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Abstract

Labour mobility is often considered a crucial factor for regional development. However, labour mobility is not good *per se* for local firms. There is increasing evidence that labour recruited from skill-related industries has a positive effect on plant performance, in contrast to intra-industry labour recruits. However, little is known about which types of labour are recruited in different stages of the evolution of an industry, and whether that matters for plant performance. This paper attempts to fill these gaps in the literature using plant-level data for manufacturing and services industries in the Netherlands for the period 2001-2009. Our study focuses on the effects of different types of labour recruits on the survival of new plants. We show that the effects of labour recruits from the same industry and from skill-related and unrelated industries on plant survival vary between the life cycle stages of industries. We also find that inter-regional labour flows do not impact on plant survival.

JEL classification: R11, R12, O18

Keywords: labour mobility, skill-relatedness, industry life cycle, industrial dynamics, firm survival

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Introduction

The industry life cycle (ILC) provides a stylized description of the evolution of an industry going through various stages (Gort and Klepper, 1982; Abernathy and Clark 1985). Scholars have investigated whether the role of agglomeration externalities changes during the ILC. Broadly speaking, they found that young industries tend to benefit from Jacobs' externalities, while mature industries tend to exploit MAR externalities (Henderson et al. 1995; Neffke et al. 2011).

However, little attention has been drawn to the importance of labour market externalities along the ILC. Following the externalities literature, one might expect that a wide set of local industries enables firms to recruit people with different skills that might be advantageous in the early, more experimental phase of the industry (Neffke et al. 2011). This might be very different in the mature phase, when recruitments from the same industry are expected to be more beneficial. Whereas in the revitalization phase of the ILC, labour recruits from other industries are needed to avoid lock-in and help firms to transform and reconfigure their routines. To our knowledge, there exists no study focusing on the type of labour that is needed for new plants in each stage of the ILC. This paper makes an attempt to fill this gap.

There have been studies at the micro-scale that show that certain types of labour mobility positively affect firm performance. Labour recruitments from related industries have been found to enhance plant performance, as compared to recruitments from the same or unrelated industries (Boschma et al. 2009; Timmermans and Boschma 2014; Borggren et al. 2016). Moreover, recruitments from outside the region, as compared to local recruits, tend to enhance the performance of firms (Boschma et al. 2009; Eriksson and Rodríguez-Pose 2017). However, these studies have not examined the role of different types of labour (including workers from related industries) for new plants in the context of the ILC.

This objective of this paper is to investigate whether the survival of new plants in young (or revitalizing) industries relies on different types of labour recruitments, as compared to survival rates of new plants in mature industries. We distinguish between new recruits from the same industry the the new plant is active in, from skill-related industries, and from skill-unrelated industries (Neffke and Henning 2013), and whether the recruitments are made from the same region or from other regions. So, we aim to determine whether it matters for the survival of new plants which types of labour they hire in each phase of the ILC. Our study on new plants established in the Netherlands between 2002 and 2005 shows that recruitments from other (related and unrelated) industries enhance plant survival in young industries. To recruit labour from the same industry is bad for plant survival in mature industries, in contrast to labour hired from skill-related industries that enhances survival chances of plants in mature industries. Plants do not seem to benefit from inter-regional labour flows, irrespective of the ILC stage.

The structure is as follows. The second section provides the theoretical embedding of the paper. The third and fourth sections introduce data and methods. The fifth section presents and discusses the findings. Section 6 concludes.

Labour mobility, skill-relatedness and plant survival in an industry life cycle

There is an extensive literature on the ILC that provides a stylized description of the evolution of an industry from its infancy (Gort and Klepper, 1982; Abernathy and Clark 1985; Klepper 1997). Product characteristics, innovation sources and competitive forces vary between the various life cycle stages. Broadly speaking, the young phase is characterized by non-standardized products, competition on product characteristics, many unexplored technological opportunities and high innovation intensity, and reliance on information from a wide range of industries (Gort and Klepper 1982; Utterback and Suarez 1993; Ter Wal and Boschma 2011). This makes Jacobs' externalities more important for young industries (Henderson et al. 1995; Neffke et al. 2011). In mature stages, products are more homogeneous, competition shifts to price, focus shifts from product to process innovation, and access to industry-specific specialized knowledge becomes more important. In those circumstances, industries prefer a local environment tailored to their specific needs (such as industry-specific institutions and specialized labour markets), and intra-industry knowledge flows become more prominent than inter-industry knowledge flows (Neffke et al. 2011).

This stylized description of the ILC has been criticized for going against the nature of economic evolution as open-ended (Martin and Sunley 2011). Such a life cycle approach is often treated as too deterministic, as if it is inevitable that industries evolve from a young to a mature phase. Indeed, some industries may rejuvenate that will cast the industry back into more infant stages, while for other industries, it is hard to find such a stylized sequential pattern. Leaving behind the stylized nature of a life cycle, research shows that some industries do evolve through young and mature stages with certain characteristics (Balland et al. 2013). Neffke et al. (2011) found for twelve Swedish industries that the importance of MAR externalities increases with the maturity of industries while Jacobs' externalities is positive in the young and negative in the mature phase.

The role of local labour markets has been prominent in the externalities literature. Marshall (1920) argued that thick specialized labour markets bring benefits to local firms, like lower search costs for employees, better matching of labour supply and demand, and access to productive workers (Duranton and Puga 2004; Glaeser and Resseger 2009). Labour pooling and mobility of workers are key mechanisms through which knowledge and skills diffuse across firms (Song et al. 2003; Singh and Agrawal 2011) and within regions (Angel 1991; Almeida and Kogut 1999; Pinch and Henry 1999; Dahl and Pedersen 2003; Breschi and Lissoni 2009; Eriksson and Lindgren 2009).

