Labor Mobility and Patenting Activity[¶]

Ulrich Kaiser[*], Hans Christian Kongsted[**], and Thomas Rønde[‖]

This version: June 10, 2008

Abstract

We use data on all applications of Danish firms at the European Patent Office (EPO) to measure the quantitative importance of labor mobility as a vehicle for the transmission of knowledge across firms. Combining linked employer-employee register data with EPO data we show that an R&D worker's patent productivity will depend significantly on having been exposed previously to patenting as well as her status as a joiner or a stayer in her current firm. Our empirical approach takes into account dynamics and unobserved firm heterogeneity applying the "Pre-Sample Mean Estimator" due to Blundell et al. (1995).

[¶]Financial support from the Danish Social Science Research Council (Forskningsrådet for Samfund og Erhverv) for the research project "Human Capital, Patenting Activity, and Technology Spillovers" is gratefully acknowledged. We are indebted to Steffen Rebien and Jens Peter Schougaard of the Danish Patent and Trademark Office for providing us with the EPO data and for sharing their data expertise with us and to Cédric Schneider for sending us a ready–to–use patent citations database. We gratefully acknowledge helpful comments received at workshops hosted by the Centre for Industrial Economics workshop and the Centre for Business and Economic Research. We particularly benefited from comments by Luigi Fanzoni, Patrick Legros, Katharine Rocket, Cédric Schneider, Frederick Schmidt and Rainer Winkelmann. Finally, we thank our student assistants Marie Ebbensgaard, Søren M. Johansen, Simon Lamech and Andreas Sloth for competent research assistance.

[*]University of Southern Denmark at Odense, Dept. of Business and Economics, Campusvej 55, 5230 Odense M, Denmark, email: uka@sam.sdu.dk; Centre for Economic and Business Research at Copenhagen Business School, Centre for Industrial Economics at the University of Copenhagen and Centre for European Economic Research, Mannheim.

[**]University of Copenhagen, Dept. of Economics, Studiestræde 6, 1455 Copenhagen K, Denmark, email: hans.christian.kongsted@econ.ku.dk; Centre for Economic and Business Research at Copenhagen Business School, Centre for Industrial Economics at the University of Copenhagen and Centre for Applied Microeconometrics (CAM), Copenhagen.

[‖]University of Copenhagen, Dept. of Economics, Studiestræde 6, 1455 Copenhagen K, Denmark, email: thomas.ronde@econ.ku.dk; Centre for Economic and Business Research at Copenhagen Business School, Centre for European Economic Research, Mannheim, Centre for Industrial Economics at the University of Copenhagen and Centre for Economic Policy Research, London.

JEL-classification: O33, O34, C23
Keywords: labor mobility, dynamic count data, patents

> "A major unresolved issue in the area of economics of technology is the identification and measurement of R&D spillovers, the benefits that one company receives from R&D activity of another." (Griliches, 1990, p. 1,688)

1 Introduction

Knowledge is one of the main sources of competitive advantage (Kogut and Zander, 1992; Teece, Pisano and Shuen, 1997). Part of this knowledge is not codified in formal documents protected by intellectual property rights, but resides in the people working in the organization (Argote and Ingram, 2000; Zucker, Darby and Brewer, 1998). Mobility represents both a threat and an opportunity to firms. Valuable knowledge that complements and strengthens the firm's resources can be acquired by hiring people from the outside. At the same time, trade secrets leak and tacit knowledge is lost when people leave, eroding the firm's competitive advantage (Mansfield, 1982).

In this paper we look at mobility between firms involved in R&D activities. The knowledge resulting from R&D is argued to have two distinct features. First, it is often general in the sense that it can be applied in different industries (Song, Almeida and Wu, 2003). Second, it is, at least partly, non-rival and can be used by many firms at the same time (Arrow, 1962; David, 1992). Inter-firm mobility is one of the mechanisms through which firms can share knowledge. Since persons primarily move between firms in their local area, it also provides a link between competitive advantage at the firm level and at the regional level. Consistent with this view, Saxenian (1994) and Almeida and Kogut (1999) have documented how engineers and technical workers in Silicon Valley change jobs repeatedly contributing to knowledge sharing and rapid technological progress.

Several recent papers have studied mobility in the financial services sector where long time-series on mobility have been collected. It has been shown that mutual funds acquire the necessary resources to introduce new products by hiring managers from the outside (Rao and Drazin, 2002) and that inflow of personnel to trading floors is associated with retention of the current organization in the foreign exchange industry (Madsen, Mosakowski and Zaheer, 2003). Looking at the other face of mobility, Wezel, Cattani and Pennings (2006) study the transfer of higher-order routines in the accounting industry and show that joint exit by a group is more likely to cause the dissolution of a partnership than individual exit.

Analysis of mobility in R&D intensive industries has been somewhat hampered by the lack of data on individual mobility. An exception is Boeker

(1997) who studies executive mobility and strategic redirection in the semiconductor industry. He shows that the hiring of a new manager is associated with an increase in the likelihood of entering into a product market in which the manager has previous experience. Progress has also been made in recent papers that analyze the effects of mobility on innovation. Song, Almeida and Wu (2003) employ the information in patent files to track the mobility of inventors. They study mobility within and across industries and technology classes and use patent citations to explore the conditions under which hiring results in knowledge acquisition for the new employer. Hoisl (2007) combines data on mobility from patent files with background information about the inventors from questionnaires. She shows that mobile inventors are on average more productive and that mobility is productivity enhancing.

Although the abovementioned studies provide interesting insights regarding mobility and its effects on innovation, using patent files to trace mobility has a major weakness: only moves by inventors that result in a patent at the new employer (successful moves) are registered whereas moves that do not result in a patent (unsuccessful moves) are not. Thus, the factors that characterize successful moves or successful inventors can be identified, but it is not possible to measure the relation between mobility and expected firm-level patenting activity. This obviously limits the conclusions that can be drawn from the studies. After all, hiring can only be a source of competitive advantage if it increases significantly the likelihood of success, here measured by patenting activity, for the acquiring firm.

We make use of a similar measure of R&D output, patent applications by Danish firms to the European Patent Office. This is combined with matched employer-employee register data that contains balance sheet information and detailed information on employee characteristics. The dataset is unique in that it contains an essentially complete record of mobility in the Danish labor market, thereby avoiding the problem of unobserved moves.

