In Search of Inspiration: External Mobility and the Emergence of Technology Intrapreneurs

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Abstract

The practice of external hiring continues unabated, despite abundant evidence that its costs often exceed its returns. In view of this, we consider whether external hiring provides value to firms that prior research has not captured: Namely, greater opportunity for intrapreneurship. Consistent with organizational learning theory, learning-by-hiring, and studies of innovation—which emphasize knowledge recombination as a key antecedent—we predict that external hires are at greater risk of intrapreneurship than internal hires. We test this prediction via a study of product managers in large technology companies. We use machine learning to operationalize intrapreneurship by comparing product manager job descriptions to the founding statements of venture-backed technology entrepreneurs. Our research design employs coarsened exact matching to balance pre-treatment covariates between product managers who arrived at their roles internally versus externally. The results of our analysis indicate that externally-hired product managers are substantially more intrapreneurial than observably equivalent internal hires. However, and consistent with prior research, we find that intrapreneurial product managers have a higher turnover rate, an effect that is amplified for intrapreneurial external hires. This suggests that hiring for intrapreneurship may be a difficult strategy to sustain.

Firms presently fill about half of their open roles with external candidates (Keller 2018). This pattern of mobility, which is especially pronounced in the technology industry (Saxenian 1994), represents a dramatic shift from the employment model that predominated during the second half of the 20th century (Arthur and Rousseau 1996, Bidwell et al. 2013). In light of this, scholars have begun to assess whether relying on external hiring to such a degree is justifiable.

Much of the accumulated evidence suggests that it is not. For example, firms pay a significant wage premium for external hires versus comparable internal hires (Harris and Helfat 1997, Bidwell 2011, DeOrtentiis et al. 2018, Carter et al. 2019). Research also documents declines in the performance of securities analysts (Groysberg et al. 2008), insurance agents (Dokko et al. 2009), and bankers (Bidwell 2011) who switch organizations. Taken together, these results invite a question: Do firms derive any benefit from external hiring?

Organizational learning theory suggests that they should. Proponents of the theory argue that external hires import knowledge that is unavailable or obscured to firm insiders (March 1991), a prediction that is corroborated by research documenting the transfer of non-redundant information via employee mobility (Almeida and Kogut 1999, Rao and Drazin 2002, Song et al. 2003, Dokko and Rosenkopf 2010). The theory further predicts that external hires—by virtue of being less socialized—are more inclined to apply non-redundant information toward experimentation and risky recombination (March 1991, Levinthal and March 1993), both of which are key antecedents of innovation (Ahuja and Lampert 2001, Phene et al. 2006, Kaplan and Vakili 2015). Jointly considered, this body of work supplies a prediction: External hires benefit firms by importing non-redundant knowledge that they are predisposed to combine with existing products or routines to create new value.

We test the validity of this prediction as it pertains to intrapreneurship. We focus on intrapreneurship because scholars view it as a critical source of new value for firms (Pinchot 1985, Zahra 1991, Zahra and Covin 1995), while numerous practitioner accounts attest to its desirability (Krippendorff 2019, Uviebinene 2019). At the same time, however, intrapreneurship has proven extremely difficult for managers to purposely engineer (Kacperczyk 2012). Most often, in fact, the "motor of corporate entrepreneurship resides in the autonomous strategic initiatives of individuals at the operational levels" (Burgelman 1983, p. 241). Determining whether internal versus external hires are "at greater risk" of such autonomous initiative is therefore of substantial importance to organizations—particularly since hiring managers typically consider a mix of internal and external applicants when filling roles (Bidwell and Keller 2014). If technology intrapreneurs are, all else equal, systematically more likely to emerge from one of these two mobility channels, it may be advisable for firms to adapt their hiring procedures accordingly.

Given this, we also consider the long-term efficacy of "hiring for intrapreneurship" as a strategy for achieving knowledge-based differentiation (Barney 1991). While prior literature suggests that intrapreneurship can be a source of competitive advantage (Zahra et al. 2006), the sustainability of this approach is subject to certain constraints regarding *appropriability*—that is, the degree to which firms are able to extract value from their employees' work (Coff 1999, Sevcenko and Ethiraj 2018). A key concern is the impediment to appropriability posed by the departure of employees engaging in inimitable work (Wezel et al. 2006), such as intrapreneurship. In order to provide some initial insight in this regard, we assess the relationship between intrapreneurship, mobility channel, and turnover.

We situate our empirical assessment in the context of product managers (PM) working at large technology firms between 1996 and 2010. Our data derive from a repository of 30 million resumes legally retrieved in 2013 from the professional networking website LinkedIn (Ge et al. 2016). To identify instances of intrapreneurship, we leveraged the fact that intrapreneurs "act like entrepreneurs by engaging in opportunity-seeking behavior and implementing strategic initiatives inside an organizational opportunity structure" (Kacperczyk 2012, p. 488). For example, Pinchot (1985, p. x)—who coined the term "intrapreneur"—described them as: "very much like entrepreneurs. They take personal risk to make new ideas happen. The difference is that they work within larger organizations instead of outside them. I call them 'intrapreneurs' – my shorthand for intracorporate entrepreneurs."

Accordingly, we trained a machine learning classifier to distinguish between the job descriptions of technology PM and the founding descriptions of venture-backed entrepreneurs (VBE) in the technology sector. We selected VBE as our point of comparison because they found high-growth entrepreneurial enterprises of significant value (Kortum and Lerner 2000, Catalini et al. 2019). We sampled VBE founding statements from Crunchbase, which tracks information on investments in—

and founding members of—early stage ventures. We then applied our classifier to a separate corpus of LinkedIn job descriptions written by PM at large technology firms, with the goal of identifying *false positives*: PM whose work resembles that of VBE to such an extent that our classifier mis-categorized them as such. As a final step, we verified the results of this operationalization with a panel of industry experts.

Regarding our identification strategy, we employed coarsened exact matching (CEM) to balance pre-treatment covariates between PM who arrived at their roles via internal versus external channels. Specifically, we matched on job role, focal firm, start date, educational cohort, previous job role, and job role tenure. Effectively, we compared the intrapreneurial activity of internally-hired PM to that of PM who were hired from outside the same company in the same year, had a similar prior job role, are of similar age, and subsequently spent the same amount of time as a PM at the focal firm. To preview our results, we find that external hires are more intrapreneurial than observably equivalent internal hires. However, we also show that intrapreneurial PM have a higher turnover rate—an effect that, consistent with Bidwell (2011), is almost entirely attributable to intrapreneurial external hires.

These results allow us to make the following contributions. First, we illustrate a meaningful way in which external hiring benefits firms. This is noteworthy because research assessing the effects of external hiring have, to date, almost exclusively documented its detriments (e.g., Groysberg et al. 2008, Bidwell 2011). However, intrapreneurial external hires' comparatively greater turnover propensity provides an important scope condition for this finding. Specifically, insofar as firms must retain intrapreneurial employees to fully appropriate value from their work (Coff 1999, Sevcenko and Ethiraj 2018), hiring externally for intrapreneurship may be a difficult strategy to sustain.

Second, we develop a method for unobtrusively and systematically assessing intrapreneurship across multiple organizations. This constitutes a contribution because, despite its economic and theoretical importance (Antoncic and Hisrich 2001), "instances of intrapreneurship are generally not visible to researchers and therefore are difficult to measure on a large scale" (Kacperczyk 2012, p. 486). Third, we are able to employ an identification strategy that, through the granularity and size of our data, addresses many of the statistical confounds commonly associated with mobility studies (Singh and Agrawal 2011), thereby strengthening the validity of our empirical claims. Finally, we make a contribution by applying large resume repository data to the study of careers. While the challenges involved in working with unstructured text are significant, we believe that this type of dataset has immense potential with regard to longstanding questions of relevance to organizations.

The Changing Employment Model

Large-scale changes in the organization of work, such as the decline of union membership (Kochan et al. 1994), coincided with the erosion—but not eradication—of internal labor markets (Cappelli and Keller 2014). Concurrent with the proliferation of merit-based evaluation systems, individual performance, as opposed to organizational tenure, became the primary determinant of reward allocation (Heneman and Werner 2005), at least in principle if not in practice (Castilla and Ranganathan 2020). Organizational tenures decreased substantially (Bidwell 2013), and external hires began to populate high-level roles (Royal and Althauser 2003), as firms, unburdened by the legal constraints and informal arrangements of the past, exercised immense flexibility in terms of employee roster construction (Bidwell et al. 2013).

This shift was especially pronounced within the technology sector. For example, in her landmark study of Silicon Valley, Saxenian (1994, p. 35) reports a representative quote: "A man who has not changed companies is anxious to explain why; a man who has (changed companies) perhaps several times, feels no need to justify his actions." This sentiment is further corroborated by a manager, who states: "There is far more mobility and there is far less real risk in people's careers. When someone is fired or leaves on the East Coast, it's a real trauma in their lives. If they are fired or leave here it doesn't mean very much. They just go off and do something else …" (Saxenian 1994, p. 54-55). While Saxenian's (1994) analysis focused on culture as an antecedent, Gilson (1999) suggests that the legal environment contributed as well, insofar as courts in California—where many major technology companies are headquartered—have historically been reluctant to enforce noncompete clauses.[1]

A growing literature assesses the consequences of this "boundaryless" approach to careers (Arthur and Rousseau 1996), which soon proliferated across other industries, and generally finds them to be

[1] Class-action litigation brought in 2013 against several prominent firms, which accused them of maintaining informal "no cold call" arrangements in order to attenuate employees' external mobility, represents a recent exception to this trend.

negative for firms. Groysberg and colleagues, for example, observed a decline in the performance of securities analysts who switched firms (Groysberg et al. 2008, Groysberg and Lee 2009, Groysberg 2010), as did Campbell and colleagues (2014) regarding basketball players who switched teams. Likewise, Dokko and colleagues (2009) demonstrated that the performance of external hires can decline even when their prior experience is highly relevant.

Yet in spite of this, external hires often command a meaningful wage premium relative to internal candidates. While this premium is particularly pronounced in research that examines CEO successions (Harris and Helfat 1997, Agrawal et al. 2006), scholars have also observed it for external hires well below the C-suite. For instance, DeOrtentiis and colleagues (2018) found that externally hired managers at a large retailer earned 28% more than comparable internal hires, while in a study of over 34,000 executives listed in the ExecuComp database, Carter and colleagues (2019) reported that switching firms was associated with a 15% pay increase relative to executives who did not switch. These results are consistent with Bidwell (2011), who found an 18% wage premium for external hires over internal ones at a large financial institution. Similarly, in a study of MBA alumni from a top business school, between-firm mobility was associated with meaningful increases in pay but not professional responsibilities compared to within-firm mobility (Bidwell and Mollick 2015), suggesting that employers received a greater return on their investment from internal hiring.

Intrapreneurship and Corporate Entrepreneurs

Accordingly, while the detriments of external hiring are widely recognized, scholarship has yet to establish clear benefits associated with the practice. In theory, however, external hiring can be a significant source of new ideas and fresh perspectives, the infusion of which should catalyze the creation of new value in established firms. We focus on a particular type of value creation, intrapreneurship, in view of its demonstrated importance to both practitioners (Krippendorff 2019, Uviebinene 2019) and scholars (Zahra 1991, Zahra and Covin 1995).

The idea that intrapreneurship benefits firms is by now axiomatic (Antoncic and Hisrich 2001; Kacperczyk 2012). A clear delineation of what precisely does and does not constitute intrapreneurship has proven somewhat more elusive. One of the most prominent definitions is “corporate entrepreneurship,” or entrepreneurship within existing organizations (Antoncic and Hisrich 2003).

Granting that entrepreneurship itself has been subject to definitional debates (Shane and Venkataraman 2000, Sorenson and Stuart 2008), research in this tradition emphasizes activity with the potential for scalability, growth, and the generation of outsized value (Antoncic and Hisrich 2003). Critically, however, the central tendency of the intrapreneurship literature is to take the firm as the theoretical and empirical unit of analysis (Covin and Miller 2014, Neessen et al. 2019). This is evident in the definitions supplied by Zahra (1995) and Fischer (2011), for example.

Assessing intrapreneurship among individuals is comparatively less common, but scholars increasingly see value in this approach (Kacperczyk 2012). Recent research has, for instance, identified the importance of *individual* employees' entrepreneurial orientation to the financial performance of large organizations (Covin et al. 2006, Wiklund and Shepherd 2005). Focusing on individuals seems particularly prudent given the link between product development and organizational outcomes (Brown and Eisenhardt 1995, p. 344; Teece 2007, p. 1,326), which remains especially strong within the technology industry (Schoonhaven et al. 1990, Deeds et al. 2000). In other words, the intrapreneurial activity of individual employees warrants scrutiny because it is a critical antecedent of organizational vitality—to which intrapreneurs contribute by creating new products and refining existing ones, via the discovery of new markets and monetization strategies (Burgelman 1983, Stevenson and Jarillo 1990, Antoncic and Hisrich, 2001, p. 498).

Yet in spite of its economic importance, organizations have historically been unable to engineer intrapreneurship within their ranks in a reliable manner (Burgelman 1983, Stevenson and Jarillo 1990). As Kacperczyk (2012, p. 488) notes, "Intrapreneurship … is largely predicated on proactive initiatives and the entrepreneurial spirit of individual employees." In lieu of simply hoping that this entrepreneurial spirit emerges organically, many firms have expanded into corporate venture capital (CVC), that is, the practice of taking a minority investment position in entrepreneurial enterprises. Notably however, such efforts are generally expensive (Chesbrough 2002), and are often impeded by concerns about the misappropriation of intellectual property—particularly for entrepreneurs operating within the same industry as their corporate partners (Dushnitsky and Shaver 2009).

The idea that firms could instead catalyze intrapreneurship via their hiring practices is therefore a compelling one. It is particularly appealing in light of the fact that, for many roles, hiring managers consider a combination of internal and external applicants (Bidwell and Keller 2014). Insofar as these applicants present commensurate levels of experience and credentialing, establishing whether their mobility channel predisposes them toward intrapreneurship would be informative.

External Mobility and Intrapreneurship

Organizational learning theory suggests that external hires are a reliable source of exploration—that is, "search, variation, risk taking, experimentation, play, flexibility, discovery, innovation" (March 1991, p. 71). March (1991) specifically implicates moderate levels of turnover as vital to exploration due to two factors: The non-redundant knowledge imported by new recruits and their propensity to apply this information in divergent ways, by virtue of the fact that they are less socialized to organizational beliefs than incumbent employees.

Subsequent empirical studies have corroborated the idea that external hires are a source of non-redundant information. Song and colleagues (2003) observed knowledge transfer in a study of engineer mobility, as did Rosenkopf and Almeida in a study of the semiconductor industry (2003). Rao and Drazin (2002) found that such learning-by-hiring helped young mutual funds to gain ground against more established rivals; Dokko and Rosenkopf (2010) extended these results by showing that firms appropriate, from external hires, non-redundant social capital as well as knowledge.

Left unassessed by these studies is the extent to which infusions of external personnel actually augur successful exploration. On this point, however, the literature on innovation—that is, the commercialization of invention (Schumpeter 1934)—is instructive. Although it does not observe instances of learning-by-hiring, research in this tradition emphasizes the importance of knowledge *recombination* as an antecedent to innovation (Henderson and Clark 1990, Galunic and Rodan 1998). For example, in a highly-cited empirical study, Fleming (2001) found that inventors' experimentation with new combinations of components increased the probability of a experiencing a breakthrough. Likewise, in a prominent study of the optical disk industry, Rosenkopf and Nerkar (2001) illustrated the importance of recombining technologies across organizational boundaries; a point echoed by Phene and colleagues (2006). More recently, Kaplan and Vakili (2015) refined this research by showing that more distant recombinations produced greater economic value—in contrast to cognitive novelty, which showed a stronger association with local search. The unifying insight, however, is that breakthroughs occur when technologies are recombined in new ways (Fleming and Sorenson 2001, Arts and Veugelers 2015).

Organizational learning theory provides a conceptual link between these empirical findings in the following manner. The possession of non-redundant information is a necessary, but not sufficient, antecedent to successful exploration. The ability, and willingness, to leverage this information asymmetry in the pursuit of novel recombination is also required (Teece 2007). Critically, new recruits are expected to face considerably fewer obstacles in both regards. Incumbent employees are subject to impediments with respect to opportunity recognition, by virtue of their degree of socialization within the firm (March 1991, Levinthal and March 1993). Furthermore, even conditional on opportunity recognition, incumbents are more risk-averse and less likely to experiment, preferring instead to exploit their existing knowledge domains (Simon 1979, Martin and Mitchell 1998, Fang et al. 2010). As Levinthal and March (1993, p. 97) note: "Knowledge and the development of capabilities improve immediate performance, but they often simultaneously reduce incentives for and competence with new technologies or paradigms."

