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Comobility

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Abstract
We present the first population-level characterization of comobility?the movement of multiple employees from one firm to another. Both in a seven-year snapshot of the entire Danish economy and several decades of employer-employee matched records from the worldwide automatic speech recognition industry, we find that 10-11% of interorganizational job moves occur jointly with co-workers. Co-movers enjoy higher productivity and an initial wage premium compared with those who move alone. These gains appear largely due to coproduction complementarities, especially among simultaneous co-movers, although information sharing (i.e., employee referrals and ?scouting? out new opportunities) helps to explain sequential comobility.

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INTRODUCTION

The interorganizational mobility of workers has attracted substantial scholarly attention given its role in the diffusion of knowledge, individual attainment, and industry evolution. Marshallian notions of disembodied knowledge spillovers have been revisited by economists showing that the mobility of personnel is responsible for the transfer of knowledge (Almeida & Kogut, 1999; Agrawal, Cockburn, & McHale 2006; Breschi & Lissoni, 2009). Mobility is moreover seen as key to industry formation as employees leave to join other firms or start new ones (Saxenian, 1994; Klepper, 2007). At least since Sørensen (1977), sociologists have challenged the classical notion that the accumulation of firm-specific capital leads to wage gains, positing that labor-market frictions entail that financial and status attainment are more likely to be attained by changing jobs (Halaby, 1988; Wegener, 1991; Fujiware-Greve & Greve, 2000). Hundreds of articles have focused on these and other implications of mobility.

Nearly all work on interorganizational mobility focuses on individuals as the unit of analysis. While this focus may not be entirely surprising given the nature of non-union employment contracts, there are nevertheless reasons to think that mobility can also be a team sport. Anecdotes abound of coworkers who quit their jobs to found a rival firm, such as the so-called Traitorous Eight who left Shockley Semiconductor to form Fairchild. Yet "comobility"—the joint migration of multiple workers from one firm to another—has been addressed only occasionally and primarily in the case of elite workers such as founders, executives, or industry "stars" (Wezel, Cattani, & Pennings, 2006; Groysberg, Lee, & Nanda, 2008; Campbell, Saxton, & Banerjee, 2013).

We lack a broad characterization of this potentially important phenomenon, including 1) its prevalence among the broad population of workers of various skill levels, 2) which sorts of workers are more likely to co-move, 3) what mechanisms are involved. Consequently, we follow Dahl, Dezső, & Ross (2012) in adopting an inductive empirical approach with the aim of generalizing stylized facts. Rather than propose and test specific hypotheses, we present a more informal theoretical discussion to provide context for our analyses. We see this work as laying a foundation for further theory and analysis to build upon regarding the causes and consequences of comobility for individuals, organizations, and industries.

We characterize comobility in two population-level datasets: a hand-collected compilation of workers in the worldwide automatic speech recognition (ASR) industry since 1952, and a seven-year snapshot of the Danish employer-employee register (IDA). We start by establishing a baseline expectation of how often comobility might occur given industry structure, forecasting via the familiar "birthday problem" with non-equal prior probabilities (Klotz, 1979). This exercise produces an expected comobility rate of 1.4%. We then characterize the actual incidence of comobility in the ASR and IDA datasets—

excluding acquisitions and dissolutions—which at the annual level are 10.5% and 10.9% respectively. Not only are these rates in the two datasets quite similar; they represent much more comobility than in our baseline prediction and a substantial percentage of overall mobility. Moreover, workers who move jointly with others enjoy productivity gains and wage premia compared with those who move alone.

We then explore mechanisms underlying comobility, including coproduction complementarities, information flow, social attachment, and bargaining power. Several results point to complementarities as a driver of comobility. Higher productivity gains are found among co-movers who had worked on joint projects. Higher wage gains are found for co-movers with similar tenure (Hayes, Oyer, & Schaefer, 2006) and who worked not just at the same firm but in the same co-located plant. Complementarities appear particularly strong among those who co-move simultaneously, where information sharing is less likely to play a role. Wage gains among sequential co-movers are higher for the first of the group to move, suggesting that the scouting out of new opportunities may be more prevalent than employee referrals.

FROM MOBILITY TO COMOBILITY

The movement of workers among organizations has long been recognized as a consequential phenomenon, with myriad articles by sociologists and economists analyzing both the antecedents and implications of mobility. A key contribution of scholars has been establishing that the knowledge spillovers proposed by Marshall (1920) to explain industrial agglomeration are not simply "as it were, in the air." Rather, knowledge resides in the minds of workers and spread by their movement between firms (Arrow, 1962). Interorganizational mobility helps to explain regional differences in knowledge flows (Saxenian, 1994; Almeida & Kogut, 1999, Breschi & Lissoni, 2009) as well as the leakage of information between firms (Kim & Marschke, 2005; Corredoira & Rosenkopf, 2010; Singh & Agrawal, 2011). Mobility has moreover been tied to industry evolution via the formation of intra-industry "spinoffs" by disaffected employees who leave to form rivals (Klepper & Sleeper, 2005; Chatterji, 2008), suggesting that Marshallian externalities may not suffice to explain patterns of agglomeration.

A related stream of work examines the implications of interorganizational mobility for individual productivity and attainment. While some have proposed that workers profit most from accumulating firm-specific capital in efficient labor markets (Topel, 1991; Neal, 1995; Le Grand & Tåhlin, 2002; Altonji & Williams 2005), empirical evidence is mixed at best. Parent (2000) shows that a better predictor of wage growth is longevity within an industry than in a single organization. Moreover, firms are known to depress (real) wages for employees they believe will stay with the firm (Baker, Gibbs & Holmstrom, 1994) and actively take steps to reduce opportunities outside the organization by imposing non-compete agreements on workers (Marx, 2011; Garmaise, 2011). Indeed, several scholars have drawn a link between mobility and wage gains (Hall & Kasten, 1976; Bartel & Borjas, 1981; Mincer & Jovanovic, 1982; Flinn, 1986; Fuller, 2008) as well as mobility and productivity (Hoisl, 2007; 2009).

Empirical work on mobility has been conducted almost entirely at the individual level. As Pfeffer (1991:795) observes, “turnover has been most often examined as the consequence of an individual decision process, with the individual acting in isolation…virtually all of the dominant models of turnover conceptualize it as an individual decision.” This focus is at some level unsurprising, given that employment contracts—at least those not involving unions—are agreements between a firm and a single worker. Even if a group of workers wanted to move from one organization to another, coordination problems might make it difficult to do so jointly.

Nevertheless, there exist many examples of workers moving jointly from one organization to another—a phenomenon we refer to as “comobility.” Multiple individuals have been known to leave their employer together to found a new firm, as with the so-called Traitorous Eight who left Shockley Semiconductor on September 8, 1957 to form Fairchild Semiconductor. Similarly, the Dodge brothers founded their eponymous automotive firm once they grew weary of working for Henry Ford. More recently, Chad Hurley, Steve Chen, and Jawed Karim left PayPal together to found YouTube. That co-workers sometimes become co-founders has not escaped the attention of scholars (Eisenhardt & Schoonhoven, 1990; Phillips, 2002; Beckman, 2006; Wezel, Cattani & Pennings, 2006), but studies of joint mobility to date have primarily focused on elite workers such as founders or “stars” (Groysberg & Lee, 2009; Campbell, et al., 2013). Prior work might lead one to conclude that comobility is limited to select types of workers as opposed to a more general phenomenon.

There are however at least anecdotal indications that comobility may occur more widely. In 2010, several software engineers left GPS device manufacturer Garmin following the company’s insistence that they relocate from San Francisco, California to Olathe, Kansas (Maker, 2010). The disaffected engineers set up a website advertising their accomplishments in building the company’s Garmin Connect service, adding: “We’re for hire.” Several of them subsequently joined rival GPS manufacturer Magellan. A few years earlier, Nuance Communications R&D scientist Larry Heck decamped for Yahoo and over the next few months enticed the entire R&D team to follow him (Mills, 2005). One motivation for comobility is captured by Jim Everingham, Chief Technical Officer of LiveOps: "We're probably the largest single collection of people who were originally involved in Netscape engineering. It's the same team, and we love to work with each other" (Festa, 2004).

