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Different people, different pathways: Human capital redeployment in multi-business firms

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Abstract

Research Summary: Multi-business firms redeploy human capital to strengthen individual business units. However, we know little about the antecedents of such redeployments and their effects on unit outcomes. Contributing to the resource redeployment and strategic human capital literatures, we test the relationships between parent–unit industry relatedness, the direction of redeployment (parent-to-unit and unit-to-parent), the type of human capital, the likelihood of redeployment, and post-redeployment unit closure. Using Norwegian population-level microdata of spinouts, we find that parent–unit industry relatedness increases the likelihood of human capital redeployment and that this effect is stronger for generalists than for specialists. Further, we find that parent-to-unit and unit-to-parent redeployment of generalists and specialists have distinct effects on unit closure, largely because of differences in post-redeployment unit performance.

Managerial Summary: Firms with multiple business units often transfer employees between units to strengthen them. However, we do not know which employees are more likely to be sent and which employees, if any, affect the receiving unit's survival and performance. Analyzing over 9000 spinouts in Norway between 2004 and 2015, we find that employees are more likely to be sent when the parent and the unit are in related industries. We further show that employees with specialized professional knowledge are sent regardless of relatedness, while generalists are sent when industries are related. Regarding post-transfer unit survival, we find that parent-to-unit and unit-to-parent redeployment of generalists and specialists have distinct effects on survival, largely because of differences in the impact on post-transfer unit performance.

KEYWORDS

human capital, multi-business firms, performance, resource redeployment, spinouts

1 | INTRODUCTION

The performance implications of the differences between focused firms and multi-business firms are a central topic in the strategy literature (Dickler & Folta, 2020; Hill et al., 1992). One key difference is multi-business firms' option to redeploy resources across units in their portfolio (Helfat & Eisenhardt, 2004; Sakhartov & Folta, 2014). Resource redeployment involves removing resources from one unit in a firm's portfolio and transferring them to another (Sakhartov & Folta, 2014). Redeploying resources allows firms to compete in multiple product markets effectively (Morandi Stagni et al., 2020) and to enter (Wu, 2013) or exit (Lieberman et al., 2017) markets in response to relative commercial opportunities (Dickler & Folta, 2020). Redeployment applies to non–scale free resources (i.e., resources that cannot be used for multiple activities simultaneously) such as human capital and equity (Helfat & Eisenhardt, 2004; Levinthal & Wu, 2010).

Recent redeployment literature focuses on human capital redeployment, the redeployment of employees (Belenzon & Tsolmon, 2016; Karim & Williams, 2012). Multi-business firms redeploy human capital to gain competitive advantage in the absence of flexible labor markets (Belenzon & Tsolmon, 2016), to change the receiving units (Karim & Williams, 2012), and to capture unit-specific opportunities (Tate & Yang, 2015). Yet little is known about the performance outcomes of human capital redeployment. In theory, human capital is redeployed when there are inducements to do so (Helfat & Eisenhardt, 2004; Penrose, 1959), but it is unclear under which conditions inducements translate into post-redeployment performance. Human capital is often seen as firms' fundamental resource (Campbell et al., 2012; Coff, 1997). Indeed, effective redeployment may improve performance at the receiving unit (Capron, 1999; Stadler et al., 2022), while its inefficient allocation is costly (Bidwell & Keller, 2014). Thus, it is essential to understand the boundary conditions of human capital redeployment. In particular, the type of receiving business unit and the attributes of the redeployed employees may steer post-redeployment outcomes.

This article examines the extent to which human capital redeployment between a corporate parent and its business units affects the units' closure due to differences in performance post-redeployment. To do so, we test the effect of the type of the receiving business unit—defined by parent–unit industry relatedness (Sakhartov & Folta, 2014)—on the likelihood of human capital redeployment. Thereafter, we examine the extent to which redeployment affects unit closure. Further, we identify two boundary conditions: (1) the direction of redeployment, distinguishing between parent-to-unit (P → U) and unit-to-parent (U → P) human capital redeployment; and (2) the characteristics of redeployed human capital, distinguishing between specialists and generalists.

Combining findings from the literatures on resource redeployment (Helfat & Eisenhardt, 2004; Penrose, 1959; Sakhartov & Folta, 2014) and strategic human capital (Becker, 1962; Chen et al., 2020), we expect that parent–unit industry relatedness positively affects both P → U and U → P human capital redeployment. This is so because of lower post-redeployment adjustment costs, the costs of transferring and adapting a resource to other operations (Hashai, 2015), such as retraining and upskilling (Helfat & Eisenhardt, 2004; Sakhartov & Folta, 2014). Also, since firms redeploy resources to where they are most productive (Helfat & Eisenhardt, 2004), we expect P → U human capital redeployment to reduce the likelihood of unit closure due to unit performance gains. In contrast, we expect U → P human capital redeployment to increase the likelihood of closure due to the loss of human capital and the subsequent reduction in unit performance. Also, we expect the effects of both P → U and U → P human capital redeployment on unit closure to be stronger for specialists than for generalists because specialists represent human capital that is more valuable and harder to replace (Hitt et al., 2001; Kor & Leblebici, 2005).

We test our hypotheses using Norwegian data on the population of corporate spinouts. The data track all newly founded spinouts and their parents and record all instances of human capital redeployment between them from 2004 to 2015. The sample includes 9248 spinouts operating in 179 industries. This unique setting allows us to test our hypotheses with limited confounding factors, as the data contain new business units from inception. In summary, we find that higher parent–unit industry relatedness leads to more P → U redeployment and U → P redeployment and that effects are stronger for generalists than for specialists. We show that P → U redeployment decreases the likelihood of unit closure and affects unit performance positively and the latter effect is stronger for specialists than for generalists. In contrast, U → P redeployment increases the likelihood of unit closure and affects unit performance negatively. U → P redeployment of specialists increases the likelihood of closure but the U → P redeployment of generalists does not. Contrary to our expectations reduced performance after U → P redeployment does not explain the effect on closure because performance declines are not different for U → P redeployment of generalists and specialists. We discuss the effects of P → U and U → P redeployment of generalists and specialists on closure and performance in the discussion section.

Our study contributes to the strategy literature in four ways. First, we extend research on the performance outcomes of human capital redeployment, which has examined unit productivity (Stadler et al., 2022) but not the characteristics of the redeployed human capital. We test this boundary condition, finding that human capital redeployment of generalists and specialists affects the likelihood of unit closure and unit performance to different degrees. Second, this study is the first to test the direction of redeployment. We argue that the direction has different effects on unit closure and performance. In contrast to the effects of P → U redeployment, U → P redeployment increases the likelihood of unit closure due to reduced unit performance. This also extends research on the effects of employee turnover (Shaw et al., 2013; Stern et al., 2021) by examining turnover through redeployment. Third, we extend research on the boundary conditions of the antecedents of human capital redeployment (Belenzon & Tsolmon, 2016; Karim & Williams, 2012), showing that the likelihood of redeployment is contingent on parent–unit industry relatedness and the characteristics of the redeployed human capital. Fourth, we extend strategic human capital research that compares external hiring and redeployment but treats redeployment as homogeneous (Bidwell & Keller, 2014; Keller et al., 2021). We show that human capital redeployment is heterogeneous with respect to post-redeployment firm outcomes based on the characteristics of redeployed employees and on the type of receiving unit. Taken together, our study strengthens the connection between the economic analysis of resource redeployment (e.g., Lieberman et al., 2017) and resource-specific considerations when human capital is redeployed (e.g., Bidwell & Keller, 2014).

2 | THEORY

2.1 | Human capital redeployment in multi-business firms

Resource redeployment describes multi-business firms' internal resource transfers from one business unit to another (Dickler & Folta, 2020; Sakhartov & Folta, 2014). Human capital redeployment is the transfer of individual employees through internal labor markets between units of a multi-business firm (Belenzon & Tsolmon, 2016; Karim & Williams, 2012). By choosing internal resource markets over external ones, firms can obtain inter-temporal economies of scope through sequential sharing (Helfat & Eisenhardt, 2004). Such sharing is distinct from the simultaneous sharing of resources in that sequential sharing applies mostly to non–scale free resources, such as physical equipment, equity, and human capital. Scale free resources, whose value is not reduced by their use across several operations (e.g., brands and patents), can be shared by multiple businesses without redeployment (Levinthal & Wu, 2010; Wu, 2013).[1]

Internal resource markets in multi-business firms vary in their vertical and horizontal complexity because such firms build pyramidal structures for investment and taxation purposes amongst other reasons (Almeida & Wolfenzon, 2006; Belenzon et al., 2019). To examine general mechanisms of human capital redeployment and their outcomes within such a setting, we reduce the complexity and focus on the vertical dimension of resource allocation (Sengul et al., 2019), similar to prior studies (e.g., Capron et al., 1998; Sengul & Gimeno, 2013). In our case, we focus on the internal labor markets between a subsidiary unit and its direct main owner (parent).[2] Studying the vertical dimension of redeployment is important because prior work shows that in a nested structure with multiple controlling entities above a unit, unit-level decisions are regularly delegated to units and direct vertical owners (Glaser et al., 2013; Sengul & Gimeno, 2013). For example, Belenzon et al. (2019) find that subsidiary units act more autonomously from the ultimate parent with an increasing number of intermediate units separating the unit from the ultimate parent.

2.2 | Parent–unit industry relatedness and human capital redeployment

For non–scale free resources, redeployment is valuable given inducements to redeploy (Sakhartov & Folta, 2015; Wu, 2013), such as lower redeployment costs (Sakhartov & Folta, 2014) and market shocks that increase the relative value of redeployment (Lieberman

[1]We follow Dickler and Folta (2020), concurring that non–scale free resources have no opportunity cost if they are not fully exploited—such as employees or plants working below capacity—and may be used simultaneously to some extent by multiple businesses without redeployment.

[2]There may be other units in the multi-business firm that partially own a focal unit and that use internal labor markets with the focal unit. While we do not discuss this theoretically, all models incorporate the effects econometrically.

et al., 2017). The direction of firms' diversification follows its resources, and underutilized indivisible resources create inducements to diversify (Chatterjee & Wernerfelt, 1991; Penrose, 1959). Excess resources promote related diversification (Chatterjee & Wernerfelt, 1991), as market similarities lower parents' resource transfer costs (Grant, 1988; Hashai, 2015). In contrast, firms might lack the human and physical capital to support unrelated diversification efforts (Penrose, 1959). In multi-business firms, resource redeployment is more likely between units with higher industry relatedness because redeployment is less costly when it is not necessary to retrain employees or modify physical assets (Lieberman et al., 2017; Sakhartov & Folta, 2014). While relatedness has been conceptualized in terms of industry codes or product markets, recent research focuses on relatedness in terms of the similarity of industries' human capital (Neffke & Henning, 2013; Sakhartov & Folta, 2014), hence, we conceptualize industry relatedness as such.[3]

Given that human capital is a non–scale free resource, it can be redeployed but not dedicated to multiple tasks simultaneously. Redeployment creates adjustment costs, but these costs are lower for related units (Helfat & Eisenhardt, 2004; Sakhartov & Folta, 2014). Consequently, we can expect that higher parent–unit industry relatedness leads to increased human capital redeployment between parent and business unit. While we differentiate between P → U, the redeployment of employees from the parent to a business unit, and U → P, the redeployment of employees from a business unit to the parent, redeployment costs should follow the same pattern irrespective of the direction of redeployment within a multi-business firm.

> **Hypothesis 1 (H1).** Industry relatedness between the parent and a business unit increases the likelihood of human capital redeployment (parent-to-unit and unit-to-parent).

2.3 | Human capital characteristics and the relatedness–redeployment relationship

Individuals' human capital varies in firm-specificity, which alters industry relatedness' effect on mobility (Neffke & Henning, 2013). Incorporating Chen et al.'s (2020) distinction, we differentiate between relatedness' effects on generalists—employees with a broader set of knowledge, not tied to a particular disciplinary domain, and specialists—employees with a narrower but deeper set of knowledge that is closely tied to a disciplinary domain.[4]

Specialists are professionals who completed extensive education prior to entering their profession and whose education sets them apart throughout their careers (Hitt et al., 2001). Certain professions, such as legal work and architecture require employees to provide proof of education and certification to conduct professional activities. Specialists are hired primarily for domain knowledge and their contribution hinges on non-firm-specific disciplinary knowledge that is costly to obtain (Becker & Murphy, 1992). Thus, while specialist tasks vary between industries and firms, they are based on a profession's knowledge, such as accounting or software development (Mayer et al., 2012), making their transfer between firms less dependent on industry relatedness.

