Paper to be presented at

DRUID15, Rome, June 15-17, 2015

(Coorganized with LUISS)

The impact of new topmanagers and toptechnicians on plant survival and diversification

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This paper investigates the impact of new topmanagers and toptechnicians on plant survival and diversification. We use matched employer-employee data from the Swedish administrative records that cover the full population of workers and plants between 1995 and 2010. Our identification strategy first identifies the loss of one?s existing topmanager or toptechnician due to death or permanent emigration, which we use to predict hiring. Subsequently, to predict what kind of topmanager or toptechnician with what kind of human capital is hired, we develop a local supply shift instrument that identifies exogenous variation in the supply pool of candidates from which plants recruit. We find evidence that new unrelated topmanagers and toptechnicians ? those that possess human capital very different from the plant?s activity ? have no impact on a plant?s survival chance. Instead, they strongly increase the chance of a plant to diversify into new activities. Those activities often match much better with the human capital of the new recruit. The impact of new toptechnicians is as strong as the impact of new topmanagers, which suggests that both occupations, regardless of a plant?s pre-existing strategy, are equally important drivers of a plant?s strategy, performance and future activities.

Jelcodes:M00,M

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1. Introduction

The entry and exit of firms, as well as the diversification of firms into new activities, are important sources of resource allocation across economies. A huge literature exists on the implications of firm entries and exits for industry dynamics (Esteban et al., 2007; Foster et al., 2008). At the same time, the recent upsurge of research using national social security registries reveals the broad scope of firm diversification. For instance, in the US, every 5 years 50% of the manufacturing firms alter their product portfolio, and these firms account for 89% of all manufacturing output (Bernard et al., 2010).

This paper aims to gain insight into the micro foundations of these findings, by investigating the impact of new topmanagers and toptechnicians on plant survival and diversification. Teece

(1982, p. 47) wrote that "*A specialized firm's generation of excess resources, both managerial and technical, and their fungible character is critical to the theory of diversification*". Abundant research exists on how excess resources arise in a firm's existing stock of workers and capital (Penrose, 1959), for instance through economies of scope, and how they can be and are re-employed in other activities. We know less about the impact of (excess) resources acquired through recruitment on diversification. Does it matter if a new topmanager or toptechnician comes from an industry that is very different from the plant's industry? As more of the new recruit's human capital might be left idle in this case, do future activities of the plant reflect the human capital of the new recruit? Hence, are plants more likely to diversify upon hiring an unrelated topmanager or toptechnician, and if so, do they diversify into activities that better match with the human capital the new recruit? And do new topmanagers exert most impact on firm diversification, or rather new toptechnicians?

In answering these questions, we focus on the extent to which resources are left idle once a plant has recruited a new worker. These could be regarded as excess resources that are acquired – contrary to those that are created within the plant. We focus on the qualitative part of human capital, namely what kind of human capital new recruits have, rather than using an aggregated measure of how much human capital is present in a plant (e.g. years of schooling), which most research has focused on. Doing so, we aim to contribute to the emerging literature on the micro foundations of human capital that aims to understand how individuals are shaped into valuable firm resources (Coff and Kryscynski, 2011; Crocker and Eckardt, 2014; Brymer et al., 2014; Khanna et al., 2014).

In the analysis we use matched employer-employee data from the administrative records of Statistics Sweden, which cover the full population of workers and plants between 1995 and 2010. These data allow us to identify the occupation of workers and to follow plants and their activities over time. We conduct the analysis on all plants with 5 to 250 employees, which covers the 99% lower bound of the economy in terms of plant size. Hence, our findings cover a different subset of organizations than those of existing research on firm diversification, which has primarily focused on much larger organizations, particularly those listed on stock exchanges.

We provide causal evidence of the impact of new topmanagers and toptechnicians on plant survival and diversification. The first part of our identification strategy identifies when a topmanager or toptechnician, arguably, is replaced for exogenous reasons, namely when one of a plant's existing topmanagers or toptechnicians passes away or emigrates permanently. Because such plants might be plants with specific properties (e.g. having an older workforce), we use propensity score matching to create a control group that serves as a counterfactual, represententing what the plant outcomes would have been had the plants in question not experienced such a loss of one's topmanager or toptechnician. The second part of our identification strategy uses a local supply shift instrument adapted from the labor economics literature. It identifies exogenous variation in the availability of human capital in the local supply pool of (replacement) candidates from which plants recruit, which we use to instrument the degree of human capital similarity between a plant and a newly-recruited topmanager or toptechnician.

The structure of the paper is as follows. Section 2 provides an overview of the existing literature on the importance of topmanagers and toptechnicians, particularly related to their human capital, for plant survival and diversification. Section 3 presents the methodology, which outlines the data as well as the identification strategy. Section 4 presents the results and Section 5 concludes.

2. Resources, recruitment, and diversification

According to the resource-based view of the firm, firms diversify to employ idle or underused resources in new activities. Because firms are bundles of idiosyncratic resources (Penrose, 1959; Rumelt, 1982; Wernerfelt, 1984; Barney, 1991), they operate most efficiently when they maximize the resources (Nelson and Winter, 1982) and technological know-how (Dosi, 1982) employed in existing operations. Because learning-by-doing may lead to idle resources, firms can benefit from leveraging those resources into new activities (Penrose, 1959). A single resource may also be able to foster a variety of activities, of which only some are currently pursued by a firm.

A key resource for diversification is the human capital of a firm's workforce. Becker (2002, p. 3) defines human capital as the *"knowledge, information, ideas, skills, and health of individuals"*. Hence, human capital includes abilities such as intelligence, cognitive ability, physical ability, analytical skills, machinery skills, and information processing ability. Workers acquire human capital through education and work experience. Unlike physical means of production, such as machinery, which can often be used for one task, human capital is neither specific to one task nor as generic as to cover all tasks possible. Teece (1982, p. 45) refers to this as the 'fungibility of human capital': *"human capital inputs employed by the firm are not always entirely specialized to the particular products and services which the enterprise is currently producing"*.

Hence, the 'human capital pool' (Wright et al, 1994) of a firm can be exploited to undertake activities other than the firm's core activity. Indeed, firms are more likely to diversify into activities in which they can re-employ the human capital of its workforce (Farjoun, 1994; Chang and Singh, 1999; Neffke and Henning, 2013). As this maximizes the value of a firm's human capital, firms can achieve sustainable competitive advantage doing so (Barney, 1991; Peteraf, 1993; Wright et al., 1994). Indeed, Alchian and Demsetz (1972, p. 7 932) write that *"Efficient production with heterogeneous resources is a result not of having better resources but in knowing more accurately the relative productive performances o those resources"*.

Diversifying by leveraging the human capital of a firm's workforce into new activities can be done through (1) re-employment of human capital resources or (2) employment of currently not-employed human capital. Human capital resources refer to human capital that is currently employed in the firm's operations (Barney and Wright, 1998; Nyberg et al. 2014; Ployhart et al. 2014). For instance, within a firm that produces cars, the ability to make cars is a human capital resource. This ability itself is a form of human capital embedded within the workforce, and becomes a human capital resource because the firm extracts value from it. Hence, human capital resources are defined at the individual-firm level. If the car producer diversifies into new activities (e.g. production of motorcycles) that use the same human capital resource, re-employment of human capital resources takes place.