Simultaneous vs. sequential comobility and possible mechanisms

These anecdotal accounts illustrate a key distinction in comobility: whether co-workers move simultaneously or sequentially. The more straightforward version of comobility involves two or more co-workers who depart at the same time to join or found another company, such as the Traitorous Eight of Fairchild, who quit on the same day. Co-movers may prefer to move as close together as possible if they wish to continue utilizing shared skills. Quitting concurrently avoids running afoul of employee non-solicitation agreements, whereby workers pledge not to recruit their former colleagues after leaving.

Comobility may also unfold sequentially, either because coordination problems introduce delays or because information takes time to diffuse. The founder of a new firm may recruit (as early employees) former colleagues who wanted to see the new venture gain some traction first. A similar chain of events can occur when someone joins another firm and then, having "scouted out" the opportunity, encourages former colleagues to follow as did Larry Heck after moving from Nuance to Yahoo (Mills, 2005).

The distinction between simultaneous and sequential comobility can help us to distinguish the mechanisms at play. We consider several possibilities including coproduction complementarities, bargaining power, scouting out opportunities, employee referrals, and social attachment. Given that our aim is to establish stylized facts, we do not state specific hypotheses but rather present an informal theoretical discussion to provide context for the empirical analyses.

Coproduction complementarities and bargaining power

Alchian & Demsetz' (1972) notion that workgroup output is "more than the sum of separable outputs" has been elaborated by theorists hypothesizing that colleagues develop complementarities as they work with each other. Variously called "organization capital" (Prescott & Visscher, 1980), "network capital" (Mailath & Postlewaite, 1990), and "team human capital" (Chillemi & Gui, 1997), the notion is that skills accrue not only to individuals as in Becker's (1962) original formulation but also collectively within workgroups. Empirical studies support the existence of this construct in three respects. First, the performance of workgroups has been shown to improve over time with joint experience (Reagans, Argote, & Brooks, 2005; Huckman, Staats, & Upton, 2009). Second, spillovers obtain among coworkers (Kendall, 2003; Gould & Winter, 2009; Arcidiacono, Kinsler, & Price, 2013). Third, executives are more likely to depart an organization when executives most similar to them do (Hayes, Oyer, & Schaefer, 2006).

Economists have theorized that the value generated by co-production complementarities will be allocated between owners and workers in efficient labor markets (Chillemi & Gui, 1997). However, firms often fail to compensate employees for the value they create. Consequently, members of workgroups may find themselves facing a somewhat different dilemma regarding the decision to remain loyal to the firm vs. pursuing external opportunities. A worker leaving the firm unaccompanied by co-workers takes along skills that are not firm-specific but forfeits any coproduction complementarities. If workers move jointly, however, they can capitalize not only on their individual skills but also shared experience. Anticipating higher productivity among groups of workers who move together, firms may be willing to pay a premium to hire co-movers. Coproduction complementarities may be reassembled over time by sequential co-movers as they eventually reunite, but we expect that the greatest productivity gains will be achieved by those who move simultaneously. Simultaneous co-movers may be able to more quickly re-create the production processes and systems that facilitated their performance at the prior firm. By contrast, one co-mover arriving earlier than others may need to adapt more to the new firm's way of doing things and require time to readapt or include former colleagues once they arrive.

Moreover, co-workers moving simultaneously may be able to achieve higher wages if they negotiate collectively (Kochan & Katz, 1988; Katz, 1993). Suppose that a firm needs to hire a number of workers quickly. It might save on search costs if it is able to source several hires from the same firm. Recognizing this, workers may seek to capture part of those savings by bargaining collectively for their employment contracts. In the strong form, bargaining power may enable higher wages even in the absence of any coproduction complementarities, simply due to "strength in numbers." If this were the case, we would expect to see wage premia increase in the size of the simultaneous co-moving group—whether controlling for, or absent, any coproduction complementarities. (We would generally not expect sequential co-movers to bargain collectively.)

Employee referrals, scouting-out opportunities, and social attachment

Comobility may also occur in the absence of complementarities given purely social interactions among workers. In analyzing collective departures, Sgourev (2011) notes that actors may base their decision to continue investing in their current employer on the belief that others will continue to as well (Greif, 2000). When they notice that others are beginning to leave, they become more likely to do likewise. If comobility were principally driven by social attachment, we might not expect either productivity or wage gains as often observed among "tied movers" (Mincer, 1977; McGoldrick & Robst, 1996). Social connections among co-workers may also lead to comobility as information is shared, in at least two ways.

First, the initial worker arriving at the new firm might provide a referral of a former colleague to the new firm (Fernandez & Sosa, 2005; Castilla, 2005; Schmutte, 2013). To the degree that comobility is facilitated by referrals, co-movement will unfold sequentially instead of simultaneously. In this scenario, the new firm might pay a premium to hire the ex-colleague given the endorsement, although the literature on the wage impact of referrals-based hiring has mixed predictions (Marsden & Hurlbert, 1988; Kugler, 2003 Mouw, 2003). If comobility were primarily due to referrals of this sort, we might expect higher wage gains for referred (i.e., later) co-movers compared to the referring (initial) co-mover. Referrals could theoretically occur even in the absence of coproduction complementarities. Suppose for example that a firm hired an engineer and needed to hire a salesperson. Even if the engineer had never worked directly with salespeople at the prior firm and thus had no complementarities with any of them, their reputation alone might lead the engineer to refer one of them to the new firm. This may seem an unusual scenario given that employees would seem more likely to recommend those they had worked with directly, but to the extent that we observe wage gains among sequential co-movers, we cannot rule out that these are facilitated entirely by referrals unless we directly observe complementarities.

A second mechanism by which information sharing could lead to sequential comobility involves not recommending former colleagues to the present firm but rather recommending the present firm to former colleagues. Suppose one of a group of workers leaves for a new firm but cannot convince others to leave at the same time. Upon arriving at the new firm, the worker having moved has "scouted out" the opportunity and can now more credibly explain to former colleagues why they too should move. If this were the case, later co-movers might be willing to accept lower wages. Moreover, although referrals could theoretically occur even in the absence of coproduction complementarities, workers may be more eager to attract ex-colleagues whose arrival would boost their own productivity.

DATA & METHODS

We employ two datasets in order to characterize comobility. The first is a hand-curated dataset of nearly 14,000 workers in the worldwide Automatic Speech Recognition (ASR) industry from 1952-2013. The second is the Danish Integrated Database for Labor Market Research (IDA) from 1999-2005. These datasets complement each other in several ways. The former is a high-tech, high-growth industry whereas the latter covers the entire Danish economy. The former is a global industry with 25% of firms outside the U.S., but the latter is a single country with very different socioeconomic institutions. The latter covers approximately seven years while the former spans six decades. In the former, names are accessible and so it is possible to merge in other data sources whereas in the latter, names are scrambled into unique identifiers. The latter is a full census whereas the former is not.

The Automatic Speech Recognition Industry

The first author collected data on more than 14,000 workers who ever held a job in the automatic speech recognition (ASR) industry. These data come from non-confidential sources, giving access to individual names and enabling correlation of multiple sources as described below. In this way, it was possible to collect information on a host of individual-level and firm-level covariates. The approach is not without its downsides, primary among them being the possibility of industry-specific factors accompanying any conclusions drawn from these data—though approximately half of the jobs collected for these workers are from their careers either before or after the ASR industry. Another limitation is that the dataset does not claim to be a full census of ASR workers. While coverage of executives and inventors is strong, it is likely that "backoffice" personnel such as HR or customer support are less well covered. Employment histories were constructed from four primary sources: industry trade journals, technology conference proceedings, U.S. patent records, and internet-based repositories.

