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How Does Labour Mobility Affect the Performance of Planets?
The importance of relatedness and geographical proximity

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Abstract:

This paper analyses the impact of skill portfolios and labour mobility on plant performance by means of a unique database that connects attributes of individuals to features of plants for the whole Swedish economy. We found that a portfolio of related competences at the plant level increases significantly productivity growth of plants, in contrast to plant portfolios consisting of either similar or unrelated competences. Based on the analysis of 101,093 job moves, we found that inflows of skills that are related to the existing knowledge base of the plant had a positive effect on plant performance, while the inflow of new employees with skills that are already present in the plant had a negative impact. Our analyses also show that geographical proximity influences the effect of different skill inflows. Inflows of unrelated skills only contribute positively to plant performance when these are recruited in the same region. Labour mobility across regions only has a positive effect on productivity growth of plants when this concerns new employees with related skills.

Keywords: Labour mobility; related variety; skill portfolio; plant performance; geographical proximity

Jel codes: R11; R12; O18

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1. Introduction

Labour mobility is one of the key mechanisms through which knowledge diffuses. Since people are the main carrier of knowledge, employees moving from one firm to the other will contribute to knowledge exchange and learning between firms. Economic geographers point out that labour mobility contributes to knowledge formation at the regional level because it is basically at that level where this type of knowledge transfer takes place. This seems to be especially true for labour market areas that are endowed with similar or related economic activities (Eriksson *et al.*, 2008). While labour mobility is often considered a driving force behind the economic success of regions like Silicon Valley (Saxenian, 1994), there is also some large scale evidence that localised labour market externalities derived via job mobility produce significant effects on the performance of firms (Eriksson and Lindgren, 2008).

We will argue in this paper that the economic effects of labour mobility can only be assessed properly when linked to different types of skills at the plant level. We take as a starting point the literature on spinoffs. This literature views spinoff companies as a particular form of labour mobility in which the type of knowledge that is transferred from a parent company to the new start-up matters for the survival of the new entrant (Klepper, 2002). We will transfer this view to labour mobility in general. New employees (besides the entrepreneur) may also bring in valuable knowledge and contribute to the performance of the firm (Almeida and Kogut, 1999). However, we argue that this depends on what kind of knowledge is brought in, and how that matches the existing knowledge base of the firm. We claim that the inflow of new employees with skills that are related but not similar to the existing knowledge base is most relevant for the performance of firms. Our paper is also embedded in the economic geography literature that investigates whether extra-regional linkages are required to avoid lock-in (Bathelt *et al.*, 2004). We will extend this thinking to the issue of labour mobility. We claim that it is not just being connected to the outside world what matters, but whether these linkages bring in new knowledge that is complementary to the existing knowledge base of the firm. In other words, we account for the inflow of different types of skills when estimating the effects of labour mobility on firm performance. Doing so, we embed our paper in the literature that accounts for the impact of related variety on regional development (Frenken *et al.*, 2007; Boschma and Iammarino, 2008).

The paper has three objectives. The first objective is to assess whether a particular set of competences at the plant level, measured as educational skills of employees, enhances the performance of plants. Besides the educational level of the work force *per se*, we argue that

particular portfolios of competences within a plant is crucial for its performance. We expect that interactive learning and real innovations will only occur when employees in a plant have complementary competences, in contrast to similar or very different types of competences. Accordingly, we examine whether a portfolio of related competences at the plant level is more beneficial than portfolios of similar and unrelated competences.

The second objective is to assess the effects of new labour inflows on plant performance, as it may bring new variety into the plant. Doing so, we expect that not labour mobility *per se* will matter, but that it depends on the types of skills that flow into the plant whether it affects plant performance. Therefore, we need to specify which types of skills are brought into the plant by new employees, and to what extent these newly acquired skills add to the existing knowledge base of plants. We hypothesise that when the newly acquired skills are the same (i.e. the new employees have working experience in the same sector the plant is already specialised in), the plant can absorb these, but the new skills will not add anything new to the existing set of skills in the plant, and therefore will not contribute to its performance. When the new skills are unrelated (i.e. the new employees have working experience in sectors that are very different from the sector the plant is specialised in), the plant cannot easily absorb these, and is unlikely to learn and benefit from it. Therefore, we claim that the inflow of new skills should be related (but not similar) to the existing knowledge base of the plant to have economic impact, because in those circumstances, real learning opportunities are present.

The third objective is to estimate the effects of labour mobility when accounting for the geographical dimension. Once again, we expect that the positive effects of labour mobility on productivity growth become visible only after differentiating between types of labour inflows, in this case depending on whether new employees are recruited from the same region or from other regions. For instance, we expect that the lock-in problem, associated with labour inflow of skills that are already present in the plant, will only get worse when the new employees are recruited from the same region. In addition, we will test the idea that inflows of unrelated skills might still contribute to plant performance, as long as these are recruited from the same region. And what about labour mobility across regions; does this contribute to plant performance, or does that, again, depend on the type of skills that flow into the plant? Our results suggest that labour mobility across regions only has a positive effect on productivity growth when it concerns new employees with related skills.

We test these theoretical statements by analysing 101,093 job moves drawn from a unique database that connects attributes of individuals (education, working experience) to features of plants (location, sector) for the whole Swedish economy. The structure of the paper is as

follows. In Section 2 we set out the main theoretical ideas. Section 3 presents the database and the variables. Section 4 presents and discusses the main outcomes of the estimation model. Section 5 concludes by setting out possible future research lines.

2. Labour mobility and economic performance

Human capital is widely regarded as a source of wealth (Becker, 1962; Glaeser, 2000). Human capital accumulates at the firm level through education, learning-by-doing and learning-by-interacting, but may also be acquired externally. Since knowledge – or work-specific skills – ultimately rests within individuals, the mobility of skilled individuals is frequently stressed as a crucial factor behind knowledge transfer and the competitiveness of firms and regions (e.g. Lawson, 1999; Gertler, 2003; Hudson, 2005; Rodriguez-Pose and Vilalta-Bufi, 2005). In contrast to factors of production such as capital and commodities, which can be traded and moved, other conditions apply for labour. For example, employers cannot hinder personnel to change work if they desire to do so. An increasingly knowledge-intensive production brings about a situation where departing workers cannot leave everything behind, because they are carriers of vital information and experiences that follow them to their next workplace. Based on this mechanism, job mobility of skilled labour is regarded to facilitate the dissemination of embodied tacit knowledge (e.g. Almeida and Kogut, 1999; Maskell and Malmberg, 1999; Cooper, 2001; Power and Lundmark, 2004). Experiences and routines accumulated by individuals at work are seldom codified in terms of texts or documents, but gained knowledge lingers within individuals and epistemic communities to which they are associated (Basant, 2002; Grabher, 2002).