At the same time, a firm's workforce may possess human capital from which the firm's current operations do not extract value. This may especially be so for new recruits that enter a firm but possess human capital different from the firm's core activity. Ployhart et al. (2014) give the example of someone who speaks Farsi as a second language. This skill is likely not a human capital resource if the person works as an engineer in an automobile firm. However, if the firm decides that value can be extracted from it and, for instance, diversifies into Farsi-translating activities, the worker's skill would become a human capital resource to the firm. Then, the firm employs human capital that was present but not employed previously.

A worker's occupation and corresponding tasks determines which part of the worker's human capital serves as a human capital resource to the firm. This, in turn, may determine the extent to which the worker's human capital is re-employed into new activities. Teece (1982, p. 47) wrote that "*A specialized firm's generation of excess resources, both managerial and technical, and their fungible character is critical to the theory of diversification advanced here"*. Much research exists on the importance of managers and technicians for firm performance, but we know less about their impact on diversification, especially in regards to the human capital they possess. To what extent is the human capital of managers reflected in a diversification move? Is it as important as the human capital of technicians?

New activities are often regarded as outcomes of re-combinations of different (knowledge) resources within the firm, but the human capital resource at the individual-firm level of a newlyhired worker with a background in biochemistry might differ depending on whether he is recruited as a topmanager or toptechnician. By analyzing the extent to which the human capital of workers in these occupations is reflected in new activities in the firm, we shed light on the extent to which occupations, which transform human capital into human capital resources, matter for the extent to which human capital of workers is reflected in new activities. This is an important question for, for instance, managers regarding how to employ new workers, especially when they want to pursue a diversification strategy. Below we elaborate on both managers and technicians.

2.1 Managers and technicians

Topmanagers decide on resource deployment and the firm's strategy (Barney, 1986; Wernerfelt, 1994; Menz, 2012). By allocating a firm's resources most efficiently, managers can increase the productivity of the firm and its workers (Sirmon et al., 2008; Holcomb et al., 2009). Indeed, the ability of managers to lead firms onto new (profitable) paths is one of the key dynamic capabilities identified by Teece and Pisano (1994). It has been found that effective managerial actions can make a firm's human capital less imitable and hence more firm-specific (Denrell et al., 2003; Sirmon et al., 2007), which yields a competitive advantage to the firm. Manager fixed effects have been found to account for substantial variation in firm performance (Adams et al., 2005; Bertrand and Schoar, 2003; Kaplan et al., 2012; Graham, 2013) and firm strategies such as leverage decisions (Frank and Goyal, 2007) and tax choices (Bamber et al. 2010; Dyreng et al., 2010). Regarding managerial human capital, most studies have investigated whether the level and breadth of a management team's human capital, such as reflected in its educational background, increases the chance of pursuing strategies such as foreign expansion (Barkema and Shvyrkov, 2007) or diversification (Hitt and Tyler, 1991; Wiersema and Bantel, 1992).

We explore the extent to which managers leverage their own human capital, some of which may be underused in the firm's current operations, into new activities. Managerial human capital can be directly involved into producing new output, and can also affect other resources, as noted by Penrose (1959, p. 5): "*the resources with which a particular firm is accustomed to working will shape the productive services its management is capable of rendering… but also that the experience of managers will affect the productive services that all its other resources are capable of rendering*". Hence, a firm that manufactures medical products and hires a manager with a background in biomechanical engineering may be more likely to diversify in the future into biomechanical engineering products. We are interested in whether such a diversification move occurs when the firm had no prior strategy of diversifying into biochemical products. We know yet little of the extent to which a manager's own human capital is reflected in the new activities of a firm, as Kor and Mesko (2013, p. 235) hypothesize: "*managerial human capital plays a key role in shaping manager's dominant logic for a firm*".

As far as we know, only few studies exist on the importance of a manager's human capital in shaping decisions related to driving the firm into new activities. Tyler and Steensma (1998) find that managers with a technical background form alliances that stay closer to the core activities of the firm. Babenkko et al. (2014) find that specialized managers run more focused conglomerates than generalists. Once a manager involves his human capital that is left idle as a human capital resource in the firm, the performance of other resources may increase due to resource complementarities and the synergies derived from it (Teece, 1984; Milgrom and Roberts, 1990; Adegbesan, 2009; Cracker and Eckardt, 2014). Furthermore, he might pursue a strategy of aligning the firm's current production resources with his own specialization, for instance by re-assigning workers to activities that he is more familiar with. Doing so, he might reduce monitoring costs. Indeed, there is increasing evidence of homogenization among human capital in firms (Ployhart et al., 2006; Rivera, 2014), which might also have a positive effect on performance (Ployhart et al., 2006). This is especially relevant in smaller firms with less heterogeneity. Managers might foster homogenization of human capital by matching human capital resources of the firm with his own specialization in new activities.

Because of asymmetric information in the hiring process of new workers (Alchian, 1969; Akerlof, 1970), a firm may experience poor fit between hired workers and the firm's current activities (Kristof-Brown et al., 2005; Sutton, 2007; Murphy, 2010). A new manager may pursue a strategy of re-employing such workers in activities that better match his own specialization, where he is better able to judge how the resources at his disposal can be employed most efficiently. Hence, the following hypotheses follow:

<u>*Hypothesis 1*</u>*: The more different the human capital of a new manager is to a plant, the more likely a plant is to diversify*

<u>*Hypothesis 2*</u>*: Conditional on diversification, a plant is more likely to diversify into activity j when the human capital of a new manager can be employed in activity j*

Contrary to managers, technicians are 'hands-on' involved in producing the output of a firm. Once they learn and become more efficient in producing the firm's output, part of their time becomes idle, which can be leveraged into new activities (Penrose, 1959). At the same time, when they diversify into new activities that require the production skills they use in their current activities, economies of scope may arise (Nayyar, 1993; Nayyar and Kazanjian, 1993; Barney, 1997). Evidence exists that the recruitment of new workers, particularly high-skilled workers such as scientists and engineers, alters the activities a firm engages in and that new activities relate to the background of the hired workers (Almeida and Kogut, 1999; Rosenkopf and Almeida, 2003; Song et al. 2003; Tzabbar, 2009). A key question in this respect is whether this would also happen when the firm had no prior strategy of diversifying into new activities. Two hypotheses follow:

Hypothesis 3: The more different the human capital of a new technician is to a plant, the more likely a plant is to diversify

Hypothesis 4: Conditional on diversification, a plant is more likely to diversify into activity j when the human capital of a new technician can be employed in activity j

Finally, we are interested which of the two are most important for diversification. As managers decide on a firm's strategy, we hypothesize that their human capital is more likely reflected in future activities of a plant than the human capital of new technicians:

Hypothesis 5: New topmanagers have a greater impact on diversification than new toptechnicians

3. Methodology

3.1 Data

We use matched employer-employee data from Swedish administrative records that cover the full population between 1995 and 2010, accessed through Statistics Sweden. From 2001 onwards, we know the occupation of workers in plants, which allows us to distinguish managers from technicians. These are classified according to the Swedish Standard Classification of Occupations, which is based on the International Standard Classification of Occupations from the International Labour Organization.

We select all plants in the private sector that existed between 2002 and 2008 (2001 is used to construct one of the instrumental variables). Plant-year observations are our unit of analysis. From the plants, we keep those that have at least 5 employees (to exclude freelancers and to accurately identify take-overs later on) and that have a maximum of 250 employees (less than 1% of all plants has more than 250 employees, some of which are very large plants with more than 2500 employees).

A newly-recruited topmanager or toptechnician is defined as a worker who first appears in a plant in year t, whose occupation is manager or technician, and who is paid at least the median of the wages of the corresponding occupation in the plant. We estimate the impact of such recruitment on the chance of the plant still being alive in $t + 2$ and the chance of having diversified between t and $t + 2$.