These resources yielded a list of 13,940 workers who ever held a job in the speech recognition industry—again, either at a de novo ASR company or performing ASR-related activities within a de alio firm. There were 64,871 jobs (including multiple job titles within a single firm) for these workers at 556 different ASR firms. The career histories were then extended to include 39,652 jobs at 15,638 firms not in the ASR industry. Company names were checked by hand so to assign like firms the same identifier. Next, names were disambiguated between the various sources. This was done first by automatically pruning name suffixes and prefixes such as "Dr." and "Jr." and then resolving nicknames such as "Bob" and "Robert." Names were sorted by first initial and last name, with further variations checked by hand to resolve spelling inconsistencies, hyphenation, etc. Although these data do not constitute an ASR census, the data probably well represent executives and inventors.

The resulting data is collapsed into a set of moves. Workers holding only one job do not move and are excluded. Next, "phantom" moves including patent reassignments or acquisitions are eliminated. For the latter, moves from target to acquirer are considered only if before the acquisition date; otherwise it might appear that dozens or hundreds of workers moved simultaneously. Patent reassignments are less straightforward to handle, as no central repository exists, but "moves" that appear when IP holding companies acquire the patents of failed companies are discarded. In addition, moves from IBM to Nuance Communications that cannot be corroborated via non-patent sources are removed because Nuance licensed the majority of IBM's speech recognition patents in 2008. Moves following dissolutions are also discarded as these likely involve different dynamics including much less bargaining power for workers.

This exercise yields 28,640 moves from one firm to another (a directional firm dyad). This count is reduced to 15,649 by discarding all moves between two non-ASR firms. In other words, a move is only considered if either the prior or new firm is in the ASR industry; including moves from non-ASR firms to non-ASR firms would likely understate the actual rate of comobility. Most directional dyads have only one person who ever made that move, but 1,202 directional dyads were traversed by multiple people, for a total of 3,984 moves that potentially could involve comobility. Of course, these moves may occur at different times and not represent comobility. The next step was to determine whether individuals making the same firm-to-firm move should be labeled as co-mobile. Several different versions of the comobility indicator were constructed given that opinions could vary regarding how closely together employees would need to move in order to be considered co-mobile. The strictest definition employed here requires that the co-moves occurred in the same month, which we refer to as "simultaneous" comobility. We define simultaneous mobility as occurring in a one-month window both because the ASR data not reported beyond the granularity of one month and also because Danish employees are required by law when resigning to stay through the remainder of the current month as well as the following month.[1] Thus if two workers leave the same firm for another within the same calendar month, we can be reasonably confident that the decision was made jointly rather than sequentially as in the case of information sharing. Sequential comobility is defined as the complement of simultaneous mobility within a calendar year, i.e. co-movers that occur within a 2-12 month window.

Control Variables

Distance between firms is calculated via latitude and longitude, correcting for the curvature of the earth. Location is determined through company headquarters and refined wherever possible by using information from the newsletters or the inventor's hometown listed in a patent filing. We also control for firm age and size, particularly because it may be easier to extract teams of workers from larger companies. Clearly, trying to hire a group of five from a four-person company is impossible.

Prior move between firms. For every move, we control for whether any other employee has made that same move in prior years. To the extent that moves have occurred previously between two firms, comobility might be more likely between them as well. Prior firm-to-firm mobility, even by those with whom the focal worker is not personally acquainted, may contribute to the belief that such a move is a safe bet. Likewise, recruiters at the new firm may examine the history of past hires from some firm and conclude that such workers are likely to be of high quality.

Ties to founders. We control for whether the worker previously worked with any of the founder(s) of the new firm. Founders with ties to the worker might be more successful in making credible representations regarding the firm's prospects. In turn, the worker might hope to be advantaged via the connection to the founder as compared to another new hire with whom the founder lacks prior experience. While we would expect such ties to bias towards mobility whether individual or joint, we expect an even greater effect on comobility given a higher decision "threshold" (Granovetter & Soong, 1983) that needs

[1] The Employers' and Salaried Employees' (Legal Relationship)(Consolidation) Act, English translation: "Termination on the part of the salaried employee shall be subject to one month's notice and until the end of the next month." (italics ours) https://www.retsinformation.dk/forms/r0710.aspx?id=123029.

to be reached to inspire collective action.

Tenure. We control for the amount of time the worker spent at the prior firm. Given that social proximity is associated with interpersonal influence (Marsden & Friedkin, 1993), we might expect the social contagion to activate the possibility of departure for workers who might otherwise be loyal to the current employer. Many studies have shown that workers with longer tenure are less likely to leave, presumably because they desire to capitalize on their firm-specific human capital (Sheldon 1971; Mortensen, 1978; Mincer & Jovanovic, 1982; Topel, 1991; Farber, 1999). If comobility is codetermined by social proximity and the influence of coworkers, we might expect such to activate workers more loyal to the firm, who would otherwise be less likely to leave and might need to be "pulled" by coworkers.

Technical workers. Comobility may be attractive for workers who are more interdependent, including technical workers. When they move, technical workers may be more likely to do so jointly given the importance of collaboration and complementarities. Engineering workgroups' performance increases over time, as "maturing may be especially critical to knowledge worker teams because of the increased complexity inherent in the work they perform" (Janz, Colquitt & Noe, 1977). In technical teams, complementarities may include learning to work with a shared set of tools or technologies. For example, a group of software developers may take time to agree on coding standards, an architectural approach, or a particular revision-control system. Individuals may be loathe to leave an engineering group with which they have gelled; thus the prospect of moving to a new firm together with colleagues may seem less daunting than moving individually. Indeed, Ganco (2013) finds that co-inventors on patents are more likely to patent together again (at a different firm) when they have worked on more complex technologies. To the extent that complementarities are amplified among technical workers, as suggested above, hiring firms may expend efforts to recruit engineers as a group.

Cofounders. Interdependence may also explain the salience of co-founders with prior joint experience. An extensive line of research has detailed the outperformance of intra-industry spinoffs where at least one founder moves from a rival firm (Klepper, 2007; Chatterji, 2008), underscoring the importance of industry knowledge in launching startups. Other scholars have shown that having multiple founders who have worked together previously boosts the survival and performance of startups (Eisenhardt & Schoonhoven, 1990; Phillips, 2002; Agarwal et al., 2014) at the expense of the parent (Wezel et al., 2006). To the extent that successful startups have multiple founders who had worked together and those prior associations become known, other founders may seek to emulate their success by including coworkers when they found companies.

Additional worker-level controls include age (interpolated by subtracting the year of their first job from 2013 and adding 21 as a likely year of entering the workforce) and executive roles based on job title. Founder status was noted from newsletters, Capital IQ, and job titles. Gender is determined by matching first names against a list of 90,000 tagged by GenderChecker.com. A research assistant then searched for photos and personal pronouns using the combined first and last names of workers with gender-ambiguous first names. Gender was successfully determined for 95% of ASR workers. Sales data are merged from Dun & Bradstreet panel data for U.S.-based firms (Walls & Associates, 2010). Finally, we measure patent productivity in the ASR dataset. This measure is limited to ASR workers who ever held a patent (and thus are presumably at risk of patenting), although observations are included for patent holders when they appear in any ASR data source (e.g., newsletters). This variable reflects the number of patents filed by a worker at a firm in a given year that were eventually granted.

The Danish IDA Register

The second author compiled comobility data from the Danish Integrated Database for Labor Market Research ("IDA"). The IDA is a database administered by Statistics Denmark that contains information on all individuals and workplaces in Denmark from 1980 onwards (see Timmermans (2010) for a detailed description). Its longitudinal character combined with the unique firm, workplace, and individual identifiers allows us to identify labor mobility by comparing employer-employee relationships in consecutive Novembers. Demographic information including occupational data on nearly all individuals enables us not only to identify co-moves and the characteristics of co-movers compared to solo movers.

Measuring IDA comobility

We constrain comobility in two ways. First, we assure that the move is joint with others. As in the ASR case, the fact that two individuals move between firms does not necessarily constitute a co-move. In IDA we deal with this issue by not only considering the movement between firms but also take into consideration the workplace or plant where the worker is employed. Importantly, comobility in IDA is identified as at least two employees moving not only from one firm to another but requires that the co-movers were in the same plant, both in the prior and the new firm. Given an average plant size of approximately 60, and that individual plants are co-located, it seems likely that a firm's employees within a single plant would know each other and possibly work together.

