Co-Worker complementarities and new firm survival

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ABSTRACT

In the present paper, we analyse the association between the skill composition of young firms and the firms’ subsequent survival. This is made possible by means of a matched employer-employee dataset from Statistics Sweden on a cohort of firms that started between 2001 and 2003. Our findings show that, compared to firms that exit, the firms that survive at least until 2012 have teams with higher complementarity at the start, and successively increase their skill complementarity over time. Subsequent discrete time hazard models, controlling for several well-known determinants of firm longevity, show that complementarity plays a crucial role for firm survival. Higher skill synergy within firms, as compared to high degrees of substitutability, is associated with a lower conditional probability of failing. The role of skill complementarity is stable across different specifications and outweighs many other determinants of firm survival, such as starting size and experience of the founder.

KEYWORDS

New firm survival; skills; human capital; complementarity; relatedness

1. Introduction

A major impediment to employment growth is the difficulty of finding recruits with the right skills (World Bank 2014). This is a particularly salient problem for new firms that need access to workers with the right skills from the start, because it takes time to build the routines and resources needed to provide in-house learning. Previous findings therefore suggest that new firms are more likely to hire workers with very heterogenous skills, which in the longer run may hamper their future survivability (Borggren, Eriksson, and Lindgren 2016). The composition of skills has many origins. On the supply side, workers can have a variety of educational fields and levels of training. On the demand side, firms can utilise workers’ skills in a variety of ways. This leads to a large set of possible skill combinations, which can be difficult to coordinate. Due to the regional division of labour, this also entails that both supply and demand vary regionally. Consequently, achieving a better understanding of how the skill composition at the firm level contributes to firm survival in different regions is essential to supporting regional environments that are conducive to entrepreneurial activity and subsequent job growth.
While previous research has argued that both the skills and human capital of founders (Bates 1990; Colombo and Grilli 2005) and employees (Weber and Zulehner 2014; Koch, Späth, and Strotmann 2013; Dahl et al. 2015; Coad et al. 2014) are crucial determinants of firm success, the role of team-specific human capital still largely remains something of a black box in the literature. Human capital instead tends to be reduced to the presence of highly educated employees or founders within firms, despite the fact that human capital is relational and therefore not fully understood when considered in isolation (Neffke 2019). This relative empirical bias is mainly explained by the difficulty of successfully quantifying the interconnectedness of skills at the firm level. This is a crucial drawback, however, as learning and potential knowledge spillovers ultimately rely on the social interaction of individuals, making place-based social interactions vital conditions for growth (Eriksson and Lengyel 2019).

The aim of the present paper is therefore to analyse how the evolution of the human capital composition of young firms is associated with the firms’ subsequent survival. By following earlier work on the combinatorial properties of knowledge elements (Teece et al. 1994; Dibiaggio, Nasiriyar, and Nesta 2014; Neffke 2019), we assess how the degree of skill complementarity of workers in new firms is associated with survival. Following Neffke (2019), we capture complementarity by defining team synergy while also accounting for the substitutability of skills. Skill synergy refers to skill combinations within workplaces that reflect the fit of diverse co-workers to one another, and substitutability refers to how similar workers’ skills are to one another.

In pursuing this aim, we make two contributions to the literature. First, we empirically advance previous studies focusing on labour flows or knowledge diversity in new firms (cf., Borggren, Eriksson, and Lindgren 2016; Martynovich and Henning 2018) by instead tracking the common fit of skills to one another. In so doing, we add new insights concerning the benefits accrued above and beyond individual workers’ contributions to firm success and instead get to the additional benefits derived from combining skills that cannot be explained by mere substitutability (similarity) between co-workers. Our second contribution concerns improving our understanding of the association between human capital externalities and the probability of firm survival. While the firm- and region-specific attributes that determine survival are well established in the literature, the role of the skill mix beyond the productivity of individual workers (Neffke 2019) and firms (Boschma, Eriksson, and Lindgren 2009) remains an open question. In this regard, by assessing how the skill-mix of teams evolves and relates to firm survival, we explicitly contribute to the literature arguing that the mix of resources regarding skills and experiences determines firm growth (Penrose 1959) and the longevity of new ventures (Coad et al. 2014; Borggren, Eriksson, and Lindgren 2016).

This is done by using a matched employer-employee dataset from Statistics Sweden on a cohort of new firms that started between 2001 and 2003, which we follow up to 2012. Our exploratory approach reveals that, compared to firms that exit, the firms that survive at least until 2012 have teams with higher complementarity from the start, and successively increase their skill complementarity over time. Subsequent discrete time hazard models, controlling for several well-known determinants of firm longevity, confirm that complementarity plays a crucial role for firm survival. Higher skill synergy within firms, as compared to substitutability, is associated with a lower conditional probability of failing. In fact, when assessing the relationship between skill complementarity and
survival, the effect of having highly educated workers diminishes. In our most conservative model, the results suggest that raising complementarity by one standard deviation surpasses raising the starting size of the firm by one standard deviation and the founders’ previous entrepreneurial experience by a factor of about 4 and 2, respectively.

2. Literature review

2.1. Coordinating skills in firms

It is well established that human capital conditions the future performance of firms (Becker 1962). The human capital literature has developed from mainly proxying human capital as years of schooling or work experience to also acknowledging the relational aspect of human capital. For instance, studies have modelled how the performance of firms depends not only on the individual workers’ specific human capital and skills, but also on how workers are combined in teams (Baumgardner 1988; Becker and Murphy 1992; Boschma, Eriksson, and Lindgren 2009). More recently, networks have been employed to assess the interdependency of skills in jobs (Alabdulkareem et al. 2018) and teams (Neffke 2019). This focus on the skill mix of teams refers to the relational and social activities that firms perform to coordinate their operations. This is because the workforce is typically coordinated to bring together different pieces of knowledge, as it is economically beneficial to coordinate teams rather than to distribute tasks individually (Lazear 1999).