[3]For a review, see Neffke and Henning (2013).

[4]This is distinct from general and specific *managerial* knowledge, which describes breadth and depth of managerial experience (Custódio et al., 2013). In contrast, we study the level of employees' specialization.

In contrast, generalists do not receive formal training for a profession and develop much of their human capital through learning on the job (Hitt et al., 2001). For generalists, learning on the job leads to the above-average development of firm-specific human capital (Lazear, 2009). Such firm-specific human capital, defined as knowledge and operating practices which are idiosyncratic to a firm (Lazear, 2009), make transfers across firm boundaries more difficult (Groysberg et al., 2008; Mayer et al., 2012). These transfers become even more difficult when two firms are in different industries (Mayer et al., 2012). Reiterating Becker and Murphy (1992): a steel worker who has learned how to operate a firm's specific furnaces (firm-specific human capital) would be less or equally productive at another firm in the same industry but much less productive at a firm in the software industry.[5] Thus, relative to specialists, generalists on average develop skills more specific to a firm and a sector making them less fungible across less related contexts (Becker & Murphy, 1992). Consequently, their transferability is more dependent on industry relatedness.

In summary, we expect that parent–unit industry relatedness increases the likelihood of both P → U and U → P human capital redeployment because it lowers adjustment costs of retraining (Sakhartov & Folta, 2014, 2015). However, while specialists can be expected to require less retraining because they are hired due to their relatively context-independent domain knowledge, the adjustment costs for generalists will likely decrease more strongly with parent–unit industry relatedness. This is so because, compared to specialists, generalists' knowledge becomes more firm-specific and consequently also more industry-specific due to learning on the job. The positive effect for generalist employees should follow the same pattern irrespective of the direction of redeployment within a multi-business firm. Therefore, we expect the P → U redeployment and U → P redeployment of generalists to be more strongly affected by parent–unit industry relatedness than the P → U redeployment and U → P redeployment of specialists.

> **Hypothesis 2 (H2).** The positive effect of industry relatedness on human capital redeployment (parent-to-unit and unit-to-parent) is stronger for generalist employees than for specialist employees.

2.4 | Human capital redeployment and unit closure

Much of the resource redeployment literature has focused on redeployment as the outcome of differential growth opportunities between business units (Dickler & Folta, 2020; Sohl & Folta, 2021; Wu, 2013). However, recent literature has begun to examine redeployment as an antecedent of performance outcomes (Giarratana et al., 2021; Stadler et al., 2022). Past studies have examined the performance of multi-business firms based on the potential to redeploy across product niches (Giarratana et al., 2021), portfolio entrepreneurs' resource redeployment to strengthen promising ventures (Santamaria, 2022), and technology improvements at the receiving unit based on the transfer of specialized employees (Stadler et al., 2022). Given that human capital redeployment is often used to make changes to the receiving business units

[5] In theory, both specialists and generalists can switch jobs. However, whereas generalists can be allocated to different tasks at a similar cost level post-retraining, specialists cannot easily become specialists in another area, and are too costly to be used outside of their profession at the same cost (Becker & Murphy, 1992).

(Karim & Williams, 2012), it can be expected to affect the productivity of the receiving firm (Stadler et al., 2022).

Unit closure is largely reflected in the performance of business units, as developing, setting up, and staffing units is costly (Feldman & Sakhartov, 2022; Lieberman et al., 2017). Thus, firms do not establish new business units arbitrarily and they try to avoid their immediate closure. Lieberman et al. (2017) show that a reduction in redeployment costs increases the likelihood of business closure when units perform below the parent's expectations. Closing business units may entail layoffs with little potential for reverse redeployment back to the parent (Lieberman et al., 2017). However, if the options to divest or discontinue are not favorable, corporate managers can also choose to redeploy resources to the unit to increase performance. Studies have highlighted human capital investment's positive effect on the performance of corporate spinouts (Chesbrough, 2003; Sapienza et al., 2004), on performance in the strategic change context (Bentley & Kehoe, 2020), and for technology-related human capital (Stadler et al., 2022). Consequently, we expect that P → U redeployment negatively affects unit closure because it increases units' performance.

> **Hypothesis 3a (H3a).** Parent-to-unit human capital redeployment reduces the likelihood of unit closure.

In contrast, a large body of literature has found that turnover can diminish performance (Hausknecht & Holwerda, 2013; Shaw et al., 2013; Stern et al., 2021) due to the loss of valuable human capital and process disruptions (Kacmar et al., 2006). In general, internally developed human capital is difficult to replace through external hiring, and it is often impossible to adequately compensate for its loss (Keller et al., 2021). Intuitively, we may think that parents use U → P redeployment in anticipation of closure (Santamaria, 2022), yet prior research equally shows that parents withdraw resources from strong units to support underperforming units (Belenzon et al., 2019; Cabral et al., 2020). Thus, there may not be a consistent selection effect that explains the relationship between U → P redeployment and performance. In the absence of strong selection effects, we expect that U → P redeployment positively affects unit closure because units decrease their performance following U → P redeployment.

> **Hypothesis 3b (H3b).** Unit-to-parent human capital redeployment increases the likelihood of unit closure.

2.5 | Human capital characteristics and the redeployment–closure relationship

We expect that the relationship between human capital redeployment and unit closure differs between specialists and generalists. Leveraging the most valuable human capital should produce the largest return (Hitt et al., 2001; Sherer, 1995). Empirical work finds that employees with specialized education on average produce the highest rents (Kor & Leblebici, 2005) and that redeploying of specialized employees positively affects performance at the receiving unit (Stadler et al., 2022). In addition, performance increases at the receiving unit may be in part because P → U redeployment enables coordination between units (Chen et al., 2019). Given that specialists are more important than generalists for such coordination because they lead problem-solving activities in specialized tasks (Garicano, 2000), P → U redeployment of specialists should provide greater performance increases from coordination than P → U redeployment of generalists. Thus, we expect that P → U redeployment of specialists increases post-redeployment performance more strongly than P → U redeployment of generalists. Building on this, we expect that post-redeployment differences in performance explain the likelihood of unit closure. P → U redeployment of specialists is more negatively related to unit closure than P → U redeployment of generalists.

> **Hypothesis 4a (H4a).** The negative effect of parent-to-unit human capital redeployment on unit closure is stronger for specialist employees than for generalist employees.

Regarding U → P redeployment, prior work finds that the turnover of employees with high human capital has the largest negative effect on the releasing unit's performance (Ployhart et al., 2011). When a unit's workflow depends on individuals' specialized knowledge, they contribute disproportionally to performance (Crocker & Eckardt, 2014; Rothaermel & Hess, 2007). As specialized professionals cannot be easily replaced—often only by other specialized professionals—this type of turnover is likely to be very detrimental to performance. Extending prior arguments, U → P redeployment may also come at a cost of diminished coordination between units (Chen et al., 2019), which may be more severe for U → P redeployment of specialists than that of generalists. Thus, U → P redeployment of specialists can be expected to decrease post-redeployment performance more strongly than U → P redeployment of generalists. We expect that such differences in post-redeployment performance increase the likelihood of unit closure.

> **Hypothesis 4b (H4b).** The positive effect of unit-to-parent human capital redeployment on unit closure is stronger for specialist employees than for generalist employees.

3 | EMPIRICS

3.1 | Empirical setting and sample

We test our hypotheses using Statistics Norway (SSB) microdata for all Norwegian firms from 2004 to 2015. The dataset encompasses panel data on the population of firms and employees. To isolate the antecedents and outcomes of human capital redeployment within multi-business firms from confounding factors, we identify newly founded corporate spinouts from their inception and analyze them at the unit-year level. Redeployment between parents and spinouts is important because spinouts[6]—new units founded by and under the continued ownership of the parent—are an increasingly important way for established firms to grow and develop new businesses (Cirillo, 2019). In contrast to redeployment away from declining markets in reaction to demand-side shocks (Dickler & Folta, 2020; Wu, 2013), parents found spinouts and supply them with resources in the expectation of market growth (Cirillo, 2019). An advantage of our dataset

[6]The term spinout is used inconsistently for new entities within the multi-business firm, new entities founded by former employees outside the parent's control (Cirillo, 2019), and divestments of listed units with parent equity (Semadeni & Cannella, 2011). We focus on new units with parent equity, not on divestments or independent ventures.

is its access to data on parent and spinout characteristics, as well as human capital redeployment for the entire population.

We define spinouts as newly incorporated for-profit firms with their own management and board that were founded by established for-profit firms. To ensure that each spinout is owned by an established firm, we only include spinouts for which the ultimate parent is at least 10 years old. Further, we exclude parents and units which are nonprivate, nonprofit, and those that do not have employees, such as shell corporations established for tax purposes. Further, we exclude spinouts in which the parent cedes control (e.g., full divestments, initial public offerings of divisions, and buyouts), corporate venture capital investments, and acquisitions to ensure that the parent is a founding owner. We exclude joint ventures in which multiple parents hold equal ownership, as coopetition between equal partners might confound our results. We also exclude the construction industry, which spins off entities to segregate risk with no intent to redeploy resources beyond the initial investment (Sainati et al., 2020). We include spinouts with more than one corporate owner if there is a main parent with dominating ownership share, and we characterize minority partners as sub-parents. We follow current research on redeployment (e.g., Dickler & Folta, 2020; Morandi Stagni et al., 2020) and human capital redeployment (e.g., Belenzon & Tsolmon, 2016; Tate & Yang, 2015), which relies on cross-industry studies.

These procedures result in a panel with 9248 spinouts (units) and 20,362 unit-years. The spinouts span 179 industries (3-digit NACE codes).[7] P → U and U → P redeployment are skewed, with 3247 P → U redeployment years (16%) in 1001 spinouts (11%) and 255 U → P redeployment years (2%) in 171 spinouts (4%). P → U and U → P redeployment are not skewed between generalists and specialists, and units transfer both types of human capital at approximately the same rate. For a detailed overview, see Table 1. Interestingly, while P → U redeployment is rare, U → P redeployment is even rarer. The finding that internal mobility across units is rare is consistent with previous studies (e.g., Benson & Rissing, 2020).

Table 2 provides aggregated individual-level characteristics of the redeployed employees at the time of their redeployment. Although we do not estimate models at the individual level, this sheds light on who is redeployed. Regarding demographics, employees are in their early 40s and are predominantly male (74%–58%). Family ties play a disproportionate role in redeployment, likely reflecting a need for close monitoring at the unit. About 1% of the redeployed

TABLE 1 Frequency of parent-to-unit redeployment and unit-to-parent redeployment.

Redeployment	Level	All observations	Any redeployment	Generalist redeployment	Specialist redeployment
Parent-to-unit	Unit-years	100% [20,362]	16% [3247]	11% [2173]	11% [2153]
	Units	100% [9248]	11% [1001]	7% [663]	7% [694]
Unit-to-parent	Unit-years	100% [13,398]	2% [255]	1% [156]	1% [133]
	Units	100% [4259]	4% [171]	3% [113]	2% [100]

Note: Percentages indicate the percentage of the sample in terms of units/unit-years. [...] indicates the number of individual unit/unit-year observations. Any redeployment includes redeployment of generalists and specialists. Generalists/Specialist redeployment includes only the redeployment of the specified group. P → U redeployment is calculated based on the full sample (20,362 spinout-years and 9248 units), U → P redeployment is calculated from the second year only (13,398 spinout-years and 4259 units), as the first year is the establishment year of the spinouts.

[7]NACE is the European Union's industry classification. Online Supplement Table S1 contains the industry split.

TABLE 2 Individual-level characteristics of redeployed employees.

