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PhD thesis

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Mobility in local labour markets:
Three essays on industrial innovation and firm location

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Contents

Preface

This thesis was written during my enrollment as a PhD-student at the Department of Economics, University of Copenhagen from February 2007 through November 2010. I am grateful for the helpful guidance from my thesis advisors Thomas Rønde and Hans Christian Kongsted. Thomas was my advisor when I wrote my Master's thesis in the area of technology spillovers and labour mobility that developed into the application for my PhD-project. Throughout my PhD-studies, he has continuously been willing to discuss potential research questions and methods with me. When I began the work on this thesis, it was a specific aim to make an empirical contribution, and I appreciate the guidance I received from HC in carrying out this work.

As part of my PhD-studies, I visited the Institute for Fiscal Studies (IFS) in London for five months in the spring of 2008. I would like to thank Rachel Griffith and the people in the Productivity and Innovation section for their hospitality during my visit. I worked on the first chapter of the thesis during this stay, and I received valuable comments and suggestions for improvements. It was rewarding to be part of the research environment at IFS, and in the process of writing this thesis I have drawn in multiple ways on inspiration from this stay and on insights into the field of economic geography that it offered. I am grateful for the financial support that I received for my stay in London from the "EliteForsk"-initiative under the Ministry of Science and Technology.

The thesis has gained from suggestions and remarks by seminar participants and encouragements from colleagues in the Department of Economics. In particular, throughout the duration of the programme I have greatly valued the friendly, informal environment among the PhD-students. Our discussions on economics, social gatherings, and importantly our exchange of invaluable know-how have contributed to making my work both easier and more fun. Finally, the many hours of encouragement and support that I have received from good friends and my family mean a lot to me.

Kathrine Thrane Bløcher

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Summary

This thesis falls within the field of economic geography. All chapters share a focus on mobility of workers in local labour markets but can be read as independent essays. The two first chapters are specifically concerned with mobility of technicians and scientists in research intensive industries whereas the aim of the third chapter is to show that interfirm mobility of labour, in general, is an explanatory force behind agglomeration of manufacturing industries.

Chapter 1 and 2 are closely related as they both are concerned with research intensive economic environments in which technicians and scientist-employees learn valuable know-how from their employer that can be used with other employers and potential competitors. On the one hand, this is costly to firms because competitors in this way buy into their knowledge-base, or simply because it forces the firms to pay higher wages to retain key workers. On the other hand, many research intensive industries are also highly agglomerated which greatly facilitates mobility, and this suggests that in some industries high rates of mobility and interfirm technology diffusion are mutually advantageous to firms. On this background both papers are concerned with the impact of mobility on the research investments of firms.

Human capital theory suggests that – since learning increases future earnings – workers should be willing to compensate employers for R&D-learning by accepting lower wages, particularly early in their career. The empirical analysis in chapter 1 uses Danish register data for the pharmaceutical industry to study this hypothesis. I estimate and compare wage-profiles for workers at R&D plants with otherwise similar workers at other types of pharmaceutical plants. I restrict the sample to workers with a technical or scientific education that is of relevance to pharmaceutical research in order to focus the analysis on workers that are most likely to be employed at the research core of the plant. Furthermore, I divide the sample into two groups according to the length of education: 1) Workers with vocational education or a Bachelor's degree (medium-level technical education) and 2) Workers with a Master's or PhD-degree.

I start by considering the male part of the workforce, and I find that male employees at R&D-active plants with a Master's or PhD degree take a wage-discount of around 4-10% early in their career in return for higher earnings later. In particular, recent R&D experience is a source of significantly higher wages for this group of workers. For the female part of the workforce with a Master's or PhD degree, the estimated coefficients are slightly smaller in magnitude than for men, but statistically as significant. The results for technical workers are mixed in the sense that R&D-workers seem to reach the

earning-levels of technical workers at other pharmaceutical plants only late in their career. Nonetheless, overall, the results suggests that the value of R&D-learning in the pharmaceutical industry is at least partly internalised in the labour market. Furthermore, the estimations provide indirect evidence in favour of theories arguing that labour mobility is a source of knowledge transfers.

The theoretical analysis in chapter 2 takes its starting point from a number of empirical investigations establishing that multinational companies increasingly locate development activities in the leading science centres of the world in order to gain access to advanced technological know-how. In this sense they can be said to "listen in on new ideas" with the aim of using these for their own purposes, and this raises questions with respect to the effect on research investments in those regions.

I develop a model of a local research intensive industry in which entering firms (imitators) learn about the latest technological know-how by hiring experienced scientists from local research firms. There are two countervailing effects on research investments. As in traditional models of innovation and imitation, a research firm invests less in its research project as imitation lowers the value of a successful innovation by e.g. lowering its commercial value. However, by modeling the contribution of scientist-employees to the research projects I specify a positive feedback effect to innovation. Entry of multiple imitators competing for human capital create an attractive labour market to scientists that have participated in successful research projects and thereby have a positive effect on their incentives. Thus, I hypothesise that these scientists contribute more, in terms of e.g. creativity and persistence, to research projects. Non-compete clauses offer protection against employee mobility, but the results of the model point to cases in which strong wage-competition increases the profitability of research projects. In these cases, the scientific output of an industry is highest if firms refrain from including such clauses in the employment contract.

Chapter 3 is empirical and broadens the focus from R&D-intensive industries to all of manufacturing. I test a prominent theory in the economy geographic literature stating that firms form industrial clusters to share a common pool of labour. The register data provided by Statistics Denmark contain the detailed labour market and geographical information necessary to carry out the analysis. I test two formal arguments. The first of these states that firms form industrial clusters in order to diminish the effect of productivity shocks on wages. The reason is that in isolation, employment changes at the establishment level affect local wages making it difficult for the establishment to expand in response to a positive productivity shock whereas clustering facilitates mobility of workers from low-productivity firms to high-productivity firms. I use a measure based on employment changes at the plant level to account for this theory.

An alternative theory proposes that competition for skills among multiple firms in the same location induces workers to invest in their human capital because workers expect a return to their investment. Hence, this idea proposes that similarity in the use of skills leads firms to locate in geographical vicinity. I use a functional definition of skills that distinguishes workers according to both length and field of education, and I use correlations between the skill mix at the plant and the rest of the industry to determine how homogeneous the industry is in its use of skills.

I find that variations across industries in the potential for re-allocating workers across low and high productivity firms explain the geographical patterns of location in the data set. On the contrary, the idea that firms locate together because it increases the skill level of workers does not find support in the data. However, the data shows that similarity in formal qualifications play a role in relation to the ability of firms to re-allocate workers. In an extension, I find that this is even more the case in the diverse, urban labour market compared to specialised industrial clusters.

Dansk resumé

Kapitlerne i denne afhandling deler et fælles tema; mobilitet af arbejdskraft i lokale arbejdsmarkeder, men kapitlerne kan alle læses uafhængigt af hinanden. I de to første kapitler er fokus på mobilitet af teknikere og forskere i forskningsintensive industrier, mens jeg i det tredje kapitel ser på mobilitet mellem virksomheder i fremstillingssektoren generelt. Formålet med det sidste kapitel er således at vise, at mobilitet af medarbejdere generelt er en årsag til, at virksomheder i nogle industrier placerer sig geografisk tæt på hinanden.

Kapitel 1 og 2 er tæt relaterede. Begge kapitler vedrører således forskningsintensive industrier, i hvilke teknikere og forskningsansatte opnår værdifuld tekniske viden fra deres arbejdsgiver, som kan anvendes hos andre arbejdsgivere og potentielle konkurrenter. På den ene side er dette omkostningsfuldt for virksomhederne, fordi konkurrenter på denne måde kan købe sig adgang til deres vidensbase, eller simpelthen fordi virksomhederne tvinges til at betale højere lønninger for at fastholde vigtige medarbejdere. På den anden side er mange forskningsintensive industrier karakteriseret ved, at virksomhederne er placeret i geografisk nærhed af hinanden, hvilket netop øger risikoen for at miste en ansat til en konkurrent. Denne observation tyder på, at høje mobilitetsrater og vidensspredning er til gensidig fordel for virksomhederne i nogle industrier. På denne baggrund omhandler begge kapitler effekter af denne type af mobilitet på virksomhedernes investeringer i forskning og udvikling.

Økonomisk teori peger på, at – siden adgang til teknisk viden er værdifuld – vil ansatte være villige til at kompensere deres arbejdsgiver for læring relateret til forsknings- og udviklingsaktiviteter. Det kan ske ved, at medarbejderne accepterer lavere lønninger specielt tidligt i deres karriere, hvor de har stor gavn af læring. Den empiriske analyse i kapitel 1 anvender danske register data for medicinalindustrien til at undersøge denne hypotese. Jeg undersøger hypotesen ved at estimere og sammenligne lønprofiler for ansatte på forskningsarbejdssteder med ansatte på andre typer af arbejdssteder i medicinalindustrien.

I analysen er datasættet begrænset til ansatte med en teknisk eller videnskabelig uddannelse, der er relevant for forskning i medicinalindustrien. Det gør jeg for at fokusere analysen på de medarbejdere, der har den højeste sandsynlighed for at være tæt på virksomhedens forskningsaktiviteter. Desuden undersøger jeg effekterne separat for ansatte med henholdsvis en mellemlang uddannelse og en længerevarende teknisk eller videnskabelig uddannelse.

I hovedanalysen ser jeg på den mandlige del af arbejdsstyrken. I gruppen med en lang videregående uddannelse betyder ansættelse på et forskningsarbejdssted tidligt i karrieren, at en ansat modtager en løn, der er mellem 4 og 10 procent lavere end lønningerne for ansatte på andre typer af arbejdspladser. Til gengæld modtager personer med erfaring fra forskningsarbejdssteder højere lønninger senere i deres karriere. For kvinder med en lang videregående uddannelse er de estimerede lønforskelle lidt mindre end for mænd, men også statistisk signifikante. Jeg finder dog lidt mere blandede resultater for teknisk personale med mellemlang uddannelse, men samlet set tyder resultaterne på, at ansatte i medicinalindustrien i nogen grad kompenserer deres arbejdsgiver for værdien af den forskningsbaserede læring.

Den teoretiske analyse i kapitel 2 tager udgangspunkt i et antal empiriske undersøgelser, der viser, at multinationale selskaber i stigende grad placerer aktiviteter i teknologisk førende regioner, fordi det hjælper selskaberne til at få kendskab til de nyeste teknologier på et tidligt tidspunkt. Dette rejser spørgsmål med hensyn til effekten på investeringer i forskning i disse regioner.

Jeg udvikler en model for en forskningsintensiv industri, hvor succesfulde projekter kræver, at virksomheden investerer kapital, og at en forskningsmedarbejder bidrager med human kapital. Samtidig kan udefrakommende virksomheder kopiere den nye teknologiske viden ved at hyre erfarne forskningsmedarbejdere. Der er to modsatrettede effekter på effektiviteten af forskning af, at den ansatte kan tage viden om projektet med sig til en imiterende virksomhed. I lighed med traditionelle modeller for sammenhængen mellem innovation og imitation, investerer virksomheden mindre i forskning, idet værdien af innovation falder. Men ved at specificere bidraget fra den forskningsansatte viser jeg, at tilgang af flere imiterende virksomheder skaber et attraktivt arbejdsmarked for succesfulde forskningsmedarbejdere, og at dette har en positiv effekt på deres incitament til at bidrage til forskningsprojektet. Med andre ord jeg foreslår, at forskningsmedarbejdere bidrager med øget kreativitet, vedholdenhed mv. til virksomhedens forskning. Konkurrenceklausuler beskytter mod spredning af viden i forbindelse med medarbejdermobilitet, men modellens resultater peger på, at når der er tilstrækkelig stærk lønkonkurrence blandt de imiterende virksomheder, er det mest profitabelt for forskningsvirksomhederne ikke at benyttes sig af sådanne klausuler. Det betyder også, at industriens produktion af forskning i nogle tilfælde vil være større, hvis virksomhederne undlader at benytte sig af sådanne klausuler.

Kapitel 3 er et empirisk papir, der har et bredere fokus forstået på den måde, at jeg ser på mobilitet mere generelt i fremstillingssektoren. Jeg tester en vigtig teori inden for økonomisk geografi, der siger, at virksomheder danner industrielle klynger for at dele en fælles arbejdsstyrke. Register data fra Danmarks Statistik indeholder detaljeret information om arbejdsmarkedet og arbejdsstedernes geografiske placering, der er nødvendig for at undersøge denne teori.

Jeg tester to formelle argumenter. Det første af disse peger på, at virksomheder foretrækker store arbejdsmarkeder, fordi produktivitetschok har en mindre effekt på de lønninger, virksomhederne skal betale. Hvis virksomheden er isoleret i et arbejdsmarked, vil det være sværere at udvide produktionen i perioder, hvor det går godt, fordi virksomhedens lønninger vil stige i takt med, at virksomheden ansætter mere arbejdskraft. Fordelen i et arbejdsmarked med mange virksomheder er derimod, at det er lettere for arbejdskraften at flytte mellem virksomhederne herunder fra lav- til højproduktive virksomheder. For virksomhederne er dette en gensidig fordel, hvis deres efterspørgsel efter arbejdskraft ikke er perfekt korreleret. På baggrund af data over årlige ændringer i antallet af ansatte på et arbejdssted, udregner jeg et mål for industriens kapacitet for at udnytte denne type af arbejdskraftsmobilitet.

En alternativ teori er, at virksomheder, der er afhængig af den samme type af kompetencer, har gavn af at hyre fra det samme lokale arbejdsmarked, da konkurrence efter human kapital øger arbejdsstyrkens incitament til at investere i uddannelse. I kapitlet er kompetencer defineret ved den højeste fuldførte uddannelse, og jeg beregner et mål for, hvor homogen industriens arbejdssteder er, der tager højde for både uddannelsens længde og fagområde.

Den empiriske analyse viser, at industrier, der har et stort potentiale for at re-allokere arbejdskraft mellem virksomhederne i højere grad er placeret i samme geografiske arbejdsmarked end andre industrier. Derimod er industrier, der består af virksomheder, der anvender lignende kompetencer ikke mere geografisk lokaliserede end andre industrier. Dog peger analysen på at ensartethed i kompetencer er en faktor i forbindelse med at udnytte et potentiale for at re-allokere arbejdskraft mellem virksomhederne. I en supplerende analyse finder jeg, at dette i højere grad er tilfældet, når potentialet for at dele arbejdskraft måles i forhold til resten af fremstillingsindustrien end blandt virksomheder, der tilhører den samme industri.

R&D spillovers and human capital accumulation in the Danish pharmaceutical industry

R&D spillovers and human capital accumulation in the Danish pharmaceutical industry

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Abstract

A prominent idea in the literature on localised knowledge spillovers is that job-mobility by technical and scientific staff is a key source of local technology diffusion. Moreover, theoretical work suggests that parts of the costs of industrial research and development expenditures are internalised in the labour market as workers pay for the value of R&D-learning by accepting lower wages. I study this question for the Danish pharmaceutical industry by estimating and comparing wage-profiles for workers at R&D-plants with otherwise similar workers at other pharmaceutical plants. I find that male employees at R&D-active plants with a Master's or PhD degree, in a field relevant to pharmaceutical research, take a wage-discount of around 4-10% early in their career in return for higher earnings later. In particular, recent R&D-experience is a source of significantly higher wages for this group of workers. For the female part of the workforce with a Master's or PhD degree, the estimated coefficients are slightly smaller in magnitude than for men, but statistically as strong. The results for workers at R&D-plants with a medium-level technical education are more mixed in the sense that they seem to reach the earning-levels of technical workers at other pharmaceutical plants only late in their career. The estimates presented in this paper are of the same magnitude as in Møen (2005) for the Norwegian machinery and equipment industry, and the results suggest that the value of technology spillovers and R&D-learning in the pharmaceutical industry is at least partly internalised in the labour market.

1 Introduction

The general view among researchers in economics is that the market under provides private investments in research and development (R&D). The argument is that the output – knowledge – is a nonrival good that spills over to other firms, making it difficult for the investing firm to appropriate the full return. A prominent idea in the literature on localised knowledge spillovers is that job-mobility by scientists and engineers is a key source of local technology diffusion (since Arrow (1962)), and moreover that parts of the costs of R&D are internalised in the labour market (Pakes and Nitzan (1983)). Møen (2005) proposes to study this question by comparing wage-profiles for similar workers at establishments of different R&D intensity and applies this method to the Norwegian machinery and equipment industry. In this paper, I also use this method, but, rather than looking across industries, I suggest looking for similar effects within one of the most research intensive industries; the pharmaceutical industry.

The pharmaceutical industry ranks among the most R&D-intensive industries. As an example, in the US – a world leader in pharmaceutical research – R&D in value added amounted to 44% in 2006 compared to 10% in all of manufacturing.[1] For this reason, the pharmaceutical industry is a natural as well as one of the most important industries to study in order to learn about industrial R&D.

Danish register data are useful for studying worker mobility, wages, and R&D in this sector. First, the data set enables me to trace workers' career trajectories and to link these to the pattern of R&D-activity. Second, the Danish pharmaceutical industry is highly clustered with about 75 percent of employment in the Copenhagen area. Thus, physical barriers to worker mobility are likely of limited importance. Finally, the Danish pharmaceutical industry is highly developed and research intensive with a ratio of R&D-expenditures to value added of around 40%.[2]

Human capital is an essential input into the research process, and, likewise, the scientist who develops a new process or a new product naturally embodies key insights with respect to its scope and potential for further advancements (Zucker et al. (1998)).[3] This is the background for considering worker mobility as one of the most important micro-foundations for inter-firm knowledge transfers. An obvious way for a firm to gain access to an external knowledge base is simply to hire key scientists in possession of the technological know-how of interest by offering a sufficiently high wage (see e.g. theoretical models by Pakes and Nitzan (1983), Kim and Marschke (2005), Combes and Duranton (2006)). The key point in Pakes and Nitzan (1983) is, however, that this need not affect project

[1] OECD STAN databases.

[2] OECD STAN databases.

[3] Zucker et al. (1998) write that knowledge possess the property of natural excludability when it is tacit and embodied in people.

profitability as the optimal employment contract specifies a wage-discount to scientists in the early research phase as a "payment" for their expected, future high earnings.

A different, but complementary, perspective on the relationship between human capital and R&D-investments is that research-intensive firms in general provide a superior learning environment compared to other firms. To undertake research is by definition associated with operating at the technological frontier where technologies are less standardised and experimentation a necessity. This leads to the hypothesis that employees at research-based firms are exposed to newer technologies and perform fewer routine-tasks compared to employees at the average firm translating into faster accumulation rates of human capital in research-intensive firms.[4] The work of Rosen (1972) on workers' willingness to pay for occupational learning implies that research-based firms can hire young workers at a wage below their outside option.

In accordance with these arguments, the key hypothesis in this paper is that workers are aware that participating in R&D increases their value in the labour market enabling firms to pay wages below the going market wage to young workers at entry into the labour market. If this holds true, workers bear part of the cost of private R&D in return for capturing part of the gains.

I seek answers to this question by studying the Danish pharmaceutical industry within the empirical framework laid out in Møen (2005). The key information in the data set is yearly observations at the individual level on wages, place of employment, and occupational information that reveals whether workers at the plant carry out scientific work in bio-technology or medicine. I use the last piece of information to divide plants into R&D-plants (employs at least one scientist) and non-R&D-plants (employs no scientists).

I start by presenting descriptive statistics on the mobility patterns of workers both between R&D and non-R&D workplaces as well as in and out of the pharmaceutical industry. Pharmaceutical R&D-plants show a larger tendency to be connected via worker mobility to hospitals and universities than other pharmaceutical plants.

In the main analysis, I estimate workers' investment in and return to R&D-learning. The empirical strategy is to divide plants into two groups according to whether or not research takes place at the plant. By comparing wage-profiles for workers at R&D-active plants with wage-profiles for similar workers at other plants, it is in principle possible to estimate a price on as well as a return to R&D-learning. Also, the panel structure of the data reveals information on the career history of each worker which allows me to separate current R&D-learning from past R&D-experience.

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[4] The dual view on the outcome of R&D-investments originates with Cohen and Levinthal (1989). It is based on the authors' empirical findings that firms invest in R&D not only to innovate but also to learn and thereby increase their capacity to absorb knowledge from external sources, i.e. from universities and other firms in the sector.

The sample that I use includes all Danish workers who have finished a formal degree providing skills relevant to pharmaceutical research, and who were employed full-time in the Danish pharmaceutical industry at some point between 1995 and 2005. In addition, I form two subgroups that better satisfy an assumption of homogeneity in worker types. The first subgroup consists of workers with a medium-level technical education, and the second group consists of workers with a Master's degree or a PhD degree. I carry out the analysis separately for the two groups of workers which should, to some extent, mitigate biases stemming from differences in unobserved worker ability. Even though the data set is a panel, I cannot solve the problem in the usual way by employing worker fixed effects since this approach would prevent me from estimating exactly the wage-levels that are necessary in order to identify wage-discounts to young workers. To the extent that high-productivity workers are more likely to work at R&D-plants, I will present conservative estimates of the wage-discount that R&D-workers accept early in their career.

I start by considering only the male part part of the sample. I find evidence that workers with a Master's or PhD degree who are employed at R&D-active plants accumulate human capital at a faster rate than workers at other types of pharmaceutical plants and receive a wage-discount early in their career of around 4%. When I include firm fixed effects to account for selection of high-productivity workers into high-productivity firms, the estimate increases to 7%. Separating out past R&D-experience further increases the estimate to 10%. These are estimates of the same magnitude as in Møen (2005).

With respect to workers with a medium-level technical education, I find that entry wages are similar at both types of plants but that wage growth in the beginning of their career are lower at R&D-active plants. For these workers it is only after about 25 years of experience that employment at R&D-active plants translate into higher yearly earnings in comparison with otherwise similar workers at other types of pharmaceutical plants. This result compares to that in Møen (2005) in the sense that he finds that technical workers with R&D-exposure catch up to otherwise similar workers markedly later than is the case for workers with a higher technical or scientific degree.

In the main analysis, women were left out in order to ease comparison with the results in Møen (2005), and to ensure a larger degree of homogeneity in the sample. As women constitute more than 50% of workers with a technical or scientific degree in the total sample, it is important to investigate whether this group shows a similar pattern in order to judge the overall impact of the effects on the industry. Moreover, investigating the existence of a wage-discount among women is new to the literature. In the group of workers with a Master's or PhD degree, I estimate the wage-discount to be between 3 and 5%. Likewise, the group of female workers with a medium-level technical education shows a similar pattern as in the male sample, though the coefficients in these regressions are not significantly different from zero.

Turning to the related literature, a number of studies seek to determine the existence and scope – geographic and technological – of technology spillovers. One method is to construct an aggregate stock of knowledge and include this measure in a knowledge production function for the firm (see Rosenthal and Strange (2001) for a survey). A very famous analysis is by Jaffe et al. (1993) in which the authors pioneer the use of patent citations to measure the geographic consentration of knowledge spillovers and a recent one is by Ellison et al. (2010) who link technology flows to co-location of pairwise US industries.

The famous case-study of the computer industries in California's Silicon Valley and Boston's Route 128 by Saxenian (1994) points to worker mobility as an important source of learning. According to this study, the culture of job-shopping in Silicon Valley was important to the region's high innovation rates compared to the computer industry in Boston in the 1980's and early 1990's. Almeida and Kogut (1999) relates localisation of technology spillovers as measured by patent citations to mobility patterns of engineers and key inventors and find that more intra-regional mobility is associated with a higher localisation-effect whereas more inter-regional mobility is associated with less localisation. Kim and Marschke (2005) find that patenting is more pronounced in industries with high mobility rates and take this as evidence that firms patent more in these industries to protect their knowledge base when former employees move to competitors.

Møen (2005) is first to use detailed register data to investigate the existence of technology spillovers by looking at individual wage and career profiles of workers. The finding, that young workers in R&D accept lower wages at entry into the labour market, suggests that these workers are indeed carriers of technological know-how. A follow-up paper by Magnani (2006) uses R&D information at the level of 2-digit industries to study this question for the US manufacturing sector but does not find a similar pattern. The author herself mentions that the impreciseness involved in using industry-level information biases her estimates of the wage-discounts towards zero.

A number of related studies suggest that looking at a narrow group of professionals can be a useful way of learning about labour market externalities. With respect to matching, Gan and Li (2004)'s study of the academic job market for new PhDs in Economics suggests that a field with more job openings and more candidates offers a higher probability of matching, and an often cited work on specialisation is Baumgardner (1988) who find that physicians perform a narrower range of activities in thick markets. Moreover, the hypothesis in the present paper is closely related to that in Stern (2004) who uses information on job-offers to young PhD job-market candidates in Biology to show that these students accept a lower wage in return for better conditions to do own research. The author interprets this finding in terms of a preference for working in research environments. The study in the present paper is different in more than one way. It focuses on industrial R&D and covers both technicians and people with a higher formal degree just as it looks at wage patterns across the career of the worker.

The rest of the paper proceeds as follows. In section 2, I summarise two relevant theoretical models. Section 3 explains the data and presents some descriptive statistics on workers and firms in the pharmaceutical industry. In section 4, I carry out a descriptive analysis of mobility patterns both within as well as in and out of the industry. I present the empirical strategy and results in section 5, and in section 6, I present results on the sample of women. Section 7 contains some robustness checks, and the paper ends with a conclusion in section 8.

2 Theory

In this paper, I use two concepts of on-the-job learning. One concept captures general accumulation of skills, and is in line with the traditional concept of human capital accumulation used in the labour market literature.

The other type of human capital that I have in mind relates to what is termed intellectual human capital by Zucker et al. (1998). This concept captures types of knowledge that are scarce and embodied in a few researchers that took part in its development. The scarcity is usually thought of as being due to a high level of complexity and/or associated with novelty.

Intellectual human capital is by definition closely related to the R&D process of the firm whereas ordinary human capital accumulation takes place in all jobs. However, accumulation of ordinary human capital takes place at different rates in different types of jobs depending on the type of tasks and the technology used. In particular, I argue that a firm undertaking R&D provides an advanced learning environment because workers are continuously exposed to the latest developments within their field and are required to learn and adapt to new methods more frequently.

In this section, I present two theoretical models that provide insights as to how I can expect workers and firms to act in an R&D-intensive labour market. The first one is a model of occupational learning in a competitive labour market in which different tasks have a different learning content. The second model derives the optimal wage-contract that an entrepreneur should offer a scientist-employee who, while working, gains access to valuable knowledge.

2.1 A model of occupational learning

The theory of compensating wage differentials suggests that R&D firms can hire young workers at a wage below their outside option. These firms provide a superior learning environment because workers use the newest technologies and generally are exposed to the latest developments within their field. Furthermore, tasks are less routine-based and requires adaptation and flexibility contributing to the speed of human capital accumulation. Rational workers who maximise their life-time income should be willing to pay for these superior learning opportunities. A more general version of this argument is due to Rosen (1972). The key idea is that workers learn on the job and jobs should therefore be seen as a tied package of work and learning opportunities. Different jobs require different skills but are also associated with different options for human capital accumulation. Based on this observation, Rosen (1972) predicts that workers move between occupations within and between firms according to their optimal learning strategy.

According to this argument the observed wage consists of two unobserved parts. An implicit price that the worker pays for his learning and a payment to the worker for her participation in production. Empirically, if labour markets are competitive, one should be able to estimate an implicit price of learning as the difference between the observed wage to a worker in a job with a high learning content and the wage received by a similar worker in a similar occupation with less scope for learning. This point is exactly what Møen (2005) exploits to determine whether the value of technology spillovers are internalised in the labour market by research workers.