While labour mobility may have positive effects for firms and regions, it may also lower incentives for firms to upgrade the skills of their employees due to labour poaching (Combes and Duranton 2006; Fallick et al. 2006). Some studies found no positive effect of intra-regional labour mobility on firm performance and regional growth (Philips 2002; McCann and Simonen 2005; Eriksson 2011; Timmermans and Boschma 2014). To assess the effects of labour mobility, it is important to account for the extent to which the new knowledge and skills, as embodied in the recruit of new employees, are related to the knowledge and skill base of the hiring firm (Boschma et al. 2009; Timmermans and Boschma 2014). Such an evolutionary take on labour mobility argues that external knowledge and skills acquired through labour mobility should be close to the firm's knowledge and skill base, so the firm can absorb and integrate it in its routines (Cohen and Levinthal 1990), but not too close, to avoid cognitive lock-in. This is in line with findings of a study (Boschma et al. 2009) on job moves using linked employer-employee data. They found that the recruitment of new skills related to the existing skill base of a plant had a positive effect on plant performance, while the recruits of new employees with skills identical to the skill base of the plant had a negative effect on their performance. Boschma et al. (2009) also found that recruits from outside the region enhance plant performance (Miguelez and Moreno 2013) but only when these bring new skills related to the skill base of the plant (see also Timmermans and Boschma 2014).

So, labour mobility *per se* is not necessarily beneficial, as worker skills need to match the existing skill base of plants, but not too much. Circulation of skills in regions is expected to have a positive impact on regional development when it concerns labour flows between related industries in a region. This is because an efficient matching of skills between related industries in a region gives rise to production complementarities and effective labour markets (Duranton and Puga, 2004). Neffke and Svensson-Henning (2013) proposed the notion of skill-relatedness to refer to industries whose skills are relevant and of high economic value to one another. Ellison et al (2010) showed that local labour pooling can work across industries if these use workers with similar skills, and that this contributes to further agglomeration and coherence in regional industrial structures (Fitjar and Timmermans 2017). Boschma et al. (2014) found evidence of agglomeration externalities stemming from the local presence of skill-related industries, lifting regional growth. Recent studies have shown that the local presence of skill-related industries also enhance resilience of regions (Diodato and Weterings 2015; Eriksson et al. 2016; Eriksson and Hane-Weijman 2017; Holm et al. 2017;

Neffke et al. 2016, 2017). And Neffke et al. (2017) showed that skill relatedness explains better local industry growth than relatedness measured by value chain or based on co-location.

But apart from the fact that the effect of labour market externalities may depend on the degree of skill-relatedness between industries, the effect of labour market externalities may also depend on the stage of development an industry is in. This might matter, as young industries are found to benefit from MAR externalities and mature industries from Jacobs'externalities (Henderson et al. 1995; Neffke et al. 2011). However, we do not yet know whether this is true for the labour market channel through which MAR and Jacobs' externalities might operate. To our knowledge, there exists no study to date that tests whether plants in young (or revitalized) industries recruit different types of labour than plants in mature industries, and how that affects plant performance.

In line with the Jacobs' externalities thesis, we expect new plants in young and revitalizing industries that recruit people with different skills to show a higher performance, as these recruits might be beneficial in this experimental, more explorative stage of industry development. So we expect new plants that recruit employees from skill-related and skill-unrelated industries to show a better performance than new plants hiring primarily employees with skills identical to the skill base of the plant (i.e. recruits from the same industry). However, it is unclear to anticipate what to expect for plants in mature industries. On the one hand, intra-industry recruits could be beneficial for new plants due to the need for exploitation of specialized knowledge. On the other hand, new plants in mature industries might need inter-industry recruits to do something else to avoid fierce competition with incumbents. Especially recruits from skill-related industries might be beneficial to enable the successful integration of the new employees. Moreover, we explore whether recruits from the same region (as compared to recruits from outside the region) are more beneficial for new plant survival, and how that differs between young and mature industries. Do new plants in young industries that recruit labour from outside their region have a higher survival rate because it might ensure newness? And will new plants in mature industries that recruit new employees from the same region have a higher survival rate? This is what we aim to examine in the empirical part.

Data

In order to test the ideas put forward in the above we make use of a panel dataset. Two register databases from Statistics Netherlands were combined: Social Statistics, which provides detailed information on employees per plant and the general firm register that provides information on the industrial activity. Using these databases (for the period from 2001 to 2009), we composed a plant-level panel dataset for all newly established plants in the Netherlands between 2002 and 2005 which we can follow until 2009.

A plant is defined as an organisational unit operating within one of the 431 municipality area of the Netherlands (division of 2010). We observe plants for every year in during the study period. The initial population includes all plants observed during the period 2001-2009 in 402 industries (4-digit NACE 2002). However, we excluded all plants in public service industries and all industries without any entering and/or exiting plants. Moreover, in line with the existing literature, we exclude both the new plants without any labour inflow over the period covered by our data (Boschma et al. 2009; Timmermans and Boschma 2014) and the new plants with spurious labour flows (Neffke et al., 2017).[1] The latter are likely to be interested by extraordinary events as mergers and acquisitions. After these restrictions[2], the sample contains 8,786 new plants belonging to 179 industries (146 manufacturing industries and 33 service industries).

For each selected industry, we identify the ILC stage. For this, we use the national employment database LISA 2011 managed by the LISA association. This database contains information on the address, number of jobs, and industry (4-digit NACE code) for all plants in the Netherlands in the period 1996-2010 which enables us to measure the ILC stage using a moving average over several years.