Variable	Workforce 2004–15	P → U	P → U Gen.	P → U Spe.	U → P	U → P Gen.	U → P Spe.
Individuals	3.63 m	14,800	9784	5016	455	251	204
Age (years)	41	41	41	41	38	38	39
Female	47	27	26	28	39	37	42
Family relation	n/a	0.89	0.84	1.03	1.28	1.99	0.49
Pre-redeployment salary	n/a	111	107	118	119	109	132
Post-redeployment salary	n/a	104	98	116	104	104	105
Firm tenure >3 years	52	60	62	56	n/a	n/a	n/a
Education type (*NUS-2000*)							
0 Compulsory education	37	25	38	0	25	46	0
1–3 Social sciences, humanities, and education	14	7	2	17	12	4	22
4 Business	11	13	10	21	21	10	36
5 Natural sciences and technical education	20	38	35	43	25	22	29
8 Transport and services	3	12	11	14	7	10	3
All other education types	15	4	3	6	9	8	9
Occupation (*ISCO-08*)							
1 Managers	8	10	5	19	17	8	26
2 Professionals	10	15	5	34	21	12	31
3 Technicians	18	17	12	27	22	23	22
5 Sales	21	8	9	6	7	11	3
8 Plant and machine operators	7	11	16	1	5	9	1
All other occupations	36	39	52	13	28	37	16

Note: All entries are percentages, but for individuals and age. Specialists (Spe.) and generalists (Gen.) indicate attainment of a higher education or not. Age is the mean age. Female is the percentage of females. Family relation is the percentage of redeployed employees which are family members (children, stepchildren, siblings, parents, grandparents, and partners) of the parent CEO, board members, or owners (>10%). Pre- and post-redeployment salary is the percent relative to the mean salary (i.e., 100) at the parent/unit. Experience is the percentage of the redeployed who have worked for more than 3 years at the parent prior to the redeployment. Selected education types and occupation categories are based on a one-digit classification of NUS-2000 and ISCO-08 respectively.

employees are close family members of the parent's CEO, board members, or owners and this percentage is higher for U → P redeployment of generalists. Regarding salary, in the year prior to P → U and U → P redeployment, all redeployed employees earn more than the firm average. Specialists earn the highest relative salaries (18%–32%). Post-redeployment salary premiums shrink to 4% for P → U and U → P redeployment. Further, employees selected for P → U redeployment are relatively senior as around 60% worked at the parent for more than 3 years prior to redeployment. Regarding education type (NUS-2000), those having natural science and technical education are most likely to be redeployed, although they only compose 20% of the workforce. For generalists, the largest category is compulsory education only. The second largest category for specialists and the fourth largest for generalists is business education. Occupational categories (ISCO-08) show that redeployment is mostly used for skilled labor (i.e., professionals, and technicians) whereas few employees work in semi-skilled occupations (i.e., sales and service, plant and machine operators).

3.2 | Variables

This study examines the effect of parent–unit industry relatedness on human capital redeployment and that of human capital redeployment on unit closure. Thus, our ultimate dependent variable is *closure*. *Closure* is a binary variable set to 1 for closure (i.e., the unit is officially closed, has filed for bankruptcy, dismisses all employees, or ceases to exist in the firm register) and 0 otherwise. We determine whether firms exit the sample due to a merger, which is not treated as closure.[8]

The independent variables *P → U redeployment* and *U → P redeployment* measure the natural logarithm of employees who switch their formal employer from parent to unit or from unit to parent, respectively. For *P → U redeployment*, we measure the total stock of employees that switch firms, as employees that quit after transferring could confound our results. For example, when one employee moves from parent to unit in year x and another moves in year $x+1$, we count redeployment as 2 in $x+1$, if both employees stay at the unit. If the first employee quits after year x, we count redeployment as 1 in $x+1$. We measure employee stock rather than employee flow because employees' ability to utilize knowledge only manifests in interactions with others over time (Zander & Kogut, 1995). Employees that quit and no longer work at the firm cannot contribute to performance outcomes at the unit. We thus create an accurate overview of employees who previously worked at the parent and are de facto employed at the unit in each given year.

The four independent variables *P → U (U → P) redeployment of generalists* and *P → U (U → P) redeployment of specialists* are built by dividing the general redeployment variables into two categories depending on the employees' formal education. Building on Chen et al. (2020), who define generalists as employees with a broader set of knowledge, not tied to a particular domain and specialists as employees with a narrower but deeper set of knowledge that is more closely tied to a domain. We define generalists as employees without higher education and specialists as employees who have obtained a university degree. This is a prudent distinction in our context, as employees in Norway largely obtain on-the-job training rather than higher education. In 2015, about 32% of the Norwegian workforce held a university degree.[9] Notably, undergraduate degrees in Norway are specialized and associated with a fixed discipline.

Parent–unit *industry relatedness* is the cosine similarity of two industry vectors in terms of human capital. A cosine similarity score between 0 (no similarity) and 1 (identical) compares the similarity of two industries' workforces in a specific year. We calculate the cosine similarity between two industries in terms of the education of their employees, thus comparing the workforces based on specialization and entry requirements. Similar work has used occupations (Sakhartov & Folta, 2014) and labor flows between industries (Neffke & Henning, 2013). We use educational profiles because they provide a more granular measure for both small firms, which often do not report employees' occupational categories, and niche industries, which have

[8]Observations that exit due to mergers are right-censored and set to 0 for the last year in which the parent company still holds ownership shares in the spinout. This applies to 381 spinouts (4% of the sample).
[9]Statistics Norway (2020). Educational attainment of the population (https://www.ssb.no/en/statbank/table/11293/).

limited labor flows. We capture yearly values based on the number of employees per education category (educational specialization × obtained level) in every industry, normalized by industry size.[10]

We control for characteristics at the spinout and parent levels. *Total spinout assets* (ln) are included to account for differences in spinouts' size and resource endowments. We account for external knowledge inflow through *sub-parent redeployment*, *external hires*, and *labor market hires*. Like redeployment, we measure these streams of employees to the spinout as the natural logarithm of the stock of employees. *Sub-parent redeployment* refers to the number of employees transferred from other units within the pyramidal structure, *external hires* refers to employees from other firms, and *labor market hires* refers to employees that were not previously registered at a Norwegian firm, such as new graduates or migrants. We also control for parents' degree of control over spinouts, including whether the CEO is redeployed from the parent (*CEO from parent*), whether parent employees are on the spinout board (*parent on spinout board*), and whether the parent is a majority (1) or a minority (0) owner of the spinout (*parent ownership*). We also control for *board size*. *Parent age* (ln), *parent ROA* (ihs), and *parent total assets* (ihs)[11] are included to account for parents' resource endowments (Lieberman et al., 2017). We also control for the *total number of spinouts* that a parent concurrently owns, as this can affect how many resources a parent can redeploy to each spinout. Further, we include the number of *sub-parents* and *sub-parent ownership* to account for resources provided by other units within the pyramidal structure. Finally, we control for the growth within a particular industry (*industry growth*). We follow the approach in the strategic human capital literature which measures market growth as employment growth at a three-digit industry level. It measures market potential as well as supply and demand of human capital (Bidwell, 2013), which is of specific importance in our context.

3.3 | Empirical strategy

Our empirical approach is split into two steps. First, using panel probit regressions we investigate whether relatedness between a business unit and the parent increases the likelihood of P → U redeployment and U → P redeployment (H1), and whether the positive effect of relatedness on P → U redeployment and U → P redeployment is stronger for generalists than for specialists (H2). To do so, we analyze P → U and U → P redeployment as functions of *industry relatedness*.

Second, we examine whether P → U (U → P) redeployment reduces (increases) the likelihood of unit *closure* [Hypothesis 3a (H3a) and Hypothesis 3b (H3b)] and whether the negative (positive) effect of P → U (U → P) redeployment on unit closure is stronger for specialists than for generalists [Hypothesis 4a (H4a) and Hypothesis 4b (H4b)]. Since a parent selects its spinouts for redeployment, there may be endogeneity issues between redeployment and *closure*.

[10]The cosine similarity between I_i and I_j is $\text{sim}(E_{ia}, E_{ja}) = \sum_a \frac{E_{ia} \times E_{ja}}{||E_{ia}|| \, ||E_{ja}||}$ where $||E_i||$, the vector length, is the Euclidean norm of vector $E_i = (E_1, E_2, ..., E_n)$ defined as $\sqrt{E_{12}, E_{22}, ..., E_{n2}}$, and E_i and E_j are the frequencies of employees with a given educational background in industries I_i and I_j, respectively. For a description of Euclidean distance in occupational profiles between industries, see Sakhartov and Folta (2014); for a description of cosine similarity, see Hoberg and Phillips (2010).

[11]Since ROA and total assets are skewed and contain negative values, we use the IHS function [$\sinh^{-1}(x) = \log(x + (x^2 + 1)^{1/2})$] to reduce the influence of outliers and retain interpretable results (Sauerwald et al., 2016). Negative total assets indicate a parent's financial distress (6% of observations). Results remain robust with the exclusion of these 6%.

Thus, our empirical approach addresses reciprocal causality and selection. To address reciprocal causality, we only sample spinouts founded during the sampling timeframe to avoid omitting previous redeployment. We use semi-parametric Cox models to estimate the likelihood of closure, which are appropriate for examining firm failure (Ertug et al., 2020; Santamaria, 2022) and do not make assumptions about the effect of time on the hazard rate, as the coefficients measure a change to the event's baseline rate (Kacperczyk, 2012). Cox models provide accurate estimates with right-censored data (Tuma & Hannan, 1984). Buenstorf and Costa (2018) use this approach to alleviate concerns about the reciprocal effects of spinoffs' hiring practices on survival.

Furthermore, as parents might favor specific strategies when redeploying human capital, we account for selection effects by estimating a two-stage model that includes first-stage residuals in the second stage (Terza et al., 2008; Wooldridge, 2010). This two-stage approach closely follows prior strategy research (Alvarez-Garrido & Dushnitsky, 2016; Berry, 2013; Ertug et al., 2020). In the first stage, we use the panel probit model with P → U redeployment as a dependent binary variable to account for the different investment strategies that parents might pursue through their redeployment patterns. In the second stage, we use semi-parametric Cox models.[12]

In the first stage, we include the instrument *total spinout failures*, which measures the total number of spinouts in the same industry that failed in the year prior to the focal spinout-year. We assume that the failure of similar spinouts in the prior year is exogenous to a focal spinout's closure, but that spinouts will receive fewer resources when redeployment is perceived to produce higher risks and lower rewards due to a decline in market attractiveness. This follows instruments that theorize that the closure of competitors' business units eases competitive market pressures, thus reducing the likelihood that a focal firm enters (Morandi Stagni et al., 2020). Indeed, declining competitive pressures can indicate lower potential returns (Fosfuri & Giarratana, 2009) and increasing competitive pressure through competitors market entry suggests higher potential returns (Zheng et al., 2016). To reduce unobserved heterogeneity, we include dummy variables for unit region, industry, and year in the first stage and for industry and year in the second stage regressions.

4 | RESULTS

Table 3 shows the descriptive statistics: Panel A for the first-stage sample [Hypothesis 1 (H1) and Hypothesis 2 (H2)] and Panel B for the second-stage sample (H3a/b and H4a/b). Online Supplement Tables S2 and S3 contain the correlation matrices for both samples. Table 3 (Panel A) shows that *industry relatedness* is high (mean = 0.801), indicating that most parents and spinouts are highly related. Table 3 (Panel B) shows that the average *P → U redeployment* (mean = $e^{0.249}$) and the average *U → P redeployment* (mean = $e^{0.017}$) are slightly above one employee, which is less than *external* (mean = $e^{1.313}$) or *labor-market hires* (mean = $e^{0.653}$). Both correlation matrices and variance inflation factor testing ($VIF_{mean} < 3.00$; $VIF_{max} = 3.88$ for *parent age*) indicate that multicollinearity is not a concern.

[12]We include *parent in different region*—a binary variable indicating whether the parent and spinout are in the same region—and *employee base*—the natural logarithm of the total number of employees at the end of the prior year—as control variables in the first stage. They are not included in the second stage, as they would be dropped in our fixed effects models (*parent in different region*) or introduce multicollinearity with transfers (*employee base*).