A potential drawback of our dataset is that we cannot identify the individual inventor(s) as specified in the patent file. Our empirical approach consists instead in identifying a group of persons who are likely to possess valuable knowledge and to measure whether their movements between firms contribute to explaining firm-level patenting activity. Specifically, a firm's work force is split into "R&D workers" and "non R&D workers" defined according to the level and the subject of the highest education obtained. Persons with a bachelor's or a master's degree in natural sciences will, e.g., be classified as R&D workers, persons with the same level of education but from humanities will be termed non R&D workers. An advantage of our approach is that we can compare the effects of mobility among different types of workers. Since the previous literature has focused solely on the formal inventors, but other persons might have been involved in the R&D process or have had access to the fruits of it, these results are of independent interest. We are also able to divide workers along a second dimension, "patent exposure", which indicate recent experience working for a R&D active firm. A person is "patent exposed" if the firm she was employed the period before applied for a patent in that period. Otherwise, she is "non patent exposed".

The aim of the paper is to analyze the effects of mobility on innovation. A third and final dimension is therefore introduced in order to keep track of mobility. A person belongs to one of the following groups: "stayers" (worked in the firm in the previous period), "joiners" (joined the firm this period), "leavers" (left the firm after the previous period), or "unknown" (entered the Danish labor market this period).

Considering all three dimensions, there are 14 different types of workers (people with unknown previous employer cannot be classified by exposure). In our empirical analysis we estimate the effect of different types of workers on firms' patenting activity. A first set of hypotheses concerns the contribution to patenting activity of R&D/non R&D workers and of patent exposed/non patent exposed workers. Our prior belief, which is confirmed by the results, is that patent exposed R&D workers contribute the most to patenting activity due to their education and experience working in a R&D active firm. A second set of hypotheses concerns hiring as a source of knowledge acquisition. We compare therefore joiners and stayers. Overall, we find that joiners contribute more to patent activity than stayers; a result consistent with the proposition that hiring is used strategically to acquire knowledge.

The literature proposing mobility as a source of knowledge sharing among firms has as underlying premise that the donor firm loses less than the recipient firm gains when a person switches employer. In spite of the great attention that this idea and its implications for regional development have received, we are not aware of any attempts to validate this crucial assumption. The third set of hypotheses compares therefore the effects of joiners and of leavers on patenting activity. Our results show evidence that mobility is indeed efficiency enhancing for R&D workers. For example, the positive effect of an increase in the share of R&D joiners with exposure is (in absolute terms) more than double the negative effect of a similar increase in the number of R&D leavers with exposure. For non R&D workers, we find mixed evidence on this hypothesis.

The rest of the paper is organized as follows. The next section details the hypotheses tested and the theory underlying them. Section 3 describes the data and outlines the definitions used in the analysis. Section 4 characterizes the econometric approach and section 5 provides some descriptive statistics. The main results are reported in section 6 whereas section 7 provides some robustness checks (to be added). Finally, section 8 concludes.

2 Theory and hypotheses

2.1 R&D vs. non R&D workers

Our empirical approach assumes that it is possible to use educational attainment to identify the persons that play a central role in the producing of patentable inventions. Our definitions of R&D workers and non R&D workers are in accordance with survey evidence on the education of inventors in Denmark (Kaiser, 2006). Still, an important consistency check for our empirical analysis is that R&D workers contribute more to the production of patentable inventions than non R&D workers. Our first set of hypotheses states as follows:

1a. R&D joiners contribute more to patenting activity than non R&D joiners.

1b. R&D stayers contribute more to patenting activity than non R&D stayers.

2.2 Patent exposure vs. non-exposure

There is evidence from questionnaries indicating that mobility is an important source of knowledge transfers between firms (Mansfield, 1985; Zander and Kogut, 1995). Almeida and Kogut (1999) provide more evidence pointing in this direction by showing that firms tend to cite other local firms more often in their patents applications in regions with high labor mobility.

The variable "patent exposure" captures whether a person has recent experience working for a firm that applied for an EPO patent. One possibility is, of course, that the person was involved in the R&D process leading to that particular patent. However, it is well known that not all innovations are patented (Arundel and Kabla, 1998; Brouwer and Kleinknecht, 1999; Cohen et al., 2001) but that patents are appropriate indicators for innovative activity (Griliches, 1990). We interpret therefore the exposure variable as an indicator of recent experience working in an R&D active firm where possibilities to acquire new knowledge were present.

For joiners to a firm, these arguments suggest that persons with patent exposure will transfer more knowledge to their new employer than persons without exposure. This should, in turn, translate into a higher innovation output as measured by patent applications for the new employer acquiring the knowledge. This leads to the following hypothesis:

2a. Joiners with exposure contribute more to patenting activity than joiners without exposure.

By similar arguments, a firm's continuing workforce should become more productive if previously exposed to R&D activities within the firm. This motivates our next hypothesis:

2b. Stayers with exposure contribute more to patenting activity than stayers without exposure.

This effect contributes to the overall positive state dependence that is usually associated with the innovative process. A finding of a positive relationship between the number of exposed stayers and the strength of state dependence is suggestive that this dependence is partly embedded in the firm's labor inputs.

Cohen and Levinthal (1990) argue that individuals differ in their abilities to identify valuable knowledge, to assimilate it, and to apply it in a new context (their "absorptive capacity"). Prior knowledge and experience with problem-solving methods increase an individual's absorptive capacity. Thus, we would expect that persons with an education in a relevant field have a higher absorptive capacity and benefit more from working in a "knowledge rich" environment than persons with other types of education. This leads to the following set of hypotheses:

3a. The difference in the contribution of joiners with and without exposure is larger for R&D workers than for non R&D workers.

3b. The difference in the contribution of stayers with and without exposure is larger for R&D workers than for non R&D workers.

2.3 Joiners vs. leavers

Technology "spillovers", or knowledge externalities, play a central role in recent theories of economic growth (Romer, 1989; Aghion and Howitt, 1990). Once knowledge is created through R&D, it spills over to other firms that can use it as an input in the production of superior goods and new knowledge. Since technology spillovers tend to be localized (Audretsch and Feldman, 1996; Keller, 2004), they are a source agglomeration economies and competitive advantage at the regional level (Porter, 2000; Saxenian, 1994). These arguments rely on the non-rival nature of knowledge that allows it to be shared. The implication is that inter-firm mobility of personnel can result in a knowledge gain for the recipient firm without a similar loss for the donor firm. We will refer to this as "spillover effects".

A person's labor input has many more components than non-rival knowledge such as human capital, problem-solving capabilities, and tacit knowledge. For our purposes, the key characteristic of these other components is that they are rival in nature. They can in other words only be employed by one firm at a time. The labor market should, as any other well-functioning market, induce an efficient match between persons and firms. Individuals work in firms where they have a high productivity and leave if their labor inputs find a better use. There will thus be mobility in the labor market that are not driven by knowledge acquisition motives, but primarily serve to match the individuals' rival labor inputs to firms' demands. We will refer to this as "matching effects". This is not to say that employment relations are not discontinued for many other reasons or that the market ensures that all labor is put to its most productive use at all points in time. Still, we would expect that mobility, on average, results in a productivity increase due to matching effects.