To clarify the argument, it is useful to sketch the key parts of Rosen's model.

Workers are risk-neutral and the labour market is competitive. A worker employed in a job k receives a net-wage of:

$$y = \omega H - P(k) \tag{1}$$

where y is income, ω is the unit rental price of human capital H, and k is an index that measures the potential for one-the-job-learning, where $k \in [0, \bar{k}]$. By the hypothesis of compensating wage-differentials, $P(k)$ is the market-equalizing wage-differential between a job with no learning content and a job with learning content k. If the marginal cost of learning is positive and increasing, then $P'(k) > 0$ and $P''(k) > 0$.

Human capital evolves according to:

$$\dot{H}_{it} = \alpha_i k_t \tag{2}$$

where α_i represents worker $i's$ ability to learn such that a higher α_i is associated with a higher ability to learn. The optimal sequence of jobs, k_t, over the life-time T is the sequence which maximises the net present value of life-time income. This is the solution to the following problem:

$$max_{wrt\ k_t}\ V = \int_0^T [\omega H_t - P(k_t)]e^{-rt}dt \tag{3}$$

subject to an initial value of human capital H_0 and where the level of human capital evolves according to (2). The optimal solution requires that at any time $t \in [0, T]$:

$$\frac{P'(k_t)}{\alpha_i} = \frac{\omega}{r}[1 - e^{-r(T-t)}] \tag{4}$$

This expression says that workers move between jobs with different learning contents such that the marginal cost of accumulating human capital equals the discounted marginal return associated with future earning opportunities. In line with human capital theory, equation (4) also shows that workers prefer jobs with a high learning content early in their career but over time gradually move to job-types with less scope for learning.

It is clear from equation (4) that the marginal cost of learning (the left-hand side) decreases with the ability to learn, α_i. Thus, more able workers will self-select into jobs with a higher learning potential. Accordingly, if α_i differs across workers, the rate of accumulation of human capital that workers at R&D-active plants experience, is not the rate that workers in genereal would experience at R&D-active plants. I return to this issue in the results section.

2.2 A model of labour mobility and technological spillovers

In contrast to the Rosen (1972) model, Pakes and Nitzan (1983) consider the case in which knowledge is scarce and innovations lead to market power. This captures a labour market in which highly skilled staff employed to carry out R&D embody essential information about new technologies and production methods providing them with bargaining power in the wage-setting process as firms compete for their skills and knowledge.

The authors consider a two-period game in which an entrepreneur in the first period hires a researcher to carry out research and if successful sells the product in the product market in the second period. The researcher is free to leave the entrepreneur in the second period either to join a competitor or to create a spin-off firm. In both cases, he can use the knowledge of the new product to produce the good and the two firms compete. The key-insight from the Pakes and Nitzan (1983) model is that the optimal two-part wage contract enables the entrepreneur to appropriate the full return to his investment.[5] The contract consists of a second-period wage that depends on second period profits

[5]This result assumes risk-neutral workers and no borrowing constraints or lower limits on wages. These are factors that limit the extent to which the firm can appropriate the full return.

and first-period fixed wage that exactly satisfies the researcher's participation constraint. This lets the entrepreneur subtract the equivalent of the high second-period earnings from the first-period wage.[6]

2.3 Empirical predictions

Both theories imply similar predictions with respect to the wage-profiles of R&D-workers. Rational workers are willing to accept a wage below their current market-value because they see an initial job in R&D as an investment in future earning-opportunities. Based on this logic, I expect on average to observe lower initial wages but steeper earning-profiles for pharmaceutical workers who choose a research career compared to otherwise similar workers at other types of pharmaceutical plants.[7]

As both of the above-mentioned theories lay emphasis on mobility - between occupations and/or between firms - it is natural to look for support of the theories in the mobility patterns of workers. However, it does not follow from the models that we should necessarily observe mobility between firms in equilibrium. In the Pakes and Nitzan (1983) model, a researcher only changes employer when it is efficient[8], and in the Rosen (1972) model some workers realise their optimal learning path by changing occupation within the firm. Therefore, it is difficult to come up with a good test of the theories based on the mobility pattern of workers.

3 Data and empirical strategy

For the empirical analysis, I use the Integrated Data Base (IDA) for Labor Market Research provided by Statistics Denmark. This is a matched employer-employee data set beginning in 1980 that contains detailed register-based demographic and labour market information for all individuals with Danish residence. For this analysis, the relevant variables are the very detailed information on income, experience, occupation, place of work, and the type and length of formal education.

[6] Other contributions building on this idea include Fosfuri and Rønde (2004) who consider the case where knowledge is cumulative and Kim and Marschke (2005) who allow firms to protect their knowledge-base by the use of patents.

[7] A priori, it is possible to distinguish empirically between the two theories. The Rosen (1972) theory emphasises learning in a traditional sense whereas Pakes and Nitzan (1983) assume that workers earn a return on the information about the latest innovations within their field before this knowledge becomes standardised and available to a larger community of researchers. As argued in Møen (2005), it is therefore natural to think that the value of knowledge depreciates faster if the Pakes and Nitzan (1983) framework is important whereas if researchers benefit from traditional learning rather than from their access to a scarce knowledge resource we should observe lower depreciation rates in the data. Thus, if intellectual human capital matters most it should only be recently accumulated human capital in research firms that have value in the labour market. The caveat is that it requires a lot from the data for this to be feasible. It requires precise information about the research exposure for each worker throughout the career at all of his employers. Even though I have access to a rich data set and though I am able to calculate a measure of previous research experience, the information that I have is not adequate for using depreciation rates to distinguish the two theories.

[8] It requires a threat of entry by a third party for mobility to take place. In this case it can be optimal for the entrepreneur to induce the researcher to leave and start on his own such that the third firm expects tougher competition and chooses to stay out of the market.

Information about individual research exposure is of key importance. Unfortunately, the data contain no information on R&D-expenditures by firms and least of all by individual plants. However, the labour market data contain detailed information on the occupation of workers and this enables me to identify pharmaceutical research. Companies in Denmark are required to report to Statistics Denmark a 6-digit code which states the occupation of each of its employees in the last week of November each year. The codes give the hierarchical position of the employee as well as a description of the type of task performed by the worker. Of relevance specifically to the present analysis of the pharmaceutical industry (NACE: 2441 and 2442), companies are asked to identify workers that carry out scientific work in bio-technology or medicine. I use this information to identify R&D-active plants.[9]

To be specific, I define an R&D-plant as a workplace at which the company states that at least one employee carries out scientific work in pharmaceuticals. I then define a research exposed worker by a dummy variable which takes a value of 1 if the worker is employed at an R&D-active plant and 0 otherwise. This is a restrictive definition as it implies that workers are distinguished by the intensity of research exposure neither across R&D-active plants nor within R&D-active plants. Thus, a key assumption is that all workers for which my R&D-indicator is 1 are exposed to a similar amount of research. Clearly, this assumption does not hold in general for a broad sample of workers at a plant. In the analysis, I limit the sample to workers with a technical or scientific degree at the vocational level or above.[10] Furthermore, I distinguish between two groups of workers: 1) workers with a medium-level technical education (workers with a vocational or Bachelor's degree)[11] and 2) employees with a Master's or PhD degree. I carry out the analysis separately for these two groups. By selecting the sample according to relevant educations, I seek to restrict the analysis to workers that carry out similar tasks at the plant and accordingly have similar exposure to R&D-activities. Likewise, these individuals are the workers for which the empirical effects of interest are likely to be most relevant.

Since, the occupational codes are only available from 1995 and educational information end in 2005, the analysis is restricted to the years 1995-2005.

I have considered the option of calculating a continuous measure of R&D-intensity as the share of workers that carry out scientific work in pharmaceuticals relative to either the total number of employees or to the total number of employees with a relevant education. The disadvantage with

[9]Unfortunately, the occupation variable does not contain an equivalent definition for workers that carry out scientific work in other industries.

[10]These are workers that I judge have an education relevant to pharmaceutical research. It is a broad definition as it for examples include all types of engineers, but I prefer this simple approach rather than risk losing important worker types by for example only selecting educations that are designed specifically for the pharmaceutical sector.

[11]Vocational education corresponds to the final stage of a secondary education. For example laboratory technicians are included in this group. I will sometimes refer to the group of workers with a medium-level education as technical employees

such a measure is that it is less robust towards errors in the classification of workers into occupational groups. Moreover, it is not clear that such a measure more adequately captures actual R&D-exposure of the worker. Instead, to account for variations in human capital intensity across plants which might interact with the intensity of research, I include the share of low-skilled workers at the workplace[12]. In this way, I also take into account that some R&D-active plants are also traditional production plants.[13]

The advantage with the present data set is that it allows me to define R&D at the plant-level which is very useful in this study that is concerned with a narrowly defined sector. In studies that rely on R&D-exposure to account for research-intensity, information is usually at the level of the firm. Furthermore, for each year I know the (anonymised) place of work for each individual which enables me to trace the recent career trajectories of workers (from 1995) and consider their past research experience.

In the main analysis, I restrict the sample to male, full-time workers. This I do primarily to ease comparison with Møen (2005), but also because the labour market experiences of women are likely to be different from those of men which would affect the cross-comparison of individuals' human capital accumulation. Finally, I exclude part-time workers, and I exclude workers who are employed at plants with less than five employees. Table 1 shows descriptive statistics for this sample. As female workers constitute more than 50% of the workforce in both groups of workers considered in this paper[14], it is nonetheless highly relevant to learn about the wage-schedules of this group also, and in section 6, I present results on this part of the workforce.

[12]The cut-off that I use is a formal vocational degree corresponding to final stage of secondary education (ISCED definition). Thus, a fraction of the workers actually possess formal qualifications at the medium-level.

[13]Møen (2005) uses both a continuous R&D measure as well as uses a dummy-definition dividing firms into those with low R&D-intensity and high R&D-intensity to make the distinction between plant types clearer.

[14]In the group of workers with a technical degree women actually constitute around 70% of the workforce. In the group of workers with Master's or PhD degree the equivalent number is 50 %.

Table 1: Descriptive statistics: Workers by education and R&D-type

	Mean	SD	P10	P90
Medium-level technical education				
At R&D-active plant (6012 obs.):				
Share with BA	0.40	0.49	0	1
Years of experience	15.3	8.6	5.1	28.0
Wage in 2000 DKK	400.000	175.000	237.000	595.000
Size of plant (workers)	1323	964	176	2982
Share of low-skilled	0.61	0.07	0.53	0.72
At non-R&D plant (4857 obs.):				
Share with BA	0.50	0.50	0	1
Years of experience	14.8	8.3	5.0	27.1
Wage in 2000 DKK	408.000	159.000	245.000	602.000
Size of plant (workers)	975	936	59	2253
Share of low-skilled	0.71	0.12	0.50	0.85
Master's or PhD degree:				
At R&D-active plant (8574 obs.):				
Share with PhD	0.22	0.41	0	1
Years of experience	14.2	9.2	3.7	28
Wage in 2000 DKK	578.000	359.000	335.000	702.000
Size of plant (workers)	1448	967	322	3321
Share of low-skilled	0.60	0.07	0.53	0.70
At non-R&D plant (4316 obs.):				
Share with PhD	0.19	0.39	0	1
Years of experience	13.4	8.7	3.4	26,0
Wage in 2000 DKK	533.000	242.000	327.000	757.000
Size of plant (workers)	1156	1054	59	3208
Share of low-skilled	0.66	0.13	0.49	0.81

Note The data set contains worker-year observations of men with respectively a medium-level technical education, or Master's or PhD degree who are employed full-time in the Danish pharmaceutical industry 1995-2005. Workers with a technical education and total yearly wage-income below 100.000 (DKK 2000) and workers with a Master's or PhD degree and total yearly wage-income below 150.000 (DKK 2000) are excluded. These are approximately the 5th percentiles for workers with less than 5 years of experience in each group. Likewise, workers at plants with less than 5 employees are left out of the sample. An R&D-active plant is a plant that reports that at least one worker carries out scientific work in bio-technology or medicine. DKK:Danish Kroner. Wage is rounded to nearest 1000.

My measure of wages is nominal total, annual, wage income. Thus, I do not distinguish between workers that have one and two employers.[15]

Even though, I construct a sample of full-time workers, it is possible that some of these individuals at an earlier point in their career did not work or worked part-time. I wish to control for this in the measure of experience. The experience variable is a measure of actual experience obtained by being a wage-earner in Denmark. In Denmark, it is compulsory for all workers to make payments to a

[15]For these high-skilled individuals one could think that controlling for hours of work is important when comparing workers. However, the data does not include information on hours worked above 37 hours of work per week. To the extent that working long hours is associated with specific company culture, I control for this when I include firm-fixed effects.

compulsory pension scheme, ATP. These payments depend on number of hours employed during the week or month and are registered for all individuals employed as wage-earner back to 1964. Thus by using the ATP-payments Statistics Denmark construct a rather precise measure of work-experience.[16]

3.1 Industry description

The most striking feature of the Danish pharmaceutical industry is that it is is highly geographically concentrated with about 75% of employment in the Copenhagen area. The industry consists of a few major firms and a number of smaller firms consisting of 1-3 plants. In the sample years, the number of plants in the industry varies between 63 and 71 plants. The total number of workers increases from around 12,000 in 1995 to 17,000 in 2005 whereas the total number of firms declines from 47 to 36. Most variables in the analysis are information about individual workers, but I control for plant size and the share of low-skilled workers. Plant-level descriptive statistics are reported in table 2.

Table 2: Descriptive statistics: Danish pharmaceutical plants by R&D-type

	Mean	SD	P10	P90
R&D-active plants(174):				
Number of employees	518	683	42	1266
Share of low-skilled	0.62	0.12	0.50	0.75
Non-R&D active plants (549):				
Number of employees	122	333	7	226
Share of low-skilled	0.73	0.20	0.43	0.92

Note The data set includes all Danish pharmaceutical plants (NACE: 2441 and 2442), years 1995-2005. An R&D-active plant is a plant that reports that at least one worker carries out scientific work in bio-technology or medicine.

As expected R&D-performing plants are larger than other plants. Even though these plants also employ a lower share of low-skilled workers, the numbers in the table indicates that at some plants both R&D and production is likely to take place.

4 Mobility

The following section provides an account of the mobility patterns of male workers in the pharmaceutical industry who hold an exam of relevance to pharmaceutical research. Both within the pharmaceutical sector and in/out of other industries. It is a purely descriptive analysis but is a useful background for the subsequent estimation results.

[16]Unfortunately, it is not until recently that self-employed made these payment. Thus for workers who have been self-employed for a number of years, I underestimate their experience-level. This might bias my results if their are more of this type of workers at either of the two types of plants.

I start by considering mobility within the industry, see table 3. Part A of the table shows all changes in worker-types (R&D or non-R&D). Some of these changes is not a result of an actual move but occurs due to a change of workplace type. Part B shows the changes in worker types that are due to actual moves between plant types. This part of the table shows that the vast amount of mobility takes place between plants with same R&D-status. This amounts to approximately 95% of all actual moves.

The theories in section 2 predict that if workers change plant-type, they will move from R&D-active plants to non-R&D active plants as they move from jobs with a high learning content to jobs with a lower learning content. The table, however, does not confirm this prediction. An explanation might be that the skills and know-how learned at R&D-workplaces is difficult to transfer to non-R&D environments. Moreover, the numbers do not reveal whether "R&D-stayers" actually move from highly research intensive plants to plants that carry out R&D but with less intensity just at it does not reveal occupational mobility of similar type within the same workplace.

Table 3: Mobility between R&D-active and non-R&D active plants

	A: all changes			B: changes due to actual moves		
	R&D(t)	non-R&D(t)	total	R&D(t)	non-R&D(t)	total
	row-percentages			row-percentages		
Master's or PhD degree:						
R&D(t-1)	84.3	15.7	6880	96.5	3.5	6010
Non-R&D(t-1)	31.7	68.3	3599	7.8	92.2	2665
Medium-level technical education:						
R&D(t-1)	81.7	18.3	4912	95.8	4.15	4188
Non-R&D(t-1)	22.3	77.7	3873	4.5	95.9	3149

Note Mobility patterns for the male part of the sample. Part A of the table does not distinguish between changes in worker type that are due to a move between workplaces and changes that occur because the workplace changes type. Part B of the table excludes all changes in worker types that are due to a workplace changing R&D-status. An R&D-active plant is a plant that reports that at least one worker carries out scientific work in bio-technology or medicine.

The empirical strategy assumes that workers choose between employment at an R&D-active pharmaceutical plant or at an non-R&D active pharmaceutical plant. Of course in reality workers have the option of moving to other industries. In particular, industries such as hospitals, universities and chemicals are natural alternative employment options for most pharmaceutical workers.

Table 4 provides an overview of these mobility patterns. The numbers show that it is only a small fraction of workers that move in and out of the sector. In the pooled sample of male workers with a medium-level technical or Master's or PhD degree, total mobility in and out of the sector amounts to 28% of workers. The table shows how inflows and outflows are distributed across the industries that constitute the most important alternative employment options for workers in the pharmaceutical industry. Also, the table distinguishes between R&D-plants and other plants. R&D-active plants show a larger tendency to be linked via worker mobility to hospitals and universities – i.e. research active workplaces – whereas the plants without R&D-activity to a larger degree are linked with the chemical industry, precision and optical equipment and the residual group of industries in the category "other".

Table 4: Mobility in and out of the pharmaceutical sector

	R&D-active plant		Non R&D-plant	
	inflow	outflow	inflow	outflow
Chemicals and Chemical products	20.8	25.6	25.2	25.2
Precision and optical instruments	1.8	1.4	3.5	2.1
Hospitals etc.	6.2	3.6	2.4	0.9
Universities, research and teaching	19.2	11.3	9.3	6.8
Pharmacies and retail sale of medical equipment	1.6	0.7	0.6	0.4
Other	50.4	57.4	60.1	64.5
Total moves in sample	2011	1623	1670	1384

Note Mobility patterns for the male part of the sample. The chemical industry: NACE 24 excluding 24.4 (pharmaceuticals); Precision and optical instruments etc. NACE: 33; Hospitals etc.: NACE 8511, 8512, 8513, 8520; Universities, research, and teaching: NACE 7310, 8030; Pharmacies and retail sale of medical equipment: NACE 5231, 5232. An R&D-active plant is a plant that reports that at least one worker carries out scientific work in bio-technology or medicine.

5 Empirical results

This section presents estimates of the degree to which workers at R&D-plants pay for learning by accepting a wage-discount early in their career in exchange for subsequent higher wages. I start by using R&D-exposure at time t and its interaction with experience as the only R&D variables. This amounts to using current R&D-exposure as a proxy for career R&D, which is a good approximation if workers choose *either* research careers or careers at other types of pharmaceutical plants. As the previous section showed there is a large amount of stability in worker R&D-types but also some mobility, and in the following subsection, I use the panel-dimension of the data set to construct a separate index of the workers previous R&D-experience.

5.1 Current R&D as a proxy of for career R&D

The baseline regression is an extended mincerian wage-regression of the following form performed on the pooled data set:

$$\begin{aligned} log\ wage_{it} = & \alpha_0 + \alpha_1 schooling_{it} + \alpha_2 experience_{it} + \alpha_3 experience_{it}^2 \\ & + \delta_0 CRD_{it} + \delta_1 CRD_{it} * experience_{it} + \delta_2 CRD_{it} * experience_{it}^2 \\ & + Z_{it}\beta \\ & + u_{it} \end{aligned} \tag{5}$$

The unit of analysis is worker i at time t, and the dependent variable of the earnings function is the log of yearly wage-income. I control for years of schooling and experience, and I include time dummies and a quadratic in plant-level number of employees as well as the share of low-skilled workers in the vector Z_{it}. The parameters of interest are δ_0, δ_1 and δ_2. CRD is a dummy variable that takes on the value 1 if worker i at time t is employed at an R&D-active plant.

The expected sign on δ_0 is negative. The parameter captures the willingness to pay for learning in a research environment for a young worker at the beginning of his career. Over the years the value of learning diminishes as the worker has fewer years left in the labour market to benefit from further accumulation of human capital, and at the same time the worker capitalises on past accumulated research experience. Accordingly, I expect the early wage-discount gradually to turn into a wage-premium at later stages of the career and therefore to observe faster wage growth for workers at R&D-active plants. This implies a positive expected sign on δ_1. The interaction between the R&D dummy and experience^2 allows the effect to differ across age-groups and for the rate of depreciation of human capital to differ between research experience and experience from plants that are not R&D-active.

I run the regression separately on the group of workers with a medium-level technical education and the group of workers with a Master's or PhD degree, respectively. The two groups of workers carry out different tasks and enter the labour market with a different set of skills, and I wish to allow for human capital accumulation and labour market effects to differ across the two groups of workers. Table 5 shows the results. Column 1 and 3 show the baseline regression, and in column 2 and 4, I have included firm-fixed effects.

Table 5: The effect of R&D-experience on earnings

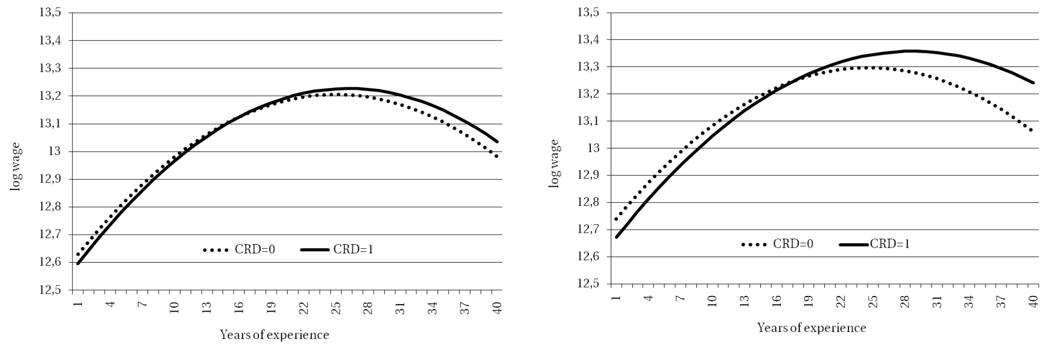
	Medium-level technical education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.0437	-0.0022	-0.1311***	-0.2008***
	(0.0270)	(0.0358)	(0.0315)	(0.0741)
Employees (1000)	-0.0283***	0.0019	-0.0124	-0.0216
	(0.0091)	(0.0252)	(0.0108)	(0.0240)
Employees $(1000)^2$	0.0132***	0.0027	0.0114***	0.0150**
	(0.0027)	(0.0061)	(0.0030)	(0.0063)
Bachelor's degree	0.3608***	0.3629***		
	(0.0052)	(0.0167)		
PhD degree			0.0224***	0.0260
			(0.0060)	(0.0158)
Experience	0.0364***	0.0354***	0.0500***	0.0492***
	(0.0019)	(0.0042)	(0.0021)	(0.0035)
Experience^2	-0.0007***	-0.0006***	-0.0010***	-0.0010***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
R&D-dummy (CRD)	-0.0031	0.0207	-0.0373**	-0.0712**
	(0.0209)	(0.0374)	(0.0182)	(0.0299)
Experience × CRD	-0.0047*	-0.0047	0.0023	0.0031
	(0.0026)	(0.0048)	(0.0026)	(0.0034)
Experience^2 × CRD	0.0002**	0.0001	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	12.2003***	12.1501***	12.6466***	12.7030***
	(0.0283)	(0.0550)	(0.0302)	(0.0520)
Firm-dummies	No	Yes	No	Yes
Observations	10869	10869	12890	12890
R^2	0.463		0.301	
Within-R^2		0.435		0.295

Dep. variable is log (yearly wage-income). Sample years 1995-2005. Time-dummies included 1996-2005. Robust standard errors in parenthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

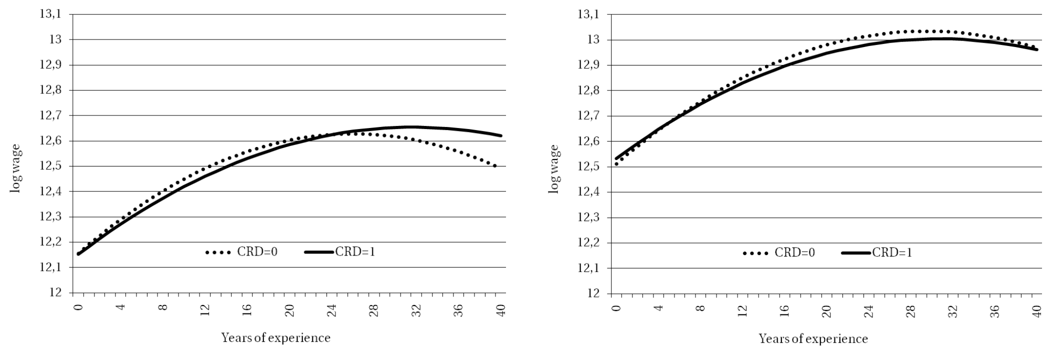
For the group of workers with a Master's or PhD degree, the coefficient on the R&D-dummy is negative and significant at the 5%-level. Consistent with the theory, the empirical results show that these workers on average earn 3.7% (column 3) less when they enter the labour market if their first job is at an R&D-active plant. The interactions with experience does not come out significant, but the parameters suggest that R&D-experience generates a slightly higher wage-growth and a lower rate of depreciation of human capital. According to these estimates, an R&D-worker with a Master's or PhD degree earns a 4.4% higher wage at the end of his career (35 years of experience). These numbers are comparable in size to those estimated in Møen (2005). Moreover, part (a) of figure 1 illustrates that the wage curves cross at around 15-16 years of experience which is in line with the similar example in the article by Møen (2005).[17]

For workers with a medium-level technical education, the results reported in column 1 also indicate that earnings develop differently over time for workers at R&D-active plants compared to workers at other plants. Though, the R&D-dummy is very close to zero, the interactions with the experience terms suggest that wages in the beginning of the career grow more slowly for workers at R&D-plants than at other plants, but also that wage growth later in the career is higher, resulting in higher wages at the end of the career. How the wages develop over the career of workers is illustrated in part (a) of figure 2. It is in line with the results reported in Møen (2005) that the curves cross rather late compared to the wage curves of workers with a longer education. In both that and the present paper, the curves cross at around 25 years of experience.



(a) No firm effects (b) With firm effects included

Figure 1: Wage profiles: Workers with Master's or PhD degree



(a) No firm effects (b) With firm effects included

Figure 2: Wage profiles: Workers with medium-level technical education

[17]Here, I refer to the example in Møen (2005) in which the author makes a graphical comparison of wage-curves for workers at plants with an R&D-intensity of 0.2 with those of workers at plants with an R&D-intensity of 0. R&D-intensity is measured as R&D man-years per employee at the three-digit line of business level within firms.

Firms use management strategies, hiring practices, and reward structures differently to attract and retain the best workers.[18] The aim of this paper is exactly to show that the payment structure at R&D-plants are different from that at other plants, but if R&D-plants in general belong to firms that are better at attracting high-productivity workers it makes the pooled sample of non-R&D workers an inaccurate comparison group. In particular, I would expect that R&D-workers would earn higher wages at a non-R&D-plant than what I observe among the pooled sample of non-R&D workers. To address this problem, I run the regressions including firm-fixed effects. These results are shown in columns 2 and 4 of table 5.