In science-based industries, there is growing evidence that the mobility of star scientists and key engineers act as a key mechanism through which knowledge diffuses among firms (Saxenian, 1994; Pinch and Henry, 1999). Almeida and Kogut (1999) have demonstrated that knowledge spillovers in regions like Silicon Valley can be mainly attributed to inter-firm mobility of engineers which were defined as major patent holders in semiconductors. These benefits of labour pooling are often believed to exceed the downsides of labour mobility (i.e. labour poaching) that reduce the incentive of firms to invest in their own employees (Kim and Marschke, 2005; Combes and Duranton, 2006; Fallick et al., 2006). Next to this knowledge transfer argument, labour mobility also enables structural change in an economy, which is crucial for long-term economic development. Since each economy is subject to processes of economic decline in some sectors now and then, it needs flexible labour markets to ensure redundant labour will move to sectors

that are still going strong (Pasinetti, 1981). Accordingly, labour mobility is required to smooth this process of creative destruction and lower the costs of adjustments (Aghion et al., 2006).

What is often implicit in this literature, however, is that the effect of labour mobility is almost taken for granted, as if the new employees are smoothly integrated in the organization of the firm, and as if the new employees will contribute to the further knowledge creation in the firm. One of the reasons is that this literature has drawn little attention to the types of knowledge and skills that are transferred between firms through job-hopping. There is a growing literature though that attaches great importance to the type of knowledge being transferred between firms through the so-called spinoff process (Klepper, 2002). Spinoff companies are being defined as new firms that are founded by former employees in the same sector. As such, spinoff companies are depicted as a particular form of labour mobility in which the type of knowledge that is transferred from a parent company to the newly established firm matters for the survival of the new entrant. Empirical studies (e.g. Klepper, 2002; Wenting, 2006; Boschma and Wenting, 2007) have demonstrated that spin-off companies and experienced firms, founded by entrepreneurs that had a background in the same or related industries, respectively, increased their survival to a considerable degree, as compared to start-ups lacking related competences and skills (inexperienced firms).

We will extend this insight to labour mobility in general. We claim that new employees, besides the entrepreneur, may also bring in valuable knowledge and contribute to the performance of firms (Dahl and Sorenson, 2007). However, we claim that this will depend on what kind of knowledge is brought in, and how that matches the existing knowledge base of the firmⁱ. This insight is well understood in innovation studies that stress the importance of absorptive capacity of firms to communicate, understand and integrate external knowledge (Cohen and Levinthal, 1990). What has attracted growing attention is that it is not just a matter of having absorptive capacity or not, but whether external knowledge is close, but not quite similar to the existing knowledge base of the firm. Nooteboom (2000) claims that inter-firm learning requires a certain degree of cognitive proximity between firms to enable effective communication, but not too much cognitive proximity to avoid lock-in. This has, for instance, been found in a study on technological alliances between large firms in chemical, automotive and pharmaceutical industries (Nooteboom et al., 2007). This study demonstrated

ⁱ In the organization literature, the mobility of top managers is analysed as a potential source of change in organizations (Sorenson, 1999). Boeker (1997), for example, has demonstrated empirically that the mobility of top management across firms influences their entry into new product markets. This study found that a firm that recruits an executive from a firm operating in a different product market is more likely to enter into a new market segment the new executive was engaged in during his or her previous job.

empirically that there exists an inverted U-shaped function between the cognitive distance with partners in technology-based alliances and the innovation performance of firms.

The economic effect of labour mobility has also drawn attention from economic geographers. One reason is that the overwhelming majority of job moves occurs within regions. This is especially true for regions with similar or related economic activities: clusters are characterized by a level of local labour mobility that is higher than elsewhere in an economy (Power and Lundmark, 2004). It is widely acknowledged that labour is the most immobile factor of production: most people stay in their home regions without reflecting on leaving the present locality, implying that knowledge transfer via job mobility predominantly is a local process. Fischer *et al* (1998) argue there is a negative relationship between duration of stay and propensity to move. Place-specific human capital takes time to accumulate and will be a sunk cost if moving elsewhere. Relations to friends, relatives, clients and colleagues would be significantly interrupted due to such a change. Empirical studies have confirmed that people with long durations of stay are less likely to change either workplace or, in particular, region of residence (Eriksson *et al*, 2008; Gordon and Molho, 1995).

Since labour mobility is a key vehicle of knowledge dissemination and learning, it contributes significantly to new knowledge formation at the regional level. Since tacit knowledge follows people and their mobility patterns, this type of knowledge is considered to be spatially sticky and locally embedded (Gertler, 2003; Iammarino and McCann, 2006). Almeida and Kogut (1999) argue that inter-firm mobility of labour may be mainly held responsible for knowledge spillovers in successful regions like Silicon Valley. In addition, labour mobility creates linkages between firms through social ties between former colleagues. These social relationships in turn facilitate knowledge flows between firms (Breschi and Lissoni, 2003). Since most of the job moves are intra-regional, these social networks are formed locally, and will enhance further knowledge accumulation at the regional level (Dahl and Pedersen, 2003)ⁱⁱ. From this line of thought, it can be concluded that mobility of skilled labour plays an important role in understanding the benefits of agglomerations (Malmberg and Power, 2005).

What remains unclear in this literature, however, is what types of knowledge inflow contribute to the performance of firms and regions. Investigating the effect of types of trade linkages on regional growth in Italy, Boschma and Iammarino (2008) found that the economic

ⁱⁱ Agrawal *et al* (2006) point out that although knowledge is admittedly highly localised, social networks maintained via more geographically distant job mobility may overcome problems associated with greater spatial distances, thereby ensuring knowledge transfers between socially interlinked individuals working for firms in different localities.

growth of regions is not affected by being well connected to the outside world *per se*, or having a high variety of knowledge flowing into the region. Accordingly, access to non-regional knowledge is not sufficient: local absorptive capacity is required to understand and transform external knowledge into economic growth. When the extra-regional knowledge originated from sectors the region was already specialised in, it did not positively impact on regional growth either: although the region could absorb it, the new knowledge did not add anything new to the existing knowledge base of the region, and therefore did not contribute to its regional growth. By contrast, a region benefited economically from extra-regional knowledge when it originated from sectors that were related, but not similar to the sectors present in the region. Apparently, when the cognitive proximity between the extra-regional knowledge and the knowledge base of the region is neither too small nor too large, real learning opportunities are present, and the external knowledge contributes to regional growth.