However, coordination costs arise when combining heterogeneous individuals, which suggests that there is some kind of optimal skill mix for each firm. If the firm forms teams with skills that are suitable for performing the same jobs, then the team is characterised by high similarity of skills and thereby high substitutability (cf., Neffke 2019). If the teams are instead too diverse, this could lead to additional coordination costs due to communication inefficiencies (Lazear 1999). Both extremes would lead to suboptimal performance. This was exemplified in the study by Boschma, Eriksson, and Lindgren (2009), who showed empirically that high degrees of related skills, captured by the variety of educational tracks within firms, contributed to firm performance to a greater extent than did the share of highly educated *per se*. They thereby argued that relatedness captured some kinds of complementarities, or different but overlapping pieces of knowledge, that induce performance-enhancing spillovers compared to heterogeneity or similarity. Following that work, numerous studies have shown that hiring new workers with skills related to the existing portfolio of the plant, rather than very similar or very different skills, has positive effects on firm productivity (Eriksson 2011) as well as innovation (Herstad, Solheim, and Engen 2019). This has also been analysed in relation to industry evolution. Martynovich and Henning (2018), for example, showed that as the Swedish IT-service sector matured, new types of skills were hired to the sector.

Despite the abundance of research examining the hiring and coordination of workers at different stages of firm growth (Coad et al. 2014) and how that influences survivability (Borggren, Eriksson, and Lindgren 2016), little is known about how skill complementarities influence the survival of new firms. Literature in line with the resource-based theory of the firm typically suggests that firms should develop complementary capabilities rather than adding more of the same if they are to sustain, and possibly expand, their scope of
operations. From an evolutionary perspective, this is because the ability to learn is determined by the collective competences embodied in the firm, the knowledge it can apply, and the routines by which it manages its growth (Metcalfe 1994). As a result, new firms introduce variation into the market because they use resources in new and idiosyncratic ways, including by hiring and combining workers with different skills, which in turn contributes to their competitive advantage and survival. In other words, the future performance of firms is largely determined by how well the resources within them can be combined in effective and novel ways (Penrose 1959).

2.2. Industrial and geographic variations

Resources in the form of human capital or skills do not necessarily need to be specific to the firm; they can also be specific to industries (Neal 1995). This means that the routines and technologies utilised in different industries are to varying degrees distinct from one another. Because team formation ultimately relies on labour flows, such inter-industry differences strongly shape the directions of job mobility (Eriksson, Lindgren, and Malmberg 2008). The regional industry mix thus shapes the possibility to form complementary teams. From the classic idea of labour pooling (Marshall 1920), we can expect that new firms benefit from externalities that arise in part from the size of the given industry in the region, but also depending on the scope of operations. For example, high-tech firms competing on global markets could be expected to be in greater need of complementary teams to be competitive, while non-traded service firms associated with low-skill work could be driven more by wage constraints and not predominantly by skill complementarity (cf., Hausmann and Neffke 2019). In an extension to the industry specificity of skills, scholars have more recently also argued that while human capital is not fully transferable between industries, some industries are more related than others, which can broaden the potential labour pool that a firm can hire from (Neffke and Henning 2013). However, while similar industries may develop similar products or services, firms are also more likely to specialise, leading to heterogeneity both within and between industries. For this reason, the same industries in different regions tend to exhibit different labour profiles (Markusen and Shrock 2006; Mellander 2009).

Thus, the composition of industries within a region acts as a determinant of a firm’s access to relevant skills (Boschma, Eriksson, and Lindgren 2014), and we can expect the regional structures of skills and industries to be associated both with firms’ possibilities to employ workers with relevant skills and with subsequent survivability. However, how regional size and the industry mix affect new firms is complex and relies on a number of factors, as indicated by the mixed results of empirical studies connecting regional environments and firm survival (see, e.g. Van Oort et al. 2012; Basile, Pittiglio, and Reganati 2017). While specialised regions could provide new firms with access to specific skills, local networks and knowledge spillovers, they also tend to be associated with fiercer competition (Porter 2000). For high-growth firms in Sweden, Borggren, Eriksson, and Lindgren (2016) found that new firms were less likely to survive in more specialised regions, while Neffke, Henning, and Boschma (2012) demonstrated insignificant effects for young firms. Meanwhile, starting a firm in a region with diverse or related industries could provide access to a larger labour pool and more efficient matching. A larger economy could however also counter survivability with negative congestion effects like
higher land prices and greater competition for resources. Some studies have found diversity and relatedness to be positively associated with survival for young firms (Renski 2011; Neffke, Henning, and Boschma 2012; Borggren, Eriksson, and Lindgren 2016). Moreover, the relationship between population density and survival is mixed. For example, studies in Germany and Sweden have found a negative correlation with survival (Brixy and Grotz 2007; Fritsch, Brixy, and Falck 2006; Neffke, Henning, and Boschma 2012), while in Italy and the Netherlands population density was insignificant and positively related to survival, respectively (Basile, Pittiglio, and Reganati 2017; Van Oort et al. 2012).

