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An Analysis Of The Graduate Labour Market In Finland: The Impact Of Spatial Agglomeration And Skill-Job Mismatches

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Abstract

The recent history of Finland has been shaped by the rollercoaster of the 1990s when the economy went from deep recession to becoming among the most innovative and competitive within merely a decade. Economic recovery driven by the surge of ICT-related industries with the active support of the higher education system gave way also to growing inequalities among regions, especially within graduate workers. The paper elaborates an empirical analysis of the returns to education of a cohort entering the labour force between 1995 and 2005; our objective is to capture the extent of spatial and occupational determinants on income distribution as Finland slid from its most troubled to most prosperous times.

1 Introduction

The objective of this paper is to investigate spatial and occupational determinants of graduate earnings in Finland. The recent history of this country has been shaped by the rollercoaster of the 1990s when the economy went from deep recession to becoming among the most innovative and competitive within merely a decade. At heart of this radical upturn was a balanced mix of industrial policies and public investments in higher-education and R&D which proved crucial for the renowned expansion of the telecommunication equipment industry and the related service sectors (Honkapohja and Koskela, 1999; Honkapohja et al, 2008; OECD, 2001). At the same time economic recovery at national scale entailed the aggravation of regional inequalities whereby traditionally industrialised southern regions played an active role in the development of high-tech sectors while other areas of the country responded slowly and lagged behind.

Against this backdrop the paper focuses on two concurrent processes: the increasingly local character of the labour markets (Böckerman and Maliranta, 2007) and the emergence of inequality among highly educated workers (Uusitalo, 1999; Kyyra, 2000; Asplund and Leijola, 2005): both are striking in consideration of Finland's established tradition of centralised wage bargaining. The paper elaborates an empirical analysis of the returns to higher education among a cohort of labour market entrants using original data by Statistics Finland. The results indicate the impact of job-skill mismatches and of agglomeration effects on earning dispersion among graduates; our analysis captures also important differences among local labour markets as measured by returns to specific occupations and skill levels. These findings resonate with 9various accounts of Finland's recent history, in particular on the connection between the emergence of new technological opportunities and the growth of domestic divergences in the wake of the recent shift from bust to boom.

The paper is structured as follows. Section two presents a concise summary of Finland's recent economic history and an overview of the main conceptual issues at stake. Section 3 presents some descriptive analysis and introduces the indexes of job-skill mismatch and regional location which are integrated and discussed in Section 4. Section 5 concludes.

2 Context and Background

The recent history of Finland offers a compelling illustration of the turbulences that follow major regime transitions such as the emergence of new Information and Communication Technologies (ICTs). This section reviews concisely key milestones of the country's long-term economic development and frames them within the relevant conceptual framework.

2.1 The 1990s in Finland: bust to boom

Industrialization began in the late 1950s Finland with the expansion of manufacturing and processing activities; by the late 1970s the service sector had gained primacy in total production and employment figures, although industry remained the main export earner. The combined pressure of the oil crisis and of increased foreign competition was a propeller for the development of high-technology industries in the 1980s which aimed at reducing dependence on transportation and energy supplies (Hjerppe and Vartia, 1997; Ollikainen, 1997). In the 1990s Finland experienced a deep crisis whose extent is well documented and best signified by data on plummeting productivity and rising unemployment (see e.g. Rouvinen and Ylä-Anttila, 2003). Most observers concur that a combination of factors contributed, in particular the untimely financial deregulation of the 1980s and the collapse of trade with the Soviet Union. To make things worse, at the peak of the downturn soaring indebtedness undermined the urgency measures adopted by the Central Bank triggering a domino effect of bankruptcies in the financial and other sectors (Kiander, 2004a; Kiander, 2004b). Notwithstanding these premises by the end of the decade Finland enjoyed renewed prosperity thanks to radical transformations in the industry structure propelled by the expansion of high-tech sectors. In the following years the country became a global leader in ICT sectors with over 6000 specialised firms (Paija and Rouvinen, 2003) and a wealth of resources for research which account for more than 50% of national industrial R&D (Castells and Himanen, 2002; Ylä-Anttila, 2005) .[1]

1 See also Daveri and Silva (2004) for a critical view of the impact of ICTs on economic expansion in Finland, as well as the critique towards the social model that emerged in association with ICT-related growth by Pelkonen (2005) and Häyrinen-Alestalo et al. (2005).

Two pillars stood beneath these remarkable transformations: the system for higher education and the labour markets, both central to the remit of this paper. Let us look at these seriatim.

Finland's higher education system shares the basic virtues of the egalitarian tradition, namely affordability and wide accessibility (Usher and Cervenan, 2005). In fact in Finland there are no fees for full-time students, there is a high ratio of university per inhabitant (21 universities and 31 polytechnics with total population around 5 million) and grants and special loan programs are widely available. Over the period 2000-2007 entry rates into tertiary education were about 70%; graduation rates for first degree programs and postgraduate qualification were respectively 47% and 2.1%, both significantly above the OECD average (OECD, 2008). Further data on average graduation times and PISA tests scores further confirm the high quality of the country's educational system (Välijärvi, et al, 2002; OECD, 2005). Two important steps marked the evolution of the system: the creation of new Universities between the 1960s and 1970s aimed at expanding access to higher education for residents of remote areas, and the upgrading of Polytechnics degree for graduate courses in the late 1990s to meet growing demand for higher vocational skills.

Finland's labour market is organized around the canons of a traditional Nordic welfare system with high labour taxes, extensive social benefits, elevated trade union membership (currently 70%, of the labour force down from more than 80% in the 1990s) which together underpin a compressed wage structure (Layard and Nickell, 1999). Wage bargaining involves centralized framework agreements between unions and employers on a fixed-term basis followed by union-level bargains.[2] Despite high women participation the pay gap is higher in Finland compared to the OECD average, mostly due to self-selection into low-wage careers like teaching (Vartiainen, 2002; Böckerman, 2006). Consistent with the international trend the expansion of ICT-related activities has altered substantially the wage structure also in Finland with growing fragmentation of the labour market across geographical areas and the emergence of earning inequalities within high-skilled workers: both, it is worth stressing, in the face

2 Böckerman and Maliranta (2002) attribute high union participation to the fact that membership fees are tax deductible and to the involvement of the unions in the administration of unemployment insurance benefits.

of Finland's traditional labour market regulation. Commenting on this Böckerman and Maliranta (2007) observe that in spite of the extent of these transformations, only a few empirical studies have thus far accounted properly for the effects of these new characteristics in Finland's labour market.