Second, we place a size restriction on the total number of joint moves. Whereas in the ASR dataset firm and person names are visible and we could inspect large co-moving groups, the same is impossible in the IDA given scrambled identifiers. Therefore, we remove all IDA co-moves that involve more than 10 employees.

To identify the timing in which comobility takes place, we use the information available on how many days they have been employed at that workplace. Based on this information we can measure narrow windows of co-moves, i.e. whether comobility occurs in the same month (i.e., simultaneously) or otherwise within the same calendar year (sequentially). Because the IDA contains annual information we are only able to identify moves that occur in the same calendar year. We identify a sample of 220,565 workers who move.

Characteristics of IDA movers

After we have selected our final sample of movers we include various characteristics. First we create a series of variables for the workplace and the workplace dyad, including: the size and age of the prior workplace; the size and age of the workplace to which the worker moves; whether the worker moves to an established firm in the same industry class; whether the new firm is a newly established firm in the same industry class; and whether the new firm is a newly established firm in another industry. To identify these startups we rely on the Danish entrepreneurship database, which contains all new registrations each year. We also include geographic workplace indicators. First we have a variable indicating whether the workplace is located in a municipality that is characterized as urban, semi-urban, rural or remote, because Copenhagen plays such a dominant role in the Danish economy we separated urban municipalities surrounding Copenhagen from urban municipalities in the rest of Denmark. The two remaining geographical indicators act as proxy for the distance between the prior and the new plant. One measure is an indicator whether the new workplace is located in the same local labor market region, and the other distance variable indicates the distance in kilometers between center of the municipalities where the prior and the new workplace are located.

The second set of variables are worker characteristics including worker age, gender, tenure, and wage. Occupations are aggregated into nine overall categories, which due to the high level of heterogeneity are aggregated in high-level white collar workers, low-level white collar workers, high-level blue collar workers and low-level blue collar workers. To create occupations as close as possible to the ASR sample we separate high skilled white collar workers into: (1) the executive roles in the organizations; (2) professionals and associate professionals in science and technology, which represents the technical role in the organization; and (3) other professionals and associate professionals, who are mainly active in administration. In addition to occupations we also include the education of the worker. For education we identified whether the worker has a college degree. The wage variable is the log value of an indicator on the average hourly wage received from the firms where the worker is employed. In addition to this wage level variable we calculate a wage change variable as the difference of the logged wage at the new firm less the logged wage at the prior firm.

Comparison of ASR and IDA datasets

Table 1 shows similarities and differences between the two datasets. Mean firm sizes are close at approximately 65 employees. The small size of the average firm provides reassurance on an important point: that the potential co-movers who knew and worked with each other. It would be more difficult to conduct a comobility study in the context of large, public firms where two employees might move from firm A to firm B without ever having interacted. To be sure, large firms do exist in our dataset, but our analysis ignores supposed co-movers that occur between two firms both of which have more than 100 employees. (Results are largely robust to including co-moves where both firms have more than 100 employees and are available from the authors.)

Continuing with our comparison, firms tend to be a bit younger in ASR vs. IDA. Three percent of ASR moves involve founding a startup compared to 1% in the IDA. The distance between ASR firms is much longer, as one would expect given that ASR is a worldwide industry as opposed to the IDA contained within the 43,094 square kilometers of Denmark. In both datasets, slightly less than one-fifth of moves occur between firms where moves had previously occurred.

Table 1 about here

Regarding worker characteristics, ASR has fewer women than IDA, though average ages are roughly similar. ASR workers have longer tenure. A higher percentage of ASR workers are executives, and a much higher percentage of ASR workers are technical. Differences including the prevalence of technical workers are useful in establishing the robustness of our results.

RESULTS

As comobility has not been previously characterized in a population-level datasets, we begin by showing how frequent comobility is as a percentage of overall mobility. Before proceeding, however, we wish to establish a baseline expectation of how much comobility we might expect.

Baseline level of expected comobility

In the spirit of Ruef, Aldrich, & Carter (2003), we construct a baseline expectation of the random occurrence of comobility. We conceptualize our baseline as a variant of the "birthday problem," in which one calculates the likelihood that at least two people in a group were born on the same month and day. Assuming an equal chance of being born each day, the probability of a shared birthday exceeds 50% in groups as small as 23. Everyone has a birthday, but not everyone changes jobs. Still, we can leverage the birthday problem as detecting collisions in month/day pairs as conditional on moving, each mover is at risk of "colliding" with another mover in terms of the firm(s) they join or leave. A naïve approach might randomly distribute moves among firms; unreported calculations with equal prior probabilities of interfirm mobility suggest that comobility should almost never occur, even within the relatively small ASR industry. However, moves are not randomly distributed between firms. Mobility generally decreases in spatial distance (Dahl & Sorenson, 2010), and it is impossible to recruit n workers from a firm with fewer than n workers.

We thus refine our baseline in the spirit of Ellison & Glaeser's (1994) "dartboard approach," incorporating into the baseline key factors in calculating prior probabilities of mobility. We create observations for more than 430,000 possible combinations of ASR firm directional dyads between 1952 and 2013 (e.g., moves from Voice Control Systems to SpeechWorks during 1997). The vast majority of these dyads contain no moves, so we employ (unreported) rare-event logistic analysis with covariates including the spatial distance between the two firms in the dyad, the size of each firm, each firm's year of entry, whether each firm was a de alio entrant, and sales growth in the previous year. We then predicted the probability of worker mobility for each directional dyad-year observation.

We then constructed a probability distribution that a given firm in a given year might have hired from one of the other firms operating in that year, using the above predictions for each directional dyad-year observation where the focal firm was the destination. These firm-year inbound mobility probability profiles were used to establish a baseline of comobility or collisions among those workers hired by each firm in each year of operation. We follow Klotz (1979) and Mase (1992) in accounting for unequal prior probabilities in the birthday problem, or more generally, in detecting collisions. For each firm that hires more than one worker in a given calendar year, we calculate the likelihood of collisions (i.e., that they had worked at the same firm immediately prior) according to the following recurrence relation derived by Mase (1992, equation 3.2):

$$r_n = 1 - \sum_{i=1}^{n} -1^{(i-1)} \frac{(n-1)!}{(n-i)!} \sum_{j=1}^{m-1} p_j^i \, r_{n-i}$$

The number of workers hired by a given firm in a given year is n. The probability of collisions in firms hiring fewer than two workers is zero, so $r_0 = r_1 = 0$. The number of firms in the industry in a given year is m; workers could have been hired from m-1 firms. The prior probability of having hired a worker from a particular firm (as generated from our procedure above) is expressed by p_j. The factorial ratio is very large for large n and i, but the power sums of the prior probability distribution of interorganizational mobility becomes quite small for large i.

The likelihood of collision was calculated for each ASR firm that hired new employees in a given year. ASR firms that did not hire any employees in a year were discarded. The expected number of collisions based on these calculations is 14.8. Dividing by the total number of mobility events among ASR firms (2,646), the expected frequency of collisions among movers is 0.7%. Given that two movers are involved in a collision, we double this figure to predict a comobility rate of 1.4%.

Observed comobility in ASR and IDA datasets

Panel A of Table 2 shows actual levels of comobility in both datasets. Although our empirical analysis distinguishes between simultaneous and sequential mobility, we begin with the one-year window as this is the window used in creating our baseline. Table 2 shows that when considering comobility within a given calendar year, the ASR database yields 10.5% of moves as joint. The figure for the IDA is 10.9%.

Three observations are in order. First, the ASR and IDA datasets yield nearly identical rates of comobility. The consistency in comobility rates between the two datasets is striking, especially considering that the ASR dataset covers a single, worldwide industry over several decades while our IDA sample is taken from a seven-year snapshot of one country. Second, the actual comobility rates substantially exceed the baseline estimate of 1.4%. Third, the fact that one in ten mobility events occurs jointly with others suggests that comobility is a substantial phenomenon.