We apply these ideas when accounting for the effects of labour mobility on the performance of firms. The basic idea is that inflows of new skills are required to avoid lock-in at the firm level, because too much reliance on internal skills may be harmful. Doing so, we need to specify which types of skills are brought into the plant by new employees, and to what extent these newly acquired skills add to the existing knowledge base of plants. Following this line of thought, we expect that no real learning will take place when the newly acquired skills are the same or when they are unrelated. Therefore, we claim that the inflow of new skills should be related, but not similar to the existing knowledge base of the plant to have economic impact, because in those circumstances, real learning opportunities are present.

Before assessing the relative importance of these different types of external knowledge though, we need to assess the impact of intra-firm learning on firm performance (Maskell, 2001; Sternberg and Arndt, 2001). While it is common knowledge that human capital at the firm level (as proxied by the level of research or the educational level of the personnel) positively impacts on firm performance, there is still little understanding of whether particular types of competence portfolios at the plant level enhance the performance of plants (Lacetera et al., 2004). While absorptive capacity is certainly needed to understand and implement the new skills at the plant level, we expect plants with employees with related or complementary competences to perform better, because this type of portfolio will particularly enhance interactive learning between employees within a plant, in contrast to plant portfolios that consist of employees with either similar or unrelated competences.

Lastly, while new employees may provide a new source of knowledge and trigger new ideas, it is still uncertain whether new employees should come from the same region or from

elsewhere to have the largest impact on firm performance. As noted above, economic geographers often claim that geographical proximity may be beneficial because it facilitates the understanding and implementation of new knowledge, but it may also be detrimental to the firm because it may worsen lock-in (Boschma, 2005). In the literature, increasing attention is paid to the role of extra-local linkages, since too much reliance on merely local knowledge may result in lock-in that may be harmful to performance of firms and regions (e.g. Scott, 1998; Bresnahan *et al*, 2001; Asheim and Isaksen, 2002; Bathelt *et al*, 2004; Faggian and McCann, 2006). We argue that the effects of labour mobility on firm performance can only be accounted for after differentiating between types of labour inflows, in this case depending on whether new employees are recruited from the same region or from other regions.

With respect to intra-regional inflows, we assume the problem of lock-in will get worse when these concern new employees that bring in skills that are already present in the firm. Accordingly, when new employees with similar skills are recruited in other regions, this might be less damaging for firm performance, because these might still bring in valuable resources acquired in distant locations. This may be attributed to the fact that the routines of firms within a sector tend to be more similar within a region than across regions. Essletzbichler and Rigby (2005) and Rigby and Essletzbichler (2006) found in the US machine tool industry that intra-regional variety of plants (in terms of production techniques) is persistently lower than inter-regional variety of plants. Consequently, when firms recruit new workers from other firms in their own region, these are less likely to bring new knowledge into the company, because local firms in the same sector tend to look more alike. Because this is less true for firms in the same sector across regions, hiring new employees from firms located in other regions might be more beneficial. The problem of lock-in due to geographical proximity will, however, not be evident for inflows of related skills, as we expect these inflows to be complementary to the existing knowledge base of the firm, and these should therefore increase firm performance. Thus, we assume this type of labour inflow will have a particularly strong and positive effect in combination with geographical proximity, as compared to inflow of related skills across larger distances. What we also expect is that the more unrelated the newly recruited skills are, the more there is a need for geographical proximity to solve problems of communication and coordination at the firm level. In other words, inflows of unrelated skills might still contribute to firm performance, as long as these are recruited from the same region.

Overall, this implies that intra-regional labour mobility is not necessarily contributing to firm performance, because that depends on the types of skill inflow. This also implies that

labour mobility crossing regional boundaries is not necessarily good or bad for firm performance. Once again, that depends on the types of skills that flow into the firms, and to what extent these match the existing skill portfolio of firms. As explained above, inflows of unrelated skills from other regions will most likely harm the performance of firms, while inflows of similar skills across regions will be less damaging for firm performance, as compared to inflows of similar skills from the same region. What we expect then is that labour mobility between regions is most beneficial for firm performance when it concerns new employees that bring related skills into the firm, as compared to either inter-regional inflows of similar skills, or inter-regional inflows of unrelated skills.

3. Research design

Data and sampling

We test these theoretical statements by analysing 101,093 job moves drawn from the ASTRID database that connects attributes of individuals (education, working experience) to features of plants (location, sector) for the whole Swedish economy. The ASTRID database is a unique longitudinal micro-database created by matching several administrative registers at Statistics Sweden (SCB). The database includes information about all Swedish inhabitants, firms and workplaces. The high resolution of socio-economic data enables us to analyse all flows of employees changing workplace within and between labour market regions.

The number of people changing jobs has altered over time in Sweden. Andersson and Tegsjö (2006) show that during the period 1988 to 2004 the annual share of job movers (in relation to all people employed) has varied between 8% and 16%. These fluctuations co-vary with business cycles to a large extent. During troughs mobility tends to be low because vacancies are scarce, while the opposite appears at peaks. From a European point of view Sweden is one of the countries with the highest job-moving rates. Denmark, Finland and the Netherlands show similar levels, whereas many countries in southern Europe (e.g. Portugal, Greece, Italy and Spain) have small flows of people changing jobs (EUROFOUND, 2006).

We have not included all job movers in our analysis, but we made a selection based on the following criteria. First of all, individuals had to meet several income and age criteria, to ensure that only job movers with an established position on the labour market were included in the analysis. Job movers had to: 1) earn more than 200 000 SEK annually, 2) be at least 25 years of age, and 3) be registered to have changed workplace identity and workplace coordinates (hectare grids) during 2001. The combination of factors in the third condition is

justified by the shortcomings of workplace identity over time. In addition, we set a fourth criterion. As mentioned in Section 2, the idea is widespread that knowledge transfers between workplaces are mainly the result of the mobility by key persons (Power and Lundmark, 2004). To accommodate this claim, a fourth criterion has been added to account for the impact of highly skilled job movers: 4) Individuals have to hold a university degree *or* be a high-income earner (belonging to the top 20 per cent). The reason for using two criteria is related to the fact that key persons do not necessarily have higher academic training, nor do they have to be high-income earners. Regarding workplaces, we chose to include all workplaces having information about sector code and value added during 2001 (256,985). In a next step, workplaces with inflows of skilled labour were selected, which resulted in a final sample amounting to 17,098 workplaces. By using only workplaces with skilled inflows, rather than all workplaces with all types of inflows, the total population of workplaces drops to 40 percent of the number of workplaces with any kind of inflow, and the number of job moves drops to 43 percent of all total job moves.