Now, the coefficient on the R&D-dummy is estimated by comparing workers within the same firm but with different R&D-status. The non-R&D workers within the same firm should provide a more accurate comparison group than all R&D-workers in the sample increasing the magnitude of the wage-discount. For workers with Master's or PhD degree, this is exactly the case as the coefficient decreases from -0.04 to -0.07. For workers with a medium-level technical education, the coefficient on the R&D-dummy turns positive, but the interactions with experience show a similar patterns as before, though in this regression all of the coefficients are insignificant. Part (b) of figure 2 shows how wages of this group of workers develop throughout the career.

Unfortunately, I am not able to address the general problem with worker heterogeneity in a similar way since in order to estimate the wage-discount it is necessary to estimate the regressions in levels. If workers differ in their general productivity levels, and this difference is systematically and positively related to R&D employment (also within the same firm), workers at R&D-active plants are, on average, more productive than other workers. Therefore, using non-R&D workers to estimate their alternative wage-profile lead me to underestimate the wage-discount early in their career.

A different source of bias is heterogeneity in workers' innate ability to learn. Rosen (1972) explicitly distinguishes between the learning potential associated with an occupation and the individual worker's ability to learn. In the model, better learners select into better learning environments. For my analysis this implies that I expect to find the better learners employed at the R&D-active plants. The implication of this is that I underestimate the steepness of the R&D-workers' alternative wage-profile by using wage-profiles of other pharmaceutical workers. Unfortunately, there is not much that I can do about this problem besides having it in mind when I interpret my results.[19]

Finally, I briefly discuss the estimated coefficients on the control variables. The plant-level control

[18] See e.g. the empirical work of Andersson et al. (2009).

[19] Of course it is a possibility that other types of learning are driving the results. For example, if a successful management career requires that workers early in their career invest heavily in acquiring managements skills of various kinds and are willing to take wage-discounts to be employed in occupations where they develop such skills. However, this is a problem to my estimation-strategy only if such learning is correlated with being employed at an R&D-active plant.

variables have the expected effects on wages. The coefficient on the share of low-skilled is negative in particular for workers with a Master's or PhD degree. This variable is included to take into account that production workers at plants with both production and R&D-facilities are characterised as R&D-workers. Running the regressions without the variable 'share of low-skilled' makes the coefficient on the R&D-dummy less negative for workers with a longer degree. This reflects that if I only rely on the R&D-dummy to characterise the R&D-intensity of plants, I will overestimate the R&D-intensity of some workers.

As expected there is a large-plant wage premium and a positive effect of longer schooling and higher experience on wages. Workers with a Bachelor's degree have a markedly higher wage-level than technical workers with shorter education. For this reason, I tried running the regression on workers with a Bachelors degree separately, but this did not alter the results. In this regression, the coefficient on the R&D-dummy is 0.03.

For both group of workers, including firm-fixed effects has a similar effect on the other plant-level variables – share of low-skilled and plant-size – as on the R&D-variables. For workers with a Master's or PhD degree, the effect of these variables becomes stronger whereas for workers with a medium-level technical education, these plant-level variables do not have an impact on wages when one compares workers within the same firm.

5.2 Separating accumulated R&D-experience from current learning

As employment at an R&D-plant at time t is correlated with R&D-status earlier in the career, the δ-coefficients in the above analysis capture both the average worker's willingness to pay for current research exposure and the return to accumulated experience from R&D-plants. Moreover, failing to take into account changes over time in worker R&D-types biases the results. According to the hypothesis of this paper, workers who switch from research plants to non-research plants have on average accumulated more human capital and have a higher productivity than their new colleagues which increases my estimate of accumulated human capital at these plants. On the other hand, workers who switch in the opposite direction have a lower productivity than other workers at research plants which decreases my estimate of their human capital. When I for a given experience level compare workers at the two different types of plants to learn about how much more human capital is accumulated at research plants, I underestimate the difference.[20]

This section presents results in which I use the panel-structure of the data to separate current

[20] Note, that the same type of bias arises if my definition of R&D-plants do not capture all plants at which R&D is carried out. This leads me to overestimate average human capital in the group of traditional plants. Likewise, plants that change status but not employees give rise to a similar bias.

R&D-exposure from past R&D-exposure. The key assumption of this paper is that one year of accumulated experience at an R&D-active plant is worth more in the labour market than a year of experience at a traditional pharmaceutical production plant. This implies that the expected sign on the coefficient on previous R&D-experience is positive whereas, I expect the sign on current R&D to stay negative and to increase in magnitude as it now only captures the value of learning to the worker.

I consider two alternative assumptions regarding the impact of previous R&D-experience on learning. In table 6, I assume that only the most recent R&D-experience is of extra value to the worker, and I report the results of a regression in which I have included the average of the R&D dummy over the latest three years. For observations with only one or two lagged values, the measure is the average over the observed past experience in the pharmaceutical sector. This assumption is closest in spirit to the Pakes and Nitzan (1983) type of models. In these models, knowledge about novel innovations is the key component of R&D-learning, and if this a good description of the nature of R&D-learning then R&D human capital depreciates fast and only the recent R&D-history matters. I restrict the sample to the years 1998-2005 in order to have at least three years of R&D-information for all workers.

The alternative hypothesis is that R&D-learning consists of on-the-job-learning in a more traditional sense, but that human capital accumulation takes place at a faster rate due to the experimentation and efforts associated with operating on the technological frontier inherent in R&D-activities. In this case, the pattern of depreciation of accumulated skills and know-how is expected to be more in line with other types of human capital accumulated on the job.

Table 7 reports the results of regressions assuming that the main part of R&D-learning takes this form. Previous R&D at time t is the average over current R&D in all previous years for which I have R&D-information available (since 1995). I assume that this measure proxies the average R&D-exposure of the worker and multiply it with his work experience to arrive at a measure of his total R&D-experience. The squared experience term allows for depreciation. Finally, I again restrict the sample to the years 1998-2005 such that I have at least three years of information available for workers with long experience.[21]

[21] Since, the measure is imprecise for workers moving into the pharmaceutical sector late in the career, I have tried including a dummy-variable taking the value of 1 for new pharmaceutical workers with more than 10 years experience. This variable is highly negative, and it lowers the absolute value of the R&D-variables in table 7 slightly though it does change the sign or significance level. Though in the alternative specification – assuming that R&D-learning depreciates fast – this kind of inaccuracy should be less of a problem, a parallel exercise produce similar conclusions.

Table 6: Effect of current R&D-experience and recent R&D-experience on earnings

	Medium-level technical education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.0573*	0.0204	-0.1537***	-0.2291***
	(0.0308)	(0.0412)	(0.0356)	(0.0640)
Employees (1000)	-0.0254**	0.0066	-0.0138	-0.0229
	(0.0100)	(0.0268)	(0.0124)	(0.0359)
Employees $(1000)^2$	0.0120***	0.0013	0.0112***	0.0157*
	(0.0030)	(0.0064)	(0.0035)	(0.0090)
Bachelor's degree	0.3604***	0.3629***		
	(0.0058)	(0.0180)		
PhD degree			0.0273***	0.0303*
			(0.0068)	(0.0164)
Experience	0.0332***	0.0325***	0.0485***	0.0484***
	(0.0021)	(0.0046)	(0.0026)	(0.0045)
Experience^2	-0.0006***	-0.0006***	-0.0009***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
RD-dummy (CRD)	-0.0445*	-0.0052	-0.0714***	-0.1029**
	(0.0242)	(0.0467)	(0.0215)	(0.0389)
Experience$\times$ CRD	-0.0026	-0.0037	0.0040	0.0046
	(0.0029)	(0.0056)	(0.0031)	(0.0049)
Experience$^2\times$ CRD	0.0001	0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Last 3 years R&D	0.0312***	0.0503**	0.0448***	0.0235
	(0.0081)	(0.0201)	(0.0090)	(0.0248)
Constant	12.2611***	12.1752***	12.6797***	12.7552***
	(0.0306)	(0.0505)	(0.0328)	(0.0402)
Firm-dummies	No	Yes	No	Yes
Observations	8742	8742	10153	10153
R^2	0.478		0.318	
Within-R^2		0.453		0.308

Dep. variable is log (yearly wage-income). Sample years 1998-2005. Time-dummies included 1999-2005. Robust standard errors in parenthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

Starting with workers with a Master's or PhD degree, it is seen that including the two alternative types of measures of previous R&D-experience has a similar impact on the coefficient on current R&D. In line with expectations, the coefficient on the current R&D-dummy stays negative and increases in magnitude both with and without firm-fixed effects. For workers with a medium-level technical education, the overall picture is likewise that the estimates of the wage-discount increase in magnitude though the tendency is not as strong as for workers with a longer education. In particular, in the fixed-effects regressions the R&D-variables remain without explanatory power.

Table 7: Effect of current R&D-experience and previous R&D-experience on earnings

	Medium-level technical education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.0596*	0.0137	-0.1548***	-0.2411***
	(0.0309)	(0.0383)	(0.0359)	(0.0649)
Employees (1000)	-0.0247**	0.0022	-0.0154	-0.0266
	(0.0099)	(0.0272)	(0.0125)	(0.0336)
Employees (1000)^2	0.0119***	0.0026	0.0118***	0.0167**
	(0.0029)	(0.0066)	(0.0035)	(0.0082)
Bachelor's degree	0.3612***	0.3638***		
	(0.0058)	(0.0190)		
PhD degree			0.0273***	0.0302*
			(0.0068)	(0.0164)
Experience	0.0336***	0.0327***	0.0473***	0.0484***
	(0.0021)	(0.0049)	(0.0027)	(0.0049)
Experience^2	-0.0006***	-0.0006***	-0.0009***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
RD-dummy (CRD)	-0.0392*	0.0004	-0.0518**	-0.0970***
	(0.0232)	(0.0429)	(0.0211)	(0.0354)
Experience × CRD	-0.0022	-0.0036	0.0019	0.0043
	(0.0029)	(0.0051)	(0.0031)	(0.0045)
Experience^2 × CRD	0.0001	0.0001	0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Experience× PRD	0.0019	0.0037	0.0057***	0.0012
	(0.0016)	(0.0023)	(0.0019)	(0.0026)
Experience^2 × PRD	-0.0000	-0.0001	-0.0001*	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	12.3190***	12.2429***	12.7449***	12.8245***
	(0.0302)	(0.0473)	(0.0327)	(0.0370)
Firm-dummies	No	Yes	No	Yes
Observations	8636	8636	10153	10153
R^2	0.442		0.282	
Within-R^2		0.428		0.281

Dep. variable is log (yearly wage-income). Sample years 1998-2005. Time-dummies included 1999-2005. Robust standard errors in parenthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

An important assumption of the theoretical foundation for this paper is that R&D-workers experience higher earnings growth that other workers. The estimations in the previous section did not produce very strong conclusions along these lines, though for workers with a Master's or PhD degree signs and magnitudes on the interactions between R&D and the experience terms were in line with the predictions. In that section, the R&D dummy in addition to capturing current R&D-status might also capture the value of accumulated R&D-experience for a worker with a given experience level. The estimations in the present section in which I have attempted to separately measure current and past R&D-exposure, seem to better capture gains from R&D-experience, specifically using the measure of recent R&D-exposure as in table 6. Though for workers with a Master's or PhD degree, including firm effects weakens the evidence of significant wage-gains.[22]

6 Sample of women

The analysis so far has been concerned with a specific group of workers in the pharmaceutical industry; male workers with either a medium-level technical degree, or a Master's or PhD degree. In this section, I investigate if female workers belonging to these two educational groups have similar wage-patterns. This group of workers constitutes more than 50% of the workforce among workers with these types of educations and are thus an important group to the industry.

Table 8 uses the sample of female workers in the regression in which current R&D is the only R&D-information. Again, there is evidence that workers with a Master's or PhD degree accept lower wages early in their career. I find that these workers accept a wage-discount of 4% increasing to 5% with firm-fixed effects included. Both estimates are significant at the 5%-level. Moreover, the coefficient on the R&D-dummy for female workers with a medium-level technical education is more negative than in the sample of male workers, though also not significant.

[22] Observing a wage-discount but no wage-gain from R&D-experience is in fact more in line with the hypothesis in Stern (2004). He finds that young PhD job-market candidates accept lower wages in positions with better conditions for research and interprets this as a preference for research.

Table 8: The effect of R&D-experience on earnings, sample of women

	Medium-level technical education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.0505***	-0.0422	-0.1059***	-0.1117**
	(0.0181)	(0.0676)	(0.0252)	(0.0430)
Employees (1000)	0.0052	0.0497***	0.0160**	0.0010
	(0.0054)	(0.0111)	(0.0073)	(0.0130)
Employees $(1000)^2$	0.0037**	-0.0102***	0.0023	0.0040
	(0.0016)	(0.0030)	(0.0021)	(0.0031)
Bachelor's degree	0.1818***	0.1762***		
	(0.0040)	(0.0176)		
PhD degree			0.0602***	0.0666***
			(0.0056)	(0.0089)
Experience	0.0239***	0.0225***	0.0462***	0.0466***
	(0.0011)	(0.0018)	(0.0017)	(0.0017)
Experience^2	-0.0004***	-0.0004***	-0.0008***	-0.0008***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
R&D-dummy (CRD)	-0.0191	-0.0309	-0.0317**	-0.0481**
	(0.0118)	(0.0234)	(0.0124)	(0.0201)
Experience × CRD	-0.0016	-0.0011	0.0028	0.0023
	(0.0014)	(0.0028)	(0.0020)	(0.0019)
$\text{Experience}^2 \times$ CRD	0.0001**	0.0001	-0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Constant	12.1605***	12.1399***	12.5173***	12.5350***
	(0.0180)	(0.0560)	(0.0241)	(0.0397)
Firm-dummies	No	Yes	No	Yes
Observations	25300	25300	13721	13721
R^2	0.340		0.469	
Within-R^2		0.283		0.455

Dep. variable is log (yearly wage-income). Sample years 1995-2005. Time-dummies included 1996-2005. Robust standard errors in parenthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

In table 9, I report the results with recent R&D-experience included. Again, this table confirms the results of the previous section. To save on space, I do not report the regressions with the alternative measure of R&D-experience as these regressions do not alter the conclusions.

Table 9: The effect of recent R&D-experience on earnings, sample of women

	Medium-level technical education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.0586***	-0.0619	-0.0956***	-0.1435**
	(0.0214)	(0.0600)	(0.0285)	(0.0565)
Employees (1000)	0.0118*	0.0573***	0.0147*	0.0059
	(0.0060)	(0.0088)	(0.0081)	(0.0136)
Employees (1000)^2	0.0009	-0.0128***	0.0021	0.0029
	(0.0018)	(0.0020)	(0.0023)	(0.0032)
Bachelor's degree	0.1883***	0.1844***		
	(0.0045)	(0.0209)		
PhD degree			0.0646***	0.0708***
			(0.0061)	(0.0084)
Experience	0.0224***	0.0215***	0.0458***	0.0460***
	(0.0013)	(0.0018)	(0.0020)	(0.0014)
Experience^2	-0.0004***	-0.0004***	-0.0008***	-0.0008***
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
RD-dummy (CRD)	-0.0458***	-0.0428	-0.0502***	-0.0672***
	(0.0142)	(0.0307)	(0.0151)	(0.0185)
Experience× CRD	-0.0015	-0.0011	0.0023	0.0023
	(0.0016)	(0.0033)	(0.0023)	(0.0017)
Experience^2× CRD	0.0001**	0.0001	-0.0000	-0.0000
	(0.0000)	(0.0001)	(0.0001)	(0.0001)
Last 3 years R&D	0.0255***	0.0154***	0.0317***	0.0144**
	(0.0049)	(0.0052)	(0.0061)	(0.0069)
Constant	12.2074***	12.1845***	12.5025***	12.5605***
	(0.0205)	(0.0448)	(0.0265)	(0.0447)
Firm-dummies	No	Yes	No	Yes
Observations	20003	20003	11224	11224
R^2	0.376		0.485	
Within-R^2		0.335		0.469

Dep. variable is log (yearly wage-income). Sample years 1995-2005. Time-dummies included 1996-2005. Robust standard errors in paranthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

7 Robustness checks

A way of verifying that the results of the paper are actually due to R&D-learning is to investigate how an equivalent analysis on the sample of male non-technical workers compares to the analysis on workers with a technical or scientific education. Non-technical workers are, supposedly, further away from the research core of the plant, and if the results of the previous section captures R&D-learning,

I should not find a similar pattern among non-technical workers.

The results of table 10 confirms this hypothesis. Though there is some indication of a negative wage-discount for workers with a higher non-technical degree in the regression with firm-fixed effects, the magnitude is markedly smaller than what was found for workers with a technical or scientific degree. Similar results (not reported here) emerge from the analyses with the two alternative measures of R&D-experience included, though the coefficient on recent R&D-experience by itself is positive and significant.

Table 10: The effect of R&D-experience on earnings for non-technical workers.

	Medium-level education		Master's or PhD degree	
	(1)	(2)	(3)	(4)
Share of low-skilled	-0.3343***	-0.4300**	0.0108	0.0266
	(0.0573)	(0.1775)	(0.1085)	(0.1846)
Employees (1000)	-0.1145***	0.0541*	-0.0593*	-0.0046
	(0.0215)	(0.0322)	(0.0350)	(0.0666)
Employees $(1000)^2$	0.0288***	-0.0024	0.0202**	0.0086
	(0.0063)	(0.0092)	(0.0096)	(0.0170)
Bachelor's degree	0.2397***	0.2313***		
	(0.0129)	(0.0334)		
Experience	0.0187***	0.0201**	0.0523***	0.0482***
	(0.0039)	(0.0075)	(0.0075)	(0.0047)
Experience^2	-0.0003***	-0.0003	-0.0009***	-0.0008***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
R&D-dummy (CRD)	0.0198	-0.0371	0.0082	-0.0256
	(0.0497)	(0.0893)	(0.0639)	(0.0753)
Experience × CRD	0.0002	-0.0007	0.0027	0.0052
	(0.0057)	(0.0100)	(0.0095)	(0.0073)
Experience^2 × CRD	0.0001	0.0001	-0.0002	-0.0002
	(0.0001)	(0.0003)	(0.0003)	(0.0002)
Constant	12.6994***	12.6587***	12.4645***	12.4422***
	(0.0609)	(0.1370)	(0.0832)	(0.0843)
Firm-dummies	No	Yes	No	Yes
Observations	3160	3160	2225	2225
R^2	0.212		0.287	
Within-R^2		0.216		0.239

In column 3 and 4, I have left out workers with a PhD degree since there are only 12 such observations in the data. Dep. variable is log (yearly wage-income). Sample years 1995-2005. Time-dummies included 1996-2005. Robust standard errors in parenthesis.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

A final comment concerns the choice of leaving out workers at plants with less that five employees. These very small plants could for example be new entrants with a wage-structure different from the rest of the sample. However, keeping workers from these plants in the sample produces similar results as the ones reported in section 5.

8 Conclusion

In this paper, I investigate how R&D-investments affect return to experience and entry-wages for a sample of full-time workers in an important high-tech industry; the pharmaceutical industry. Mobility of key research personnel constitutes a potential cost to employers as mobility is a source of technology transfers to competitors. This acts to lower incentives to undertake R&D-investments. At the same time, formal models of worker mobility in research-intensive industries and models on occupational learning emphasise that in a dynamic perspective worker mobility need not have a negative impact on R&D-investments. By the logic of these models, research-workers compensate their employers for R&D-learning by accepting a lower wage than they could achieve in alternative employments with a lower learning content.

In a pooled sample of workers with a technical or scientific degree in the Norwegian machinery and equipment industry, Møen (2005) finds evidence that male workers in R&D-environments accept lower wages early in their career. The contribution of this paper is to investigate this question within a single highly research-intensive industry; the pharmaceutical industry. Moreover, the present study uses plant-level information on R&D-activity to measure R&D-exposure which is an advantage over firm-level R&D-measures.

In the main analysis, I estimate and compare wage-curves for male employees at R&D-active plants and otherwise similar workers employed at other types of pharmaceutical plants, and I find that workers with a Master's or PhD degree, take a wage-discount of around 4-10% early in their career in return for higher earnings later. In particular, recent R&D-experience is a source of significantly higher wages for this group of workers.

With respect to workers with a medium-level technical education, I find that entry wages are similar at both types of plants but that wage growth in the beginning of the career are lower at R&D-active plants. For these workers it is only after about 25 years of experience that employment at R&D-active plants translates into higher yearly earnings compared to workers at other types of plants. This result compares to that in Møen (2005) in the sense that he finds that technical workers with R&D-exposure catch up to otherwise similar workers markedly later than is the case for workers with a higher technical or scientific degree.

An additional contribution is to present results on the female part of the workforce. This group was left out in the main analysis to ease comparison with the results in Møen (2005), but as this group of workers constitute more than 50% of the labour force it is important to investigate the hypothesis on this sample as well. The estimated coefficients are slightly smaller in magnitude than for men, but statistically as strong.

Finally, I do not find that similar effects are at play in the group of non-technical workers which is re-assuring as it confirms that the estimated coefficients capture the value of R&D-learning. Even if non-technical workers are employed at R&D-active plants this group of workers are likely to be further away from the research core and generally less able to transfer technical know-how.

Together these results suggest that the value of R&D-learning in the pharmaceutical industry is at least partially internalised in the labour market. Furthermore, the estimations provide indirect evidence in favour of theories arguing that labour mobility is a source of knowledge transfers.

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Technology sourcing via hiring and the use of non-compete clauses

Technology sourcing via hiring and the use of non-compete clauses.

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Abstract

A number of empirical investigations have established that multinational companies increasingly locate development activities in the leading science centres of the world in order to gain access to advanced technological know-how. In this sense they can be said to "listen in on new ideas" with the aim of using these for their own purposes, and this raises questions with respect to the effect on research investments in those regions. I model the sourcing of technologies as an imitative activity, and I build on insights from the economic geography literature on localised knowledge spillovers to suggest a positive feedback effect from imitation to innovation. In particular, I suggest that labour market competition among a group of imitators generate positive incentives for young scientist-employees to contribute effort to research projects. At the same time the threat of future imitation via employee-mobility is detrimental to the incentives of the research firm because it lowers the value of successful innovation. Non-compete clauses offer protection to employers against worker-mobility, but the results of the model suggest that when wage competition among imitators are sufficiently strong profitability of projects are higher if firms refrain from including such clauses in their employment contracts.

1 Introduction

Increasingly, multinationals establish research and development activities away from the headquarter, in the leading science centres of the world (OECD (2008), OECD (2010)). The conventional view on foreign R&D-activities is that they are aimed at adapting core-technologies to a local market, but case-studies and econometric evidence indicate that a major motive for locating R&D-activities abroad is a need for sourcing advanced technologies and know-how (see e.g. Almeida (1996), Gerybadze and Reger (1999), von Zedtwitz and Gassmann (2002), Griffith et al. (2006), Todo and Schimizutani (2008), Blit (2009)). For example, firms use technology sourcing as a way of catching up with technology leaders (Kuemmerlee (1999)), to expand technical diversity (Song et al. (2003)), or as a spring board to carry out own R&D-activities at a later stage (Chung and Yeaple (2008)).

The existing literature on this topic is primarily empirical, and the focus is on the recipient firm, but it is natural to think that technology sourcing has a considerable impact on the research conducted in the donor-region. The aim of this paper is to address this issue in a theoretical framework. For this purpose, I view the sourcing of technologies as imitative activities.

Traditionally, models of industrial R&D stress that imitation prevents the investing party from appropriating the full return to a successful innovation from which it follows that R&D is underprovided by the market. In contrast, this paper builds on insights from the economic geography literature on localised knowledge spillovers to suggest a positive feedback effect from imitation to innovation. In particular, in the model of this paper, multiple imitators who each relies on hiring to access new technologies and to adapt these to the market compete for experienced scientists. The tougher is wage-competition, the higher the return to innovative efforts of scientist-employees and the better are their incentives to contribute effort at an early research-stage. I show that when wage competition among imitators are sufficiently strong, entry of imitators are beneficial to the innovative efforts of the industry.

This motivation highlights that the term imitation does not refer to copying of simple production technologies. Rather, my focus is on imitation at an early stage of the technology's life-cycle when knowledge is tacit in nature, and the human capital input of the researcher is essential for its dissemination. Empirical research by Lynne Zucker, Michael Darby, and co-authors confirm that star-scientists play a key role for start-ups in the US bio- and nano-technology industries (see e.g. Zucker et al. (1998), Zucker et al. (2002), Zucker and Darby (2006)). Likewise, results by Almeida and Kogut (1999), Song et al. (2003), and Kim and Marschke (2005) for US-engineers indicate that mobility is a driver of technology diffusion. Locating close to technology leaders facilitates hiring of key engineers and scientists and is a way for firms to stay at the forefront of the technological development while at the same time offering a way for researchers to capitalise on their know-how.[1]

Of course, an inventing firm has a strong incentive to protect itself against mobility of research personnel to avoid both loss of human capital and diffusion of new knowledge. One obvious way of achieving this is to include a non-compete clause in the employment contract limiting an employee's ability to move to a competing firm in a specific geographic area and period of time. Gilson (1999) argues that refraining from using such contracts can be jointly advantageous for firms in some industries. According to the author, lack of enforcement of these covenants by Californian courts contributed to the culture of job-hopping in the Silicon Valley computer industry – a regional characteristic that, since Saxenian (1994)'s famous study, is often emphasised as one of the key factors behind its high rates of innovation.

The hypothesis of Gilson finds support in Fallick et al. (2006) who study monthly job-changes in California and other US-states. They find that IT-clusters in California generally have higher mobility rates than IT-clusters elsewhere in the U.S. whereas other industries do not show similar regional differences. The authors argue that the computer industry distinguishes itself from many other industries by its strong modularity of innovations acting to make gains from access to know-how outweigh the cost of losing human capital.[2] The present paper likewise adds to the literature on the optimal use of non-compete clauses but is concerned with a different trade-off. The advantageous effects associated with refraining from using such clauses stem from a positive employee-incentive effect rather than from future access to competitor's know-how.

In the model, research firms initially choose whether to locate in a region in which non-compete clauses are enforced by courts (NC-region), or in a region in which firms cannot protect their innovations by including such clauses in wage contracts (C-region). Subsequently, they choose whether to undertake a research project or not. The probability of success depends on both firm investments and the effort of its scientist-employee, and workers are borrowing constrained. This is equivalent to the set-up in Aghion and Tirole (1994). Technological output is advanced and has value to entering imitators who can copy the technology by hiring experienced research personnel. This is a source of wage-competition which improves worker incentives but also lowers firm investments in research because imitation decreases the value of successful projects. When non-compete clauses are in use, the research firm is a monopsonist employer and scientist-employees have no way of capitalising on their research effort. Hence, the research firm appropriates the full return to a successful innovation,

[1] Almeida (1996) in the concluding section, notes that a close review of U.S. patent citation patterns suggests that foreign firms may not be targeting just regions but even specific firms in their learning efforts.

[2] Other empirical studies on the role of non-compete clauses are Garmaise (2009) and Marx et al. (2009) who use variation in enforcement regimes across U.S. states to investigate whether non-compete clauses matter for mobility patterns and R&D-investments. Both studies are positive towards the hypothesis in Gilson (1999)

but it is also the sole contributor to research.

The optimal choice of location trades off these effects. Naturally, it depends on whether the investment in the research project by the firm or the worker are most important, but the contribution of this paper is to show that sufficiently strong wage-competition increases total monetary incentives at the research stage and contributes to making the C-region attractive to research firms. There are two distinct cases to consider.