4a. The positive effect of R&D joiners to patenting activity is larger in absolute terms than the negative effect of R&D leavers.

4b. The positive effect of non R&D joiners to patenting activity is larger in absolute terms than the negative effect of non R&D leavers.

Because we measure productivity by the firm's innovation output we expect the effect to be less strong for non R&D workers.

3 Data

Data on all patent applications to the EPO that were filed for between 1978 and 2002 by at least one applicant with Danish residency constitute the core of our data set. The "time stamp" of these patent applications is the "priority date", the date at which the invention was first filed for patent protection at the EPO or any national patent office. That date coincides with the application date at EPO if the application was sent to EPO directly and it differs if the application was first sent to a national patent office.

Our "EPO data", which is how we shall refer to it hereafter, consist of 11,784 patents in total by 2,627 unique non–private Danish applicants. Patents solely applied for by private inventors — individuals without an affiliation to a firm or corporation — are discarded from the analysis since these patents cannot be matched to our firm–level data.

The EPO data do not come with a unique firm identifying number of the kind used by Statistics Denmark, the provider of the firm–level and employee–level data. We hence, mostly manually, attached our EPO data with Statistics Denmark's firm identifiers. As described by Kaiser and Schneider (2005), we exactly matched 95 percent of all unique patent applicants. The unmatched five percent refer to firms that went out of business before 1996. The corresponding information would have been lost in our analysis anyway since our firm–level data starts in 1999 only.

Statistics Denmark provided us with firm registry data, most importantly sector affiliation and the book value of physical capital, and with registry data on employee characteristics, most importantly the number of employees and their highest level of education. Our firm–level data is available only for the years 1999 to 2002. Our control group of non–patenting firms is the universe of firms active in Denmark. We do discard, however, sectors without any EPO patent applications between 1978 and 2002. Sectors are defined according to the three digit NACE Rev. 1 industrial classification level. We "expand" our patent data such that we obtain one observation for each applicant per year. Applicants that did not file for an application at the EPO in a particular year are assigned a 0 for the number of patent applications. In a final step we merge the firm–level data with employee–level data which allows us to track the employment history of each worker across firms.

We lose some observations due to missing values, in particular due to missing values in the firm–level data. We lose the first year of observation for each firm since we use lagged explanatory and endogenous variables.

Our main estimation results are based on 206,645 firm-year observations on 90,725 unique firms. A total of 352 unique firms patented between 2000 and 2002 and the total number of patents in that period is 484.

It is well known that the distribution of the economic and technological value of patents is heavily skewed in the sense that few patents have a very high value while the bulk of patents have very little value as discussed, e.g., by Harhoff et al. (1999), Lanjouw et al. (1998), and Hall et al. (2005).

In a seminal paper in the economics of innovation literature, Trajtenberg (1990) shows that there is a close relationship between patent forward citations and the social value of the inventions in the computer tomography industry. Thus, he suggests to approximate value by the number of citations a patent receives ("forward citations") since they capture the enormous heterogeneity in the "quality" or "importance" of patents. The idea is that valuable patents receive many citations by patents that follow while invaluable patents will receive few citations or no citations at all. Like Trajtenberg (1990), we weight each patent by one plus the number of citations the patent received within a three years period after the EPO publication. Most applied researchers use a time window of five years but proceeding this way would have implied to only count a fraction of all possible citations given publication lags and given that our patent data ends in 2002.

Our patent citations data stem from the "EPO/OECD patent citations database" that is available from the OECD (Webb et al. 2005) and covers the period 1978–2006.

4 Empirical model

4.1 Framework

Our point of departure is a standard patent production function that maps innovation input into patent counts and controls for both unobserved and observed firm–specific heterogeneity. Controlling for unobserved heterogeneity is likely important since two firms, although alike in all observable characteristics, could well produce a different number of patents on average over extended periods due to e.g. differences in management ability or historic factors that are not well captured by our explanatory variables.

Given that innovation is an inherently dynamic process, we also account for possible state dependence in patenting activity: past patenting activity is very likely to having a positive impact on current patenting activity.

4.2 Human capital variables

We consider the number of R&D workers as the most important input factor in patent production. According to German survey data, labor costs make up about two thirds of all R&D costs in German firms (Stifterverband). We do not have data on R&D expenditures on tangible assets at our disposal but control for capital stock — as measured by its book value — in the estimations. While existing studies measure R&D inputs by either the overall number of R&D workers or total R&D expenditures (Blundell et al. 1995, 2002; Hall et al. (1986); Crépon and Duguet 1997; Hall and Ham Ziedonis (2000); Kim and Marschke 2005; Licht and Zoz 1998), the richness of our data allows us to take a more differentiated look at the marginal contributions of a number of different types of labor. Our interest hence is in the *composition* of the human capital effects of patenting activity.

We distinguish human capital effects along three critical definitions. The first concerns the meaning of an "R&D worker", the second the meaning of "mobility" and the third refers to the meaning of "patent exposure". This yields a total of 14 different types of labor:

(1) R&D joiners with patent exposure.

(2) R&D joiners without patent exposure.

(3) R&D stayers with patent exposure.

(4) R&D stayers without patent exposure.

(5) R&D workers without prior employment history.

(6) Non R&D joiners with patent exposure.

(7) Non R&D joiners without patent exposure.

(8) Non R&D stayers with patent exposure.

(9) Non R&D stayers without patent exposure.

(10) Non R&D workers without prior employment history.

(11) R&D leavers with patent exposure.

(12) R&D leavers without patent exposure.

(13) Non R&D leavers with patent exposure.

(14) Non R&D leavers without patent exposure.

Groups (1) through (10) constitute the firm's current labor force. Workers in groups (11) through (14) are no longer part of the firm's labor force.