Table 2 about here

Next, we decompose overall comobility according to how it unfolds temporally. More than half of comobility in Denmark (6.1% of 10.9%) occurs within a one-month window, while in the ASR data slightly less than half of comobility is simultaneous (4.4% of 10.7%). This relatively even split between simultaneous and sequential comobility helps us to distinguish mechanisms in our empirical analysis.

Antecedents of Comobility

Multivariate analysis of comobility antecedents is found in Table 3. The unit of observation is a realized move; non-moving workers either in the IDA or ASR dataset are not analyzed. The dependent variable indicates whether a given move occurred jointly with others; hence, coefficients should be interpreted relative to moving on one's own. Given our interest in simultaneous vs. sequential comobility, we cannot simply adopt a dichotomous model. Instead, we employ a multinomial logistic model with a base state of moving solo. The first and second column of each model contains coefficients for simultaneous comobility and the second for sequential comobility. As noted above, comobility is observed only where both firms do not have more than 100 employees.

As one might expect in two non-overlapping datasets, antecedents of comobility do not match perfectly. Older workers in Denmark are more likely to co-move than are younger workers, while the opposite is true among ASR workers (for simultaneous co-moves). Danish workers are more likely to co-move from and to larger firms, whereas the opposite is true in ASR. Comobility in both datasets is more likely to occur when moving to younger firms, though. Other similarities include that comobility is decreasing in distance—again, relative to solo moves. Gender effects are not evident in either dataset.

Moreover, there we see some differences between simultaneous and sequential comobility, especially in the ASR database. Sequential comobility is more likely for longer-tenured workers and to smaller, younger firms. By contrast, age, technical role, and distance are correlated with simultaneous comobility. In both datasets, simultaneous comobility is more common when the worker previously worked with the founder of the new firm. In IDA, executives are more likely to co-move sequentially.

Contrary to what one might expect given accounts such as the "Traitorous Eight," neither dataset indicates that co-workers tend to become co-founders. In the IDA dataset, comobility is strongly negatively correlated with entrepreneurship. (Moreover, this result is robust to excluding single-founder startups.) While inconsistent with accounts such as the "Traitorous Eight," perhaps these salient anecdotes are the exception rather than the rule. Note that this result does not contradict prior findings that joint prior experience helps founding teams (Eisenhardt & Schoonhoven, 1990; Phillips, 2002; Agarwal, et. al, 2013). Rather, that co-founding with prior colleagues is uncommon may suggest that more founders should convince co-workers to join them than actually do.

Table 3 about here

These cross-sectional results are at least suggestive of mechanisms underlying comobility. Previous mobility between firms is a strong predictor of comobility in both datasets, suggesting a possible role for information sharing such as employee referrals or "scouting" out opportunities. Also indicative of social ties is that longer-tenured workers, when they move, are more likely to do so with co-workers. It may be that those who have built up greater firm-specific capital need to be "pulled" by others. Moreover, moves to companies where the individual previously worked with the founder of that company are more likely to happen jointly and simultaneously. Technical workers, for whom complementarities may be particularly prevalent (Janz, et al., 1977), are more likely to co-move in both datasets.

In unreported models available from the authors, we test the robustness of these findings in several ways. First, we restrict comobility to co-moving groups of three or more. Although doing so eliminates nearly two-thirds of comobility, results are rather consistent although distance no longer appears to attenuate comobility among groups of three or more in the ASR dataset. Second, we relax the restriction that comobility is not observed between two firms that both have more than 100 employees. Third, although a fixed-effects multinomial logit model cannot be estimated in Stata 13, we approximate such an analysis by performing two logistic regressions. Results are largely though not entirely consistent with the multinomial models; in particular, the coefficient on technical workers cannot be estimated reliably because few workers switch in and out of technical roles during their careers.

Comobility and productivity

To the extent that non-firm-specific coproduction complementarities are responsible for comobility, we expect that co-moving coworkers will enjoy higher productivity than those who move on their own. Although individual productivity is difficult to observe, even in the Danish census, the ASR dataset affords an opportunity to measure individual productivity among the subset of workers who patent. Indeed, prior work has used patents to measure both mobility and productivity among patent holders (Schankerman, Shalem & Trajtenberg, 2006; Hoisl, 2007). Less than half of ASR workers hold a patent, but we can calculate their productivity by measuring the number of patents filed (and subsequently granted) in a given window. The dependent variable is the number of patents filed in the final year of working at the prior firm subtracted from those filed in the first year of working at the new firm.

The models of Table 4 explore the connection between comobility and patent productivity, conditional on moving and controlling for patent productivity at the prior firm. As in prior analyses, the observation is a move; however, the sample is restricted to ASR workers who ever had a patent. We retain controls for the size and age of the prior and new firms, as well as an indicator for prior mobility between the firms in order to account for additional spillovers that may facilitate innovation. Worker age, tenure, and gender are likewise controlled for.

Table 4 about here

In Model 1 we see some evidence of a connection between comobility and patent productivity, though only among simultaneous co-movers. The coefficient on sequential comobility is statistically insignificant, suggesting that comobility based on information flow (i.e., employee referrals or “scouting” opportunities) does not play a clear role in driving productivity among ASR workers. It may also be that complementarities are more difficult to realize when colleagues move sequentially.

In Models 2 and 3 we attempt to identify complementarities more directly. Our first approach is to distinguish co-moves that occurred with direct collaborators as in prior work by Reagans, et al. (2005) and Huckman, et al. (2009). For each worker, we identify their co-inventors for all patents filed at the prior firm. If any subset of those co-inventors is among the group of co-movers, the comobility event is designated as with co-inventor. The indicators for simultaneous and sequential comobility are replaced with four dummies, for comobility with or without a co-inventor in both simultaneous and sequential cases. (Less than half of comobility among patent holders occurs with co-inventors.) Model 2 shows that simultaneous comobility is correlated with higher patent productivity only when moving with a co-inventor. Sequential mobility is not associated with higher patent productivity. These results suggests that comobility may enhance productivity when coproduction complementarities are involved.

Our second approach measures the degree of overlap in technical experience among patent holders. Recognizing that technical personnel may collaborate directly even if that collaboration is not captured by a joint patent filing, we expect that those with experience in similar technical areas will be more likely to work together. In Model 3, we create a new variable to measure the similarity in technical skills among workers. Specifically, for each worker who ever held a patent, in each year we track all USPTO primary technical classifications in which that worker's patent(s) had been classified until that point. When a worker moves with others, we count the number of technical classes that overlap with those of any other co-mover. This count is then scaled by the number of co-movers and logged for skew. As the desired comparison is among co-movers depending on the extent of skills overlap, in Model 3 we restrict the sample to those who co-moved. In this considerably smaller subsample, some covariates including firm age are no longer statistically significant. However, the coefficient measuring the extent of technical overlap with co-movers is positive and statistically significant at the 0.1% level. Coupled with Model 2, Model 3 likewise indicates that comobility contributes positively to productivity when co-movers carry complementarities with them.

Models 4-6 repeat the foregoing analysis while accounting for an important alternative explanation: that innovative, productive firms may recruit more workers who are similarly innovative or productive. If such firms hire many such workers, they may happen to hire multiple workers from the same firm. Thus it may appear that co-mobile workers are more productive whereas this effect is epiphenomenal with the productivity of the hiring firm. While our tests for prior co-inventors in Model 2 and for technical overlap in Model 3 help to assuage this concern, we cannot rule it out entirely. The final three models of Table 6 account for this possibility using fixed-effects models with robust standard errors. Because a firm's patent productivity may vary over time, we specify fixed effects at the hiring-firm/year level. We moreover restrict this analysis to firms that hired both solo and co-movers in the same year. (Doing so likely omits smaller firms from the analysis, but relaxing this restriction yields similar results, as does simply controlling for patent productivity of the hiring firm instead of using firm-year fixed effects.) In this stricter test of comobility and productivity, we no longer see a significant connection between and patent productivity and simultaneous comobility in Model 4, where we do not measure complementarities directly. However, higher productivity continues to be achieved by those who move simultaneously with their co-inventors (Model 5) as well as for those who co-move with those who share a more similar technical profile (Model 6).