To sum up, we expect geography to influence the possibility of building teams that can stimulate survivability. On the one hand, similarity at the sector and city levels can be positively linked to performance because it contributes to a larger pool of labour for firms to draw upon (Farinha et al. 2019). On the other hand, similarity (or substitutability) at the plant level often has a negative relationship to performance because it represents too much overlap, which hampers new performance-enhancing combinations of knowledge (Boschma, Eriksson, and Lindgren 2009). However, higher levels of similar knowledge in a region can benefit the new firm if this knowledge-specific specialisation is distributed across many different firms, as opposed to being concentrated in only a few. This partly explains the positive effects of same-industry labour flows identified by Timmermans and Boschma (2013) in the Copenhagen region compared to other Danish regions. Due to the relative size of metropolitan regions, the heterogeneity of skills within the same industry tends to be greater and hence less detrimental to performance. Accordingly, in the present paper we delve into the micro-level and examine the evolving workforce composition of firms, but we also relate that to industry- and region-specific attributes.

2.3. The Swedish context

The empirical analysis is focused on firms in Sweden, whose geography and labour market institutions set the stage for the young ventures. To begin with, the distribution of small and high-growth firms mirrors the population distribution across Swedish regions, as described by Borggren, Eriksson, and Lindgren (2016). While almost half of Sweden’s population resides in one of the three largest metropolitan regions, the other parts of Sweden are relatively sparsely populated. In fact, 85% of the population is found on 1.3% of the land area. Furthermore, employment growth has differed greatly across Sweden’s regions during the decade of this study, with most of the growth occurring in the large metropolitan regions (Eriksson and Hane-Weijman 2017). This makes it particularly salient to understand the limitations and supporting mechanisms for potential job creation across all regions.

Sweden has some of the strictest employment protection regulations among the OECD countries, which includes its last-in-first-out policy. This policy means that if a firm needs to downsize, then the last-hired employee is let go, which, according to Bornhäll, Daunfeldt, and Rudholm (2015), is one explanation for why Sweden has lower employment growth rates among firms with ten or more employees than the rates found in other countries. Meanwhile, in comparison to other EU-15 countries, Sweden’s survival rate for new firms is the highest. This might be because fewer companies are started, and those that do form are relatively well-planned and competitive (Andersson
Thus, compared to other institutional contexts, the growth rates of the firms in the present study may be dampened by employment protection legislation, but they also have greater chances of survival compared to similar firms in other OECD countries.

3. Empirical approach

We utilise anonymised panel microdata from Statistics Sweden (SCB) that match workers and their employers. These data allow us to examine firms’ workforce skill composition as well as capture other firm-specific attributes and characteristics of their industry and region. We use a cohort of firms that started their operations in either of the years 2001, 2002, or 2003. We then follow these firms until 2012. A firm is considered an entry if it fulfils two criteria: 1) observed in t but not in t-1 (t = {2001, 2002, 2003}) and 2) classified as an entry per the Statistics Sweden FAD code (i.e. the business registers). In the case of the latter, the FAD code is based on tracking labour flows between establishments and years to determine whether new firms are created because of mergers and acquisitions, splits, or otherwise. In the present study, new firms generated from mergers and/or acquisitions or splits are excluded from the sample. Furthermore, we do not include multi-establishment firms, which refers to a firm with employees in multiple locations. The reason for focusing on newly started single-plant firms only is that incumbent firms opening new establishments likely have existing recruitment structures and strategies in place that can easily be transferred to the new branch plant. Thus, their hiring may be affected by internal policies concerning how tasks are divided between different branches. Another reason is that we want to analyse firms that are similar in age and resources.

Firms are required to have at least two employees by their second year. This threshold is used because our interest is in examining the characteristics of co-worker combinations. For this reason, the analysis starts in the second year (i.e. if a firm is established in 2001, the team formation process is examined starting in 2002). This is done because many firms start with one worker, and this allows us to also include firms that grow slowly in the beginning. Of the 19,753 new entries fulfilling the above criteria, 48 percent survive beyond 2012. The highest exit rates are in the second and third year (around 10%), and this rate drops by about 1 to 2% each subsequent year.

When assessing whether the mix of co-worker skills is associated with the performance of new firms, we use firm exit as the outcome. There are different ways of assessing the performance of newly founded firms, but focusing on survival is justified by the fact that it, apart from being a straightforward proxy for success, captures whether a firm is competitive with other firms on the market (Boschma 2015). A common alternative to survival is using a growth indicator, such as employment or productivity growth. However, rate of growth and growth ambitions can vary considerably by sector, geographic context, and for lifestyle-driven reasons (Reichstein and Jensen 2005; Cassar 2007; Habersetzer et al. 2021). The relationship between growth and survival is also not straightforward, as a faster pace of growth can be risky and is associated with higher failure risk (Delmar, McKelvie, and Wennberg 2013).

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1We also conducted the analysis on firms with at least two employees in their first year to test the sensitivity of the results to the sample selection criteria. This gave similar findings.
3.1. Explanatory variables

As mentioned above, the main focus is on analysing how the skill composition of co-workers influences survival. To capture the composition of workers’ skills in firms, two indicators are used: co-worker synergy and co-worker substitutability. These are based on detailed educational and occupational data, following the approach developed by Neffke (2019). We treat the education of an individual as a source of specialised skill gained from formal learning. The data include the highest level and field of education attained by each worker. The four-digit education field describes the specific subject, such as ‘Town planning and architecture,’ ‘Animal health,’ and ‘Marketing.’ To incorporate the level of education, five educational levels are used. Then the four-digit field and one-digit level are combined, resulting in 491 educational tracks, where each worker is assigned one code. This combination of field and level has been done in studies examining the effect of variety in workers’ educational backgrounds on productivity at both the individual (Neffke 2019) and regional level (Wixe and Andersson 2017). Additionally, we utilise data on occupations by drawing upon 355 occupational codes.