Accordingly, when jointly considered, this research suggests that the prevalence of intrapreneurship will be affected by mobility channel in the following way:

Hypothesis 1: *Externally-hired product managers are at greater risk of intrapreneurship than observably equivalent internally-hired product managers.*

Intrapreneurship and Subsequent Employee Turnover

An established view holds that intrapreneurship, if executed successfully, can provide firms with an enduring source of competitive advantage (Covin and Miles 1999, Zahra et al. 2006). Proponents of this perspective view intrapreneurial activity as a means for achieving the knowledge-based differentiation that enhances firm performance relative to industry peers (Barney 1991). This intuition is consistent with an emerging emphasis, among strategy scholars, on the "microfoundations" of advantage—that is, the extent to which the behavior of individuals impacts firm-level outcomes (Teece 2007, Felin et al. 2015). A key mechanism is *appropriability*: the degree to which firms are able to capture the value generated by employees, particularly with respect to inimitable work (Coff 1999, Sevcenko and Ethiraj 2018).

Appropriability varies on the basis of numerous factors, such employee bargaining power (Coff 1999) or local intellectual property regimes (Conti 2014). A superordinate assumption, however, is that appropriability erodes with the departure of employees who hold relevant, tacit, and potentially idiosyncratic knowledge (Coff 1997, Wezel et al. 2006). For example, in a study of the legal services industry, Campbell and colleagues (2012) found that the departure of high-earning employees to found new ventures adversely impacted their prior firms. With respect to intrapreneurship specifically, the concern is that the product or process in question is sufficiently complex (Rivkin 2000) that the employee's departure will circumscribe the ability of the firm to extract value from it. Firms can mitigate this risk via non-compete clauses (Marx et al. 2009) or patent protection (Agarwal et al. 2009), but enforcement can be costly and is not guaranteed to succeed.

It is therefore important to consider employee turnover insofar as it precludes firms from fully appropriating the value generated by intrapreneurship. Prior research provides us with a baseline expectation regarding relative departure rates: External hires exhibit shorter organizational tenures than comparable workers who are internally hired (Bidwell 2011). Echoing this finding, Benson and Rissing (2020) reported that high-performing internal hires in a retail organization were particularly *unlikely* to leave. Our point of departure is therefore twofold. First, we consider whether intrapreneurial PM are more likely to turn over, regardless of the mobility channel through which they arrived at their focal role. Second, we examine the mutual influence of intrapreneurial activity and mobility channel on PM departure. The implication is as follows: If external hires are indeed more intrapreneurial, as we predict, then it would be detrimental from the standpoint of the firm if this activity further amplified their propensity to leave.

Regarding the first question, prior work on inventor mobility offers some guidance. In an unusually rigorous mobility study, Singh and Agrawal (2011) demonstrate that firms hire inventors away from rivals in order to exploit their prior inventions. This suggests that, insofar as employees engage in intrapreneurial activity, they will be more attractive to rival firms—an intuition that is supported by Palomeras and Melero (2010), who showed a positive association between inventors' possession of non-redundant knowledge and their external mobility. Related research on careers suggests that enhanced visibility is a plausible mechanism.[2] For example, in his in-depth study of equity researchers, Groysberg (2010) describes how analysts listed on *Institutional Investor's* widely read All-America Research Team are regularly poached by rival firms. Similarly, Rider and Tan (2015) show that law firm profitability enables partners to make advantageous lateral moves to high-status competitors.

As a result, insofar as it makes PM more visible, we expect a positive association between intrapreneurial activity and subsequent turnover. With this in mind, we hypothesize the following:

Hypothesis 2: *There is a positive association between intrapreneurship and subsequent turnover among product managers.*

We next consider whether the positive association between intrapreneurship and turnover may be materially different for internal versus external hires. Here, studies of careers are once again instructive. Research in this tradition assesses moves between destination states, such as transitioning from wage employment to self-employment, in the context of opportunity structures, or the professional pathways available to a person at a given time (Burton et al. 2016). For workers in wage employment specifically, the availability of opportunity is determined by the intersection of firm-level characteristics—such as the span of control or immediate job openings—and individual factors, such as a person's experience, education, caregiving responsibilities, and so on (Sorenson and Sharkey 2014, Thebaud 2016). A key implication is that any career transition must be understood in the context of all viable alternatives that an individual could have realistically pursued.

In view of this, Kacperczyk's (2012) study of intrapreneurship in the mutual fund industry is especially relevant. The central insight of this research is that intrapreneurial opportunities within large and established firms are enticing enough to make entrepreneurial exit comparatively less appealing for employees who are deciding where to pursue a new venture. In the same vein, upon the completion of an intrapreneurial job spell, technology PM must decide whether they can capitalize on their recent success to better effect by remaining with the firm or by leaving it.

[2] We are grateful to an anonymous reviewer for providing this suggestion.

Prior studies of internal labor markets suggest that the formal boundaries imposed by job ladders can be successfully navigated by workers in possession of the right tacit knowledge (DiPrete 1987). We expect internally-mobile PM to be more likely, all else equal, to possess this type of knowledge, by virtue of the fact that they have already completed at least one mobility event within the firm. Insofar as internal hires are more capable of using this knowledge to leverage their intrapreneurial activity toward upward mobility within the firm, we expect external opportunities to be relatively less alluring to them. With this in mind, we hypothesize the following:

Hypothesis 3: *The positive association between intrapreneurship and subsequent turnover among product managers is stronger for external hires than internal hires.*

METHODS

Setting: Product Managers in the Technology Sector

We test our hypotheses via an assessment of product managers (PM) in the technology sector. We selected this setting for two main reasons. First, product management is typically a mid-career job that requires prior experience (Murphy and Gorchels 1996). This is important because it suggests there will be sufficient variance in the mobility channel—internal versus external—through which individuals advance into the role.

Second, the technology sector is an ideal context in which to address our research question, due to its established history of both external mobility (Saxenian 1994) and intrapreneurship (Burgelman 1983). Indeed, many technological products that are now household names were created by intrapreneurial PM. For example, PM at Xerox produced both the computer mouse and the Graphical User Interface (Hiltzik 1999), while Steve Jobs directly attributed the development of the Macintosh computer to intrapreneurship at Apple (Lubenow 1985). More recent examples include Google's Gmail product and Amazon's drone delivery service (Knippen 2017).

Overall, PM tend to operate in a manner that is comparable to CEOs (Cagan 2018). They display fluency with the technical aspects of their product, and a deep level of expertise—though not required—is possessed by many. Resource mobilization and broad strategic vision, however, are equally critical. As Murphy and Gorchels (1996, p. 49) describe, "Much of the work of a product manager is through various departments and cross-functional teams, almost as if the product manager were operating a business within a business." However, at least at large technology firms, PM are not hired to be generalists: They are, instead, hired with respect to a specific product or project (McDowell and Bavaro 2014). As a former PM and current partner at Google Ventures noted: "The first thing you notice at a big company is the amount of specialization … Usually when you're hiring you have a very specific role in mind, and the likelihood that that responsibility will change is low" (McDowell and Bavaro 2014, p. 351).

Identifying Intrapreneurial Product Managers

A central empirical challenge that confronts us, due to our research question, is the absence of a database that systematically and credibly catalogues intrapreneurial activity (Kacperczyk 2012). Consequently, in order to identify instances of intrapreneurship, we leveraged the fact that intrapreneurs closely resemble entrepreneurs (Pinchot 1985, Kacperczyk 2012)—the key difference being, of course, that the former operate within the boundaries of established firms (Antoncic and Hisrich 2003). However, while this approach is straightforward conceptually, it is somewhat more complicated in practice. At issue is the fact that consensus regarding the definition of entrepreneurship has, to date, proven elusive (e.g., Carland et al. 1984, Shane and Venkataraman 2000, Sorenson and Stuart 2008, Levine and Rubinstein 2017). To wit: a self-employed website designer and the founder of a biotechnology venture are engaged in activity that, while perhaps entrepreneurial at a superordinate level, is nonetheless fundamentally different in both economic and sociological terms.

In view of this, entrepreneurship scholars have recently made a conceptual distinction between new ventures that can be classified as "high-growth" and those that cannot (Guzman and Stern 2020). For example, Guzman and Kacperczyk (2019) employed this distinction in an assessment of the gender gap in entrepreneurship, as did Azoulay and colleagues (2020) regarding founder age and venture success (see also Ng and Stuart 2016). In essence, high-growth ventures are those that aim to secure outside investment, scale up, and achieve a liquidity event in the form of a profitable acquisition or IPO (Aldrich and Ruef 2018). They are vastly outnumbered by small-business "subsistence" ventures (Schoar 2010)—such as restaurants (Hurst and Pugsley, 2011)—whose founders often exhibit little desire to grow in a meaningful way (Kim 2018).

Accordingly, we relied on high-growth entrepreneurs as a comparison group through which to identify instances of intrapreneurship. This approach is especially appropriate given our research setting, since many large technology firms began as high-growth enterprises funded by venture capital. As we describe below, to implement this comparison methodologically we leveraged the domain-specific expertise of venture capital firms, who are adept at identifying—and motivated to invest in—high-growth entrepreneurial ventures (Stuart et al. 1999, Kortum and Lerner 2000, Catalini et al. 2019).

Data and sample

The founding statements of venture-backed technology entrepreneurs recorded in Crunchbase served as our examples of high-growth entrepreneurship. Crunchbase tracks information on investments in, and founding members of, early-stage enterprises. As a database, it constitutes a selected sample of new ventures, insofar as it oversamples those with venture backing, compared to the overall distribution of nascent firms. In this case, however, the selection effects with regard to high-growth entrepreneurship work to our advantage, given our methodological approach. Of further utility is the fact that these founders also report their social media information: Specifically, they link to their online resume profiles, which we also retrieved.

We paired these data with individual-level PM career histories that we derived from over 30 million public resumes posted to LinkedIn, a prominent website for professional networking and related activities (Ge et al. 2016).[3] These career histories allowed us to construct matched samples of internally- and externally-hired PM, as well as providing a means for operationalizing intrapreneurship using job descriptions vis-à-vis the Crunchbase founding statements. We sampled these data in 2013, at which point they constituted 15% of the total resumes available.

LinkedIn resumes represent a promising data source for scholars interested in assessing career trajectories, due largely to four notable features. The first is that LinkedIn profiles provide a more accurate account of organizational affiliations than some traditional data sources, such as the

[3] The use of which is compliant with LinkedIn's user terms and conditions at that time. We note that only public profiles were collected, and this was done in a manner that did not overload the company's servers or disrupt its services in any way.

inference of mobility from assignment changes in patenting data (Ge et al. 2016). Second, profiles posted to LinkedIn are unconstrained by the space requirements of a traditional one-page hard copy resume. As a result, these resumes provide individual self-reported, longitudinal data that includes role and organizational changes that can date back decades. Third, the highly networked nature of the website deters users from fraudulently misrepresenting their employment affiliations. Lastly, and perhaps most importantly, career-relevant aspects of these data—job titles, job descriptions, and organizational affiliations—are granular and include well-defined beginnings and endpoints for role changes both within and between firms. This provides us with rich between-firm mobility data at a greater scale than can generally be gleaned from traditional survey sources, which is important insofar as it enables the use of methodologically rigorous identification strategies such as CEM.

With that being said, the use of LinkedIn profiles also involves certain drawbacks. First, the profiles are unstructured: Setting aside the required fields, individuals have substantial leeway when constructing their profiles. This means that the process for extracting the necessary data is not straightforward. In addition, platform adoption is clearly not uniform across the population of workers, which may interfere with the generalizability of results derived from these data. This issue is, however, somewhat mitigated by our exclusive focus on PM within technology firms, a subsample for which LinkedIn adoption is indisputably high.[4]

It is important to explicate several terms we derive from LinkedIn resumes in order to characterize career episodes. The first and most important is the *job title*: For instance, “PIX Firewall Product Line Manager”; “Cisco Services Product Manager”; “Product Wizard”; or just “Product Manager.”[5] A second related but distinct term is the *job role*. For instance, while the preceding job titles are distinct, they share a common job role of “product manager.” A third term is *employment spell*, which refers to a period of continuous employment in a particular job role at a particular

[4] While a 2014 Pew Research survey indicated that 28% of adult internet users utilized LinkedIn (Olmstead et al. 2016), research into LinkedIn adoption in the technology sector reports much higher numbers. Archambault and Grudin (2012) report that 77% of Microsoft employees maintained a LinkedIn Profile in a 2011 survey, while Ge et al. (2016) finds that of all patent inventors surveyed, 70% report that they have a public LinkedIn profile.

[5] All these are actual examples of job titles in our data.

company. A final term is *company spell*, which refers to a period of continuous employment at a particular company—though clearly, a company spell could contain several distinct employment spells as a result of internal mobility events.

Each LinkedIn resume contains the information we need to leverage these terms into assessments of career trajectories. Typically, resumes report—for each employment spell—the start date, end date, the job title, company name and a job description. Entry into an organization is marked by the start date of a company spell. Similarly, departure is marked by the end date of the same company spell. Internal mobility events are indicated by consecutive employment spells within a company spell. Finally, the job description typically describes the individual's main activities and achievements within each job role. Approximately 80% of public resumes pair job descriptions with their resume listing, and the norm is to include substantial detail in these descriptions.[6]

Our sampling strategy consisted of two steps. First, we isolated the resumes of workers affiliated with a set of comparable large technology companies. Second, we identified PM within this group and extracted their resumes to serve as the basis of our analysis. We address each step in turn.

Selecting Comparable Technology Companies

From the initial 30 million public profiles, we extracted the resumes of LinkedIn users employed by the technology companies listed in the *Forbes* Global 2000 list for the period 1996-2010. As a first step, we standardized the formatting in the "Company Name" field of both the LinkedIn database and *Forbes* 2000 list by lower-casing all company names and pruning non-alphanumeric characters. Next we manually identified and removed company name stop words (e.g., "Inc.," "Corporation," etc.). Finally, we derived a set of company synonyms using Logo associations on LinkedIn profiles to further standardize the data. For instance, even if one worker lists her employer as "Hewlett-Packard" while another lists his as "HP," both would link their personal profiles to the company's official LinkedIn page, effectively tagging both company name variants with the same Logo. A full list of companies represented in this list is found in **Appendix A**.

[6] We further find that 95% of the remaining 20% job spells report job descriptions behind the "log-in" wall. Unfortunately, however, we were unable to retrieve these non-public job descriptions, as doing so violates the terms and conditions of LinkedIn at the time.

We retrieved a total of over 3.34 million individuals who have worked or are working at these companies.

Identifying Product Manager Job Roles

Our goal is to extract, from all the employees of these comparable technology companies, individuals whose careers contained an employment spell in the "product manager" job role. However, we are unable to rely solely on LinkedIn users' self-reported job titles when doing so. Consider that we observe, in the primary LinkedIn data from which we derive our sample, millions of uniquely spelled job titles. While some of this variation is attributable to substantive underlying differences in job roles, the majority is due to equivalent job roles being titled differently by LinkedIn users. Therefore, in order to delineate a reliable and manageable taxonomy of job roles, we applied an unsupervised machine learning algorithm to users' job descriptions. Our use of the algorithm rests on the intuition that equivalent job roles will have semantically similar underlying job descriptions, regardless of the different synonyms, abbreviations, acronyms, and spelling errors that users insert into their self-reported job titles. The machine learning algorithm recognizes these underlying patterns and, on this basis, accurately creates a job role taxonomy at scale.

We developed this taxonomy in three steps. First, we built a text model for job descriptions—in which words were stemmed, such that "manager" and "managing" became "manag", for example—by implementing a multinomial bag-of-words model. This model accounts for the frequency of each word in the job descriptions but ignores word order; see **Appendix B** for more detail. Second, to further reduce the complexity of this task and to uncover the main underlying dimensions of variation in the job description text, we employed Principal Component Analysis (PCA). This revealed 12 dimensions which accounted for 95% of the variation in job titles. Third, we employed Ward hierarchical clustering (Ward 1963) to group similar job descriptions via their Euclidean proximity in this description-space. Hierarchical clustering allows us to select the granularity of the classification taxonomy; accordingly, we selected a 50 cluster/class solution, as this is the most parsimonious solution from which a clear "product-manager" job role cluster emerges from the hierarchy of job role categories.

We extracted all the resumes of workers with an employment spell in the "product-manager" job role from the more than three million individuals who have worked in the *Forbes*-listed technology companies. See **Appendix C** for a full discussion of job descriptions and PCA statistics. Further detail regarding the clustering process and a sampling of the job role clusters are shown in **Appendix D**.[7] This process provided us with 20,095 individuals who have held 24,019 PM job spells in large technology firms. We also note that this step reduces the universe of job roles held by these individuals to 23.