The relatively short length of data suggests that industries are stable in an ILC stage or subjected to very few changes. The estimation results discussed in the main text are based on the sample of industries that do not change ILC stage during the observed period. The final sample contains 6,277 new plants belonging to 86 industries (64 manufacturing and 22 service industries).[3]

Through matching of employer and employee data, we identify the labor inflows of the plants with information on the industry in which the employee used to work.[4] In order to distinguish between intra- regional and inter-regional labor flows, we define local labour markets as all municipalities that are within a 50 km range from the municipality where the plant is located. All the other variables that incorporate a geographical dimension are calculated using this definition. This way, 431 overlapping local labour markets are defined. All other variables with a geographical dimension are calculated in the same way.

Plant survival

The dependent variable is a binary variable that indicates whether a plant is still active in a certain year after entry (0) or not (1). Both entry and exit of plants were defined using information on the plant's workforce on December 31 of each year. A plant enters when it reports at least one employee in year *t* but no employees in *t-1*, while a plant exits when it had some employees in year *t-1* but is no longer included in the dataset in year *t*.[5]

Using the longitudinal data for the period 2001-2009, entering plants can be identified from the year 2002 onwards. Although nine different yearly cohorts of entering plants are identified, the analysis of this paper are restricted to the first four cohorts (i.e. the cohorts covering the period 2002-2005) to ensure that each plant can survive for at least five year.

Industry life cycle stage

An important measurement issue for the empirical analysis is the identification of the ILC stages. ILC is a term used to describe some observed regularities in the evolution over time of industries. One aspect is the nature of the innovative activity and the different role played by young and old firms over the ILC (Winter 1984; Audretsch and Feldman 1996). The earliest period of the ILC is characterised by a technological regime where young firms are the key sources of product innovations. On the other hand, with the advent of a dominant design (Abernathy and Utterback 1978), old firms are more able to pursue economy of scale through process innovations. Based on these premises, Neffke et al. (2011) introduced a maturity index to identify life cycle stages using the market share of young firms. The underlying idea is that in young industries, the product innovative advantage of young firms allows these firms to capture large shares of the market, while in mature industries old firms are able to increase their market shares at the expense of young firms.

Due to the lack of data on value added or any other business indicators, we constructed a modified version of the Neffke et al. (2011) maturity index using the number of employees to capture market shares of old plants (at least 5 years old). In particular, the maturity index I_{it} is calculated as follows:

$$[1]\ I_{it} = \frac{emp_{it}^{old} / emp_{it}^{tot}}{emp_{t}^{old} / emp_{t}^{tot}}$$

where emp_{it}^{old} is the number of employees in old plants in industry *i* at year *t*, emp_{it}^{tot} is the number of employees in all plants in industry *i* at year *t*, emp_{t}^{old} is the number of employees in all old plants in the Netherlands at year *t* and emp_{t}^{tot} is the number of employees in all plants in the Netherlands at year *t*. Next, the maturity index I_{it} is normalised using its mean and standard deviation. Following Neffke et al. (2011), the mean -0.3 times the standard deviation and +0.3 times the standard deviation are used as margins to distinguish between young, intermediate and mature stages across industries. To neutralize the effect of short-term changes in the ILC, we took the 3-years uncentered moving average based on two years before the year *t*.[6]

This way, three independent variables were generated that represent the life cycle stage of the industry in which a plant is active, i.e. young stage, intermediate stage and mature stage. These dummies are constructed according to the maturity index and are set equal to 1 when the industry is in the corresponding life cycle stage. The 86 industries selected for this study are mainly in the mature phase (44), followed by intermediate phase (15) and by the young phase (27). Service industries are mainly identified in the young and intermediate phases, while manufacturing industries are mainly identified in the intermediate and mature phases.

Labour inflows

The aim of this paper is to analyse to what extent labor inflows, that is, the hiring of new employees affects the survival chances of new plants. We assume that this effect depends on both the prior working experience of the employee and the stage of the ILC in which the hiring firm is active. Therefore, we have composed several independent variables for labor inflows distinguishing between both dimensions.

Labour mobility is defined as an event where an employee changes job between two establishments in two consecutive years. The affiliated industry of the previous employer is used to identify the working experience of the mobile worker (Boschma et al 2009; Timmermans and Boschma 2014). Labour inflows are considered as similar when employees are recruited from the same industry. We also distinguish two other types of labour flows, using information on the skill relatedness between the industry in which the employee used to work and the industry in which the hiring firm is active. As pointed out by Neffke and Svensson-Henning (2013), skill-related industries are industries that share similar (not identical) skills which facilitates the labour recruitment process (efficient job matching) that may lead to creativity and innovation in hiring plants. To assess whether two industries are skill related, we use the skill-relatedness index developed by Diodato and Weterings (2015) for the Netherlands. Following Neffke and Henning (2013), this index is based upon the intensity of labour flows between industries.[7] In particular, a skill-relatedness measure for each pair of industries is generated using the following equation:

$$[2]\ \widehat{Skill\_relat_{ij}} = \frac{Flow_{ij}}{\widehat{Flow_{ij}}}$$

where $Flow_{ij}$ are the observed flows from industry *i* to industry *j* (unidirectional outflows from i to j) and $\widehat{Flow_{ij}}$ are the predicted labour flows from industry *i* to industry *j*. The latter are estimated using a zero inflated negative binomial model where the dependent variable is the observed labour flows ($Flow_{ij}$), and the independent variables are represented by a set of controls that take into account industry characteristics such as their size, their employment growth and their wage levels.