Two regional definitions of job movers were used in the study – intraregional job movers and interregional job movers. Regional refers to local labour markets (n=108) which are based on empirically observed commuting flows between municipalities (n=290) and defined by Statistics Sweden. Local labour markets are defined by amalgamating municipalities according to a specific commuting-minimising algorithm (Statistics Sweden, 1991). In comparison to using municipalities, mobility between local labour markets tends to be associated with labour market reasons to a much larger extent rather than housing considerations. Changing job to another local labour market usually involves changing place of residence and the loss of accumulated local insider advantages.

Dependent variable: Productivity Growth

This paper uses growth in labour productivity between 2001 and 2003 to measure firm performance. Since the database does not carry information on employees' hours of work, labour productivity has been defined as value added per employeeⁱⁱⁱ. Value added is chosen because of three reasons. First, and foremost, value added is the most straightforward measure on the level of industrial output (e.g. Rigby and Essletzbichler, 2002). Secondly, value added

ⁱⁱⁱ To control for part-time and increased efficiency which would have been made possible with information on hours of work, a proxy controlling for this was created. It held information on the per capita social benefits received of all employees at each workplace (including parental leave, unemployment insurances and sick-leave) which implicitly account for the relative share of absence from work during 2001 (Eriksson and Lindgren, 2008). This variable did not affect the estimates and was omitted from the final model.

is available for all firms in the dataset which makes it possible to assess the impact of job mobility on performance throughout the entire national economy and not only for certain high-tech sectors where, for instance, patents and citations are found. Third, value added tells us more about economic performance than, for instance, patents because patents do not automatically generate value added to the plant. However, value added in our dataset is reported for firms and not workplaces. For 38 percent of all firms in the data with more than one division, value added was distributed to these workplaces in the same proportion as the distribution of the sum of wages across workplaces (Victorin, 2007). Thereafter, the calculated sum of value added was divided by the number of employees of the workplace. This procedure potentially takes both education and experience into account when measuring labour productivity at the plant level. This aspect would be neglected if only distributing value added according to the workplace's share of firm employees. Finally, the level of productivity in 2001 was subtracted from the 2003 level in order to measure the degree of growth^{iv}. In the model, log values are used to reduce the impact of skewed distributions.

Independent variables

All independent variables are measured at the beginning of the period (i.e. 2001). When estimating the effects of competence portfolio and inflows of skills on firm performance, this paper employs entropy measurements similar to Frenken *et al* (2007). Since the database does not provide information on specific occupations or work-tasks within workplaces, data on educational background linked to each employee are applied^v. Based on this information, 95 different three-digit education categories, 22 two-digit categories and 9 one-digit categories were extracted on which the variables on competence portfolio are based.

We have calculated three variables to capture the competence portfolio within each workplace. First of all, we determined the degree of portfolio similarity (INHOUSE SIMA), which measures the degree of similarity as far as the educational background of all employees at the plant level is concerned. This variable is measured as the inverted entropy at the three-

^{iv} Following workplaces over time was made possible by using a unique identification number associated to each workplace. From our analysis, we excluded 3,154 workplaces that could still be identified in 2001, but which showed missing data in 2003 due to, for instance, administrative changes or close downs. All numbers were adjusted to 2001 price levels.

^v It can be argued that using educational background is not an accurate proxy for the competence level of an employee, especially for more senior workers who have acquired work-specific experience through learning-by-doing and on-the-job training during their working career. Therefore, we cannot rule out that these workers employ a work task that does not fully correspond to their formal education. It would have been better to add previous work experience of each employee, and see how similar the work experiences of all employees are at the plant level. However, the database does not provide that kind of information at the workplace level.

digit educational level. Let p_i^{III} be the share of three-digit educational background i and let N^{III} be the number of three-digit classes. The portfolio similarity is now calculated as:

$$\text{INHOUSE SIMA} = 1 / \sum_{i=1}^{N^{III}} p_i^{III} \log_2 \left(\frac{1}{p_i^{III}} \right) \quad (1)$$

The higher the score, the more similar the educational background of all employees within the plant, and the less advantageous it is assumed to be for plant performance. As explained in section 2, a high degree of portfolio similarity is not assumed to enhance interactive learning nor the creation of new knowledge within the plant, since the knowledge base is too much alike.

As noted in Section 2, we assume that the more related the set of competences within a workplace is, the more knowledge will spill over, and the higher the economic performance of the plant will be. To measure whether related, yet different competences within the workplace increase learning processes and performance, the weighted sum of entropy at the three-digit level within each two-digit education category is calculated. Doing so, we expect employees with a similar educational background at the two-digit digit level (*e.g.* an university degree in chemistry) to understand each other, but it requires variety at the three-digit level within that two-digit level (*i.e.* many employees with university degrees in different sub-categories of chemistry) to induce real learning processes at the plant level. As a consequence, the more variety at the three-digit level within that two-digit level, the more real learning opportunities there are, and the more the plant will benefit from such a set of different (but related, not similar) competences. Following Frenken *et al.* (2007), we have calculated related variety at the plant level as follows. All three-digit educational backgrounds S_i^{III} belong to a two-digit category S_j^{II} , where $j=1, \dots, N^{II}$. Therefore, we can derive the two-digit shares p_j^{II} by summing the shares of all three-digit education categories belonging to S_j^{II} :

$$p_j^{II} = \sum_{i \in S_j^{II}} p_i^{III} \quad (2)$$

Related variety (INHOUSE RELVAR) is now defined as the weighted sum of entropy within each two-digit education category. Log values of related variety were used in the analysis due to problems of skewness. This is given by:

$$\text{INHOUSE RELVAR} = \sum_{j=1}^{N''} p_j'' H_j \quad (3)$$

where:

$$H_j = \sum_{i \in S_j''} \frac{p_i'''}{p_j''} \log_2 \left(\frac{1}{p_i''' / p_j''} \right) \quad (4)$$

We also calculated a variable capturing whether or not a workplace is characterised by very different types of competences, since it is assumed that a portfolio of very different competences will hinder interactive learning processes, due to problems of communication and, therefore, will have a negative effect on plant performance. The degree of unrelatedness within the plant (INHOUSE UNRELVAR) is measured as the entropy at the one-digit level. A high variety of educational backgrounds at the one-digit level means a plant employs workers with very different educational backgrounds. Because of the decomposable nature of the entropy measure differentiating variety at various digit levels, this variable should not be interpreted as the inverse of the INHOUSE SIMA variable (see for more details Frenken, 2007). Let p_i^I be the share of one-digit education category $S_i^I \in S_1^I, \dots, S_{N'}^I$. We now get:

$$\text{INHOUSE UNRELVAR} = \sum_{l=1}^{N'} p_l^I \log_2 \left(\frac{1}{p_l^I} \right) \quad (5)$$

where the higher the score, the more unrelated the skill portfolio of the plant is.