Variables

Dependent Variable: Intrapreneurship

We leveraged the LinkedIn job descriptions of PM to construct our measure of intrapreneurship. Intuitively, we want to identify PM whose job descriptions closely resemble the founding descriptions of VBE. That is, by just reading the job descriptions, there is a chance that these PM could be mistaken for VBE. Suppose we train a machine to distinguish VBE from a pool of PM and VBE descriptions with a respectable level of accuracy. In this case, PM whose job descriptions most closely resemble VBE founding descriptions will be falsely labeled, by the machine, as VBE. We consider these *false positive* PM to be engaging in intrapreneurship.

We began by creating a text corpus comprising PM and VBE job descriptions. We retrieved 20,014 job descriptions[8] of technology PM from our LinkedIn dataset and 33,324 VBE founding descriptions from Crunchbase.[9] Next, we prepared these documents for analysis as discussed above and in **Appendix B** (e.g., word stemming, stop-word removal, feature selection). Finally, we used a LASSO (Least Absolute Shrinkage and Selection Operator) regression model to learn and classify the job descriptions into the classes of PM and VBE (Tibshirani 1996). **Appendix E** discusses the characteristics and inner workings of the LASSO model. Essentially, it regresses—with some

[7] We note that Cluster 10 in Table A2 of Appendix D identifies the PM of interest.
[8] The proportion of PM who make their job descriptions publicly available in their resumes reflects the general LinkedIn population (~80%).
[9] We restrict our definition of VBE to founders who have successfully raised capital from a venture capital firm as defined by CrunchBase.

important modifications—the binary dependent variable $\boldsymbol{y}$ (VBE = 1, PM = 0) on the word proportions which form the predictor matrix $\boldsymbol{X}$.

At its core, LASSO is a predictive model. To assess its performance in this capacity we adopt a 10-fold prediction test, wherein we use 90% of the text corpus (the "training set") to estimate model parameters. Subsequently, the trained model is then used to identify VBE in the remaining 10% of data, that is, the out-of-sample prediction "test set." We then evaluate the model's effectiveness in four ways: Calculating its quantitative predictive accuracy; inspecting its coefficients (also known as "feature weights"); qualitatively assessing the PM job descriptions labelled by the model as intrapreneurship; and replicating our findings using a supplementary training set, curated with the assistance of five domain-specific experts. We report our replication models in **Appendix G**, and discuss each of the prior steps here in turn.

Calculating the classifier's predictive accuracy. We call the ground truth—whether a description actually constitutes a *PM* or a *VBE*—the "reference classes" and the machine labels (PM' or VBE') the "predicted classes." With this in place, we can build a confusion matrix: A type of contingency table utilized in machine learning to evaluate the accuracy of a classifier. The confusion matrix representing the 10-fold cross-validation of the LASSO model is shown in **Figure 1**.

[Figure 1 about here]

The left and right halves of the confusion matrix are populated by *true* PM and VBE, respectively; *predicted* PM' and VBE' constitute the top and bottom halves. As such, the left diagonal represents cases which were correctly classified: true negatives (tn)—that is, PM classified as PM—on the top left quadrant, and true positives (tp)—that is, VBE classified as VBE—on the bottom right quadrant. The right diagonals show the numbers that were misclassified: False negatives (fn)—VBE classified as PM—on the top right quadrant, and false positives (fp)—PM classified as VBE—on the bottom left quadrant. We measured intrapreneurship through *misclassification* by relying on *false positives* (the bottom left cell): PM who were incorrectly identified by the machine as VBE. Intuitively, this implies that these PM had job descriptions that resembled those of VBE strongly enough to result in a false-positive classification.

The overall accuracy of the classifier ($(tp + tn)/(tp + fp + tn + fn)$) is 92.6%—considerably higher than the random classifier accuracy of 64.3%—demonstrating that it provides significant gains in detecting VBE when compared with a random draw. The false negative rate is 4.5% ($(fn)/(tn + fn)$), while the false positive rate is about 12% ($(fp)/(tp + fp)$); the classifier is a lot more consistent in identifying VBE than PM. Without reading too much into this difference, it could be due to PM demonstrating a much wider scope of professional responsibilities than vice-versa.

Inspecting the classifier's feature weights. The first step we took to assess the face validity of our measure involved examining the words that feature most prominently in the PM job descriptions that the LASSO model considers indicative of intrapreneurship. Table 1 shows two sets of word weights. The first is an unweighted set showing two lists: The top positive and negative word-stems of the classifier. The second set then weights these two lists with their respective PM-cells: The top positive word-weights are weighted with the overall fp word frequency, while the top negative word-weights are weighted with the overall tn word frequency. These two sets of word weights seek to illustrate two characteristics of the corpus. The first offers a peek into the most definitive words that separate VBE from PM. The seconds then zooms in on the PM to show the words that matter the most in determining intrapreneurial PM activity versus mundane PM activity. [10] We interpret these in turn.

[Table 1 about here]

The first list picks up terms that clearly identify VBE and PM. As there are activities between VBE and PM that are mutually exclusive—such as fundraising for the former, or claiming an organizational affiliation for the latter—we expect the classifier to highlight some of these. We find this to be the case: Words like "entrepreneur," "raise," and "investor," are heavily positive, while in the opposite direction, we find terms that would almost never occur in VBE job descriptions: Mainly company names ("Google," "Microsoft," "Cisco," etc.) and the job title itself ("product").

We then examine what kinds of PM activities result in accurate classification versus *mis-classification* as VBE. We find good face validity: Positive features are words associated with new

[10] Essentially, we weighted the model coefficients with the normalized sum of feature occurrences in the PM cells of Figure 1.

ventures (found, start up, build, company) and those pertaining to users and branding (brand, use). Conversely, the more commonplace functions of testing, support, and marketing comprise negative features. We consider this pattern reassuring.

Qualitative assessment of PM job descriptions. In order to further verify the face validity of our measure, we qualitatively evaluated the PM job descriptions that were classified as intrapreneurial compared to those that were not. Specifically, we randomly sampled 200 PM job descriptions equally across four probability quartiles of intrapreneurship for manual coding by research assistants who were blind to our study's intent. We find good inter-rater reliability, as well as agreement between manual and machine coding. In summary, job descriptions that scored above 75% classifier probability are very likely to be rated with a high level of agreement—between human intuition and machine learning—as intrapreneurial, a process that we further detail in **Appendix F**. Consequently, in order to best leverage the convergence between manual and machine coding, we model the incidence of intrapreneurial PM work using a binary variable that we set to 1 if the classifier mistakes their job description for a VBE (at a 75% probability threshold) and 0 otherwise. We also include, in Table 2, examples of PM job descriptions reflecting intrapreneurial and mundane PM work activity, respectively, as well as VBE founding statements, for the purpose of comparison.[11]

[Table 2 about here]

Independent Variable: External Hire. We considered an individual to be externally hired if they are hired from a different company, i.e. their immediate previous job spell is at a different firm. We therefore exclude from our analysis individuals who are hired directly after graduating from an educational institution. Likewise, an individual is internally hired if they move into the PM role from a different position within the company, that is, their immediate previous job spell is at the same firm.

Additional Variables

We included the following additional variables in our analysis. First, with respect to *PM Tenure*, we recorded the total number of years at the company within the PM role. Second, we included the

[11] As part of this assessment we also evaluated job descriptions on "posturing," that is, the use of jargon and buzzwords. The PM job descriptions did not exhibit variation in this type of language across the quartiles of intrapreneurship, suggesting that this was not a confounding factor with respect to our classification. We provide further detail regarding this procedure in **Appendix F**.

immediate previous job role at either the focal company (internal hires) or the company from which the PM arrived (external hires) as *Previous Job Role*. Third, although person-age is not included in our data, we are able to approximate it based on college-year completion cohorts. Accordingly, we include the variable *Age* as measured by the number of years from each individual's awarded bachelor's degree. Fourth, we include a variable for *Job Description Length*, measured in number of words, in order to account for variance in the amount of information provided by each PM regarding their job role. The mean job description length was 79 words and the median was 57 words; both correspond to the norm of reporting a job description in a resume with three short bullet points.

Finally, we recorded *Post-PM Destination* as one of three outcomes of the PM job spell: (1) company departure (the employee leaves the firm *as a PM*), (2) internal move (the employee remains in the firm but adopts a new job role), and (3) unknown, because the employee still occupied the PM job role at the point of data collection. To measure the risk of company departure as a PM, we counted the number of years to outcome (1), and consider (2) and (3) to be examples of right censoring. We proceeded in this manner in order to ensure that we made the most conservative comparisons possible regarding the relationship between intrapreneurial activity and departure propensity. We rely on this measure to assess Hypotheses 2 and 3.

Control group definition

A straightforward way to estimate our treatment effect would be via a pooled regression, which we employ as a first step in order to illustrate the importance of coarsened exact matching (CEM) for these data. At issue is the expectation that employees who are internally hired into PM job roles will differ systematically from those who are externally hired in ways that are relevant to intrapreneurship. They may, for example, arrive into their roles from different occupational backgrounds, or there may be meaningful cohort differences as a result of changing hiring patterns. Likewise, while prior research has identified several important contextual antecedents of intrapreneurship—such as resource endowment, organizational structure, and corporate culture (Zahra 1991, Hornsby et al. 2002, Kuratko et al. 1990)—our identification strategy allows us to control for heterogeneity in these differences. For example, we can account for the fact that Microsoft, Apple, and Amazon have top-down product approval processes, whereas Facebook and Google have a more democratic approach focused on building support among engineers (McDowell and Bavaro 2014).

Accordingly, we utilize a non-parametric CEM procedure in order to optimize covariate balance between treated and control product managers *prior* to treatment (Iacus et al. 2011, Blackwell et al. 2009). If implemented successfully, CEM will create a control group of internally-hired PM who are observably equivalent to externally-hired ones before each mobility event. The key objective is therefore to construct the most credible control group possible while still retaining sufficient sample size to recover precise parameter estimates—a tradeoff often referred to as the "curse of dimensionality." In short, increasing the number of dimensions creates more precise matches between treatment and control observations, but also limits the number of observations that can reliably be matched to one another.

CEM addresses the curse of dimensionality by "coarsening," or binning, treatment and control observations into meaningful groups, generally at the investigator's discretion in light of the research question. Intuitively, for example, researchers often "coarsen" a continuous measure of age into discrete age bracket bins. CEM procedures then match exactly on these groups and drop any observations that fail to inhabit a group. The observations that remain are assigned weights on the basis of their frequency and distribution across treatment and control groups. CEM is therefore distinct from—and according to a recent assessment (King and Nielsen 2018), superior to—exact matching procedures such as those that rely on propensity scores.

We selected the following dimensions on which to match in order to assess Hypothesis 1: (1) job role (i.e., product manager), (2) firm (e.g., Oracle), (3) job role start date, (4) age (educational cohort), (5) previous job role, and (6) job role tenure (in years). We refer to this as Set 1. We employ the same set of matching criteria in our models examining departure hazard—which test Hypotheses 2 and 3—but also substitute (7) intrapreneurship, i.e. our primary dependent variable, for (6) job role tenure. We refer to this as Set 2.

Imposing these criteria further shrinks our sample: We are left with 3,599 technology PM who have held or are holding 4,139 PM job spells for the criteria in Set 1, and 4,806 technology PM who have held or are holding 5,593 PM job spells for the criteria in Set 2.

If successfully implemented, the CEM procedure ensures that no covariates of interest can differentiate internal from external hires in the matched sample. To assess this, we examined the probability distributions of a selected job spell being an *externally* hired one in the treatment and control groups, post-CEM. **Figure 2** shows these probability distributions: Compared with the pooled sample, the post-CEM sample shows a complete overlap between the predicted probabilities of internal versus external hire. As such, conditional on observable covariates, the post-CEM sample exhibits no selection differences into treatment versus control. To further verify this, we regressed the covariates on the treatment indicator. If the matching performs well, there should be covariate orthogonality with respect to the treatment indicator: That is, all covariate coefficients in this regression should be non-significant and null, suggesting that there are no significant differences in the covariate means between treatment and control groups. We find that this is indeed the case.[12]

[Figure 2 about here]

However, the implementation of CEM will produce data loss and—by design—alter the proportionate representation of some types of workers within the analytic sample. We have investigated these differences and describe here only the most salient one: The shift in proportion of prior job roles, illustrated by **Figure 3**. In comparison with the unmatched sample, the prior job roles of research and engineering are more highly represented when subjected to matching with external hires. In contrast, prior job roles of legal, quality control, and human resources are reduced almost to the point of excision. Our belief is that these prior job roles reflect less accurate matches, given the nature of our research context, and as such their excision produces a better control group.[13] Accordingly, we report results derived from the CEM samples.

[Figure 3 about here]

Statistical Approach

Assessing Mobility and Intrapreneurship

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[12] We did not include the regression table here, as the coefficients are a list of non-significant zeros.

[13] It is possible, for example, that the distribution of prior job roles among internal hires is broader than that of external hires. Consistent with this intuition, in analyses that we performed but did not report in the manuscript, we found that our effects were larger—and in the same direction—within the pooled (unmatched) sample.

To assess Hypothesis 1, we regress intrapreneurial (1) or mundane (0) PM work activity on the main independent variable: External (1, treatment) or internal (0, control) hires. As such, we specify and estimate linear probability models.[14] Further, while the CEM procedure ensures common support between treatment and control groups, we nonetheless—as noted above—include an additional control for the length of job description, as well as age cohort and company fixed effects.

We estimated three models. The first examines the main effect of mobility channel on intrapreneurship. The second enters the tenure-at-job variable, while the final explores any heterogeneous effect of tenure via an interaction term between mobility channel and tenure.

Assessing Mobility, Intrapreneurship, and Departure

To test Hypothesis 2 and 3, we investigate the probability of departure from a focal company *as a PM*. This specification leads us to employ hazard models, which account for the time-distributed nature of the dependent variable and the right-censored nature of the data. In addition, the data provides us with a common temporal starting point to alleviate concerns of left-censoring: Entry into the focal PM role. We therefore track length of job-role tenure subsequent to this point of entry, even though our data include career events prior to the PM job role. This prevents any biases that might arise from the inclusion of left-censored data.

We begin by modeling the mean time-to-departure differences between treatment and control groups with Kaplan-Meier (K-M) curves. This allows for a non-parametric observation of the event function. The K-M estimator is written as:

$$\widehat{H}(t) = \prod_{i:\, t_i \leq t} \frac{d_i}{n_i},$$

where t_i is the time at which turnover occurs, d_i the number of events that occur at time t_i and n_i the number of "surviving" individuals at time t_i. The shape of the K-M curves estimates the hazard function. Treatment and control group hazards can be modeled separately, and subsequently compared both visually and via Log Rank tests against the null of no-difference-in-curves. Similarly,

[14] While the binary dependent variable might suggest a logit specification, we note that the interpretation of interaction effects in non-linear models is not straightforward (Ai and Norton 2003) and often produces misleading conclusions (Hoetker 2007).

subsequent faceting between intrapreneurial and non-intrapreneurial PM allows for visual examination of any heterogeneous differences between the departure likelihoods of internals and externals.

A drawback of K-M curves is that the non-parametric characteristics do not allow for conditioning on observable covariates. In this case, the issue is minor: CEM ensures that the observed covariates are orthogonal between treatment and control. Regardless, we subsequently estimate conditional coefficient magnitudes through the Cox-proportional hazards model. Formally, the Cox-proportional hazards model is written as:

$$H(t|X_i) = H_0(t)^{X_i \cdot \beta},$$

where t is time to event, H_0 the base hazard function, X_i are the variables of interest and βs are coefficients to be estimated. Essentially, the model regresses the outcome variable of time-to-firm-departure on variables of interest.

As we are interested in how mobility channel and intrapreneurial activity moderates turnover (Hypothesis 2), we specify three models. The first two enter the mobility and intrapreneurship variables separately. The final model examines the interaction effect of mobility and intrapreneurship on turnover hazard.

RESULTS

Intrapreneurship

Table 3 shows a cross tabulation of intrapreneurship base rates across internal and external hires in the pooled and CEM samples, respectively. In the pooled sample, the intrapreneurship rate among internal hires is 4.5%, compared to 5.3% in the CEM sample. The 6.7% rate among external hires, however, remained unchanged across both samples. Importantly, the CEM procedure attenuates the main effect of external mobility on intrapreneurship from 47% to 26%. This is as expected: The CEM procedure removes the effect of confounding correlates such as prior job role, thereby producing a more conservative estimate.

[Table 3 about here]

Table 4 shows the CEM weighted, OLS estimated results of the LPM for incidence of intrapreneurship across internal and external hires. Model 1 shows a strong significant main effect.

Compared to the base rate incidence of six percent, external hires are on average 31% more likely to exhibit intrapreneurial PM job spells. Accordingly, we find support for Hypothesis 1.