Diversification is defined as a change in the first 3 digits of a plant's industry code. This code reflects the main activity of a plant and is measured at the 5-digit level according to the Swedish Standard Industrial Classification 2002, which reflects the EU's NACE Rev 1.1 classification[1]. It only changes after multiple check-ups by the tax office and Statistics Sweden as to whether a plant has truly changed its main activity. We focus on changes in the first 3 digits of the industry code as we are interested only in substantial changes in a plant's main activity.

3.2 Human capital match between plant and new topmanager or toptechnician

We want to know the match of the human capital of a new topmanager or toptechnician to the plant, which we infer from the extent to which the industry he or she is recruited from employs similar human capital as the industry of the plant he is recruited into. Following Ellison, Glaeser and Kerr (2010) and Neffke and Henning (2014), we calculate inter-industry human capital similarity using data on inter-industry labor mobility flows, based on the idea that people want to minimize the destruction of their human capital when switching jobs and hence tend to switch to industries in which they can re-employ their human capital. As we note later, we also use information on a new recruit's penultimate job, as well as a measure of human capital similarity based on the NACE industry classification.

We calculate inter-industry human capital similarity, or skill-relatedness (Neffke and Henning, 2014), using inter-industry labor flows in Sweden between 1995 and 2000. After selecting the

[1] Because we use the years 1995-2000 to calculate human capital similarity between industries, we created a concordance between the Swedish SNI92 and SNI2002 industry classifications, which we will include in the online Appendix.

workforce, consisting of the people aged 18 to 65, we first calculate skill relatedness anually between 1995 and 2000. Formally, let year be indexed by t and summation over omitted categories be indicated by '.', which yields:

$$SR_{ijt} = \frac{F_{ijt}}{(F_{.jt}F_{i.t})/F_{..t}} \tag{1}$$

where F_{ij} is the observed labor flow from industry i to industry j. Industries are defined at the 3-digit level (220 in total). Where a dot replaces the index i or j, the labor flows are summed over this omitted category, such that $F_{i.} = \sum_j F_{ij}$, $F_{.j} = \sum_i F_{ij}$ and $F_{..} = \sum_{i,j} F_{ij}$. The term $\left(F_{i.}F_{.j}\right)/F_{..} = F_{i.}\frac{F_{.j}}{F_{..}}$ represents the expected flows from i to j, assuming that j receives workers from i proportional to j's share in the total labor flows. SR_{ij} values higher than 1 indicate that industries are skill-related, whereas values between 0 and 1 indicate that industries are unrelated. Because this measure is highly asymmetric, ranging from zero to 1 and from 1 to infinity, we use map SR_{ijt} onto the interval [-1, 1):

$$\widetilde{SR}_{ijt} = \frac{SR_{ijt}-1}{SR_{ijt}+1} \tag{2}$$

Hence, industry i is skill related to industry j if $\widetilde{\mathrm{SR}}_{\mathrm{ijt}} > 0$. Then, for every industry-industry pair, we average $\widetilde{\mathrm{SR}}_{\mathrm{ijt}}$ over all flows between 1995 and 2000:

$$\mathrm{M}\widetilde{\mathrm{SR}}_{\mathrm{ij}} = \frac{1}{5}\sum_{\mathrm{t}=1995}^{2000}\widetilde{\mathrm{SR}}_{\mathrm{ijt}} \tag{3}$$

Finally, we symmetrize the measure so that $S\widetilde{SR}_{ij} = S\widetilde{SR}_{ji}$:

$$S\widetilde{SR}_{ij} = \frac{M\widetilde{SR}_{ij}+M\widetilde{SR}_{ji}}{2} \tag{4}$$

We use this measure of inter-industry human capital similarity to calculate the extent to which the industry a new toptechnician or topmanager is recruited from matches with the industry he is recruited into.

As this is an estimate of inter-industry human capital similarity, it contains measurement error, which would bias its coefficient towards zero (i.e. having no effect). To gain insight into the degree of measurement error, we create another measure of inter-industry relatedness based on the NACE industry classification and its hierarchical structure, part of which captures inter-industry human capital similarity. We assign every industry-industry pair a value of 0 (different 1-digit industries) to 3 (same 3-digit industries). This measure is correlated with the SSR value (r = 0.23). As the construction of the NACE classification is based on a wholly different logic and methodology, instrumenting the SSR measure with NACE-relatedness should rid the coefficients of the measurement error that originates from the measurement of inter-industry human capital similarity.

Another source of measurement error is that we infer the human capital of a new employee only from the industry he or she is recruited from. However, one's human capital is the experience one has accumulated in all of the industries he or she has previously worked in, as well as the education that he or she has followed. Therefore, we also instrument our SSR measure with the NACE-relatedness of the plant's industry to the penultimate industry a new recruit worked in (the industry the recruit worked in before he or she started working in the industry where he or she was recruited from).

3.3 Identification strategy

Recruitment is endogenous because plants choose whether to recruit, and if so, what kind of employee to recruit. Hence, to obtain an estimate of the causal effect of new recruits on plant outcomes, one has to tease out (unobservable) plant-specific effects, particularly those related to a plant's strategy. Our identification strategy works as follows. First, we try to identify a situation in which a topmanager or toptechnician is hired due to reasons that are arguably exogenous to the plant, namely when one's existing topmanager or toptechnician passes away or emigrates permanantly. Second, to instrument the degree of human capital similarity of a new topmanager or toptechnician to the plant, we try to identify exogenous variation in the supply pool of candidates from which plants recruit. We exploit exogenous shifts over the past 15 years in Sweden in the amount of graduates with certain skills that enter the local labor markets.

Losing one's topmanager or toptechnician as a result of death or permanent emigration

First, we try to identify a situation in which a plant has to recruit a new topmanager or toptechnician regardless of its pre-existing strategy, namely when one of its topmanagers or toptechnicians passes away or emigrates permanently (i.e. does not return to Sweden). We identify such loss to a plant by the fact that a worker disappears from the Swedish administrative records in *t* and does not re-appear in subsequent years. For instance, a worker that last appears in the records in 2001 and does not re-appear until at least 2011 (the last year of data we have access to), we regard as having passed away or having emigrated permanently. We exclude people that were born outside of Sweden as they might move in and out of the registry more frequently for other reasons.

Plants that experience such a loss, called treated plants below, are unlikely to be similar to any other plant randomly picked from the Swedish population of plants. For instance, as the chance of passing away increases with age, plants with older topmanagers more likely experience a topmanager's death. Such plant properties might impact the chance of survival and diversification as well (e.g. plants with an older workforce might be less likely to diversify due to a lock-in effect), which would confound the results.

Therefore, we try to create a counterfactual to the treated plants by creating a comparable control group, the aim of which is to infer how the plant outcomes would have been had plants not experienced the loss of one's topmanager or toptechnician. We do so by using propensity score matching. We regress losing a topmanager or toptechnician due to death or permanent emigration on variables related to the size and age of the plant, industry, being part of a multi-plant firm, employment growth of the past 3 years (hence only including those plants that have existed for at least 3 years), the age distribution of the workforce of the plant, the gender and mean age and educational level of its topmanager(s)/toptechncian(s), as well as the interaction between educational level of the latter and size of the plant. From the propensity score that follows, we create a control group of 'statistical twins' for every treated plant. We apply nearest-neighbor matching, namely we match every treated plant to 10 plants in the economy that have propensity scores that are closest to the propensity score of the treated plant, whilst matching exactly on the year in which the treated and control plants are observed[2].