R&D workers and non–R&D workers: We define "R&D workers" vs. "non R&D workers" by using information on the highest level of education attained by the worker. We differentiate between nine skill groups in total: (1) "Unskilled workers", workers without a completed formal education; (2) "Skilled workers", workers with completed formal education like plumbers, electricians, blacksmiths, carpenters, photographers or waiters; (3) "R&D technicians", workers with a technical education in R&D–related subjects like process technicians, food processing technicians, dairy farm technicians, laboratory technicians or food business engineers; (4) "Other technicians"; workers with a technical education in non–R&D–related subjects like multi media designer, visualizer, actor, real estate agent, hotel technician, transport logistics; (5) "R&D medium length"; workers with a medium length education in R&D–related subjects like machine engineer, electrical engineer, food business engineer, architect, chemists, construction engineer, bio analytic; (6) "Other medium length"; workers with a medium length education in non–R&D–related subjects like social workers, high school teacher, journalist, librarian, photo journalist, language degrees, musician, insurance agent; (7) "R&D long"; workers with a bachelor or master in R&D–related subjects like natural sciences, technology, mathematics, statistics, physics, chemistry, biology; (8) "Non R&D long"; workers with a bachelor or master in non–R&D–related subjects like humanities, theology, religion, history of thought, literature, languages and (9) "Unknown education"; workers with an education unknown to Statistics Denmark.

Our main definition of R&D workers includes both workers with a long R&D education and workers with a medium length R&D education (skill groups 5 and 7). This definition corresponds most closely to the finding of Kaiser (2006) who uses patent inventor survey data to show that Danish inventors are most likely to hold a Bachelor's degree or higher.[1] In addition to the main definition we also consider a "narrow" one which defines R&D workers as workers with a long R&D education (skill group (7), and a "broad" definition that comprises also of workers with a short R&D education (skill groups 3, 5 and 7). We focus attention on the main definition of R&D workers but present key results for the alternative definitions as a robustness check in section 7.

Mobility: We also differentiate workers in terms of their mobility. "Stayers" are workers who have been employed with firm i both at time t and time $t-1$. "Joiners" are workers who have been employed with firm i at time t but not at time $t-1$. Workers who are employed with firm i but whose employment history is unknown have typically just graduated. Although a small fraction of the "unknown" workers are workers from foreign countries, we shall refer to these workers as "recent graduates" hereafter.

Patent exposure: We define a worker as being "patent exposed" if the firm she was employed with at $t-1$ applied for a patent at time $t-1$. A patent exposed "stayer" hence is a worker who was employed with firm i at both t and $t-1$ and where firm i applied for at least one patent at $t-1$. Since the employment history of the recent graduates is not tracked, there is no distinction being made here with respect to their patent exposure.[2]

Human capital specification: We specify human capital effects as (i) a standard "scale effect" measured by the total number of workers,[3] (ii) "composition effects" measured by the shares of each type of labor currently

[1] More precisely, 30.5 percent hold a Bachelor's degree, 40.8 percent a Master's degree and 17.4 percent a PhD degree.

[2] Note that defining patent exposure contemporaneously, i.e. at t implies to perfectly predict patenting activity at t and also that all workers of all types are contemporaneously "exposed" for firm that patent at t which is why we use exposure at $t-1$ instead of at t. We have also experimented with wider time windows for mobility and exposure but our estimation results under the alternative definitions differ even quantitatively very little from the results obtained using the definitions listed above. Note also that, given our definition, all exposed R&D stayers are internally exposed.

[3] All firms in the sample have at least one employee.

employed, i.e. skill groups (1) through (10) with the share of non–exposed non–R&D workers (group 10) left out as the comparison group,[4] and (iii) "leaver" effects in terms of the ratio of the number of workers in each of the groups (11) through (14) relative to the current total number of workers of the firm:

$$\underbrace{\alpha ln(N)}_{\text{scale effect}} \quad + \quad \underbrace{\sum_{k=1}^{9} \gamma_k s_k}_{\text{composition effects}} \quad + \quad \underbrace{\sum_{l=1}^{4} \delta_l r_l,}_{\text{leaver effects}} \tag{1}$$

where s_k denotes the share of labor type k in total employment of firm, r_l denotes the ratio of leaver group l to total employment, and N is the total number of workers of the firm.

The coefficients in Equation (1) do not have a direct economic interpretation such as marginal effects or elasticities. We therefore also present results in terms of semi–elasticities (the percentage effects of a one unit — i.e. a one worker — change on the number of patents)[5] and absolute changes in the number of patents.

4.3 State dependence

The standard treatment of state dependence in patent production relies on a measure of a firm's previous success in patenting: the discounted stock of previous patents. The discounted patent stock of firm i in period $t-1$ is:

$$G_{it-1} = P_{it-1} + (1-\delta)G_{it-2}, \tag{2}$$

where P_{it-1} denotes the number of patent applications of firm i at time $t-1$ and δ is a discount factor. State dependence is hence introduced to the model through the term P_{it-1}, the lagged number of patent applications. We follow the suggestion of Blundell et al. (1995) and use a 30 per cent depreciation rate. Our results remain robust to alternative discount factors.

While such a state dependence measure is usually found to be significant even when controlling for firm size, e.g. by the stock of capital, Hausman et al. (1984), Blundell et al. (1995, 1999), it leaves open the interpretation of the reasons for such state dependence. With our complete longitudinal data on labor flows we can add much more detail. Our approach allows the effects of state dependence (that is, previous patenting exposure) to reside

[4] The coefficient estimates on the remaining groups are to be interpreted relative to the effects of this comparison group.

[5] Appendix 1 shows how these semi–elasticities are calculated.

to different degrees within the different types of workers that constitute the firm's labor force. If our worker–related exposure terms are found to dominate the lagged patent stock measure, we will interpret this as an indication of the effect of patenting experience residing primarily with workers rather than being an inherent general property of the firm as implied by previous papers.

4.4 Unobserved heterogeneity

A second main econometric issue relates to unobserved firm heterogeneity: firms, irrespective of their previous history in patenting and the size and composition of their current labour force, may differ in terms of their patent productivities. This creates a potential problem in separating out the contributions of different factors in the patent production function. For example, a firm with unobservably high "patent abilities" may attract R&D workers who are also (unobservably) more able than the average R&D worker, or it may employ capital more intensively than firms of lower ability due to its private knowledge on success probabilities. In such cases, and with no correction for unobserved patent productivity, one would tend to overestimate the contributions of the number of R&D workers or capital in the patent production function.

To obtain a correction for unobserved permanent patent productivity we utilize the fact that we have very long "pre–sample" histories on firms' patenting acitivities at our disposal, namely 22 years of observations (1977-1998) on patenting activity prior to our "sample" data on workforce characteristics and other observable firm characteristics (1999 - 2002). Specifically, we employ the suggestion of Blundell et al. (1995) to use each firm's average number of patents over this pre-sample as an observable proxy for unobservable permanent productivity. They show that their "Pre–Sample Mean Estimator" (PSME) yields superior results compared to alternatives that are based on the generalized methods of moments (GMM) framework (Blundell et al. 1999).