[Table 4 about here]

Models 2 and 3 explore the effects of job role tenure. While Model 2 shows that intrapreneurial individuals typically spent less time as PM, we do not find a heterogeneous effect of tenure on intrapreneurship across internal and external hires. Shorter job role tenure does appear to be associated with incidences of intrapreneurship; however, this does not necessarily imply a higher probability of firm departure, as it simply measures how long the individual has spent in the role of PM. For instance, the shorter job role tenure could be attributable to a higher likelihood of promotion for intrapreneurial PM, or the selection of intrapreneurial individuals into key internal job rotation programs.

Company Departure

Figure 4 shows the Kaplan-Meier (KM) curves of departure hazard across external and internal hires. Visually, evidence of external hires departing at greater rates than internal hires is immediately evident. Unsurprisingly, the log-rank test of difference between the two curves is highly significant ($p = 0.000$). In addition, external hires are more likely to leave the firm in the earlier years, while the rate of departure picks up for internal hires later on: Specifically, the gap is the largest during the 2nd to 4th years in the job. Overall, this set of initial KM curves replicates prior findings (e.g., Bidwell 2011): External hires in general are more likely to depart the company earlier than internal hires.

[Figure 4 about here]

Figure 5 subsets the transition curves between intrapreneurial and non-intrapreneurial PM. We observe that in general, the "gap" between the curves of externals and internal hires is larger for the former PM (right panel) compared to the latter (left panel). While Log-rank tests for differences between the curves are both significant for the two curves (*p*-value is as good as zero for the non-intrapreneurial, and < 0.001 for the intrapreneurial), we note that the curves for non-intrapreneurial PM exhibit considerably larger confidence intervals. This is not surprising: Considering the low incidence of intrapreneurship (six percent), the smaller size of the data in this split-sample produces less precise estimates.

[Figure 5 about here]

To unpack this further, we show the results of the Cox regressions in Table 5. We specify three models to assess Hypotheses 2 and 3. Model 1 considers the main effect of external and internal hire on the likelihood of departing the firm as a PM. Model 2 then tests Hypothesis 2 by entering the dummy variable for intrapreneurship. Finally, Model 3 examines the heterogeneous effects of intrapreneurship and mobility to test Hypothesis 3. To reiterate, the dependent variable is the time to event, with the event being that the individual leaves the focal company *as a product manager*. Thus, all other incidences of internal mobility are coded as being right censored.

Model 1 reiterates the findings in the first set of KM curves (**Figure 4**). On average, external hires are 1.28 times more likely to leave the company at any given time in comparison with internal hires.

In Model 2, we find that intrapreneurial PM are 2.41 times more likely to depart the company than non-intrapreneurial PM, lending support for Hypothesis 2. Model 3 further examines this effect between internal and external hires. The results appear substantial. Intrapreneurial external hires are over four times more likely to depart than intrapreneurial internal hires. In addition, we find that the main effect of intrapreneurship on company departure as PM is fully attenuated: The effect size plummets and is no longer significant. This provides support for Hypothesis 3: The pattern of company departure by intrapreneurial employees can be fully attributed to the actions of intrapreneurial external hires.

There are, however, some caveats to this finding that are mirrored in the KM curves. The data loss (again, just six percent of PM are characterized as intrapreneurial) implies that these estimates are imprecise. The effect size of the interaction term is noisy and has an extremely large confidence interval, as evidenced by the large standard errors shown in Table 5. At the lower bound, the proportionate difference attributed to intrapreneurial external hires reduces to about 1.5 times. Regardless, we note that these effects are still statistically significant at the $p < 0.01$ level.

In sum, we find support for Hypotheses 1, 2, and 3.

ALTERNATIVE INTERPRETATIONS AND ROBUSTNESS CHECKS

Impression Management and Reverse Causality. One alternative interpretation of our results is that external hires purposely include more “intrapreneurial” language in their job descriptions as a form of impression management, in order to make themselves more appealing recruitment targets. This interpretation rests upon two testable suppositions: First, that externally-hired PM edit their resumes in anticipation of job hunting, and second, that they do so in a manner that portrays their work activity in a more “intrapreneurial” light—such as recasting their role as one involving product creation and innovation.

In order to assess this possibility, we matched a random sample of 2,000 PM from our 2013 data to a set of LinkedIn resumes collected in 2015—thereby constructing a dataset of LinkedIn profiles associated with the same individual in both 2013 and 2015. This allowed us to test for any changes that these individuals—specifically, “leavers” who switched firms in 2014-2015—might have made to their PM job descriptions.

We began by creating a *resume change* dummy variable. We coded this variable as 1 for individuals who made any changes to their description of the PM role, such as correcting grammatical errors or editing incomplete sentences, and as 0 for those whose 2013 and 2015 PM job description pair were identical. In addition, we created a *to intrapreneurial* dummy variable. This variable indicated, among the subset of *resume change* PM, whether resume changes reflected intrapreneurial activity. To determine this, we applied our classifier to both the 2013 and 2015 descriptions. We coded the *to intrapreneurial* variable as 1 if it detected intrapreneurial activity in the 2015 description but not the 2013 description, and as 0 otherwise. We then examined differences in these rates between remainers and leavers. These results are cross-tabulated in Table 6.

We observe that 26% of remainers made at least one change to their PM job descriptions between 2013 and 2015, compared with 34% of leavers. This validates the first supposition: Externally-mobile PM are more likely to make resume changes. These results, however, do not support the second supposition. We find that an extremely low percentage of these changes—approximately one percent—recast non-intrapreneurial 2013 PM work as intrapreneurial. Furthermore, a close inspection of these changes indicated that they predominately involved the addition of content to a prior job description, which is consistent with the possibility that their work became intrapreneurial over time. Most importantly, however, this rate of change did not differ significantly between remainers and leavers. Accordingly, this exercise rules out one alternative interpretation of our main results.

People versus jobs. One could also interpret our results as suggesting that firms are more likely to hire externally for PM roles that demand more intrapreneurial activity. In this case, our results would not reflect a greater propensity for intrapreneurship among external hires, but rather an increased propensity for firms to target external hires to fill roles in which the need for intrapreneurship is elevated. To be clear, we do not view these mechanisms as mutually exclusive. Rather, we expect them to co-occur. With that being said, we sought to glean some insight into the relative contribution that each one makes to our observed results, via the following supplementary analysis.

Our approach was guided by the fact that job descriptions on personal resumes consist of two components: The responsibilities that a professional role demands of the person (job) and the work activity produced while occupying the role (person). To disentangle the two effects, we turned to a source of data that only specifies the former: technology PM job postings. The intuition is that if we are able to estimate a base rate of job ads that solicit intrapreneurial activity, we may be able to effectively differentiate between the two mechanisms.

Our first step was to obtain a random sample of over two million job postings from Indeed.com for the period of 2015-2017.[15] From this sample, we extracted and isolated 3,235 PM jobs posted by similar large technology companies. We include examples of these postings, selected at random, in **Appendix H**. Within these postings, we restricted our analytical focus to the field of role responsibilities; in other words, we disregarded stated credentialing and experience requirements. We then applied our classifier to this corpus in order to detect the incidence of PM jobs that might credibly fall into the category of hiring for intrapreneurship.

Our classifier flagged 62 of these postings, or approximately two percent, as soliciting intrapreneurial activity using the same criteria we relied upon for our primary analysis.[16] This is significantly different (two-sided binomial proportion test: $p < 0.0001$) from the six percent

[15] Ideally we would rely on job postings from same window as the first study, that is, retrospective from 2013. Unfortunately job postings from this time period were unavailable to us at the time of our study.
[16] We unpack this further: we excerpted and examined both intrapreneurial and non-intrapreneurial PM job listings. A sample is provided in **Appendix H**. We observe that regardless of intrapreneurship demands, these job requirements all share similarities: (1) as discussed, they are hired for a singular product/product category and (2) they all demand a plethora of job activities that surround but are not directly related to venturing: e.g. marketing, sales, team building/leading, servicing, maintenance, product launches, product support and so on.

intrapreneurship rate of PM job descriptions. Regressing these rates on job listing year fixed effects indicates no significant differences in hiring for intrapreneurship across the three years of 2015, 2016, and 2017.

What we glean from this exercise is that a very small proportion of PM job postings explicitly demand intrapreneurial activity from applicants, with respect to the requirements of the role. With that said, it is important to interpret this percentage in light of the intrapreneurship base rate that we observed among PM in our main analysis. Accordingly, in decomposing the incidence of intrapreneurial activity, we believe it is reasonable to presume that the majority is autonomously provided by the person who fills the PM role, as opposed to being explicitly demanded by it. This is consistent with the perspective that intrapreneurship is primarily an emergent phenomenon that resists purposeful managerial engineering (Burgelman 1983, Kacperczyk 2012).

We also find the results of this exercise reassuring with respect to the efficacy of our classifier. We would assume, *a priori*, that there are some PM positions that explicitly delineate a set of intrapreneurial responsibilities as essential to the role. It would be worrying if our classifier suggested that no such jobs exist. In other words, our findings are consistent with the existence of both treatment (person) and selection (job) effects.

More importantly though, we view these results as broadly supportive of our main conclusion. Our research question, in effect, is whether external hires are at greater risk of intrapreneurship compared with otherwise equivalent internal hires. If the majority of intrapreneurial activity were attributable to job demands, as opposed to heterogeneity across product managers' approach to their work, we would be unable to answer this question. However, in light of the fact that the majority of intrapreneurial work appears to have its locus in the worker, and not in stated role requirements, we believe that our analysis and our research question are effectively calibrated.

DISCUSSION

The erosion of internal labor markets, and the commensurate increase in external hiring at all levels of the firm, represent a dramatic shift in the organization of work (Bidwell et al. 2013). Scholars have only just begun to systematically analyze the benefits and detriments of these changes, which were especially pronounced within the technology sector (Saxenian 1994). The early returns to this research, however, do not paint a promising picture for firms. External hires earn more than comparable candidates promoted from within (Bidwell 2011), tend to experience performance declines upon joining (Groysberg et al. 2008), and their recruitment often incurs fees payable to third parties (Fernandez and Fernandez-Mateo 2016).

These findings contrast with organizational learning theory (March 1991, Levinthal and March 1993), which suggests that external hiring should catalyze the creation of new value—insofar as newcomers import information that is obscured or otherwise unavailable to firm insiders, and by virtue of the fact that they are less socialized than incumbent employees. In view of this, we investigated whether external hires provide value to firms that prior research has not captured, in the form of a greater propensity for intrapreneurship. Consistent with the predictions of organizational learning theory, as well as empirical evidence produced by studies of learning-by-hiring (Rao and Drazin 2002, Song et al. 2003, Dokko and Rosenkopf 2010) and innovation (Ahuja and Lampert 2001, Phene et al. 2006, Kaplan and Vakili 2015), we predicted that external hires would be at greater risk of intrapreneurship than observably equivalent internal hires.

We found support for this prediction in a study of product managers in the technology sector. This finding constitutes a contribution because both scholars (Pinchot 1985, Zahra and Covin 1995, Kacperczyk 2012) and practitioners (Krippendorff 2019, Uviebinene 2019) consider intrapreneurship to be extremely valuable to firms. In fact, it is frequently cast as a source of competitive advantage (Covin and Miles 1999, Zahra et al. 1999), particularly insofar as it results in knowledge-based differentiation (Teece et al. 1997, Zahra et al. 2006). At the same time, however, intrapreneurship has proven exceedingly difficult for firms to intentionally generate (Burgelman 1983, Kacperczyk 2012). Alternatives to relying on employee proactivity in this regard, such as corporate venture capital efforts, are often stymied by concerns about misappropriation of intellectual property (Dushnitsky and Shaver 2009). Accordingly, our central finding offers guidance to hiring managers—who often consider a mix of internal and external applicants (Bidwell and Keller 2014)—regarding the relative incidence of intrapreneurship: All else equal, hiring from outside the firm appears to be a sensible strategy.

Yet we must urge caution in generalizing from this finding, given our second result. Specifically, and consistent with Bidwell (2011), our models showed that intrapreneurial PM depart at a faster rate (Hypothesis 2), but that this effect was almost entirely attributable to intrapreneurial external hires (Hypothesis 3). This is problematic to the extent that that the departure of these PM precludes firms from fully appropriating the value of their work (Coff 1999, Sevcenko and Ethiraj 2018). The implication is that reliance on external hires to catalyze intrapreneurial activity may be a difficult strategy to sustain—particularly given the financial cost incurred when recruiting external replacements. In fact, from the perspective of the firm, cultivating intrapreneurial internal hires seems far more preferable. At issue, of course, is their numerical rarity compared with intrapreneurial external hires.

More broadly, however, this finding also has bearing on the careers perspective in organizational research (Burton et al. 2016). Specifically, it reinforces the idea that mobility channel shapes opportunity structure, conditional upon exceptional performance. This result, while admittedly preliminary, adds to a growing body of research that seeks to document the mutual impact of mobility and performance on careers (Bidwell 2011, Keller 2018, Benson and Rissing 2020).

We make a second contribution through our ability to measure—unobtrusively and at scale—intrapreneurship across firms in the technology sector. This represents a contribution because intrapreneurship is extremely difficult for researchers to observe (Kacperczyk 2012) despite its economic importance (Antoncic and Hisrich 2001). One logical extension of this methodology would be its application to other industry clusters, such as biotechnology, that scholars have identified as fonts of entrepreneurship (Sorensen and Sharkey 2014, Burton et al. 2016). The advantage of this approach lies in its ability to specify the full risk set of potential entrepreneurs, by identifying nascent founders *before* they take the steps—such as incorporating and securing outside investment—that lead to their inclusion in traditional datasets (Ng and Stuart 2016). Moreover, we believe that the logic of false positive classification using machine learning, which we employed in this study, has the potential for wider application. For example, it may be possible for firms to optimize their consideration set with regard to employee promotions: False positive classification could identify those employees who are already acting in a managerial capacity, and may therefore warrant further scrutiny regarding their potential elevation to a position of leadership. Conducting this exercise with an algorithm that is agnostic to race and gender could have meaningful implications for equality in attainment, given the popularity of anonymous personnel procedures.

A final contribution of this research was its application of large scale resume data to the study of careers. We believe the potential that these data have for addressing longstanding questions of relevance to organizational scholars is substantial. Of particular promise is the ability to marry the depth of single-firm datasets (e.g., Srivastava and Sherman 2015, Keller 2018) with the breadth of between-firm surveys (Brett and Stroh 1997, Keith and McWilliams 1999). While recent studies leveraging MBA alumni surveys (Barbalescu and Bidwell 2013, Merluzzi and Phillips 2016) has provided an important middle ground between these two types of dataset, they generally lack the sample size necessary to implement identification strategies such as CEM.[17] With that being said, we readily concede that the firm-level heterogeneity netted out by CEM may itself be of theoretical interest. For example, researchers may wish to investigate the extent to which resource endowment, organizational structure, or corporate culture operate as antecedents to intrapreneurship (Zahra 1991, Hornsby et al. 2002, Kuratko et al. 1990), as well as the impact of prior job role on future intrapreneurial activity. In such cases, the use of CEM would be inadvisable.

Its contributions notwithstanding, this work is subject to several notable limitations. First and foremost, our analysis exploited the congruence between intrapreneurship and entrepreneurship in the technology sector, which raises legitimate questions about the generalizability of our findings. In other words, we willingly acknowledge that the link between external hiring and intrapreneurship may be attenuated, or entirely non-existent, outside of the technology industry. A related boundary condition is the prevalence of firms for which intrapreneurship is a desired outcome. While it was certainly desirable within our chosen research context, there are undoubtedly other areas where exploitation is more highly valued; and the creation of new value, aside from incremental improvements in production efficiency, is less highly sought after. In such cases our findings would have different implications, or would be altogether irrelevant.

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[17] Of course, one weakness of LinkedIn data compared with these sources is the absence of salary information.

We conclude by discussing a number of possible extensions to this work. The first pertains to the destination states of intrapreneurs. Analyses that we conducted, but did not report in our results section due to space constraints, offer some preliminary conjecture. First, externally-hired intrapreneurs are 200% more likely to exit into entrepreneurship than internally-hired intrapreneurs, a finding that is consistent with extant research in this domain (e.g. Lazear 2003). In addition, and consistent with Hypothesis 3, externally-hired PM were 25% less likely than internally-hired PM to be promoted into managerial positions. At the same time, however, externally-hired PM were also 10% more likely to leave their focal firm for managerial roles in other companies, further reinforcing existing literature (Bidwell 2011). Taken together, these findings bolster the primary implication that we note above: Enhancing the retention of intrapreneurial talent—for example, via job-rotation programs (Campion et al. 1994)—should be a strategic imperative for firms.