In *case 1*, wage-competition among entering imitators is strong in the sense that the original employer prefers losing the scientist-employee rather than offering a wage that matches the wage-level in the imitating sector. This implies that the incentive *gain* to the worker exceeds the incentive *loss* to the firm, and in this case, expected profit is always increasing in the wage to experienced researchers. Only if the contribution of the worker to the research project is relatively unimportant does the industry locate in the NC-region. I argue that the computer industry fits well with the criteria for an industry that gains from locating in the C-region. It depends to a large degree on the creative input of workers to generate innovations, and IT-technologies have multiple uses just as they can be built upon making it likely that the value to imitators of copying new technologies exceeds any loss to the original inventing firm.

In *case 2*, wage-competition is weak, and it is optimal for the research firms to retain experienced scientists by offering the prevailing wage in the imitating sector. In this case, the positive effect of wage-competition on worker effort is exactly out-weighed by a negative effect on firm investments. As the wage-payment in addition lowers the return to a successful innovation, a marginal increase in the wage-level of the imitating sector serves to lower the attractiveness of the C-region.

The welfare analysis shows that it is never optimal to force industries to include non-compete clauses in their employment contracts. On the contrary, research-employees have higher expected earnings when non-compete clauses are not in use, and this makes the social planner prefer the C-region over the NC-region as long as firm investments are not too important for the success of the research project. However, the positive worker incentives in regions without non-compete clauses act to lower the range of industries for which the equilibrium location differs from the socially optimal location.

The model framework and results are related to other models of innovation and imitation in the following way. In North-South models, as in Grossman and Helpman (1991), Northern producers face high labour cost but have a comparative advantage in innovation whereas imitators located in the South pay lower wages. Innovations in terms of quality improvements on existing product lines provide the Northern producers with market power until the new quality is successfully copied by a producer in the South. Product market competition takes place in prices and the lower production cost in the South forces the Northern producer out of the market until its research investment again allows it to advance the technological frontier. In this way production alternates between the high cost North and the low cost South.[3]

These models address imitation of well-developed codified technologies that can easily be transferred across the globe whereas the present paper is motivated by imitation at an early stage in which geographic proximity is important and the novelty of knowledge makes it likely that both first and second users can extract profits from the market. As I have argued this adds a different dimension to the relationship between innovators and imitators.

Bessen and Maskin (2009) are concerned with advanced technology absorption by imitators and draw attention to a possible positive impact of imitation on innovation, though their idea is different from the one in this paper. In that model, innovation is a sequential process and research by competitors complementary in the sense that methods and ideas do not perfectly overlap, for example because the imitator possesses specialised information about a market. In this case, imitation may be a help to innovators because it increases the probability of success at future research stages, and it follows that strict patent laws may lower research and development expenditures. Interestingly, the authors support their argument by noting that patent protection in some of the most innovative industries of the last forty years – software, computers and semiconductors – has been weak and thus these industries have been characterised by favourable conditions for imitation.

Other papers are concerned with the role of labour mobility for technology diffusion and research activities. Pakes and Nitzan (1983) deduce the optimal wage contract when an entrepreneur risks that a scientist-employee leaves to join a competitor and reveal essential knowledge about production technologies. The optimal wage contract consists of two parts. A variable part that is tied to the firm's profit and a fixed part that exactly satisfies the scientist's participation constraint. As the entrepreneur can withdraw the future high earnings of the scientist from the first-period skill-adjusted wage, this type of technology diffusion does not affect the profitability of projects. Moreover, in the baseline model there is no mobility in equilibrium.[4] Other authors have extended on this framework and have studied conditions for mobility as well as added different forms of intellectual property rights protection. Kim and Marschke (2005) consider the firm's patenting decision, Fosfuri and

[3]Models of escape-competition argues that entry or catching-up of technological lagging firms by generating competition pushes firms to innovate to escape the downward pressure on profits from product market competition (see Aghion and Griffith (2005) for a review).

[4]In an extension, Pakes and Nitzan (1983) model entry by a third party and show that it can be optimal for the entrepreneur to induce the researcher to leave and start on his own such that the entrant expects tougher competition and chooses to stay out of the market.

Rønde (2004) are concerned with a set-up with cumulative knowledge and trade secrets, and Franco and Mitchell (2008) study the optimality of non-compete clauses in a model in which it is private information to the employee whether he/she has learned. The results of this paper add to this range of models by considering worker investment incentives and showing that even if there is a lower bound on wages, a highly competitive labour market with mobility might be mutually advantageous to scientist-employees and firms.

In Combes and Duranton (2006) firms hire a continuum of workers who accumulate strategic human capital during the first period. Hiring competitor-employees in the second period is a source of cost reductions and this drives wage competition for workers. Workers are heterogeneous with respect to their cost of changing employer allowing for both poaching and retention of workers in equilibrium. The model links product market competition and labour market competition, but in contrast to this paper, it leaves aside any investment-choices by workers or firms. A different aspect of worker-mobility is formation of spin-outs by former employees. This is the topic in Franco and Filson (2006) . Workers simultaneously contribute to research and learn the know-how of their employers which they can use to found a new research firm. The likelihood of success in research depends on the level of know-how of the employer which varies across agents. The authors test their model empirically and note that it is particular relevant for a young industry in which technology adoption and firm creation are driven by a small group of forerunners.

Finally, the present paper draws on insights from the economic geography literature emphasising beneficial effects from reduced employer monopsony power in industrial clusters. In Rotemberg and Saloner (2000), a thick local labour market induces workers to invest in industry-specific human capital as competition between employers forces firms to pay high-skilled workers their marginal value thereby ensuring workers a return to their investment and increasing overall productivity in the region. Matouschek and Robert-Nicoud (2005) consider the opposing impact on worker and firm investments. However, in contrast to this paper they only consider cases where either the firm or the worker is the investing party just as workers are unproductive while acquiring skills. Almazan et al. (2007) combine the labour pooling model of Krugman (1991) with industry specific human capital investments by firms or workers. Clustering may be attractive because it increases the pool of skilled workers available to a firm upon a positive productivity shock, but at the same time it discourages firm investments in human capital.

The rest of the paper is organised as follows. Section 2 introduces the model, and in section 3, I carry out the analysis. Section 4 determines how the socially optimal location decision compares with the market equilibrium. Finally, in section 5, I conclude.

2 Model introduction

The model describes a research intensive industry faced with a threat of imitation by a large number of multinationals that scan the global economy for new technological advancements and establish themselves in regions at the technological forefront to learn about the latest innovations. Accordingly, in the model research firms make the long term decision with respect to which line of research to pursue knowing that if successful, a global pool of competing producers will make an effort to imitate and market the innovation before the full market potential of the new technology has been realised by the original inventor.

I consider a three-period model of a research-intensive industry. Initially, before any research-decisions have been taken, firms decide irreversibly on the legal environment in which they will continue their operations. They choose between locating in a region in which courts do not enforce non-compete covenants (the Compete-region/C-region) or in the Non-Compete region (NC-region) in which firms can use such clauses to prevent scientist-employees from leaving for a competitor.[5] There are two stages in product development. A stochastic innovation stage which requires the joint effort of the firm and a scientist-employee, and a final, deterministic development stage. At the beginning of period 2, before the final development stage is completed, imitators can enter and hire successful scientists. Below, I lay out the details of the model.

Research stage: There is a continuum of potential research firms each having capacity to carry out at most one project with market potential Δ in case of success but generating zero output otherwise (when I analyse the model, I normalise Δ to 1). Firms differ with respect to the fixed cost of implementation, $F_r = \phi r$, for example because they use different methods or are heterogenous with respect to their overall capacity for research. In other words, to some firms projects are fairly easy to undertake and require few initial investments by the firm, but to other firms projects are complex and cost-intensive. I order firms in ascending order by the size of the fixed cost.[6]

Conditional on implementation, projects are symmetric. The research technology is given by a probability of success $P(success) = \mu k + (1-\mu)e$ where e is worker effort, k is an investment made by the firm and $\mu \in]0,1[$ is the relative importance of the investment by the two parties. For simplicity,

[5]This is the only type of IP-protection that I consider. In this sense, the model concerns competition over non-patentable parts of new technologies. Kim and Marschke (2005) model the firm's patenting choice as a response to employee mobility. In their model, patenting not only protects the competitive advantage of the firm in case of mobility but also changes the value to the employee of leaving relative to staying.

[6]Even though I associate each research project with a different firm, the number of firms in the model is actually unspecified. The set-up is equally consistent with a research sector consisting of one big firm that undertake a number of differentiated projects each with unit labour requirement. As a matter of fact, these small projects could add to one big project. The important point is that the marginal contribution of an extra project to aggregate profit in the R&D sector is falling in the number of projects.

conditional on μ, the parties are equally good at contributing to research. Their cost-function is quadratic and given by $c(h) = \frac{1}{2}\lambda h^2$, $h = k, e$. I restrict λ to $\lambda > \Delta$, which ensures that the probability of success never exceeds one.

The parameter μ captures differences in research technology at the industry level. For example, μ close to zero represents industries in which human capital is essential to the research process as for example the computer software industry. At the same time, μ close to one does not imply that research takes place without any contribution by workers. Rather, k captures any research intensity induced by firm investments including investment in management and reward structures. This implies that industries in which verifiability and monitoring of research is fairly easy are industries in which firm investments are important.

Having this in mind, in the model research firms cannot monitor the worker and though the outcome of the research process is observable to the firm and the scientist-employee, it is not verifiable in court. That is, incentive contracts are not enforceable. This means that an outside employment option that depends on scientist effort is essential for inducing the worker to contribute $e > 0$ to research.

Development stage: At the end of period 1, the research firm knows whether the project succeeded or failed, but before the product can be marketed it takes a period of further development. This could for example be the case if the research process results in a prototype of a new product, but final commercialisation requires further testing and adaption to specific consumer groups. The process is deterministic and costless, but if the firm fails to keep the worker at this stage the firm incurs a loss of δ, $0 < \delta < \Delta$. This parameter can be interpreted in two ways. First, the worker's human capital may simply be essential for the final development phase. This would be in line with the assumption made in Dechenaux et al. (2008) on inventor moral hazard and university licensing. Another interpretation is that a new innovation provides the innovator with market power for two periods, each of which contributes $\frac{1}{2}\Delta$ to the profit of the research firm. If an imitator hires the researcher at the beginning of period 2, it copies the technology and steals some of the market (of value δ). Such an interpretation is similar to the quality-ladder interpretation of innovation used in Aghion and Griffith (2005). I cannot distinguish between these interpretations in the model. With respect to the implications and predictions of this paper it only matters how the size of δ compares with the equilibrium wage in the imitating sector.

Imitation: Imitation takes place in a discrete number of firms. There is free entry into this sector and entry takes place at the beginning of period 2 after the research projects have finished but before the final development stage. Imitators produce by hiring last periods successful scientists who are capable of transferring the technological know-how to a new employer. In the following, I denote these researchers "experienced scientists".

An imitator pays a fixed cost of F to enter, and hereafter the production technology exhibits decreasing returns to scale and is given by:

$$y(l_i) = \beta l_i - \frac{1}{2}\gamma l_i^2 \tag{1}$$

where l_i is the number of successful researchers hired by an imitator, and β measures the maximum value of technology transfers by each worker. A reasonable assumption is that the imitator cannot extract more value from each innovation than the inventing firm which is ensured by $\beta < \Delta$. A restriction on the entry cost of $F < \left(\frac{\beta}{\gamma}\right)^2$ ensures that the equilibrium wage in the imitating sector is positive.

The aim of this paper is to analyse the impact of international technology sourcing on host country research. As such F captures the cost of establishing facilities abroad to learn and source technologies. One can think of two types of imitators: Imitators that establish traditional production in the host region, and a different type of imitators that establish "listening posts" in the host region but transfer any acquired technological know-how out of the region to produce at facilities abroad. Entry costs of the last type are likely to be higher than entry costs of the first type.

The production function is identical across imitators such that every imitator is equally good at copying knowledge. At the same time, the degree of decreasing returns to scale as measured by γ reflects a limit with respect to the firms' capacity to absorb new technology. Thus, in contrast to the R&D-sector, an extra imitator raises the average productivity of the sector. As will become clear, F and γ together determine the aggregate capacity of the imitating sector for absorbing technology and thereby determine the intensity with which firms compete for experienced researchers.[7]

Workers: There is a large number of workers who each lives and works for the two periods of innovation and development/imitation. They are risk neutral and maximise expected total life-time income less of costs of research effort. A worker who fails to find employment in the research or imitating sector has the option of moving to a different industry. I normalise their outside option to zero, $\bar{w} = 0$. I assume that workers are unable to borrow against future income, which renders scientist-employees unable to compensate their employer fully for the value of human capital accumulation in the research process. In this type of setting, in which the value of learning about the latest and most advanced technological know-how is potentially very high, this seems reasonable. In the model, it serves the role of maintaining the traditional arguments against imitation (imitation lowers research

[7] In addition to this economic intuition, the decreasing returns to scale specification for the imitating sector ensures competition *between* imitators for experienced researchers in equilibrium which is crucial to the results of this paper.

investments by firms) while at the same time studying its relation to the positive incentive effect with respect to workers.[8]

Figure 1 summarises the timing and economic decisions of the model. In addition to the parameters already introduced, N_R is the number of research firms, w_{1R} is the period 1 wage offered to a researcher, N_I is the number of entering imitators, and w_I, w_{2R} are the period 2 wage offers made by firms in the imitating sector and research sector respectively. In the analysis, I use superscripts 'NC' and 'C' to distinguish the NC-region equilibrium from the C-region equilibrium. In the subsequent sections, I solve for the equilibrium expected profits to research firm r in each of the two regions and compare these to determine the equilibrium location of industry μ. In the C-region, research firms are faced with a threat of entering imitators (N_I) whereas these have no incentives to enter in the NC-region. For this reason, labour market dynamics are completely different in the two locations.

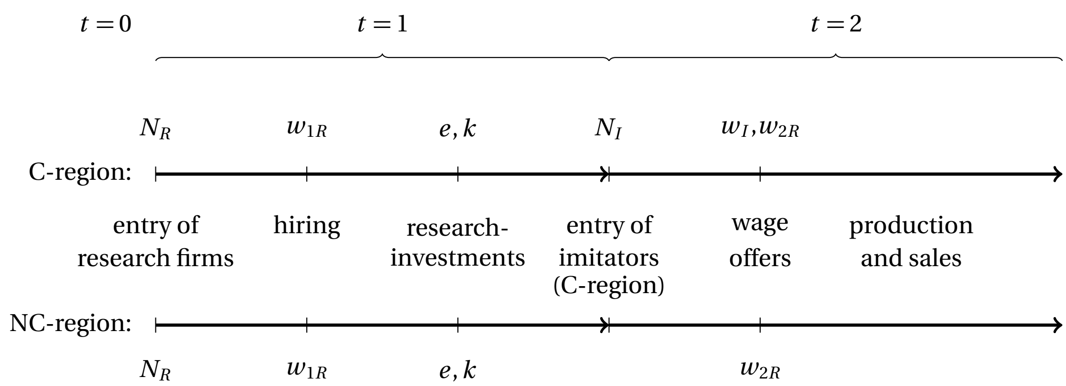


Figure 1: Timing of the game

3 Analysis

This section begins with a derivation of the outcome in the NC-region in which non-compete clauses are enforced by courts. I then move on to the analysis of the subgame where the industry is located in the C-region. Finally, I solve for the optimal location of firms in industry μ by comparing expected profits in the two regions.

I will assume that research firms that refrain from using covenants in the employment contract always locate in the C-region even though the model framework does not provide a formal argument for this assumption. A sketch of the underlying reasoning runs as follows. First, ex ante uncertainty

[8]In a number of other models of mobility induced technology spillovers, researchers are assumed to compensate employers for their future labour market value. Probably an assumption in between these two extremes is closest to reality. In the present model, the important thing is that workers cannot fully compensate employers for their expected future higher earnings as this introduces the trade-off between firm and worker incentives to invest in research.

from the point of view of imitators with respect to the industry's use of non-compete covenants would render imitators more prone to locating in the C-region. Second, even though a scientist-employee is not subject to a non-compete clause he only contributes positive effort if he expects entry upon completion of the research stage. Accordingly, if labour market competition is beneficial to the research firms of an industry, they should locate in the C-region as this offers the most efficient incentive mechanism with respect to their scientist-employees.

3.1 Non-Compete region

As I explained in the previous section, I assume equivalency between locating in the NC-region and including a non-compete clause in the employment contract. Since imitators are prevented from hiring experienced researchers and thereby accessing new technologies, they have no reason to pay the fixed entry cost F. With no imitators in period 2, the alternative employment option of experienced scientists is the outside labour market in which all workers earn $\bar{w} = 0$. Therefore, the optimal wage offer by the research firm to an experienced researcher is $w_{2R}^{NC} = 0$ which the researcher accepts and stays with the original employer.

In period 1, the young scientist knows that independently of the outcome of the research stage, he earns a wage of zero in period 2. Therefore, he contributes an effort level of zero to the research project. The firm chooses k to optimise $E(\pi(k)) = \mu k - \frac{1}{2}\lambda k^2$ and, thus, the optimal choice of research-intensity is: $k^{NC} = \frac{\mu}{\lambda}$.

Expected profit from undertaking research project r is $E(\pi_r^{NC}) = \mu k^{NC} - c(k^{NC}) - \phi r = \frac{\mu^2}{2\lambda} - \phi r$. Projects are undertaken until the value of the last project is zero, thus the number of research projects is: $R^{NC} = \frac{\mu^2}{2\phi\lambda}$.

Finally, since scientist-employees receive a wage of zero in both periods, and there is no entry by imitators, expected total welfare is the sum of expected profits on all projects undertaken: $E(W^{NC}) = \int_0^{R^{NC}} \frac{\mu^2}{2\lambda} - \phi r dr$.

3.2 Compete region

In the C-region, the only way of retaining a research-employee upon a successful research outcome is to offer a sufficiently high wage. This section analyses how the existence of an imitating sector that competes for labour input of researchers affect research incentives.

3.3 Period 2 equilibrium

I start by considering the entry decision of imitators and allocation of workers within the imitating sector for a given mass of experienced scientists. In the following, let the number of successful experienced scientists that move to the imitating sector be given by L_I. Below, I solve for the equilibrium wage, w_I^C and the allocation of experienced scientists conditional on L_I and N_I.[9]

Conditional on the number of imitating firms and the number of experienced researchers, two conditions must be met in equilibrium. First, an entrant is willing to hire experienced researchers as long as the marginal product of labour exceeds the prevailing wage. From equation (1), the marginal product of labour is given by $\beta - \gamma l_i$, and it follows that firm-level labour demand is given by:

$$\begin{aligned} w_I &= \beta - \gamma l_i \\ l_i &= \frac{\beta - w_I}{\gamma} \end{aligned} \tag{2}$$

Second, imitators are symmetric and thus within the sector workers must be distributed equally. Else, some scientist could earn a higher wage by changing employer.[10] Inserting $l_i = \frac{L_I}{N_I}$ in (2) yields:

$$w_I = \beta - \gamma \frac{L_I}{N_I} \tag{3}$$

Equation (3) shows that the fewer experienced researchers to imitating firms, the tougher is competition for their skills and know-how and the higher the wage to an experienced scientist. Similarly, the decreasing returns to scale parameter is also a measure of the degree of wage-competition.

3.3.1 Wage in the imitating sector

The free-entry assumption implies that imitators enter and hire labour until the expected profit of entering is zero.

Profit is given by revenue minus wage-cost and the fixed cost of entry:

$$\pi_i = y(l_i) - w_I l_i - F \tag{4}$$

Insert production technology $y(l_i) = \beta l_i - \frac{1}{2}\gamma l_i^2$ and the expression for the wage (3):

$$\begin{aligned} \pi_i &= \beta l_i - \frac{1}{2}\gamma l_i^2 - (\beta - \gamma \frac{L_I}{N_I}) l_i - F \\ &= -\frac{1}{2}\gamma l_i^2 + \gamma \frac{L_I}{N_I} l_i - F \end{aligned} \tag{5}$$

[9] In the rest of the paper, I assume that at least two imitators enter. This requires research output to be of a certain size (ϕ sufficiently small). In principle, one could imagine that only one imitating firm finds it attractive to enter such that only the research firm and the imitator competes for scientists. This would change the game. Specifically, the maximum wage to an experienced scientist would be δ. I am specifically interested in the outcome in which competition for labour takes place *between* imitators, and I abstract from the alternative case. Since the research sector in this model represents the leading science centres of the world, I find that it is reasonable to assume that they are of a size that supports entry by multiple imitators.

[10] This also means that I allow for a worker to split his time between multiple employers.

In equilibrium, all imitators employ the same share of workers, $l_i = \frac{L_I}{N_I}$ and earn identical profit:

$$\pi_I = \gamma(\frac{L_I}{N_I})^2 - \frac{1}{2}\gamma(\frac{L_I}{N_I})^2 - F$$
$$\pi_I = \frac{1}{2}\gamma(\frac{L_I}{N_I})^2 - F \tag{6}$$

The free-entry condition implies that imitating firms enter the production sector until $E(\pi_I) = 0$. This expression is satisfied whenever:

$$\frac{1}{2}\gamma(\frac{L_I}{N_I})^2 - F = 0$$
$$\frac{L_I}{N_I} = \sqrt{\frac{2F}{\gamma}} \tag{7}$$

By inserting expression (7) in (3), I arrive at the equilibrium wage as a function of the parameters of the model:

$$w_I^C = \beta - \sqrt{2\gamma F} \tag{8}$$

Free entry of imitators implies that the sector adapts to the supply of experienced researchers, and the young researcher faces no uncertainty with respect to the wage that he receives in the second period if he succeeds in research and is hired by an imitator.

3.3.2 Period 2 labour market equilibrium

Expression (8), $w_I^C = \beta - \gamma\sqrt{2\gamma F}$, represents the outside option of an experienced scientist in the C-region. If successful in research, competition among imitators ensures that he receives this wage if he accepts employment in the imitating sector. This is then also the wage that a research firm must pay its scientist-employee in period 2 to prevent him from leaving. An innovating firm experiences a loss of δ if it fails to retain the scientist, and therefore is willing to pay any wage below δ but prefer the loss to any wage above δ. Thus for $w_I^C \leq \delta$, the scientist stays with the innovating firm whereas for $w_I^C > \delta$, the scientist moves to an imitator. In any case, the scientist receives a wage of w_I^C.[11]

Since w_I^C represents the highest period 2 wage that lets an imitator cover its fixed cost of entry, F, there is no alternative equilibrium with $w_I > w_I^C$. Likewise, in the $\delta < w_I^C$ case, the free entry condition ensures that exactly the number of imitators enters that ensures a wage of w_I^C.

Finally, to close the period 2 equilibrium conditional on the number of experienced researchers, the number of entering imitators is given by:

$$N_I^C = \begin{cases} \frac{L_I}{\sqrt{\frac{2F}{\gamma}}} & \text{if } w_I^C > \delta \\ 0 & \text{if } w_I^C \leq \delta \end{cases} \tag{9}$$

[11]Note that in the break-even case $w_I^C = \delta$, I assume that the scientist stays with the research firm. This would be the outcome if I had modeled some of the mobility costs associated with changing employer.

The upper part of this expression says that the higher the fixed cost of production relative to the degree of decreasing returns, the fewer firms enter the imitating sector, and the more experienced scientists each imitator employs.[12] A high value of γ translates into weak labour market competition because the value of technology transfer falls quickly with the number of hired workers. Thus, when γ is high profit per worker is high, and it takes less workers to let the firm cover its entry cost. For a given L_I, this allows for more entry into the imitating sector in equilibrium.

3.4 Period 1 equilibrium

I now show how labour market competition in period 2 affects investments at the research stage by firms and scientist-employees.

3.4.1 Contribution to research by worker and firm

When a young worker is hired into a research-project, he decides on how much effort to contribute. From the point of view of the worker, all projects are identical, and the effort choice is independent of the project. In the following, I therefore remove subscript, r, on projects.

A young scientist knows that if successful, he earns $w_I^C = \beta - \sqrt{2\gamma F}$ in the period 2 labour market. Therefore, a young scientist maximises the expected value of learning given by $E(U_y^C(k,e)) = (\mu k + (1-\mu)e) \times w_I^C - c(e)$. This is equivalent to solving the following maximisation problem:

$$max\ (1-\mu)e \times w_I^C - c(e) \tag{10}$$

Using $c(e) = \frac{1}{2}\lambda e^2$ and differentiating with respect to e yields:

$$\begin{aligned} (1-\mu)w_I^C - \lambda e = 0 \\ e^C = \frac{(1-\mu)w_I^C}{\lambda} \end{aligned} \tag{11}$$

The prospect of capitalising on the research effort in the subsequent period is the source of incentives to the young researcher. The more intense the competition for technological input relative to the cost of effort is, the more effort the worker puts into research.

In contrast to the worker's investment problem, the maximisation problem of the firm depends on whether the firm is able to retain the scientist-employee in the period 2 labour market, or the imitating sector offers the highest wage. The firm maximises expected profits, $E(\pi_1^C(k,e)) = (\mu k^C +$

[12] With a discrete number of imitators, this number is in principle the highest integer such that $N_I^C \leq L_I \frac{1}{\sqrt{\frac{2F}{\gamma}}}$. However, to maintain simplicity, I allow for the last entrant to scale down production – reducing F – such that it is profitable to enter and to employ the residual number of workers at wage w_I^C.

$(1-\mu)e^C) \times (1 - min\{\delta, w_I^C\}) - c(k^C)$ with respect to k. This amounts to:

$$max \begin{cases} \mu k \times (1-\delta) - c(k) & \text{if } w_I^C > \delta \\ \mu k \times (1 - w_I^C) - c(k) & \text{if } w_I^C \leq \delta \end{cases} \tag{12}$$

where the upper part represents the case in which a successful researcher is known to leave the research firm in period 2 such that the firm incurs a loss of δ. The lower part of the expression represents the other case in which the threat of entry induces the research firm to pay w_I^C to an experienced researcher.

With $c(k) = \frac{1}{2}\lambda k^2$, the solution to the above maximisation problem is:

$$k^C = \begin{cases} \frac{\mu(1-\delta)}{\lambda} & \text{if } w_I^C > \delta \\ \frac{\mu(1-w_I^C)}{\lambda} & \text{if } w_I^C \leq \delta \end{cases} \tag{13}$$

Because the firm cannot fully protect its investment in period 2, it undertakes fewer investments in research than it would have had, had it been located in the NC-region, $k^{NC} = \frac{\mu}{\lambda} > k^C$. Moreover, the expression shows that for low values of the wage in the imitating sector $w_I^C < \delta$, research-investments of the firm are decreasing in the wage because it is optimal for the research firm to meet the wage-offers made by imitators and to retain a successful scientist-employee. On the contrary, in the other case tougher wage-competition does not affect the investment made by the firm. The reason is that the loss to the research firm from employee-mobility is independent of the degree of wage-competition among imitators. When imitators push the wage-level above δ, a research firm prefers to let the worker go even though it lowers the value of the project by δ.

3.4.2 Wage to a young researcher

In the C-region, young workers are aware that employment on a research project improves their future earnings potential either due to their own effort or because of investments made by the firm. Accordingly, a young worker is willing to work at a research project at a wage w_{1R}^C such that $w_{1R}^C \geq \bar{w} - w_I^C(\mu k^C + (1-\mu)e^C) - c(e^C)$ where $\bar{w} = 0$ is the wage in the outside labour market. The wage that exactly satisfies this condition is negative reflecting that a rational worker is willing to compensate the research firm for the learning potential at a research project. However, workers are borrowing constrained implying that any wage-offer needs to satisfy $w_{1R}^C \geq 0$. Hence, the period 1 wage is given by $w_{1R}^C = 0$.[13]

[13]See footnote 8 for a brief discussion of this assumption.