[2] Because plant-year observations are the unit of analysis, we make sure that a treated plant in one year cannot be assigned to the control group in previous or subsequent years as this may confound the results because the effect of death/emigration of one's topmanager/toptechnician on plant outcomes may stretch across years.

Using this sample of plants, we apply a Heckman correction to the recruitment of a topmanager or toptechnian. First, we run a probit to predict the hiring of a new topmanager or toptechnician following the loss of (one of) its pre-existing one(s). The Inverse Mills Ratio that results we include in subsequent regressions, thereby capturing the selection effect of the decision of a plant to hire a new topmanager or toptechnician.

Local supply shifts in the availability of human capital

Plants choose not only whether to hire, which we address with the Heckman correction, but also what kind of employee is recruited. In our case, we want to identify exogenous variation in the degree of human capital similarity of new recruits to a plant. We do so by exploiting exogenous variation in the availability of human capital in the supply pool of candidates from which plants recruit – with the idea that once the local supply of human capital related to the plant increases, there is downward pressure on the wages associated with it, which makes such human capital more attractive for plants to hire. We create an instrument that builds on the "shift-and-share" approach that was introduced by Bartik (1991) to predict local supply shifts in labor market areas, and which has subsequently been used in different adaptations by others (Card, 2007; Moretti, 2010; Faggio and Overman, 2014).

We focus on shifts over the past 15 years in the local availability of graduates with certain degrees. For instance, had there been substantial growth in graduates with a degree in computer science in Lund over the past decade (i.e. many more people from Lund would have graduated with such a degree each year), such increasing supply would have put downward pressure on the wages of people with such human capital. This would make such people more attractive for plants in Lund to hire. As such a local supply shift is endogenous to local plants if, for instance, it has been driven by university-industry collaboration in the region, we will, following the core idea of Bartik (1991), exploit national growth rates of graduates with certain degrees in Sweden.

First, let G_{cmb} be the number of graduates *G* with degree type *c* in municipality *m* in base period *b* (where municipality is the place where students lived at the time of graduation). Our base period goes from 1990 until 1995 (in 1995 a major reform of education was undertaken in Sweden). Hene, G_{cmb} measures the initial distribution of graduates with certain degrees across municipalities. Next, we calculate the predicted number of graduates with a certain degree in a municipality in future year *t* based on the national growth of the corresponding graduates. In national growth, the municipality itself is excluded:

$$PG_{cmt} = \frac{(G_{cmb}/G_{cb})}{(1-(G_{cmb}/G_{cb}))} \times (G_{ct} - G_{cmt}) \tag{5}$$

which reflects the number of graduates with degree *c* in region *m* in year *t* had the supply of graduates with degree *c* in region *m* grown according to the national trend. Because region-specific effects are excluded from it, it should be exogenous to local plants.

Next, we calculate which educational degrees are overrepresented in which occupation-industry combinations. For instance, technicians in the aerospace industry might be more likely to possess an aerospace engineering degree than other occupation-industries. Let E_{ciot} be the number of workers *E* with degree *c* employed in industry *i* with occupation *o* in year *t,* then our specialization measure is constructed as follows:

$$S^c_{iot} = \frac{(E_{ciot}/E_{iot})}{(E_{ct}/E_{t})} \tag{6}$$

which goes from 0 to 1 (a degree is under-represented in a certain occupation-industry) and from >1 to infinity (over-represented). We create this measure using the full workforce of Sweden in 2001. Linking this measure to the supply shift measure of Eq. 5, we can predict which occupation-industries in which regions likely receive a supply shock of suitable workers:

$$G_{iomt} = \sum_c PG_{cmt} * I\left(S^c_{iot} > 1\right) \tag{7}$$

where $I(S^c_{iot} > 1)$ is an indicator function that is either 0 or 1. We now have a measure that predicts the number of graduates in year *t* in region *m* that are suitable for industry *i* with occupation *o*. We transform this measure to the industry-industry level using our earlier created inter-industry skill-relatedness measure:

$$G^{rel}_{iomt} = \sum_c G_{jomt} * I(SR_{ij} > 1) \tag{8}$$

The intuition behind this instrument is that if, for instance, there is an increase of graduates in a region suitable for being a technician in the automobile industry (industry *j* in this example), it would put downward pressure on the wages of the technicians in the automobile industry in the region and hence make them more attractive to hire. In turn, if industry *j* is skill-related to industry *i* (e.g. motorcycle producers), this would increase the chance of industry *i* hiring a related rather than an unrelated technician.

Because we are interested in the shift of local supply, we divide the measure above by the total number of people in a region with degrees suitable for industry *j* which are related to industry *i*:

$$\mathrm{SHIFT}_{\mathrm{iomt}}^{\mathrm{rel}} = {G_{iomt}^{rel}}\Big/{Gpop_{iomt}^{rel}} \tag{9}$$

Finally, we aggregate this measure from the municipal level to the labor market level, since the latter is more appropriate when recruitment of plants is concerned. 110 labor market regions are distinguished by Statistics Sweden based on commuting patterns of workers between place of living and place of work. In sum, we now have a local supply shift instrument that identifies exogenous variation in the local supply pool of human capital from which plants recruit.

4. Results

Of all plant-year observations that have at least 1 manager (264333 in total), 726 experience the death or permanent emigration of a top-manager, and of all plant-year observations that have at least 1 technician (106390 in total), 550 experience such an event. Hence, losing one's topmanager or toptechnician is a relatively rare event, which anually happens to about 0,004% of all plants.

The propensity score matching procedure results in a control group of 6929 plants that have at least 1 topmanager, and a control group of 5007 plants that have at least 1 technician[3]. Comparative statistics on the matching variables of the control group after matching, and the control group if it were consisting of the full population of plants, are presented in Table 1 (topmanagers) and Table 2 (toptechnicians). As can be seen, treated plants tend to have a larger workforce, as well as older and better-educated topmanagers and toptechnicians than the average plant in the population. The

[3] The sum of these numbers is not equal to the size of treated group multiplied by 10 because the propensity score matching procedure sometimes assigns the same plant as a control (counterfactual) to multiple treated plants.

matching procedure substantially improves the comparability of the control groups to the treated groups, as can be seen from the large reduction of % bias in 57 of the 58 variables in both tables.

Using the treated and matched control groups, Table 3 (topmanagers) and Table 4 (toptechnicians) show the impact of death/permanent emigration of a topmanager/toptechnician on exit, diversification and take-over of the plants (survival being the reference category). The relative risk ratios show that plants are about twice as likely to exit due to failure or take-over following the loss of a topmanager. The exit due to failure effect is similar for the loss of a toptechnician, only the take-over effect is a bit smaller (1.5). There is no significant impact on the chance of diversifying in either of the groups. The coefficient of the death/permanent emigration variable in both tables in Model 1 does not differ significantly from its corresponding coefficient in Model 2 that includes the matching variables as regressors, which implies that there are no longer confounding effects of these variables on the plant outcomes.

Table 5 (topmanagers) and Table 6 (toptechnicians) show the effect of recruiting a new topmanager/toptechnician on the chance of diversifiying into another industry (Models 5 to 8). This is conditional on survival, hence only survivors are included (in the Appendix we show that the balance on the matching variables does not change significantly for this group). The hiring of a topmanager has no impact on diversification, neither in the OLS nor the 2SLS regressions, whereas the hiring of a toptechnician raises the probability of diversification in the OLS regressions. Our instrument of death/permanent emigration, however, does not work well for toptechnicians, as can be seen from the low Cragg-Donald F Statistics in Table 6. Hence, toptechnicians, once lost, are not necessarily replaced by new toprecruits by plants, contrary to topmanagers.