We also explored the persistence of intrapreneurship within individuals and across organizational boundaries (e.g., Hoang and Gimeno 2010). Our data offer a starting point in this regard. We find that, among PM with multiple PM job spells, prior intrapreneurship is extremely predictive of future intrapreneurship. Specifically, 85% of PM with prior intrapreneurial activity demonstrate intrapreneurship during a subsequent PM spell. Interestingly, this result does not exhibit variation across mobility channel. With that being said, we view these results as merely suggestive, due to the fact that our data included only 48 such cases.

Finally, future research could fruitfully explore firm heterogeneity in fomenting intrapreneurship and subsequent retention across internal and external hires. This extension would be consistent with the substantial literature on intrapreneurial orientation (e.g., Covin et al. 2006). We believe that this literature, and organizational research more broadly, stands to gain from the further application of large-scale resume data toward questions of longstanding relevance to firms.

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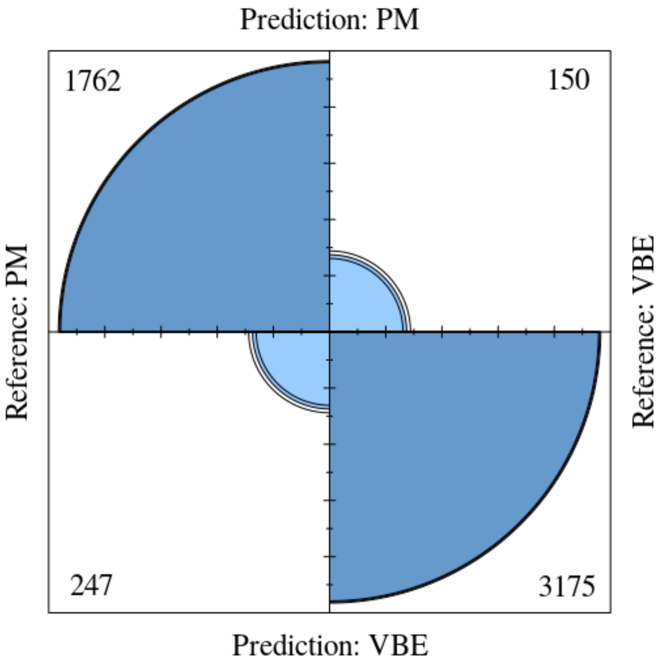


Figure 1. Four-fold plot of LASSO classifier confusion matrix, 10-fold, out-of-sample prediction. Default assessment cut-off set at 0.5 (job descriptions with > 0.5 predicted probability of being a VBE is labelled as a VBE). Reference categories indicate ground truth numbers (left and right halves); Prediction categories indicate predicted numbers (top and bottom halves). 95% confidence interval bands shown.

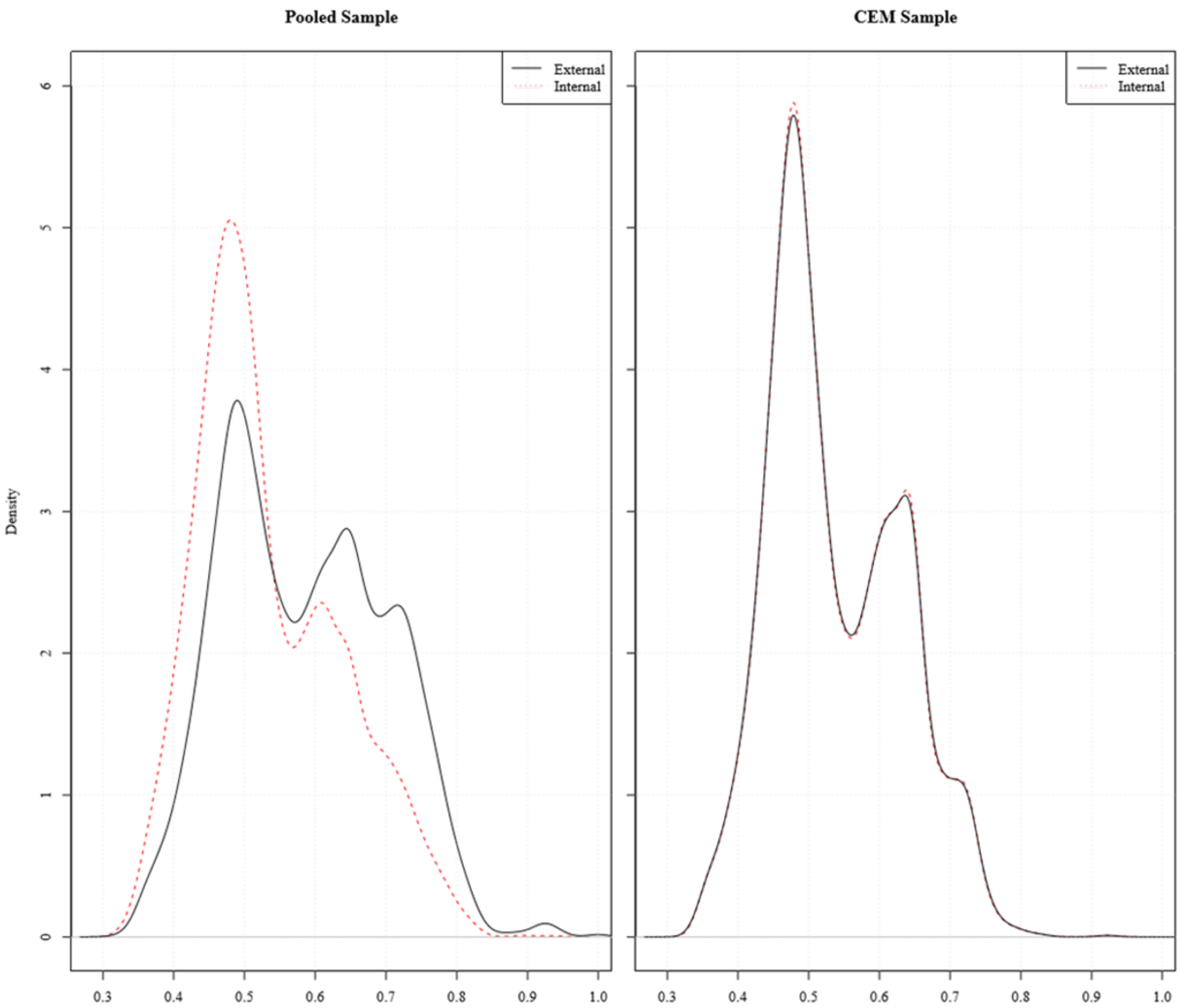


Figure 2: Kernel density plots for the distribution of the predicted probability of being an externally hired PM, pooled (pre-match) and CEM (post-match) samples. Predicted probabilities calculated through a logit model regressing externally hired "treatment" (1 for external hires, 0 for internal hires) on observed career covariates.

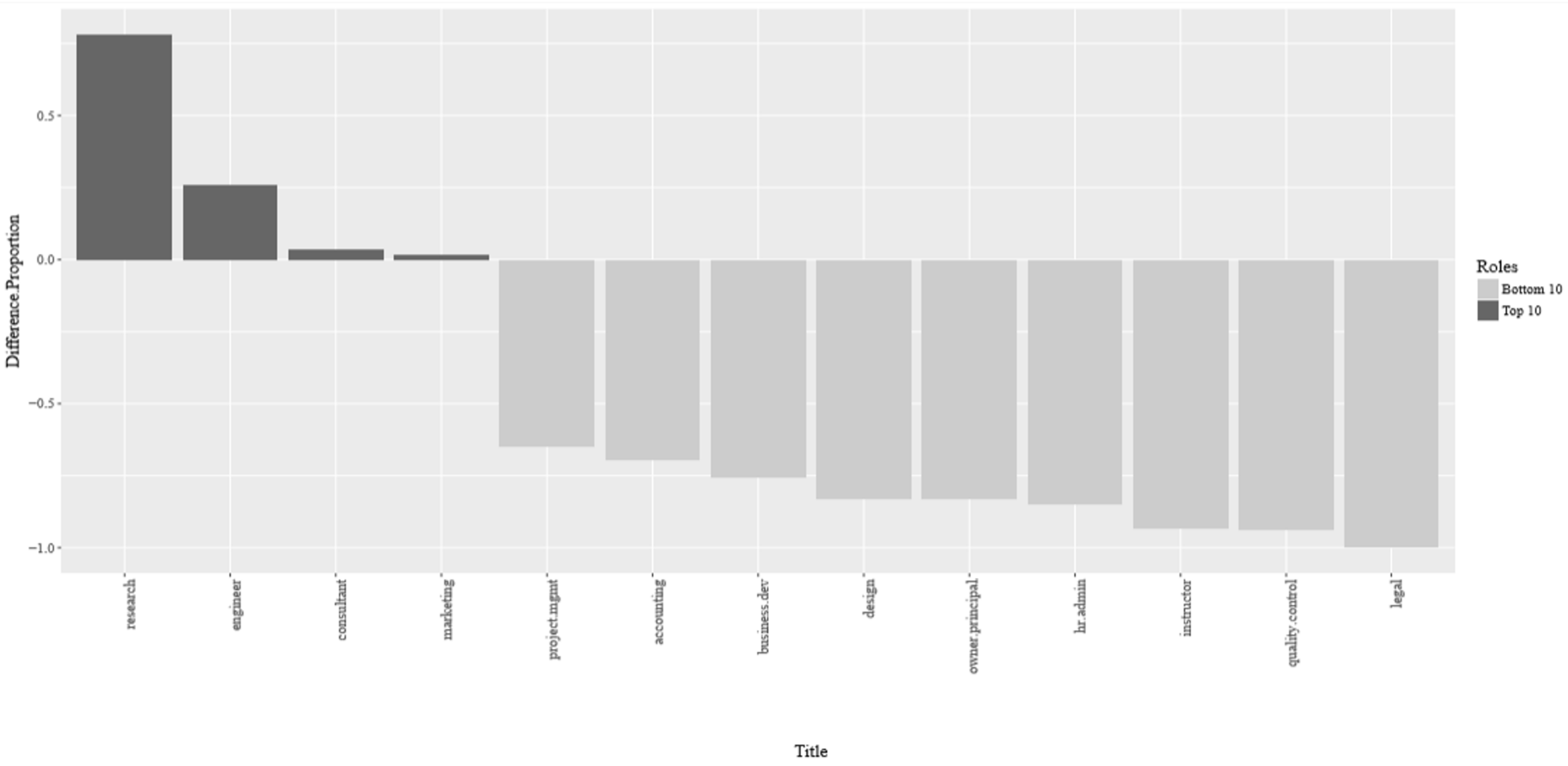
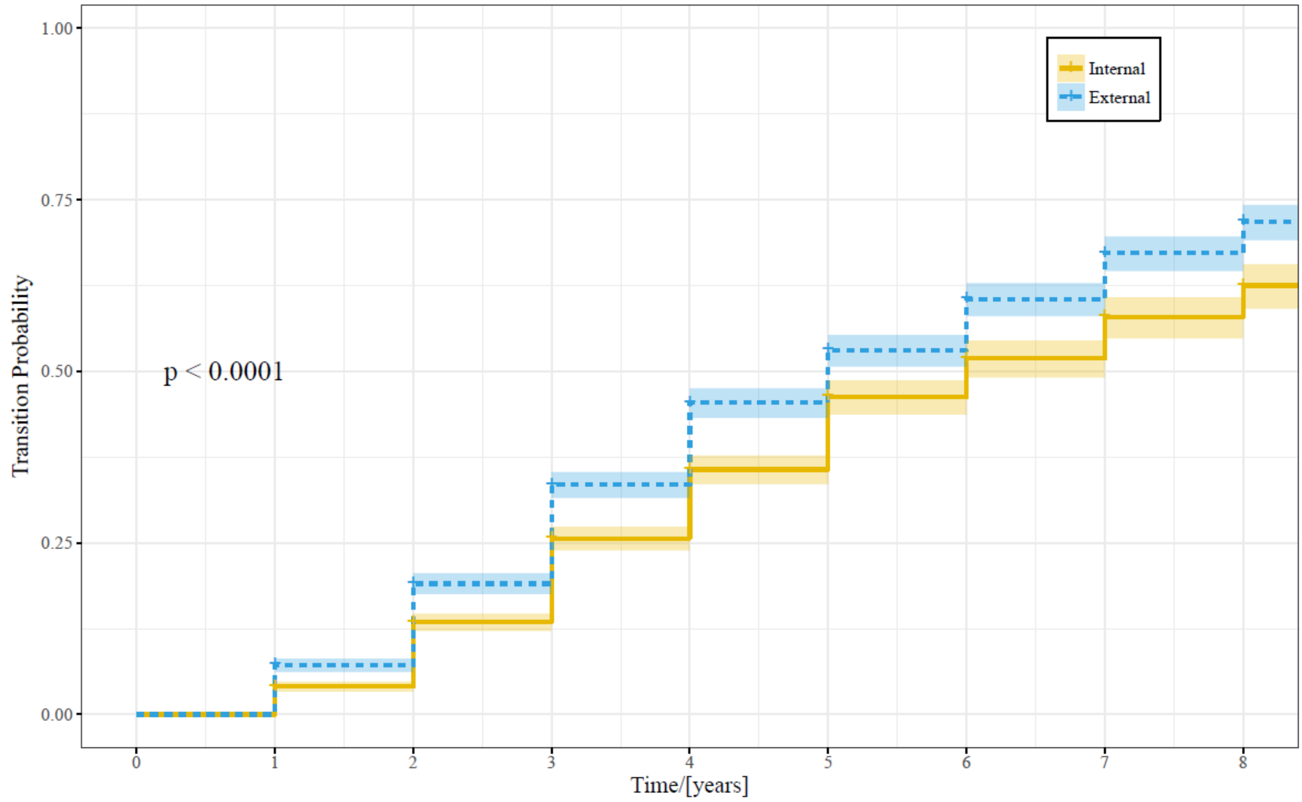


Figure 3. Prior job role representation differences between pooled (pre-match) and CEM (post-match) samples. Job roles are named by the most representative words of the constituent job titles. Scaled proportionate differences are shown, as calculated by: $\Delta n_i = \frac{(n_{i,CEM} - n_{i,pooled})}{n_{i,pooled}}$, where n is the proportion of hires into a particular job role i. As examples, $\Delta n_i = -1$ indicates a complete excision of the job role i in the CEM sample, while $\Delta n_i = 2$ indicates a 200% increase in proportionate representation of job role i.



Number at risk

	0	1	2	3	4	5	6	7	8
Internal	2922	2922	2729	1962	1169	688	459	290	201
External	2671	2671	2394	1821	1152	751	542	371	258

Figure 4. Kaplan-Meier curves for departure hazard of internal and external hires with corresponding risk table, CEM weighted sample. Shaded width of lines indicates 95% confidence intervals. The p-value for the non-parametric log-rank test against null hypothesis of no difference between survival curves is shown. Risk table indicates the number of “survivors” (i.e. hires still working at the company) measured each year.

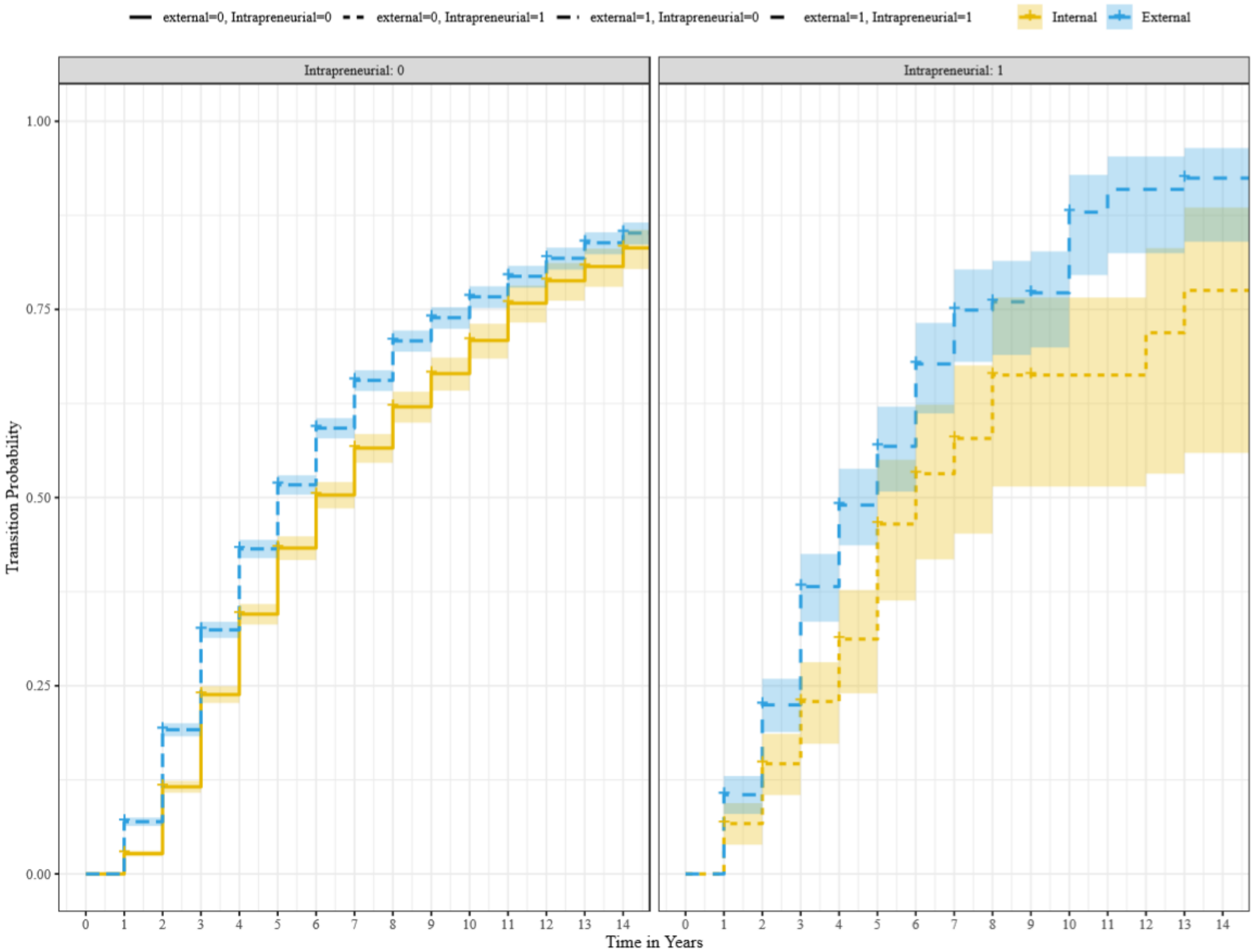


Figure 5. Split sample Kaplan-Meier curves for the departure hazard of internal and external hires across intrapreneurial and non-intrapreneurial, CEM weighted samples. Shaded width of lines indicates 95% confidence intervals. The p-value for the non-parametric log-rank test against null hypothesis of no difference between survival curves is shown.