2.2 Economic growth and rising inequalities in Finland

The reorganization of the industrial structure and the rapid economic growth of the late 1990s placed Finland in the public conscience as a successful example of emergent knowledge-intensive society, and fuelled talks of the 'Finnish model' and the 'Finnish miracle' (see e.g. Castells and Himanen 2002; Schienstock 2004). There is wide agreement that Finland reaped the opportunities of the nascent ICT industry more effectively and rapidly than other European countries thanks to a mix of forward-looking industrial policies and public investments in higher-education and R&D which stimulated and supported ICT-complementary clusters in manufacturing and service sectors (Honkapohja and Koskela, 1999; Honkapohja et al, 2008; OECD, 2004).

Empirical evidence indicates also that the industrial revitalization of the 1990s was the backdrop to another story, one that has arguably attracted less attention: the increase of domestic differences across regions. To be sure geographical concentration of innovative activities is common during periods of economic expansion (Krugman, 1991; Feldman and Audretsch, 1999; Moretti, 2004b). Finland was no exception as the Southern regions joined the nascent high-tech trajectory while Central and Northern areas remained anchored to declining industries like paper, pulp and metal processing. A large and diverse body of empirical literature confirms the emergence of marked differences across Finnish regions. Hanell et al (2002) find evidence of massive migration towards Helsinki and the South at the peak of the crisis; Kautto (2003) reports significant and growing divergences in capital income shares and average household incomes after 1994; Kangasharju and Pekkala (2004) show remarkable differences in sectoral expansion between fast- and low-growing regions, especially in the business service sectors (with a gap of 4,5% over the period 1995-2000); Loikkanen et al (2005) identify divergent patterns of capital deepening, with the Helsinki region ahead of the Southern regions (+20% in the period 1996-2000) and even more of the Central and Northern areas (+40%); Loikkanen and Lönnqvist (2007) confirm post-recovery imbalances in the patterns of investments and migration in favour, again, of the Southern regions and Helsinki.

Numerous studies report that concurrent to the structural change of the industry and the growth of domestic divergences was the growth of inequalities across regional labour markets in both unemployment and earnings distribution (OECD, 2001; Asplund, 2001; Böckerman, 2002; Tervo, 2005; Neubauer et al., 2007). Böckerman and Maliranta (2007) add an important insight to the debate by distinguishing disparities due to a sharp rise in the job destruction rates – faster in Eastern and Northern Finland – during the crisis from inequalities due to differential job creation driven by the expansion of hi-tech sectors in Helsinki and the Southern regions. The authors conclude that job reallocation occurred during the transition from slump to recovery stimulated the expansion of wage differentials. Empirical studies by Uusitalo (1999), Kyyra (2000) and Asplund and Leijola (2005) confirm that, in spite of centralised wage bargaining and tight labour market regulation unexplained wage dispersion among graduates increased substantially after the mid-1990s.

A number of authors associate the foretold phenomena to the emergent ICT regime transition, and in particular to deepening local-factor bias which ultimately gave an advantage to the Southern regions of Finland. In this and other aspects the Finnish experience resembles those of Anglo-Saxon countries where labour markets, it needs be reminded, are organised very differently. Empirical evidence points to statistical association between earning inequalities and the concentration of highly educated workers in large metropolitan areas in the South, the home of the ICT-related expansion (Uusitalo, 1999; Kyyra, 2000; Asplund and Leijola, 2005). Moreover various authors argue that the tight regulatory regime of the Finnish labour market played a dual role by preventing the growth of between-group inequality on the one hand, while eliciting within-group inequality on the other. Asplund and Liljia (2000) and Kyyra (2000) in particular concur that regulation thwarted the swift adaptations demanded by the changing industrial structure, thus amplifying the impact of job-skill mismatches and agglomeration effects which triggered within-group inequality among highly educated workers.

2.3 Conceptual issues at stake

A short digression on the theoretical background is useful at this point. Labour economists conventionally use observable worker characteristics – such as educational attainment, age, experience – to explain returns to education. Over the last two decades, however, structural changes at the interface of technological and educational domains have altered interrelations and weakened the explanatory power of those variables (Juhn et al. 1993; Goldin and Katz, 2008; Vona and Consoli, 2009). In the ensuing picture wages have been observed to increase more in the upper tail of the earning distribution while gaps have grown both within graduates and between graduate and postgraduate workers. Looking at the US, Eckstein and Nagypal (2004) notice that the substantial expansion of postgraduate wage premium of the last 40 years concurs with the increase of earnings among professional groups with high levels of educational attainment – namely managers, physicians, lawyers, scientists, engineers, computer specialists and college professors. While such inequalities are relatively more common in systems with soft regulatory regimes the outlined changes in the upper tail earning distribution have been observed across countries with rather diverse labour market institutions (Martins and Pereira, 2004).

To date comprehensive studies on the determinants of within-graduate wage inequality are limited to the US and, to a lesser extent, the UK. In relation to those contexts, the specialized literature has put forth a variety of plausible causes for observed earning differentials within workers with similar educational attainments: the impact of innate abilities (Card, 1994); differences in university quality (Brewer et al, 1999; Dale and Krueger, 2002); job-skill mismatches (Green and McIntosh, 2007); firm-specific effects (Dunne et al, 2004; Faggio et al, 2007); and geographical location (Moretti 2004a). By and large these studies concur that standard human capital theory does not capture adequately the extent to which structural change bears on the relationship between the dynamics of skills and the distribution of earnings. In agreeing with this remark it is worth reiterating that while the general features of the phenomenon are widely accepted, further analysis is needed to appreciate the specificities that characterise different institutional settings.