3.4.3 Expected profit to a research firm

Expected profit to research firm r is given by $(\mu k^C + (1-\mu)e^C) \times (1 - min\{\delta, w_I^C\}) - c(k^C) - F_r$. Inserting the previously found expressions for k^C and e^C, I arrive at:

$$E(\pi_r^C) = \begin{cases} \left(\frac{\mu^2(1-\delta)}{\lambda} + \frac{(1-\mu)^2 w_I^C}{\lambda}\right) \times (1-\delta) - \frac{\mu^2(1-\delta)^2}{2\lambda} - F_r & \text{if } w_I^C > \delta \\ \left(\frac{\mu^2(1-w_I^C)}{\lambda} + (\frac{(1-\mu)^2 w_I^C}{\lambda}\right) \times \left(1 - w_I^C\right) - \frac{\mu^2(1-w_I^C)^2}{2\lambda} - F_r & \text{if } w_I^C \le \delta \end{cases} \tag{14}$$

where w_I^C is given by equation (3). Reducing this expression and inserting $F_r = \phi r$ yields:

$$E(\pi_r^C) = \begin{cases} \frac{1-\delta}{\lambda}\left(\frac{\mu^2(1-\delta)}{2} + (1-\mu)^2 w_I^C\right) - \phi r & \text{if } w_I^C > \delta \\ \frac{1-w_I^C}{\lambda}\left(\frac{\mu^2(1-w_I^C)}{2} + (1-\mu)^2 w_I^C\right) - \phi r & \text{if } w_I^C \le \delta \end{cases} \tag{15}$$

Thus, for $w_I^C > \delta$, expected profit of a research project is unambiguously increasing in w_I^C due to the positive incentive effect on workers. When $w_I^C < \delta$, w_I^C has a negative impact on the profitability of successful projects, and expected profit of a research firm is therefore decreasing in w_I^C unless μ is small.[14]

3.4.4 Number of research projects

In equilibrium, expected profits of the marginal project equals 0, and the number of projects, R^C, is determined by $E(\pi_R^C) = 0$. From (15) it follows that the number of research projects undertaken each period is:

$$R^C = \begin{cases} \frac{1-\delta}{\phi\lambda}\left(\frac{\mu^2(1-\delta)}{2} + (1-\mu)^2 w_I^C\right) & \text{if } w_I^C > \delta \\ \frac{1-w_I^C}{\phi\lambda}\left(\frac{\mu^2(1-w_I^C)}{2} + (1-\mu)^2 w_I^C\right) & \text{if } w_I^C \le \delta \end{cases} \tag{16}$$

Finally, from an ex ante perspective, $E(N_I^C) = \frac{E(L_I)}{\sqrt{\frac{2F}{\gamma}}}$. Where L_I is the number of successful scientists that move to the imitating sector. When $w_I^C > \delta$, all successful scientists move to the imitating sector such that $E(L_I) = (\mu k^C + (1-\mu)e^C) \times R^C$, and in the opposite case no scientist moves such that $L_I = 0$.

3.4.5 Equilibrium in C-region

Below, I summarise the equilibrium in the C-region subgame. It depends on how the loss from researcher-mobility to the firm (δ) and the gain from wage-competition to the workers (w_I^C) compare.

[14]For $w_I^C < \delta$, $\frac{\partial E(\pi_r^C)}{\partial w_I^C} < 0$ if $\frac{\mu^2}{(1-\mu)^2} < \frac{2w_I^C - 1}{1 - w_I^C}$.

Equilibrium effort, equilibrium wage offers, and expected profit to an imitating firm are independent of δ:

$$w_I^C = \beta - \sqrt{2\gamma F}$$
$$e^C = \frac{(1-\mu)w_I^C}{\lambda}$$
$$E(\pi_i) = 0,\ \ i = \{1, N_I^C\}$$

Research employment, mobility, expected profit to a research firm, expected utility to researchers, and the number of entering imitators depend on δ:

Case 1 (mobility) $w_I^C > \delta$:

$$w_R^C = 0$$
$$k^C = \frac{\mu(1-\delta)}{\lambda}$$
$$E(\pi_r^C) = \frac{1-\delta}{\lambda}\left(\frac{\mu^2(1-\delta)}{2} + (1-\mu)^2 w_I^C\right) - \phi r,\ \ r = [0, N_R^C]$$
$$N_R^C = R^C = \frac{1-\delta}{\phi\lambda}\left(\frac{\mu^2(1-\delta)}{2} + (1-\mu)^2 w_I^C\right)$$
$$E(N_I^C) = \frac{\left(\mu k^C + (1-\mu)e^C\right) \times N_R^C}{\sqrt{\frac{2F}{\gamma}}}$$
$$E(U^C) = \frac{w_I^C}{\lambda}\left(\mu^2(1-\delta) + \frac{(1-\mu)^2 w_I^C}{2}\right)$$

Case 2 (no mobility) $w_I^C - \delta \leq 0$:

$$w_R^C = w_I^C$$
$$k^C = \frac{\mu(1-w_I^C)}{\lambda}$$
$$E(\pi_r^C) = \frac{1-w_I^C}{\lambda}\left(\frac{\mu^2(1-w_I^C)}{2} + (1-\mu)^2 w_I^C\right) - \phi r,\ \ r = [0, N_R^C]$$
$$N_R^C = R^C = \frac{1-w_I^C}{\phi\lambda}\left(\frac{\mu^2(1-w_I^C)}{2} + (1-\mu)^2 w_I^C\right)$$
$$N_I^C = 0$$
$$E(U^C) = \frac{w_I^C}{\lambda}\left(\mu^2(1-w_I^C) + \frac{(1-\mu)^2 w_I^C}{2}\right)$$

The next section solves for the optimal location of the firm according to the relative size of expected profits in the two regions.

3.5 Location choice

Since research projects are identical conditional on the initial fixed cost of implementation, it is the per-project profitability that determines where the industry locates. As the previous discussion indicates, low costs of worker-mobility to research firms (low δ) and dependence on human capital (low μ) make the C-region attractive, just as high-powered incentives to workers (high w_I^C) in some cases increases the profitability of projects in the C-region. However, the exact interaction between these parameters are most easily shown graphically.

Figure 2 illustrates how the preferred region depends on μ, w_I^C, and δ. For a given r, firms compare $E(\pi_r^{NC}) = \frac{\mu^2}{2\lambda}$ with $E(\pi_r^C)$ as given by expression (15). In the figure, $\overline{v}, \underline{v}$ represent combinations of μ and w_I^C that equalise profits in the two regions making research firms indifferent between the two locations. $\overline{v}$ indicates that $w_I^C > \delta$ such that we are in *case 1*:

$$\overline{v} : \{(\mu, w_I^C) | \frac{1-\delta}{\lambda} \left(\frac{\mu^2(1-\delta)}{2} + (1-\mu)^2 w_I^C \right) - \frac{\mu^2}{2\lambda} = 0\} \tag{17}$$

This relationship between μ and w_I^C that equalises profit in the two regions is such that:

$$\frac{\mu^2}{(1-\mu)^2} = \frac{2w_I^C}{\frac{1}{1-\delta} - 1 + \delta} \tag{18}$$

where the fraction $\frac{\mu^2}{(1-\mu)^2}$ measures the importance of the investment by the firm in research relative to the worker's contribution. This expression depends on δ since there is mobility in the C-region equilibrium, and research firms incur the loss of δ if they choose to locate in this region. In the figure, $\overline{v}$ is drawn for $\delta = \frac{1}{4}$ and $\delta = \frac{1}{3}$. Below $\overline{v}$, $E(\pi_r^C) > E(\pi_r^{NC})$ and firms prefer locating in the C-region, whereas above $\overline{v}$, firms prefer locating in the NC-region. The right-hand side of (18) is increasing in w_I^C since the nominator is positive for $0 < \delta < 1$. Accordingly, if w_I^C increases, industries with higher values of μ move to the C-region.

The intuition behind this reasoning is that w_I^C only has an effect on expected profitability of a project via the worker's effort decision, and this effect is positive. Thus, conditional on $w_I^C > \delta$, expected profits in the C-region is always increasing in w_I^C. This means that as wage-competition among imitators increases, it becomes attractive for industries with higher values of μ to locate in the C-region. Firms in these industries locate in the C-region to take advantage of the higher total monetary incentives offered in the C-region. For values of μ between $\overline{v}$ and $\frac{1}{2}$ this implies that research investments of the most efficient part – the firm – actually decreases.

Similar to the above, $\underline{v}$ represents combinations of μ and w_I^C for which research firms are indifferent between the two locations conditional on $w_I^C \leq \delta$:

$$\underline{v} : \{(\mu, w_I^C) | \frac{1-w_I^C}{\lambda} \left(\frac{\mu^2(1-w_I^C)}{2} + (1-\mu)^2 w_I^C \right) - \frac{\mu^2}{2\lambda} = 0\} \tag{19}$$

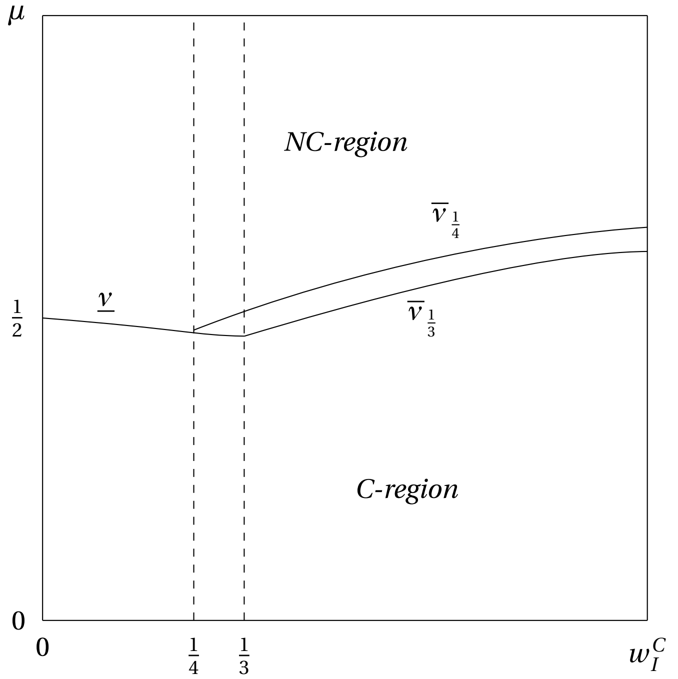
Again this amounts to:

$$\frac{\mu^2}{(1-\mu)^2} = \frac{2(1-w_I^C)}{2-w_I^C} \tag{20}$$

Note, that δ does not enter this expression since there is no mobility in case 2, and accordingly research firms never experience the loss of δ but prefers paying scientist-employees the wage of w_I^C

upon successful completion of a research project. The right-hand side of this expression is decreasing in w_I^C, and thus a marginal increase in w_I^C lowers the value of μ that equalises profits in the two regions. The reason is that an increase in monetary incentives to the scientist-employee is exactly countervailed by a decrease in the incentives of the firm and moreover reduces the profitability of a successful project. This means that, in contrast to case 1, tougher wage-competition makes some industries move to the NC-region even though the contribution of workers to research is actually more important ($\mu < \frac{1}{2}$) than the contribution of firms.

As the figure illustrates for the two values of δ, the higher the cost to the research firm of losing an experienced scientist, the tougher wage-competition is needed to make firms in the industry prefer the C-region.



The figure illustrates how the location decision of research firms depends on the parameters of the model. The choice of location is independent of the costs of carrying out research as given by ϕ and λ.

Figure 2: Location

The previous analysis can be related to the results in other models of mobility induced knowledge diffusion. One important result is due to Pakes and Nitzan (1983) who show that if wages are not constrained mobility-induced spillovers do not have an effect on research investments. In that setting, the optimal wage contract specifies that the value of R&D-learning to a young scientist-employee is deducted from first period wages. The present analysis shows that even if there is a lower limit on first period wages such that firms cannot appropriate the full value of R&D-learning, wage-competition and mobility do not necessarily constrain R&D-output. On the contrary, it can have a positive effect on the profitability of projects and the scientific output of an industry. This is a relevant result for these advanced industries in which the value of sourcing technologies might by far exceed what can be internalised in the labour market.[15]

4 Socially optimal location

This section discusses how the socially optimal location decision compares to the market equilibrium. I start by considering whether, from society's point of view, a given project in industry μ should be carried out in the NC-region or in the C-region. This amounts to letting the social planner decide the location of industry μ *and* whether a project should be undertaken or not, but maintaining that the social planner does not control neither the research-intensity of firms and scientist-employees nor the entry decision of imitators. However, a full consideration of welfare in the two locations requires that one takes into account the number of projects undertaken in each region and not only welfare per project. This, I discuss in the subsequent section.

Before continuing, an additional remark is needed. The starting point for the analysis of this paper is that new technological developments have value to the research firms, the scientists and entering imitators. However, the combination of free entry of imitators and a homogeneous cost of entry, F, implies that the value to imitators of copying technological know-how is competed away, and therefore the total contribution of imitators to social welfare is zero in both locations. Hence, in the following, only research firms and employees enter the analysis.[16]

4.1 Optimal location of a given project in industry μ

Expected utility to a scientist-employee in the C-region $E(U^C) = \frac{w_I^C}{\lambda}\left(\mu^2(1-\delta)+\frac{(1-\mu)^2 w_I^C}{2}\right)$ is independent of the project undertaken and positive[17] whereas expected utility to workers in the NC-region, $E(U^{NC})$ is zero. Accordingly, for a given μ, the difference in total welfare for a project undertaken in the C-region and the NC-region is:

$$E(W_r^C) - E(W_r^{NC}) = E(\pi_r^C) - E(\pi_r^{NC}) + E(U^C) \tag{21}$$

[15]Without borrowing constraints the tendency towards clustering in the C-region is even stronger. The welfare analysis in the subsequent section illustrates this.

[16]With heterogenous cost of entry, some imitators would earn positive profits. In this case, one can re-interpret the welfare analysis of this section as capturing that of a national planner who is not concerned with the welfare of foreign-owned imitators when evaluating the pros and cons of labour market competition.

[17]This is the case as long as there is a threat of entry pushing the period 2 wage above zero, and is due to young scientist-employees being borrowing constrained.

Since $E(U^C)$ is positive the social planner prefers the C-region to the NC-region whenever the firm does (cases for which $E(\pi_r^C) - E(\pi_r^{NC}) > 0$). It also implies that there are combinations of μ and w_I^C for which the social planner prefers the C-region even though firms choose to locate in the NC-region. These are cases for which $E(\pi_r^C) - E(\pi_r^{NC}) < 0$ is outweighed by $E(U^C) > 0$.

A graphical illustration of how the decision of the social planner compares to the market equilibrium is given in figure 3. It is drawn for a loss from scientist mobility of $\delta = \frac{1}{3}$. As in figure 2, $\underline{v}$, $\overline{v}_{\frac{1}{3}}$ represent combinations of μ and w_I^C that make the firm indifferent between the two locations. Similarly, $\overline{\omega}, \underline{\omega}$ represent combinations of w_I^C and μ which make the social planner indifferent between the two locations (values of μ and w_I^C such that (21) is zero.).

Again, $\overline{\omega}$ indicates that $w_I^C > \delta$:

$$\overline{\omega}: \{(\mu, w_I^C) | \frac{1-\delta+w_I^C}{\lambda}\left(\mu^2(1-\delta)+(1-\mu)^2 w_I^C\right) - \frac{\mu^2(1-\delta)^2}{2\lambda} - \frac{(1-\mu)^2(w_I^C)^2}{2\lambda} - \frac{\mu^2}{2\lambda} = 0\} \tag{22}$$

Again, for a given δ this is equivalent to combinations of the parameters such that:

$$\frac{\mu^2}{(1-\mu)^2} = \frac{2w_I^C(1-\delta+\frac{w_I^C}{2})}{1-(1-\delta)(1-\delta+2w_I^C)} \tag{23}$$

The above expression differs from equation (18) because the social planner takes into account that w_I^C is not only a source of incentives and added research-efficiency but also a source of utility to the scientist-employee. Rewriting the right-hand side of (18) to $\frac{2w_I^C(1-\delta)}{1-(1-\delta)(1-\delta)}$ and comparing with the right-hand side of expression (23), it is easily seen that the social planner for a given $w_I^C > \delta$ prefers the C-region for industries with higher values of μ. Thus $\overline{\omega}$ lies above $\overline{v}$. Moreover, the gap between the socially optimal equilibrium and the market equilibrium is increasing in w_I^C for a given μ. The reason is that $E(U^C)$ is increasing in w_I^C.

Turning to the other case, $\underline{\omega}$ reflects that $w_I^C \leq \delta$:

$$\underline{\omega}: \{(\mu, w_I^C) | \frac{1}{\lambda}\left(\mu^2(1-w_I^C)+(1-\mu)^2 w_I^C\right) - \frac{\mu^2(1-w_I^C)^2}{2\lambda} - \frac{(1-\mu)^2(w_I^C)^2}{2\lambda} - \frac{\mu^2}{2\lambda} = 0\} \tag{24}$$

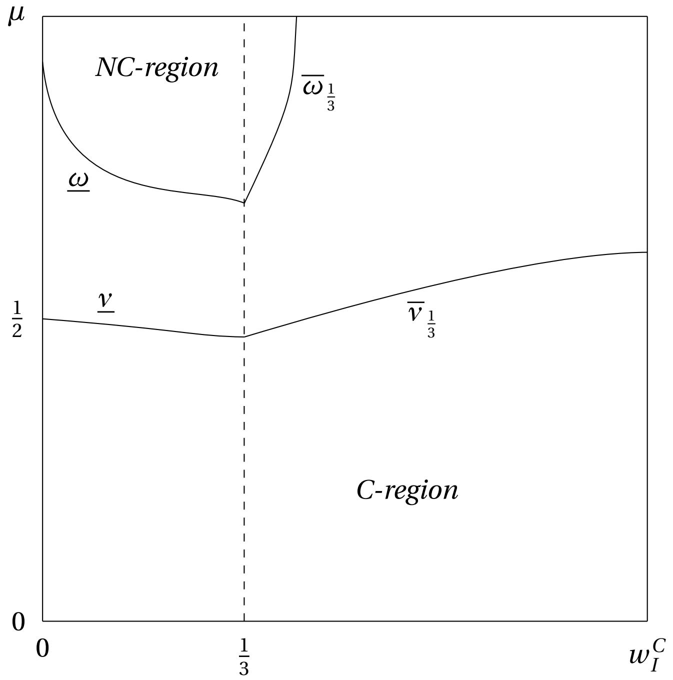
The relationship between μ and w_I^C is determined by:

$$\frac{\mu^2}{(1-\mu)^2} = \frac{2}{w_I^C} - 1 \tag{25}$$

When $\delta \leq w_I^C$, there is no mobility in equilibrium, and the gain to workers from labour market competition is exactly outweighed by the loss to the research firm as it ends up paying the research-employee to stay during period 2. Consequently, the total value of a successful project that is jointly realised by the firm and its scientist-employee is $\Delta \equiv 1$ and hence independent of w_I^C.

Still, the socially optimal location varies with w_I^C, and this is because there is a gain from splitting costs due to the convex cost-functions. In other words, the choice of location is a choice between optimal distribution of monetary incentives (according to μ) and splitting costs. The gains from splitting costs are of course largest for intermediate values of μ, since for w_I^C close to one or close to zero, only one of the parties has incentives to contribute to the research project.

The intuition behind the negative slope on $\underline{\omega}$ is as follows. For low values of μ, the C-region is of course always preferred as monetary incentives to the worker is more important than monetary incentives to the firm. When $\mu = \frac{1}{2}$ both parties are equally efficient at carrying out research, and the gains from splitting costs implies that the C-region is always preferred. As μ increases from $\frac{1}{2}$, the value of locating in the NC-region in which the firm has the better incentives increases relative to the gains from splitting costs.



The figure illustrates the location decision of research firms and the socially optimal location. These are independent of the costs of carrying out research as given by ϕ and λ. The socially optimal location is drawn for $\delta = \frac{1}{3}$.

Figure 3: Socially optimal location for a given project in industry μ

4.2 Optimal location of an industry μ

The above analysis was useful for clarifying the sources of divergence between the equilibrium location decision and the socially optimal location. Yet, it is more in line with reality that the social planner only has power over the institutional setting and does not does decide if firms should undertake projects or not. Therefore, this section considers the socially optimal location choice when the social planner only controls the location decision of firms in an industry, and thus are forced to trade off gains from worker utility in the C-region against lower profitability of projects and thus fewer research projects in the C-region.

The total difference in welfare between the two regions consists of three terms:

$$\begin{aligned}E(W_T^C)-E(W_T^{NC}) = &\int_0^{min\{R^C,R^{NC}\}} \Big(E(\pi^C)-E(\pi^{NC})+E(U^C)\Big)\,dr \\ &-\int_{R^C}^{max\{R^C,R^{NC}\}} \Big(E(\pi^{NC})-\phi r\Big)\,dr \\ &+\int_{R^{NC}}^{max\{R^C,R^{NC}\}} \Big(E(\pi^C)-\phi r+E(U^C)\Big)\,dr \end{aligned} \tag{26}$$

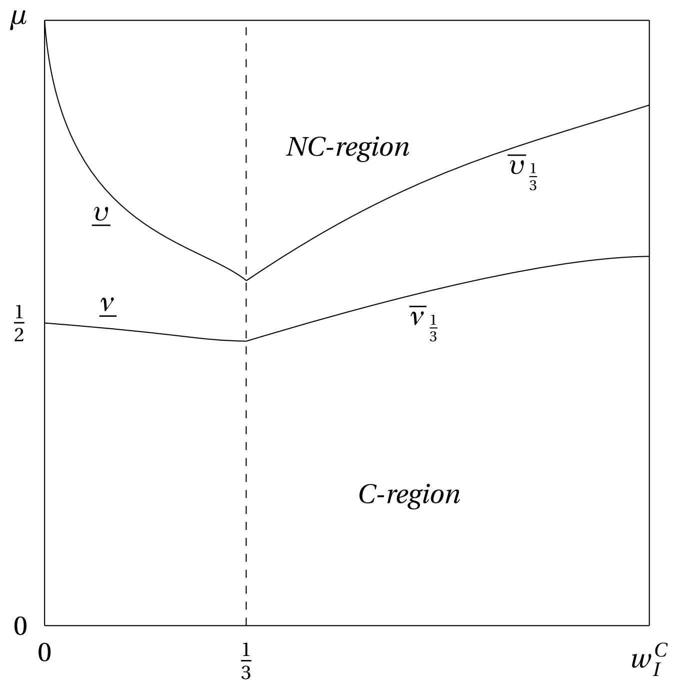
where $E(\pi^C), E(\pi^{NC})$ are expected profits net of fixed costs of initiating a project. The first term captures the sum of the differences in welfare on projects that are profitable and thus undertaken in both regions. The second term captures foregone welfare (i.e. profits to research firms) on projects that are only undertaken if the industry is located in the C-region. Clearly this term is zero if $E(\pi^C)\geq E(\pi^{NC})$ since then more projects are undertaken in the C-region and $R^C\geq R^{NC}$. Equivalently, the last term represents extra welfare on projects that are only undertaken in the C-region. This term is zero if $E(\pi^C)\leq E(\pi^{NC})$ for the equivalent reason. In contrast to the above analysis, the welfare-decision now depends on the cost parameters ϕ and λ as the sizes of these affect the number of projects undertaken.

If $E(\pi^C)\geq E(\pi^{NC})$ both research firms and the social planner prefer the C-region to the NC-region for a given project and expression (26) is positive. Thus, the interesting cases arise when $E(\pi^C)<E(\pi^{NC})$, but $E(\pi^C)-E(\pi^{NC})+E(U^C)>0$, and this is the case that I need to consider in order to determine how the socially optimal region differs from the equilibrium choice of location. The third term in expression (26) is then zero, and the expression can then be rewritten as:

$$\begin{aligned}E(W_T^C)-E(W_T^{NC}) = &\frac{E(\pi^C)}{\phi}\times\Big(E(\pi^C)-E(\pi^{NC})+E(U^C)\Big) \\ &-\frac{E(\pi^{NC})-E(\pi^C)}{\phi}\left(E(\pi^{NC})-\frac{1}{2}\phi^2\right)\end{aligned} \tag{27}$$

The first line looks like equation (21), only the difference in welfare per project is multiplied by the number of projects undertaken in the C-region. The last line captures lost welfare on projects that would have been undertaken in the NC-region given by the number of "lost" projects ($\frac{E(\pi^{NC})-E(\pi^C)}{\phi}$) times foregone profit on these projects. The term $\frac{1}{2}\phi^2$ is due to savings on the fixed cost of initiating projects.

There is not a simple expression for the combinations of μ and w_I^C that make the social planner indifferent between the two locations (make expression (27) zero), but figure 4 gives an example of how the socially optimal location decision differs from the optimal location decision of the firm for $\delta = \frac{1}{3}$, $\phi = 0.01$ and $\lambda = 2$. $\overline{\upsilon}_{\frac{1}{3}}$, $\underline{\upsilon}$ represent combinations of μ and w_I^C for which the social planner is indifferent between the two locations. Again, $\overline{\nu}_{\frac{1}{3}}$, $\underline{\nu}$ show how the equilibrium location decision of research firms depends on μ, w_I^C.



The figure gives an example of how the socially optimal location decision differs from the optimal location decision of the firm for $\delta = \frac{1}{3}$, $\phi = 0.01$ and $\lambda = 2$.

Figure 4: Socially optimal location for industry μ

Though, the figure is only drawn for chosen values of the cost-parameters[18], it clearly illustrates that taking into account the number of "lost" projects in cases for which the interests of the social planner and the research firms differ, has important welfare implications. The area between $\overline{\upsilon}_{\frac{1}{3}}$ and $\overline{\nu}_{\frac{1}{3}}$, respectively $\underline{\upsilon}$ and $\underline{\nu}$ represent combinations of μ and w_I^C for which the social planner prefers the C-region, but research firms prefer the NC-region. This area is markedly smaller than the equivalent area in figure 3. At the same time, the figure highlights that as long as firm investments are not too important relative to the contribution of the scientist-employee, there are gains to welfare if the industry cannot use non-compete clause. In these cases, profits and thereby the number of projects only decrease a little if the industry cannot use non-compete clauses.

As I mentioned in the introduction to this section, a further source of welfare in the C-region that I have not considered would be positive profit to imitators. However, the same line of reasoning as

[18] In reality, small changes in ϕ does not matter much to $\overline{\upsilon}_{\frac{1}{3}}$, $\underline{\upsilon}$.

used above with respect to figure 4 applies to this situation. Positive profits to imitators would play a similar role as positive utility to scientist-employees in the previous analysis. It makes the C-region more attractive from a global perspective, but forcing industries to refrain from using non-compete clauses would be at the cost of lowering the number of projects undertaken in the industry.

5 Conclusion

Recent empirical investigations have established that research and development activities by multinational companies in foreign locations do not only serve the purpose of adapting core technologies to local markets but are increasingly undertaken in order to source technologies from the leading science centres of the world. The purpose of this paper is to study the response of research firms in the donor region to such activities.