A prominent feature of our sample is that the overall level of patenting was trending during the pre-sample period. We therefore extended the Blundell et al. (1995) approach by normalizing a firm's number of patents in a pre-sample year by the total number of patents applied for during that year. We provide more details on the normalization in Appendix 2.

Many of the firms in our data never applied for a single patent. We again follow Blundell et al. (1995, 1999) and include a dummy variable for a firm having applied for at least one patent during the pre-sample period. This variable acts as a remedy for the so-called zero-inflation problem that is common to many analyzes of economic count data (Mullahy, 1997).

4.5 Count data models

Our count data models use a common specification of the mean function. We specify the mean number of patents applied for, Y_{it}, by firm i in year t as $E(Y_{it}|\boldsymbol{x_{it}}, \eta_i) = e^{\boldsymbol{x_{it}\beta}+\eta_i}$. The exponential specification is standard in the patenting literature. The vector $\boldsymbol{x_{it}}$ denotes observable patent determinants, including the discounted stock of past patent applications and measures of the size and composition of the labor force. The parameter vector β contains the corresponding parameters in (1). The term η_i captures unobserved differences between firms in their permanent patent productivity. The latter term is proxied by two observable items, the pre-sample yearly average number of applications relative to the total number of EPO applications and a dummy variable for having at least one EPO patent application during the pre-sample period.

It is commonplace in the count data literature to consider several different specifications of the conditional variance. We start from a Poisson model which imposes equality between the mean and the variance since the conditional mean function of that model is robust to various types of mis–specification. The negative binomial allows the variance to exceed the mean a phenomenon which is called "overdispersion". This is commonly found in patent data and economically motivated by unobserved firm–specific heterogeneity. We use a very flexible specification of the negative binomial, denoted RE NegBin, in which the dispersion parameter can vary randomly between firms.[6]

5 Descriptive statistics

Table 1 provides descriptive statistics for two different samples: The full sample of 90,725 firms with a total of 206,645 in-sample observations and a subsample of 14,811 firms that employ at least one R&D worker (16.3 per cent of the full sample). The latter includes 31,193 firm-year observations (15.1 per cent of the full sample) and accounts for 96.7 per cent of the total number of patents. Overall patenting acitivity is fairly modest with the average patenter applying for 1.2 patents per year.

In terms of firm size as measured by the number of employees, the standard picture emerges: Patenters are on average much larger than non-patenters

[6] The inverse of the dispersion parameter has a Beta distribution.

although there are very small firms among the patenters (firms with just one employee) as well as very large non-patenting firms (with a maximum of more than 26,000 employees). Recall that we included the population of active firms with one or more employees while excluding industries from the analysis only if no patents were applied for at all from firms in that industry during the full observation window 1978 through 2002. Most industries are therefore included in the sample.

Insert Table 1 about here!

Table 1 also details the distribution of (firm, year) observations in the estimation sample over groups of workers with differences in terms of the relevance of their education for R&D, their mobility status in year t (joiners vs. stayers), and whether or not they were exposed to patenting in the previous year $t-1$. For the full sample, the table shows that 21 per cent of workers in patenting firms are classified as R&D workers. Of those workers, around one in five was mobile during any given year. The mobility status could be determined for the vast majority (97 per cent) of R&D workers in patenting firms. For non-patenters the corresponding numbers are lower: Only 4 per cent of workers in non patenting firms are classified as R&D workers with one in nine being mobile during any given year.

Within the sample of firms with at least one R&D worker, about one in four worker is classified as an R&D worker. Somewhat surprisingly, this holds equally for patenting and non-patenting firms. This suggests that the latter follow alternative strategies to patenting in utilizing their R&D output. Again, one in five R&D workers was mobile during any given year for patenters whereas mobility was lower among R&D workers employed by non-patenters (one in nine).

6 Results

We report our empirical results in three steps. First, we comment briefly on the estimates of the regression coefficients in (1). Although, as noted above, the coefficients have no direct economic interpretation, their significance and sign form the basis for later inference. Second, to gain insight into the economic magnitude and significance of effects, we transform our results into more readily interpretable semi-elasticities. Finally, we infer the empirical validity of each of the hypotheses forwarded in section 2.

6.1 Estimation results

Our main estimation results are presented in Table 1. This is for the full sample of 90.725 firms that (1) have at least one employee and (2) for which all variables observed.[7] Results are reported both for the standard Poisson model ("Poisson") and the random effects Negative Binomial model ("RE NegBin"). Our comments will focus on the latter because the random effects turn out strongly significant. Moreover, our findings are fairly consistent across specifications in terms of sign and magnitude of the estimated parameters.

The variables included to control for scale effects, state dependence and unobserved permanent heterogeneity, are all found to be significant and signed according to expectation.[8] The estimated scale effects of the total number of workers and the capital stock (both in logs) are positive and strongly significant. Like other existing studies that consider dynamic specifications, we find ample evidence for positive state dependence in patenting. The standard term included to capture state dependence, the lagged discounted stock of patents, has a positive and statistically significant impact on current patenting activity according to the RE NegBin results although the term is not significant in the Poisson model. Our finding that this effect remains even though our specification includes an extended set of human capital variables, suggests that state dependence is partly embedded in the firm itself. Finally, our PSME proxies for unobserved permanent heterogeneity, the dummy variable for patenting activity prior to 1999, $FEdum$, and the continuous measure FE based on the mean pre-sample patent count, both add positively and significantly to current patenting activity. This is consistent with the pre-sample level of patenting reflecting permanent differences in unobserved patent abilities among firms.

Our results for the composition effects related to the shares of different labor types (relative to the reference share of non-exposed non R&D workers), are also in line with expectations. A central finding is that the group of R&D workers contribute positively and significantly to patenting. In contrast to the R&D workers, we generally find little effect of non R&D workers. Only for the case of non R&D stayers in firms that recently exposed their employees to patenting do we find an effect which is statistically significant at conventional

[7] Results for two different samples are reported in section 7 as robustness checks: a sample of 136.079 firms for which sectoral, geographical or capital stock information could be missing; and a sample of 14.811 firms that have full information and employ at least one R&D worker.

[8] Our specification also includes 14 sectoral dummies, 14 regional dummies, year dummies for 2001 and 2002, and a constant term.

levels. Finally, the picture is mixed for leavers with negative signs for some groups and positive for others. The only significant leaver effect is found for non R&D workers who left the firm with no patent exposure.

Insert Table 2 about here!

6.2 Semi-elasticities

In the second step, we calculate the semi-elasticity of changing the number of workers in each group. These calculations are based on the estimaton results we obtained for the RE NegBin model.

