.046**	0.000	-0.045**	0.000	-0.044**	0.000	-0.931**	0.000	-0.773**	0.000	-0.873**	0.000
	(0.001)		(0.003)		(0.002)		(0.042)		(0.018)		(0.052)	
Ratio, distant rival incumbent, lagged	-0.047**	0.000	-0.046**	0.000	-0.047**	0.000	-1.332**	0.000	-0.790**	0.000	-0.819**	0.000
	(0.003)		(0.003)		(0.002)		(0.223)		(0.066)		(0.165)	
Ratio, local nonrival inc, lagged	-0.046**	0.000	-0.043**	0.000	-0.042**	0.000	-0.696**	0.000	-0.655**	0.000	-0.750**	0.000
	(0.001)		(0.003)		(0.002)		(0.026)		(0.020)		(0.046)	
Ratio, distant nonrival inc, lagged	-0.045**	0.000	-0.045**	0.000	-0.046**	0.000	-0.597**	0.000	-0.626**	0.000	-0.837**	0.000
	(0.002)		(0.003)		(0.003)		(0.090)		(0.057)		(0.133)	
Ratio, h-p to other, lagged	-0.040**	0.000	-0.041**	0.000	-0.037**	0.000	-0.432**	0.000	-0.466**	0.000	-0.525**	0.000
	(0.002)		(0.003)		(0.002)		(0.042)		(0.024)		(0.068)	
rank_key, lagged	0.136**	0.000	0.183**	0.000	0.193**	0.000	1.110**	0.000	1.517**	0.000	1.447**	0.000
	(0.017)		(0.022)		(0.022)		(0.079)		(0.066)		(0.155)	
Constant	-1.832	0.412	9.598**	0.000	3.579	0.105	165.531**	0.000	181.507**	0.000	87.234*	0.034
	(2.235)		(2.073)		(2.206)		(33.354)		(24.208)		(41.126)	
R^2							0.20		0.21		0.19	
Adjusted R^2							0.20		0.21		0.19	
Log-likelihood	-432		-2754		-683		-218680		-448191		-103106	
Observations	42803		83162		19867		44453		89795		20125	

Exponential survival model (AFT). Fixed effects panel regression of sales growth. Clustered standard errors in parentheses. P-values to the right.
We include controls for the number of high-performing employees, legal form (dummy for unlimited liability), wage level (average gross wage level of top managers, white collar, and blue collar workers (all logged)), year dummies, and labor market regions (12 dummies). The sales growth models also include firm age (logged).

Appendix

Matching parent firms' likelihood of high-performer migration

We supplemented the preceding analysis with a matching approach to further ensure that firms are comparable at the point of origin (the year in which a high-performing employee departs). More precisely, we wish to ensure that our results are not driven by parent firms' unequal likelihood of losing high-performing employees. Table 7 illustrates our approach.

Table 7
Matching approach

Time	Firm ID	Year_t	$\ln(\text{sales})_{t+1}$	$\ln(\text{sales})_{t-1}$	High-performing employee departs	Years since last departure
$t-8$	5	2000	80		1	0
$t-7$	5	2001	60		1	1
$t-6$	5	2002	25	80	0	1
$t-5$	5	2003	10	60	1	2
$t-4$	5	2004	20	25	**0**	1
$t-3$	5	2005	30	10	**0**	2
$t-2$	5	2006	10	20	**1**	3
$t-1$	5	2007	25	30	**0**	1
t	**5**	**2008**	**15**	**10**	**0**	**2**
$t+1$	5	2009	10	25	0	3

We apply a conservative design without allowing for collective or repeated migration. First, we restrict the sample to firms experiencing a single departure within a five-year window, meaning that no other high-performing employees resigned in the two years prior or two years after this event (see Table 7 for an illustration of the approach). Firms satisfying these criteria are matched with a sample of firms with no high-performing employees departing in a five-year window. Referring to the latter as *controls*, we use propensity score matching to match the two groups on the likelihood of losing a high-performing employee at time $t-2$ to any destination, spin-off entrepreneurship, nonrival entrepreneurship, a rival incumbent firm, a nonrival incumbent firm, or other destination (see categories in Table 7).

We estimate the average treatment effect on three variables: $Sales_t$ (logged), $Sales\ growth_t$ and $Survival\ time_t$ (logged). We estimate the latter using the specification from model 5 in Table 2. While all firms survive until time t, a firm might exit the following year. If a firm exited at time $t+1$, we replaced the dependent variable value (i.e., the estimated years until exit at time t) with 0 for these firms.