Common across the foretold studies, albeit with variable emphasis, is an appreciation of the role exerted by expanding ICT-related activities on labour market dynamics. It is well known that the large scale diffusion of General Purpose Technologies engenders composite phenomena. First, high-tech firms and qualified labour force tend to cluster around particular geographical areas during intense phases of technological change; this in turn favours the emergence of earning inequalities as illustrated by Moretti (2004b) and Acemoglu and Angrist (1999). Second, imperfect geographical mobility and non-convexities in the returns to education reinforce such inequalities, the former by preventing the equalization of graduate wage premia across regions and the latter by reinforcing gaps as advanced regions endowed with skilled workers manage to stay close to the technological frontier (Aghion and Howitt, 2004). Furthermore large scale reorganizations following the emergence of a new technological regime like that of ICTs generates, at least in the short term, mismatches between job requirements, or tasks, and the skills that are needed to perform them. These mismatches operate as a selection mechanism among the educated workforce. Studies on the US labour market along these tracks show that computerization stimulated, in accord with other institutional forces, the reconfiguration of the task structure within occupations as well as the emergence of wholly new occupations (Autor et al 2003; 2008). The associated skill gaps thereby entail two forms of mismatch: first, individuals are employed in jobs that require a level of education which is either higher or lower than their own (under- or over education); and, secondly, the reconfiguration of tasks modifies permanently the job-skill association and calls for adaptive changes in the educational system (Abramovitz and David, 1996; Vona and Consoli, 2009).

The remainder of the paper brings together these themes and analyses the determinants of earnings among a cohort of labour market entrants in Finland. In so doing two questions are tackled: (1) what is the premium associated to a perfect job-degree match? And (2) to what extent do agglomeration effects affect earning distribution?

3 Data and descriptive analysis

This section proposes an analysis of the relation between individual characteristics and their earnings. Before presenting the statistical exercise it is necessary to describe briefly the database and the criteria that guided the construction of specific variables.

3.1 The dataset

The source of the data is the Longitudinal Census of Statistics Finland. Data on 8787 individuals [4292 men (49%); 4495 women (51%)] are collected by means of a two-step survey: in 1995, year of enrolment at a Finnish University, and in 2005. The information available on each individual includes (for 1995) gender; high-school mark; university of enrolment; field of study; degree aiming at; (for 2005) degree accomplished (if any); region of residence; occupational status; and income.[3] It is worth reiterating the cohort under analysis entered the labour force as the crisis levelled off and Finland's economy started to enjoy a new phase of expansion. Focussing on this particular group reduces the influence of unobservable characteristics like, for example, over-rewarding of tenure due to tight regulation.

A key feature of the proposed analysis is the use of ad-hoc variables to capture occupational and spatial determinants. To construct the former Statistics Finland's original occupational categories have been expanded with the aid of the International Standard Classification of Occupations (ISCO)[4] and obtain a finer classification which is better suited to deal with a sample unbalanced towards the category 'professionals'; subsequently occupation-specific requirements, as listed in ISCO, are compared with detailed information on the content of each degree and use the second digit of the degree codes to establish the matching occupation (perfect match =1, 0 otherwise).[5] This fits the context of Finland where educational programs have a manifest occupation-specific content (Asplund, 1993).

For what concerns spatial agglomeration effects two directions are pursued. First, a test for region-specific characteristics in pooled regressions with two different indexes of regional human capital (see Moretti, 2004a) – a weighted average of the educational

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3 This representative sample accounts for 52% of all university entrants in 1995. See the appendix for details on data cleaning and treatment of missing data.

4 http://www.ilo.org/public/english/bureau/stat/isco/index.htm

5 Note that this measure of job-skill mismatch includes both over-educated workers as well as cases of perfect match. In a companion paper we analyse over-educated and perfect match separately and observe that results remain robust. For those observations listed as 'not employed' it is not possible to check for a mismatch we assign 1 if the educational attainment is higher than the minimum level and 0 otherwise. In future research, we seek to disentangle the effect of over-(under-)education from that of qualitative match.

attainment of the residing population[6] and the share of post-graduates within the population; subsequently separate regressions are run on for four macro-areas: the Helsinki region, the South of Finland, Central Finland and the Northern regions. This geographical breakdown is appropriate to capture regional-level details while offering wider indications about the macro dynamics at work in the key geographical areas (see Loikkanen et al, 2005).[7] Throughout our estimates unobservable effects such as relocation after completing studies (Relocate), change of degree or drop-out (Shift) and duration of formal schooling weighted by expected length of study (Years of Education), are controlled for.

3.2 Descriptive Analysis

Let us now take a look at the descriptive statistics in Table 1. More than 90% of individuals in the sample are in employment in 2005; as expected, the average educational attainment is high with 70% holding Master's Degree; the most preferred degrees are Business and Social Sciences (23%), first among women, followed by Engineering (18%), first among men. For what concerns occupations, in the lower half of the Table, the largest share of individuals are employed in Medium-Skill Jobs (20%)[8] followed by Teachers (18%), which is the primary destination for women. Finally, the population is split almost equally between those who took residence in the capital city Helsinki and those who live elsewhere in Finland – a slight majority of which are women.

6 The index is obtained by assigning to the human capital of those with secondary education ½ of the human capital of the graduate, whereas we weight 1.5 the human capital of the postgraduates and 0 the human capital of those with less than secondary education. Similar arbitrary scores are widely used in the literature (e.g. Katz and Murphy, 1992) as they stress more than, for example, the average of the years of education required to attend a degree the difference associated to the attainment of a high qualification. Our results remain robust to different human capital indexes such as the weighted years of education.

7 Regions are grouped within macro-areas following Loikkanen et al, 2005. South Finland: Ahvenanmaa, Itä-Uusimaa, Kymenlaakso, Pirkanmaa, Varsinais-Suomi, South Karelia, Satakunta and Päijät-Häme; Central Finland: Central-Finland, Kanta-Häme, Pohjois-Savo, Central Ostrobothnia, Etelä-Savo, North Karelia, South Ostrobothnia, Ostrobothnia; North-Finland: Lapland, Kainuu, North Ostrobothnia.

8 Medium-High Skill Occupations include specialised professionals, like Matrons and ward sisters, Archivists, Librarians, as well as generic ones like Science associate professionals and technicians, Computer associate professionals, Instructors, Entertainment and sports professionals. Low-skill occupations include trades workers, painters, cleaners, metal workers, machinery mechanics and fitters, plant operators, machine operators, assemblers, drivers, caretakers, labourers and handlers.