The above results are consistent with the notion that comobility drives productivity gains thanks to complementarities among coworkers. (If comobility were driven solely by social ties, we would not expect to see such gains.) That we also see simultaneous comobility in the absence of clear complementarities (i.e. no productivity gains among those who move without co-inventors) may be an indication of purely social attachment among some co-movers. Alternatively, there may be complementarities at play that are unrelated to co-invention or are otherwise unobservable to us.

Comobility and wage attainment

If comobility leads to productivity gains, it seems reasonable that firms would attempt to capture these gains by hiring groups of workers and also would compensate workers in anticipation of those gains. Table 5 explores comobility with the dependent variable as the difference between the final wage at the prior firm and the initial wage when joining the new firm. We begin with cross-sectional analysis in Model 1. Workers achieve higher wage gains when their move covers greater geographic distance. Larger and older firms reward newcomers with greater wage gains. Workers accept lower wages when founding a startup. Women receive lower wage gains when changing jobs. Older workers gain more financially from changing jobs, as do workers with greater tenure and executives. Wage gains are smaller for higher-paid workers. Finally, co-movers obtain higher wage gains than those who moved on their own. Exponentiating the coefficient on simultaneous comobility suggests approximately a 6% wage premium, slightly less than a month's salary.

Table 5 about here

Although we control for several individual characteristics including age, gender, tenure, role, and prior wage, this cross-sectional result is vulnerable to alternative explanations. One such concern is that comobility may be driven not by coproduction complementarities but simply by the gravitational pull of high-performing companies that are hiring aggressively. If they succeed in hiring a large number of employees, it may be that they happen to attract multiple employees from the same firm even in the absence of complementarities. If such firms also offer higher salaries in order to facilitate hiring, it may be that the wage premium for comobility occurs for these reasons as opposed to coproduction complementarities, information sharing, or other mechanisms discussed previously. We attempt to account for this alternative explanation in Models 2 and 3. Given that the root of our concern is characteristics of the hiring firm at a given point in time, we include hiring-firm/year fixed effects in Model 2. Moreover, Model 2 includes only firms that hired both solo movers and co-movers in the same year. Although the coefficient on co-movement is smaller in magnitude than in the cross-section (closer to a 2% wage premium), it retains statistical significance. These stricter tests suggest that the wage premium associated with comobility is not wholly epiphenomenal with aggressive hiring by high-paying companies that happen to draw multiple workers from the same firm. Of course, requiring that a firm hire both solo and co-movers in a given year may exclude smaller firms from our analysis. As an alternative approach, instead of firm-year fixed effects Model 3 includes controls for sales and employment growth of the hiring firm over the prior year, with consistent results.

In the remaining models of Table 5, we explore the mechanisms underlying the wage premium for co-movers. We begin by noting that wage gains are seen both among simultaneous and sequential co-movers. Social attachment (alone) would predict stable or falling wages among co-movers, so some combination of complementarities and/or bargaining power seems responsible for simultaneous comobility. That we see a wage premium among simultaneous co-movers suggests that information sharing—either in the form of referrals or scouting—cannot be wholly responsible for comobility as these are only likely to occur among sequential co-movers. We attempt to identify complementarities more directly in Models 4 and 5. Unlike patent holders in the ASR dataset, we cannot observe direct collaborations among Danish workers and must proxy for complementarities among colleagues.

Our first proxy for coproduction complementarities follows Hayes, et al., who argue that "the quality of a match between two executives should increase depending on the amount of time the two managers have worked together" (2006:191). Referencing the literature regarding match quality between a worker and a firm (see Farber, 1999 for an overview), they claim shared tenure as an indicator of complementarities for two reasons. First, just as the quality of a match between employer and employee may be unclear ex ante and is revealed over time, so may the degree of complementarity between coworkers. Good matches are more likely to persist as colleagues request to continue working together and as supervisors observe their joint productivity. Second, employees may invest in colleague-specific capital and thus seek to earn returns from said investments by continuing to work together. Model 4 shows that variance in tenure among co-movers is negatively related to the wage differential between the prior and new firm. We restrict analysis to the approximately 10% of moves that are joint with others so that we can compare wage differentials among co-movers by tenure. Whereas Hayes, et al. (2006) employ a dichotomous measure of shared tenure (whether greater or less than 5 years), we construct a continuous measure of the variance in tenure among co-movers. As above, we note that half of IDA co-movers have tenure within one year of each other. The negative coefficient on variance in tenure in Model 4 indicates that co-movers who have less similar tenure enjoy smaller wage gains than those with more similar tenure, consistent with the notion that complementarities play a key role in comobility.

Our second approach to measuring complementarities involves exploiting the difference between co-movers who transfer from the same plant vs. those who worked at different plants in the prior firm. We have thus defined comobility in the IDA as same-plant comobility as a more reliable indicator of workers who likely knew and worked with each other at a co-located plant compared with employees of the same firm who work in different plants. In Model 5, we relax this constraint and expand the set of co-moves to include employees who moved jointly from one firm to another but who did not work in the same plant; doing so raises the number of observations from 14,268 to 19,731. The explanatory variable of interest in Model 5 is an indicator for comobility that does not originate from the same plant (i.e., a dummy for the new observations compared to Model 4). The negative and highly significant coefficient indicates that co-movers originating from different plants within a firm enjoy less of a wage premium than those who originated in the same plant. This differential is consistent with the notion that complementarities, and not social attachment or information sharing alone, are a key mechanism underlying comobility.

Having demonstrated a likely role for complementarities, we address the possibility that the associated wage gains are not merely a result of collective bargaining (although we imagine that collective bargaining occurs in the presence of complementarities). Returning to Model 4, we note no statistically-significant relationship between the size of the co-moving group and the magnitude of the wage differential between the prior and new firm. If bargaining power were a key driver of comobility independent of complementarities, we would expect higher wage gains among larger group but do not find such. As a second piece of evidence that bargaining power is unlikely to be the primary mechanism behind wage gains for simultaneous co-movers, Model 5 restricts the observations to "displaced" workers following the shutdown of their employers. Such workers have little bargaining power, so if collective bargaining were primarily responsible for comobility (to the exclusion of complementarities) we would not expect to see wage gains among co-moving displaced workers. Yet the coefficient on simultaneous comobility is positive and significant at the 1% level. (We would not expect collective bargaining to be practical among sequential co-movers; moreover, sequential comobility following firm failure is quite rare.) Again, it seems hard to argue that bargaining power alone explains comobility's wage gains.

Finally, in Model 7 we examine mechanisms underlying sequential comobility and thus restrict our analysis to those who co-move sequentially. Wage gains accompany sequential co-movers in all models of Table 7 that do not analyze displaced workers, consistent with the notion that referrals might play a role in facilitating the gradual co-movement of coworkers over a period of months. We decompose sequential comobility into movement by the first member of the co-mobile group vs. later movers. As mentioned above, it could be that later movers are enticed by positive reports from the first worker, who could be said to "scout out" the opportunity, or it could be that later movers were referred to hiring managers at the new firm. If the referral mechanism dominates, wages should rise for later co-movers, as they have been endorsed by the initial co-mover. If however the scouting mechanism dominates, we might expect later movers to enjoy less of a wage premium because the initial mover has in a sense scouted the opportunity for them. Indeed, the evidence in Model 7 lines up more closely with scouting than with referrals (though both mechanisms could be at play to some extent), as subsequent co-movers in a sequential group enjoy a smaller wage premium. While not ruling out the possibility of complementarities among sequential co-movers, Model 7 suggests that information sharing via scouting out opportunities may be a key mechanisms underlying sequential comobility.

CONCLUSION

We believe this to be the first population-level study of comobility. Although joint or cascading departures have been examined (Sgourev, 2011; Bartunek, Huang &Walsh, 2008), only a few studies of have addressed comobility and moreover in the context of elite workers such as founders and "stars" (Eisenhardt & Schoonhoven, 1990; Beckman, 2006; Wezel, Cattani & Pennings, 2006; Groysberg, et al., 2008; Campbell, et al. 2013). Based on the prior literature, one might wonder whether comobility is a rare event which is inconsequential for most workers.