TABLE 3 Descriptive statistics.

		N	Mean	SD	Min	Max
Panel A: Redeployment						
1	Parent-to-unit redeployment	20,362	0.159	0.366	0	1
2	Parent-to-unit redeployment: Generalists	20,362	0.107	0.309	0	1
3	Parent-to-unit redeployment: Specialists	20,362	0.106	0.308	0	1
4	Unit-to-parent redeployment	20,362	0.017	0.129	0	1
5	Unit-to-parent redeployment: Generalists	20,362	0.011	0.102	0	1
6	Unit-to-parent redeployment: Specialists	20,362	0.009	0.093	0	1
7	Industry relatedness	20,362	0.801	0.239	0	1
8	Parent ownership	20,362	0.715	0.451	0	1
9	Parent in diff. region	20,362	0.244	0.430	0	1
10	Industry growth	20,362	0.032	0.100	−0.337	3.156
11	Employee base	20,362	0.936	1.203	0	7.460
12	Parent on spinout board	20,362	0.723	0.936	0	8
13	Board size	20,362	3.003	1.400	0	11
14	Parent age	20,362	2.042	0.804	0	3.045
15	Parent ROA	20,362	1.074	1.466	−9.514	9.781
16	Parent total assets	20,362	13.94	8.666	−18.71	27.05
17	Total parent spinouts	20,362	2.404	3.580	1	41
18	Sub-parents	20,362	0.347	2.647	0	159
19	Sub-parent ownership	20,362	0.031	0.104	0	0.921
20	Year	20,362	2010	3.182	2004	2015
21	Industry	20,362	5.038	2.201	0	8
22	Region	20,362	2.281	1.346	1	5
23	Total spinout exits	20,362	19.15	29.72	0	161
Panel B: Closure						
1	Closure	18,483	0.193	0.395	0	1
2	Parent-to-unit redeployment (ln)	18,483	0.249	0.708	0	7.541
3	Parent-to-unit redeployment: Generalists (ln)	18,483	0.168	0.603	0	7.432
4	Parent-to-unit redeployment: Specialists (ln)	18,483	0.139	0.479	0	6.658
5	Unit-to-parent redeployment (ln)	18,483	0.017	0.144	0	4.382
6	Unit-to-parent redeployment: Generalists (ln)	18,483	0.010	0.109	0	4.277
7	Unit-to-parent redeployment: Specialists (ln)	18,483	0.008	0.092	0	3.091
8	Industry relatedness	18,483	0.809	0.230	0	1
9	Parent ownership	18,483	0.707	0.455	0	1
10	Industry growth	18,483	0.032	0.100	−0.337	3.156
11	Total spinout assets	18,483	5.519	2.329	0	15.32
12	Sub-parent redeployment	18,483	0.024	0.199	0	4.654
13	External hires	18,483	1.313	1.183	0	7.660

TABLE 3 (Continued)

		N	Mean	SD	Min	Max
14	Labor market hires	18,483	0.653	0.943	0	6.915
15	CEO from parent	18,483	0.062	0.242	0	1
16	Parent on spinout board	18,483	0.739	0.942	0	8
17	Board size	18,483	3.078	1.385	0	11
18	Parent age	18,483	2.069	0.791	0	3.045
19	Parent ROA	18,483	1.078	1.452	−9.514	9.781
20	Parent total assets	18,483	14.17	8.550	−18.71	27.05
21	Total parent spinouts	18,483	2.305	3.413	1	41
22	Sub-parents	18,483	0.346	2.458	0	159
23	Sub-parent ownership	18,483	0.032	0.105	0	0.921
24	Year	18,483	2010	3.172	2004	2015
25	Industry	18,483	4.978	2.186	0	8

Note: Panel A contains the descriptive statistics of the first-stage regressions with different redeployment types as binary dependent variables. Panel B contains the descriptive statistics of the second-stage regressions with closure as dependent variable and different redeployment types as continuous independent variables.

Table 4 shows the first-stage probit models estimating the likelihood of $P \rightarrow U$ and $U \rightarrow P$ *redeployment* based on *industry relatedness*. *Industry relatedness* positively and significantly affects $P \rightarrow U$ *redeployment* (Model 1: $\beta = 1.552$, $p < .001$) and $U \rightarrow P$ *redeployment* (Model 2: $\beta = .285$, $p = .071$). This is in line with H1, predicting that parent–unit industry relatedness increases the likelihood of human capital redeployment. In absolute terms, when computing the relative probabilities (rp) from marginal effects (me) in Models 1 and 2 ($rp = [me_{same}/me_{unrelated}] - 1$), the probability for $P \rightarrow U$ *redeployment* within same-industry dyads (+1SD or 100% relatedness) is 83% greater than $P \rightarrow U$ *redeployment* within unrelated dyads (10% relatedness). When we compare same-industry and unrelated dyads (−2SD or 34% relatedness), the probability of same-industry dyads is 55% greater than $P \rightarrow U$ *redeployment* within unrelated dyads (−2SD). Similarly, the probability for $U \rightarrow P$ *redeployment* within same-industry dyads is 52% greater than $U \rightarrow P$ *redeployment* within unrelated dyads (10% relatedness). This difference remains large (34%) when we examine $U \rightarrow P$ *redeployment* between same-industry and unrelated dyads (−2SD).

Models 3 and 4 examine the effect of *industry relatedness* on $P \rightarrow U$ and $U \rightarrow P$ *redeployment of generalists*, indicating positive and significant associations (Model 3: $P \rightarrow U$, $\beta = 1.913$, $p < .001$; Model 4: $U \rightarrow P$, $\beta = .448$, $p = .015$). Models 5 and 6 show the effect of *industry relatedness* on $P \rightarrow U$ and $U \rightarrow P$ *redeployment of specialists*, also indicating a positive and significant association for $P \rightarrow U$ ($\beta = .942$, $p = .001$) but an insignificant association for $U \rightarrow P$ *redeployment of specialists*. To determine whether the positive effect of relatedness on human capital redeployment is stronger for generalists than for specialists (H2), we compare the slopes of both relationships in Models 3(4) and 5(6). To make both models comparable, we compute the marginal effects for both models at the means of all independent variables and plot the marginal effects for *industry relatedness*. Figure 1a,b shows that the slope for redeployment of generalists is steeper than the slope for redeployment of specialists for both $P \rightarrow U$ and $U \rightarrow P$, echoing the difference in coefficients. This provides support for H2, indicating that *industry relatedness* affects redeployment of generalists more strongly than redeployment of specialists.

TABLE 4 First-stage probit regressions on parent-to-unit and unit-to-parent redeployment.

DV: Redeployment by employee type Direction	(1) Probit All employees P → U	(2) Probit All employees U → P	(3) Probit Generalists P → U	(4) Probit Generalists U → P	(5) Probit Specialists P → U	(6) Probit Specialists U → P
P → U redeployment		0.135 (0.038)		0.105 (0.040)		0.054 (0.040)
Total spinout failures	−0.010 (0.003)	−0.003 (0.002)	−0.012 (0.003)	−0.003 (0.002)	−0.006 (0.003)	−0.003 (0.002)
Industry relatedness	1.552 (0.230)	0.285 (0.158)	1.913 (0.283)	0.448 (0.183)	0.942 (0.296)	0.106 (0.175)
Parent ownership	−0.471 (0.110)	0.959 (0.105)	−0.087 (0.121)	0.971 (0.122)	−0.339 (0.127)	0.842 (0.127)
Industry growth	0.582 (0.332)	−0.093 (0.405)	0.446 (0.400)	0.124 (0.373)	0.798 (0.427)	−0.925 (0.546)
Parent in diff. region	−0.809 (0.112)	−0.033 (0.075)	−0.776 (0.141)	−0.015 (0.083)	−0.710 (0.141)	−0.007 (0.085)
Employee base	0.519 (0.034)	0.176 (0.025)	0.467 (0.033)	0.158 (0.030)	0.416 (0.035)	0.203 (0.028)
Parent on spinout board	0.237 (0.046)	0.135 (0.030)	0.227 (0.053)	0.113 (0.034)	0.228 (0.055)	0.155 (0.033)
Board size	0.138 (0.034)	−0.056 (0.026)	0.107 (0.040)	−0.046 (0.029)	0.183 (0.039)	−0.072 (0.030)
Parent age	1.116 (0.090)	−0.014 (0.048)	1.064 (0.101)	−0.005 (0.054)	1.027 (0.096)	−0.002 (0.055)
Parent ROA	−0.027 (0.022)	−0.006 (0.022)	−0.011 (0.025)	0.022 (0.025)	−0.022 (0.031)	−0.034 (0.025)
Parent total assets	−0.003 (0.005)	0.009 (0.005)	−0.011 (0.005)	0.003 (0.005)	0.006 (0.006)	0.019 (0.007)
Total parent spinouts	−0.110 (0.021)	−0.077 (0.021)	−0.133 (0.034)	−0.076 (0.023)	−0.080 (0.021)	−0.096 (0.025)
Sub-parents	0.046 (0.017)	−0.052 (0.035)	0.021 (0.013)	−0.196 (0.120)	0.043 (0.016)	−0.022 (0.022)
Sub-parent ownership	−0.281 (0.406)	−0.367 (0.515)	−0.045 (0.475)	0.031 (0.733)	−0.133 (0.480)	−0.666 (0.640)
Constant	−8.624 (0.450)	−4.423 (0.445)	−8.923 (0.528)	−3.913 (0.357)	−8.836 (0.570)	−4.071 (0.479)
Year, industry, region dummies	Yes	Yes	Yes	Yes	Yes	Yes
Unit-years	20,362	13,398	20,362	13,056[a]	20,362	13,398

TABLE 4 (Continued)

DV: Redeployment by employee type Direction	(1) Probit All employees P → U	(2) Probit All employees U → P	(3) Probit Generalists P → U	(4) Probit Generalists U → P	(5) Probit Specialists P → U	(6) Probit Specialists U → P
Units	9248	4259	9248	4162[a]	9248	4259
Chi^2	615.8	339.9	527.9	224.5	571.5	241.8
Loglikelihood	−4125	−1664	−3074	−1211	−3145	−1060

Note: The table contains the first-stage regressions with industry relatedness as main independent variable and different types of human capital redeployment as dependent variables. All models are panel probit models with standard errors clustered at the unit level in parentheses. Models 1 and 2 estimate the likelihood of redeployment for all employees, Models 3 and 4 estimate the likelihood of generalists, and Models 5 and 6 estimate the likelihood of specialists. Models 1, 3, and 5 estimate the likelihood of P → U redeployment and Models 2, 4, and 6 estimate the likelihood of U → P redeployment. Models 1, 3, and 5 contain observations from unit age = 2 as no U → P redeployment can be detected before employees have worked at the unit in its inception year.

[a]Year 2004 predicts failure perfectly, leading to a loss of observations.

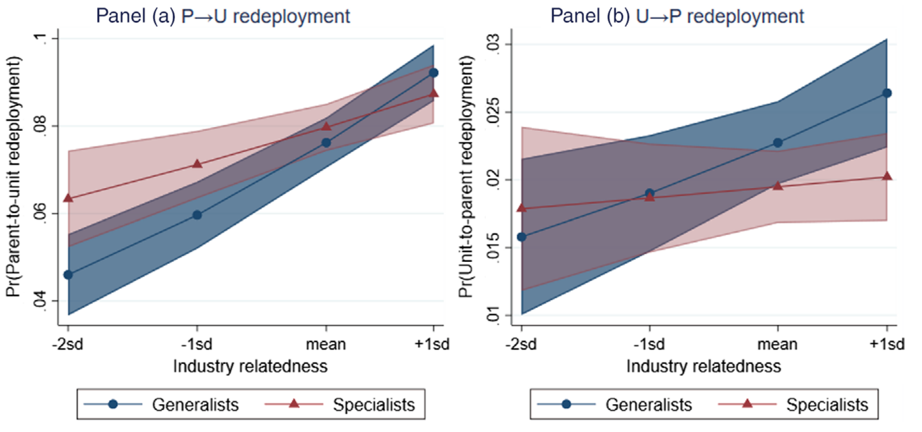

FIGURE 1 Parent-unit-industry relatedness and different redeployment types. Panel a contains the graphs for P → U redeployment of generalists and specialists, while Panel b contains the graphs for U → P redeployment of generalists and specialists. Graphs are based on marginal effects analyses of Table 3. Shaded areas depict 95% confidence intervals of the marginal effects.