TABLE ONE ABOUT HERE

A crucial element in our analysis, vis-à-vis the recent history of Finland, is the regional dimension of economic development and, in particular, the extent to which this has fuelled differences across the local labour markets. A first hint is provided by the descriptive statistics of Table 2 where the sample is broken down by macro-area of residence. While the proportions of postgraduates are broadly comparable, clear differences emerge in the other dimensions: the Human Capital indexes indicate that skilled labour force reside relatively more in the capital city and the Southern regions; for what concerns Field of study, in the middle part of the Table, dispersion increases from the South to the North; also, disciplinary orientations differ whereby residents of Helsinki and of the Southern regions are mostly graduates in Business Studies, Engineering and to a smaller extent Humanities whereas those of Central and Northern areas spread across all degrees, with relatively more Education graduates compared to the capital city. In turn the breakdown by occupations shows a reversal in terms of dispersion with medium-skill jobs having the highest share in Helsinki – recall the data concern labour market entrants – followed by broadly comparable frequencies of Teachers, Legal and Business Professionals, Public Service Professionals and Scientists; by contrast the workforce of the remainder regions features less variety due to the large shares of Teachers, up to 32% in the North.

The bottom part of Table 2 indicates Helsinki residents earn more compared to other areas at all levels of educational attainment with the exception of Graduates. [9] The breakdown by occupation further indicates that Managers, Scientists, Legal and Business professionals, Medium-skill and notably low-skill jobs earn more in the capital city: this should be read in symbiosis with the fact that while a comparatively higher share of individuals with No Degree reside in the South of the country, the average wage differential with the Northern-Central regions is not very high. Conversely, Teachers, Engineers and Medical Doctors residing in the Northern-Central regions earn more compared to their peers in the capital.

TABLE TWO ABOUT HERE

Let us now turn to the empirical analysis of earnings distribution.

9 The average monthly wage in Finland in the year 2005 was €. 2500. Source: Statistics Finland.

4 Econometric analysis of earnings

This section focuses on the determinants of earnings (Log Monthly Wage) among a cohort of individuals who enrolled at a Finnish University in 1995. A basic version of the classic Mincer regression is progressively enriched with additional controls and ad-hoc dummy variables for job-skill match and agglomeration effects. The variables used in the OLS estimates are listed in the Appendix.

4.1 OLS Estimates

The basic model includes standard controls for individual characteristics (gender, age, individual abilities, proxy for tenure, etc) and specific occupation dummies to allow for variation of returns by type of profession. [10] Each of the blocks contains two regressions, one for the whole population (Table 3, Columns 1, 2, 3, 4) and the other individuals in employment only (Column 1', 2', 3', 4'). The distinction between the two groups and their comparison is useful to account for particular features of Finland's context: the first set of estimates for all individuals (i.e. employed and unemployed) captures the bias of welfare benefits that are available to unemployed job-seekers; the second set, with employed individuals only, captures the returns of those who managed to enter the labour market.

TABLE THREE ABOUT HERE

The OLS regressions for the basic model (1) and (1') yield positive and significant coefficients for educational degrees, as expected, especially for postgraduates. Taking those with no degree as reference group, returns vary from 66% to Master's degree to 89% for PhD for the whole population, and from 41% to 57% for employed only. Looking at the coefficients for occupations high dispersion is observed across professionals and significantly higher returns for Medical doctors, Engineers, Legal professionals and Scientists. Note that this result is sensitive to how occupations are grouped: using an alternative specification with broader classes (e.g. Managers, all Professionals, Medium-Skill Jobs, etc) the wage gap between professionals and medium

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10 OLS techniques produce consistent parameter estimates across a number of studies on the relation between human capital and wage determination in Finland. See Asplund and Leijola (2005).

skill jobs disappears;[11] the finer specification employed here captures important details, in particular the lower wage premium of some professional occupations compared to that of medium-skilled jobs.

The second model (columns 2 and 2') incorporates the two central features of our analysis: the dummy variables for regional agglomeration and job-skill match. The results show that returns to a perfect match are more than three times higher for all individuals than for employed only (18.5% and 5%): this can be associated to the availability of generous benefits for high-skilled individuals who can wait in unemployment until they find a 'good match' in the job market. As noticed by Acemolgu and Pischke (2003) generous unemployment benefits for graduate workers enhance the incentive to invest in higher education, improve the average quality of matching and hence labour productivity.

The estimated coefficient of the spatial dummy is significant and positive too thus suggesting that, as expected, residence in the capital area yields a 5% extra premium: this is a first, undoubtedly crude, indication of the location effect on earnings. After the inclusion of these two new variables returns to all occupations increase while returns to postgraduate studies fall: 46% less for Master Degrees and 23% for PhDs among all individuals (Columns 1 and 2), and by 10% and 1% for employed only (Columns 1' and 2').

The general trend of the latter model is robust to the inclusion of the additional control variable 'Field of Study' (columns 3 and 3'). With the exception of Medicine, coefficients for degree areas are significant only for employed individuals and, in particular, Engineering, Business and Humanities have the expected sign (+,+,-). The finding that returns to formal education are lower compared to the previous model resonates with other studies (Asplund, 1993; Asplund and Leijola, 2005) showing that the type of specialisation that is acquired with a degree matters for labour market entrants. Finally the higher coefficients to Engineering and Business Science compared to general ICT-related degrees, such as Information Sciences, confirm Asplund´s (1997) finding that the premium of generic to specific computer skills in Finland fell during the 1990s. Overall and crucial to our broad argument, the impact of both skill-job match

11 Estimates are available by the authors. Note that the category 'medium skilled jobs' consists essentially of associate professionals.

and the Helsinki dummy do not substantially decrease and remain statistically significant at 1%.

The low coefficients of the spatial dummy observed in the last two sets of estimates are attributed to the rather crude way in which the variable is constructed. In fact it is worth stressing that a number of different issues are at stake when assessing the impact of location on earnings. In general it is plausible that skilled workers sort themselves into metropolitan areas with high level of human capital (Glaeser and Mare, 2001); in such cases the correlation between wage levels and graduate share is affected by unobservable individual factors, like innate ability positively correlated with the skill of the workforce, rather than productivity differentials. On the other hand the causation between earning levels and the share of graduates living in large cities may depend on unobservable characteristics of the location, such as the industrial mix: in this case the wage levels cause the increase of the skilled workers, not the other way round (Moretti, 2004a). While the data do not allow a proper test of local spillovers, agglomeration effects can be captured by means of an index of Human Capital in the region, namely the weighted average of the educational attainments among residents. Columns 4 and 4'show that after its inclusion an increase of one standard deviation in the human capital in the region yields a remarkable extra premium ranging between 1.2% for the whole sample and 1.7% for employed only.[12] To reiterate, this does not warrant the conclusion that spillover effects are at work but can be taken as an indication of imperfect substitution between high and low skills in the local labour markets, and of the impact that location bears on earning levels.