Co-Worker synergy quantifies the degree to which skills tend to be matched together in the same firm. Analogous to how individual workers have multiple skills to draw upon for carrying out tasks, synergy is meant to capture this at the organisational level, where tasks are divided between multiple workers with different but complementary skills. In a broad sense, it is a co-occurrence measure based on educational tracks within establishments nationally, normalised by educational track and establishment size. Similar to how other work builds on the co-occurrences of technologies as a measure of relatedness between activities (Teece et al. 1994; Dibiaggio, Nasiriyar, and Nesta 2014), the co-occurrence of educational tracks reflects bundles of skills that are frequently found within workplaces.

However, it could be that co-workers with different skills still perform the same tasks. Therefore, the second measure of substitutability is included to control for skills that are similar but otherwise not synergistic. Substitutability is based on the degree to which two workers can perform the same job (occupation). More specifically, to construct the substitutability measure, we aggregate the number of workers with each education in each occupation into education-occupation vectors, and then correlate these vectors to get the correlation coefficient representing the similarity between skills. Thus, when controlling for substitutability, synergy can be interpreted as how related the skills are beyond how similar they are, and thus how complementary skills are to one another. Both measures are first applied at the individual level for workers, then the weighted average within firms represents the respective dimension of collective workforce skills. Consult the Appendix for a technical description of both measurements taken from Neffke (2019).

These proxies for workforce skills are assumed to be associated with firm survival through the mechanisms discussed earlier: Firms compete for the skills they need, but they also use them in different combinations, which results in different levels of synergy and substitutability. This in turn is suggested to be a factor associated with diverging hazard outcomes. We expect firm exit to be positively correlated with higher levels of co-worker substitutability, which is in line with research showing that skill similarity hampers firm performance (see, e.g. Eriksson 2011). On the other hand, we expect firm
exit to be negatively correlated with higher synergy, given that synergy is meant to capture the combination of workers with the different yet complementary skills that allow firms to subsequently develop their capabilities.

Moreover, several variables at the firm level that are known to co-determine survival are also included. The literature on the relationship between firm size and performance is huge, but it can generally be assumed that larger firms have a higher probability of surviving (Dunne, Roberts, and Samuelson 1989; Geroski, Mata, and Portugal 2010). Multiple studies have also documented the ‘liability of smallness,’ which describes a negative relationship between firm survival and small firm size at the start (Audretsch and Mahmood 1995; Segarra and Callejon 2002). The argument is that larger starting sizes provide more efficient scales for production and that larger firms can more easily attract capital and skilled workers. Additionally, synergy and substitutability vary with firm size, so including firm size explicitly controls for this relationship. The logarithm of the number of employees in the firm is used to account for its non-linearity (Size). Furthermore, the average age (Average age) of the workers in each firm is used to proxy the accumulated experience of workers from their current and past jobs. The share of workers with a bachelor’s degree or higher is also included (Share with higher ed.) to separate the level of education in the firm from the compositional properties of skills captured in synergy and substitutability.

We also include three variables that control for the background of the founder, as the founders’ experience and human capital also influence firm performance (see, e.g. Bates 1990; Colombo and Grilli 2005). These entrepreneur-specific variables are: a dummy for whether the founder has a higher education (Higher education), a dummy for whether the founder started another firm any time in the five years previous to the firm in the study (Start-up experience), and the founder’s income prior to starting the firm (Previous income).

The firms’ access to local skills might also influence survival. We therefore include several regional variables. The region-specific variables are measured at the functional analysis regions (FA-regions) developed by the Swedish Agency for Growth Policy Analysis (2011). These regions were created by aggregating the 290 municipalities in Sweden to 72 FA-regions based on a combination of observed commuting flows and labour market analyses. They are meant to describe labour market areas where workers can both reside and work, as pre-defined administrative municipal borders may not capture actual commuting and work behaviours.

*Industry specialisation* is included as a proxy for absolute specialisation and general industry-wide externalities at the regional level. This is defined as the number of workers within each respective firm’s 4-digit industry, minus the employees of the firm itself. Rather than relative specialisation, the absolute number tends to be a more straightforward measure of specialisation (Kemeny and Storper 2015). Additionally, employment in related industries is defined as the size of the 2-digit industries, minus the firm’s industry (*Related industries*). We also include a diversity measure using the Shannon entropy of industries in the region, as diverse regions may contribute to inter-industry knowledge spillovers (*Industry diversity*). Such diversity could potentially also contribute to unrelated knowledge combinations in firms. Lastly, the size of the region (*Regional size*) is used as a proxy for urbanisation economies. In these data, regional size correlates highly
with the share of workers with higher education and the diversity of educational tracks within the region. Thus, the size reflects the general market size and diversity of the workforce.

Dummy variables for broad sector groups are also included, as survival rates tend to vary significantly between segments due to factors such as capital intensity, initial costs and different regional or global market demands. Different market demands imply that firms in traded industries face fiercer competition and therefore cannot afford to hire a team with a suboptimal skill-mix (see Hausmann and Neffke 2019). Non-traded activities, especially those in smaller regions, may, on the other hand, have some monopoly power in local markets and perhaps focus more on cutting costs than on building teams with optimal skill-mixes. Industries are divided into several broad categories (Manufacturing; KIBS; Restaurant, hotel, recreation; Other services and Primary sectors). While KIBS include finance and knowledge-intensive business services, other services include activities related to personal care and health, hairdressing, and cleaning and sanitation.