Table 3 reports the semi-elasticities, *i.e.*, the percentage change in the expected number of patents from adding an additional worker of a particular type to the current workforce. This calculation is performed for each group of R&D or non R&D workers. Variables are evaluated at the mean values within the subsample of firms with at least one R&D worker. The effects are generally modest, ranging from a 1.7 per cent expected change for an R&D worker joining the firm after having received patent exposure in her previous firm, to 1 per cent for R&D graduates and .6 per cent for R&D stayers with exposure. Interestingly, R&D graduates have a higher patent productivity than R&D stayers without exposure. A possible interpretation of this result could be that these workers bring knowledge of the recent developments in the field to the firm, which increases patenting activity.

Insert Table 3 about here!

6.3 Tests of Hypotheses

As a final step in our empirical analysis we investigate the validity of the hypotheses forwarded in section 2. We base this inference on the differences in the estimated coefficients, γ_k and δ_l.

Our results are summarized by Table 4. We provide two pieces of empirical evidence and conclude on each hypothesis. "Direction of differences" shows if the sign of estimated differences are either in accordance with or contrary to the theoretical prediction (or mixed, which is possible in the case of a composite hypothesis that refers to more than one contrast between groups of workers). The column headed "p-value of statistical null" reports the p-value of the corresponding statistical null hypothesis of no difference between groups. A small p-value suggests that the statistical null of no difference be rejected. If the statistical null is rejected and differences are signed in accordance with theory, then our economic hypothesis is validated.

First, we find that the evidence strongly corroborates Hypotheses 1.a and 1.b. These were forwarded mainly as consistency checks on our definition of R&D workers. Second, there are strong effects of patent exposure in the directions suggested by Hypotheses 2.a and 2.b. Third, in regard to "absorptive capacity" our empirical results on Hypotheses 3.a and 3.b point in the direction suggested by theory although p-values are in an inconclusive range. Finally, the evidence on matching effects (Hypotheses 4.a and 4.b) is that mobility is indeed efficiency enhancing for R&D workers whereas for non R&D workers, we find mixed evidence.

Insert Table 4 about here!

7 Robustness checks [To be completed]

7.1 Alternative firm samples

Gross firm sample:
No sectoral, geographical or capital stock information included. Very similar results.

R&D worker sample:
Firms that employ at least one R&D worker. Less significant scale effects. Significant R&D intensity effect. Generally moderated human capital effects, numerically lower and statistically less significant. Signs of all significant variables remain. Non R&D graduates now show positive significant effect.

Insert Table with XT neg bin results in the Appendix!

7.2 Alternative R&D worker definition

Standard sample. Broad, narrow R&D worker definition.

Insert Table with XT neg bin results in the Appendix!

8 Conclusions

We find that that there is ample evidence for positive state dependence in the EPO patenting experience of Danish firms, both through the lagged discounted stock of patents and through variables measuring pre-sample patenting activity. The importance of labour mobility as a vehicle for the spread of innovation across firms is evidenced by our results in that joining R&D

workers contribute more to patent productivity than stayers. The estimated elasticities of expected patent productivity with respect to labour inputs of different types show that both mobility and previous patent exposure matters quantitatively.

Our approach tracks the moves of the vast majority of workers and thus includes moves that do not result in patents at the new employer. Our estimates of the effects of mobility are thus much less likely to be affected by the upward bias inherent in studies that rely on patent data sources only where this outcome is usually not observed.

Table 1: Sample averages and standard deviations (italics)

	Full sample (206,645 firm-year observations)						Firms with at least one R&D worker (31.193 firm-year observations					
	All firms		Patenting firms		Non--patenting firms		All firms		Patenting firms		Non--patenting firms	
Number of workers												
Joiners	4,1	*35,8*	56,2	*190,5*	3,8	*32,5*	15,2	*90,3*	65,4	*205,2*	13,5	*83,0*
Stayers	11,3	*101,2*	213,9	*585,8*	10,1	*89,4*	46,0	*256,6*	249,0	*628,6*	38,9	*229,9*
Graduates	1,5	*15,6*	17,1	*49,6*	1,4	*15,1*	5,3	*39,3*	19,8	*53,3*	4,8	*38,6*
Total	15,4	*130,4*	270,1	*737,7*	13,9	*116,0*	61,2	*330,1*	314,4	*791,6*	52,3	*297,7*
Shares (relative to total number of employees)												
Joiners	0,150	*0,214*	0,171	*0,171*	0,150	*0,214*	0,156	*0,165*	0,174	*0,165*	0,155	*0,165*
R&D joiners with exposure	0,000	*0,011*	0,014	*0,058*	0,000	*0,010*	0,003	*0,028*	0,017	*0,063*	0,003	*0,026*
R&D joiners without exposure	0,004	*0,034*	0,027	*0,073*	0,004	*0,033*	0,026	*0,084*	0,032	*0,078*	0,025	*0,084*
Non R&D joiners with exposure	0,003	*0,028*	0,013	*0,032*	0,003	*0,028*	0,005	*0,024*	0,014	*0,034*	0,005	*0,023*
Non R&D joiners without exposure	0,143	*0,209*	0,117	*0,126*	0,143	*0,210*	0,122	*0,135*	0,111	*0,108*	0,122	*0,136*
Stayers	0,744	*0,277*	0,755	*0,197*	0,744	*0,277*	0,755	*0,212*	0,753	*0,191*	0,755	*0,213*
R&D stayers with exposure	0,001	*0,017*	0,097	*0,173*	0,000	*0,006*	0,004	*0,043*	0,114	*0,183*	0,001	*0,017*
R&D stayers without exposure	0,032	*0,132*	0,066	*0,160*	0,032	*0,131*	0,213	*0,276*	0,078	*0,171*	0,218	*0,278*
Non R&D stayers with exposure	0,002	*0,038*	0,310	*0,344*	0,000	*0,014*	0,012	*0,087*	0,311	*0,334*	0,001	*0,028*
Non R&D stayers without exposure	0,709	*0,296*	0,282	*0,354*	0,712	*0,294*	0,526	*0,277*	0,250	*0,332*	0,535	*0,270*
Graduates	0,105	*0,188*	0,074	*0,087*	0,106	*0,188*	0,089	*0,127*	0,072	*0,077*	0,090	*0,128*
R&D graduates	0,002	*0,029*	0,006	*0,025*	0,002	*0,029*	0,014	*0,074*	0,008	*0,027*	0,014	*0,076*
Non R&D graduates	0,103	*0,186*	0,067	*0,083*	0,104	*0,186*	0,075	*0,102*	0,065	*0,072*	0,075	*0,103*
Leavers	0,244	*1,187*	0,203	*0,859*	0,244	*1,188*	0,182	*0,736*	0,167	*0,626*	0,183	*0,740*
R&D leavers	0,008	*0,120*	0,047	*0,329*	0,008	*0,117*	0,026	*0,175*	0,042	*0,281*	0,026	*0,170*
Non R&D leavers	0,236	*1,136*	0,156	*0,621*	0,237	*1,138*	0,156	*0,664*	0,125	*0,444*	0,157	*0,670*
R&D workers	0,039	*0,146*	0,211	*0,244*	0,038	*0,144*	0,260	*0,288*	0,248	*0,246*	0,261	*0,289*
Non R&D workers	0,961	*0,146*	0,789	*0,244*	0,962	*0,144*	0,740	*0,288*	0,752	*0,246*	0,739	*0,289*
Exposed	0,006	*0,057*	0,434	*0,406*	0,004	*0,035*	0,024	*0,121*	0,457	*0,403*	0,009	*0,052*
Non exposed	0,888	*0,195*	0,492	*0,402*	0,891	*0,191*	0,886	*0,172*	0,471	*0,398*	0,901	*0,138*