The first major contribution of this study is to establish the frequency of comobility in two complementary population-level datasets. While our baseline calculation predicts that 1.4% of annual moves should be joint with others, we find that the actual percentage of comobility to be 10.5% in the ASR dataset and 10.9% in the IDA. Not only are these two figures remarkably similar; they substantially exceed our baseline prediction. If one in ten moves occurs jointly, then comobility is hardly an infrequent occurrence. Even if looking only at simultaneous comobility (i.e., in a one-month window) approximately 5% of moves occur jointly with a co-worker. Given that nearly all of the hundreds of articles on worker mobility have focused on solo moves, additional attention on comobility may be warranted.

Our second contribution is establishing a population-level connection between comobility, productivity, and wages. Prior studies of comobility have shown performance differentials between solo movers and co-movers (Groysberg, et al. 2008; Campbell, et al., 2013); however, these results were established among a subset of elite workers or "stars" whereas our study includes workers of various ranks and occupations including a full census. Moreover, ours is the first study to show that co-mobile inventors achieve higher initial wage gains than those who move alone.

Our third contribution is an initial exploration of the mechanisms underlying simultaneous and sequential comobility. Our strongest evidence points to the role of coproduction complementarities. First, productivity gains are higher among co-moving ASR inventors, especially when they move with direct collaborators or those whose technical expertise most closely resembles their own. Second, technical workers in both databases are considerably more likely to co-move than are non-technical workers. Third, the wage gain among co-movers is higher for those who move from the same plant as opposed to different plants within the same firm. Fourth, following Hayes, et al. (2006) we find higher wage gains among co-movers with similar tenure at the prior firm. While we lack an experiment or instrument and thus do not assert strong causality claims, these results are nonetheless highly suggestive that comobility is motivated at least in part by the desire to capitalize on coproduction complementarities among coworkers.

We also see some evidence that information sharing contributes to sequential comobility. Although we cannot rule out that complementarities are active among sequential co-movers, it may be that wage gains accruing to sequential comobility are driven by information sharing. A diminishing wage premium among later movers suggests that sequential comobility seems to be best explained by workers "scouting out" opportunities and then enticing former colleagues to join them, although employee referrals may also play some role.

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Table 1: Descriptive statistics

	worldwide ASR industry					Danish IDA register				
Variable	Obs	Mean	Stdev	Min	Max	Obs	Mean	Stdev	Min	Max
Firm characteristics										
Prior firm size (L)	11820	4.23	2.40	0.69	15.11	219616	4.26	1.88	0.00	10.19
Prior firm age	14717	12.65	13.67	1.00	99.00	219828	17.57	16.62	1.00	201.00
New firm size (L)	12020	4.10	2.18	0.69	15.11	219541	4.30	2.06	0.00	10.31
New firm age	14717	11.59	12.66	1.00	107.00	219541	17.30	17.94	1.00	109.00
Worker founded startup	14717	0.03	0.16	0.00	1.00	218467	0.01	0.10	0.00	1.00
Distance between firms	9291	1638.80	1710.48	0.00	10530.78	219083	16.14	24.44	0.00	227.55
Previous move between firms	14717	0.19	0.39	0.00	1.00	220565	0.16	0.36	0.00	1.00
Worker characteristics										
Female	13850	0.18	0.38	0.00	1.00	220565	0.27	0.45	0.00	1.00
Age	14717	32.91	8.35	21.00	70.00	220565	35.13	8.57	22.00	55.00
Tenure	14717	5.50	5.05	0.00	54.00	220565	2.34	3.48	0.00	25.00
Executive role	14717	0.14	0.35	0.00	1.00	185416	0.04	0.19	0.00	1.00
Technical role	14717	0.55	0.50	0.00	1.00	185416	0.05	0.23	0.00	1.00
Worked with founders previously	14717	0.06	0.24	0.00	1.00	218467	0.01	0.08	0.00	1.00
Patent productivity (filings/year)	6104	0.70	0.92	0.00	10.00					
Change in patent productivity	6104	-0.05	1.15	-8.00	9.00					
Wage at prior firm (L)						220565	5.10	6.10	0.00	11.52
Change in wage (L)						220565	-0.01	0.86	-7.76	7.29
Year	14717	2002.92	6.80	1961	2014	220565	2002.07	2.11	1999	2005

Table 2: Univariate comobility statistics

Panel A: Comobility rates, overall and by window

	ASR	IDA
calendar year	10.50%	10.90%
simultaneous (same month)	4.30%	6.10%
sequential (within 2-12 months)	6.20%	4.80%

Panel B: Comobility rates by job rank/function, ASR

	simultaneous	sequential
individual contributor	4.7%	6.5%
non-executive manager	3.5%	7.2%
executive	4.1%	5.1%
technical (all ranks)	5.6%	6.7%

Panel C: Comobility rates by job rank/function, IDA

	simultaneous	sequential
managers	5.4%	4.8%
technologists	8.3%	6.5%
high-skilled white collar	6.6%	5.3%
low-skilled white collar	1.8%	1.1%
high-skilled blue collar	6.1%	5.0%
low-skilled blue collar	6.3%	4.9%

Panel D: Size of co-mobile groups

# of co-movers	ASR	IDA
2	70.9	74.2
3	16.2	14.3
4	7.3	5.3
5-6	3.5	4.0
7-9	1.8	1.8
10+	0.3	0.3
	100%	100%

Table 3: Antecedents of simultaneous and sequential comobility in the ASR and IDA datasets.

	(1)		(2)	
dataset	ASR		IDA	
outcome (vs. solo mobility)	simultaneous	sequential	simultaneous	sequential
Prior firm size (L)	-0.2597***	-0.1873***	0.1048***	0.1587***
	(0.034)	(0.027)	(0.007)	(0.007)
Prior firm age	-0.0062	0.0065+	-0.0049***	-0.0024***
	(0.006)	(0.004)	(0.001)	(0.001)
New firm size (L)	-0.0295	-0.0928***	0.1849***	0.1650***
	(0.031)	(0.027)	(0.005)	(0.006)
New firm age	-0.0109+	-0.0219***	-0.0050***	-0.0028***
	(0.006)	(0.005)	(0.001)	(0.001)
Worker founded startup	-0.0551	0.2871	-1.4868***	-1.3770***
	(0.400)	(0.416)	(0.279)	(0.357)
Distance between firms	-0.0965***	-0.0205	-0.0065***	-0.0141***
	(0.024)	(0.020)	(0.001)	(0.001)
Previous move between firms	2.2085***	3.1673***	1.4122***	1.3372***
	(0.157)	(0.138)	(0.023)	(0.025)
Female	0.1722	0.1302	0.0407	0.0018
	(0.185)	(0.127)	(0.026)	(0.028)
Age	-0.1089*	0.0085	0.0454***	0.0416***
	(0.049)	(0.042)	(0.011)	(0.012)
Age^2	0.0011+	-0.0003	-0.0003*	-0.0005***
	(0.001)	(0.001)	(0.000)	(0.000)
Tenure	0.0260	0.0577*	0.0664***	0.0611***
	(0.033)	(0.024)	(0.007)	(0.008)
Tenure^2	-0.0017	-0.0022*	-0.0020***	-0.0023***
	(0.002)	(0.001)	(0.000)	(0.000)
Executive role	0.2028	0.2290	-0.0220	0.1373*
	(0.210)	(0.154)	(0.063)	(0.064)
Technical role	0.6524***	-0.1257	0.1627***	0.1881***
	(0.155)	(0.109)	(0.047)	(0.051)
Had worked w/founders	0.7449***	0.0912	0.4318**	0.3403+
	(0.216)	(0.185)	(0.148)	(0.194)
Previous wage			0.1578***	0.3252***
			(0.033)	(0.036)
Constant	5.6238	-19.4117	-6.9373***	-7.7098***
	(23.911)	(19.539)	(0.237)	(0.270)
pseudo-R2	0.228		0.129	
log likelihood	-2483		-68043	
# individuals	4767		146,527	
# observations	7,834		180,636	

Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Notes: All models include year fixed effects. IDA analysis also includes industry fixed effects. Some variables used in IDA estimation are not shown, including an indicator for higher education and geographic indicators for urban, semi-urban, rural, and remote areas. Also not shown in IDA analysis are indicators for high-skilled (non-technical) white collar workers, high-skilled blue-collar workers, and low-skilled blue-collar workers.