Table 1 lists the variables used in the study, including their means and standard deviations. We show the statistics for all firms in the sample, then for firms in non-metropolitan regions in the sample (which are all regions excluding the largest three regions: Stockholm, Malmö and Gothenburg), and then for all firms outside the sample. This is done to detail whether the metropolitan regions drive these patterns and to what extent this sample deviates from the general population of firms. Interestingly, the main variables of interest – synergy and substitutability – do not seem to vary between metropolitan and other regions. However, both values are lower in the new firms compared to the general population of firms. Intuitively, it makes sense that incumbent firms are better at recruiting well-matched co-workers, as they are more experienced in doing so. In general, however, firms tend to be a little larger in metropolitan regions and to have a slightly younger workforce. There are also more knowledge-intensive business services (KIBS) startups in metropolitan regions, and conversely more new firms in the manufacturing, service, and primary sectors in non-metropolitan regions. For information about the pair-wise relationship between the variables, see the correlation matrix in the Appendix (Table A1).

3.2. Empirical model

Given that survival is our dependent variable, we use a discrete-time hazard model with the assumption that the hazard rates reflect a logit function. Because the data are provided on an annual basis, the discrete-time model is appropriate (Allison 1984; Jenkins 1995). Hazard models are well suited to dealing with right-censored data, which is the case in this study, because the time spells begin with the entry of the firms and end in 2012, regardless of whether the firms continue to survive. The results from the discrete-time hazard model can be interpreted as the proportional odds of failure, or the

The time parameter in the hazard model is a cubic polynomial, a flexible parametric specification for the baseline hazard function. Other functional forms were tested to check for sensitivity to the chosen parameter and led to similar results.
conditional probability of exiting given that the firm survived up to a given point. The dependent variable takes a value of 1 if the firm closes, and it remains at 0 as long as the firm survives.

A few challenges are associated to estimating the association between workforce quality and firm survival. The first relates to possible endogeneity between the firm-level controls and synergy and substitutability. While we expect a more complementary workforce to be associated with firms’ chances of survival, this can also in turn attract
better workers. Consequently, we fix all covariates associated with firm survival at their initial values. This means that the initial covariate values follow each firm until they either exit or survive the entire study period. A model with time-varying covariates is also reported in the appendix that captures changes over time within firms and regions.\footnote{In this case, the exit is instead defined as the first time the firm drops to one or zero employees, as two of our main variables of interest rely on the mix of co-workers, not just one person.}

Besides the mix of co-workers affecting survival, there may also be a causal relationship that goes from the way a company is run (or even its reputation), to its ability to hire the right mix of workers, to its subsequent success. For instance, unobserved characteristics of founders and firms (e.g. founder risk tolerance, confidence, ignorance, etc.) are known to affect their strategic hiring decisions (see, e.g. Rocha et al. 2019). One way in which we account for between-firm variability in the hazard of firm exit is by incorporating a random effect at the firm level. This accounts for homogeneity in outcomes (failure risk) within firms (Austin 2017). However, as Rocha et al. (2019) suggested, this may still lead to an overestimation of the relationship between initial workforce quality and firm exit in hazard models. Thus, the results can also be somewhat biased upwards for our main variables of synergy and substitutability, even though we control for observable founder characteristics and use random effects.

4. Results

Overall, the distribution of firm start-ups across region types is 56% in metropolitan regions, 28% in large regions, 5% in semi-peripheral regions, and 11% in rural regions. As noted earlier, this reflects the population distribution to a large degree (Borggren, Eriksson, and Lindgren 2016). The survival rate distribution is very similar, but it is 3 percentage points lower in metropolitan regions. This underscores the notion that entrepreneurship is important to all regions – both large and small – and that the competition in larger markets might be fiercer. Furthermore, Figure 1 shows the average relationship of co-worker synergy (white line) and substitutability (black line) to region size in the first year of the new venture. It is clear that average co-worker synergy and substitutability within new firms are similar across regions, although with greater heterogeneity in the respective tails.

While co-worker synergy and substitutability are distributed somewhat similarly geographically, the underlying skills contributing to the measures can be qualitatively different. To illustrate this, Table 2 shows the top five educational tracks based on the number of employees in different regions from the sample of new firms. Because skills also differ by industry, KIBS were chosen for the example. In a more peripheral university region, the most common educations are electronic, computer, and automation engineering and general education. In a small remote inland region, there is a wider variety including teachers and social workers in addition to engineers. In a metropolitan region, the most common educational tracks are in business and economics and general education. This illustrates that while the co-worker matches may be quantitatively similar in two regions, the types of skills this complementarity builds upon may still differ.
As firms age, the composition of workers evolves with new recruits and turnover. As mentioned earlier, when substitutability is controlled for, synergy can be understood as how complementary the co-workers’ skills are to one another. Put differently, it captures an aspect of the division of labour beyond how similar team members in a firm are to one another. Thus, in Figure 2, we show how complementarity evolved during the study period by plotting residuals from ordinary least squares (OLS) regressions with synergy as the dependent variable and substitutability as the independent variable; the slopes and

![Figure 1. Fitted lines and confidence intervals (at 95% level) of co-worker synergy (white line) and substitutability (black line) in firms’ first year.](image)

| Region type                                       | Specialisation                                      | Level               |
|--------------------------------------------------|-----------------------------------------------------|---------------------|
| Peripheral university region, densely populated  | General, computer, automation                       | Lower secondary     |
|                                                  | General social science                              | Post-secondary, 2+ years |
|                                                  | Electronics, computer, automation                   | Upper secondary     |
|                                                  | Electronics, computer, automation                   | Post-secondary, 2+ years |
| Small remote inland region                       | Pre-school teacher                                  | Post-secondary, 2+ years |
|                                                  | Social work                                         | Post-secondary, 2+ years |
|                                                  | Computing                                           | Upper secondary     |
|                                                  | Engineering                                         | Upper secondary     |
| Metropolitan region                              | General social science                              | Lower secondary     |
|                                                  | Business and economics                              | Post-secondary, 2+ years |
|                                                  | General natural science                             | Upper secondary     |
|                                                  | Business and economics                              | Upper secondary     |
|                                                  | Business and economics                              | Upper secondary     |