Table 2: Estimation results for the full sample

	Poisson			RE NegBin		
Variable	Coeff.	Std. Err.	p-val	Coeff.	Std. Err.	p-val
Disc. stock of applications	0.0002	0.0005	0.7060	0.0041	0.0014	0.0040
ln(\# workers)	0.2836	0.0521	0.0000	0.4594	0.0500	0.0000
Share R\&D joiners w/ exp.	4.2253	0.6239	0.0000	4.3508	0.5349	0.0000
Share R\&D joiners w/o exp.	3.2192	0.4467	0.0000	2.9383	0.4440	0.0000
Share R\&D stayers w/ exp.	2.3073	0.5010	0.0000	2.5033	0.5530	0.0000
Share R\&D stayers w/o exp.	1.2255	0.4647	0.0080	1.3094	0.4386	0.0030
Share R\&D graduates	2.4437	0.7788	0.0020	2.6061	0.6274	0.0000
Sharenon R\&D joiners w/ exp.	0.5325	0.3574	0.1360	0.1274	0.5078	0.8020
Share non R\&D joiners w/o exp.	0.6770	0.2652	0.0110	0.0433	0.2665	0.8710
Share non R\&D stayers w/ exp.	1.1106	0.2518	0.0000	0.4981	0.2317	0.0320
Share non R\&D graduates	1.0209	0.4200	0.0150	0.6742	0.4479	0.1320
Share R\&D leavers w/ exposure	-0.2670	0.8436	0.7520	-1.7755	1.1008	0.1070
Share R\&D leavers w/o exposure	0.6511	0.2473	0.0080	0.4776	0.2838	0.0920
Share non R\&D leavers w/ exposure	0.0489	0.0510	0.3380	0.1696	0.1233	0.1690
Share non R\&D leavers w/o exposure	-1.7382	1.5447	0.2600	-0.9695	0.3841	0.0120
ln(capital stock)	0.1456	0.0349	0.0000	0.0688	0.0288	0.0170
ln(fixed effect)	0.4715	0.0588	0.0000	0.5019	0.0639	0.0000
Fixed effect dummy	6.9634	0.5762	0.0000	7.0618	0.5633	0.0000
Log-likelihood	-3,174.64			-2,384.15		
# obs.	206,645			206,645		
# firms	90,725			90,725		
# firms w/ patent	352			352		
# patents	1,987			1,987		
Deviance	2,531			962		
Pseudo R2	0.1808			0.0687		

Our specification also includes sectoral and regional dummies, year dummies for 2001 and 2002, and a constant term.

Table 3: Semi-elasticities (full sample, RE NegBin specification)

	Elasticity	**Std. Err.**	**p-val.**
R&D joiners w/ exposure	*0.0172*	0.0021	0.0000
R&D joiners w/o exposure	*0.0119*	0.0018	0.0000
R&D stayers w/ exposure	*0.0103*	0.0022	0.0000
R&D stayers w/o exposure	*0.0059*	0.0017	0.0005
R&D graduates	*0.0107*	0.0025	0.0000
Non R&D joiners w/ exposure	*0.0015*	0.0020	0.4288
Non R&D joiners w/o exposure	*0.0012*	0.0010	0.1966
Non R&D stayers w/ exposure	*0.0029*	0.0009	0.0011
Non R&D stayers w/o exposure	*0.0011*	0.0004	0.0076
Non R&D graduates	*0.0036*	0.0016	0.0266
R&D leavers w/ exposure	*-0.0066*	0.0041	0.1067
R&D leavers w/o exposure	*0.0018*	0.0010	0.0924
Non R&D leavers w/ exposure	*0.0006*	0.0005	0.1690
Non R&D leavers w/o exposure	*-0.0036*	0.0014	0.0116

Table 4: Tests of hypotheses.

	Hypothesis	Direction of differences	p-value of statistical null	Conclusion
1a.	R&D joiners contribute more to patenting activity than non R&D joiners	Confirmed	0.000	Validated
1b.	R&D stayers contribute more to patenting activity than non R&D stayers	Confirmed	0.000	Validated
2a.	Joiners with exposure contribute more to patenting activity than joiners without exposure	Confirmed	0.040	Validated
2b.	Stayers with exposure contribute more to patenting activity than stayers without exposure	Confirmed	0.000	Validated
3.a	The difference in the contribution of joiners with and without exposure is larger for R&D workers than for non R&D workers.	Confirmed	0.070	Weakly validated
3.b	The difference in the contribution of stayers with and without exposure is larger for R&D workers than for non R&D workers.	Confirmed	0.138	Not validated
4.a	The positive effect of R&D joiners to patenting activity is larger in absolute terms than the negative effect of R&D leavers	Confirmed	0.000	Validated
4.b	The positive effect of non R&D joiners to patenting activity is larger in absolute terms than the negative effect of non R&D leavers	Mixed	0.010	Not validated

Table 4 is based on differences in γ_k and δ_l coefficients estimated from the RE NegBin specification for the full sample of 90.725 firms. Reported p-values are for one-sided tests.

References

Abramovitz, M. (1993), The Search for the Sources of Growth: Areas of Ignorance, Old and New, Journal of Economic History 53, 217–243.

Almeida, P. and B. Kogut (1999), Localization of Knowledge and the Mobility of Engineers in Regional Networks, Management Science 45, 905–916.

Arora et al. 2003

Blundell, R., R. Griffith and F. Windmeijer (2002), Individual effects and dynamics in count data models, Journal of Econometrics 108, 113–131.