We use logistic treatment models (the default) to estimate the likelihood of losing a high-performing employee. The explanatory variables in the treatment models all refer to the last observation before departure, year $t-2$ (Table 7).[13] We match each "treated" firm with the two nearest controls.[14] Table 8 describes the categorization into different treatment and control groups. After matching, we compare the performance of the treated and control firms at time t, i.e., two years after a potential departure (see Table 7).

We follow the order of the survival and sales growth analyses when we estimate the effect of high-performer migration (see Table 8). We first estimate the impact of general high-performer migration. Next, we estimate the effects of departures to spin-off entrepreneurship, nonrival startups, incumbent rivals, nonrival incumbents, and other in turn. Finally, the matching approach permits a direct test

[13]These variables included lagged employment growth (employment growth_{t-3} and employment growth_{t-4}) and the number of high-performing employees (logged).

[14]Using a single-match approach might rely on too little information. On the other hand, using too many matches increases the risk of incorporating dissimilar observations (Abadie et al., 2001). For these reasons, we use two matches as a standard.

Table 8
Categories in Table 9

1)	Treatment:	One high-performing employee departs.
	Control:	No high performers depart in the five-year window.
2)	Treatment:	One high-performing employee departs to spin-off entrepreneurship.
	Control:	No high performers depart in the five-year window.
3)	Treatment:	One high-performing employee departs to nonrival startup.
	Control:	No high performers depart in the five-year window.
4)	Treatment:	One high-performing employee departs to an incumbent rival.
	Control:	No high performers depart in the five-year window
5)	Treatment:	One high-performing employee departs to a nonrival incumbent.
	Control:	No high performers depart in the five-year window
6)	Treatment:	One high-performing employee departs to other.
	Control:	No high performers depart in the five-year window

for differences in effects from different types of high-performer migration. In Table 10, we pair all destinations to perform such a test.

Table 9
Matched regressions

	Sales growth$_t$	P-val	**Ln(sales)$_t$**	P-val	**Ln(mean survival$_t$)**	P-val
1) One high-performing employee departs vs. no high-performing employees depart						
Estimate	-18.423	0.195	-0.118	0.000	-0.3094	0.000
	(14.223)		(0.014)		(0.064)	
# Observations	28,957		29,027		29,733	
# Controls	24,473		24,536		25.152	
# Treatments	4,491		4,491		4,581	
2) Departure to spin-off entrepreneurship						
Estimate	-71.839	0.000	-1.225	0.000	-0.623	0.000
	(4.762)		(0.153)		(0.129)	
# Observations	24,604		24,667		25.283	
# Controls	24,473		24,536		25.152	
# Treatments	131		131		131	
3) Departure to nonrival startup						
Estimate	-26.16	0.310	0.506	0.007	-0.355	0.001
	(25.76)		(0.189)		(0.105)	
# Observations	24,649		24,712		25.331	
# Controls	24,473		24,536		25.152	
# Treatments	176		176		179	
4) Departure to incumbent rival						
Estimate	-19.452	0.305	-0.197	0.000	-0.497	0.000
	(18.957)		(0.045)		(0.061)	
# Observations	25.343		25.406		26.038	
# Controls	24.473		24.536		25.152	
# Treatments	870		870		886	
5) Departure to nonrival incumbent						
Estimate	-23.342	0.007	0.042	0.859	-0.422	0.000
	(8.727)		(0.237)		(0.073)	
# Observations	26,634		26,702		27,368	
# Controls	24,473		24,536		25.152	
# Treatments	2,161		2,166		2,216	
6) Departure to other						
Estimate	-3.784	0.864	-0.006	0.993	-0.413	0.183
	(22.113)		(0.588)		(0.310)	
# Observations	25,619		25,684		26,321	
# Controls	24,473		24,536		25.152	
# Treatments	1,146		1,148		1,169	

Robust standard errors in parentheses.