Table 1. Top 10 Positive and Negative LASSO Feature Coefficients: Unweighted (Left) and Weighted by PM Word Frequency (Right)

Main classifier word weights

Positive	Coefficient	Negative	Coefficient
cofound	1.8734	*ibm*	-0.9692
rais	1.1928	*microsft*	-0.8204
investor	1.1434	*product*	-0.7846
entrepreneur	0.9747	*character*	-0.7591
compani	0.9416	*drove*	-0.6795
can	0.7759	*resolv*	-0.6285
founder	0.7574	*oracl*	-0.6171
found	0.7369	*intel*	-0.6081
easi	0.7188	*cisco*	-0.5503
empow	0.6989	*googl*	-0.5353

Intrapreneurial PM weighted		Non-Intrapreneurial PM weighted	
Positive	Coefficient	Negative	Coefficient
compani	0.9426	*product*	-2.7906
startup	0.2520	*manag*	-0.9033
provid	0.2206	*test*	-0.8641
build	0.2087	*support*	-0.7485
brand	0.2030	*ibm*	-0.7209
found	0.1901	*microsoft*	-0.5980
use	0.1889	*engin*	-0.4117
platform	0.1779	*respons*	-0.4078
onlin	0.1690	*window*	-0.3979
oper	0.1688	*market*	-0.3957

Note: Feature stems are shown. Left table shows feature coefficients for the base model. Right table shows feature positive coefficients with intrapreneurial product manager (PM) feature frequency weights and negative coefficients with non-intrapreneurial product manager (PM) feature frequency weights (i.e. coefficients are multiplied by the normalized frequency of features in the corpus of the respective PM job descriptions).

Table 2. Intrapreneurial Product Manager, Non-intrapreneurial Product Manager, and Venture Backed Entrepreneur Job Descriptions

Intrapreneurial	*Analyzed main business problems and devised a solution: a new, automated way for customers to access the service. A Voice Response System was the quickest and most cost effective way of doing so. Hooking into existing databases, the VRS provides access to customers' accounts and allows them to make payments over the phone. The VRS was created using XML, ASP with SQL Server.*
	Created GUESS, a crowdsourcing and human computing game for the enterprise. GUESS leverages the playfulness of a game to harness "the wisdom of the crowd" in order to solve problems that computers still struggle with like image processing, speech recognition, and more. Filed two patents, co-authored a CHI conference paper on the game, and collaborated with Haifa University to expand research of the game's scoring systems.
Non-intrapreneurial	*Implemented product test control activities, reviewed production performances with equipment engineers, product engineers, planners, and manufacturing supervisors and achieved 85% overall equipment efficiency. Evaluate, characterize and debug test programs of digital devices for yield improvement, test time reduction and test program optimization. Generated and maintained Open/Short test program for non-turnkey devices and achieved 100% no assembly defect prior to shipment.*
	Managed channel launch activities of Microsoft Office 97, Office 97 Small Business Edition, Office 97 Small Business Edition V2, Publisher 98 Deluxe Edition and Outlook 98. Lead in executing Office 97 top account tour to 15 retailers and distributors providing product information, demonstrating Office 97, new IntelliMouse, developed video for customers and provided information. Trained 2000. Managed communication release of Office 97, Office 97 Small Business Edition, Office 97 Small Business Editionv2, Publisher 98 and Publisher 98 Deluxe Edition and Outlook 98 to the retail and OEM channels. 75M+ Office 97 licenses sold.
Venture Backed Entrepreneurs	*Web-based project-execution platform focusing on cost-reduction projects. Allowing CFOs to run employee-driven cost-reduction projects. Already helping Fortune 500s to save millions of euros without firing people. Founded start-up during my MBA out of frustration with existing tools to execute projects. Attracted a total of 275K capital. Signed up several Fortune 500 customers working with board level executives. Selected by Wayra (Telefonica incubator) out of 500 signups.*
	Artifact Uprising creates tangible photo books, prints, and gifts for digital photos. Founded in 2012, the company is driven by a mission to move stories "Off your device, into your life". Signature products include premium quality photo books whose interior pages are printed on 100% recycled paper and a collection of wooden products handcrafted with mountain beetle pine. As Founder and Chief Creative Officer, Katie has: "created a company with brand equity recognized in media outlets including Real Simple, Travel + Leisure, InStyle and more." "Spearheaded a social media strategy to grow channels organically to 200K + while earning the trust of influentials." "Created the AU Ambassador Program with 56 photo ambassadors whose reach exceeds 10.3 million." "Collaborated with brands including Madewell, New Belgium Brewing, Warby Parker, Sevenly etc."

Note: Evidence of intrapreneurial activity determined by the LASSO prediction algorithm; PM job descriptions are first scored a probability between 0 and 1 of being "mistaken" for a venture-backed founding description. Intrapreneurship is dummy coded: 0 for non-intrapreneurial and 1 for intrapreneurial. A PM job description is deemed intrapreneurial and coded 1 if its LASSO prediction scores in the top quartile(> 0.75), and 0 otherwise.

Table 3. Cross Tabulation of Intrapreneurship Rates across Internal and External Hires (Main Effect), Pooled and CEM Sample

	Pooled	CEM
External Intrapreneurship Rate	0.0662	0.0670
Internal Intrapreneurship Rate	0.0449	0.0534
Rate Difference	0.0213 ***	0.0136 ***
Percentage Difference/[%]	47%	26%
n/[Job Spells]	15619	4139

Note: 2 tailed t-tests ** p<0.05, **p<0.01; ***p<0.0001*

Note: Statistical significance values indicated for 2 tailed t-tests of mean tenure differences.

Table 4. Linear Probability Models of Intrapreneurial Activity

	Model 1	**Model 2**	**Model 3**
External Hire	0.0188 **	0.0182 **	0.0392 **
	(0.0070)	(0.0070)	(0.0149)
Log(Tenure/[years])		-0.0205 **	-0.0097
		(0.0068)	(0.0096)
External Hire × Log(Tenure/[years])			-0.0205
			(0.0128)
n	4139	4139	4139
df	4046	4045	4044
F	4.197 ***	4.257 ***	4.241 ***

*· p<0.01, * p<0.05, **p<0.01; ***p<0.001*

Note: All models are linear probability models, OLS estimated with CEM derived weights, with the outcome of interest as the dummy indicator variable for intrapreneurship. Standard errors in parentheses. Internal hires form the baseline comparison group. Results shown control for length of job description and include cohort, previous job role, and company fixed effects.

Table 5. Cox-proportionate Hazard Models of Departure Likelihood

	Model 1	**Model 2**	**Model 3**
External Hire	0.2528 ***	0.2551 ***	0.2464 ***
	(0.0406)	(0.0406)	(0.0407)
Intrapreneurial		0.8672 **	0.0027
		(0.2706)	(0.5177)
External Hire × Intrapreneurial			1.5060 **
			(0.5961)
n	5593	5593	5593
Concordance	0.632 ***	0.633 ***	0.633 ***
Wald Test	432.2 ***	442.2 ***	457.4 ***
Logrank Test	465.6 ***	477.1 ***	499.7 ***

*· p<0.01, * p<0.05, **p<0.01; ***p<0.001*

Note: All models are cox proportional hazard models with CEM derived weights, with the outcome of interest as the number of days until leaving the company. Standard errors in parentheses. Internally hired, non-intrapreneurial product managers form the baseline comparison group. Results shown include cohort, previous job role, and company fixed effects.

Table 6. Cross-Tabulation of Resume Change Rates

	Changed Resume…	To Intrapreneurial
Remained in company/[%]	26.073	1.648
Left for another company/[%]	34.275	1.646
Difference/[%]	8.202 ***	0.002
Mobility Effect Size/[%]	31.457	0.001
n/[description-pairs]	2000	607

Note: 2 tailed t-tests ** p<0.05, **p<0.01; ***p<0.0001*

Note: We examined a random sample of 2013 product manager resume descriptions paired to their 2015 counterparts. “Changed Resume” indicates that the product manager job description was changed (in any form or manner). “To Intrapreneurial” indicates that the job description was changed to reflect intrapreneurial activity. Intrapreneurial changes were only examined in the sub-pool of individuals who have changed their resumes; accordingly, this variable will be 0 for the individuals whose resumes remained the same.

Appendix A. *Forbes* Global 2000 Technology Companies Represented in the Data

Cisco Systems

Corning

Harris

Arista Networks

Palo Alto Networks

Apple

HP

Hewlett-Packard Enterprise

Dell Technologies

Alphabet

Google

IBM

Facebook

Cognizant

Synnex

Splunk

Western Digital

Netapp

Amphenol

Arrow Electronics

Tech Data

Jabil Circuit

Avnet

Agilent Technologies

Intel

Broadcom

Micron Technology

Texas Instruments

Applied Materials

Qualcomm

NVIDIA

Lam Research

Analog Devices

Skyworks Solutions

KLA-Tencor

ON Semiconductor Corp.

Xilinx

Maxim Integrated Products

Microchip Technology

Advanced Micro Devices

IPG Photonics

Microsoft

Oracle

Adobe Systems

VMware

Salesforce.com

Fiserv

Intuit

CDW

Symantec

CA

Verisign

ServiceNow

Red Hat

Autodesk

Workday

Square

Match Group

Appendix B. Job Title Preprocessing

The following details our preprocessing steps.

1. We created a dictionary of common acronyms (e.g. VP, V. President, Vice President; CEO, Chief Executive Officer) through qualitative examinations of the most common job titles.
2. We employed a language detection algorithm (R package textcat) to remove individuals that post non-English resumes.
3. We purged all stop words ("of", "the", "from") from the descriptions.
4. The frequency of words in job titles and descriptions is extremely skewed and resembles a power law distribution. Figure A1 below shows log-log frequency distributions of the top 1 million job titles (top) and job description tokens (bottom). We purge all words that occur less than 500 times in the pool of job titles. Setting the threshold at 500 occurrences retains 93% of all words used in the corpus.
5. We alphabetized all job title words. For example, "ios developer expert" and "expert ios developer" both become "developer expert ios".
6. These steps reduce the number of unique titles from 14.4 to 8.69 million.

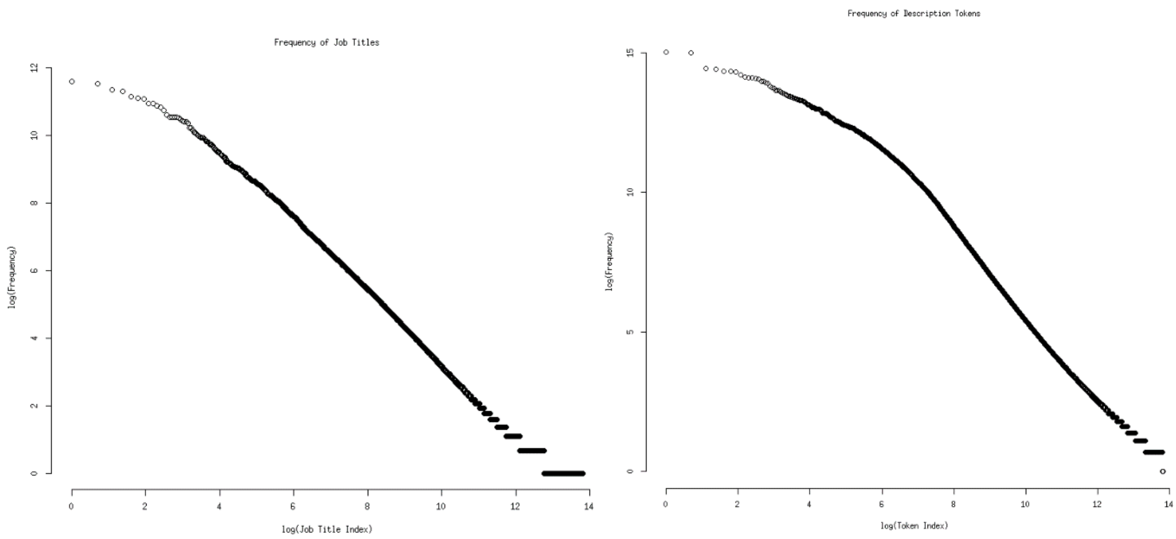


Figure A1. Log-log curves of ranked word frequency (left: job titles, right: job description words). The straight line portions indicates a power-law relationship frequency and rank. Initial and end patterns are numerical artefacts.

Appendix C: Principal Component Analysis

The PCA of the job titles is calculated using the princomp command in R. The following observations are made:

1. The top 12 principal components represent 0.953399 of the total variation in the text descriptions, as shown in Figure A2.
2. Table A1 shows the rotation weights of the first 4 principal components.
3. The component rotation weights make intuitive sense. PC1, for instance, separates business-types and "miscellaneous" odd jobs. PC2 separates front-of-house sales and software development. PC3 separates IT and technical supervision vs. design. PC4 separates sales management and program/research interns.

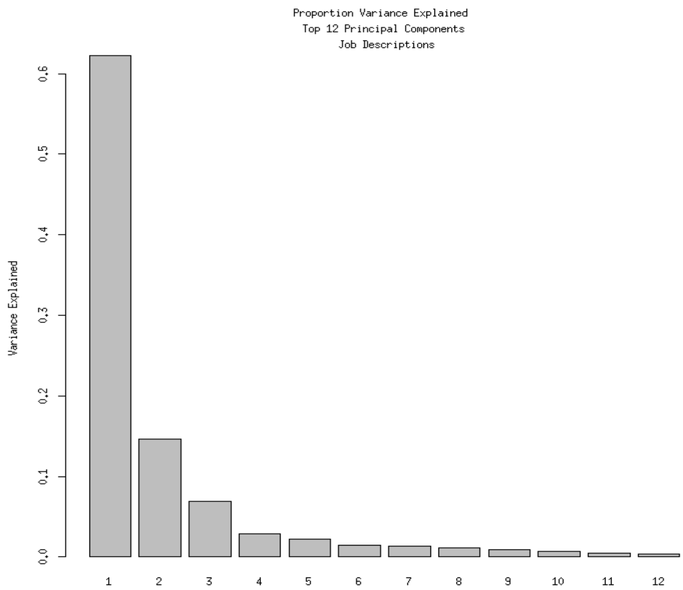


Figure A2. First 12 principal components of job description text, variance explained.