Table 2. Top 5 educational tracks in three different FA regions in KIBS.
intercepts are allowed to vary by year after entry. The figure is divided into four groups (regressions) on different samples depending on time in operation prior to exit. Figure 2 reveals that, for the surviving firms (solid black line), teams on average have more complementary skills already at the start and also increase their complementarity at a faster rate compared to the firms that do not survive the entire study window. Both initial level and the subsequent development of complementarity are on average lower the shorter the firms survive.

While Figure 2 indicates that firms that hire more complementary teams in the beginning also tend to survive longer, we also need to consider other factors that are associated with survival and the respective roles of synergy and substitutability. Thus, in Table 3, we report results from the discrete hazard models, which are the conditional probabilities of failure given that the firm lasted to each specific time point. A variable with negative log odds indicates failure is less likely, while positive log odds indicate failure is more likely. The models are shown stepwise, with Model 1 starting with only synergy, substitutability and firm size. Model 2 includes control variables related to the firm, the founder and industry, Model 3 adds regional controls, and Model 4 also includes industry (2-digit) and region fixed effects to reduce the impact of potential unobserved confounders that are specific to the industry or region. Although it could be argued that Model 1–3 suffer from omitted variable bias, the stepwise approach allows us to assess the stability of the association between firm failure and synergy and substitutability.

Turning first to the firm-level synergy and substitutability measures, we find that synergy decreases the likelihood of failure as suggested in Figure 2. Depending on the model specification, a one-unit increase in synergy reduces the failure odds by between...
75% in Model 1 and about 60% in the more conservative Model 4. On the other hand, substitutability has a positive association with the likelihood of failure. Increasing the co-workers with substitutable skills increases the failure odds by between 41% (Model 4) and 93% (Model 1). Although the point-estimates change when adding more variables, the respective roles of synergy and substitutability are remarkably stable across the specifications and even trumps the other well-established determinants of survival. For example, the education level of the workforce is not significant when estimated together with synergy and substitutability (significant when synergy and substitutability are omitted). Because the scales of the variables vary, we calculated the predicted probabilities

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4The natural log odds are transformed to odds ratios in the following manner: \((1 - \exp(\text{natural log odds})) \times 100\). In this way, the results can be discussed as the change in the odds of firm exit in relation to a one-unit change in the given variable while all the other variables are held constant.
(marginal effects) of a one-standard-deviation change in each respective variable as suggested by Long and Freese (2014). Increasing synergy by one standard deviation on average decreases the probability of exit by 0.023, while a one-standard-deviation increase in initial firm size and previous income of the founder decreases the probability of failure by 0.004 and 0.010, respectively. The probability of failure is also on average 0.011 less for experienced entrepreneurs compared to inexperienced ones. Thus, the effect of synergy is more than two times higher than for the other firm- and founder-level determinants. Overall, the robustness of the estimates when adding important controls should provide some reassurance that the estimates are not confounded by omitted variables.

Regarding factors related to the industries and regions, compared to manufacturing the likelihood of survival is higher in primary industries and lower in the different service sectors. The results also show that the likelihood of survival for these new firms is higher in smaller regions. This is in line with other studies that have identified a negative correlation between region size and survival (Brixy and Grotz 2007; Fritsch, Brixy, and Falck 2006; Neffke, Henning, and Boschma 2012). Moreover, the likelihood of exit for these new firms is higher in larger industry agglomerations. Altogether, this is likely due to fiercer competition in areas with many firms (Melitz and Ottaviano 2008). On the other hand, complementary activities proxied like related sectors that perhaps are not direct competitors do seem to increase the likelihood of survival, while diversity as such is not significant. However, when also controlling for industry- and region-specific unobservables in Model 4, neither of the regional variables remains significant.

### 4.1. Time-varying model

As discussed earlier in the empirical approach, the models in Table 3 are designed with variables fixed at the start of the study period. This was done to avoid the potential influence of the explanatory variables on each other, which would in turn affect the estimates of firm exit. However, a number of things can happen within firms over the course of several years. We therefore include time-varying models in Table A2 in the Appendix. Keeping in mind that these models are estimated with a relaxed assumption on endogeneity, the results from the time-varying estimates are nevertheless similar to the estimates in Table 3. However, the role of firm size grows in magnitude, as does the influence of the education level of the workforce. Thus, in these time-varying models, firms that are increasing in size and recruiting higher shares of highly educated workers have a lower likelihood of exit. Furthermore, a few of the regional variable estimates are different from the main specification discussed above. These regional factors can be affected by changes over time, such as a firm relocating or differential rates of growth between industries and regions. In the time-varying models, both industry diversity in the region and regional size are associated with higher likelihoods of firm failure when controlling for regional- and industry-specific unobservables in Model 4.