For the purpose of this paper, I model the sourcing of technologies as imitative activities. Several authors have argued that the tacitness of knowledge and technological know-how at early stages of a technology's life-cycle make hiring an important way of learning about new technological developments. This paper takes its starting point from this observation and suggests that labour market competition among a group of imitators for technological know-how embodied in people generate positive incentives for young scientist-employees to contribute effort to a research project.

In the model, innovation requires the joint effort of the research-firm and a scientist-employee. The threat of future imitation via employee-mobility is detrimental to the incentives of the research firm because it lowers the value of a successful research project, but it has a positive impact on the incentives of the scientist. The reason is that entry of imitators create an alternative labour market that protects the scientist-employee against the opportunism of the research firm. Thereby, the analysis shows that even if there is a lower limit on first period wages such that firms cannot appropriate the full value of R&D-learning, wage-competition and mobility do not necessarily constrain R&D-output. On the contrary, it can have a positive effect on the profitability of projects and the scientific output of an industry. This is a relevant result for advanced research intensive industries in which the value of sourcing technologies might by far exceed what can be internalised in the labour market.

The loss to the research firm from losing a scientist-employee to an imitator determines the maximum wage that a research firm is willing to pay to retain a scientist upon completion of a research project. It is independent of the toughness of wage-competition among imitators and entry of a large number of imitators serves to push wages to experienced scientists above this critical level. This generates mobility and transfer of know-how to the imitating sector, *but* it also increases the joint monetary incentives of the research firm and the scientist-employee to invest in the research project.

I argue that the beneficial effects of wage-competition are likely to be present in the multi-purpose technologies of the computer industry.

The model has implications for the optimality of allowing for non-compete clauses in employment contracts. It is often emphasised that the lack of enforcement of such clauses by Californian courts has contributed significantly to the success of the computer industry in Silicon Valley. Locating in such a region is attractive to a research intensive industry if labour market competition contributes positively to the profitability of projects. Even though I do not formally model the reasoning, I argue that prior to entry, imitators might find it difficult to learn if covenants are in use or not, for example because they do not know exactly the type or research-technology that characterises the industry. In this case, it is easier for a research intensive industry to attract imitators if they locate in a region in which covenants are not enforced by courts because this sends a clear signal that hiring is ex post possible.[19]

At the same time the welfare analysis shows that even though tough wage-competition to some extent serves to aline the interests of the social planner and the research sector, there are industries for which the socially optimal location differs from the equilibrium location. The social planner prefers research to be undertaken in the region in which covenants are not enforced whenever it is optimal for the industry, but also prefers it for a wider set of industries than induced by the location equilibrium. The reason is that the social planner takes into account the utility of scientist-employees who are able to capitalise on successful projects when imitators compete for their know-how.

[19]Technology spillovers between research firms is also a factor that contributes to the attractiveness of regions in which firms do not use non-compete clauses.

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Agglomeration and labour sharing

Agglomeration and labour sharing

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Abstract

The purpose of this paper is to investigate if firms agglomerate to hire from a common pool of labour. I use Danish register data with detailed plant-level information on yearly employment numbers, geographical location, and workers' education to test two formal arguments. The first of these is the labour pooling argument due to Krugman (1991). It states that firms form industrial clusters in order to iron out idiosyncratic productivity shocks because geographical closeness facilitates mobility of workers from low to high productivity firms. As in Overman and Puga (2009), I use a measure based on plant-level employment changes to account for the industry's scope for labour pooling, but I adapt the measure to an economy of a small scale like the Danish economy. An alternative theory proposes that competition for skills among multiple firms in the same location induces workers to invest in their human capital because workers expect a return to their investment. Hence, this idea proposes that similarity in the use of skills leads firms to locate in geographical vicinity. I use a functional definition of skills that distinguishes workers according to both length and field of education, and I use correlations between the skill mix at the plant and the rest of the industry to determine how homogeneous the industry is in its use of skills. The findings are in support of the idea in Krugman (1991), but the idea that firms locate together because it increases the skill level of workers does not find support in the data. However, the data shows that similarity in formal qualifications play a role in relation to the ability of firms to re-allocate workers. In an extension, I find that this is even more the case in the diverse, urban labour market compared to specialised industrial clusters.

1 Introduction

In a recent review, Puga (2010) summarises empirical work on the magnitudes and causes of agglomeration economies and concludes that a doubling of city size leads to a productivity increase of between 3 and 8 %. Hence, the existence of agglomeration economies is well-established. At the same time, more work is needed to understand the exact mechanisms that create advantages to firms and workers in large and dense cities, and on this background this paper test a prominent theory in the economic geography literature stating that firms form industrial clusters to share a common pool of labour.

In his Principles from 1890, Alfred Marshall identified three motives for industrial agglomeration; to access local suppliers, to benefit from technology spillovers, and to gain from sharing a common pool of labour (see Marshall (1961)). Since then, extensive theoretical work has been done to formalise and extend these and related ideas (see Duranton and Puga (2004) for an overview)[1]. In the empirical literature, much effort has been devoted to identifying the existence and impact of localised technology spillovers (e.g. Jaffe et al. (1993), Audretsch and Feldman (1996), Zucker et al. (1998), Keller (2002)), and, likewise, authors have documented localised vertical linkages by linking location to flows of goods and services (Holmes (1999), Rosenthal and Strange (2001), and Overman and Puga (2009)). In contrast, and in spite of formal work on the topic, much less is known about the empirical significance of labour pooling. This is not less noticeable as the motive applies to a broad set of skills and industries, having a potentially large economic impact on local economies.

Ellison et al. (2010) and Overman and Puga (2009) are two recent empirical papers addressing the labour pooling hypothesis. The work of Ellison et al. (2010) suggests that a similar occupational mix of two industries is an agglomerating factor, and Overman and Puga (2009) find that industries composed of plants with a large idiosyncratic component in labour demand form industrial clusters. This paper adds to this line of research. I use a very detailed employer-employee data set for the Danish manufacturing industry to combine information on the formal education of workers with plant-level employment changes to study the role of labour pooling in agglomeration. First and foremost, it allows me to consider the relative importance of an uncorrelated labour demand and a homogeneous skill mix for agglomeration which is new to the literature. Moreover, using formal qualifications of the labour force to account for skills sheds light on a different – but equally important – dimension of human capital compared to a functional definition.

Marshall observed that a large labour market for workers with similar skills is an advantage to

[1]Rather than keeping to the original grouping by input-type; labour, suppliers, and ideas, Duranton and Puga (2004) emphasise that similar mechanisms are at play across all three of these, and the authors group these under the headings; sharing, matching, and learning externalities.

both workers and firms in the sense that it offers 'a constant market for skills'. This idea is formalised in Krugman (1991) who considers the location decision of establishments and workers in sectors that are subject to idiosyncratic productivity shocks. In this model, establishments can either locate in isolation or in an industrial cluster. The key point is that in isolation, employment changes at the establishment level affect local wages making it difficult for the establishment to expand in response to a positive productivity shock whereas clustering facilitates mobility of workers from low-productivity firms to high-productivity firms. Therefore, clustering of similar firms with a large idiosyncratic component in labour demand, increases the elasticity of labour supply which makes it easier for the firm to expand in good times.

Overman and Puga (2009) test this hypothesis on a panel of workers and plants in UK manufacturing. As a novel measure of the industry's scope for labour market pooling, the authors suggest calculating the average difference between yearly relative changes in industry employment and yearly relative changes in plant employment. This provides a proxy for the degree of idiosyncracy of shocks in the industry which can then be related to its pattern of location.

An analysis based on the present data set requires a measure suitable for an economy with many small plants, and therefore I use an adjusted version of the measure suggested in Overman and Puga (2009). Rather than looking at relative changes, I suggest calculating deviations between the absolute change in the employment of a plant and the average absolute change in employment of all plants in the industry. In this way, I avoid inflating the contribution of employment expansions relative to employment contractions at small plants.

An important assumption in Overman and Puga (2009) is that same-industry plants depend on the same type of skills in production. This is probably a good approximation in many industries, but one can think of examples for which this is not the case. For example, low-tech and high-tech production plants might have little scope for sharing labour despite belonging to the same industry. Therefore, I consider how the tendency of same-industry plants to agglomerate varies across industries characterised by low and high levels of similarity in the mix of formal qualifications in the labour force.

I measure homogeneity in formal qualifications within the industry by grouping workers according to both level and field of their highest education, and I use correlations between the skill mix at the plant and the rest of the industry to determine how homogeneous the industry is in its use of skills.

A similar need for skills might in itself be a reason for plants to agglomerate. This is the case in Rotemberg and Saloner (2000) in which competition for skilled labour among multiple firms in the same location protects workers against the opportunism of their employers thereby encouraging investments in human capital. This line of thinking suggests a separate, positive effect of a similar skill use on the tendency of plants to agglomerate.[2]

Dumais et al. (1997)[3] and Ellison et al. (2010) already find that two industries with a similar mix of occupations tend to locate together, and I add to their findings by investigating whether this result carries over to formal qualifications and within industries.

The outcome variable is observed agglomeration of 4-digit NACE-industries. In the main analysis, I consider co-location of same-industry plants as measured by the Ellison-Glaeser index (Ellison and Glaeser (1997)) used by many to study industrial agglomeration. It is calculated from knowledge of administrative geographic units and measures agglomeration arising from industry-level factors, i.e. by using this index one takes into account any uneven distribution of general economic advantages across locations, and controlling for the size distribution of plants.

To control for alternative determinants of agglomeration at the industry level relating to natural resource use, transport costs, technology spillovers, and vertical linkages, I supplement the Danish register data with data from input-output tables from Statistics Denmark and the OECD ANBERD database, and I seek to control for the human capital intensity of the industry by including the industry's share of workers with a Bachelor's degree or higher in the regressions.

The overall finding is that a large idiosyncratic component in labour demand among same-industry plants is correlated with the formation of industry-specific clusters. This finding is robust across a number of different specifications and is supportive of the results in Overman and Puga (2009) for UK-industries while at the same time adding to the literature by suggesting that the labour pooling argument is important also at the far smaller geographic scale of the Danish economy.

The data confirms that same-industry plants that are similar both in terms of the formal qualifications of the labour force *and* have an idiosyncratic labour demand have a higher tendency to cluster than other plants. I distinguish industries according to three levels of the skill correlation measure, and I find that this effect is most evident when comparing heterogenous industries to industries that are moderately similar in terms of the formal qualifications of their labour force.

One explanation for this finding is that I use a rather detailed educational measure to account for skill similarity in the industry, taking into account both level and field. For example, I distinguish between engineering degrees in machinery, chemistry and electronics. If workers are in fact substitutes across these groups then industries gain only little in terms of labour pooling from being very simi-

[2]Almazan et al. (2007) introduce human capital formation in Krugman's model. The tendency to cluster is strongest when workers bear the cost of human capital investments, and there is a lot of variation in firm-level productivity shocks.

[3]I refer to the working paper version as the relevant part is excluded from the final version of the paper; Dumais et al. (2002).

lar. In the robustness section, I carry out the analysis assuming that workers are substitutes across a wider set of fields than in the main analysis, and in this section I find that the effect of skill similarity on the tendency to agglomerate for same-industry plants is most evident at higher values of the skill correlation measure.

At the same time, a similar use of skills does not by itself have an impact on the tendency to locate in specialised industrial clusters. Thus, ideas in line with those put forward in Rotemberg and Saloner (2000) are not supported by the findings in this data set.

In an extension, I turn to an analysis of location in urban labour markets. In general, local labour markets that evolve around a single industry and an urban, diverse labour market are thought to differ in their dynamics, and it is interesting to investigate whether sharing of labour plays a role in urban labour markets. The idea in this analysis is that labour sharing takes place between the industry and the rest of manufacturing rather than within the industry.

In this analysis the dependent variable is the share of industry employment in the Greater Copenhagen area.[4] Moreover, instead of comparing each plant to the other plants in the industry, I compare each industry to all of manufacturing, both with respect to the Overman and Puga (2009)-index of labour pooling and with respect to the composition of formal qualifications. I find that industries with a large idiosyncratic component in labour demand relative to manufacturing are more urban than other industries. However, since the reference industry is broadly defined, taking into account the similarity in skill use relative to the rest of manufacturing is important. The results indicate that industries with both an uncorrelated labour demand relative to all of manufacturing *and* with a skill composition that resembles manufacturing have a significantly higher tendency to agglomerate in urban areas than other industries. Moreover, this effect seems stronger than in the analysis on specialised industrial clusters.

Turning to the related literature, a number of benefits of a common labour pool has been suggested. Helsley and Strange (1990) provide a formal model showing that the quality of a match between workers and firms is higher in larger markets. Similarly, Henderson (1974) and Henderson and Becker (2000) incorporate gains from specialisation at the firm and individual level into an urban framework. Finally, the idea that worker mobility facilitates diffusion of new technological know-how is prominent in the theoretical literature on localised technology spillovers (e.g. Pakes and Nitzan (1983), Combes and Duranton (2006)), and, by a related line of reasoning, Glaeser (1999) argues that cities promote exchange of skills from experienced workers to young workers.[5]

[4]In the sample period, around one fourth of the manufacturing labour force was located in the Greater Copenhagen area compared to around one tenth in the commuting area around the second largest city, Århus. The aim of limiting the definition to the labour market around Copenhagen is to focus the analysis on a diverse metropolitan area.

[5]Here, I only provide selected references. The handbook chapter by Duranton and Puga (2004) provides a detailed overview

As hinted to above, most empirical work on agglomeration concerns localised spillovers. The work of Zucker, Darby and co-authors (e.g. Zucker et al. (1998)) links the development of new high-tech industries to mobility of star scientists, and Kim and Marschke (2005) find that industries with high rates of engineer-mobility also patent more in order to protect their knowledge base. Moretti (2004) considers human capital spillovers rather than technology spillovers and shows that the share of college-educated workers in a city has a positive effect on the productivity of plants in that city. Evidence of gains from matching and specialisation is more scarce and generally comes from looking at specific groups of professionals. With respect to matching, Gan and Li (2004)'s study of the academic job market for new PhDs in Economics suggests that a field with more job openings and more candidates offers a higher probability of matching. Also, an often cited work on specialisation is Baumgardner (1988) who finds that physicians perform a narrower range of activities in large markets. The study in this paper addresses a different source of agglomeration, labour sharing, and moreover uses an extensive panel on plants and workers covering all of Danish manufacturing.

Finally, this paper compares *levels* of agglomeration across industries. Dumais et al. (2002) study *changes* in the spatial concentration of US-industries from 1972 to 1992, and one of their motivations is to investigate whether equilibrium mechanisms of the kind discussed in this paper or historical accidents determine today's location of plants. The authors look at the geographic mobility of industries by decomposing changes in industry geographic concentration into a mean reversion part and a dispersion part. For 5-year periods, they find that even though the overall concentration measure never changes by more than 4%, industry mobility amounts to 8-16% in both directions pointing to plant-mobility and equilibrium mechanisms as important for today's pattern of agglomeration. Barrios et al. (2005) reproduce this analysis for Portuguese and Irish manufacturing over the years 1985-1998 and likewise find persistent overall patterns of agglomeration but large magnitudes of underlying industry mobility.

The rest of the paper proceeds as follows. In section 2, I introduce the data set and explain the empirical variables. Section 3 contains the results. It consists of two subsections. In the first, I present the results on industrial agglomeration, and, in the second, I move on to discuss urbanisation. Section 4 contains robustness checks, and, finally, I conclude in section 5.

2 Data

I combine data from three sources. For the main variables of interest; geographic concentration, labour market pooling, and the education-based variables, I use register data from the integrated

of the literature.

database for labour market research (IDA) that is provided by Statistics Denmark. To calculate control variables for other important determinants of industrial agglomeration related to natural resource use, transport costs, and supplier linkages, I supplement the register data set with information from the input-output tables from Statistics Denmark. Finally, I draw information on R&D expenditures from the OECD ANBERD database.

The analysis is at the level of the industry, but the key variables of interest are calculated from plant and worker information. Importantly, the register data contain plant level information on yearly employment levels, information on the municipality and industry that plant j belongs to, and detailed educational information on the employees at plant j.

Plants are classified into industries according to a 6-digit code of which the first 4 digits correspond to the EU NACE-codes (In this paper, I use DB93 which corresponds to NACE rev 1). To facilitate comparison with other studies and to ensure that industries have a certain size, I classify plants according to the first 4 digits. Bertinelli and Decop (2005) likewise choose NACE 4 as their industry definition for Belgian manufacturing. The authors support their choice with a detailed discussion of the issues involved, and I will come back to their main points in the subsequent section.[6,7]

The analysis covers all manufacturing plants (DB93 150000-372000) in years 1992 to 2006. Earlier than 1992, the industry-code is less detailed and only allows for 36 subgroups in manufacturing compared to more than 220 subgroups from 1992 and onwards. There are 256,829 plant-year observations in the raw data, and I observe each plant 5.8 times on average. Table 1 shows the development in selected summary statistics for the manufacturing industry from 1992 to 2006.

[6]Note that only industries consisting of more than one plant add to the analysis in a meaningful way. For the 4-digit industries, there are some one-plant industries, and I leave these out of the analysis.

[7]The industry classification system underwent a revision in 2003. The revision has implications for the industry-codes from 2004 and onward. However, within manufacturing this only has implications for 29.40.00: Manufacturing of machine tools which was split into three groups 29.41.00 29.42.00 29.43.00. I re-classify these under the 29.40.00 group. The main part of the revision concerned services, but as I only use the industry-classification for services to calculate 1992-1999 concentration-measures this has no effect on the analysis.

Table 1: Summary statistics for the Danish manufacturing industry 1992-2006

	1992	1997	2001	2006
Manufacturing employment (1000)	397.8	411.2	402.2	349.8
Industry average plant size:				
Mean	36.2	38.7	41.9	35.4
Median	23.1	24.9	26.9	24.0
10^{th} percentile	6.0	5.0	6.0	5.4
90^{th} percentile	66.0	83.7	102.3	79.8
Industry number of plants:				
Mean	78.3	71.3	67.1	60.6
Median	29.0	25.0	23.5	21.0
10^{th} percentile	3.0	3.0	3.0	3.0
90^{th} percentile	205.0	180.0	159.0	143.0

Employment numbers in the table are based on full-time equivalents.

Total manufacturing employment increases in the first half of the period but then falls by 13% from 402.2 to 349.8 thousand full-time equivalents. The overall picture is that there are a few industries with on average large plants and many industries consisting of small and medium-sized plants. The number of plants per industry also varies heavily. Both are factors that I need to take into account when I carry out the analysis. Below, I define and explain the variables that I construct for the analysis. Summary statistics of these are provided in table 3 of subsection 2.5.

2.1 Measures of localisation and urbanisation

I consider two types of location decisions: locating in an industry-specific cluster (localisation) and locating in a dense metropolitan environment (urbanisation). This section contains a discussion of the issues involved in assessing geographic concentration.

2.1.1 The Ellison-Glaeser index of geographic concentration

As a measure of localisation of industry, I use the Ellison-Glaeser index of geographic concentration (hereafter EG-index) due to Ellison and Glaeser (1997). This index measures concentration of the industry in excess of what would be expected from the industrial concentration and the geographic distribution of overall manufacturing activities. To see this, it is useful to sketch the derivation of the index.[8]

The authors define an index of raw concentration $G_i = \sum_l (x_l - x_{li})^2$ that measures the extent to which employment in industry i is more or less geographically concentrated than manufacturing employment as a whole. x_l measures location l's share of total manufacturing employment, and

[8]Here, I follow the presentation in Bertinelli and Decop (2005).

x_{li} is location l's share of manufacturing employment in industry i. If there are no agglomeration economies, and regions are equally attractive in terms of natural resources then G_i should be proportional to industry i's industrial concentration H_i. They write the expectation of G_i as:

$$E(G_i) = (1 - \sum_l x_l^2)[H_i + \gamma(1 - H_i)] \tag{1}$$

where $H_i = \sum_j z_j^2$ is a Herfindahl index of the J plants in the industry with z_j being the employment share of the jth plant. The parameter γ captures excess concentration arising from dependency on natural resources or advantages associated with agglomeration economies. By isolating γ, the authors derive their index of agglomeration:

$$EG_i \equiv \hat{\gamma}_i = \frac{G_i - (1 - \sum_l x_l^2)H_i}{(1 - \sum_l x_l^2)(1 - H_i)} \tag{2}$$

The term $(1 - \sum_l x_l^2)$ ensures that the expected value of EG_i is zero if the distribution of the industry's employment across locations matches the distribution of total manufacturing employment taking into account H_i. A positive value of EG_i indicates that the industry is spatially more concentrated than would be expected if plant locations were random whereas a negative value indicates that it is less spatially concentrated. In a perfectly competitive industry with a large number of small plants, H_i is close to zero, and in this case EG_i is close to $\frac{G_i}{(1-\sum_l x_l^2)}$.

In the data, the administrative units of the 275 Danish municipalities that existed until January 1st 2007 constitute the geographic information.[9] As the purpose of this paper is to account for agglomeration-effects related to the labour market, I aggregate the 275 municipalities to 27 commuting areas and use these as my geographic units.[10] This is in line with Overman and Puga (2009) who use UK Travel to Work Areas and, moreover, in agreement with the directions provided in Barrios et al. (2003) and Bertinelli and Decop (2005) on how to apply the EG-index to small-size countries. These are studies on Belgian, Portuguese, and Irish manufacturing, and in both of them the authors prefer results based on regional geographical units over smaller municipalities. The regional units amount to 43 districts in Belgium, 18 districts in Portugal, and 27 counties in Ireland.

Using larger geographical units helps to address two short-comings of the EG-index. First, it limits problems with spatial auto-correlation due to disagreements between administrative and economic boundaries (Barrios et al. (2003)). Note that using commuting areas as the geographic unit further mitigates this concern as it improves agreement between economic and geographic boundaries. Second, it addresses a second issue associated with an upward bias in the measure for industries com-

[9]To be exact, the number was reduced to 271 in 2003 and to 270 in 2006. After January 1st 2007, the number of municipalities is 98 due to a reform of the local government structure and, thus, the administrative units that I refer to are identical to the structure prior to this date.

[10]I use commuting areas as defined by the Ministry of the Environment, in SPD (2006).

posed of only a few plants. Kim et al. (2000) argue that whenever the number of plants in an industry is smaller than the number of spatial units, the EG-index is upward biased. I come back to this issue when I consider the robustness of my results in section 4.

The upper part of table 2 summarises the development in the concentration indices in the time period of interest. In Ellison and Glaeser (1997), the authors note that there is no obvious value of γ that can be associated with significant departures from a random allocation. In that paper, the authors themselves distinguish between three levels: not very concentrated ($\gamma < 0.02$), relatively concentrated ($0.02 < \gamma < 0.05$), and highly concentrated ($\gamma > 0.05$). According to these definitions, the Danish manufacturing industry shows high levels of concentration and much higher levels than those reported by Ellison and Glaeser as well as in other studies for the US.

In an empirical study based on US state, county and zip-code units Rosenthal and Strange (2001) find that industries tend to show less concentration on a more detailed geographical scale. Therefore, even though it is informative to compare levels of geographic concentration across countries, this requires some caution, and, in particular, it suggests that patterns of agglomeration in countries of similar size are more comparable than if countries are heterogeneous in terms of size. The numbers in table 2 are of similar magnitude as those found in Barrios et al. (2005) for 4-digit industries in Portugal in years 1985-1998. In the same study the authors find that average concentration of manufacturing in Ireland measured by the EG-index is around 0.03. However, the development over time in their sample contrasts that for Danish manufacturing in years 1992-2006 as they observe decreasing levels of concentration whereas the average EG-index increases for Danish industries.

Table 2: Mean levels of geographic concentration 1992-2006

	1992	1997	2001	2006
EG-Index (EG)	0.047	0.051	0.097	0.100
Raw geographic concentration (G)	0.235	0.238	0.244	0.251
Plant Herfindahl (H)	0.221	0.222	0.228	0.229
Conc. of manufacturing ($\sum_l x_l^2$)	0.145	0.133	0.130	0.128
Employment weighted EG-index	0.057	0.079	0.087	0.103
Urbanisation	0.276	0.253	0.248	0.227

The table reports means of the EG index of geographic concentration and three components: A raw concentration index, a Herfindahl index of plant-level concentration of employment, and a measure of the geographic concentration of manufacturing. Employment-numbers are full-time equivalents. It also include the measure of urbanisation, see subsection 2.1.2.

In the table, I include all industries with a Herfindahl less than 1 in the reported year.

2.1.2 Urbanisation

In addition to industrial agglomeration, I wish to investigate whether plants locate in a diverse, urban area to hire from a broad set of manufacturing skills. Therefore, I consider an alternative index of geographic concentration; the sample fraction of industry employment in an urban area.

Around one fourth of Danish manufacturing employment is located in the Greater Copenhagen area compared to one tenth around the second largest city of Århus. My preferred definition of a thick and diverse urban labour market is therefore the labour market around Copenhagen.[11] In the years 1992 to 2006, manufacturing employment in the Greater Copenhagen area falls with 21.6% from 102,298 to 80,117 full-time equivalents. This is a decrease above what was found for manufacturing as a whole. The lower part of table 2 summarises this development in the gradually decreasing index of urbanisation.

The index of urbanisation are simple compared to the EG-index. When measuring localisation of industries, the concern is that scale economies at the plant level show up as spatial localisation if one neglects to control for the degree of concentration in the industry, but measuring urbanisation does not lead to similar concerns. The urban index can for any industry that consists of two or more plants take on any value between 0 and 1. However, in section 4, I check whether the results are sensitive to controlling for industry concentration and the average size of plants in the estimations.

2.2 Measure of the potential for labour market pooling

Overman and Puga (2009) develop the link between the labour pooling model of Krugman (1991) and empirical work. They consider a multi-location setting in which establishments are exposed to a productivity shock after they as well as workers have chosen their location.[12] In the industry, there is a continuum of workers and a discrete number of establishments operating under decreasing returns to scale. This is essential for generating the labour pooling effect as it implies that establishment profits are convex in the productivity shock. Finally, the industry is characterised by the magnitude of idiosyncratic productivity shocks across its establishments.

The key point is that in an isolated labour market wages are heavily affected by changes in employment at the establishment whereas in a location with many other plants workers can easily move from low-productivity establishments to high-productivity establishments which helps keeping wages constant facilitating an expansion of production in good times. In this sense, the advantage of an industrial cluster is that productivity shocks are ironed out instead of being heavily reflected in local wages, and this increases expected profits.

When establishments choose their location they trade off this advantageous effect of clustering against a negative effect from a tighter labour market as more establishments per worker pushes the

[11] I use the definition in SPD (2006). The Greater Copenhagen area consists of the municipalities of Copenhagen and Frederiksberg as well as a number of smaller municipalities surrounding Copenhagen.

[12] Here, I refer to the version in which firms and workers choose their location simultaneously. The authors also consider an alternative definition with a fixed labour pool in each location but with free entry of firms.

general wage-level up. The authors show that the more uncorrelated productivity shocks are, the stronger is the tendency towards agglomeration.

To test this prediction, Overman and Puga (2009) suggest calculating, for any given year and plant, the absolute value of the difference between the percentage change in the plant's employment and the percentage change in the industry's employment, and then for each industry average across years and plants. I use a slightly modified version of the measure in that paper:

$$Pool_i^{PI} = \frac{1}{T}\sum_t \frac{1}{J}\sum_j (\frac{1}{E_j}|d_j - \bar{d}_i|) \tag{3}$$

where subscript i denotes industry and j denotes plant. J is the number of plants, T number of years, d_j measures plant absolute changes in employment and $\bar{d}_i = \frac{d_i}{J}$ is the industry average absolute change in employment. Finally, E_j is average employment at the plant in year $t-1$ and t. In this application, employment is given by full-time equivalents rather than number of employees at each plant in order to account for part-time workers.