Besides estimating the effect of the competence portfolio within workplaces, we will assess the inflow of new skills through labour mobility. As set out in Section 2, too much reliance on intra-firm competences may harm the performance of workplaces, making inflows of new skills essential in order to avoid lock-in. Therefore, additional variables are created to capture the effects of skilled inflows. Rather than using educational background as for the measurements for competence portfolio, our data allow us to create inflow-variables based on

sector-specific (SNI-codes) work experience at the five-digit level (in total 753 different five-digit categories nested within 224 different three-digit categories). The argument for using this kind of information, rather than educational data, is that sector-specific work experience measures both work- and branch-specific skills in a better way than formal education, and therefore also more efficiently captures the transfer of both formal (via the sampling procedure) and informal (industrial sector) skills. It should be noted that the database does only provide information on the main output for each workplace, whereby workplaces have only one single five-digit sector code. Hence, it is not possible to use entropy measures when estimating inflows at the level of the workplace. However, by comparing the background of the new employees and summarising the total number of different types of inflows, it is possible to retrieve information on which type of extra-firm inflows increase plant performance.

Relating to the variables on skill portfolio, a total of nine variables measuring the similarity, relatedness and unrelatedness of inflows are created. In order to assess the overall impact of the different types of skill inflows, three variables measure the total number of inflows, irrespective of the spatial scale of job moves. The degree of similar inflows is measured as the total number of inflows originating from the same five-digit industrial-code, while the related inflows are defined as the number of new employees from the same three-digit code, excluding the inflows from the same five-digit code (i.e. similar). Finally, unrelated inflows are defined as the number of employees with a background in all other five-digit industries. As explained in Section 2, inflows similar to what is already inhouse will make the workplace capable of absorbing the new knowledge, but such inflows will not add to the already existing knowledge base. Consequently, we assume that a high degree of similar inflows will not increase the performance of workplaces. On the other hand, a high degree of related - but not similar - inflows is assumed to complement the existing knowledge base, increase learning opportunities within the workplace and thus positively contribute to performance. Our final assumption is that a high degree of unrelated inflows, as compared to the workplace, will neither add new knowledge, nor contribute to higher performance because the cognitive distance between the existing knowledge base and the knowledge of the new employee will be too far apart and therefore causes problems of communication.

Dependent on the geographical scale, different types of labour inflows may have different effects on firm performance. As noted in Section 2, there is literature arguing that extra-local flows of knowledge are crucial, since too much reliance on local knowledge flows may result in lock-in. Therefore, we constructed variables to differentiate between

geographically proximate labour inflows (intra-regional) and geographically distant labour inflows (inter-regional). Based on the discussions in Section 2, we expect that geographically proximate inflows of similar skills might have a more severe effect on the problem of cognitive lock-in, as compared to inflows of new employees with similar skills recruited in other regions, because persons coming from other regions may bring new place-specific resources into the new region. The problem of lock-in due to geographical proximity will, however, not be evident for related inflows, as we expect these inflows to be complementary to the existing knowledge base and to increase the performance of plants. Thus, we assume this type of inflows will have a particularly strong effect in combination with geographical proximity, as compared to inflows over larger distances. We also expect that the problem of communication associated with inflows of unrelated skills might be reduced if the new employees are from the same region. By constructing six additional variables separating inflows from within the same local labour market region (intra-regional job changes) from those outside the same local labour market (inter-regional job changes), we open up the possibility of carrying out detailed analyses on the effects of geographical proximity in relation to the variation of skill inflows. In the analyses, log values on all inflows are used.

Control Variables

In line with previous studies on labour productivity at the plant level (see e.g. Haltiwanger *et al.*, 1999; Rigby and Essletzbichler, 2002), variables that control for other co-explaining determinants of productivity, like industry and plant size, are accounted for in the models (see Table 1 for further information on the estimated variables). In order to control for industry-specific effects among the 753 industries included in the analysis, nine dummy variables were created (definition produced by the Swedish Business Development Agency; NUTEK, 2000). In summary, all industries were first defined as being capital-, knowledge- or labour intensive based on their relative use of production factors. Thereafter these sectors were labelled either manufacturing or service oriented based on information about their unique SNI-code. Finally, the identified knowledge-based service sector was further divided into three new categories to differentiate between R&D, finance-oriented service and the public sector. This procedure thus allows us not only to control for whether plants belong to the manufacturing or service sector but also for the relative use of production factors within each type of sector. All dummies are compared to the finance sector in the analyses. Two further controllers concerned the size of the plant and the size of the region. We expect large plants to show higher levels of productivity, but it is not expected that they show as high levels of relative

productivity growth as smaller firms. In general, we expect plants in larger urban areas to perform better than those located in more sparsely populated regions. To assess more carefully the effects of competence portfolios and variety of labour inflows on productivity growth, control variables for the general educational level of the plants and the number of labour inflows of each plant were also included in our estimations. It should be noted that we also included controllers for workforce characteristics (age- and gender-composition) and for the number of workplaces within the same firm, since one could expect these factors would both influence productivity growth as well as the number and variety of labour inflows. However, neither of these did affect our key variables, nor had they any major effect on productivity growth, whereby they were excluded from the final models.

- Table 1 -

Despite the evident risks of multicollinearity related to this kind of analyses, no serious multicollinearity problems have occurred^{vi}.

The analytical model

For the empirical analysis, ordinary least-squares (OLS) models have been applied. As explained above, since the main focus of this paper is to assess how a diverse set of skill inflows impacts on plant performance, the models only include workplaces with registered inflows of highly educated or high income earners, because it is more likely that knowledge transfer actually does occur via the mobility of skilled personnel (Power and Lundmark, 2004). In addition, we have conducted an additional variance analysis (ANOVA) to assess the partial effect of each covariate on productivity growth (Rogerson, 2006). The partial sums of squares (S.S.) indicate the relative effect each variable has on plant performance, and not only the sign and level of significance of each variable.

Despite the large and increasing share of small firms since the 1980s, the Swedish economy is typically characterised by large and old firms. These employ a majority of the labour force (in this sample, five per cent of all workplaces employ 49 per cent of all employees) and also stand for the lion's share of total productivity (Andersson, 2006). In

^{vi} For example, the highest obtained correlation significant at the 5% level was between INTRA and INTER INFLOW RELVAR and between INTRA and INTER INFLOW UNRELVAR in Model D2, with a correlation of 0.74 and 0.73 respectively. If omitting any of the correlated variables from the model, the estimates indicate robustness since neither the signs nor the level of significance of these variables is affected.

order to reduce the disproportionately large impact of all the small workplaces and to make the entropy-calculations more robust, all models have been weighted on employment size. This gives larger workplaces a more proportional share of the total explained variance and also gives us more robust entropy calculations since the variation within workplaces with only one or a few employees otherwise would be exaggerated.