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5In separate models, we also checked whether the strength of the association between firm failure and firm-level synergy and substitutability varied by broad regional groupings and sectors. However, the results showed minimal differences between regions and sectors.
5. Discussion

Although human capital among founders and employees has long been identified as a key determinant of success for new firms, we still have limited knowledge about exactly how different forms of knowledge should be coordinated in teams and firms. Following recent studies highlighting the relational nature of human capital as a mechanism for firm-level differences in productivity (Neffke 2019), we explored the relationship between skill coordination within firms and their subsequent survivability. This was done by analysing new firms’ likelihood of survival up until at least 2012 in relation to how complementary the skills of co-workers are to one another.

Our results, based on a cohort of 19,753 Swedish firms that began their operations between 2001 and 2003, indicate that surviving firms tend to be firms that have teams with more complementary skills already from the start. Moreover, surviving firms also succeed in building a workforce consisting of more complementary skills. Even when controlling for other factors known to affect survivability, co-worker synergy still significantly reduces the likelihood of failure. The positive relationship between synergy and survival, when also accounting for the substitutability of skills, show that hiring workers with complementary skillsets is important for firms’ survival. The role of complementarity is stable across different specifications (both when using fixed and time-varying models) and surpasses the effect of other well-known determinants of firm survival. Akin to previous general findings on how the composition of skills influences firm performance (Boschma, Eriksson, and Lindgren 2009) and the role of co-worker synergy in particular (Neffke 2019), our results indicate that complementary skills also translate to the higher survivability of firms that build complementary teams.

Our findings highlight the importance of planning for a firm’s most important resource – its employees. The results indicate that the right skills make a significant difference for the success of a new firm, even when controlling for other characteristics of firms that are associated with exit. Because the supply of skills is largely determined by the location, these findings imply that a vital consideration when starting a new firm or attracting new firms or industries to a region must be how well they fit with the skills in the region. Hence, new economic activities should build on existing regional resources, as advocated in both the research (Boschma 2017) and the recent Smart Specialisation Agenda of the EU (McCann and Ortega-Arguiles 2015). Thus, policymakers and others working on attracting start-ups need to be realistic and strategic about where to pour their resources if they are to gain the maximum benefit and create sustainable businesses within the region. Policymakers could also focus resources on helping entrepreneurs connect with people in the early stages of the start-up process, as worker-firm matching seems to be crucial to firm survival already at the beginning. In cases where local skills do not match the profile of new companies, inter-regional recruitment increases in importance (cf., Hausmann and Neffke 2019). This is a more difficult task, however, due to the relatively low inter-regional migration rates in Sweden and most of the EU.

One caveat when interpreting the present study is that the results may not apply to older firms or to other measures of firm success such as employment growth. Consequently, studying how the results vary for older and more mature firms could be promising extensions of this research. Additionally, while we controlled for many factors related to firm quality – such as including random effects at the firm level and the
founders’ characteristics – this is not sufficient to disentangle the exact causal mechanisms. For example, some firms may be more attractive to potential employees for unobservable reasons, or some firms may be better at identifying the best new recruits for their team. Future studies should find ways to address the question of why some firms are better at recruiting than others are. Further attempts at disentangling the effect of the mix of workforce skills from the effect of unobserved founder and firm characteristics would also be an important pursuit for future studies.

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Data availability statement

The micro-data analyzed in this study are compiled by Statistics Sweden and made available to researchers by permission from Statistics Sweden only. A fee applies. By law, the authors of the present study cannot share the data; interested researchers must approach Statistics Sweden directly.

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Appendix

Calculating co-worker synergy and substitutability

The measures used in the present paper for calculating the composition of skills within firms were proposed by Neffke (2019), where more details can be found. Yet this section briefly describes how these measures of skill complementarity are constructed. We start with a matrix of establishments, denoted by \( p \), and educational tracks \( e \). If education \( e \) is overrepresented in workplace \( P \), then \( P_{ep} \) equals 1, otherwise 0. As larger establishments tend to have more diverse workforces, the presence of an educational track in an establishment is normalised by the establishment’s total number of co-occurrences (represented by co-occurrence \( ab \)). Thus, each establishment contributes one co-occurrence to the total.

\[
N_{ee'} = \sum_p \frac{P_{ep}P_{ep'}}{\sum_{ab} P_{ap}P_{bp}}
\]

Then, to control for the number of workers with each educational track, the ratio of observed to expected co-occurrences is calculated. The expected can be thought of as the co-occurrences that would be expected if skills were distributed randomly.

\[
c_{ee'} = \sum_p \frac{N_{ee'}}{N_{ee'} / N}
\]

However, as this measure is by construction skewed, it is transformed and limited to the interval \([0, 1]\) by using the ratio \( c_{ee'}/(c_{ee'} + 1) \).

Substitutability is calculated by constructing occupational vectors where \( E_{eo} \) is the number of workers with education \( e \) in occupation \( o \).

\[
s_{ee'} = corr(E_{eo}, E_{e'o})
\]

Both of these \( (R_{ee'} \text{ and } s_{ee'}) \) generate networks of skill synergy and substitutability that need to be transformed to the individual and co-worker levels. The following equations take the measure to the individual worker level. Here, \( C \) stands for synergy, \( S \) stands for substitutability, \( w \) refers to worker, \( e \) refers to the educational track, \( p \) stands for plant (the term plant is analogous to establishment in this study), and \( t \) refers to calendar time (year). Thus, \( E_{pw,t} \) captures the number of workers in worker \( w' \)’s establishment.

\[
C_{wpw,t} = \frac{1}{E_{pw,t} - 1} \sum_{w' \in P_w \text{, } w' \neq w} c_{ww'eo'} \text{ and } S_{wpw,t} = \frac{1}{E_{pw,t} - 1} \sum_{w' \in P_w \text{, } w' \neq w} s_{ww'eo'}
\]

In the last step, the worker-level measures are summed and averaged within each establishment.