To take into account the right-skewed distribution of $\widehat{Skill\_relat_{ij}}$, we used the following transformation (Neffke and Henning 2013) that gives a score between -1 and 1: $(\widehat{Flow_{ij}} - 1)/(\widehat{Flow_{ij}} + 1)$. Industry pairs with a skill relatedness index value greater than 0 are considered as related industries, while the remaining industry pairs are considered as unrelated.

To determine the effect of the ILC, another set of labour inflow variables were constructed integrating the previous variables with information about the life cycle stage of the industry in which the hiring firm is active. In particular, for each of the three types of labor inflow measures we made a distinction on whether the hiring firm is active in the young, intermediate or mature stage. From this disaggregation, we obtain a new set of nine labour inflow variables.

For each of the variables, a new set of two variables was generated on the basis of the geographical dimension of labour flows. A distinction is made between intra-regional and inter-regional mobility on the basis of the municipality code of the old and the new workplace of the employee that changed jobs. If the two plants are located within one of the 431 overlapping labour markets, labour mobility is defined as intra-regional, otherwise it is considered inter-regional.

In the analysis, all the above variables are expressed as the ratio of the total number of inflows and the total number of employees at the establishment level (share of labour inflows).[8] The labour inflows observed in the foundation year are disregarded in order to avoid biases in the estimates due to the incorporation in a unique variable of two different measures of plant skills, i.e. a measure of stock and a measure of flows. In the foundation year, all the employees of a plant are by definition new employees, while from the second year onwards the plant workforce is given by mixture of pre-existing employees and new employees. This means that the labour inflows observed in the foundation year can be more or less considered as a measure of the plant's stock of skills.

Control variables

Apart from the role of external knowledge, a plant's survival chance may be affected by other factors at plant, industry and regional level. A stylised fact in the literature on survival analysis is that the failure risk falls with firm size (Dunne et al. 1989; Geroski et al. 2010). In this regards, several explanations like financial constraints (Carreira and Silva 2010) and cost disadvantages (Audretsch and Mahmood 1994) are provided. To control for plant size, we use the logarithm of the number of full time equivalentemployees. Moreover, we include the share of high skilled employees to take into account of the composition of plant workforce (Geroski et al. 2010). Since information about the educational level of employees are not available, we rely on wage data to identify high-skilled people (Groot et al., 2013). In particular, employees are grouped into seven age categories, and we use the median wage value of each category as cutoff value to distinguish between high-skilled employees and low-skilled employees.

The human capital of a plant is the result of hiring strategies that determine labour inflows and outflows of the plant. Although new employees are important to renew the human capital, an excessive labour turnover may be dangerous for plant performance. Several studies (Lane et al. 1996; Burgess et al. 2000) have provided evidence that higher churning flows raise the failure risk of young plants. Therefore, we included a measure of plant turbulence that is calculated as the ratio between the sum of labour inflows and labour outflows and the total number of employees.

Moreover, we control for industry and local labour market characteristics that might affect both the size of labour flows and plants survival chances. In particular, our estimates are performed including a set of industry dummies (4-digit level) and the logarithm of the total number of plants in the local labour market.[9] Finally, a set of cohort dummies and year dummies are included to control,respectively, for the heterogeneity of each cohort and for the economy-wide shocks like the recent financial crisis.

Since labour inflows and key control variables like plant turbulence can be determined from one year after the entry, plants were included in the panel data one year after their entry.[10][11]

Descriptive statistics of the variable used in the regressions are shown in Table 1.

Table 1. Descriptive statistics (No obs: 20,306)

Variable	Description	Mean	SD	Min	Max
Dependent variable					
Exit	Dummy equal to 1 if plant exits the market	0.181	0.385	0.000	1.000
Industry life cycle stage					
Young	Dummy equal to 1 if plant's industry is in young stage	0.833	0.373	0.000	1.000
Interm	Dummy equal to 1 if plant's industry is in intermediate stage	0.082	0.274	0.000	1.000
Mature	Dummy equal to 1 if plant's industry is in mature stage	0.085	0.279	0.000	1.000
Type of inflow over the industry life cycle stage					
Similar_Young	Share of total inflows from within same industry in young/rejuvenation stage t-1	0.034	0.092	0.000	1.000
Related_Young	Share of total inflows from related industries in young/rejuvenation stage t-1	0.050	0.100	0.000	1.000
Unrelated_Young	Share of total inflows from unrelated industries in young/rejuvenation stage t-1	0.022	0.066	0.000	1.000
Similar_Intermediate	Share of total inflows from within same	0.002	0.026	0.000	1.000