To further this line of argument in the next set of OLS estimates we let the graduate wage premium vary across four macro-regions – the capital city Helsinki, Southern Finland, Central Finland and Northern Finland (see Loikkanen et al, 2005). This exercise highlights striking spatial differences (Table 4). In particular, being employed in Helsinki (0.55) and having relocated there (0.05) yield large extra returns with respect to the other regions; secondly, occupation-specific coefficients are higher in Central and Northern Finland compared to the capital city; furthermore perfect job-degree match yields higher returns especially in Central Finland (20%) and in Southern

12 The regression with an alternative measure of Human Capital (share of Postgraduates in a region) produces broadly similar results. Estimates are available by the authors.

Finland (21%); finally, being Graduate pays relatively more in central Finland with respect to the capital city. The latter result is rather surprising considering that under the standard skill-bias argument (Acemoglu 1999) the graduate wage premium should be positively related to the level of human capital in regions which enjoy high levels of innovation and productivity. Notice, however, that in our cohorts of entrants being 'just' a graduate is rewarded significantly less than holding a postgraduate degree; this suggests that postgraduates have replaced graduate workers as input of innovative activities in regions closer to the technological frontier and hence that the graduate wage premium is insensitive to agglomeration effects.

TABLE FOUR ABOUT HERE

The estimates of the post-graduate to graduate wage premium in Table 5 seems consistent with the expected positive relationship between the average human capital level of a region and the returns to higher education. Returns to postgraduate education are significant only in Helsinki (0.17 and 0.2 versus 0.12 and 0.13 in Table 5): this is plausibly a reflection of the particular composition of the workforce in the capital city post economic recovery, especially to the abundance of scientists and researchers (cf. descriptive statistics of Table 2). Similar to the previous set of estimates job-degree match is lower in Helsinki compared to other areas. Taken together the last two indications suggest that observable worker characteristics have different importance across the macro regions.

TABLE FIVE ABOUT HERE

4.2 Discussion

The empirical analysis of the determinants of earnings presented above fits the broader picture of the historical developments unfolding in Finland at the turn of the Century.

More in detail, coefficients for the regional human capital index are high and significant in the pooled regressions thus suggesting a strong agglomeration effect of the kind discussed by Moretti (2004a). While our cross-sectional analysis does not warrant specific conclusions as on the underpinning causation mechanisms, it seems plausible that such effect genuinely reflects persistent technological gaps rather than imperfect factor mobility. In turn, regressions for individual macro-regions elucidate on the extent of cross-regional differences: looking at specific occupational patterns, the earnings of medium- and low-skill professions are higher for residents of the capital city region; this is also true for Scientists, Managers and Legal & Business professionals residing in the Southern regions. These indications echo broader empirical evidence on the wage premium of knowledge-intensive occupations in large metropolitan centres in the US (see e.g. Eckstein and Nagypal, 2004). By contrast, traditionally unionized professionals like Teachers and Medical Doctors earn more in Northern and Central Finland. A key role in this is to be attributed to the subsidies used by local governments to encourage relocation of public sector professionals towards remote areas of the country, especially the Northern regions; although these formally ended in the 1990s Kouvonen and Katainen (2004) argue that the current pay structure of regulated professions is a legacy of the former system.[13]

The broader point is that observable individual characteristics play a stronger role in the areas that lagged behind during the recent economic recovery, namely Central and Northern Finland. Furthermore the dispersion of graduate earnings is observed to be higher in Southern regions where ICT-led technological change propelled the recovery. Similar to what has been observed in the US (Eckstein and Nagypal, 2004) higher dispersion entails the polarization of earnings between graduate and postgraduate workers. How can we make sense of these results vis-à-vis the historical background outlined in the opening sections?

Our conjecture is that the degree of complementarity between highly creative and medium-low specialized workers differs widely across regions, and is stronger in more developed areas. Such differences, it is worth stressing, do not concern only quantitative differences in the demand for skills but also qualitative differences in the particular mix of skills that are needed to match the needs of local industries. This connects with the earlier remark concerning significant changes on local occupational structures due to the large scale diffusion of ICTs. Thereby expanding regions like the South of Finland required highly skilled labour force (e.g. postgraduates) to keep up with the shifting technological frontier of ICT-related activities while lagging regions, mostly engaged in imitative activities, employed relatively less qualified workforce. The finding that the

13 Looking at the case of medical doctors, Kouvonen and Katainen (2004) and Ruskoaho (2008) find that the wage premium for residents in areas where there is no faculty of medicine is higher, due to the local paucity of physicians. A recent report for the Finnish Ministry of Economic Affairs (2008) resonates with these results and emphasises the resistance of medical doctors and teachers to relocate in North Finland due to the geography and the climate of the areas.

postgraduate wage premium is higher in Helsinki compared to other areas confirms these remarks.

Overall, our empirical study adds an important caveat to the 'distance to the frontier approach' (Nelson and Phelps, 1969, Aghion and Howitt 2004). As long as the skill content of occupations changes during the course of large scale technological transitions, new qualifications are required to fill the knowledge gap opened by the new technologies. This in turn calls for adjustments in the supply of training that match the changing needs of the local productive structure (Antonelli, 2006; Goldin and Katz, 2008). Put another way, the systematization of emerging new knowledge is crucial to keep up with a turbulent technological environment (Vona and Consoli 2009). The expansion of higher education in Finland played this role by sustaining the availability of an aptly educated workforce; as observed above, the process turned out to be more effective in Southern regions with greater readiness to capture the opportunities entailed by the expansion of ICT-related sectors compared to other Finnish regions.