4. Empirical results

The effects of competence portfolios on productivity growth between 2001 and 2003 have been estimated on 17,098 workplaces. Additionally, a total of 101,093 job moves – of which nearly 40% were interregional – have been used to calculate the effects of job mobility on productivity growth for the same workplaces. All independent variables are measured at the beginning of the observed period (2001). We expect that the effects of variables like labour mobility will only materialize at the plant level after some years. That is why we have taken productivity growth 2001-2003 as the dependent variable.

The effects of plant characteristics and the level and nature of formal education on productivity growth of plants are displayed in Table 2. Model A shows the outcomes of a model that only contains the control variables common to this type of analysis. The outcomes are in line with expectations. Plant size has by far the greatest effect on productivity growth: small plants show relative higher levels of productivity growth than larger ones. Compared to the finance sector, more capital- and labour-intensive industries as well as R&D-oriented activities show lower degrees of productivity growth^{vii}. Plants located in regions with a higher urban size show higher productivity growth than plants in smaller regions. Despite the high degree of unobserved heterogeneity usually involved when modelling large sets of micro data, the original model fits the data well, with an R^2 indicating that the model explains about 63% of the total variance. In addition, the estimates on all control variables, except the dummy-variables for service sectors and other capital intensive industries in Model B1, remain consistent when adding variables on competence portfolio and skill inflows^{viii}.

^{vii} The relatively weak growth rates in the R&D sector as compared to the finance sector during this period can be explained by a number of factors. For instance, a depression that hit the Swedish economy during this period may have had a greater influence on R&D activities than on the finance sector. Another issue could be differences in output between different sectors as R&D units are likely to capitalise their innovations in different ways than, for instance, manufacturing units.

^{viii} These variables are significant only in Model B1 when controlling for high education ratio. This may be attributed to the fact that the share of highly educated and/or high income earners is relatively low in these sectors which may affect the score when not explicitly controlling for educational level

- Table 2 -

In Models B1 and B2, we assess the economic impact of educational level and competence portfolios of plants. Model B1 shows that a higher educational level of the workforce within plants promotes productivity growth. When differentiating education in Model B2, we observe that this effect depends on the nature of the competence portfolio of plants. As expected, plant performance benefits from a high degree of relatedness in their set of competences. However, a portfolio consisting largely of exactly the same competences, or a portfolio consisting of a set of competences without much coherence do not appear to affect plant performance. These estimates reveal the importance of complementary competences within plants for their performance. What is also encouraging is that these results on competence portfolios remain consistent as we add variables on labour mobility.

In Table 3, we assess the impact of labour mobility on productivity growth. In Model C1, we first show the general effect of labour inflows on plant performance, while in Model C2, we differentiate between different types of skills. Model C1 shows that labour inflows in general have a negative impact on productivity growth of plants. This stands in contrast to the literature that emphasizes the crucial importance of mobility of skilled labour for firm performance. However, we argued in Section 2 that not labour mobility *per se* would matter for performance, but that it would depend on the types of skills that flow into the plant. The outcomes of Model C2 confirm that it is crucial to differentiate between types of skill inflows when assessing the effect of labour mobility on plant performance. As expected, inflows of related skills have a significant positive effect on the performance of plants, while inflows of identical skills have a significant negative effect. Apparently, the inflow of new skills should be related, but not similar to the existing knowledge base of the plant to have a positive economic effect. Comparing models C1 and C2, our results suggest that many plants are hiring employees with similar skills, despite the fact that it lowers their plant performance. For inflows of unrelated skills, the outcome in Model C2 suggests that the cognitive distance seems to be too large to have any significant effect on plant performance. Because the new employees have working experience in sectors that are very different from the sector the plant is specialised in, it is plausible that the plant cannot easily absorb the incoming knowledge, and therefore is unlikely to benefit from it.

- Table 3 -

In the final two models D1 and D2, we assess the relevance of geographical proximity when estimating the effects of different types of skill inflows. Once again, the positive effects of labour mobility on productivity growth of plants become visible only after differentiating between different types of labour inflows, in this case depending on whether new employees are recruited from the same region or from other regions. As Model D1 shows, intra-regional inflows of labour do not have a significant impact on plant performance, despite the general claim in the literature that it should. In a study on Finnish high-technology industries, McCann and Simonen (2005) even found that local labour mobility had a negative effect on innovative performance. Inter-regional inflows of labour have a damaging effect on productivity growth, as the negative and significant coefficient of INTER INFLOWS in Model D1 indicates. However, when we differentiate between different types of labour mobility (intra- versus inter-regional), the outcomes look different.

We observed earlier that inflows of similar skills in general harm the performance of plants. This remains true for both intra-regional and inter-regional inflows, as Model D2 shows. While the coefficient of intra-regional labour inflows (INTRA INFLOW) is still positive (though not significant), it turns into a negative and significant effect when it concerns new employees recruited from the same sector (INTRA INFLOW SIMA). This stands in contrast to intra-regional inflows of new employees with related skills and unrelated skills, which positively impact on plant performance. We also expected that the problem of lock-in would be reduced when new employees with similar skills are recruited from other regions, because these might bring in different place-specific attitudes. However, our analyses show otherwise: this type of labour mobility (INTER INFLOW SIMA) has even a slightly stronger negative effect than the type of labour mobility that concerns inflows of people with similar skills from the same region (INTRA INFLOW SIMA).

We demonstrated earlier that inflows of unrelated skills in general do not influence productivity growth, but when we account for their geographical origin, a different picture emerges. In line with our expectations, we find that the inflow of unrelated skills turns into a positive and significant effect when these concern intra-regional inflows, as compared to more geographically distant inflows of labour. Even though recruited from totally different sectors, these new employees are likely to share the same place-specific attitudes as the existing work force of their new employer, which may have enhanced their integration. In contrast, the effect of inflows of unrelated skills becomes negative and significant when these concerns employees from different regions (INTER INFLOW UNRELVAR). This comes as

no surprise, because this type of labour mobility represents two types of distance (i.e. cognitive and geographical distance) that may cause insurmountable problems of communication, and which prevent this type of labour mobility to contribute positively to plant performance (Boschma, 2005).