The measure is zero if plant-level changes in employment exactly mimic changes in industry employment, and it is increasing in the degree of idiosyncracy of changes. Observing a positive relationship between this measure and the degree of agglomeration of the industry is consistent with the hypothesis that industry employment is concentrated because it improves plants' ability to adapt to positive and negative shocks. As alternative specifications, I define $Pool^{PM}$ as the equivalent index for plants relative to manufacturing, and likewise $Pool^{IM}$ for the industry relative to manufacturing.

The difference compared to the measure suggested in Overman and Puga (2009) is that, instead of comparing relative changes, I compare the absolute change in employment at plant j with the industry mean-absolute change. To be able to compare the size of shocks across plants, I weigh each observation with the average size of the plant across year $t-1$ and t. The motivation behind using absolute changes is that expression (3) allows for changes from zero and is less sensitive with respect to changes from small levels of employment. This makes it better suitable for an analysis based on the present data set. There are many small plants in the data and a significant amount of entry. The latter are observations that I avoid losing by taking this approach.[13] However, note, that by writing $Pool_i^{PI} = \frac{1}{T}\sum_t \frac{1}{J}\sum_j (|\frac{d_j}{E_j} - \frac{d_i}{J*E_j}|)$, it is seen that for industries composed of plants of equal size my measure is very similar to the Overman and Puga (2009)-measure. In this case, the only adjustment is to allow for entering plants as I view employment-changes relative to the average size of the plant instead of relative to lagged employment.

[13]Statistics Denmark assigns an identical identifier to a workplace in two consecutive years if one of three criteria are fulfilled: 1) same owner + same industry, 2) same owner + same workforce, 3) same workforce + same industry and/or address. Thus, only when all of these three criteria are violated do I observe exit or entry.

2.3 Measuring the skill-composition of the industry's labour input

This section defines an index that compares the skillmix of plants with the industry, and equivalently the skillmix of the industry with total manufacturing. The hypothesis is that a similar use of skills is favourable to agglomerations because it allows plants to form a common pool of labour.

Other authors have constructed measures of the skill-match of the industry relative to other industries or to the local economic environment in order to determine the scope for labour pooling (see Dumais et al. (1997), Henderson (2003), and Ellison et al. (2007)). The novelty of this paper is to use formal educations to define skills and to include a measure of the average similarity of the plant relative to the industry.

I start by considering whether an industry consists of plants that, in terms of skill use, are on average similar to or different from the rest of the industry:

$$Corr_i^{PI} = \frac{1}{J}\sum_j \frac{\sum_e \left(l_{je} - \frac{1}{n_i}\right)\left(l_{-je} - \frac{1}{n_i}\right)}{\sqrt{\sum_e \left(l_{je} - \frac{1}{n_i}\right)^2}\sqrt{\sum_e \left(l_{-je} - \frac{1}{n_i}\right)^2}} \tag{4}$$

where e indexes skill group, and n_i is the number of skill groups in the industry. l_{je} denotes the share of workers at plant j in skill group e, and l_{-je} is the share of workers in skill group e in the rest of the industry.[14] I use superscript PI to indicate that the index measures correlation of the plants relative to the industry. In a similar fashion, I calculate how correlated the skill mix of the industry is with the distribution of skills in all of manufacturing. I refer to this index as $Corr^{IM}$.

The educational variable is based on yearly reportings to Statistics Denmark from the educational institutions, and it indicates the highest level of education for each worker at plant j in any given year. It is an 8-digit code of which the first two digits indicate length of education from primary school to PhD, and digit 3 to 8 represent field (higher digits are nested in lower digit-groups). The aim in this paper is to group workers with respect to education in a way that captures substitutability from the point of view of firms. The challenge is the difficulty of assessing exactly which groups of workers are substitutes, and moreover that substitutability might differ across fields.

I have chosen the 6^{th} digit as my preferred level of detail. In the years 1993 to 1999 (the sample years from which industry characteristics are calculated), the number of 6-digit groups represented in manufacturing increases from 269 to 308. At the 6^{th} digit, fields of engineering at both the Bachelor's and Master's level are divided into machinery, chemistry, electronics, etc., and one can, to a reasonable extent, distinguish between languages studied. Likewise, sociologists, political scientists, and economists are separately grouped. The risk of choosing a more specialised classification is to

[14] As information on education is per individual worker independently of hours worked, I use head-count as my measure of total employment. This is different from the labour pooling measure for which I use full-time equivalents.

treat degrees that are in fact very close substitutes as dissimilar. In the robustness section, I carry out the analysis using the 4^{th} and the 8^{th} digit, and discuss how the results are affected.[15,16]

Unfortunately, educational information is missing for about 4% of of workers. Rather than excluding these from the calculations, I have chosen to treat a missing educational code as a separate skill group.

2.4 Controlling for other forces of agglomeration

The location decision of establishments are affected by a multiple of factors ranging from the availability of inputs and skills to the cost of transporting goods to the market. In this section, I briefly introduce the set of controls, but also refer to the discussion of these in the results section.

From the register data set, I calculate the industry share of workers with a Bachelor's degree or higher and include these in the regressions. This is a standard variable to include in studies of agglomeration, and most studies find a strong positive relationship between this variable and agglomeration. The analysis of this paper characterises the labour market in more detail compared to what is usually the case, and the expectation is that this, to some degree, moderates the importance of this variable in explaining agglomeration. In this analysis, the variable captures effects relating to better conditions for workers and firms to find a good match as well as to learning externalities.

The human capital intensity might also capture how technologically advanced an industry is. A number of theories predict clustering of plants because it facilitates transmissions of technological know-how, i.e. via labour mobility. However, I seek to separately control for the role of technology and knowledge spillovers in forming industrial clusters and urban areas by including R&D expenditures as share of value added. The data source for R&D expenditures is OECD's ANBERD database, and one should note that it is only available at the 2-digit industry level (18 manufacturing industries).

The input-output tables from Statistics Denmark and industry value added from the national accounts allow me to control for the role of natural advantages, transport costs and vertical linkages. Rosenthal and Strange (2001) carefully define relevant variables, and I take their paper as my starting point.[17]

[15]When I calculate the plant skill composition, I restrict the employee-educational observations to workers for whom Statistics Denmark reports that their main occupation is with the respective plant. This excludes workers for whom the main occupation is at a different workplace either as a wage-earner or as a self-employee. This, however, does not in general exclude part-time employees.

[16]The short-coming of this method is that workers who are hired on grounds different from the educational background are classified wrongly. For example, a formally trained hairdresser who does manual work at a manufacturing plant enters in the measure as a hairdresser, but to the extent that he does not use his formally acquired skills he should be grouped with other unskilled workers.

[17]The Danish Input-Output tables use a 130 industry classification of which 55 are manufacturing industries. Two manufacturing industries cannot be separated at the 4^{th} digit (Industrial production of bread: 158109 and bakery stores: 158120), and I sum the input-variable for these. Accordingly, I end up with 54 manufacturing industries, and I assign the same value

The variables 'Primary input as share of value added', 'Energy as share of value added', and 'Water as share of value added' capture reliance on natural resources, and price differences on water and energy across regions. Dependency on one or more of these inputs could lead to industrial clustering. However my expectation is that these factors are weaker predictors of location in a country of the size of Denmark than in the US and UK which are the countries analysed in the referenced paper.

Industries that depend on producers of intermediates have an incentive to cluster near these plants. I seek to capture this by including 'Manufactured input as share of value added' and 'Service input as share of value added' in the analysis.

These variables, however, do not depend on whether suppliers are in fact geographically concentrated or not. Overman and Puga (2009) improve on this by including an input-share weighted sum of the EG-index across all industries to capture the spatial concentration of suppliers:

$$V_i = \sum_{k \neq i} I_{ik} EG_k \tag{5}$$

where I_{ik} is the value of industry i's input purchased from industry k relative to value added in industry i, and EG_k is the EG-index of industry k.

In this analysis, an alternative is to replace the EG-index of geographic concentration with $G_i = \sum_l (x_l - x_{li})^2$; the measure of raw geographic concentration. The idea behind the EG-index is to measure geographic concentration that arises from factors external to the plant, and therefore it is important to adjust for the part of geographic concentration that arises from a highly concentrated industrial structure. If production of intermediates takes place only at a few large suppliers then this could also be an agglomerative force. I wish to compare my results with those in Overman and Puga (2009), and therefore I continue to use the EG-index in the reported regressions. I discuss how the alternative choice of using G_i impacts the results.

An industry that relies on own-industry input is similarly expected to be concentrated. Therefore, I include I_{ii} in the regressions to capture industry i's share of inputs purchased from producers within the industry.

In models of new economic geography, the cost of transporting goods is central in determining the relative size of agglomeration and dispersion forces. I include 'Road transports as share of value added' in the analysis, but controlling for transport costs is problematic since producers with high transport cost will tend to locate production facilities close to their markets. This acts to lower observed costs of transportation for these (dispersed) industries even though the underlying relationship is the converse. Therefore, a priori the expected sign on this variable is undetermined.

to any 4-digit industry under the same IO-industry group.

Finally, I control for expenditures on shipping by rail, sea, or air as share of value added. To the extent that plants rely on these modes of transport associated with a localised infrastructure, they are likely to choose location so as to facilitate access to ports, railways, and airports.[18]

2.5 Descriptives

Table 3 summarises key statistics of the empirical variables.

In the previous section, I found that Danish manufacturing shows high levels of overall industrial agglomeration compared to other countries. However, the table shows variation in the EG-index across industries, and a similar picture holds for the urban index.

Despite the rather narrow definition of an industry, the measure of within industry similarity in formal skills, $Corr^{PI}$, varies from 0.10 at the 10^{th} percentile to 0.67 at the 90^{th} percentile. Thus, it is not given that same-industry plants make use of the same type of formal qualifications.

A different characteristic of the Danish Manufacturing industry which is worth commenting on is the high average value of services in value added compared to manufactured inputs in value added. One explanation is that I only see inputs bought from Danish suppliers, and therefore the variables exclude imported intermediate goods. This is likely to be more important with respect to manufactured inputs than with respect to service inputs.

Table 3: Descriptives

	Mean	Median	SE	P10	P90
Dep. variables:					
EG-index	0.075	0.040	0.455	-0.082	0.305
Urbanisation	0.244	0.169	0.243	0.008	0.645
Labour market variables:					
Pool^{PI}	0.947	0.666	0.867	0.351	1.823
Pool^{PM}	0.355	0.343	0.117	0.251	0.482
Pool^{IM}	0.159	0.092	0.182	0.038	0.390
Corr^{PI}	0.454	0.537	0.276	0.096	0.669
Corr^{IM}	0.820	0.860	0.137	0.634	0.952
Share of workers with BA-degree or higher	0.129	0.109	0.079	0.053	0.238
Other input variables:					
R&D exp. as share of value added	0.033	0.014	0.046	0.003	0.078
Primary exp. as share of value added	0.185	0.002	0.871	0.000	0.368
Water exp. as share of value added	0.002	0.001	0.002	0.000	0.004
Energy exp. as share of value added	0.041	0.032	0.043	0.012	0.073
Shipping by rail, sea, and air as share of value added	0.008	0.005	0.009	0.003	0.019
Road transport as share of value added	0.029	0.019	0.025	0.006	0.068
Manufactured goods as share of value added	0.492	0.421	0.250	0.276	0.810
Services as share of value added	0.398	0.359	0.200	0.259	0.520
Input-share weighted EG-index.	0.089	0.025	0.580	0.011	0.125
Input-share weighted urban index	0.324	0.278	0.271	0.196	0.471
Own-industry exp. as share of value added	0.146	0.087	0.153	0.021	0.312

For the dependent variables, the table variables are averages over the years 2000-2006. The right-hand side variables are averages over the year 1993-1999. This corresponds to the regression tables.

[18]Other studies, do not include this as a separate measure. However, I judge that this variable is less endogenous compared to the Road transport component.

Before I move on to the empirical results, I show the simple correlation coefficients of the main variables of interest in table 4.

Table 4: Correlations of the main variables of interest

	EG	Urban	Pool^{PI}	Pool^{PM}	Pool^{IM}	Corr^{PI}	Corr^{IM}
EG-index	1.000						
Urban	-0.405	1.000					
Pool^{PI}	0.296	-0.044	1.000				
Pool^{PM}	0.081	0.071	0.249	1.000			
Pool^{IM}	0.013	0.157	0.438	0.474	1.000		
Corr^{PI}	0.019	-0.221	-0.150	-0.371	-0.584	1.000	
Corr^{IM}	0.030	-0.325	-0.073	-0.189	-0.318	0.499	1.000

The EG-index and the urbanisation measure are averages over 2000-2006. The other variables are averages over the years 1993-1999. This corresponds to the regression tables.

With respect to the labour market characteristics of the industry, note that some of these are correlated. This is in particular true for the two measures of correlation and also the labour pooling variables show high levels of correlation.

3 Empirical results

The starting point for the empirical analysis is the following empirical equation:

$$\begin{aligned} Concentration_i = &\beta_0 + \beta_1 Pool_i^k + \beta_2 MedCorr_i^k + \beta_3 HighCorr_i^k \\ &+ \beta_4 Pool_i^k \times MedCorr_i^k + \beta_5 Pool_i^k \times HighCorr_i^k \\ &+ \phi X_i + \epsilon_i \end{aligned} \tag{6}$$

where $Concentration_i$ is the chosen measure of spatial concentration – industrial or urban. The parameters of interest are $\beta_1 - \beta_5$ that capture labour market effects. $Pool_i^k$, $k = PI, PM, IM$ is the potential for labour pooling due to idiosyncratic volatility in labour demand. $Corr_i^k$, $k = PI, IM$ is the chosen measure of skill correlation which I divide into three groups; Low, Medium, and High as reflected by the prefixes. I return to the exact cut-offs when I present the results.

In some specifications, I include the interaction of the labour pooling variable and the skill correlation variable in order to investigate whether there is a stronger relationship between idiosyncratic volatility and geographic concentration in industries that are homogeneous in terms of skill-use. Finally, X_i is a vector of control variables as described in section 2.4, and ϵ_i is an identically and independently distributed error term.

In the analysis on localisation of industries, I estimate equation (6) by OLS. In the analysis on urbanisation, the dependent variable is share of the industry in an urban area which is censored at zero, and, therefore, I report the results of a tobit regression.

The data set is a panel covering years 1992-2006, but neither location nor industry-characteristics change much over time. Therefore, there is little information in using differences in place of levels. Instead, I use averages of the right-hand side variables from 1993-1999 (I lose one year when I calculate the labour pooling measure) and averages of the concentration index from 2000-2006. This approach is consistent with plants observing industry-characteristics before choosing their location which to some extent diminishes concerns of reverse causality. Moreover, Rosenthal and Strange (2001) note that the role of natural advantages are likely to be exogenous to the extent of agglomeration. And even though the role of labour market factors and supplier-linkages are outcomes of an equilibrium relationship in which agglomeration might also impact the right-hand side variables, agglomeration in itself is costly (e.g. due to congestion costs). Therefore, plants have no incentives to agglomerate unless it is to benefit from positive factors in the external economic environment.

Finally, Ellison et al. (2010) construct instrumental variables to address endogeneity concerns in an analysis of co-location among pairwise US industries. They show that the positive effect of the labour market characteristic – occupational similarity - on the EG-index is robust to the IV approach.[19]

With these remarks in mind, I now turn to the results. I start by presenting the results on factors that lead to specialised industrial clusters. Then, I move on to the question of whether the labour pooling motive applies to the decision of locating in an urban environment.

3.1 Industrial localisation

Table 5 shows the outcome of the analysis of industrial agglomeration. Standard errors in parenthesis are clustered at the level of the 54 industries in the input-output tables.

Rows 1 to 7 report the coefficients of interest. In column 1, the coefficient on the labour pooling variable of plants relative to the industry, $Pool^{PI}$ is 0.14 and significant at the 5% level confirming Krugman's labour pooling hypothesis. Moreover, I check if idiosyncratic volatility relative to manufacturing has similar effects on the agglomeration patterns of industries. In column 2, I compare plants to total manufacturing, and, in column 3, I distinguish between idiosyncratic volatility within the industry and of the industry relative to manufacturing. In neither of these regressions does an idiosyncratic labour demand relative to manufacturing come out significant. With respect to the labour pooling hypothesis it is reassuring that it is specifically idiosyncratic volatility relative to same-industry plants

[19]The authors report results using two sets of instruments. The first set of instruments uses UK-variables to instrument for US variables. The second set of instruments is based on disaggregated data. The "innate" relatedness of an industry pair is estimated using data on characteristics of industry i in regions where industry j is least present and vice versa. See the paper for more detail on this approach.

Table 5: Regressions of the EG-index on industry characteristics

	(1)	(2)	(3)	(4)	(5)
$Pool^{PI}$	0.1381**		0.1679**	0.1438**	0.1330***
	(0.0636)		(0.0709)	(0.0634)	(0.0458)
$Pool^{PM}$		0.2068			
		(0.3614)			
$Pool^{IM}$			-0.2903		
			(0.2438)		
$0 \leq Corr^{PI} \leq 0.4$				-0.0079	-0.0885
				(0.1624)	(0.1542)
$Corr^{PI} > 0.4$				0.0743	0.0434
				(0.0676)	(0.0697)
$Pool^{PI} \times (0 \leq Corr^{PI} \leq 0.4)$					0.4312*
					(0.2222)
$Pool^{PI} \times (Corr^{PI} > 0.4)$					0.0498
					(0.0509)
Share of high-skilled	0.3086	0.7642	0.2078	0.3078	0.2496
	(0.4088)	(0.4834)	(0.3720)	(0.4270)	(0.4047)
R&D expenditures	-0.3756	-0.4170	-0.4486	-0.4604	-0.2538
	(0.6059)	(0.5648)	(0.6094)	(0.6350)	(0.6447)
Primary	-0.1353	-0.1330	-0.1431	-0.1444	-0.1251
	(0.1119)	(0.1209)	(0.1129)	(0.1136)	(0.1064)
Water	7.8161	11.2898	11.1574	6.0337	-0.0880
	(20.5289)	(18.8400)	(20.9479)	(20.1237)	(20.5595)
Energy	-1.9592	-1.7471	-1.8123	-1.9213	-1.5657
	(2.0650)	(2.0472)	(2.1396)	(2.1203)	(2.1365)
Shipping by rail, sea, and air	13.4879*	14.1449*	13.0477*	13.5932*	12.3782*
	(6.9754)	(7.4883)	(7.2710)	(7.0226)	(6.2745)
Road transport	1.2013	2.0752	0.9505	1.1643	-0.1624
	(2.5888)	(3.2620)	(2.5239)	(2.6152)	(1.9412)
Services	-0.4437	-0.6405	-0.4571	-0.4437	-0.2906
	(0.3354)	(0.4272)	(0.3294)	(0.3324)	(0.2621)
Manufacturing	0.0300	0.1060	0.0487	0.0372	0.0880
	(0.1825)	(0.1976)	(0.1754)	(0.1781)	(0.1755)
IO-weighted EG-index	0.1892	0.1911	0.2006	0.2052	0.1809
	(0.1530)	(0.1639)	(0.1558)	(0.1574)	(0.1519)
Own industry	0.2448	0.1156	0.2206	0.2543	0.1610
	(0.3492)	(0.3520)	(0.3171)	(0.3378)	(0.3396)
Constant	-0.0282	-0.0142	0.0054	-0.0883	-0.0820
	(0.1067)	(0.1373)	(0.1030)	(0.1197)	(0.1178)
Observations	217	217	217	217	217
R^2	0.144	0.087	0.154	0.150	0.237

OLS regression. Standard errors, in parenthesis, are clustered according to the 54 industrial groups in the input output tables.

Dep. variable is the EG-index (see section 2.1.1). The measure of labour pooling is based on full-time equivalents. The educational variables are based on the number of workers at plants. The group of industries for which $Corr^{PI}$ is negative constitutes the reference group in column 4 and 5. The interactions in column 5 are evaluated at the mean of the variables.

The variables from R&D-expenditures down to Own-industry are calculated as input relative to value added.

* Significant at 10%, **Significant at 5%, ***Significant at 1%.

that predicts industrial clustering. The findings in these three columns are in line with the results by Overman and Puga (2009).[20]

In column 4 and 5, I add the measure of the average correlation between the skill mix of plants and the rest of the industry. It is novel to consider both the skill-dimensions and the structure of labour demand in one analysis. In the reported regressions I have chosen to group industries according to three levels of the $Corr^{PI}$-variable; low, medium, and high. The first group consists of those with a negative correlation, the second group consists of those industries that show a correlation between 0 and 0.4, and the last group consists of industries showing a correlation measure higher than 0.4. The 0.4-cut-off corresponds approximately to the 25th percentile.[21] In column 5, I have subtracted the mean of the variables when I calculate the interaction term. Therefore, the coefficient of $Pool^{PI}$ is the effect of an increase in the idiosyncratic component of labour demand on the EG-index at the averages of the correlation dummies, and equivalently for the coefficients on $Corr^{PI}$. This makes the coefficients on $Pool^{PI}$ and $Corr^{PI}$ comparable with those reported in column 1 and 4. In the regressions the group with a negatively correlated skill mix is the reference group.

The results in column 4 and 5 indicate that a similar use of formal qualifications by itself does not have an impact on the tendency of industries to form a cluster. The interactions, on the contrary, are positive and for the medium correlated group significant.[22] These results confirm to some extent the hypothesis that plants benefit from co-location if they depend on the same type of formal qualifications *and* are characterised by a large idiosyncratic component in their labour demand. However, the Rotemberg and Saloner (2000) type of idea is rejected by the data. A similar need for skills does not in itself lead to agglomeration in specialised industrial clusters.

I have tried restricting the effect to a linear relationship using the continuous version of the measure but with little success. Both the direct effect and the interaction came out with highly insignificant coefficients. Also, I have experimented with different thresholds. In particular, dividing the high correlation group in two. This did not add to the analysis. Overall, the positive effects arise when one compares industries characterised by negative correlations with the group of industries characterised

[20]Unfortunately, it is difficult to compare the magnitudes of the estimates. First, I have adjusted the index of labour market pooling. Second, as I have discussed in an earlier section, the exact size of the EG-measure is difficult to interpret. In particular, the geographical scale has an impact on its size.

[21]$Corr^{PI}$ is unevenly distributed. There are 14 observations in the low-group, 40 observations in the medium-group (the cut-off is approximately the 25^{th} percentile), and 183 observations in the high-group.

[22]Rotemberg and Saloner (2000) predict regional specialisation around skills and the most direct way of accounting for this is to use the within industry correlations in skill mix $Corr^{PI}$, but it is interesting to describe the formal qualifications of the industry's labour force a long a different dimension. An alternative interpretation is that a localised industry uses a specialised set of skills relative to the rest of the economy. In a regression not reported here, I tried including $Corr^{PI}$, but the data actually shows quite the opposite picture. Industries that look like the rest of manufacturing show a tendency to be localised. An explanation is that a very agglomerated industries cannot specialise production to the same degree as for example industries located together with a large number of suppliers. The measure $Corr^{PI}$ is therefore better suited to test the hypothesis.

by a medium level of skill correlation. One explanation could be that the correlation-measure takes into account both the level and field of education. The results indicate that conditional on a certain degree of skill-match, informal learning at the job is sufficient for labour-sharing.

The final labour market characteristic that I include in the analysis is the share of the industry's workforce with a BA, Master's or PhD-degree. The hypothesis is that these workers in particular have much to gain from thick labour markets if these generate better matching of workers and firms and/or superior conditions for learning. The data does not support this. Since this is a variable that is often found to be positively correlated with gains from agglomeration, I checked whether excluding the pooling variable from the estimations would produce different results. I do not include the results here but just note that the coefficient does increase while the coefficient continues to be insignificant. Rather than putting too much emphasis on this finding, I hypothesise that the specialised clusters in the present data set might be too small to generate these types of effects. The estimations in the next section that is concerned with the urban labour market show very different results.

I now turn to the variables that control for non-labour market characteristics of the industry. These variables are based on the input-output tables from Statistics Denmark and are only available at a higher level of aggregation amounting to 54 industries. Therefore, they are less precise than the labour market variables. Bertinelli and Decop (2005) discuss in detail how to apply the EG-index to small countries and conclude that it can be difficult to compare levels across countries of different size. Since the studies that I mostly refer to are on the scale of the UK or US economy, I find it relevant to devote some space to the discussion of the results.

Except for the extent to which the industry relies on localised infrastructure (Shipping by rail, sea, and air) non-labour market characteristics do not seem important determinants of agglomeration. The lack of significance is in contrast to results on agglomeration in UK local labour markets (Overman and Puga (2009)) though the estimated signs for the most part are consistent with those in that analysis. Except for manufacturing as share of value added and transport cost, the signs on the coefficients in the present analysis are in agreement with the results in that paper. However, as I discussed previously (section 3), the costs of transporting goods are difficult to measure and therefore also difficult to interpret, and Overman and Puga (2009) are themselves somewhat surprised of the negative, significant sign on manufactured goods.[23,24]

[23]Additional support for the findings in the present analysis is that Barrios et al. (2003) in a pooled sample of Belgian, Portuguese, and Irish manufacturing data find no significant effects of similar variables using geographic units that are comparable in size with the Danish local labour markets. This is in line with results in Rosenthal and Strange (2001) using US zip-codes as the geographical unit.

[24]One of the local labour markets contains the urban area of Copenhagen in which the labour market dynamics might be different from those of the rest of the local labour markets. For this reason, I also tried including a dummy-variable taking on the value of one if the industry is urban. Here urban industry was defined as having more than 50 percent of employment

Other authors have found that the concentration of input suppliers is a positive determinant of agglomeration (see Holmes (1999), Overman and Puga (2009)). Following the suggestion by Overman and Puga (2009), I include an input-share weighted EG-index to capture effects of vertical linkages, but this variable is insignificant in all regressions. This is a little surprising as proximity to suppliers are usually thought to be important. To be able to better compare the results with those in Overman and Puga (2009) who do not correct for clustering of their input-output measures, I calculated non-clustered, robust standard errors. Using these, I find that the coefficient on the input-share weighted EG-index is significant at the 10% level. Furthermore, before I reject that this is not an important factor in Danish manufacturing, I refer to the analysis on the urban labour market in which I find different results.[25]

In summary, the analysis in this section suggests that even after controlling for a wide range of potential agglomerative forces, the labour sharing motive is a significant determinant of industrial localisation. This naturally raises a parallel question of whether a similar effect is at play in urban labour markets. This is the subject of the subsequent section.

3.2 Urbanisation

The EG-measure is constructed to capture clustering of same-industry plants. In this section, I turn to an analysis of location in urban areas. In general, local labour markets that evolve around a single industry and an urban labour market differ in their dynamics. In particular, diversity in skills and knowledge is often emphasised as an advantage of urban areas in contrast to the specialised nature of industrial clusters.[26] Keeping this in mind, the purpose of this section is not to draw in new empirical effects. Rather, in a parallel manner to the above analysis, I investigate whether sharing labour can be considered a motive for industries that locate in an urban area.