Table 7 (topmanagers) and Table 8 (toptechnicians) show the impact of the human capital match of a new topmanager or toptechnian on survival. As our supply shift instrument relies on region and industry variation, we now exclude region and industry fixed effects. In all models, we find no impact of a technician's human capital match on survival. As for topmanagers, we find that in the OLS models, the more similar a topmanager's human capital is to the plant, the less likely a plant is to survive. This finding is somewhat surprising, but disappears once we instrument human capital similarity with NACE-relatedness of the penultimate job of the topmanager as well as our supply shift instrument. Hence, once accounting for measurement error and endogeniety, there is no impact of a manager's human capital match on survival. Hence, plants that hire an unrelated topmanager seem to fare as well as plants that hire a related one. The same goes for plants that hire an unrelated toptechnician.

At the same time, the human capital similarity of a new topmanager or toptechnician has a strong impact on the chance of diversifying into another industry. The results are shown in Table 9 (topmanagers) and Table 10 (toptechnicians). In all models, as expected, the higher the human capital similarity of a new recruit, the less likely a plant is to diversify. The 2SLS coefficients of our supply shift instruments are significant but higher and less accurate than the OLS coefficients, which is due to the fact that there is substantial measurement error involved in measuring the degree of human capital similarity between the plant and new topmanager or toptechnician. This can be seen from the 2SLS models that instrument human capital similarity with NACE-relatedness – and hence only take out measurement error -, which strongly increases the coefficients compared to the corresponding OLS ones.

Interestingly, the impact on diversification of new topmanagers and toptechnicians appears to be equally strong. In all models, the coefficients are of almost equal value and shift in the same direction with similar precision once we instrument them. Hence, new topmanagers and toptechnicians, although they occupy different positions within plants, possess, and possibly excercise, equally important industry-specific human capital that drives diversification within plants. The hiring of a toptechnician or topmanager with human capital that is mostly unrelated to a plant has no impact on a plant's survival chance but, conditional on survival, strongly increases the chance of diversification. Hence, diversification might serve as another kind of 'exit strategy' for plants; instead of closing the plant down following the recruitment of a new topmanager or toptechnician with unrelated human capital, the strategy would be to reshift its focus towards other activities.

Table 11 (topmanagers) and Table 12 (toptechnicians) investigate the direction of diversification, whether plants are more likely to diversify into industries that are related to their existing activities as well as the human capital of the new topmanager or toptechnician. We select all diversifying plants from the full population and assign every of these plants a vector of all industries they could diversify into (220 in total), assigning a score of 1 to the industry they have actually they diversifed into and a score of 0 to the others. We then regress this vector on the human capital match of every of these industries with the plant and the new topmanager or toptechnician. As can be seen, plants are more likely to diversify into an industry that is related to their pre-existing activity as well as the human capital of the new topmanager or toptechnician. The interaction term shows that this is especially so when the target industry is related to both the plant and the new topmanager or toptechnician. As before, the coefficients of topmanagers and toptechnicians are almost of equal value, suggesting an equally important impact of both on the direction of diversification.

Another way of investigating this is by analyzing the chance of diversifying into a related industry rather than an unrelated industry, of which the results are shown in Table 13 (topmanagers) and Table 14 (toptechnicians). Conditional on actually diversifiying, the more the human capital of a new topmanager or toptechnician matches with the plant, the more likely a plant is to diversify into a related industry. Hence, the hiring of an unrelated topmanager or toptechnician increases the chance of diversifying into activities that are unrelated to the plant's existing activities, but, as shown in Tables 11 and 12, yet such activities are often related to the human capital of the new topmanager or toptechnician.

5. Conclusion

Using matched employer-employee data from Statistics Sweden, we find causal evidence that new unrelated topmanagers and toptechnicians – those that possess human capital very different from the plant's activity – have no impact on the chance of a plant to exit, but increase the chance of a plant to diversify into new activities. Those activities often match much better with the human capital of the new topmanager or toptechnician. It is often suggested that topmanagers are the main drivers of a plant's future. However, across the board, we find that the strength of the impact of new toptechnicians is equal to the impact of new topmanagers. Hence, both occupations seem to be equally important drivers of a plant's strategy, performance and activity. The aim of our identification strategy is to ensure that these results are independent from a plant's pre-existing strategy.

The plants we analyze differ from the organizations that have been mostly researched so far. Those are often large organizations, often those that are listed on the stock exchange, whereas our sample of plants consists of 5 to 250 employees. It is likely that in very large firms, the top management team is much more important than one of the toptechnicians, or that the impact of one might dependent on the degree of human capital similarity with the other. Especially interesting in this respect is to further investigate the role of new recruits in branches of multi-plant firms.

There are many other avenues for future research on this topic. First, it is worth further exploring the interaction between new recruits and a plant's existing workforce, which might condition the impact of new recruits. For instance, new unrelated toptechnicians might have a particularly strong impact when of the plant's existing topmanagers possesses similar human capital. Our identification strategy of propensity score matching in combination with a local supply shift instrument might help in separating the impact of one from the other.

Second, a natural follow-up question would be the impact of diversification on performance following the recruitment of a new topmanager or toptechnician. It might be that diversification moves driven by new toptechnicians are more successful than those driven by managers, as the former are more directly involved in the production of a plant's output.

Third, there is much to learn from changes in the product portfolios of plants. The data we used limited us to investigating a change in a plant's industry code. While this provides information on the shift of a plant's main activity, and its direction, it misses out on much of what is going on underneath. Plants might drop certain products, might add other ones, and might do both at the same time (churning). It is worth investigating what impact is of new recruits on these dynamics – something which might be fostered by the increasing availability of micro-data across countries that link workers to plants and their activities.

Reference list

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers. Management Science 45(7): 905–917

Amburgey, T.L., Kelly, D. and Barnett, W.P. (1993) Resetting The Clock: The Dynamics of Organizational Change and Failure. Administrative Science Quarterly 38 (1), pp. 51-73.

Amit R., Schoemaker P. (1993) Strategic assets and organizational rent. Strategic Management Journal 14, pp. 33-46.

Asheim, B. (1996) Industrial districts as `learning regions': A condition for prosperity. Eruopean Planning Studies 4 (4), pp. 379-400.

Barney, J.B. (1991) Firm resources and sustained competitive advantage. Journal of Management 17, pp. 99 – 120.

Bernard, A.B., Redding, S., Scott, P. (2010) Multiple-Product Firms and Product Switching. American Economic Review 100 (2), pp. 444-448.

Biggadike, E.R. (1979) Corporate Diversification: Entry, Strategy and Performance. Cambridge, MA: Harvard University Press.

Boschma, R. and Iammarino, S. (2009) Related Variety, Trade Linkages, and Regional Growth in Italy. Economic Geography 85 (3), pp. 289-311.

Boschma, R., Minondo, A. and Navarro, M. (2012) Related variety and regional growth in Spain. Papers in Regional Science 91 (2), pp. 241-256.

Bryce, D.J. and Winter, S.G. (2009) A General Interindustry Relatedness Index. Management Science 55 (9), pp. 1570-1585.

Cohen, W.M. and Levinthal, D.A. (1990) Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly 35 (1), pp. 128-152.