Subsequently as the range of application of the GPTs expanded and new standards emerged interoperability became essential to facilitate the growth of related industries and activities. Here the division of labour triggers new patterns of specialisation whereby high-skill workers concentrate on highly creative non-routine cognitive tasks (Autor et al 2008), while medium skilled workers develop a narrow repertoire of technical and firm-specific competences. In the context of Finland this process unfolded faster in the regions which were closer to the technological frontier (e.g. Helsinki and the Southern regions) which could enjoy emergent complementarities between low- and high-level skills. Empirical evidence confirms the shift in importance of some types of skills in the more developed regions whereby returns to general ICT skills had dissipated by the mid-1990s while returns to specialized ICT skills has grown – especially those that complement Knowledge Intensive Business activities (Aplund, 1997). Overall the observed effects on earnings reflect the extent of local complementarities whereby high (or low) specialisation within the dominant regime stimulates (or reduces) the integration of workers with different levels of skills and, accordingly, yields different returns.

In the case at hand the structural differences between the Southern regions and the Central-Northern regions of Finland led the former to catch the opportunities entailed by the expansion of ICT-related sectors faster than the latter; the corollary of this were divergent economic performances and the geographical fragmentation of the labour market. The evidence available suggests that a concurrent factor may have been the evolution of the occupational structure whereby by the mid-1990s the share of upper level non-manual workers within high-growth sectors had increased to almost 40% at the expense of clerical non-manual workers, while the occupational structure of low-growth sectors had changed only marginally (Asplund and Vuori, 1996).

5. Concluding remarks

In this paper technological change does not appear explicitly as a variable but rather as a thread that connects complementary processes of structural change, regional economic development, and earning distribution. Finland's recent history has a lot to contribute to the understanding of these processes, either individually or jointly. Within merely a decade the country weathered a deep recession to become a central actor in the global knowledge economy thanks to the impressive expansion of ICT-related activities. In turn, the associated structural changes elicited far-reaching effects on the economic and social structure of the country. A wealth of empirical evidence indicates clearly that the Southern regions of Finland played an active role in the development of high-tech sectors while other areas of the country remained behind. This, in turn, gave way to persistent cross-regional differences in terms of migration flows, productivity, unemployment and income distribution.

The paper connects these themes by focusing on two complementary phenomena: the geographical fragmentation of the labour market and the emergence of inequality among highly educated workers. Both are striking in consideration of Finland's long-standing tradition of centralised wage bargaining and highly regulated labour market.

Our multivariate analysis on the determinant of earnings contributes to various streams of literature. The direct observation of the impact of job-skill mismatches and agglomeration effects, both emblematic symptoms of radical technological change, enriches the existing studies on the cause of earning inequality. Conversely, the result that returns to employment differ by geographical areas adds to the wealth of empirical works on Finland by providing an empirical measure of the extent of the divergence across regional labour markets. Finally, the explicit appreciation of the complex interconnections among technological change, income distribution and local economic development is suggestive for the emerging area of evolutionary economic geography (e.g. Boschma and Frenken, 2009).

It is important to emphasize two limitations of the current study. First, the data that are available to us only include one cohort, and this obviously precludes an appreciation of the inter-temporal aspects of the dynamics analysed here; in future work we seek to acquire data on multiple cohorts to disentangle the long-term characteristics of spatial agglomeration and to investigate the extent to which the expansion of higher education has affected intergenerational mobility in Finland. A second limitation is the lack of indications of how the sectoral dimension influences the allocation of the labour force and the distribution of earnings. To the best of our knowledge however this information is not included in the database of Statistics Finland.

A final observation is in order. The present paper raises the question of what the continental European experience might bring to the wider debate, so far limited only to Anglo-Saxon countries, on the relation between technological change, education and income distribution. The inherent diversity that characterises the regions within the European Union offers a clear opportunity to extend the debate much further; hopefully this paper is but the first step in that promising direction.

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	Frequencies		
	Tot	M	F
N	8787	4292	4495
Empl	8141	4057	4084
Education (%) (Tot=8787)			
No degree	16.17	22.83	9.81
Upper Secondary/Vocational	1.83	2.00	1.67
Lowest tertiary	2.98	2.17	3.76
Upper tertiary	6.67	7.15	6.21
Master's degrees	69.10	62.28	75.62
Doctorate	3.24	3.56	2.94
Field of Degree (%) (Tot=8787)			
No degree	16.17	22.83	9.81
Education	9.50	3.70	15.04
Humanities and Arts	13.12	6.99	18.98
Business and Social Sciences	22.94	20.08	25.67
IT and science	8.96	10.11	7.85
Engineering and Architecture	17.84	29.57	6.65
Agriculture and Forest	2.03	1.84	2.20
Health and Welfare	7.90	3.45	12.15
Services	1.54	1.42	1.65
Occupation (%) (Tot=8141)			
Manager	5.47	7.60	3.33
Scientist	7.6	11.95	3.43
Medical Doctor	4.45	3.39	5.51
Engineer	7.11	11.04	3.17
Teaching	19.46	9.72	29.22
Legal/Business	7.17	8.12	6.21
Public Service	10.47	9.04	11.89
Other Prof	2.83	2.62	2.97
Medium-Skill	15.59	21.32	9.86
Clerk	3.77	2.59	4.94
Unskilled	16.07	17.53	14.61
Residence (%) (Tot=8787)			
Helsinki	47.75	50.54	45.09
Elsewhere	52.25	49.46	54.91

Table 1: Database Description

	Helsinki	North	Centre	South	Finland
Tot. Residents	4196	775	1386	2430	8787
Human Capital Indexes					
Postgraduates per Population	0.10	0.05	0.04	0.05	0.07
Average Educational level	0.46	0.37	0.37	0.39	0.41
Resident by Field of Study (%)					
Education	5.77	17.42	15.51	10.00	
Humanities	12.77	11.48	13.85	13.83	
Business & Social Sciences	27.84	15.74	18.83	19.14	
Information Sciences	7.58	9.55	12.91	8.89	
Engineering	17.99	18.58	10.68	21.44	
Agriculture	2.12	0.90	3.03	1.65	
Medicine	6.17	11.74	11.47	7.61	
Services	1.31	1.94	2.09	1.48	
No Degree	18.45	12.65	11.62	15.97	
Resident by Occupation (%)					
Manager	6.17	4.39	5.12	4.81	
Scientist	9.56	5.03	5.70	6.13	
Medical Doctor	3.93	6.97	5.27	4.07	
Engineer	6.94	8.77	4.69	8.27	
Teaching	12.73	28.13	32.32	20.99	
Legal/Business	10.20	3.35	3.39	5.31	
Public Service Professional	10.72	10.97	10.03	10.12	
Other Professionals	3.69	0.90	2.45	2.18	
Medium-Skill	16.75	15.10	11.47	16.09	
Clerk	4.00	2.19	4.04	3.70	
Unskilled	15.30	14.19	15.51	18.31	
Average wages (Euros)					
All	3176	3113	2972	2976	3083
Non-Graduates	2699	2582	2483	2334	2564
Graduates	2781	3072	2775	2901	2845
Post-Graduates	3355	3222	3096	3145	3243
Manager	4235	3974	3877	3934	4090
Scientist	3503	3166	3064	3234	3371
Medical Doctor	4196	4515	4461	4085	4262
Engineer	3588	3903	3470	3710	3649
Teaching	2702	2920	2947	2849	2838
Legal/Business	3920	3491	3150	3366	3732
Public Service	2590	2619	2516	2484	2553
Other Professional	2858	2845	2687	2774	2816
Medium-Skill	3326	3180	2842	3011	3167
Clerk	2377	1959	2109	2042	2219
Unskilled	2522	2453	2656	2545	2544