In this analysis, the dependent variable is the share of industry employment in the Greater Copenhagen area, and I take all of manufacturing to be the relevant reference industry. Since in some industries it might be optimal for plants not to be present in urban areas in which case the variable is zero, I report the results of a tobit regression allowing for a corner response at zero (11 out of the 217 industries are not present in the Greater Copenhagen area).[27,28] To save on space, marginal effects are left out of the table. These can be found in Appendix A.

in an urban area. This did not change the results. In the next subsection, I return to the issue of urban labour markets.

[25]As I briefly discussed in section 2.4, an alternative measure of the localisation of suppliers uses the raw concentration index in place of the EG-index. I experimented with this and found that this alternative measure likewise generates positive but insignificant coefficients.

[26]See Jacobs (1969).

[27]Naturally, the dependent variable is also censored at 1, but this upper limit is only relevant for 2 industries, and I abstract from this in the analysis.

[28]In this section, I maintain leaving out 1-plant industries of the regressions.

In the discussion that follows, I contrast the findings with the results in the previous section. However, note that, since the scales of the outcome variables differ, it is only signs and significance levels that one can compare.

Column 1 in table 6 contains the result when I only include the variable $Pool^{IM}$ together with the set of controls in the regression. The coefficient is positive and significant at the 5%-level. This is in contrast to the result reported by Overman and Puga (2009) who find a positive but insignificant coefficient on their measure of urbanisation. However, a short-coming of the $Pool^{IM}$-variable is that the reference industry might be too broadly defined, and that the positive correlation captures something else than a potential for labour sharing. Therefore, it is even more important in this analysis to take into account the overlap in skill use between industry i and manufacturing.

Jumping to column 3, I test whether industries characterised by a large idiosyncratic component in labour demand relative to manufacturing *and* a matching use of formal qualifications show a larger tendency to be urban than other industries. As in the analysis on industry-specific clusters, I have grouped industries according to the degree of correlation with the reference industry. Since $Corr^{IM}$ is distributed differently than $Corr^{PI}$ (for example, none of the industries has a negative value of this variable), I use different cut-off values than above. The first group of industries are those with an average correlation with manufacturing of less than 0.6, the second group are those with a correlation in the range of 0.6 and 0.7, and the last group are those industries with a correlation measure above 0.7.[29] Again, I have subtracted the mean of the variables before calculating the interaction term such that the coefficients on $Pool^{IM}$ represent the effects at the averages of the correlation-dummies and similarly for the coefficient on $Corr^{IM}$.

The results in column 3 confirm the hypothesis that plants cluster if they have a large scope for sharing labour. As in the analysis on industry-specific labour markets, a correlated use of skills does not by itself lead to agglomeration, in contrast it has a negative coefficient.

Importantly, the interactions with $Pool^{IM}$ are positive and significant at the 5%-level and the relationship seems stronger than in the previous analysis. As I discussed above, the explanation might lie in the definition of the skill-correlation variables. They address the workers' formal qualifications neglecting the other important source of human capital accumulation; on-the-job-learning. It might be reasonable to assume that informal skills and know-how accumulated while working have a large industry-specific component whereas skills acquired through formal schooling are of a more general nature. The implicit assumption in the urban analysis is that workers move between industries in which case they lose industry-specific know-how thereby raising the importance of their formal

[29]There are 18 observations in the low correlation group, 27 observations in the medium correlation group and 72 observations in the high correlation group.

Table 6: Regressions of urban-index on industry characteristics

	(1)	(2)	(3)	(4)
$Pool^{IM}$	0.2356**	0.1606*	0.1919*	0.3550***
	(0.0915)	(0.0937)	(0.1063)	(0.1195)
$0.6 \leq Corr^{IM} \leq 0.7$		-0.0188	-0.0817	-0.0738
		(0.0790)	(0.0718)	(0.0678)
$Corr^{IM} > 0.7$		-0.1302**	-0.1779***	-0.1691***
		(0.0608)	(0.0496)	(0.0478)
$Pool^{IM} \times (0.6 \leq Corr^{IM} \leq 0.7)$			0.5904**	0.5771**
			(0.2322)	(0.2307)
$Pool^{IM} \times (Corr^{IM} > 0.7)$			0.4917***	0.5616***
			(0.1486)	(0.1327)
$Pool^{PI}$				-0.0680***
				(0.0195)
Share of high-skilled	0.6362**	0.5133*	0.6106**	0.8367***
	(0.3185)	(0.3046)	(0.2835)	(0.2928)
R&D expenditures	0.6734	0.6851	0.6363	0.6622
	(0.5831)	(0.5117)	(0.5004)	(0.5076)
Primary	-0.0282	-0.0162	-0.0130	-0.0094
	(0.0696)	(0.0592)	(0.0568)	(0.0563)
Water	-10.7049	-5.1680	-5.3559	-6.1707
	(13.6672)	(12.0545)	(12.6696)	(12.5399)
Energy	-0.0575	0.1555	0.1650	0.2370
	(0.9047)	(0.8656)	(0.8737)	(0.9002)
Shipping by rail, sea, and air	-3.9561	-4.4986*	-4.5703*	-3.9324
	(2.7414)	(2.5580)	(2.6659)	(2.6919)
Road transport	-0.7462	-0.4782	-0.4937	-0.0245
	(0.8641)	(0.8260)	(0.8159)	(0.7933)
Services	-0.5532	-0.4445	-0.4488	-0.4518*
	(0.3567)	(0.2968)	(0.3102)	(0.2730)
Manufacturing	-0.4196**	-0.3660**	-0.3617**	-0.3023*
	(0.1951)	(0.1745)	(0.1786)	(0.1567)
IO-weighted EG-index	-0.3837**	-0.3679***	-0.3631**	-0.3330***
	(0.1554)	(0.1379)	(0.1409)	(0.1237)
Urban EG-index	1.5814***	1.3915***	1.3796**	1.2374***
	(0.6034)	(0.5218)	(0.5404)	(0.4643)
Own industry	0.1329	0.0145	0.0010	-0.0623
	(0.4175)	(0.3556)	(0.3577)	(0.3413)
Constant	0.1013*	0.2205***	0.2597***	0.2645***
	(0.0603)	(0.0776)	(0.0697)	(0.0696)
σ	0.2224***	0.2182***	0.2154***	0.2098***
	(0.0174)	(0.0183)	(0.0175)	(0.0174)
Observations	217	217	217	217
Log-likelihood	6.020	10.05	12.72	18.12

Tobit regression with censoring at zero. Standard errors, in parenthesis, are clustered according to the 54 industrial groups in the input output tables. Marginal effects, evaluated at the mean of the variables, are left out of the table but can be found in appendix A.
Dep. variable is the fraction of industry-employment in the Greater Copenhagen Area. The measures of labour pooling are based on full-time equivalents. The educational variables are based on the number of workers at the plants. The reference group consists of industries that have a skill correlation with the rest of manufacturing of less than 0.6. The interactions in column 3 and 4 are evaluated at the mean of the variables.
P:plant, I: industry, M: manufacturing.
Variables R&D-exp.– Own-industry are inputs relative to value added.
* Significant at 10%, **Significant at 5%,***Significant at 1%.

qualifications relative to workers who rely on an industry-specific labour market.

In the last column, I add $Pool^{IP}$ to the regressions. The variable comes out negative and significant in these estimations and this confirms the conclusion from the previous section that a large idiosyncratic component in labour demand within the industry is a factor in the formation of industry-specific clusters. In principle, a high value of the EG-index could be a result of the industry being over-represented in an urban area compared to overall manufacturing. But this result re-enforces the conclusion that an idiosyncratic labour demand is associated with clustering in industry-specific locations. At the same time, note that including this measure also increases the coefficient on $Pool^{IM}$.

Finally, in these regressions, I have controlled for the same set of factors as in the analysis on industrial localisation but furthermore added an extra control variable. To better capture the potential external effects in this new setting, I have added an index that captures dependency on local urban suppliers to account for the parallel effect of the input-share weighted EG-index in the previous section. In that analysis clustering of local suppliers did not seem important, but that conclusion is rejected in this section. Dependency on urban suppliers has a strong positive effect on urbanisation and its pole – localisation of suppliers – comes out negative and significant.[30,31] Likewise, in the previous section, I discussed the apparent lack of significance of the share of high-skilled workers in that analysis. Table 6 shows different results. Use of high-skilled labour has a significant positive impact on the tendency of industries to agglomerate in urban areas which is in accordance with results found in other studies.

4 Robustness

In this section, I present a number of robustness checks. The upper part of table 7 presents results on the industry location analysis, and the lower part presents results on the urbanisation analysis. In order to save on space, I only report the coefficients on the main variables of interest; the labour pooling variables, the correlation dummies and their interactions. Table 8 in a similar manner presents regressions in which additional variables are included to control for possible effects of industry structure.

[30] I also ran the regressions using a broader definition of urban. In these regressions I used the share of industry-employment in the Copenhagen and Århus commuting areas as the dependent variable. According to this definition, only one industry has a zero share of employment in an urban area.The regressions showed a similar pattern as in table 6, but the effect are weaker.

[31] Adding this control variable does not change the reported results on labour pooling and skill correlation.

Table 7: Robustness checks

	4^{th} digit	8^{th} digit	Balanced sample	Spin-outs
Localisation (EG-index)				
$Pool^{PI}$	0.1381**	0.1154***	0.1389***	0.0804***
	(0.0672)	(0.0366)	(0.0323)	(0.0415)
$0 \leq Corr^{PI} \leq 0.4$	0.1123	-0.0616	-0.0065	-0.1335
	(0.1492)	(0.1294)	(0.1272)	(0.1520)
$Pool^{PI} > 0.4$	0.1189	0.0493	0.904	0.0323
	(0.1324)	(0.0553)	(0.1074)	(0.0733)
$Pool^{PI} \times (0 \leq Corr^{PI} \leq 0.4)$	0.2435	0.3041*	0.3583	0.1728*
	(0.1836)	(0.1689)	(0.2663)	(0.1563)
$Pool^{PI} \times (Corr^{PI} > 0.4)$	0.3268*	0.0366	-0.0569	0.0206
	(0.1867)	(0.0422)	(0.0996)	(0.0493)
R^2	0.149	0.207	0.336	0.132
	4^{th} digit	8^{th} digit	Balanced sample	
Urbanisation				
$Pool^{IM}$	0.2475**	0.2129*	-0.0292	
	(0.1078)	(0.1263)	(0.1332)	
$0.6 \leq Corr^{IM} \leq 0.7$	-0.2809***	-0.0518	-0.0431	
	(0.0883)	(0.0586)	(0.0769)	
$Corr^{IM} > 0.6$	-0.2064**	-0.1541***	-0.1810***	
	(0.0815)	(0.0435)	(0.0502)	
$Pool^{IM} \times (0.6 \leq Corr^{IM} \leq 0.7)$	-0.9716**	0.4667**	2.2213**	
	(0.4831)	(0.2072)	(0.9362)	
$Pool^{IM} \times (Corr^{IM} > 0.7)$	0.7054***	0.4227**	1.1900**	
	(0.1919)	(0.1803)	(0.4836)	
ll				
Number of obs.	217	217	193	217

The upper part of the table corresponds to column 5 of table 5. The lower part corresponds to column 3 of table 6. Standard errors, in parenthesis, are clustered according to the 54 industrial groups in the input output tables.
P:plant, I: industry, M: manufacturing.
Control variables as presented in section 2.4 are included in the regressions.
* Significant at 10%, **Significant at 5%,***Significant at 1%.

4.1 The skill mix variables

The use of formal qualifications to determine homogeneity or heterogeneity in the skill mix of plants and industries is new in the empirical literature on agglomeration. There is not a one to one relationship between skills acquired in schools and the jobs one can hold, and this offers some freedom on how to group workers. In the main analysis, I have grouped workers according to the 6^{th} out of 8 digits, but in the tables I present results for two alternative choices. The first column of the table uses a less detailed level of aggregation; the 4^{th} digit instead of the 6^{th} digit, and column 2 reports the results if a more detailed classification is chosen; the 8^{th} digit.[32]

Starting with the localisation analysis, the upper part of the table shows that using the 4^{th}-digit definition, makes the interaction between $Pool^{PI}$ and the high-correlation dummy relatively more

[32]I am aware that different levels of detail could apply to different subgroups of educations due to different degrees of substitutability, but I do not address this issue in this paper.

important compared to the medium-correlation dummy. This is in line with workers being less substitutable across 4-digit groups than 6-digit groups. Using the 8^{th} digit does not alter the coefficient on the interactions much compared to the 6^{th}-definition. It does have a small negative impact on the coefficient on the $Pool^{PI}$-index

For the analysis on urbanisation, using the 8^{th}-digit does not impact the analysis markedly. However, using the 4^{th}-digit in place of the 6^{th}-digit have an impact in the sense that it lays more importance on the high-correlation group compared to the medium-correlation group.

In light of the discussion on the relationship between formal schooling and human capital accumulated on the job in facilitating mobility, it is not surprising that the choice of detail in the skill-definition has an impact on the exact outcome of the analysis though the overall picture is robust to these changes.

4.2 Balanced sample

The variables EG, $Pool^{PI}$, and $Corr^{PI}$ are only defined for industries that consist of more than one plant. In the sample, there are a number of one-plant industries which are then left out of the analysis. However, for a number of small industries entry or exit of plants imply that they change status during the sample period.[33] Three additional industries (1588, 2630, 2721, and 3410) were left out of the main analysis because of missing observations in many years, but in order to keep as many industries as possible in the analysis the sample generally included all industries with observations in both time-periods 1993-1999 and 2000-2006. To address any concerns with respect to this choice, Column 3 of table 7 reports the results using only the balanced sample with 193 observations instead of 217 observations in the main analysis. All the industries that I leave out have at least 8 yearly observations and include both industries with a growing, decreasing, and stable number of industries.[34]

In the analysis on specialised industrial clusters (upper part of the table), the coefficient on $Pool^{PI}$ is robust to this change whereas the interaction within $Corr^{PI}$ loses significance. The analysis on urbanisation shows the opposite picture as $Pool^{IM}$ completely loses importance whereas the inter-

[33]In addition to real plant-openings or plant-closures, re-classifications of plants from one industry to another can cause this.

[34]The excluded industries are: 1585 (Manufacture of macaroni, noodles, couscous and similar farinaceous products), 1586 (Processing of tea and coffee), 1594 (Manufacture of cider and other fruit wines), 1810 (Manufacture of leather clothes), 2233 (Reproduction of computer media), 2413 (Manufacture of other inorganic basic chemicals), 2464 (Manufacture of photographic chemical material), 2465 (Manufacture of prepared unrecorded media),2611(Manufacture of flat glass), 2622 (Manufacture of ceramic sanitary fixtures), 2623 (Manufacture of ceramic insulators and insulating fittings), 2652(Manufacture of lime), 2731(Cold drawing), 2741 (Precious metals production), 2743 (Lead, zinc and tin production), 2744 (Copper production), 2745 (Other non-ferrous metal production), 2752 (Casting of steel), 3520 (Manufacture of railway and tramway locomotives and rolling stock), 3621 (Striking of coins), 1558 (Manufacture of homogenized food preparations and dietetic food), 2630 (Manufacture of ceramic tiles and flags), 2721 (Manufacture of cast iron tubes), 3410 (Manufacture of motor vehicles).

actions with the correlation-dummies become more important. Together, these results might reflect that within the industry plants are fairly similar such that skill-correlation only matters to some industries, making the interactions sensitive to the composition of the data set, whereas between industries the degree of skill-correlation interacted with the labour pooling index is the relevant explanatory variable with respect to labour sharing.

4.3 Spin-outs and the labour pooling index

I have constructed $Pool^{PI}$ such that it uses information on employment at all workplaces in the industry. One concern is that spin-outs contribute positively to the value of the index but are located in proximity to the founder's previous employer for reasons different than labour pooling. This would contribute to a positive relationship between the index that I have constructed and the EG-index. Therefore, I report the outcome of an estimation in which I have excluded entrants from $Pool^{IP}$. The coefficient on $Pool^{PI}$ decreases to 0.0804 revealing that entrants might, partly, be contributing to the relationship reported in the main analysis. Similarly, the interactions with the skill correlation variables decrease in magnitude.

In the urban analysis, where manufacturing is the reference industry, this type of robustness check is not relevant.

4.4 Industry structure: EG-index

Kim et al. (2000) argue that the EG-index is biased upwards for industries consisting only of a few plants relative to the number of geographic units. If these industries also differ systematically with respect to the measures of labour pooling and skill correlation, it is a concern to the reported results. To address this issue, I include the number of plants in the industry as an extra control variable to investigate if it has an impact on the relationship between $Pool^{PI}$, $Corr^{PI}$ and the EG-index. The results are reported in table 8, and they show that the conclusions are robust to expanding the set of controls in this way. Moreover, the variable "number of plants" does not by itself have an impact on the tendency of same-industry plants to cluster.

4.5 Industry structure: Urbanisation

The index of urbanisation that I use is a simple one, and, in contrast to the EG-index, I do not take into account the structure of the industry. When measuring localisation of industries, the concern is that scale economies at the plant level show up as spatial localisation if one neglects to control for the degree of concentration in the industry, but measuring urbanisation does not lead to similar concerns. However, to address concerns with respect to a possible link between the structure of the industry and urbanisation, I carry out the analysis with a Herfindahl index and a measure of the average size of plants included. Table 8 shows the results. The direct effect of $Pool^{IM}$ on urbanisation loses importance, but the interactions with the skill correlation dummies are robust to this change.

Table 8: Robustness check: Industry structure

Localisation (EG-index)		Urbanisation	
$Pool^{PI}$	0.1336***	$Pool^{IM}$	0.0902
	(0.0462)		(0.1613)
$0 \leq Corr^{PI} \leq 0.4$	-0.0890	$0.6 \leq Corr^{PI} \leq 0.7$	-0.0667
	(0.1544)		(0.0699)
$Corr^{PI} > 0.4$	0.419	$Corr^{IM} > 0.7$	-0.1674***
	(0.0711)		(0.0522)
$Pool^{PI} \times (0 \leq Corr^{PI} \leq 0.4)$	0.4317	$Pool^{IM} \times (0.6 \leq Corr^{PI} \leq 0.7)$	0.6139**
	(0.2231)		(0.2529)
$Pool^{PI} \times (Corr^{PI} > 0.4)$	0.0506	$Pool^{IM} \times (Corr^{PI} > 0.7)$	0.4889
	0.0522		(0.1447)
Number of plants	0.0000	Herfindahl	0.0945
	(0.0001)		(0.0007)
		Size of plants	-0.0008
			(0.1603)
Number of obs.	217		217

Column 1 of the table corresponds to column 5 of table 5. Column 2 of the table corresponds to column 3 of table 6. Standard errors, in parenthesis, are clustered according to the 54 industrial groups in the input output tables.
P:plant, I: industry, M: manufacturing.
Control variables as presented in section 2.4 are included in the regressions.
* Significant at 10%, **Significant at 5%,***Significant at 1%.

5 Conclusion

The purpose of this paper is to investigate empirically whether sharing a common pool of labour is a source of agglomeration. I study two sources of labour sharing. The first of these is the labour pooling argument due to Krugman (1991). It states that firms form industrial clusters in order to iron out idiosyncratic productivity shocks because geographical closeness facilitates mobility of workers from low to high productivity firms. An alternative idea due to Rotemberg and Saloner (2000) is that clustering of firms using similar skills in production encourages investments in human capital as competition for labour among employers prevents ex post appropriation.

I test these theories using a detailed employer-employee data set on Danish Manufacturing covering years 1992 to 2006. A study by Overman and Puga (2009) on UK data shows that the Krugman-motive is important, and Ellison et al. (2010) find, using a functional definition of skills, that two industries co-locate if they use the same type of skills. This paper adds to these findings in several ways. First, I consider the relative importance of these effects, and I investigate how the Krugman-motive varies with the degree of homogeneity in the skill mix of the labour force. Second, I use formal qualifications of the labour force to account for the skills which sheds light on a different perspective than a functional definition.

The economic theories that inspire this paper are themselves motivated by observed patterns of agglomeration in industry-specific clusters, and this is the focus of the main analysis. Thus, the analysis relates clustering of same-industry plants to their scope for sharing labour. The estimations suggest that even after having controlled for a large set of alternative agglomerative forces, an idiosyncratic labour demand is a strong driver behind the formation of industrial agglomeration. I do not find a similar strong support for the Rotemberg-Saloner type of idea.

In an extension, I turn to an analysis of location in urban labour markets. In general, local labour markets that evolve around a single industry and an urban, diverse labour market are thought to differ in their dynamics, and it is interesting to investigate whether sharing of labour plays a role in urban labour markets. The idea in this analysis is that labour sharing takes place between the industry and the rest of manufacturing rather than within the industry. The key finding is that the Krugman motive also in this analysis comes out significant. Specifically, industries with both an uncorrelated labour demand relative to all of manufacturing *and* with a skill composition that resembles manufacturing have a significantly higher tendency to agglomerate in urban areas than other industries. This suggests that matching formal qualifications play a more important role in facilitating worker mobility in the urban labour market than in the industry-specific clusters.

This paper raises questions about the role of formal qualifications in facilitating mobility of workers between employers and inducing agglomeration that are interesting to pursue in future work. Even though I find that homogeneity in the mix of formal qualifications play a role both in the industry-specific and the urban labour market, the effect seems strongest in the urban labour market in which mobility is likely to take place across industries. One explanation is that workers to a larger degree rely on industry-specific on-the-job learning when moving across employers within the industry whereas they lose this type of informal know-how when they move across industries. To learn more about this question, one can use the Ellison-Glaeser index to measure industrial localisation of plants from different industries and relate this to the indexes of labour pooling and skill correlation used in the analyses of this paper.

A Urban analysis, marginal effects

Table 9: Regressions of urban-index on industry characteristics (marginal effects)

	(1)		(2)		(3)		(4)	
	reg-coef.	marg	reg-coef.	marg	reg-coef.	marg	reg-coef.	marg
$Pool^{IM}$	0.2356**	0.2019**	0.1606*	0.1384*	0.1919*	0.1659*	0.3550***	0.3093***
	(0.0915)	(0.0808)	(0.0937)	(0.0823)	(0.1063)	(0.0932)	(0.1195)	(0.1064)
$0.6 \leq Corr^{IM} \leq 0.7$			-0.0188	-0.0161	-0.0817	-0.0678	-0.0738	-0.0620
			(0.0790)	(0.0670)	(0.0718)	(0.0569)	(0.0678)	(0.0547)
$Corr^{IM} > 0.7$			-0.1302**	-0.1164**	-0.1779***	-0.1610***	-0.1691***	-0.1538***
			(0.0608)	(0.0571)	(0.0496)	(0.0472)	(0.0478)	(0.0457)
$Pool^{IM} \times$					0.5904**	0.5106**	0.5771**	0.5028**
$(0.6 \leq Corr^{IM} \leq 0.7)$					(0.2322)	(0.1993)	(0.2307)	(0.2007)
$Pool^{IM} \times$					0.4917***	0.4252***	0.5616***	0.4893***
$(Corr^{IM} > 0.7)$					(0.1486)	(0.1258)	(0.1327)	(0.1137)
$Pool^{PI}$							-0.0680***	-0.0593***
							(0.0195)	(0.0170)
High-skilled	0.6362**	0.5452**	0.5133*	0.4423*	0.6106**	0.5280**	0.8367***	0.7289***
	(0.3185)	(0.2734)	(0.3046)	(0.2617)	(0.2835)	(0.2459)	(0.2928)	(0.2546)
R&D exp.	0.6734	0.5771	0.6851	0.5903	0.6363	0.5502	0.6622	0.5769
	(0.5831)	(0.4990)	(0.5117)	(0.4409)	(0.5004)	(0.4312)	(0.5076)	(0.4414)
Primary	-0.0282	-0.0241	-0.0162	-0.0140	-0.0130	-0.0113	-0.0094	-0.0082
	(0.0696)	(0.0598)	(0.0592)	(0.0511)	(0.0568)	(0.0492)	(0.0563)	(0.0491)
Water	-10.7049	-9.1741	-5.1680	-4.4530	-5.3559	-4.6314	-6.1707	-5.3761
	(13.6672)	(11.7974)	(12.0545)	(10.4242)	(12.6696)	(10.9961)	(12.5399)	(10.9745)
Energy	-0.0575	-0.0493	0.1555	0.1340	0.1650	0.1427	0.2370	0.2065
	(0.9047)	(0.7752)	(0.8656)	(0.7464)	(0.8737)	(0.7561)	(0.9002)	(0.7853)
Shipping by	-3.9561	-3.3904	-4.4986*	-3.8762*	-4.5703*	-3.9521*	-3.9324	-3.4261
rail, sea, and air	(2.7414)	(2.3379)	(2.5580)	(2.1895)	(2.6659)	(2.2847)	(2.6919)	(2.3250)
Road transport	-0.7462	-0.6395	-0.4782	-0.4120	-0.4937	-0.4269	-0.0245	-0.0214
	(0.8641)	(0.7445)	(0.8260)	(0.7143)	(0.8159)	(0.7087)	(0.7933)	(0.6913)
Services	-0.5532	-0.4741	-0.4445	-0.3830	-0.4488	-0.3881	-0.4518*	-0.3936*
	(0.3567)	(0.3060)	(0.2968)	(0.2556)	(0.3102)	(0.2682)	(0.2730)	(0.2375)
Manufacturing	-0.4196**	-0.3596**	-0.3660**	-0.3153**	-0.3617**	-0.3128**	-0.3023*	-0.2634*
	(0.1951)	(0.1685)	(0.1745)	(0.1512)	(0.1786)	(0.1551)	(0.1567)	(0.1373)
IO-weighted	-0.3837**	-0.3288**	-0.3679***	-0.3170***	-0.3631**	-0.3140**	-0.3330***	-0.2901***
EG-index	(0.1554)	(0.1329)	(0.1379)	(0.1187)	(0.1409)	(0.1217)	(0.1237)	(0.1077)
urband	1.5814***	1.3553***	1.3915***	1.1990***	1.3796**	1.1930**	1.2374***	1.0781***
EG-index	(0.6034)	(0.5186)	(0.5218)	(0.4497)	(0.5404)	(0.4673)	(0.4643)	(0.4043)
Own industry	0.1329	0.1139	0.0145	0.0125	0.0010	0.0008	-0.0623	-0.0543
	(0.4175)	(0.3585)	(0.3556)	(0.3065)	(0.3577)	(0.3094)	(0.3413)	(0.2972)
Constant	0.1013*		0.2205***		0.2597***		0.2645***	
	(0.0603)		(0.0776)		(0.0697)		(0.0696)	
σ	0.2224***		0.2182***		0.2154***		0.2098***	
	(0.0174)		(0.0183)		(0.0175)		(0.0174)	
Observations	217		217		217		217	
Log-likelihood	6.020		10.05		12.72		18.12	

This table reports the marginal effects, evaluated at the average values of the variables, of the regressions reported in 6.
Tobit regression with censoring at zero. Standard errors, in parenthesis, are clustered according to the 54 industrial groups in the input output tables. Dep. variable is the fraction of industry-employment in the Greater Copenhagen Area. The measures of labour pooling are based on full-time equivalents. The educational variables are based on the number of workers at the plants. The reference group consists of industries that have a skill correlation with the rest of manufacturing of less than 0.6. The interactions in column 3 and 4 are evaluated at the mean of the variables.
P:plant, I: industry, M: manufacturing.
Variables R&D-exp.– Own-industry are inputs relative to value added.
[*] Significant at 10%, **Significant at 5%,***Significant at 1%

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