Blundell, R., R. Griffith and J. van Reenen (1995), Dynamic count data models of technological innovation, The Economic Journal 105, 333–344.

Cameron, A.C. and F. Windmeijer (1996), R–squared measures for count data regression models with applications to health–care utilization, Journal of Business and Economics Statistics 14, 209–220.

Combes, P.-P. and G. Duranton (2006), Labour pooling, labour poaching, and spatial clustering, Regional Science and Urban Economics, 36, 1–28.

Crépon, B. and E. Duguet (1997), Estimating the innovation function from patent numbers: GMM on count panel data, Journal of Applied Econometrics 12, 243–263.

David, P. A. (1992), Knowledge, property, and the system dynamics of technological change. Proceedings of the World Bank Annual Conference on Development Economics, 215–248.

Fosfuri, A., M. Motta, and T. Rønde (2001), Foreign Direct Investments and Spillovers through Workers' Mobility. Journal of International Economics 53, 205–222.

Fosfuri, A. and T. Rønde, 2003. High-tech clusters, technology spillovers, and trade secret laws,International Journal of Industrial Organization 22, 45–65.

Gersbach, H. and A. Schmutzler (2003), Endogenous Spillovers and Incentives to Innovate, Economic Theory, 21, 59–79.

Hausman, J.A., B.H. Hall and Z. Griliches (1984), Econometric models for count data with an application to the patents–R&D relationship, Econometrica 47, 909–938.

Hall, B.H. and R.H Ham Ziedonis (2001), The determinants of patenting in the U.S. semiconductor industry, 1980-1994, Rand Journal of Economics 32, 101–128.

Hall, B.H., J.A. Hausman and Z. Griliches (1986), Patents and R&D: Is There a Lag?, International Economic Review 27, 265–83.

Hoisl, K. (2007): Tracing Mobile Inventors — The Causality between Inventor Mobility and Inventor Productivity, Research Policy 36, 619–636.

Jaffe, A., M. Trajtenberg and R. Henderson (1993), Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. Quarterly Journal of Economics 108, 577–598.

Kaiser, U. and C. Schneider

Kim, J. and G. Marschke (2005), Labor mobility of scientists, technological diffusion, and the firm's patenting decision, RAND Journal of Economics 36(2), 298–317.

Licht, G. and K. Zoz (1998), Patents and R&D: an econometric investigation using applications for German, European and US patents by German companies, Annales d'Économie et de la Statistique 49/329–360.

McCullagh, P. and J.A. Nelder (1989), Generalized linear models, Chapman and Hall, London.

Møen, J.: (2005), Is mobility of technical personnel a source of R&D spillovers?" Journal of Labor Economics 23(1), 81–114.

Pakes, A. and S. Nitzan (1983), Optimum contracts for research personnel, research Employment, and the establishment of 'rival' enterprises, Journal of Labor Economics 1, 345–365.

Saxenian, A. (1994), Regional advantage: culture and competition in Silicon Valley and Route 128. Cambridge, Massachusetts: Harvard University Press.

Solow, R. M. (1957), Technical change and the aggregate production function. Review of Economics and Statistics 39, 312–320.

Winkelmann, R. (2003), Econometric analysis of count data, Springer, Heidelberg.

Appendix 1: semi–elasticities

Recall that the conditional mean function for a count data model is $E(Y_{it}|\boldsymbol{x_{it}}, \eta_i) = e^{X_{it}\boldsymbol{\beta}+\eta_i}$. Given our definition of human capital variables as in Equation (1), the semi–elasticity of a worker from the kth skill group related to joiners or stayers on patenting activity — e.g. the percentage change in the number of patents due to a one unit (one worker) change in the number of workers of skill group k — then is:

$$\eta_{P,L_k} = \frac{\partial P}{\partial L_k}\frac{1}{P} = \frac{\alpha}{N} + \frac{\gamma_k - (\sum_{j=1}^{9}\gamma_j s_j + \sum_{h=1}^{4}\delta_h r_h)}{N} \tag{3}$$

where P denotes the number of patents and L_k denotes the absolute number of workers in skill group k. For the comparison group of non–exposed non–R&D workers currently in the firm, $\gamma_k = 0$.

The leavers are not part of the firm's current workforce which leaves the semi-elasticity of the lth leaver skill group as:

$$\frac{\partial P}{\partial L_l}\frac{1}{P} = \frac{\delta_l}{N} \tag{4}$$

Appendix 2: trend correction of the PSME

Let T_P denote the number of pre-sample observations on the dependent variable, let Y_{it} denote the number of patents applied for by firm i in year t, let S_{it} denote latent innovation search activity as in Blundell et al. (1995), let A denote a measure of all firms and let θ_t aggregate time effect in year t. These are all macro–economic effects including business cycle effects, general patenting propensity (vs. secrecy), the propensity to patent at the EPO, etc. This term is not restricted in any special way across time and it is the same for all firms.

Assume that $Y_{it} = S_{it}\theta_t$. We define our *weighted* proxy variable for firm–specific fixed effects, FE_i, by

$$
\begin{aligned}
FE_i &= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{Y_{it}}{\sum_{j\in A}Y_{jt}} \\
&= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{S_{it}\theta_t}{\sum_{j\in A}S_{jt}\theta_t}
\end{aligned}
$$

Define $S_{it} = \overline{S}_i + u_{it}$ where $\overline{S}_i$ as the Blundell et al. (1995) equilibrium value which is proportional to the firm fixed effect, η_i, and u_{it} simply defines the deviation from equilibrium for firm i at time t. Assume further that these deviations add to zero across all firms at any given point in time (note that general business cycles are part of θ_t). Then,

$$
\begin{aligned}
&= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{\overline{S}_i + u_{it}}{\sum_{j\in A}(\overline{S}_j + u_{jt})} \\
&= \frac{1}{T_P}\sum_{t=1}^{T_P}\frac{\overline{S}_i + u_{it}}{\sum_{j\in A}\overline{S}_j} \\
&= \frac{1}{\sum_{j\in A}\overline{S}_j}\overline{S}_i + \frac{1}{\sum_{j\in A}\overline{S}_j}\frac{1}{T_P}\sum_{t=1}^{T_P}u_{it}
\end{aligned}
$$

The last term goes to zero in expectation as T_P increases (which is essentially the same as argument in Blundell et al. 1995). The first term is proportional to $\overline{S}_i$ which in turn proxies η_i as in Blundell et al. (1995).

Essentially, we now allow non–stationarity in a way that vanishes once the fixed effect proxies are weighted.