	industry in intermediate stage t-1				
Related_Intermediate	Share of total inflows from related industries in intermediate stage t-1	0.002	0.023	0.000	0.667
Unrelated_Intermediate	Share of total inflows from unrelated industries in intermediate stage t-1	0.003	0.024	0.000	0.625
Similar_Mature	Share of total inflows from within same industry in mature stage t-1	0.002	0.027	0.000	1.000
Related_Mature	Share of total inflows from related industries in mature stage t-1	0.002	0.021	0.000	0.667
Unrelated_Mature	Share of total inflows from unrelated industries in mature stage t-1	0.004	0.027	0.000	1.000
Intra_Young	Share of intra-regional inflows in young/rejuvenation stage t-1	0.082	0.131	0.000	1.000
Inter_Young	Share of inter-regional inflows in young/rejuvenation stage t-1	0.025	0.071	0.000	1.000
Intra_Intermediate	Share of intra-regional inflows in intermediate stage t-1	0.007	0.042	0.000	1.000
Inter_Intermediate	Share of intra-regional inflows in intermediate stage t-1	0.001	0.014	0.000	0.500
Intra_Mature	Share of intra-regional inflows in mature stage t-1	0.007	0.041	0.000	1.000
Inter_Mature	Share of intra-regional inflows in mature stage t-1	0.002	0.019	0.000	1.000
Intra_Similar_Young	Share of intra-regional inflows from within same industry in young/rejuvenation stage t-1	0.025	0.077	0.000	1.000
Inter_Similar_Young	Share of inter-regional inflows from within same industry in young/rejuvenation stage t-1	0.009	0.045	0.000	1.000
Intra_Related_Young	Share of intra-regional inflows from related industries in young/rejuvenation stage t-1	0.038	0.087	0.000	1.000
Inter_Related_ Young	Share of inter-regional inflows from related industries in young/rejuvenation stage t-1	0.012	0.045	0.000	1.000
Intra_Unrelated_Young	Share of intra-regional inflows from unrelated industries in young/rejuvenation stage t-1	0.018	0.060	0.000	1.000
Inter_Unrelated_Young	Share of inter-regional inflows from unrelated industries in young/rejuvenation stage t-1	0.004	0.027	0.000	0.500
Intra_Similar_Intermediate	Share of intra-regional inflows from within same industry in intermediate stage t-1	0.002	0.024	0.000	1.000
Inter_Similar_Intermediate	Share of inter-regional inflows from within same industry in intermediate stage t-1	0.000	0.007	0.000	0.333
Intra_Related_Intermediate	Share of intra-regional inflows from related industries in intermediate stage t-1	0.002	0.022	0.000	0.667
Inter_Related_Intermediate	Share of inter-regional inflows from related industries in intermediate stage t-1	0.000	0.006	0.000	0.500
Intra_Unrelated_Intermediate	Share of intra-regional inflows from unrelated industries in intermediate stage t-1	0.002	0.022	0.000	0.625
Intra_Unrelated_Intermediate	Share of inter-regional inflows from unrelated industries in intermediate stage t-1	0.000	0.009	0.000	0.333
Intra_Similar_Mature	Share of intra-regional inflows from within same industry in mature stage t-1	0.002	0.023	0.000	0.938
Inter_Similar_Mature	Share of inter-regional inflows from within same industry in mature stage t-1	0.001	0.012	0.000	0.500
Intra_Related_Mature	Share of intra-regional inflows from related industries in mature stage t-1	0.002	0.019	0.000	0.667
Inter_Related_Mature	Share of inter-regional inflows from related industries in mature stage t-1	0.000	0.008	0.000	0.333

Intra_Unrelated_Mature	Share of intra-regional inflows from unrelated industries in mature stage t-1	0.003	0.023	0.000	0.800
Inter_Unrelated_Mature	Share of inter-regional inflows from unrelated industries in mature stage t-1	0.001	0.012	0.000	1.000
Other control variable					
Turbulence	Churning flow rates t-1	0.233	0.294	0.000	7.500
log(plant_size)	Number of employees in the plant t-1 (log)	1.742	0.996	0.000	6.406
High_skilled	Share of employees with a university degree or a technical college t-1	0.326	0.281	0.000	1.000
log(local_plant)	Total number of local plants t-1 (log)	11.283	0.701	8.371	12.265

Note: Industry dummies, cohort dummies and year dummies are omitted.

Methodology

In the database, the dependent variable is measured for each year during the period. To estimate the probability that a firm will exit in a certain year, we use event history analysis because that is the most appropriate methodology in case of censored data (Guo, 1993). While our data are not left censored as we follow a plant from its year of entry, our data is characterized by right censoring because not all plants stopped activities in 2009, the last year for which we can observe the plants. Contrary to standard regression, the observations that do not exit during the study period will not be dropped from the event history analysis which is important since they may have specific characteristics that affect the probability of plant survival.

The methodology adopted to model the event of plant exit is the complementary log-log discrete time hazard function with time varying covariates. Although a firm can exit at any moment in time and, therefore, an exit actually occurs in continuous time, our dataset only observes the event of plant exit on a yearly basis. If time is actually continuous but is only observed in intervals, the complementary log-log specification is the most suitable as this is the discrete time representation of a continuous time proportional hazard model (Prentice and Gloeckler 1978; Allison 1984; Jenkins 2005). In all models, duration-interval-specific dummy variables have been included for each year at risk to control for differences in the occurrence of plant exits per year. Furthermore, we included time varying covariates in the model since several of the plant characteristics, including the labour inflows, change over time.

The general form of this model is:

$$[3]\ h(j, \boldsymbol{X}) = 1 - exp[-exp(X'\beta + \gamma_j)]$$

where $h(j, \boldsymbol{X})$ is the hazard rate of a plant in interval j given the scores of that plant on all covariates in interval j; $\boldsymbol{X}$ is a matrix of covariates. This tells how likely it is that a plant exits in interval j, given that it has not stopped activities so far. This hazard is based on two components, namely the value of all covariates for the plant in that period (i.e. $X'\beta$), and γ_j which captures the log of the difference between the integrated baseline hazard evaluated at the end of the interval and the beginning of the interval. In other words, γ_j can be seen as the increase in the base hazard of plant exit in interval j and has a strong analogy with the base hazard rate in continuous time analyses. For technical details regarding complementary loglog models, we refer to Jenkins (2005).

To take into account of unobserved heterogeneity, all estimates are performed including a random component (the likelihood-ratio tests signal the presence of unobserved heterogeneity). Different parametric distributions can be used for the random component. Nicoletti and Rondinelli (2010) shows that a misspecification on the distribution does not seriously bias the results. We assume a normal distribution for the random component. The results of both estimators are similar.[12]

Empirical results

The estimation results of the survival analysis are shown in Table 2.[13] Model 1 presents the results of the analysis of the probability to exit in the young and intermediate stage (the mature stage is used as reference category). The other models include the variables for labour inflows. Model 2 presents the effects of similar, related and unrelated inflows over the different ILC stages. The geographical dimension is introduced in Model 3, which presents the results of total labour inflows distinguishing between intra- and inter-regional inflows. Model 4 makes a further distinction whether these inter- and intra-regional inflows concern similar, related or unrelated labour flows.