Table 5 shows the second-stage results of the Cox regressions, which estimate the effects of *P → U* and U → P redeployment on *closure*. The coefficients of the first-stage residuals are significant throughout, indicating that there is a selection effect that does not further influence the association between redeployment and closure (Alvarez-Garrido & Dushnitsky, 2016). To further validate instrument strength, we mirror Wooldridge's (2010, pp. 809–813) approach for the strong instrument test in nonlinear control functions by adding the first stage residuals as an additional instrument in the first stage of a 2SLS regression. The Stock–Yogo *F*-value in this case is 19.93 and well above the commonly acknowledged threshold of 10 (Stock & Yogo, 2005).[13]

Model 1 (Table 5) estimates the effect of *P → U redeployment* on *closure*, finding a negative and significant effect ($\beta = -.544$, $p = .003$). This is in line with H3a, which predicts such a negative relationship. The redeployment of one additional parent employee reduces the likelihood of *closure* by ~29% in absolute terms.[14] Model 2 estimates the effect of *U → P redeployment* on *closure*, finding a positive and significant effect ($\beta = .284$, $p = .001$). This is in line with H3b, suggesting that U → P redeployment is positively associated with the likelihood of *closure*. In absolute terms, the U → P redeployment of one additional employee increases the likelihood of *closure* by ~23%. Both effects are stable in Model 3, which includes *P → U redeployment* ($\beta = -.542$, $p = .003$) and *U → P redeployment* ($\beta = .272$, $p = .001$).

To determine whether the negative effect of P → U redeployment on unit closure is stronger for specialists than for generalists (H4a), we compare the coefficients, which rely on the same unit and transformation. We also run interaction models to test for the disproportionate effects of idiosyncratic redeployment patterns. For *P → U redeployment of generalists*, the results are consistently and mostly significantly negative across multiple specifications: generalists only

[13]We use performance as dependent variable for the 2SLS, which mirrors the mechanism tests that are discussed later in the manuscript. Results of redeployment on performance are positive and significant in the 2SLS specification.

[14]To obtain the true coefficient, it must be transformed, so that $\beta_{real} = (\exp(\beta) - 1) \times \ln(1 + \Delta y)$.

TABLE 5 Second-stage Cox proportional hazards models on closure.

DV: Closure	(1) Cox	(2) Cox	(3) Cox	(4) Cox	(5) Cox	(6) Cox	(7) Cox	(8) Cox	(9) Cox	(10) Cox	(11) Cox	(12) Cox	(13) Cox
P → U redeployment (ln)	−0.544 (0.185)		−0.542 (0.185)										
U → P redeployment (ln)		0.284 (0.083)	0.272 (0.083)										
P → U redep. generalists (ln)				−0.381 (0.191)		−0.266 (0.181)	−0.894 (0.240)					−0.261 (0.180)	−0.887 (0.240)
P → U redep. specialists (ln)					−0.534 (0.274)	−0.388 (0.266)	−1.256 (0.315)					−0.387 (0.265)	−1.257 (0.315)
P → U redep. gen × spec (ln)							0.728 (0.072)						0.725 (0.072)
U → P redep. generalists (ln)								0.162 (0.088)		−0.041 (0.107)	0.138 (0.142)	−0.033 (0.100)	0.129 (0.137)
U → P redep. specialists (ln)									0.454 (0.151)	0.475 (0.160)	0.712 (0.212)	0.452 (0.158)	0.661 (0.204)
U → P redep. gen × spec (ln)											−0.274 (0.140)		−0.267 (0.135)
Industry relatedness	−0.145 (0.037)	−0.220 (0.040)	−0.149 (0.037)	−0.184 (0.038)	−0.181 (0.039)	−0.167 (0.038)	−0.114 (0.035)	−0.216 (0.040)	−0.222 (0.040)	−0.222 (0.040)	−0.224 (0.040)	−0.174 (0.039)	−0.122 (0.035)
Parent ownership	1.767 (0.168)	1.763 (0.167)	1.764 (0.168)	1.775 (0.167)	1.758 (0.168)	1.766 (0.168)	1.705 (0.147)	1.765 (0.167)	1.765 (0.167)	1.765 (0.167)	1.764 (0.167)	1.765 (0.168)	1.702 (0.147)
Industry growth	−0.133 (0.082)	−0.159 (0.082)	−0.129 (0.082)	−0.152 (0.082)	−0.144 (0.082)	−0.141 (0.082)	−0.123 (0.081)	−0.161 (0.082)	−0.164 (0.082)	−0.165 (0.082)	−0.166 (0.082)	−0.142 (0.082)	−0.125 (0.082)
Total spinout assets	0.004 (0.003)	0.002 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.004 (0.003)	0.005 (0.002)	0.003 (0.003)	0.002 (0.003)	0.002 (0.003)	0.002 (0.003)	0.004 (0.003)	0.004 (0.002)
Sub-parent redeployment	0.008 (0.395)	−0.099 (0.386)	0.002 (0.395)	−0.011 (0.390)	−0.073 (0.384)	−0.022 (0.390)	−0.064 (0.338)	−0.096 (0.386)	−0.090 (0.384)	−0.088 (0.384)	−0.092 (0.385)	−0.021 (0.389)	−0.065 (0.338)
External hires	−2.208 (0.112)	−2.212 (0.112)	−2.201 (0.112)	−2.215 (0.112)	−2.213 (0.112)	−2.211 (0.112)	−2.242 (0.114)	−2.216 (0.112)	−2.213 (0.112)	−2.213 (0.112)	−2.210 (0.112)	−2.206 (0.112)	−2.233 (0.114)
Labor market hires	−1.208 (0.179)	−1.237 (0.180)	−1.201 (0.179)	−1.226 (0.179)	−1.231 (0.178)	−1.221 (0.178)	−1.326 (0.179)	−1.242 (0.180)	−1.239 (0.179)	−1.240 (0.179)	−1.237 (0.180)	−1.215 (0.178)	−1.318 (0.180)
CEO from parent	−1.920 (0.306)	−2.428 (0.312)	−1.912 (0.306)	−2.263 (0.299)	−2.160 (0.287)	−2.090 (0.291)	−1.670 (0.331)	−2.436 (0.312)	−2.429 (0.312)	−2.429 (0.312)	−2.425 (0.312)	−2.083 (0.290)	−1.660 (0.331)
Parent on spinout board	0.003 (0.007)	−0.010 (0.008)	0.000 (0.007)	−0.004 (0.008)	−0.002 (0.008)	−0.001 (0.008)	0.007 (0.007)	−0.008 (0.008)	−0.011 (0.008)	−0.011 (0.008)	−0.011 (0.008)	−0.004 (0.008)	0.004 (0.007)
Board size	−0.003 (0.006)	−0.009 (0.007)	−0.003 (0.006)	−0.007 (0.007)	−0.008 (0.007)	−0.006 (0.007)	0.001 (0.006)	−0.009 (0.007)	−0.009 (0.007)	−0.009 (0.007)	−0.009 (0.007)	−0.006 (0.007)	0.001 (0.006)
Parent age	−0.079 (0.019)	−0.131 (0.021)	−0.081 (0.019)	−0.106 (0.020)	−0.104 (0.021)	−0.095 (0.021)	−0.058 (0.018)	−0.129 (0.021)	−0.131 (0.021)	−0.131 (0.021)	−0.131 (0.021)	−0.097 (0.021)	−0.060 (0.018)
Parent ROA	−0.006 (0.003)	−0.004 (0.003)	−0.006 (0.003)	−0.005 (0.003)	−0.005 (0.003)	−0.005 (0.003)	−0.006 (0.003)	−0.004 (0.003)	−0.004 (0.003)	−0.004 (0.003)	−0.004 (0.003)	−0.005 (0.003)	−0.005 (0.003)
Parent total assets	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.005 (0.001)	0.004 (0.001)
Total parent spinouts	0.011 (0.003)	0.017 (0.003)	0.011 (0.003)	0.014 (0.003)	0.014 (0.003)	0.013 (0.003)	0.008 (0.003)	0.017 (0.003)	0.017 (0.003)	0.017 (0.003)	0.017 (0.003)	0.013 (0.003)	0.008 (0.003)
Sub-parents	0.131 (0.034)	0.132 (0.033)	0.131 (0.033)	0.132 (0.034)	0.132 (0.034)	0.132 (0.034)	0.119 (0.014)	0.132 (0.034)	0.132 (0.034)	0.132 (0.034)	0.132 (0.033)	0.131 (0.034)	0.118 (0.014)
Sub-parent ownership	−0.508 (0.208)	−0.504 (0.209)	−0.503 (0.207)	−0.515 (0.210)	−0.511 (0.209)	−0.513 (0.209)	−0.438 (0.110)	−0.508 (0.210)	−0.506 (0.209)	−0.506 (0.209)	−0.505 (0.208)	−0.509 (0.208)	−0.433 (0.109)
First stage residuals	−0.005 (0.001)	−0.008 (0.001)	−0.005 (0.001)	−0.006 (0.001)	−0.006 (0.001)	−0.005 (0.001)	−0.003 (0.001)	−0.007 (0.001)	−0.008 (0.001)	−0.008 (0.001)	−0.008 (0.001)	−0.006 (0.001)	−0.003 (0.001)

TABLE 5 (Continued)

DV: Closure	(1) Cox	(2) Cox	(3) Cox	(4) Cox	(5) Cox	(6) Cox	(7) Cox	(8) Cox	(9) Cox	(10) Cox	(11) Cox	(12) Cox	(13) Cox
Year and industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit-years	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483	18,483
Units	7974	7974	7974	7974	7974	7974	7974	7974	7974	7974	7974	7974	7974
Chi^2	2076	1984	2142	1991	2019	2049	2168	1951	1958	1957	1994	2083	2254
Loglikelihood	−28,505	−28,520	−28,503	−28,515	−28,514	−28,512	−28,462	−28,521	−28,519	−28,519	−28,518	−28,509	−28,459

Note: The table contains the second-stage regressions with human capital redeployment as main independent variable and closure as the dependent variable. All models are Cox regression models with robust standard errors clustered at the unit level in parentheses. All models estimate the probability of closure whereby Models 1–3 present findings for all redeployed employees by direction, Models 4–7 for P → U redeployment of generalists and specialists, Models 8–11 for U → P redeployment of generalists and specialists, and Models 12 and 13 combine both directions.