Chakrabarti, A. and Mitchell, W. (2013) The persistent effect of geographic distance in acquisition target selection. Organization Science 24 (6), pp. 1805-1826.

Coff, R. & Kryscnski, D. (2011), Drilling for Micro-Foundations of Human Capital-Based Competitive Advantages. Journal of Management 2011.

Cooke P.H., Morgan K. (1998). The Associational Economy. Firms, Regions, and Innovation. Oxford: Oxford University Press.

Crocker, A. and Eckardt, R. (2014) A Multilevel Investigation of Individual- and Unit-Level Human Capital Complementarities. Journal of Management 40 (2), pp. 509 - 530.

Dosi, G. (1982) Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. Research Policy 11 (3), pp. 147-162.

Duranton, G. and Puga, D. (2001) Nursery Cities: Urban diversity, Process innovation, and the life cycle of products. American Economic Review 91 (5), pp. 1454-1477.

Faggian A. McCann Ph. (2006). Human capital flows and regional knowledge assets: a simultaneous equation approach. Oxford Economic Papers 52: 475–500.

Fleming, L. and Sorenson, O. (2001) Technology as a complex adaptive system: Evidence from patent data. Research Policy 30, pp. 1019-1039.

Florida R, Mellander C, Stolarick K. 2012. Geographies of scope: an empirical analysis of entertainment, 1970–2000. Journal of Economic Geography,12(1): 183-204.

Fortune, A. and Mitchell, W. (2012) Unpacking Firm Exit at the Firm and Industry Levels: The Adaptation and Selection of Firm Capabilities. Strategic Management Journal 33, pp. 794–819.

Foster, L, Haltiwanger, J and Krizan, C.J. (2006) Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s. The Review of Economics and Statistics 88 (4), pp. 748-758.

Faggio, G. and Overman, H. (2014) The effect of public sector employment on local labour markes. Journal of Urban Economics 79, pp. 91-107

Giroud, X. (2013) Proximity and investment: evidence from plant-level data. The Quarterly Journal of Economics 128 (2), pp. 861-915.

Glaeser, E.L., Kallal, H.D., Scheinkman, J.A., Schleifer A. (1992) Growth in Cities, Journal of Political Economy, 100 (6): 1126-1152.

Grant, R.M. (1996) Towards a Knowledge-Based Theory of the Firm. Strategic Mangement Journal 17, pp. 109 – 122.

Hansberg, E.R. and Wright, M.L.J (2007), Establishment Size Dynamis in the Aggregate Economy. American Economic Review 97 (5), pp. 1639-1666.

Helfat, C.E. and Lieberman, M.B. (2002) The birth of capabilities: market entry and the importance of pre-history. Industrial and Corporate Change 11 (4), pp. 725-760.

Helfat, C. E. and Peteraf, M. A. (2003) The dynamic resource-based view: Capability lifecycles. Strategic Management Journal 24, pp. 997-1010.

Henderson, J.V., Kuncoro, A., Turner, M. (1995) Industrial development in cities, Journal of Political Economy, 103:1067-1085.

Katila, R. and Ahuja, G. (2002) Something Old, Something New: A Longitudinal Study of Search Behavior and New Product Introduction. Academy o Management Journal 45 (6), pp. 1183-1194.

King, A.A. and Tucci, C.L. (2002) Incumbent entry into new market niches: the role of experience and managerial choice in the creation of dynamic capabilities. Management Science 48 (2), pp. 171-186.

Klepper, S.and Simons, K.L. (2000) Dominance by birthright: Entry of prior radio producers and competitive ramifications in the U.S. television receiver industry. Strategic Management Journal 21, pp. 997-1016.

Lee, G.K. and Lieberman, M.B. (2009 Acquistion vs. internal development as modes of market entry. Strategic Management Journal 31 (2), pp. 140-158.

March, J.G. (1991) Exploration and Explotation in Organizational Learning. Organization Science 2 (1), pp. 71-87.

Maskell P, Malmberg A. 1999. Localised learning and industrial competitiveness, Cambridge Journal of Economics 23(2): 167-185.

McCann Ph., Simonen J. (2005). Innovation, knowledge spillovers and local labour markets. Papers in Regional Science 84(3): 465-485.

Moretti, E. (2010). Local Multipliers. American Economic Review Papers and Proceedings 100 (2), pp. 1–7.

Morgan, K. (1997) The Learning Region: Institutions, Innovation and Regional Renewal. Regional Studies 41 (1), pp. S147-S159.

Neffke, F.M.H, Henning, M. and Boschma, R. (2012) The impact of aging and technological relatedness on agglomeration externalities: a survival analysis. Journal of Economic geography 12 (2), pp. 485-517.

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

Nelson, R.R. and Winter, S.G. (1982) An evolutionary theory of economic change. Cambridge, MA: Belknap.

Nerkar, A. and Roberts, P.W. (2004) Technological and product-market experience and the success of new product introductions in the pharmaceutical industry. Strategic Management Journal 25, pp. 779-799.

Palich L. E., Cardinal L. B., Miller C. C. (2000) Curvilinearity in the diversification–performance linkage: An examination of over three decades. Strategic Management Journal 21, pp. 155-174.

Penrose, E.G. (1959) The Theory of the growth of the firm. New York: Wiley.

Porter, M.E. (1990) The Competitive Advantage of Nations. London: Macmillan.

Rumelt, R.P. (1982) Diversification strategy and profitability. Stategic Management Journal 3, pp. 359-369.

Stalk, G. and Hout, T.M. (1990) Competing against Time: How Time-based Competition is Reshaping Global Markets. New York: Free Press.

Storper M. 1995. The resurgence of regional economies, ten years later: The region as a nexus of untraded interdependencies, European Urban and Regional Studies 2: 191-221.

Teece, D. and Pisano, G. (1993) The dynamic capabilities of firms: an introduction. Industrial and Corporate Change 3 (3), pp. 537-556.

Wan, P.W., Hoskisson, R.E., Short, J.C., Yiu, D.W. (2011) Resource-based Theory and Corporate diversification: Accomplishments and Opportunities. Journal of Management 37 (5), pp. 1335 – 1368.

Wang, L., Madhok, A. and Li, X.S. (2013) Agglomeration and clustering over the industry life cycle: Toward a dynamic model of geographic concentration. Strategic Management Journal, DOI: 10.1002/smj.2141.

Wernerfelt, B. (1984) A resource-based view of the firm. Strategic Management Journal 7, pp. 171 – 180.