First, we briefly describe the results for the control variables. As expected, we find a negative effect of plant size (*plant_size*) on the probability of plant exit. Moreover, plant turbulence (*Turbulence*) has a positive effect on plant exit which confirms that excessive labour turnover raises failure risk. The effect of the size of the labour market (*local_plant*) is not statistically significant. Contrary with the expectations, the effect of the share of high-skilled employees (High_skilled) is positive, but it is not robustly significant.

The results of the estimate of the probability to exit in the different ILC stages (Model 1) do not support the hypothesis that plants are less likely to exit in the young stage than in the mature stage. Indeed, the coefficient for the variable *Young* is negative but statistically insignificant.

Model 2 introduces the variables for the different types of labour inflows. We observe that inter-industry labour inflows, both form related (*Related_Young*) and unrelated (*Unrelated_young*) industries, has a negative effect on plant exit in the young phase. This result is coherent with the literature that stresses the importance of knowledge flows from other industries in the earlier stages of the ILC (Gort and Klepper 1982; Neffke et al. 2011). However, contrary to the conventional hypothesis stressed in the ILC literature, plants do not benefit from intra-industry inflows in the mature phase. Indeed, the coefficient for the variable *Similar_Mature* is positive and significant. Moreover, the results show a negative effect of related inflows on plant exit in the mature phase (*Related_Mature*), although the coefficient is statistically significant only at the 10% level. Thus, inter-industry labour inflows enhance the survival chances of plants active in mature industries, but only when people are recruited from related industries.

The estimates that consider intra- and-inter-regional labour inflows (Model 3) show a negative effect of intra-regional inflows (*Intra_Young*) on plant exit in the young stage. It seems that plants do not benefit from inter-regional labour inflows over the different ILC stages. We observe only a positive and significant effect for the variable *Inter_Intermediate*.[14] Model 4 makes a further distinction disaggregating the total labour inflows (both intra-regional and inter-regional) into similar, related and unrelated inflows. The results confirm that inter-industry inflows (*Intra_Related_Young* and *Intra_Unrelated_Young*) are significant in the young stage only when employees are recruited in the same labour market. These results support the hypothesis of a dominant role of Jacob externalities in the young stage. Again, we see a positive and slightly significant effect of intra-regional inflows from related industries in the mature stage (*Intra_Related_Mature*).[15]

Table 2. Results of survival analysis (coefficient values)

Variable	Model 1		Model 2		Model 3		Model 4	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Young	-0.604	(1.126)						
Interm	-0.039	(1.107)						
Similar_Young			-0.021	(0.201)				
Related_Young			-0.685***	(0.190)				
Unrelated_Young			-0.555**	(0.260)				
Similar_Intermediate			1.418**	(0.565)				
Related_Intermediate			-0.527	(0.836)				
Unrelated_Intermediate			-0.486	(0.833)				
Similar_Mature			1.234**	(0.592)				
Related_Mature			-1.965*	(1.040)				
Unrelated_Mature			0.109	(0.670)				
Intra_Young					-0.567***	(0.157)		
Inter_Young					0.002	(0.242)		
Intra_Intermediate					0.103	(0.483)		
Inter_Intermediate					2.321**	(1.097)		
Intra_Mature					0.042	(0.496)		
Inter_Mature					0.617	(0.866)		
Intra_Similar_Young							-0.062	(0.285)
Inter_Similar_Young							0.129	(0.356)
Intra_Related_Young							-0.822***	(0.214)
Inter_Related_ Young							-0.217	(0.353)
Intra_Unrelated_Young							-0.752**	(0.293)
Inter_Unrelated_Young							-0.315	(0.564)

Intra_Similar_Intermediate							1.067*	(0.630)
Inter_Similar_Intermediate							4.741***	(1.777)
Intra_Related_Intermediate							-0.969	(0.912)
Inter_Related_Intermediate							1.527	(2.266)
Intra_Unrelated_Intermediate							-0.592	(0.916)
Intra_Unrelated_Intermediate							0.338	(2.005)
Intra_Similar_Mature							1.182*	(0.681)
Inter_Similar_Mature							1.641	(1.316)
Intra_Related_Mature							-2.084*	(1.172)
Inter_Related_Mature							-1.536	(2.406)
Intra_Unrelated_Mature							-0.123	(0.821)
Intra_Unrelated_Mature							0.652	(1.197)
Turbulence	0.366***	(0.047)	0.459***	(0.059)	0.449***	(0.061)	0.447***	(0.061)
log(plant_size)	-0.147***	(0.022)	-0.142***	(0.022)	-0.144***	(0.002)	-0.147***	(0.022)
High_skilled	0.119*	(0.072)	0.119*	(0.071)	0.120	(0.073)	0.111	(0.073)
log(local_plant)	0.002	(0.028)	0.007	(0.027)	0.011	(0.028)	0.013	(0.028)
Entry year cohort dummies	Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes		Yes	
Lr test chibar2(01)	1.55		1.00		3.23**		2.03*	
No obs	20,306		20,306		20,306		20,306	
No Plants	6,277		6,277		6,277		6,277	
Log Pseudolikelihood	-9245.44		-9229.76		-9235.45		-9223.46	

Notes: standard errors are reported in parentheses; levels of significance: *=0.1, **=0.05, ***=0.01.