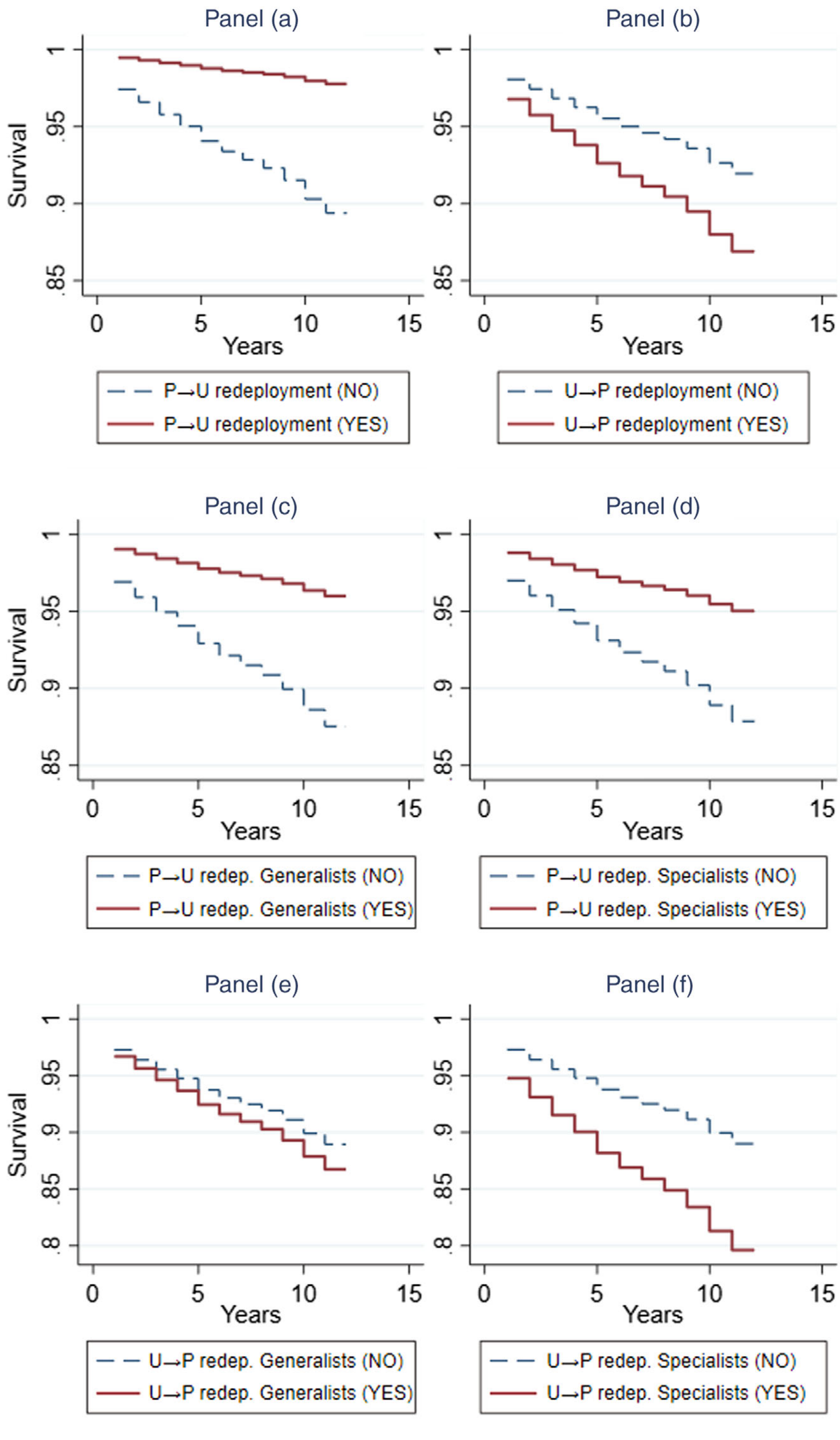

FIGURE 2 Legend on next page.

(Model 4: $\beta = -.381$, $p = .046$), generalists and specialists (Model 6: $\beta = -.266$, $p = .141$), generalist–specialist interaction (Model 7: $\beta = -.894$, $p < .001$), full model with all P → U and U → P redeployment (Model 12: $\beta = -.261$, $p = .147$), and full model with all P → U and U → P generalist–specialist interactions (Model 13: $\beta = -.887$, $p < .001$). This suggests that *P → U redeployment of generalists* is associated with a lower likelihood of *closure*.

The results for *P → U redeployment of specialists* follow the same pattern across model specifications: specialists only (Model 5: $\beta = -.534$, $p = .051$), generalists and specialists (Model 6: $\beta = -.388$, $p = .144$), generalist–specialist interaction (Model 7: $\beta = -1.256$, $p < .001$), full model with all P → U and U → P redeployment (Model 12: $\beta = -.387$, $p = .145$), and full model with all P → U and U → P generalist-specialist interactions (Model 13: $\beta = -1.257$, $p < .001$). Wald tests indicate no difference between coefficients (Model 6: $\chi^2 = .15$, $p = .696$; Model 7: $\chi^2 = .69$, $p = .406$; Model 12: $\chi^2 = .16$, $p = .406$; Model 13: $\chi^2 = .72$, $p = .395$). Thus, H4a cannot be confirmed because *P → U redeployment* of both employee types affects closure similarly strong.

To determine whether the positive effect of U → P redeployment on *closure* is stronger for specialists than for generalists (H4b), we repeat the previous process. For U → P *redeployment of generalists*, the results are consistently insignificant irrespective of model specification. In contrast, *U → P redeployment of specialists* is consistently and significantly associated with a higher likelihood of *closure*: specialists only (Model 9: $\beta = .454$, $p = .003$), generalists and specialists (Model 10: $\beta = .475$, $p = .003$), generalist–specialist interaction (Model 11: $\beta = .712$, $p = .001$), full model with all P → U and U → P redeployment (Model 12: $\beta = .452$, $p = .004$), and full model with all P → U and U → P generalist–specialist interactions (Model 13: $\beta = .661$, $p = .001$). We again compare the coefficients (Model 10: $\chi^2 = 5.42$, $p = .019$; Model 11: $\chi^2 = 6.19$, $p = .013$; Model 12: $\chi^2 = 5.13$, $p = .024$; Model 13: $\chi^2 = 5.86$, $p = .016$) and find that the coefficients for *U → P redeployment of generalists* and *U → P redeployment of specialists* are substantially different. This provides support for H4b.

Figure 2 contains Kaplan–Meier survival plots that show the heterogeneity of closure over time. Panels a and b are based on Table 5 (Model 3) and panels C–F on Table 5 (Model 12). Panel a reiterates that *P → U redeployment* is negatively associated with *closure* and Panel b that *U → P redeployment* is positively associated with *closure*, providing evidence for H3a/b. Panel c (*P → U redeployment of generalists*) and Panel d (*P → U redeployment of specialists*) reiterate the lack of a distinction between the two effects, providing no evidence for H4a. Finally, panel e (*U → P redeployment of generalists*) and panel f (*U → P redeployment of specialists*) provide further support for the distinction between the two effects, supporting H4b.

4.1 | Performance as a mechanism

To test the performance mechanism underlying H3a/b and H4a/b, we re-estimate the second-stage analysis with a panel OLS on *performance*. Unit *performance* is operationalized as the

FIGURE 2 Kaplan–Meier plots showing effects of redeployment on closure over time. Figure depicts the effects of Cox models with adjusted covariates on closure reported in Table 4. Panel a (b) contains the graphs for *P → U* (*U → P*) redeployment (Model 3). Panels c and d contain the graphs for *P → U* of generalists and specialists respectively and Panels e and f contain the graphs for *U → P* of generalists and specialists respectively (Model 12).

natural logarithm of unit revenues in thousands of Norwegian kroner. Given that spinouts need years to attain profitability (Chesbrough, 2003), revenue is a useful performance indicator. We measure performance forwarded by 1 year to lessen concerns of reverse causality and to account for training and socialization in employee mobility (Brymer & Sirmon, 2018). Table 6 contains the models with *performance* as the dependent variable. We estimate fixed effects models to control for unobserved heterogeneity and because we are interested in within-unit changes in *performance*. There are 9248 spinouts in the main analyses and 3798 in the analyses of *performance*. This is due to missing values in *performance* and the forwarding of *performance* $(t + 1)$.

Substantiating the mechanism behind H3a and H3b (Table 6), Models 1 ($\beta = .157$, $p = .022$) and 3 ($\beta = .168$, $p = .013$) show that *P → U redeployment* is associated with increased performance. This is mirrored for *U → P redeployment* in Models 2 ($\beta = -.252$, $p = .012$) and 3 ($\beta = -.268$, $p = .007$) which show that *U → P redeployment* is associated with lower *performance*. Revenues increase by ~1.5% with a 10% increase in *P → U redeployment*.[15] Revenues decrease by ~2.4% for a 10% increase in *U → P redeployment*. While we cannot fully discard that there is a selection effect—expected closure affects *U → P redeployment*—in addition to our proposed treatment effect, we do not find a tendency for such selection in the data. In the unrestricted sample with 20,362 unit-year observations, parents use *U → P* redeployment in 351 unit-years, but only 51 occurrences are in a closure year or in the year before closure (15%). Similarly, prior studies find that parents redeploy resources from high-performing units to underperforming units to strengthen their performance (Belenzon et al., 2019; Cabral et al., 2020).

The models on *closure* (Table 5) showed that the coefficients for *P → U redeployment of specialists* are larger than those for *P → U redeployment of generalists*, even though they are not statistically different. This may be explained by the differences in the effects on performance, substantiating the mechanism behind H4a. Examining the coefficients for *P → U redeployment of generalists* across models in Table 6 (Model 4: $\beta = .046$, $p = .473$; Model 6: $\beta = -.059$, $p = .372$; Model 7: $\beta = .025$, $p = .712$; Model 12: $\beta = -.046$, $p = .487$; Model 13: $\beta = .039$, $p = .565$), we do not find a significant relationship with *performance*. In contrast, *P → U redeployment of specialists* is significantly and positively related to *performance* in all models (Model 5: $\beta = .262$, $p = .009$; Model 6: $\beta = .292$, $p = .005$; Model 7: $\beta = .389$, $p = .002$; Model 12: $\beta = .297$, $p = .005$; Model 13: $\beta = .395$, $p = .002$). Overall, we cannot confirm H4a because *P → U redeployment of specialists* and *P → U* redeployment *of generalists* influences *closure* similarly. However, we provide evidence for our proposed mechanism that *P → U redeployment of specialists* contributes more strongly to unit performance than *P* → U redeployment *of generalists*.

Finally, we address the mechanism behind H4b and test whether *U → P redeployment of specialists* affects *performance* more strongly than *U → P redeployment of generalists*. Examining the coefficients for *U → P redeployment of generalists* across models in Table 6 (Model 8: $\beta = -.295$, $p = .026$; Model 10: $\beta = -.226$, $p = .048$; Model 11: $\beta = -.171$, $p = .143$; Model 12: $\beta = -.241$, $p = .034$; Model 13: $\beta = -.189$, $p = .106$), we find a consistent and mostly significantly negative relationship with *performance*, in line with our predictions. Similarly, *U → P redeployment of specialists* is negatively related to *performance*, but this relationship is not consistently significant (Model 9: $\beta = -.310$, $p = .052$; Model 10: $\beta = -.229$, $p = .109$; Model 10: $\beta = -.154$, $p = .250$; Model 12: $\beta = -.230$, $p = .107$; Model 13: $\beta = -.167$, $p = .211$). Thus, there

[15]To obtain the true coefficient, it must be transformed, so that $\Delta(y) = (1 + \Delta(x))^{\beta(x)} - 1$.

TABLE 6 Second stage fixed effects regressions on unit performance.

DV: Performance	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE	(9) FE	(10) FE	(11) FE	(12) FE	(13) FE
P → U redeployment (ln)	0.157 (0.068)		0.168 (0.068)										
U → P redeployment (ln)		−0.252 (0.100)	−0.268 (0.100)										
P → U redep. generalists (ln)				0.046 (0.064)		−0.059 (0.066)	0.025 (0.067)					−0.046 (0.066)	0.039 (0.067)
P → U redep. specialists (ln)					0.262 (0.101)	0.292 (0.105)	0.389 (0.126)					0.297 (0.104)	0.395 (0.125)
P → U redep. gen × spec (ln)							−0.074 (0.040)						−0.074 (0.040)
U → P redep. generalists (ln)								−0.295 (0.133)		−0.226 (0.114)	−0.171 (0.117)	−0.241 (0.114)	−0.189 (0.117)
U → P redep. specialists (ln)									−0.310 (0.159)	−0.229 (0.143)	−0.154 (0.134)	−0.230 (0.143)	−0.167 (0.133)
U → P redep. gen × spec (ln)											−0.142 (0.299)		−0.133 (0.299)
Full control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Unit-years	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951	11,951
Units	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798	3798
Within-R^2	0.131	0.131	0.132	0.130	0.131	0.131	0.132	0.131	0.130	0.131	0.131	0.133	0.133
F-value	12.82	12.68	12.53	12.74	12.91	12.57	12.25	12.68	12.65	12.32	12.03	11.95	11.43

Note: The table contains the regressions with human capital redeployment as main independent variable and unit performance as the dependent variable. All models are FE OLS regression models with robust standard errors clustered at the unit level in parentheses. All models estimate unit performance whereby Models 1–3 present findings for all redeployed employees by direction, Models 4–7 for P → U redeployment of generalists and specialists, Models 8–11 for U → P redeployment of generalists and specialists, and Models 12 and 13 combine both directions.

is no indication that *U → P redeployment of specialists* has a stronger relationship with *performance* than *U → P redeployment of generalists*. While both are negatively related to *performance*, this relationship is more consistent for *U → P redeployment of generalists*. In summary, we find support for our proposed mechanism for both *P → U* and *U → P* redeployment, as both consistently affect performance. However, while *P → U redeployment of specialists* is more strongly related to *performance* than *P → U redeployment of generalists*, the same does not apply for *U → P* redeployment.