Table 10

Matched regressions

TREATMENT:	**Spin-off**			**Nonrival ent**			**Rival inc**			**Nonrival inc**		
	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged
Nonrival ent	-9.940	-0.445	-0.019									
	(5.791)	(0.110)	(0.049)									
# Obs	307	307	310									
Rival incumbent	-5.907	-0.248	0.001	2.649	0.205	0.074						
	(4.727)	(.091)	(0.036)	(4.228)	(0.085)	(0.034)						
# Obs	1,001	1,001	1,017	1,046	1,046	1,065						
Nonrival inc.	-2.317	-0.253	-0.044	2.112	0.109	-0.050	1.495	-0.058	-0.066			
	(4.117)	(0.071)	(0.036)	(3.865)	(0.068)	(0.040)	(1.838)	(0.045)	(0.022)			
# Obs	2,292	2,297	2.347	2,337	2,342	2,395	3,031	3,036	3,102			
Other	-6.350	-0.197	-0.172	3.852	0.182	-0.142	-2.643	-0.013	-0.196	-2.737	0.042	-0.131
	(4.712)	(0.089)	(0.037)	(4.005)	(0.077)	(0.038)	(2.038)	(0.054)	(0.024)	(1.691)	(0.045)	(0.018)
# Obs	1,277	1,279	1,300	1,322	1,324	1,348	2,016	2,018	2,055	3,307	3,314	3,385

Treatment is the horizontal category. We compare these to the vertical listed categories. For example, upper left corner shows the impact of spin-offs *relative* to nonrival entrepreneurship. Robust standard errors in parentheses.

Table 11

P-values for Table 10

TREATMENT:	**Spin-off**			**Nonrival ent**			**Rival inc**			**Nonrival inc**		
	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged	Sales growth$_t$	sales$_t$ logged	Survival$_t$ logged
Nonrival ent	0.086	0.000	0.704									
Rival incumbent	0.211	0.006	0.985	0.531	0.015	0.028						
Nonrival inc.	0.573	0.000	0.222	0.585	0.106	0.217	0.416	0.193	0.003			
Other	0.178	0.028	0.000	0.336	0.019	0.000	0.195	0.810	0.000	0.106	0.350	0.000

Treatment is the horizontal category. We compare these to the vertical listed categories.

We find a negative effect on parent firm performance from the departures of high-performing employees independent of the postdeparture destination (regression 1, Table 9). This effect, however, is only significant for two of three variables: *Ln(sales)* ($p = 0.000$), *Ln(sales) growth* ($p = 0.195$), and *survival* ($p = 0.000$). For example, the estimated survival time for the treatment group (two years from departure) is on average reduced by 31 pct. ($p = 0.000$). Then, we estimate the average treatment effect of departures to our five destinations in turn. For spin-offs, we find the largest negative effects on parent firm performance of all five categories.[15] For all but one destination (departures for other reasons), we find significant and adverse impacts on parent firm survival from high-performer migration. The effects do not differ significantly across these five destinations. Thus, this analysis does not support Hypothesis 1. For all types of migration (except migration for other reasons), we find an adverse and significant effect on either parent firm sales or sales growth.

Finally, for a direct comparison of high-performer migration to different destinations, we matched all types of migration to each other. Table 10 and Table 11 show the results. The evidence is weak when we investigate the impact on parent firm sales growth and survival. Consistent with the preceding analyses, we do not find significant differences in the effects on sales growth and survival time for the two types of competitive migration (spin-off entrepreneurship and rival incumbent firms). However, Table 10 shows a greater impact on parent firm sales (logged) when high performers migrate to spin-offs compared to all other destinations. For example, spin-off entrepreneurship decreases parent firm sales by 24.8% ($p = 0.006$) (two years from departure) relative to high-performer migration to incumbent rivals. Departures for rival incumbents show greater impact on parent firm sales than the three types of noncompetitive migration.

While the matching analysis confirmed the previous results of negative effects on parent firm performance following all types of departures, we cannot conclusively confirm a stronger effect of high-performer migration to competitive destinations (spin-off entrepreneurship and rival incumbent firms). It seems plausible that this nonsignificance is due to the smaller number of observations for spin-off departures. Power is clearly an issue with this test on a subsample of firms that experience a single departure event. It is not a representative sample of the population of firms, but the approach isolates the effect of one departure and one destination compared to a control. This is akin to a quasi-experiment for a smaller subsample. The matching approach should be treated as a supplement to the previous analysis and as a control for potential endogeneity.

[15] These effects are substantial. Recall, however, that our conservative design, allowing for only one high-performer departure in a five-year window, restricts our sample to smaller firms. We expect that high-performer migration (in particular, to spin-offs) would have larger impact on smaller parent firms because small firms are more sensitive to the loss of individuals. Therefore, these results are not generalizable to our full sample of parent firms.