Table 1: Propensity score matching variable results: loss of one's top-manager

Variable	Mean: Treated group	Mean: Control group full population	% bias	Mean: Control group after matching	% bias
Multi-plant firm	0.249	0.247	0.6	0.25	-0.8
Manufacturing industry	0.205	0.188	4.4	0.198	2.2
Age plant	11.111	10.746	10	11.132	-0.6
Employment plant (log)	2.899	2.674	24.1	2.886	0.2
Employment growth plant - last 3 years	1.242	1.347	-8.4	1.256	-1.4
Mean age topmanager(s)	52.688	47.545	53.7	52.734	-0.1
Gender topmanager(s)	1.107	1.15	-13.5	1.113	-2.2
N of top manager(s) with primary educ. < 9 years	0.104	0.053	18.3	0.1	1.4
N of top manager(s) with primary educ. => 9 years	0.136	0.129	1.8	0.132	0.4
N of top manager(s) with upper secondary education	0.57	0.567	0.4	0.557	0.3
N of top manager(s) with post-secondary educ. < 2 years	0.129	0.137	-2.3	0.122	1.4
N of top manager(s) with post-secondary educ. => 2 years	0.44	0.259	25.7	0.393	2.1
N of top manager(s) with post-graduate education	0.021	0.008	10.3	0.017	1.3
N of top manager(s) with other education (9)	0.012	0.004	8.7	0.011	1.4
Mean age workforce	41.749	40.133	25	41.698	0.7
N of workers aged 18 - 30	7.73	5.966	14.6	7.68	-0.6
N of workers aged 31 - 40	9.233	6.2	25.2	8.954	0.6
N of workers aged 41 - 50	7.204	5.065	22.6	7.065	0.2
N of workers aged 51 - 60	6.11	4.09	24.2	6.028	-0.2
N of workers aged 61 - 64	1.711	1.044	26	1.671	0.1
N of workers aged 64	0.31	0.181	19.8	0.299	0.2
N of workers aged 64 and higher	0.504	0.316	19.9	0.486	1.5
Emp_plant X N of top manager(s) with primary educ. < 9 years	0.282	0.132	18.4	0.267	1.8
Emp_plant X N of top manager(s) with primary educ. => 9 years	0.368	0.335	3.3	0.355	0.3
Emp_plant X N of top manager(s) with upper secondary education	1.754	1.528	9.7	1.682	0.5
Emp_plant X N of top manager(s) with post-secondary educ. < 2 years	0.443	0.403	3.3	0.41	1.7
Emp_plant X N of top manager(s) with post-secondary educ. => 2 years	1.597	0.811	26.2	1.372	2.3
Emp_plant X N of top manager(s) with post-graduate education	0.071	0.027	10	0.061	0.8
Emp_plant X N of top manager(s) with other	0.04	0.013	9.1	0.033	1.8

education (9)					

Table 2: Propensity score matching variable results: loss of one's top-technician

Variable	Mean: Treated group	Mean: Control group full population	% bias	Mean: Control group: after matching	% bias
Multi-plant firm	0.391	0.304	18.4	0.391	0
Manufacturing industry	0.256	0.242	3.3	0.254	0.4
Age plant	10.713	10.558	3.9	10.794	-2.1
Employment plant (log)	3.406	2.93	48.2	3.382	2.3
Employment growth plant - last 3 years	1.458	1.425	1.8	1.438	1.1
Mean age toptechnician(s)	44.933	42.498	24.8	45.361	-4.5
Gender toptechnician(s)	1.119	1.12	-0.5	1.121	-1.1
N of top technician(s) with primary educ. < 9 years	0.051	0.03	10.2	0.062	-4.1
N of top technician(s) with primary educ. => 9 years	0.178	0.112	15.3	0.181	-0.5
N of top technician(s) with upper secondary education	2.193	1.08	49.9	2.055	5.1
N of top technician(s) with post-secondary educ. < 2 years	1.302	0.55	51.3	1.212	5.1
N of top technician(s) with post-secondary educ. => 2 years	2.967	1.07	64.3	2.658	8.4
N of top technician(s) with post-graduate education	0.238	0.058	25.3	0.128	14.3
N of top technician(s) with other education (9)	0.027	0.006	13.5	0.013	8.6
Mean age workforce	41.379	40.984	6.9	41.52	-2.5
N of workers aged 18 - 30	10.155	6.91	25.8	10.03	0.9
N of workers aged 31 - 40	15.435	8.907	44.8	14.697	4.4
N of workers aged 41 - 50	12.033	7.147	39.2	11.645	2.7
N of workers aged 51 - 60	9.551	5.649	33.6	9.236	2.4
N of workers aged 61 - 64	2.567	1.453	31.2	2.516	1.3
N of workers aged 64	0.425	0.249	20.7	0.433	-0.7
N of workers aged 64 and higher	0.545	0.393	14.5	0.538	0.6
Emp_plant X N of top technician(s) with primary educ. < 9 years	0.207	0.103	12.1	0.249	-3.8
Emp_plant X N of top technician(s) with primary educ. => 9 years	0.721	0.377	19.4	0.726	-0.2
Emp_plant X N of top technician(s) with upper secondary education	8.642	3.567	51.5	7.934	5.9
Emp_plant X N of top technician(s) with post-secondary educ. < 2 years	5.103	1.824	54.1	4.65	6.1
Emp_plant X N of top technician(s) with post-secondary educ. => 2 years	11.382	3.531	64	9.953	9.3

Emp_plant X N of top technician(s) with post-graduate education	0.95	0.192	27.5	0.479	15.7
Emp_plant X N of top technician(s) with other education (9)	0.105	0.02	14.2	0.045	9.3

Table 3: Impact of death/permanent emigration of top-manager on chance to exit, diversify or being taken-over (reference category: survival) – multinominal logistic regression, presented are relative risk ratios

	Model 1			Model 2		
Variable	Exit due to failure	Diversification	Exit due to take-over	Exit due to failure	Diversification	Exit due to take-over
Death / perm. emigration top manager	2.253*** (0.352)	1.133 (0.239)	1.915*** (0.227)	2.311*** (0.368)	1.115 (0.237)	1.979*** (0.245)
Constant	0.042*** (0.006)	0.034*** (0.006)	0.002*** (0.001)	0.461 (0.352)	0.021*** (0.020)	0.081*** (0.072)
Year dummies included?	Yes	Yes	Yes	Yes	Yes	Yes
Matching variables included?	No	No	No	Yes	Yes	Yes
Observations	7,655	7,655	7,655	7,655	7,655	7,655

S/E in parentheses, **** p<0.01, ** p<0.05, * p<0.1*

Table 4: Impact of death/permanent emigration of top-technician on chance to exit, diversify or being taken-over (reference category: survival) – multinominal logistic regression, presented are relative risk ratios

	Model 1			Model 2		
	Exit due to failure	Diversification	Exit due to take-over	Exit due to failure	Diversification	Exit due to take-over
Death / perm. emigration top technician	2.031*** (0.368)	0.987 (0.237)	1.509*** (0.230)	2.042*** (0.377)	0.926 (0.227)	1.515*** (0.237)
Constant	0.041*** (0.006)	0.040*** (0.007)	0.006*** (0.002)	0.058*** (0.052)	0.285 (0.284)	0.043*** (0.033)
Year dummies included?	Yes	Yes	Yes	Yes	Yes	Yes
Matching variables included?	No	No	No	Yes	Yes	Yes
Observations	5,557	5,557	5,557	5,557	5,557	5,557

S/E in parentheses, **** p<0.01, ** p<0.05, * p<0.1*

Table 5: Impact of recruiting a new topmanager on chance of plant to diversify – linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	IV 2SLS	OLS	IV 2SLS	OLS	IV 2SLS	OLS	IV 2SLS
Recruitment new top manager	-0.000 (0.008)	0.014 (0.106)	0.000 (0.008)	0.001 (0.110)	-0.000 (0.008)	-0.004 (0.116)	0.003 (0.008)	-0.013 (0.104)
Constant	0.041*** (0.009)	0.035** (0.014)	0.026 (0.036)	0.029 (0.046)	-0.002 (0.039)	-0.002 (0.042)	0.009 (0.037)	-0.003 (0.044)
Observations	5,917	5,917	5,917	5,917	5,917	5,917	5,917	5,917
R-squared	0.001	0.000	0.014	0.014	0.034	0.034	0.034	0.033
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES
Matching variables included?	NO	NO	YES	YES	YES	YES	YES	YES
Region FE included?	NO	NO	NO	NO	YES	YES	NO	NO
Industry FE included?	NO	NO	NO	NO	NO	NO	YES	YES
First stage Cragg-Donald F-statistic		23.06		22.77		19.98		24.33