Table 4: Analysis of individual patent productivity in ASR dataset.

	(1)	(2)	(3)	(4)	(5)	(6)
sample	all moves	all moves	co-moves only	all moves	all moves	co-moves only
hiring-firm/year fixed effects	no	no	no	yes	yes	yes
Simultaneous comobility	0.2206*			0.1085		
	(0.089)			(0.082)		
Simultaneous comobility with coinventor		0.3838**			0.2581*	
		(0.127)			(0.114)	
Simultaneous comobility w/o coinventor		0.0600			0.0315	
		(0.121)			(0.096)	
Sequential comobility	0.0991			-0.0225		
	(0.081)			(0.111)		
Sequential comobility with coinventor		0.0675			-0.4549	
		(0.236)			(0.433)	
Sequential comobility w/o coinventor		0.0959			-0.0083	
		(0.083)			(0.114)	
Technical overlap with co-movers			0.5343***			0.3615**
			(0.057)			(0.138)
Worker's patent productivity at prior firm	-0.7903***	-0.7941***	-0.9040***	-0.8293***	-0.8329***	-0.9050***
	(0.023)	(0.023)	(0.046)	(0.041)	(0.042)	(0.067)
Prior firm size (L)	0.0115*	0.0119*	0.0105	0.0087	0.0091	-0.0590*
	(0.005)	(0.005)	(0.022)	(0.013)	(0.013)	(0.024)
Prior firm age	-0.0054***	-0.0054***	-0.0041	-0.0059**	-0.0059*	0.0013
	(0.001)	(0.001)	(0.003)	(0.002)	(0.002)	(0.004)
New firm size (L)	0.0262*	0.0271**	-0.0210			
	(0.010)	(0.010)	(0.016)			
New firm age	0.0047+	0.0046+	0.0042			
	(0.003)	(0.003)	(0.004)			
Previous move between firms	0.2817***	0.2886***	0.2024*	0.2049*	0.2108*	0.0465
	(0.053)	(0.052)	(0.093)	(0.083)	(0.083)	(0.195)
Female	-0.0381	-0.0370	-0.0971	-0.0447	-0.0362	-0.2207*
	(0.045)	(0.044)	(0.080)	(0.089)	(0.090)	(0.107)
Age	0.0209	0.0217	0.1230**	0.0940*	0.0965*	0.1365+
	(0.025)	(0.024)	(0.042)	(0.038)	(0.038)	(0.080)
Age^2	-0.0003	-0.0003	-0.0016**	-0.0011*	-0.0011*	-0.0020+
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	-0.0321***	-0.0316***	-0.0440*	-0.0632**	-0.0630**	-0.0748*
	(0.008)	(0.008)	(0.019)	(0.021)	(0.021)	(0.036)
Tenure^2	0.0006*	0.0006*	0.0013+	0.0020*	0.0020*	0.0028*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	51.8345***	51.6712***	74.1033***	-0.8131	-0.8614	-1.0915
	(7.157)	(7.046)	(14.277)	(0.637)	(0.637)	(1.432)
r^2	0.453	0.454	0.543	0.284	0.284	0.478
Observations	3659	3659	567	1297	1297	441

Robust standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Notes: The dependent variable is the differential in patents filed in the worker's last year at the prior firm and the first year at the new firm. Analysis is restricted to ASR workers who ever held a patent during their career. All models include year fixed effects.

Table 5: Analysis of IDA wages for movers. All models have year/industry fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
sample	moves	moves	moves	co-moves	co-moves	moves	sequential co-moves
hiring firm / year fixed effects	no	yes	no	no	no	no	no
displaced workers (failed firms)	excluded	excluded	excluded	excluded	excluded	only	excluded
co-movers must work in same plant	yes	yes	yes	yes	no	yes	yes
Simultaneous comobility (same plant)	0.0541***	0.0173**	0.0276***			0.0530**	
	(0.006)	(0.006)	(0.006)			(0.018)	
Sequential comobility (same plant)	0.0706***	0.0286***	0.0476***			-0.0448	
	(0.006)	(0.007)	(0.005)			(0.059)	
Variance in tenure among co-movers				-0.0162*			
				(0.006)			
Number of co-movers				0.0016			
				(0.002)			
Comobility from different plants in firm					-0.0237***		
					(0.006)		
Subsequent (i.e., non-initial) comover							-0.0243*
							(0.010)
Prior firm size (L)	-0.0065***	-0.0029***	-0.0053***	-0.0049*	-0.0059**	-0.0266***	0.0032
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.004)
Prior firm age	0.0002**	0.0001*	0.0003***	0.0001	0.0004**	-0.0016*	-0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
New firm size (L)	0.0433***		0.0210***	0.0136***	0.0120***	0.0276***	0.0191***
	(0.001)		(0.001)	(0.002)	(0.002)	(0.006)	(0.003)
New firm age	0.0004***		0.0003***	-0.0000	0.0001	0.0014**	-0.0004
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Worker founded startup	-3.3732***	-3.3614***					
	(0.064)	(0.048)					
Distance between firms	0.0005***	0.0004***	0.0004***	0.0010***	0.0007***	0.0010+	0.0007+
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Previous move between firms	0.0271***	0.0102**	0.0091**	-0.0131+	-0.0131*	0.0046	-0.0493***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.006)	(0.027)	(0.011)
Female	-0.1495***	-0.1476***	-0.1560***	-0.1279***	-0.1189***	-0.1984***	-0.1286***
	(0.004)	(0.003)	(0.004)	(0.012)	(0.009)	(0.020)	(0.019)
Age	0.0502***	0.0464***	0.0533***	0.0224***	0.0288***	0.0884***	0.0180*
	(0.002)	(0.001)	(0.002)	(0.005)	(0.004)	(0.008)	(0.008)
Age^2	-0.0006***	-0.0005***	-0.0006***	-0.0003***	-0.0003***	-0.0011***	-0.0002*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.0090***	0.0081***	0.0114***	0.0031	0.0054**	0.0154**	0.0061+
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.003)
Tenure^2	-0.0005***	-0.0005***	-0.0006***	-0.0001	-0.0003**	-0.0008**	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Executive role	0.0934***	0.2091***	0.1595***	0.1742***	0.1628***	0.2057***	0.2180***
	(0.014)	(0.007)	(0.010)	(0.032)	(0.026)	(0.056)	(0.060)
Technical role	0.0140*	0.0034	0.0274***	0.0111	0.0132	0.0378	-0.0238
	(0.007)	(0.006)	(0.005)	(0.013)	(0.010)	(0.037)	(0.025)
Wage at the prior firm (L)	-0.6731***	-0.7849***	-0.6897***	-0.5258***	-0.5425***	-0.9428***	-0.4830***
	(0.008)	(0.003)	(0.009)	(0.039)	(0.031)	(0.009)	(0.052)
New firm past year sales growth			0.0089**	-0.0028	-0.0038	0.0080	-0.0039
			(0.003)	(0.005)	(0.004)	(0.010)	(0.007)
New firm past year employment growth			0.0125**	0.0328***	0.0272***	-0.0038	0.0444**
			(0.004)	(0.008)	(0.006)	(0.023)	(0.014)
Constant	2.3003***	3.2367***	2.4474***	2.3218***	2.2700***	3.0388***	1.9204***
	(0.042)	(0.027)	(0.040)	(0.165)	(0.129)	(0.172)	(0.226)
r^2	0.370	0.708	0.390	0.315	0.323	0.906	0.347
Observations	170,277	124,172	135,202	14,268	19,731	4,824	6,088