Table A1: Top and Bottom Rotation Loadings of First 4 Principal Components

PC	1		2		3		4	
Rank	**Title.tokens**	**Weight**	**Title.tokens**	**Weight**	**Title.tokens**	**Weight**	**Title.tokens**	**Weight**
1	business development intern	-1.39E-02	and intern marketing sales	-0.01342	manager service	-0.01573	sales specialist	-0.01838
2	management trainee	-1.37E-02	intern sales	-0.01335	technician	-0.01555	representative sales	-0.01773
3	business development manager senior	-1.35E-02	area manager sales	-0.01224	administrator systems	-0.01497	consultant sales	-0.01763
4	business development manager	-1.35E-02	coordinator sales	-0.01213	engineer support technical	-0.01486	sales	-0.01756
5	analyst business intern	-1.34E-02	management trainee	-0.01192	administrator system	-0.01473	engineer sales	-0.01718
6	director senior	-1.34E-02	manager sales territory	-0.01176	support technical	-0.0147	sales vp	-0.01711
7	business development director	-1.34E-02	rep sales	-0.01157	clerk	-0.01449	rep sales	-0.01711
8	business development vp	-1.32E-02	manager marketing sales	-0.01149	customer manager service	-0.01438	salesman	-0.0168
9	business development head	-1.32E-02	district manager sales	-0.01148	supervisor	-0.01435	inside representative sales	-0.0166
10	manager senior	-1.31E-02	manager national sales	-0.01146	intern it	-0.01427	inside sales	-0.01636
11	business consultant development	-1.31E-02	manager sales senior	-0.01146	it specialist	-0.01404	manager sales territory	-0.01633
12	business development	-1.31E-02	and manager marketing sales	-0.01139	engineer field	-0.01389	executive sales senior	-0.01622
13	commercial director	-1.30E-02	manager sales	-0.01139	it manager	-0.01366	head sales	-0.01619
14	country manager	-1.30E-02	manager territory	-0.01135	administrator office	-0.01359	manager national sales	-0.01576
15	senior vp	-1.30E-02	representative sales	-0.01132	accounting intern	-0.01355	manager regional sales	-0.01575
16	general manager vp	-1.29E-02	district manager	-0.01127	customer representative service	-0.01351	area manager sales	-0.01569
17	gm	-1.29E-02	director marketing sales	-0.01119	administrator	-0.01346	director sales	-0.01556
18	coo	-1.29E-02	and marketing sales	-0.01109	assistant hr	-0.0134	and marketing sales vp	-0.01526
19	business development executive	-1.29E-02	branch manager	-0.01107	officer	-0.01333	manager territory	-0.0152
20	business manager	-1.28E-02	account manager national	-0.01106	administrator network	-0.01333	manager sales senior	-0.01519
-20	physician	-1.99E-03	engineer ii software	0.019279	copywriter	0.018512	assistant professor	0.018802
-19	clerk law	-1.98E-03	c developer	0.019282	designer graphic web	0.018667	assistant project	0.018912
-18	staff writer	-1.97E-03	engineer junior software	0.019343	art director	0.018694	assistant director	0.01892
-17	translator	-1.95E-03	design engineer software	0.019353	designer graphic senior	0.018728	advisor resident	0.019015
-16	3d artist	-1.90E-03	engineer senior software	0.019396	designer visual	0.019051	secretary	0.019064
-15	advisor resident	-1.86E-03	developer ui	0.019417	designer interactive	0.019067	human intern resources	0.019148
-14	rn	-1.85E-03	engineer r&d	0.019433	creative director	0.019116	assistant resident	0.019432
-13	lifeguard	-1.74E-03	developer junior software	0.019629	designer freelance	0.019233	teacher	0.019781
-12	assistant resident	-1.67E-03	intern r&d	0.019697	designer graphic	0.019317	assistant graduate teaching	0.019801
-11	teacher	-1.66E-03	developer software	0.01975	consultant digital marketing	0.019321	intern pr	0.020552
-10	camp counselor	-1.61E-03	engineering intern mechanical	0.019834	intern marketing	0.019364	assistant teaching	0.020719
-9	assistant graduate teaching	-1.37E-03	engineer software	0.019891	design intern	0.019793	development intern	0.020743
-8	nurse registered	-1.26E-03	engineering intern	0.020892	designer freelance graphic	0.0198	editorial intern	0.020862
-7	animator	-1.17E-03	development engineer intern software	0.021313	co creative director founder	0.020358	intern public relations	0.021695
-6	assistant teacher	-1.04E-03	developer intern web	0.021637	intern marketing media social	0.020451	assistant teacher	0.022533
-5	substitute teacher	-9.21E-04	engineering intern software	0.023186	art director freelance	0.020459	assistant s teacher	0.022925
-4	assistant teaching	-8.69E-04	development intern software	0.023356	creative director founder	0.021128	coordinator program	0.023183
-3	english teacher	-6.21E-04	intern software	0.023497	creative intern	0.021721	assistant graduate	0.024294
-2	assistant s teacher	-1.01E-04	engineer intern software	0.023928	digital intern marketing	0.02214	communications intern	0.026476
-1	tutor	5.72E-05	developer intern software	0.024543	design graphic intern	0.022745	assistant program	0.026934

Appendix D: Ward Hierarchical Clustering

We employ the ward hierarchical clustering algorithm to cluster job titles. The following steps are taken:

1. The Euclidean distances of the job title's positions in the first 12 principal components are calculated.
2. Following which the job titles are clustered using the hclust function in R. The base of the tree gives 150 clusters.
3. Unclustered jobs are then assigned to the clusters based on the distance of the particular *job title* to the first nearest cluster centroid (thus 1-Nearest Neighbor).

Table A2 illustrates with a sample of 30 clusters as shown with their associated top 3 most frequent titles.

Table A2: 30 Job Role Clusters and their associated Top 3 Job Titles

Cluster Number	1	2	3	Description
1	"engineer software"	"developer software"	"engineer senior software"	developer.software.engineer
2	"ceo"	"president"	"director"	board.director.ceo
3	"manager project"	"manager senior"	"manager project senior"	manager.project.assistant
4	"assistant research"	"researcher"	"assistant graduate research"	research.researcher.fellow
5	"developer web"	"developer ios"	"developer end front"	developer.end.front
6	"associate"	"cfo"	"attorney"	investment.associate.attorney
7	"account executive"	"account manager"	"business development manager"	account.business.manager
8	"manager"	"general manager"	"manager operations"	manager.hr.human
9	"cto"	"engineer senior"	"engineering vp"	engineer.technical.director
10	"manager product"	"manager product senior"	"director management product"	product.manager.director
11	"vp"	"business development director"	"director operations"	vp.business.director
12	"manager marketing"	"director marketing"	"marketing vp"	marketing.manager.director
13	"designer graphic"	"designer"	"creative director"	designer.director.graphic
14	"associate sales"	"representative sales"	"sales"	sales.representative.senior
15	"analyst"	"associate research"	"analyst senior"	analyst.research.scientist
16	"assistant teaching"	"instructor"	"lecturer"	assistant.professor.adjunct
17	"manager sales"	"director sales"	"sales vp"	sales.manager.marketing
18	"analyst business"	"analyst business senior"	"engineer process"	engineer.analyst.business
19	"engineer"	"design engineer"	"engineer mechanical"	engineer.design.mechanical
20	"administrative assistant"	"manager office"	"assistant"	assistant.operations.office
21	"assistant manager"	"manager store"	"branch manager"	manager.assistant.branch
22	"director executive"	"member"	"mentor"	member.board.chief
23	"producer"	"editor"	"assistant production"	editor.producer.production
24	"manager program"	"leader team"	"engineering manager"	manager.engineering.program
25	"teacher"	"tutor"	"english teacher"	teacher.tutor.english
26	"coordinator marketing"	"assistant marketing"	"associate marketing"	marketing.communications.coordinator
27	"associate senior"	"advisor financial"	"auditor"	associate.audit.senior
28	"analyst financial"	"controller"	"director finance"	analyst.finance.controller
29	"customer representative service"	"server"	"specialist"	customer.service.manager
30	"engineer systems"	"it manager"	"engineer system"	engineer.systems.analyst

Appendix E: LASSO Model explications

1. The biggest issue here is that in the cases where $p >>> n$, the loss function does not have a generic global minimum. Hence the requirement of regularization.

2. Consider the classic linear regression model, wherein we predict a response variable $\boldsymbol{y}$ from a matrix of predictors $\boldsymbol{X}$ by estimating the vector of coefficients β:

$$\boldsymbol{y} = \boldsymbol{X}^T \beta \tag{1}$$

To solve for β we solve for the global minimum of the Residual Sum of Squares (RSS) of β:

$$RSS(\beta) = (\boldsymbol{y} - \boldsymbol{X}\beta)^T(\boldsymbol{y} - \boldsymbol{X}\beta) \tag{2}$$

3. Equation (2) is also known as the loss function, and has a derivative:

$$\boldsymbol{X}^T(\boldsymbol{y} - \boldsymbol{X}\beta) \tag{3}$$

Solving for equation (3) = 0 yields the coefficients β.

4. Regularization entails adding an additional penalty term to the loss function. This makes an otherwise ill-posed problem solvable, and also constrains over-fitting.[18] Specifically, we introduce a regularization term $R(\beta)$ to the loss function:

$$(\boldsymbol{y} - \boldsymbol{X}\beta)^T(\boldsymbol{y} - \boldsymbol{X}\beta) + R(\beta) \tag{4}$$

5. The choice of the regularization term characterizes the Machine Learning regression model. Here, we employ the LASSO (Least Absolute Shrinkage and Selection Operator) regression technique, which minimizes the L_1-norm of β (Tibshirani 1996). The LASSO regression adds a L_1 penalty to the loss function with an arbitrarily small tuning parameter λ. The LASSO loss function to minimize becomes:

$$(\boldsymbol{y} - \boldsymbol{X}\beta)^T(\boldsymbol{y} - \boldsymbol{X}\beta) + \lambda|\beta| \tag{5}$$

[18] For training data with a large set of training features (such as most unrestricted text classification learning cases), over-fitting will minimize the error of the training model. However, such a model will be optimized to the training data and will generalize badly to out-of-sample data sets; over-fitted models compromise general validity for internal validity (see Hastie et al., 2009, p. 219-223). As our final model assessment is an out-of-sample prediction evaluation, over-fitting is of significant concern.

6. The LASSO logistic regression is frequently used due to the efficacy and parsimony of model results. In particular, the inclusion of the L_1 penalty term in eq. 5 will drive certain coefficients to exactly 0. This represents an added layer of feature selection. The LASSO model highlights the text features that most determine differences in the two groups while suppressing statistical noise. This produces parsimonious, interpretable models (Tibshirani, 1996), which is necessary for qualitative assessment of results. In addition, the LASSO technique has had success in Machine Learning competitions[19] and the consistency of its estimates have been rigorously demonstrated (e.g. Zhao and Yu, 2006).

[19] For instance, the Kaggle-Yelp competition of 2013: "Exploring the Yelp Data Set: Extracting Useful Features with Text Mining and Exploring Regression Techniques for Count Data." Anonymous, http://www.cs.ubc.ca/~nando/540-2013/projects/p9.pdf, last accessed 12/12/2017.

Appendix F. Model Assessment: Qualitative Coding

We assessed the validity of our classifier results in the following manner:

1. We held a session to train two undergraduate research assistants (RAs). In this session we provided them with job description samples of PM who exhibit intrapreneurship and PM who do not. In addition, we retrieved profiles that are either high or low on posturing, that is, the use of language that suggests an attempt to "sell" the reader with unnecessary jargon and buzzwords. These examples were selected by the authors with the assistance of two individuals with domain-relevant experience and expertise: A hiring manager and a senior product manager at a large, defense-technology related engineering organization.
2. We tasked the RAs with rating 200 PM profiles, sampled uniformly across four classifier probability quartiles, for evidence of intrapreneurship: (1) for presence and (0) for absence.
3. In addition, they rated these profiles for high (1) and low (0) posturing.
4. Results are shown in Figures A3 and A4 below.
5. We find good inter rater reliability in both measures (Agreement of 88.5% and Cohen's K of 0.725 for intrapreneurship; Agreement of 93% and Cohen's K of 0.7 for posturing).
6. The intrapreneurship coding corresponds well with our classifier results. This is evidenced in Figures A3 and A4. Figure A3 and Figure A4 show a box plot of coding result distributions across four quartile VBE probability bins. These plots show minimum, lower quartile, median, upper quartile, and maximum of the coder averaged ratings.
7. The overall mean ratings of the 200 descriptions was 0.298 for intrapreneurship and 0.135 for posturing.
8. Figure A3 shows that manual coding is congruent with the classifier probability assignments. In particular, the agreement is the highest for PM descriptions assigned 0.75 or more. This was therefore the threshold we selected to indicate the presence of intrapreneurship.
9. Figure A4 indicates that posturing shows little correlation across classifier quartiles. That is, PM are *not* being coded as intrapreneurial because they employ the language of posturing.

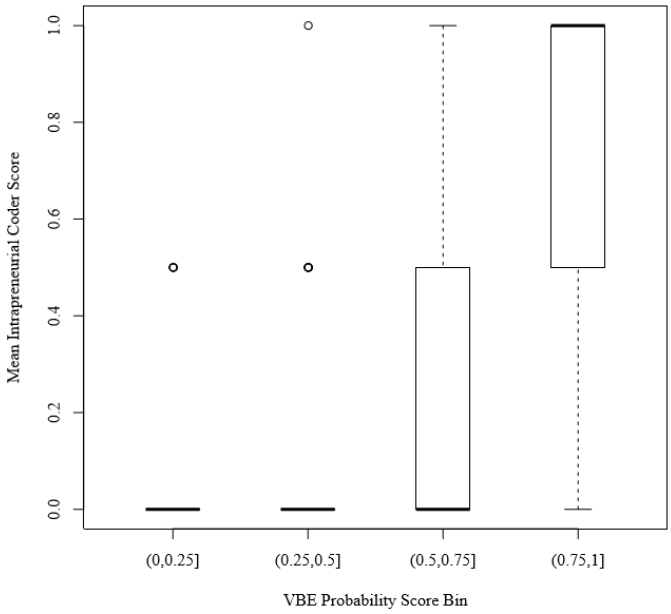


Figure A3. Box and whiskers plot of coder averaged scores of intrapreneurship (yes = 1, no = 0) across 4 quartiles of classifier assigned VBE probability.

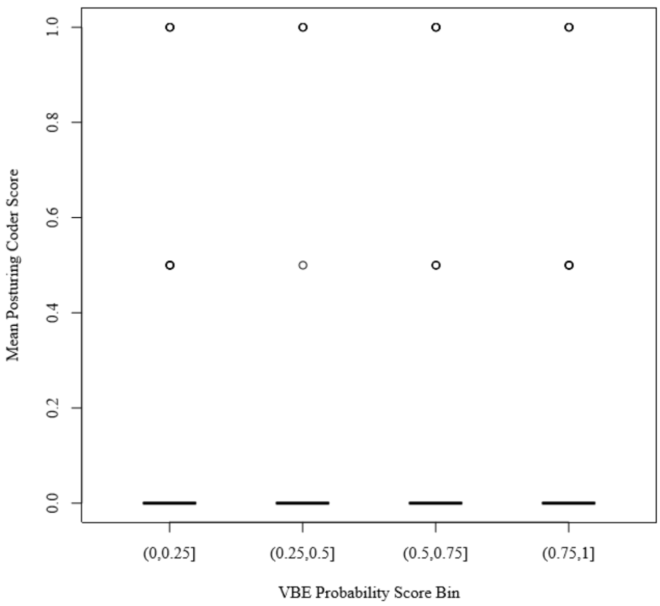


Figure A4. Box and whiskers plot of coder averaged scores of posturing (presence = 1, absence = 0) across 4 quartiles of classifier assigned VBE probability.

Appendix G. Replication Exercise: Panel Expert Dictionary Coding of Intrapreneurship

To further ascertain the construct validity of our intrapreneurship measure, we asked a panel of experts to assemble a list of words that either indicated the presence or absence of intrapreneurial activity. We then used this to code the PM descriptions for the purpose of replicating our initial findings. We detail this process below.

1. We assembled a panel of five domain-specific experts: a HR hiring manager of a mid-sized technology firm, a HR director of a defense related technology firm, a talent manager of an incubator, a corporate executive of a corporate incubator within a large technology firm, and a product manager in a large technology firm.
2. We discussed what forms of intrapreneurship panel members found most desirable. Each panel member then independently generated a list of 20-30 words that would be salient when assessing—from a job description—whether a product manager's past work is intrapreneurial (positive weightage) or more suited to everyday expectations (negative weightage).
3. Words generated by two or more panelists were selected (a total of 30 words altogether).
4. The panel independently rated these words on a five-point scale ranging from -2 to 2, whereby -2 indicates mundane PM activity and +2 indicates intrapreneurial PM activity. The word ratings are found in Table A3 below.
5. We aggregated and normalized these ratings between 0 and 1 and used them to rate the job descriptions in our corpus. Consistent with our initial analysis, we labelled descriptions that scored above 0.75 as instances of intrapreneurship.

We call this new measure the *rated* scores, while the main measure using ML the *learned* scores. The characteristics of these measures are as follows:

1. A statistically significant 0.41 correlation between the *rated* and *learned* job description scores.
2. The vast majority of *learned* descriptions are *rated* as intrapreneurial, but not vice versa (see Figure A5). There were also a lot more *rated* versus *learned* descriptions.