A very consistent outcome of model D2 is that the effect of inflows of related skills remains positive and significant, no matter whether the new employees with related skills are recruited from the same region or from other regions. What is more, this type of labour mobility is the only type that turns the negative impact of inter-regional inflows (INTER INFLOWS) into a positive effect. This is a very robust result, which indicates that labour mobility as such does not positively impact on plant performance, unless it concerns inflows of skills that are complementary to the plant. In Section 2, we expected that inter-regional inflows of labour would help plants to get access to new resources. Our results indicate that inflows of employees from different regions only have a positive impact on plant performance when these concerns employees with complementary skills.

It should be noted that our analyses also show that inflows of skills as such have only a marginal effect on plant performance. This is displayed by the moderate increase in R^2 as compared to Models A to B2 that only assessed the effect of plant characteristics. The moderate effects of labour mobility are though in line with previous empirical findings on the relation between job mobility and productivity in Sweden: more traditional agglomerative effects internal to the workplace affect productivity the most (Eriksson and Lindgren, 2008).

5. Conclusions

We have made an attempt to estimate the impact of skill portfolios and different types of labour mobility on productivity growth of plants by means of a unique database for the whole Swedish economy. Besides the usual control variables, our analysis of 101,093 job moves accounted for: (1) the set of competences that is present at the plant level; (2) the types of skills that are brought into the plant by new employees, and the extent to which these newly recruited skills add to the existing knowledge base of the plant; and (3) whether these inflows concern intra-regional or inter-regional labour mobility. Doing so, we were able to demonstrate that the effects of labour mobility on firm performance can only be accounted for after differentiating between different types of labour inflows. Our empirical results showed that labour mobility *per se* does not positively impact on plant performance, despite the many claims in the literature, but that it depends on the types of skills that flow into the plant, and on whether new employees are recruited from the same region or from other regions.

At the intra-plant level, we found that a portfolio of related competences goes together with higher productivity growth of plants, in contrast to plant portfolios that merely consist of a set of similar competences or a set of unrelated competences. We found a very moderate effect of labour mobility on plant productivity growth in general. Nevertheless, as expected, related skill inflows had a positive effect on the performance of plants, while the inflow of similar skills had a negative impact. With respect to the inflow of unrelated skills, the outcomes suggest that the cognitive distance is too large between these newly recruited skills and the knowledge base of the plant to have any significant impact on plant performance. Our analyses also showed that geography matters when assessing the effects of different types of labour mobility. Inflows of unrelated skills only contributed positively to plant performance when these are recruited in the same region. This is in line with expectations, because the problem of communication is more likely to increase when unrelated skills are recruited from other regions. We also found that labour mobility across regions only has a positive effect on productivity growth of plants when this concerns new employees with related skills.

There is still much room for further advancement in this field of research. It would be interesting to focus more on particular clusters, in order to examine whether labour mobility is indeed a driving force of clusters, and to assess the relative importance of extra-firm linkages for the performance of cluster firms, as compared to the internal skill portfolio of firms. We would also like to explore more in detail what kinds of extra-regional linkages are required to enhance firm performance. In addition, instead of doing a cross-section of plants, a more dynamic approach could investigate how the skill portfolios of plants change over time due to labour mobility, and how that affects plant performance. Moreover, there is a need to account for the social dimension of labour mobility, and how that affects plant performance (Breschi and Lissoni, 2003; Agrawal et al., 2006; Timmermans, 2008). A next step to take is to determine the degree of social and geographical proximity of each plant based on their labour market flows, and how that impacts on their performance. Finally, we would like to refine our relatedness indicator, which is now based on predefined and static SIC codes. An option is to determine which combinations of skills occur most frequently in people and plants, in order to obtain a measure of revealed relatedness (Neffke and Svensson-Henning 2008).

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Table 1: Variable description (n=17,098)

Variable		Mean	S.D.	Min	Max
Productivity Growth (log)	Change labour productivity 2001-2003 (log)	-4.7	1.7	-13.5	5.9
Tot. Inflow Sima (log)	Number of total inflows from similar workplaces (log)	0.8	1.3	0.0	5.3
Tot. Inflow RelVar (log)	Number of total inflows from related workplaces (log)	0.2	0.6	0.0	3.6
Tot. Inflow UnrelVar (log)	Number of total inflows from unrelated workplaces (log)	1.4	1.5	0.0	5.7
Tot. Inflows (log)	Total number of inflows (log)	2.6	1.6	0.0	6.3
Intra Inflow Sima (log)	Number of intra-regional inflows from similar workplaces (log)	0.5	1.2	0.0	5.3
Intra Inflow RelVar (log)	Number of intra-regional inflows from related workplaces (log)	0.1	0.5	0.0	3.6
Intra Inflow UnrelVar (log)	Number of intra-regional inflows from unrelated workplaces (log)	1.1	1.4	0.0	5.7
Inter Inflow Sima (log)	Number of inter-regional inflows from similar workplaces (log)	0.4	0.9	0.0	4.2
Inter Inflow RelVar (log)	Number of inter-regional inflows from related workplaces (log)	0.1	0.3	0.0	3.5
Inter Inflow UnrelVar (log)	Number of inter-regional inflows from unrelated workplaces (log)	0.7	1.1	0.0	4.7
Tot. Intra Inflows (log)	Total number of intra-regional inflows (log)	2.1	1.6	0.0	6.2
Tot. Inter Inflows (log)	Total number of inter-regional inflows (log)	1.4	1.4	0.0	5.5
Inhouse Sima	Degree of similar skills within workplaces	0.3	0.3	0.0	5.8
Inhouse RelVar (log)	Degree of related skills within workplaces (log)	2.5	2.6	0.0	7.1
Inhouse UnrelVar	Degree of unrelated skills within workplaces	1.2	0.3	0.0	2.0
High Educ Ratio	Share of employees with a bachelor degree or higher	0.3	0.2	0.0	1.0
Capital Manu	Dummy =1 if workplace is defined as capital intense manufacturing	0.1	0.2	0.0	1.0
Labour Manu	Dummy =1 if workplace is defined as labour intense manufacturing	0.1	0.3	0.0	1.0
Know Manu	Dummy =1 if workplace is defined as knowledge intense manufacturing	0.3	0.5	0.0	1.0
R&D	Dummy =1 if workplace is defined as R&D unit	0.0	0.1	0.0	1.0
Finance	Dummy =1 if workplace is defined as finance industry or financial service (base)	0.3	0.5	0.0	1.0
Public	Dummy =1 if workplace is defined as public sector	0.1	0.3	0.0	1.0
Capital Service	Dummy =1 if workplace is defined as capital intense service	0.1	0.3	0.0	1.0
Labour Service	Dummy =1 if workplace is defined as labour intense service	0.2	0.4	0.0	1.0
Other capital	Dummy =1 if workplace is defined as other capital intense industry	0.0	0.2	0.0	1.0
Plant Size (log)	Number of employees within plant (log)	4.9	1.7	0.0	8.5
Urban Size (log)	Number of plants within labour market (log)	7.5	1.8	1.6	9.4