To further validate our findings on performance and check whether our results suffer from endogeneity biases due to the inherently entangled nature of P → U and U → P redeployment, we use system GMM models to re-examine the effects on performance. We explain this approach in-depth and present the findings in Table S4 in the Online Supplement. All results remain consistent for *P → U redeployment* and *performance*, but not for *U → P redeployment*, probably stemming from a further loss of observations, as we must lag the dependent variable to avoid overidentification in system GMM. To eliminate alternative explanations for these results, we test whether the antecedents of *U → P redeployment* may further differ from those of *P → U redeployment*, which may explain in part which units are selected for *U → P redeployment*. We re-test the effect of parent ownership on the likelihood of redeployment similar to Belenzon et al. (2019) in post hoc tests and generally confirm findings on the positive effects of ownership (See the discussion and Figures S1 and S2 in the Online Supplement). Yet, we find that parent ownership may affect P → U and U → P redeployment differently. P → U redeployment increases linearly with relatedness for any unit but is less likely for majority-owned units. In contrast, U → P redeployment is more likely for majority-owned units at any level of relatedness.

5 | DISCUSSION

We examine the antecedents and outcomes of human capital redeployment. Analyzing a population dataset of Norwegian spinouts, we find robust empirical evidence that parent–unit industry relatedness is positively associated with parent-to-unit and unit-to-parent human capital redeployment. This is consistent with prior research, which has found that firms redeploy managers to structurally similar units (Karim & Williams, 2012) and that firms have lower redeployment costs when the sending and receiving units are in similar industries (Sakhartov & Folta, 2014).

Extending current literature, we show that the relatedness–redeployment relationship varies with employee characteristics. We show that the redeployment of generalists (i.e., employees with a broader body of knowledge that is not tied to a particular domain) is more strongly affected by parent–unit industry relatedness than that of specialists (i.e., those with a narrower but deeper body of knowledge that is more closely tied to a specific domain). We attribute this to generalists' tendency to develop human capital profiles that are more specific to an industry or firm (Lazear, 2009). Such human capital is more difficult to transfer between dissimilar industries. Thus, inducements to redeploy human capital within multi-business firms depend on employees' human capital profiles. The finding that individuals' human capital imposes limits on internal mobility complements arguments of the strategic human capital literature that individual and organizational factors are complements (Crocker & Eckardt, 2014; Stadler et al., 2022).

Regarding the direction of redeployment, we show that industry relatedness affects the likelihood of redeployment in both directions. This is important, as prior work mostly assumes unidirectional redeployment (e.g., Karim & Williams, 2012; Stadler et al., 2022) and does not test whether boundary conditions hold for multidirectional redeployment. This extends prior work that examines the performance implications of re-hiring former employees (Keller et al., 2021) by showing that the likelihood of unit-to-parent redeployment depends in part on the characteristics of the individuals and the parent–unit relationship (e.g., industry relatedness, and ownership ties).

Regarding the outcomes of redeployment, we extend research that has focused on receiving units' productivity post-redeployment (Stadler et al., 2022) and temporary mobility (Choudhury, 2017). While prior work distinguishes between neither redeployment directions nor employee characteristics, we take both into account. We find that the likelihood of unit closure decreases with P → U redeployment and increases with U → P redeployment. We attribute this to post-P → U redeployment performance gains and post-U → P redeployment performance losses, respectively. We examine these performance effects, finding that P → U redeployment increases the receiving unit's post-redeployment financial performance, while U → P redeployment decreases it. This extends work that has found that strong parent–subsidiary ties reduce failure (Bradley et al., 2011).

We further test whether performance effects differ between P → U and U → P redeployment of specialists and generalists. We find that both generalist and specialist P → U redeployment decreases the likelihood of unit closure. However, specialist P → U redeployment is associated with higher financial performance of the receiving unit, while generalist P → U redeployment is not. Human capital ties to the parent are generally important for business units, because they constitute a bidirectional channel between both firms (Corredoira & Rosenkopf, 2010), facilitating spill-ins of knowledge for the parent (Kim & Steensma, 2017). Thus, parent–unit human capital ties may explain the similar effects of P → U redeployment of generalists and specialists on unit closure.

The fungibility of firm-specific human capital may create a paradox in which parents are more likely to redeploy generalists to related units in which they can use a substantial part of their firm-specific human capital efficiently, while they redeploy specialists on average to more unrelated units in which they can use a substantial part of their discipline knowledge, but less of their firm-specific human capital. For example, Huckman and Pisano (2006) show that individual performance of surgeons (specialists) that operate at different hospitals during the same time period perform better when they have generated experience at the same hospital. This reinforces the notion that a specialist with more firm-specific human capital should have a greater effect on a unit than an otherwise identical specialist with less firm-specific human capital (Becker, 1962; Lazear, 2009). In our context, this may mean that specialists are on average redeployed to more unrelated units than generalists. In those more unrelated units, specialists can use their firm-specific human capital to a lesser extent, which limits their effect on unit closure.

We further find that the effects of U → P redeployment on unit closure are largely different for generalists and specialists. Specialist U → P redeployment increases post-redeployment unit closure, while generalist U → P redeployment does not. Examining these dynamics further, we test whether financial performance is the underlying mechanism of these closure patterns. We find that reductions in performance after U → P redeployment are similar for specialists and generalists, but not consistently significant. Thus, lower performance after U → P redeployment does not seem to drive unit closure. Therefore, even though our study reconfirms employee turnover's negative effect on firm performance (Hausknecht & Holwerda, 2013; Shaw et al., 2013; Stern et al., 2021), this does not seem to be the main reason for differences in effects on unit closure between U → P redeployment of specialists and generalists.

A plausible explanation for this finding is related to parent–unit knowledge exchanges. The strategic human capital literature argues that units in multi-business firms that have fewer interpersonal exchanges about knowledge and innovation-related projects receive fewer resources from the controlling unit over time (Choudhury, 2017). In our case, U → P redeployment of specialists may diminish such parent–unit exchanges, reducing access to other resources and ultimately increasing the likelihood of closure. This may be so, as specialists are particularly involved in knowledge exchange. However, interfirm ties are unlikely to completely dissolve after U → P redeployment. Units are likely to retain an informal communication channel with the parent after U → P redeployment (Kim & Steensma, 2017), which may help to align their goals with the parent, affecting closure despite performance below expectations.

5.1 | Limitations and future research

Our study faces limitations. While the unit closure results are mostly consistent with the proposed mechanism of post-redeployment performance, we cannot directly test the redeployment of other non–scale free resources. For example, rather than redeploying employees, parents may transfer equity to allow units to hire externally. We do not detect such equity transfers except for ownership shares. Similarly, it is not possible to determine whether employees remain formally employed with the parent but work with the unit; our analysis only registers formal changes of employment. However, it is likely that core roles and decision-makers must be formally filled at the unit to be operational. As those roles are rarely informal, such cases are expected to be negligible. Interviews with firms confirm that it is unusual to informally switch employees to spinout companies for extended periods due to workload, internal organization, and formal labor regulations. Future studies could aim to address informal arrangements of employee mobility.

Further, it is important to note that horizontal resource allocation instead of vertical resource allocation could have been studied (Sengul et al., 2019). However, while horizontal allocation has been studied with product-market entry and exit (e.g., Giarratana & Santalo, 2020; Wu, 2013), studying vertical allocation is more suitable for human capital redeployment. Human capital redeployment requires direct contact and decision-making rights between the sending firm and the receiving firm, in addition to individual employee consent. Those conditions are more typically occurring in vertical ownership relations in comparison to horizontal group affiliation in which the sending firm may have no decision-making powers over the receiving firm.

It should be noted that notwithstanding the use of a two-stage design and system GMM to reduce endogeneity concerns, further factors may limit causal inferences, such as non-observable differences between related and unrelated spinouts and the heterogeneity of redeployed human capital. While we address human capital heterogeneity by creating two groups based on formally obtained education, other experience-based criteria may be valuable to consider in further studies. To spark interest and enable such research, we provide individual-level descriptive statistics of the redeployed employees. Finally, while Norway is similar to other high-income OECD countries, scholars should investigate whether its social security system and labor laws influence redeployment. While prior studies on strategic management in Norway have found generalizable results (e.g., Greve, 2008; Sasson, 2008), research has also shown that redeployment in various institutional environments may differ (Belenzon & Tsolmon, 2016).

In conclusion, our study focuses on the analysis of parent-to-unit and unit-to-parent human capital redeployment. We show that human capital characteristics, the direction of redeployment, and parent–unit relatedness affect the likelihood of human capital redeployment and post-redeployment unit closure and financial performance. This extends the nascent literature on micro-foundations of redeployment. We hope that future research will explore additional individual-level characteristics of the redeployed, incorporate the direction of redeployment, and study the behavioral outcomes of redeployment, such as the development of redeployment experience or human capital allocation experience in general.

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DATA AVAILABILITY STATEMENT

The data are subject to third party restrictions and cannot be shared. The data that support this study are available from Statistics Norway (SSB) and are subject to confidentiality. Access to these data is restricted and under NDA.

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REFERENCES

Almeida, H. V., & Wolfenzon, D. (2006). A theory of pyramidal ownership and family business groups. *The Journal of Finance*, *61*(6), 2637–2680.

Alvarez-Garrido, E., & Dushnitsky, G. (2016). Are entrepreneurial venture's innovation rates sensitive to investor complementary assets? Comparing biotech ventures backed by corporate and independent VCs. *Strategic Management Journal*, *37*(5), 819–834.

Becker, G. S. (1962). Investment in Human Capital: A theoretical analysis. *Journal of Political Economy*, *70*(5), 9–49.

Becker, G. S., & Murphy, K. M. (1992). The division of labor, coordination costs, and knowledge. *The Quarterly Journal of Economics*, *107*(4), 1137–1160.

Belenzon, S., Hashai, N., & Patacconi, A. (2019). The architecture of attention: Group structure and subsidiary autonomy. *Strategic Management Journal*, *40*(10), 1610–1643.

Belenzon, S., & Tsolmon, U. (2016). Market frictions and the competitive advantage of internal labor markets. *Strategic Management Journal*, *37*(7), 1280–1303.

Benson, A., & Rissing, B. (2020). Strength from within: Internal mobility and the retention of high performers. *Organization Science*, *31*(6), 1475–1496.

Bentley, F. S., & Kehoe, R. R. (2020). Give them some slack—They're trying to change! The benefits of excess cash, excess employees, and increased human Capital in the Strategic Change Context. *Academy of Management Journal*, *63*(1), 181–204.

Berry, H. (2013). When do firms divest foreign operations? *Organization Science*, *24*(1), 246–261.

Bidwell, M. (2013). What happened to long-term employment? The role of worker power and environmental turbulence in explaining declines in worker tenure. *Organization Science*, *24*(4), 1061–1082.

Bidwell, M., & Keller, J. (2014). Within or without? How firms combine internal and external labor markets to fill jobs. *Academy of Management Journal*, *57*(4), 1035–1055.

Bradley, S. W., Aldrich, H., Shepherd, D. A., & Wiklund, J. (2011). Resources, environmental change, and survival: Asymmetric paths of young independent and subsidiary organizations. *Strategic Management Journal*, *32*(5), 486–509.

Brymer, R. A., & Sirmon, D. G. (2018). Pre-exit bundling, turnover of professionals, and firm performance. *Journal of Management Studies*, *55*(1), 146–173.

Buenstorf, G., & Costa, C. (2018). Drivers of spin-off performance in industry clusters: Embodied knowledge or embedded firms? *Research Policy*, *47*(3), 663–673.