We also test whether the above described effects of intra-industry and inter-industry labour flows on plants' survival chances are driven by the mobility of high-skilled people. Table 3 compares the results obtained considering labour inflows of high skilled employees with the results obtained considering the labour inflows of all employees, i.e. irrespective of the skill level of the employees. Model 5a shows the effects of high-skilled labour inflows from similar, related and unrelated industries without taking into account of the geographical dimension. The latter is introduced in Model 6a which disaggregates the high-skilled labour inflows into intra- and inter-regional inflows. Models 5b and 6b show the estimation results obtained considering the labour inflows of all employees, i.e. considering both high-skilled and low-skilled employees. Note that the number of observations in Table 3 (14,698) is lower than Table 2 (20,306) because of the two different criteria used to select the sample of plants to perform the estimates. In particular, the estimation results of

Table 2 consider the sample of plants which have hired at least an employee, while the estimates results of Table 3 consider only the sub-sample of plants that hired at least a high-skilled employee.

Overall, from Models 5a and 6a appear that labour inflows of high-skilled people do not exert any significant role in increasing the plants' survival chances. Indeed, we do not observe any significant negative coefficient values for all types of labour inflows, while significant and positive values are observed for similar and unrelated inflows in the intermediate and mature stage. On the other side, Models 6a and 6b confirms the previous findings about the role of inter-industry labour inflows in the young and mature stage, but only for related inflows.

Table 3. Results of survival analysis (coefficient values) – high-skilled inflows Vs all employee inflows

Variable	Model 5a		Model 5b		Model 6a		Model 6b	
	High skilled		All employees		High skilled		All employees	
	Coeff	SE	Coeff	SE	Coeff	SE	Coeff	SE
Similar_Young	-0.058	(0.316)	-0.144	(0.220)				
Related_Young	-0.355	(0.278)	-0.637***	(0.211)				
Unrelated_Young	-0.146	(0.463)	-0.495	(0.307)				
Similar_Intermediate	4.416**	(1.778)	1.552**	(0.683)				
Related_Intermediate	1.684	(1.663)	0.069	(1.132)				
Unrelated_Intermediate	2.774*	(1.680)	-0.664	(1.227)				
Similar_Mature	1.497	(1.343)	1.136*	(0.649)				
Related_Mature	-2.217	(2.204)	-2.842**	(1.309)				
Unrelated_Mature	2.520**	(1.229)	1.448*	(0.755)				
Intra_Similar_Young					-0.194	(0.376)	-0.238	(0.260)
Inter_Similar_Young					0.337	(0.520)	0.169	(0.373)
Intra_Related_Young					-0.468	(0.324)	-0.862***	(0.244)
Inter_Related_ Young					-0.034	(0.465)	0.049	(0.369)
Intra_Unrelated_Young					-0.004	(0.530)	-0.559	(0.350)
Inter_Unrelated_Young					-0.451	(0.879)	-0.182	(0.654)
Intra_Similar_Intermediate					3.494*	(1.957)	1.477**	(0.745)
Inter_Similar_Intermediate					21.706*	(12.684)	2.929	(2.550)
Intra_Related_Intermediate					2.441	(1.639)	-0.143	(1.239)
Inter_Related_Intermediate					-0.616	(18.561)	1.814	(4.570)
Intra_Unrelated_Intermediate					4.261**	(2.018)	-0.625	(1.366)
Intra_Unrelated_Intermediate					-0.780	(3.398)	-0.614	(2.758)
Intra_Similar_Mature					0.641	(1.305)	1.072	(0.732)
Inter_Similar_Mature					4.400*	(2.246)	1.875	(1.419)
Intra_Related_Mature					-2.786	(2.547)	-3.371**	(1.512)
Inter_Related_Mature					-1.396	(4.518)	-0.234	(2.922)
Intra_Unrelated_Mature					2.811*	(1.563)	1.663*	(0.943)
Intra_Unrelated_Mature					2.531	(1.794)	1.283	(1.183)
Turbulence	0.353***	(0.056)	0.424***	(0.062)	0.338**	(0.054)	0.399***	(0.064)

log(plant_size)	-0.122***	(0.024)	-0.121***	(0.023)	-0.120***	(0.022)	-0.123***	(0.023)
High_skilled	0.367***	(0.096)	0.356***	(0.090)	0.344***	(0.086)	0.346***	(0.090)
log(local_plant)	-0.033	(0.032)	-0.027	(0.032)	-0.028	(0.031)	-0.017	(0.033)
Entry year cohort dummies	Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes	
Year dummies	Yes		Yes		Yes		Yes	
Lr test chibar2(01)	0.10		0.07		0.00		0.27	
No obs	14,698		14,698		14,698		14,698	
No Plants	4,471		4,471		4,471		4,471	
Log Pseudolikelihood	-6645.19		-6639.22		-6641.74		-6635.34	

Notes: standard errors are reported in parentheses; levels of significance: *=0.1, **=0.05, ***=0.01.

In general, it is difficult to reconcile the results obtained considering labour inflows in general with the results obtained considering only the inflows of high-skilled people. However, we provide three possible explanations for these mixed results. First, it can be the case that the methodology adopted to identify high-skilled people fails to fully discern this category of employees from the other ones. Indeed, the employee's wage level might reflect individual characteristics like the personal bargaining power which are not related to the educational level and, in general, to employee's skills and abilities. Employee's wage level could also reflect plant characteristics. This means that, irrespective of employees' skills, we can observe higher (lower) wage level for all the employees of higher (lower) productive plants. It follows that the results obtained using high-skilled inflows might confound different aspects which result in not-significant coefficient estimation. Second, a positive effect of high skilled workers on plants' survival chance cannot be for granted. For instance, some authors (Vinding 2006) argue that the share of highly educated people is not necessarily correlated to the ability of firms to innovate. This hypothesis is also supported by the observed positive effect on plant exit of the share of high-skilled employees. Again, these unexpected results could be explained by the inadequateness to measure human skills using wage or educational level which reveal the necessity to rely on more qualitative aspects of human skills.