Table 2: OLS-regressions on the effects of plant characteristics on productivity growth (2001-2003) for all workplaces with inflows of skilled personnel 2001. An additional effect-analysis (ANOVA) displays the partial sum of squares (S.S.) for each covariate. All estimates are weighted on employment size and estimated in STATA9

Productivity Growth	<u>MODEL A</u>				<u>MODEL B1</u>				<u>MODEL B2</u>			
	Coef	S.E.	P>t	S.S.	Coef	S.E.	P>t	S.S.	Coef	S.E.	P>t	S.S.
Inhouse Sima									0.007	0.032	0.837	0
Inhouse RelVar (log)									0.016	0.004	0.000	15
Inhouse UnrelVar									-0.030	0.026	0.252	1
High Educ Ratio					0.374	0.044	0.000	75				
Capital Manu	-0.519	0.041	0.000	163	-0.412	0.043	0.000	94	-0.543	0.042	0.000	176
Labour Manu	-0.417	0.033	0.000	169	-0.299	0.035	0.000	74	-0.420	0.033	0.000	168
Know Manu	-0.594	0.027	0.000	514	-0.514	0.028	0.000	341	-0.596	0.027	0.000	517
R&D	-1.185	0.073	0.000	275	-1.229	0.073	0.000	294	-1.199	0.073	0.000	281
Public	-0.186	0.034	0.000	31	-0.193	0.034	0.000	34	-0.199	0.034	0.000	36
Capital Service	0.007	0.032	0.826	0	0.121	0.035	0.000	13	0.014	0.032	0.675	0
Labour Service	0.005	0.027	0.848	0	0.111	0.029	0.000	15	0.002	0.027	0.947	0
Other capital	-0.002	0.054	0.975	0	0.056	0.055	0.306	1	-0.018	0.055	0.741	0
Plant Size (log)	-0.675	0.005	0.000	16666	-0.676	0.005	0.000	16726	-0.683	0.006	0.000	12654
Urban Size (log)	0.074	0.005	0.000	234	0.063	0.005	0.000	155	0.073	0.005	0.000	223
Intercept	-1.640	0.047	0.000		-1.714	0.047	0.000		-1.592	0.054	0.000	
R ²		0.634				0.635				0.634		
Adj R ²		0.634				0.635				0.634		
N		17 098				17 098				17 098		

Table 3: OLS-regressions on the effects of labour mobility on productivity growth (2001-2003) for all workplaces with inflows of skilled personnel 2001. An additional effect-analysis (ANOVA) displays the partial sum of squares (S.S.) for each covariate. All estimates are weighted on employment size and estimated in STATA9

Productivity Growth	<u>MODEL C1</u>				<u>MODEL C2</u>				<u>MODEL D1</u>				<u>MODEL D2</u>			
	Coef.	S.E.	P>t	S.S.	Coef.	S.E.	P>t	S.S.	Coef.	S.E.	P>t	S.S.	Coef.	S.E.	P>t	S.S.
Tot. Inflow Sima (log)					-0.038	0.009	0.000	18								
Tot. Inflow RelVar (log)					0.179	0.017	0.000	114								
Tot. Inflow UnrelVar (log)					-0.004	0.009	0.628	0								
Tot. Inflows (log)	-0.029	0.009	0.001	11												
Intra Inflow Sima (log)													-0.037	0.010	0.000	9
Intra Inflow RelVar (log)													0.133	0.026	0.000	27
Intra Inflow UnrelVar(log)													0.070	0.011	0.000	35
Inter Inflow Sima (log)													-0.059	0.013	0.000	28
Inter Inflow RelVar (log)													0.145	0.036	0.000	10
Inter Inflow UnrelVar(log)													-0.079	0.012	0.000	59
Tot. Intra Inflows (log)									0.004	0.009	0.609	0				
Tot. Inter Inflows (log)									-0.042	0.009	0.000	23				
Inhouse Sima	0.003	0.032	0.924	0	0.015	0.032	0.643	0	0.003	0.032	0.919	0	0.019	0.032	0.545	0
Inhouse RelVar (log)	0.016	0.004	0.000	15	0.013	0.004	0.002	10	0.018	0.004	0.000	17	0.012	0.004	0.005	47
Inhouse UnrelVar	-0.032	0.026	0.232	1	-0.019	0.027	0.470	1	-0.037	0.026	0.164	2	-0.026	0.027	0.328	1
Capital Manu	-0.571	0.043	0.000	187	-0.532	0.043	0.000	158	-0.582	0.043	0.000	192	-0.535	0.043	0.000	173
Labour Manu	-0.434	0.033	0.000	177	-0.415	0.034	0.000	158	-0.437	0.033	0.000	179	-0.415	0.033	0.000	163
Know Manu	-0.610	0.027	0.000	527	-0.558	0.027	0.000	431	-0.607	0.027	0.000	525	-0.548	0.027	0.000	434
R&D	-1.196	0.073	0.000	279	-1.131	0.073	0.000	247	-1.212	0.073	0.000	286	-1.198	0.074	0.000	271
Public	-0.198	0.034	0.000	35	-0.301	0.036	0.000	74	-0.192	0.034	0.000	33	-0.286	0.036	0.000	68
Capital Service	0.010	0.032	0.747	0	0.029	0.033	0.380	1	-0.003	0.033	0.927	0	0.025	0.033	0.439	0
Labour Service	-0.002	0.027	0.933	0	0.004	0.027	0.896	0	-0.002	0.027	0.929	0	0.008	0.027	0.773	0
Other capital	-0.030	0.055	0.582	0	0.007	0.055	0.896	0	-0.033	0.055	0.549	0	0.008	0.055	0.880	0
Plant Size (log)	-0.661	0.009	0.000	5295	-0.685	0.009	0.000	6634	-0.661	0.010	0.000	5013	-0.679	0.008	0.000	7152
Urban Size (log)	0.079	0.005	0.000	231	0.075	0.005	0.000	203	0.071	0.006	0.000	152	0.061	0.006	0.000	104
Intercept	-1.658	0.058	0.000		-1.610	0.059	0.000		-1.619	0.062	0.000		-1.528	0.061	0.000	
R ²		0.635				0.637				0.635				0.638		
Adj R ²		0.634				0.636				0.635				0.638		
N		17 098				17 098				17 098				17 098		