\[
C(p), \text{ or } S(p)_t = \frac{1}{W_p} \sum_{w \in P_w} S_{wpw,t}
\]

---

5 The location quotient (LQ) for educations in workplaces defines ‘presence,’ as some educations are more ubiquitous than others.
**Table A1.** Correlation matrix.

|            | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|
| (1) Synergy| 1   |     |     |     |     |     |     |     |     |      |      |      |
| (2) Substitutability | 0.874 | 1   |     |     |     |     |     |     |     |      |      |      |
| (3) Size   | 0.116 | 0.085 | 1  |     |     |     |     |     |     |      |      |      |
| (4) Average age of employees | 0.071 | 0.007 | -0.245 | 1  |     |     |     |     |     |      |      |      |
| (5) Share with higher education | 0.056 | -0.055 | -0.039 | 0.103 | 1  |     |     |     |     |      |      |      |
| (6) Founder with higher education | 0.051 | -0.047 | -0.003 | 0.097 | 0.700 | 1  |     |     |     |      |      |      |
| (7) Founder with start-up experience | -0.024 | -0.003 | -0.063 | 0.127 | -0.041 | -0.030 | 1  |     |     |      |      |      |
| (8) Founder's previous income | 0.251 | 0.140 | 0.167 | 0.103 | 0.099 | 0.102 | -0.077 | 1  |     |      |      |      |
| (9) Region size | 0.000 | 0.000 | 0.022 | -0.031 | 0.173 | 0.129 | 0.006 | 0.005 | 1  |      |      |      |
| (10) Industry specialisation | -0.003 | -0.008 | 0.063 | -0.067 | 0.156 | 0.119 | -0.006 | -0.008 | 0.778 | 1  |      |      |
| (11) Related industries | 0.014 | -0.003 | 0.027 | 0.002 | 0.175 | 0.131 | -0.009 | 0.036 | 0.829 | 0.677 | 1  |      |
| (12) Industry diversity | -0.007 | -0.003 | 0.013 | -0.023 | 0.104 | 0.077 | 0.011 | -0.001 | 0.705 | 0.534 | 0.581 | 1  |

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|                | (1)          | (2)          | (3)          | (4)          |
|----------------|--------------|--------------|--------------|--------------|
| **Firm-level** |              |              |              |              |
| Synergy        | $-2.279^{***}$ | $-1.673^{***}$ | $-1.663^{***}$ | $-1.586^{***}$ |
|                | (0.106)      | (0.093)      | (0.093)      | (0.094)      |
| Substitutability | $0.893^{***}$ | $1.278^{***}$ | $1.226^{***}$ | $1.178^{***}$ |
|                | (0.100)      | (0.090)      | (0.089)      | (0.090)      |
| Size           | $-1.599^{***}$ | $-1.972^{***}$ | $-2.049^{***}$ | $-2.057^{***}$ |
|                | (0.061)      | (0.027)      | (0.028)      | (0.028)      |
| Average age    | $-0.003$     | $-0.002$     | $-0.002$     | $-0.002$     |
|                | (0.002)      | (0.002)      | (0.002)      | (0.002)      |
| Share with higher ed. | 0.076 | 0.063 | 0.070 | 0.070 |
|                | (0.066)      | (0.066)      | (0.066)      | (0.066)      |
| **Founder**    |              |              |              |              |
| Higher education | 0.131*      | 0.113*      | 0.128*      |              |
|                | (0.047)      | (0.059)      | (0.059)      |              |
| Start-up experience | $-0.206^{***}$ | $-0.221^{***}$ | $-0.231^{***}$ |              |
|                | (0.047)      | (0.047)      | (0.047)      |              |
| Previous income | $-0.069^{***}$ | $-0.076^{***}$ | $-0.077^{***}$ |              |
|                | (0.006)      | (0.006)      | (0.006)      |              |
| **Sector (reference = manufacturing)** |              |              |              |              |
| KIBS           | 0.472^{***}  | 0.516^{***}  | 0.177       |              |
|                | (0.065)      | (0.070)      | (0.223)      |              |
| Restaurant, hotel, recreation | 0.515^{***} | 0.466^{***} | $-0.522$ |              |
|                | (0.068)      | (0.071)      | (0.362)      |              |
| Other services | 0.151^{**}   | 0.212^{***}  | $-0.169$    |              |
|                | (0.058)      | (0.061)      | (0.231)      |              |
| Primary        | 0.227*       | 0.201*       | $-0.098$    |              |
|                | (0.093)      | (0.094)      | (0.228)      |              |
| **Regional context** |              |              |              |              |
| Regional size  | 0.101^{***}  | 2.941^{***}  |              |              |
|                | (0.023)      | (0.249)      |              |              |
| Industry specialisation | 0.004 | $-0.001$ | (0.012) | (0.013) |
| Related industries | $-0.046^{***}$ | $-0.012$ | (0.013) | (0.026) |
| Industry diversity | $-0.046$ | 1.166^{***} | (0.170) | (0.322) |
| Industry FE    | No           | No           | No           | Yes          |
| Region FE      | No           | No           | No           | Yes          |
| Log likelihood | $-35,568$    | $-33,194$    | $-32,939$    | $-32,768$    |
| Wald Chi² (df) | 3,340 (6)    | 5,769 (15)   | 6,253 (20)   | 6,509 (135)  |
| N              | 89,849       | 89,849       | 89,849       | 89,849       |
| n              | 19,751       | 19,751       | 19,751       | 19,751       |

Note: Discrete hazard models with random intercepts; standard errors shown in parentheses below coefficients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$