Cabral, J. J., Deng, C., & Kumar, M. V. S. (2020). Internal resource allocation and external Alliance activity of diversified firms. *Journal of Management Studies*, *57*(8), 1690–1717.

Campbell, B. A., Coff, R., & Kryscynski, D. (2012). Rethinking sustained competitive advantage from human capital. *Academy of Management Review*, *37*(3), 376–395.

Capron, L. (1999). The long-term performance of horizontal acquisitions. *Strategic Management Journal*, *20*(11), 987–1018.

Capron, L., Dussauge, P., & Mitchell, W. (1998). Resource redeployment following horizontal acquisitions in Europe and North America, 1988–1992. *Strategic Management Journal*, *19*(7), 631–661.

Chatterjee, S., & Wernerfelt, B. (1991). The link between resources and type of diversification: Theory and evidence. *Strategic Management Journal*, *12*(1), 33–48.

Chen, G., Huang, S., Meyer-Doyle, P., & Mindruta, D. (2020). Generalist versus specialist CEOs and acquisitions: Two-sided matching and the impact of CEO characteristics on firm outcomes. *Strategic Management Journal*, *42*(6), 1184–1214.

Chen, M., Kaul, A., & Wu, B. (2019). Adaptation across multiple landscapes: Relatedness, complexity, and the long run effects of coordination in diversified firms. *Strategic Management Journal*, *40*(11), 1791–1821.

Chesbrough, H. (2003). The governance and performance of Xerox's technology spin-off companies. *Research Policy*, *32*(3), 403–421.

Choudhury, P. (2017). Innovation outcomes in a distributed organization: Intrafirm mobility and access to resources. *Organization Science*, *28*(2), 339–354.

Cirillo, B. (2019). External learning strategies and technological search output: Spinout strategy and corporate invention quality. *Organization Science*, *30*(2), 361–382.

Coff, R. W. (1997). Human assets and management dilemmas: Coping with hazards on the road to resource-based theory. *Academy of Management Review*, *22*(2), 374–402.

Corredoira, R., & Rosenkopf, L. (2010). Should auld acquaintance be forgot? The reverse transfer of knowledge through mobility ties. *Strategic Management Journal*, *31*(2), 159–181.

Crocker, A., & Eckardt, R. (2014). A multilevel investigation of individual- and unit-level human capital complementarities. *Journal of Management*, *40*(2), 509–530.

Custódio, C., Ferreira, M. A., & Matos, P. (2013). Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics*, *108*(2), 471–492.

Dickler, T. A., & Folta, T. B. (2020). Identifying internal markets for resource redeployment. *Strategic Management Journal*, *41*(13), 2341–2371.

Ertug, G., Kotha, R., & Hedström, P. (2020). Kin ties and the performance of new firms: A structural approach. *Academy of Management Journal*, *63*(6), 1893–1922.

Feldman, E. R., & Sakhartov, A. V. (2022). Resource redeployment and divestiture as strategic alternatives. *Organization Science*, *33*(3), 926–945.

Fosfuri, A., & Giarratana, M. S. (2009). Masters of war: Rivals' product innovation and new advertising in mature product markets. *Management Science*, *55*(2), 181–191.

Garicano, L. (2000). Hierarchies and the Organization of Knowledge in production. *Journal of Political Economy*, *108*(5), 874–904.

Giarratana, M. S., Pasquini, M., & Santalo, J. (2021). Leveraging synergies versus resource redeployment: Sales growth and variance in product portfolios of diversified firms. *Strategic Management Journal*, *42*(12), 2245–2272.

Giarratana, M. S., & Santalo, J. (2020). Transaction costs in resource redeployment for multiniche firms. *Organization Science*, *31*(5), 1159–1175.

Glaser, M., Lopez-De-Silanes, F., & Sautner, Z. (2013). Opening the black box: Internal capital markets and managerial power. *The Journal of Finance*, *68*(4), 1577–1631.

Grant, R. M. (1988). On 'Dominant Logic', relatedness and the link between diversity and performance. *Strategic Management Journal*, *9*(6), 639–642.

Greve, H. R. (2008). A behavioral theory of firm growth: Sequential attention to size and performance goals. *The Academy of Management Journal*, *51*(3), 476–494.

Groysberg, B., Lee, L.-E., & Nanda, A. (2008). Can they take it with them? The portability of star knowledge Workers' performance. *Management Science*, *54*(7), 1213–1230.

Hashai, N. (2015). Within-industry diversification and firm performance—An S-shaped hypothesis. *Strategic Management Journal*, *36*(9), 1378–1400.

Hausknecht, J. P., & Holwerda, J. A. (2013). When does employee turnover matter? Dynamic member configurations, productive capacity, and collective performance. *Organization Science*, *24*(1), 210–225.

Helfat, C., & Eisenhardt, K. (2004). Inter-temporal economies of scope, organizational modularity, and the dynamics of diversification. *Strategic Management Journal*, *25*(13), 1217–1232.

Hill, C., W. L., Hitt, M. A., & Hoskisson, R. E. (1992). Cooperative versus competitive structures in related and unrelated diversified firms. *Organization Science*, *3*(4), 501–521.

Hitt, M. A., Bierman, L., Shimizu, K., & Kochhar, R. (2001). Direct and moderating effects of human capital on strategy and performance in professional service firms: A resource-based perspective. *Academy of Management Journal*, *44*(1), 13–28.

Hoberg, G., & Phillips, G. (2010). Product market synergies and competition in mergers and acquisitions: A text-based analysis. *The Review of Financial Studies*, *23*(10), 3773–3811.

Huckman, R. S., & Pisano, G. P. (2006). The firm specificity of individual performance: Evidence from cardiac surgery. *Management Science*, *52*(4), 473–488.

Kacmar, K. M., Andrews, M. C., Van Rooy, D. L., Steilberg, R. C., & Cerrone, S. (2006). Sure everyone can be replaced… but at what cost? Turnover as a predictor of unit-level performance. *The Academy of Management Journal*, *49*(1), 133–144.

Kacperczyk, A. (2012). Opportunity structures in established firms: Entrepreneurship versus intrapreneurship in mutual funds. *Administrative Science Quarterly*, *57*(3), 484–521.

Karim, S., & Williams, C. (2012). Structural knowledge: How executive experience with structural composition affects intrafirm mobility and unit reconfiguration. *Strategic Management Journal*, *33*(6), 681–709.

Keller, J. R., Kehoe, R. R., Bidwell, M., Collings, D., & Myer, A. (2021). In with the old? Examining when boomerang employees outperform new hires. *Academy of Management Journal*, *64*(6), 1654–1684.

Kim, J., & Steensma, H. (2017). Employee mobility, spin-outs, and knowledge spill-in: How incumbent firms can learn from new ventures. *Strategic Management Journal*, *38*(8), 1626–1645.

Kor, Y. Y., & Leblebici, H. (2005). How do interdependencies among human-capital deployment, development, and diversification strategies affect firms' financial performance? *Strategic Management Journal*, *26*(10), 967–985.

Lazear, E. (2009). Firm-specific human capital: A skill-weights approach. *Journal of Political Economy*, *117*(5), 914–940.

Levinthal, D., & Wu, B. (2010). Opportunity costs and non-scale free capabilities: Profit maximization, corporate scope, and profit margins. *Strategic Management Journal*, *31*(7), 780–801.

Lieberman, M. B., Lee, G. K., & Folta, T. B. (2017). Entry, exit, and the potential for resource redeployment. *Strategic Management Journal*, *38*(3), 526–544.

Mayer, K., Somaya, D., & Williamson, I. (2012). Firm-specific, industry-specific, and occupational human capital and the sourcing of knowledge work. *Organization Science*, *23*(5), 1311–1329.

Morandi Stagni, R., Santaló, J., & Giarratana, M. S. (2020). Product-market competition and resource redeployment in multi-business firms. *Strategic Management Journal*, *41*(10), 1799–1836.

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal*, *34*(3), 297–316.

Penrose, E. (1959). *The theory of the growth of the firm* (1st ed.). Blackwell Publishers.

Ployhart, R. E., Van Iddekinge, C. H., & MacKenzie, W. I. (2011). Acquiring and developing human Capital in Service Contexts: The interconnectedness of human capital resources. *Academy of Management Journal*, *54*(2), 353–368.

Rothaermel, F. T., & Hess, A. M. (2007). Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effects. *Organization Science*, *18*(6), 898–921.

Sainati, T., Locatelli, G., Smith, N., Brookes, N., & Olver, G. (2020). Types and functions of special purpose vehicles in infrastructure megaprojects. *International Journal of Project Management*, *38*(5), 243–255.

Sakhartov, A. V., & Folta, T. B. (2014). Resource relatedness, redeployability, and firm value. *Strategic Management Journal*, *35*(12), 1781–1797.

Sakhartov, A. V., & Folta, T. B. (2015). Getting beyond relatedness as a driver of corporate value. *Strategic Management Journal*, *36*(13), 1939–1959.

Santamaria, S. (2022). Portfolio Entrepreneurs' behavior and performance: A resource redeployment perspective. *Management Science*, *68*(1), 333–354.

Sapienza, H. J., Parhankangas, A., & Autio, E. (2004). Knowledge relatedness and post-spin-off growth. *Journal of Business Venturing*, *19*(6), 809–829.

Sasson, A. (2008). Exploring mediators: Effects of the composition of organizational affiliation on organization survival and mediator performance. *Organization Science*, *19*(6), 891–906.

Sauerwald, S., Lin, Z., & Peng, M. W. (2016). Board social capital and excess CEO returns. *Strategic Management Journal*, *37*(3), 498–520.

Semadeni, M., & Cannella, A. (2011). Examining the performance effects of post spin-off links to parent firms: Should the apron strings be cut? *Strategic Management Journal*, *32*(10), 1083–1098.

Sengul, M., Costa, A. A., & Gimeno, J. (2019). The allocation of capital within firms. *Academy of Management Annals*, *13*(1), 43–83.

Sengul, M., & Gimeno, J. (2013). Constrained delegation: Limiting Subsidiaries' decision rights and resources in firms that compete across multiple industries. *Administrative Science Quarterly*, *58*(3), 420–471.

Shaw, J., Park, T.-Y., & Kim, E. (2013). A resource-based perspective on human capital losses, HRM investments, and organizational performance. *Strategic Management Journal*, *34*(5), 572–589.

Sherer, P. D. (1995). Leveraging human assets in law firms: Human capital structures and organizational capabilities. *ILR Review*, *48*(4), 671–691.

Sohl, T., & Folta, T. B. (2021). Market exit and the potential for resource redeployment: Evidence from the global retail sector. *Strategic Management Journal*, *42*(12), 2273–2293.

Stadler, C., Helfat, C. E., & Verona, G. (2022). Transferring knowledge by transferring individuals: Innovative technology use and organizational performance in multiunit firms. *Organization Science*, *33*(1), 253–274.

Stern, I., Deng, X., Chen, G., & Gao, H. S. (2021). The "butterfly effect" in strategic human capital: Mitigating the endogeneity concern about the relationship between turnover and performance. *Strategic Management Journal*, *42*(13), 2493–2510.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press.

Tate, G., & Yang, L. (2015). The bright side of corporate diversification: Evidence from internal labor markets. *The Review of Financial Studies*, *28*(8), 2203–2249.

Terza, J., Basu, A., & Rathouz, P. (2008). Two-stage residual inclusion estimation: Addressing endogeneity in health econometric modeling. *Journal of Health Economics*, *27*(3), 531–543.

Tuma, N. B., & Hannan, M. T. (1984). *Social dynamics models and methods*. Academic Press Inc.

Wooldridge, J. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

Wu, B. (2013). Opportunity costs, industry dynamics, and corporate diversification: Evidence from the cardiovascular medical device industry, 1976–2004. *Strategic Management Journal*, *34*(11), 1265–1287.

Zander, U., & Kogut, B. (1995). Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. *Organization Science*, *6*(1), 76–92.

Zheng, Y., Devaughn, M. L., & Zellmer-Bruhn, M. (2016). Shared and shared alike? Founders' prior shared experience and performance of newly founded banks. *Strategic Management Journal*, *37*(12), 2503–2520.

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