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Impact of recruiting a new toptechnician on chance of plant to diversify – linear probability models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	IV 2SLS	OLS	IV 2SLS	OLS	IV 2SLS	OLS	IV 2SLS
Recruitment new top technician	0.012* (0.006)	-0.132 (0.502)	0.013* (0.007)	-61.252 (21,326.398)	0.015** (0.007)	-1.389 (14.058)	0.011 (0.007)	8.168 (339.265)
Constant	0.033*** (0.013)	0.087 (0.192)	0.119** (0.048)	9.638 (3,310.734)	0.083 (0.052)	0.631 (5.876)	0.108* (0.059)	2.162 (86.294)
Observations	4,389	4,389	4,389	4,389	4,389	4,389	4,389	4,389
R-squared	0.005	-0.112	0.019	-16,531.837	0.059	-8.405	0.033	-287.204
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES

Matching variables included?	NO	NO	YES	YES	YES	YES	YES	YES
Region FE included?	NO	NO	NO	NO	YES	YES	NO	NO
Industry FE included?	NO	NO	NO	NO	NO	NO	YES	YES
First stage Cragg-Donald F-statistic:		0.746		8.18e-06		0.0108		0.000568

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

Table 7: Impact on survival chance of degree of human capital similarity of new topmanager to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift
Human capital similarity (SSR) of new top manager(s) to plant	-0.051*** (0.020)	-0.045* (0.023)	0.049 (0.050)	0.057 (0.164)	-0.056*** (0.020)	-0.051** (0.024)	0.083 (0.058)	0.185 (0.205)
Inverse Mills Ratio	0.130 (0.126)	0.129 (0.126)	0.104 (0.136)	0.103 (0.136)	0.188 (0.126)	0.187 (0.124)	0.166 (0.137)	0.132 (0.143)
Constant	0.692*** (0.221)	0.807*** (0.213)	0.796*** (0.227)	0.792*** (0.217)	0.095 (0.273)	0.212 (0.259)	0.197 (0.284)	0.120 (0.285)
Observations	875	875	750	875	875	875	750	875
R-squared	0.086	0.086	0.056	0.056	0.163	0.163	0.119	0.032
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES
Matching variables included?	NO	NO	NO	NO	YES	YES	YES	YES
First stage Cragg-Donald F-statistic		2384	174.4	17.23		2180	117.9	11.49

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

Table 8: Impact on survival chance of degree of relatedness of new toptechnician to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift
Human capital similarity of new top technician(s) to plant	-0.021 (0.013)	-0.024 (0.018)	0.000 (0.038)	0.026 (0.071)	-0.009 (0.014)	-0.012 (0.019)	0.041 (0.045)	0.111 (0.109)
Constant	0.817*** (0.052)	1.000*** (0.011)	0.987*** (0.019)	0.977*** (0.034)	0.626*** (0.124)	0.774*** (0.117)	0.748*** (0.129)	0.685*** (0.145)
Observations	1,900	1,900	1,706	1,900	1,900	1,900	1,706	1,900
R-squared	0.046	0.046	0.044	0.041	0.086	0.086	0.079	0.051
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES
Matching variables included?	NO	NO	NO	NO	YES	YES	YES	YES
First stage Cragg-Donald F-statistic		3874	283.7	67.26		3395	202.2	29.33

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

Table 9: Impact on diversification chance of degree of relatedness of new topmanager to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: NACE previous job	IV 2SLS: NACE of penultimate job	IV 2SLS: graduate supply shift
Human capital similarity (SSR) of new top manager(s) to plant	-0.054*** (0.016)	-0.040*** (0.015)	-0.107*** (0.033)	-0.244** (0.120)	-0.051*** (0.017)	-0.034** (0.016)	-0.121*** (0.037)	-0.252* (0.150)
Inverse Mills Ratio	0.097 (0.068)	0.093 (0.068)	0.116 (0.078)	0.151* (0.086)	0.109 (0.071)	0.104 (0.070)	0.134* (0.081)	0.167* (0.092)
Constant	-0.132 (0.120)	-0.090 (0.115)	-0.110 (0.129)	-0.071 (0.131)	-0.383** (0.152)	-0.345** (0.144)	-0.373** (0.161)	-0.306* (0.167)
Observations	759	759	655	759	759	759	655	759
R-squared	0.030	0.028	0.009	-0.214	0.076	0.074	0.052	-0.169
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES
Matching variables included?	NO	NO	NO	NO	YES	YES	YES	YES
First stage Cragg-Donald F-statistic		2148	166.8	12.23		1911	114.4	7.586

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

Table 10: Impact on diversification chance of degree of relatedness of new toptechnician to plant

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV 2SLS: SR instrumented with NACE previous job	IV 2SLS: SR instrumented with NACE of last job before previous job	IV 2SLS: graduate supply shift	OLS	IV 2SLS: instrumented with NACE previous job	IV 2SLS: instrumented with NACE of last job before previous job	IV 2SLS: graduate supply shift
Human capital similarity (SSR) of new top technician(s) to plant	-0.037***	-0.052***	-0.110***	-0.183***	-0.033***	-0.042***	-0.107***	-0.214**
	(0.012)	(0.014)	(0.030)	(0.062)	(0.012)	(0.014)	(0.036)	(0.099)
Constant	0.037*	0.085***	0.106***	0.145***	0.119	0.175**	0.265***	0.300***
	(0.022)	(0.016)	(0.023)	(0.033)	(0.080)	(0.082)	(0.100)	(0.116)
Observations	1,722	1,722	1,552	1,722	1,722	1,722	1,552	1,722
R-squared	0.016	0.015	-0.002	-0.070	0.035	0.035	0.021	-0.087
Year dummies included?	YES	YES	YES	YES	YES	YES	YES	YES
Matching variables included?	NO	NO	NO	NO	YES	YES	YES	YES
First stage Cragg-Donald F-statistic		3465	255.8	68.55		3018	177.8	29.60

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

Table 11: Impact of human capital similarity of new topmanager on chance of diversifying into target industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of plant to target industry	0.023*** (0.001)
Human capital similarity (SSR) of new topmanager to target industry	0.024*** (0.002)
Interaction: Human capital similarity (SSR) plant X Human capital similarity (SSR) new topmanager	0.037*** (0.003)
Constant	0.013*** (0.001)
Observations	84260
R-squared	0.03

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

Table 12: Impact of human capital similarity of new toptechnician on chance of diversifying into a certain industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of plant to target industry	0.024*** (0.001)
Human capital similarity (SSR) of new toptechnician to target industry	0.026*** (0.001)
Interaction: Human capital similarity (SSR) plant X Human capital similarity (SSR) new toptechnician	0.041*** (0.002)
Constant	0.014*** (0.001)
Observations	164120
R-squared	0.04

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

Table 13: Impact of human capital similarity of new topmanager to plant on chance of diversifying into a related industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of new topmanager to plant	0.136*** (0.041)
Constant	0.775*** (0.028)
Observations	383
R-squared	0.03

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

Table 14: Impact of human capital similarity of new toptechnician to plant on chance of diversifying into a related industry (sample: all plants that diversify)

	(1)
Human capital similarity (SSR) of new toptechnician to plant	0.198*** (0.034)
Constant	0.766*** (0.021)
Observations	746
R-squared	0.06

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1