Finally, it is possible that hiring high-wage people increases the risk of exit of new entering plants. In general, job-mismatching is a general risk that firms face hiring people because of asymmetric information. However, the risk of job-mismatching might be greater in new plants than in established plants because of the relatively lower experience in the labour market. Moreover, in case of effective job-mismatch, the negative impacts on survival chances of entering plants might be severe because these plants are in general of small size (average plant size is about 5.5) and, thus, also a single high-wage employee might represent an important part of the plants' budget.

Conclusion

This article has examined the role of different types of labour recruits for the performance of new plants in the context of the ILC, comparing young and mature industries. Our study on the Netherlands shows that the effect of labour mobility on new plant survival depends on the type of industries from which new employees are recruited, and on the life cycle stage of an industry the new plant is active in. New plants in young industries have a higher survival rate when hiring new employees from both skill-related and unrelated industries. Apparently, recruits drawn from other industries tend to benefit new plants in industries that are in an explorative stage. In mature industries, recruiting labour from the same industry tends to be bad for plant survival, which seems to contradict the reliance of mature industries on MAR externalities (Neffke et al. 2011). What young and mature industries have in common is that new plants show higher survival rates when hiring new employees from skill-related industries. Newly established plants also do not seem to benefit from inter-regional labour flows, irrespective of the ILC stage.

These findings may have interesting implications for business companies and policy makers alike. Our findings suggest that labour mobility across skill-related industries should be encouraged through information provision and removal of institutional bottlenecks. Awareness should increase among economic stakeholders that intra-industry recruitment is not necessarily beneficial for their performance, especially in more established industries. Firms need to know that labour recruited from the same industry may be detrimental for their performance, workers should be aware that changing job within the same industry may not always be in their own interest, while labour mediation offices and public employment agencies could consider encouraging companies and workers to make crossovers between industries. Crucial is to inform stakeholders which industries are related to their own industry, to identify those opportunities. Local policy makers could exploit the potential of a large local presence of related industries by facilitating local labour mobility across these industries. This also implies that institutional bottlenecks (laws, rules) that prevent companies to connect and exchange labour across industries should be removed.

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Notes

[1] Spurious flows are identified using the bilateral labour flows between plants (Neffke et al., 2017). For plants with more than five employees, labour flows are considered spurious when the ratio between the bilateral flows and the total number of employees of the receiving/sending plant is greater than 0.8. For plants with less than five employees, labour flows are considered spurious when the ratio between the bilateral flows and the total number of employees of the receiving/sending plant is equal to 1.

[2] We also exclude smaller plants, i.e. plants with less than one full time equivalent employee.

[3] Additional estimates are performed for the complete sample of 179 industries and for the sub-sample of 140 industries that moved from one industry life cycle stage to another one. The estimates results (available from the authors upon request) are qualitative similar.

[4] Individuals with a short-term contract (less than 3 months) and/or with less than half-time contract are excluded from the analysis.

[5] Plants that alternate periods with some employees and periods without any employees are disregarded because of the lack of reliable information about their real status (i.e. temporarily exiting plants or not). Furthermore, also plants that change industry affiliation or relocate between regions are excluded in order to accurately investigate the relevance of intra- and inter-industry inflows and of intra- and inter-regional inflows.

[6] We adopt an uncentered moving average instead of a centered moving average because LISA data allow us to reconstruct the number of employees in old plants and, thus, the maturity index I_{it} until the year 2008.

[7] See Neffke and Henning (2013) and Diodato and Weterings (2015) for a more detailed description of the methodology used to construct the skill relatedness index.

[8] All the shares of labour inflows with a value greater than 1 are replaced with the maximum value of 1 to reduce the impact of potential outliers. As a robustness check, additional estimates are performed using the original shares. The results (available from the authors upon request) are very similar.

[9] We also considered to include a control for possible local agglomeration effects using the density of plants within the local labour market. This variable was not included in the regressions because highly correlated with the number of plants at local level.

[10] Plants exiting within one year after entering are excluded from the analysis.

[11] All the independent variables are lagged one period.

[12] To avoid biases in the estimates, plants with extreme growth rate values (1th and 99th percentile) are excluded from the analysis.

[13] Looking at pair wise correlations between variables, we do not find high correlations. Moreover, the VIF test confirms that multicollinearity problems are not observed in our sample.

[14] The recent financial crisis might play a role in explaining the plant exit rates. In 2009 the observed exit rate is about 21.9%, while the average exit rate for previous years is about 13.3%. This difference is statistically significant (Fischer exact test is significant at 1% level). The inclusion of year dummies might not completely remove the potential bias due to the recent financial crisis. Thus, as robustness check, we perform additional estimates excluding the year 2009. In general, the estimates results (available from the authors upon request) are similar. The main differences are that only related labour inflows matter in the young stage and the effect of related inflows in the mature stage is significant at 5% instead of 10% level.

[15] As robustness check, we perform additional estimates including a dummy variable to control for plants that are part of multiplant firms. The results of the most extended model (i.e. Model 4), available from the authors upon request, are similar. In particular, the negative and significant effect of the variables *Intra_Related_Young* and *Intra_Unrelated_Young* is confirmed. Moreover, we observe a positive and significant effect of the dummy for multiplants firm, that means that plants belonging to multiplant firms are more likely to exit.