Table 2: Descriptive statistics

Log_Monthly_Wage	(1)	(1')	(2)	(2')	(3)	(3')	(4)	(4')
Employed	.272***		.269***		.263***		.264***	
	(.079)		(.078)		(.078)		(.078)	
MALE	.116***	.146***	.107***	.143***	.102***	.127***	.102***	.127***
	(.016)	(.010)	(.016)	(.011)	(.017)	(.011)	(.017)	(.011)
Age_19	-.006	-.055**	-.022	-.061***	-.012	-.057**	-.013	-.058**
	(.054)	(.023)	(.054)	(.023)	(.054)	(.023)	(.054)	(.023)
Age_20	.012	-.040*	-.002	-.046**	.012	-.035	.011	-.036
	(.055)	(.023)	(.055)	(.023)	(.054)	(.023)	(.054)	(.023)
Age_23	.003	-.055***	-.008	-.062***	.006	-.050**	.005	-.051**
	(.047)	(.021)	(.047)	(.021)	(.047)	(.021)	(.047)	(.021)
Ability_low	-.058	-.054**	-.063	-.057**	-.05	-.046**	-.051	-.046**
	(.043)	(.023)	(.042)	(.022)	(.043)	(.023)	(.043)	(.023)
Ability_aver	-.055	-.038*	-.064	-.044**	-.056	-.040*	-.056	-.040*
	(.047)	(.021)	(.047)	(.021)	(.047)	(.021)	(.047)	(.021)
Ability_high	-.075	-.043*	-.085*	-.052**	-.078	-.048**	-.078	-.047**
	(.049)	(.022)	(.049)	(.022)	(.049)	(.022)	(.049)	(.022)
Shift Study	.006	.014	.003	.016	.021	.034**	.020	.033**
	(.016)	(.014)	(.016)	(.014)	(.017)	(.013)	(.017)	(.013)
Relocate	.016	.008	.022	.016	.022	.019*	.025*	.023**
	(.015)	(.010)	(.014)	(.010)	(.015)	(.010)	(.015)	(.010)
Years of Education	-.036***	-.024***	-.031***	-.026***	-.015	-.006	-.014	-.005
	(.009)	(.007)	(.009)	(.007)	(.011)	(.009)	(.011)	(.009)
Vocational Degree	.255***	.115***	.158***	.098***	.062	-.013	.061	-.017
	(.044)	(.035)	(.046)	(.037)	(.070)	(.055)	(.071)	(.055)
Master´s Degree	.507***	.346***	.348***	.314***	.214**	.151**	.209**	.143*
	(.059)	(.049)	(.066)	(.054)	(.092)	(.073)	(.092)	(.073)
PhD	.637***	.453***	.518***	.447***	.336***	.219**	.327***	.205**
	(.092)	(.074)	(.095)	(.078)	(.120)	(.094)	(.121)	(.094)
Manager	.552***	.571***	.581***	.577***	.558***	.547***	.560***	.549***
	(.036)	(.035)	(.037)	(.036)	(.037)	(.036)	(.037)	(.036)
Scientist	.391***	.395***	.432***	.406***	.429***	.394***	.429***	.396***
	(.034)	(.034)	(.037)	(.035)	(.037)	(.035)	(.037)	(.035)
Medical Doctor	.597***	.631***	.604***	.639***	.489***	.569***	.489***	.568***
	(.039)	(.038)	(.039)	(.038)	(.045)	(.043)	(.045)	(.043)
Engineer	.413***	.432***	.438***	.443***	.397***	.385***	.397***	.385***
	(.037)	(.036)	(.038)	(.036)	(.039)	(.037)	(.039)	(.037)
Legal/Business	.436***	.469***	.482***	.475***	.453***	.435***	.455***	.437***
	(.037)	(.036)	(.039)	(.037)	(.041)	(.039)	(.041)	(.039)
Teacher	.177***	.217***	.219***	.238***	.239***	.273***	.239***	.273***
	(.035)	(.034)	(.037)	(.035)	(.037)	(.035)	(.037)	(.035)
Public Service	.084**	.116***	.131***	.134***	.123***	.120***	.123***	.120***
	(.036)	(.034)	(.038)	(.036)	(.038)	(.036)	(.038)	(.036)
Other Profess.	.237***	.255***	.277***	.264***	.298***	.298***	.299***	.300***
	(.040)	(.039)	(.042)	(.041)	(.042)	(.040)	(.042)	(.040)
Medium-skill Jobs	.307***	.330***	.356***	.346***	.330***	.316***	.330***	.315***
	(.033)	(.032)	(.036)	(.034)	(.036)	(.034)	(.036)	(.034)
Low-skill Jobs	-.054	-.040	.000	-.022	0	-.023	.000	-.022
	(.043)	(.043)	(.045)	(.045)	(.045)	(.044)	(.045)	(.044)
Education					.005	-.019	.005	-.019
					(.063)	(.041)	(.063)	(.041)
Humanities					-.048	-.091**	-.050	-.094**
					(.061)	(.039)	(.061)	(.039)
Business/ Soc.Sci.					.063	.079**	.062	.079**