3. The vast majority of word weights generated for *rating* were in alignment with that of the *learning* classifier. This is evidenced in Table A4.
4. We note, however, that the distribution of *rated* and *learned* job descriptions are starkly different. Figure A6 plots the distributions of *rated* and *learned* scores. As expected, the *learned* scores exhibit a bimodal distribution (near 0 and 0.9), while the *rated* scores exhibit a near-normal distribution.
5. This is attributable to the fact that classifier algorithms are designed to enforce a bimodal distribution, while human-generated keyword coding are bounded by the central limit theorem. One implication is that the binary cut-off point of 0.75 here is considerably *less* arbitrary for *learned* scores in comparison with *rated* scores.

Using these *rated* job descriptions, we replicated our initial findings: These are shown in Tables A5 and A6 below. All coefficients remained statistically significant and in the predicted direction. Regarding Hypothesis 1, the main effect of external mobility on *rated* intrapreneurship is similar to its effect on *learned* intrapreneurship. Regarding Hypothesis 2, the main effect of *rated* intrapreneurship, and the corresponding interaction effect between *rated* intrapreneurship and external mobility on the risk of departure, are lower. However, in both cases, the standard errors are *proportionately larger* in the replication.

In order to further triangulate our replication, we shared blind examples of these manually-coded job descriptions with our expert panel. While the panel of raters acknowledged evidence of intrapreneurial activity in the descriptions that were *rated* as such, they viewed the *learned* descriptions as more representative. In particular, when asked which descriptions better captured the kind of intrapreneurial experience they valued, the corporate and stand-alone incubator executives leaned heavily on the *learned* descriptions.

Table A3. Panel Selected Word Ratings

Positive	Rating	Negative	Rating
start up	5	*support*	-4
patent	5	*service*	-4
company	4	*maintain*	-4
venture	4	*product*	-4
found	4	*manage*	-4
create	4	*client*	-2
entre/intrapreneur	2	*test*	-2
build	1	*cost*	-2
new/novel	1	*engineer*	-2
develop	1	*resolve*	-2
pioneer	1	*process*	-1
initial	1	*response*	-1
problem	1	*drive*	-1
solve	1	*cost*	-1
user	1	*market*	-1

Note: Panelists were asked to put words into 3 bins: intrapreneurial leaning (1), indifference (0), and non-intrapreneurial leaning (-1). The final rating score is calculated by summing across all 5 panelists; the rating range is [-5,5]. Panelists were told that these words include their inflectional affixes (e.g. *found* includes the words *founded*, *founding*, *founder*).

Table A4. OLS Regression of Panel Rated Words with Classifier Score

Word	Coef	Std. Err	
Intercept	0.3842	(0.0031)	***
build	0.0541	(0.0054)	***
client	0.0225	(0.0035)	***
company	0.0239	(0.0018)	***
cost	0.0009	(0.0030)	
create	0.0020	(0.0024)	
develop	-0.0218	(0.0031)	***
drive	0.0295	(0.0022)	***
engin	0.0244	(0.0018)	***
found	0.0197	(0.0027)	***
initial	-0.0052	(0.0059)	
maintain	-0.0001	(0.0017)	
manage	0.0144	(0.0008)	***
market	0.0078	(0.0021)	***
new	-0.0202	(0.0035)	***
patent	0.0088	(0.0026)	***
pioneer	0.0128	(0.0236)	
platform	0.0435	(0.0052)	***
problem	-0.0032	(0.0091)	
process	0.0473	(0.0039)	***
product	0.0387	(0.0008)	***
resolve	0.0313	(0.0069)	***
respons	0.0435	(0.0034)	***
service	0.0013	(0.0009)	
solve	0.0105	(0.0130)	
startup	0.0297	(0.0035)	***
support	0.0165	(0.0009)	***
test	0.0993	(0.0040)	***
entre/intrapreneur	0.0233	(0.0209)	
user	0.0518	(0.0059)	***
venture	0.0294	(0.0059)	***
n	20007		
df	19977		
F	248.8		***

· *p<0.01, * p<0.05, **p<0.01; ***p<0.001*

Note: Positive coefficients indicate a linear alignment of Panel Raters with the classifier scores; negative coefficients indicate linear non-alignment. Non-significance indicates that the panel selected words have no direct linear relationship with the classifier scores.

Table A5. Linear Probability Models of Intrapreneurial Activity

	Model 1	Model 2	Model 3
External Hire	0.0223 *	0.0204 *	0.0462 *
	(0.0093)	(0.0093)	(0.0198)
Log(Tenure/[years])		-0.0551 ***	-0.0418 **
		(0.0091)	(0.0128)
External Hire × Log(Tenure/[years])			-0.0251
			(0.0171)
n	4139	4139	4139
df	4046	4045	4044
F	4.898 ***	5.281 ***	5.25 ***

*· p<0.01, * p<0.05, **p<0.01; ***p<0.001*

Note: Intrapreneurial activity is determined by a panel rated dictionary. All models are linear probability models, OLS estimated with CEM derived weights, with the outcome of interest as the dummy indicator variable for intrapreneurship. Standard errors in parentheses. Internal hires form the baseline comparison group. Results shown control for length of job description and include cohort, previous job role, and company fixed effects.

Table A6. Cox-proportionate Hazard Models of Departure Likelihood

	Model 1	Model 2	Model 3
External Hire	0.3018 ***	0.3030 ***	0.2893 ***
	(0.0286)	(0.0286)	(0.0293)
Intrapreneurial		0.1795 **	0.0180
		(0.0635)	(0.1037)
External Hire × Intrapreneurial			0.2658 *
			(0.1290)
n	6028	6028	6028
Concordance	0.632 ***	0.633 ***	0.633 ***
Wald Test	432.2 ***	442.2 ***	457.4 ***
Logrank Test	465.6 ***	477.1 ***	499.7 ***

*· p<0.01, * p<0.05, **p<0.01; ***p<0.001*

Note: Intrapreneurial activity is determined by a panel rated dictionary. All models are Cox proportional hazard models with CEM derived weights, with the outcome of interest as the number of days until leaving the company. Standard errors in parentheses. Internally hired, non-intrapreneurial product managers form the baseline comparison group. Results shown include cohort, previous job role, and company fixed effects.

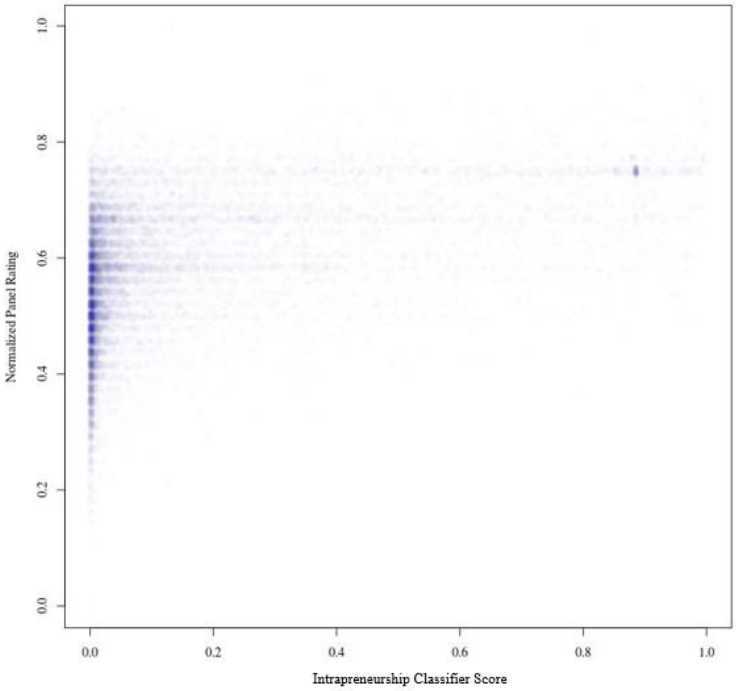


Figure A5. Scatter plot of intrapreneurship classifier score against normalized panel ratings. Transparency and jitter set to visualize data density. Notes: (1) Ab sence of data in the lower right corner of the graph suggests an association. (2) High classifier scores are limited to high normalized panel ratings, but not vice-versa. (3) Distributions of normalized panel rating and classifier score are starkly different, with the former resembling a skewed gaussian, and the latter exhibiting two modes: one at 0, and another at ~0.9.

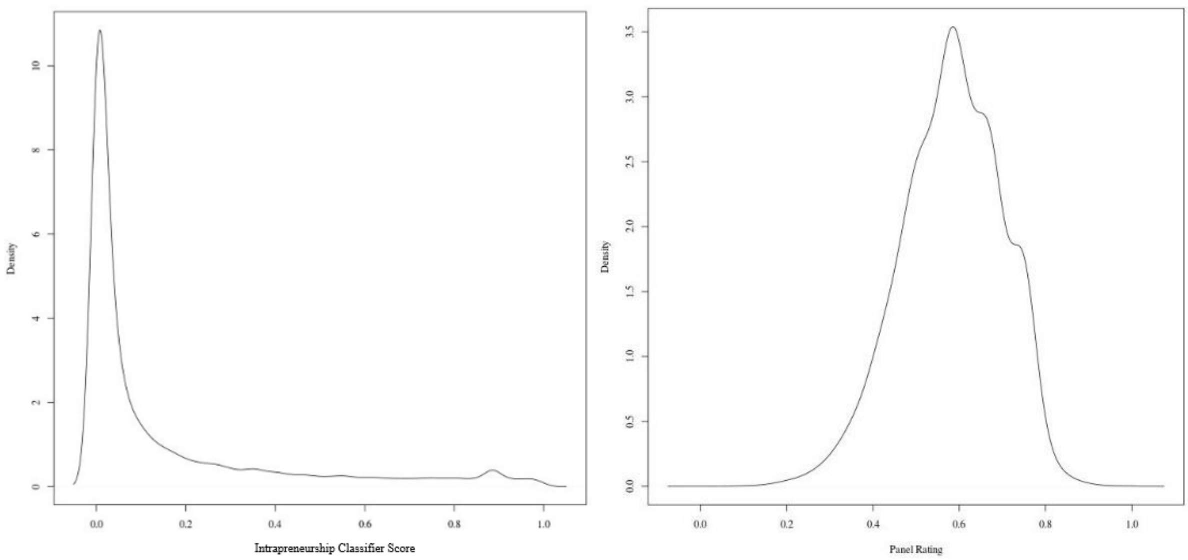


Figure A6. Kernel density plots of intrapreneurship classifier score (left) and normalized panel ratings (right). Note: (1) The difference in the shape of the distributions and (2) difference in modes.

Appendix H: Randomly Selected Job Advertisements From Indeed.com

Product Manager Job Advertisements With Intrapreneurial Role Demands:

1) **Principal Product Manager, Amazon RDS Postgres**. Our goal is to be the best DBA a customer can find, providing the best database technology in the world, enabling companies to accelerate their growth and maintain as many 9's of reliability and uptime as they need on their most crucial systems. Customers use RDS in thousands of different ways for experimentation, startup acceleration and mission-critical enterprise workloads, in fields as varied as tax preparation, space mission data analysis, business analytics, IOT data processing and social networks, to name a few. Amazon RDS is one of the largest and fastest-growing businesses in the AWS cloud with no end in sight as businesses are rediscovering the strength of relational databases and the easy application development that leverages mutable schemas, scalable ACID transactions, and modern language interfaces such as JSON. . One of our most exciting business is RDS Postgres - both of which are two of the most popular open source databases in the world. As customers move to the cloud, they are also finding that it's time to move both upscale from less performant open source databases and down-cost from proprietary databases. · Understand our customers inside and out via regular calls, visits, customer briefings, your own customer advisory board and travel to conferences, summits and customer sites. · Lead teams across AWS, directly or by influence, that drive the Amazon RDS business forward. · Develop the RDS product strategy and vision and translate it into creative, high quality, simple project features. · Make the business decisions that grow adoption and usage of RDS. Set prices, target the right customers, and focus our investments in the right areas. · Work closely with all RDS engineering teams to design, schedule and deliver in an agile environment. · Launch new features and make sure our sales, marketing, and PR teams are telling the most compelling RDS story. · Dive deep into database technology to chart the vision for the next big things from Amazon and RDS Postgres. If you think you have what it takes and you want to grow yourself while you grow a business, come talk to us!.

2) **Principal Product Manager, IoT Security – Norton IoT**. As a leading Fortune 500 Technology & Security Company, Symantec already protects more than a billion IoT devices, putting Symantec among the biggest providers of IoT security today, and first to deliver a comprehensive security reference architecture for how to build-in security to make your IoT systems "secure by design." Symantec brings an unrivaled breadth of leading security solutions for device protection, encryption, authentication, key management, and code signing. Symantec also has unmatched depth in security expertise from monitoring, analyzing and processing more than 10 trillion security events per year worldwide for Symantec's Global Intelligence Network.. This particular team is building an exciting new security solution to extend Norton Security to everything connected in the consumer home. With IoT, the number of connected devices is growing at an exponential rate. While, these new devices offer a new range of possibilities, they also are increasing the attack vectors for the hackers exponentially. These devices collect a lot more sensitive personal data. Securing these devices and the personal information has never been so crucial. This team operates as a separate entity within the Norton Business Unit to find creative, bold & innovative solutions to solve some of the most complex problems in the IoT space. Connected Home is the next big thing that's taking shape in the technology industry. • Has a passion and vision for connected home space and can be the voice of the customer;. • Is driven to solving some of the toughest security issues on connected devices.. Responsibilities include:. • Working with various device manufacturers/service providers and/or ODMs for HW and SW integration;. Zigbee, Z-Wave, Bluetooth, 6LoWPAN, etc.;. • Good understanding of ARM architecture, embedded Linux, and security solutions;. • Strong knowledgeable of software development life cycle;. ~. #LI-SB1.

Product Manager Job Advertisements Without Intrapreneurial Role Demands:

3) **Product Manager, ECG and Implanted Device Cardiac Monitoring – Scott Care.** ScottCare is a leader in non-invasive cardiology diagnosis, rehabilitation and therapy. Since 1989, ScottCare has designed, manufactured and marketed high quality telemetry and remote monitoring software and electronics for hospitals and physician practices. Based in Cleveland, Ohio, ScottCare is a division of the Scott Fetzer Company. Ambucor Health Solutions, a division of The ScottCare Corporation, is a provider of consultative and contracted Ambulatory Electrocardiographic and Remote Device Monitoring labor services for cardiology practices and hospitals that are focused on providing the highest quality of care while retaining ownership of the clinical services that they offer. This includes the development and maintenance of sales tools, product/technical sales training and customer demonstrations. In addition, this position plays an integral role in product development and the launch of new products. This position also assists the marketing communications team with the development of messaging and marketing collateral. Job Responsibilities: Be the in-house product expert for ScottCare's ambulatory ECG monitoring products, including cardiac monitors and analysis/reporting software. Prepare sales tools such as customer sales presentations and demonstration software. Prepare and maintain an on-boarding product training curriculum for new sales representatives.

4) **Product Manager, Network Solutions – First Data**. First Data is a global leader in commerce-enabling technology solutions, serving more than six million business locations and 4,000 financial institutions in 118 countries around the world. Our 23,000 owner-associates are dedicated to helping companies, from start-ups to the world's largest corporations, conduct commerce every day by securing and processing more than 2,300 transactions per second and $1.9 trillion per year. There are many exciting opportunities for talented individuals who would like to join our team and play a meaningful role in helping us shape the future of global commerce.. First Data Network and Security Solutions provides a wide range of value-added technology solutions to financial institutions of all sizes, enterprise clients and small businesses. Network Solutions include Electronic Funds Transfer (EFT) network services, such as STAR debit and ATM processing, and prepaid network services, including Valuelink, MoneyNetwork, Transaction Wireless, and Gyft. Security Solutions include best-in-class solutions such as TransArmor and TeleCheck, and our suite of advanced fraud prevention solutions. NSS also supports our other digital strategies including mobile payments and online and mobile banking. Position Description Overview. Security and fraud market awareness is requested.. Job Responsibilities. Involved from conception through end of life for a specific product, product group or product line including product management, product development and business development. PRODUCT MANAGEMENT: Assist in tracking and reporting product performance throughout its lifecycle including product strategy, product planning and issue prioritization. Assist with analysis that drives product pricing and bundling. Draft internal product communication and information. Monitor customers/prospects for awareness of customer needs and perspectives. Assist in the development of business case to support new product recommendations. Assist in managing issues throughout the process including problem identification, root cause analysis, and client communication.. Scope of Job. Decisions have considerable impact on the end result of the business unit. Frequent contact with internal customers. Occasional contact with external customers.. Autonomy. Works independently under minimal supervision. Individual Contributor. Business Case Justification. Project Management. Manage a Matrix Environment. Competitive Environment. Solutions Development. Knowledge of Product Line. Prod Dev Strategy & Influence. Product Dev Life Cycle.