					(.059)	(.038)	(.059)	(.038)
Information Science					-.055	-.043	-.057	-.046
					(.061)	(.038)	(.061)	(.038)
Engineering					.076	.098***	.073	.095**
					(.060)	(.037)	(.060)	(.037)
Medicine					.159**	.105**	.157**	.103**
					(.062)	(.042)	(.062)	(.042)
Service					.036	.052	.034	.050
					(.072)	(.058)	(.073)	(.058)
Match			.161***	.057***	.151***	.043***	.151***	.042***
			(.025)	(.015)	(.026)	(.015)	(.026)	(.015)
Helsinki			.046***	.066***	.042***	.061***		
			(.015)	(.010)	(.015)	(.010)		
HC Region							.434**	.606***
							(.180)	(.119)
Constant	7.597***	7.794***	7.519***	7.786***	7.329***	7.557***	7.151***	7.308***
	(.128)	(.088)	(.133)	(.091)	(.157)	(.109)	(.162)	(.115)
Observations	8787	8141	8787	8141	8787	8141	8787	8141
R-squared	.16	.22	.16	.22	.17	.24	.17	.23

Table 3: Basic and Augmented Model

Robust Standard Errors in brackets; * significant at 10%; ** 5%; *** 1%

Log_Monthly_Wage	**Helsinki**		**South FN**		**Centr FN**		**North FN**	
Employed	.549***		.134		-.019		-.197	
	(.129)		(.111)		(.217)		(.300)	
MALE	.120***	.149***	.103***	.155***	.061	.103***	.113*	.137***
	(.022)	(.015)	(.030)	(.019)	(.049)	(.032)	(.062)	(.043)
Age_19	-.051	-.091***	-.023	.008	.079	-.074	.092	.097
	(.068)	(.031)	(.094)	(.045)	(.193)	(.052)	(.123)	(.107)
Age_20	-.010	-.049*	-.040	-.006	.093	-.075	.123	.110
	(.070)	(.029)	(.091)	(.046)	(.198)	(.052)	(.119)	(.104)
Age_23	-.010	-.067**	-.017	.002	.076	-.091**	-.013	-.006
	(.062)	(.027)	(.081)	(.042)	(.162)	(.046)	(.108)	(.101)
Ability_low	-.073	-.057*	-.059	-.082*	-.037	.035	-.185*	-.196**
	(.057)	(.033)	(.077)	(.042)	(.154)	(.054)	(.109)	(.098)
Ability_aver	-.056	-.008	-.062	-.100**	-.052	.015	-.195*	-.198**
	(.062)	(.028)	(.085)	(.042)	(.158)	(.049)	(.107)	(.090)
Ability_high	-.020	-.005	-.102	-.095**	-.197	-.016	-.336**	-.267**
	(.057)	(.029)	(.085)	(.043)	(.198)	(.055)	(.152)	(.120)
Shift Study	.020	.041**	.049	.059**	-.068	-.038	.037	-.005
	(.025)	(.020)	(.042)	(.029)	(.043)	(.035)	(.076)	(.047)
Relocate	.045**	.041***	.038	.020	.051	.024	-.087*	-.054
	(.020)	(.014)	(.025)	(.018)	(.046)	(.027)	(.052)	(.048)
Graduate	.120***	.103***	.102	.165***	.216**	.090	.074	.125
	(.046)	(.031)	(.071)	(.044)	(.094)	(.064)	(.164)	(.103)
Manager	.528***	.534***	.564***	.547***	.725***	.754***	.884***	.874***
	(.045)	(.044)	(.051)	(.047)	(.132)	(.131)	(.223)	(.224)
Scientist	.382***	.362***	.411***	.374***	.515***	.531***	.686***	.681***
	(.046)	(.044)	(.051)	(.047)	(.125)	(.123)	(.218)	(.220)
Medical Doctor	.503***	.551***	.584***	.603***	.849***	.911***	1.093***	1.076***
	(.051)	(.049)	(.060)	(.058)	(.111)	(.110)	(.220)	(.222)
Engineer	.326***	.342***	.441***	.424***	.599***	.647***	.837***	.837***
	(.048)	(.047)	(.056)	(.051)	(.132)	(.127)	(.216)	(.216)
Legal/Business	.456***	.465***	.394***	.366***	.327***	.374***	.524**	.520**
	(.046)	(.044)	(.064)	(.058)	(.125)	(.120)	(.228)	(.230)
Teacher	.093**	.104**	.232***	.242***	.458***	.519***	.629***	.633***
	(.045)	(.042)	(.046)	(.043)	(.124)	(.118)	(.218)	(.221)
Public Service	.048	.058	.141***	.125***	.511***	.556***	.836***	.827***
	(.046)	(.044)	(.050)	(.045)	(.138)	(.133)	(.242)	(.244)
Other Profess.	.192***	.190***	.271***	.256***	.401***	.443***	.753***	.712**
	(.053)	(.051)	(.067)	(.063)	(.130)	(.124)	(.275)	(.277)
Medium-skill Jobs	.312***	.307***	.325***	.300***	.390***	.422***	.696***	.686***
	(.043)	(.042)	(.047)	(.043)	(.130)	(.126)	(.217)	(.218)
Low-skill Jobs	-.013	-.032	-.113	-.155*	.182	.155	.272	.244
	(.058)	(.057)	(.083)	(.081)	(.126)	(.125)	(.252)	(.253)
Match	.152***	.056***	.190***	.068***	.177***	.081**	.165**	.097
	(.032)	(.019)	(.048)	(.022)	(.056)	(.038)	(.084)	(.066)
Constant	6.969***	7.572***	7.280***	7.414***	7.189***	7.319***	7.432***	7.228***
	(.136)	(.039)	(.111)	(.053)	(.248)	(.101)	(.232)	(.190)
Observations	4196	3941	2430	2206	1386	1275	775	719
R-squared	.19	.22	.17	.26	.14	.23	.20	.25

Table 4: Graduate wage premium Intra-Region

Robust Standard Errors in brackets; * significant at 10%; ** 5%; *** 1%

Log_Monthly_Wage	**Helsinki**		**South FN**		**Centr FN**		**North FN**	
Employed	.298**		.154		-.387*		-.249	
	(.138)		(.132)		(.226)		(.343	
MALE	.129***	.155***	.103***	.155***	.116***	.106***	.116**	.170***
	(.021)	(.016)	(.031)	(.018)	(.035)	(.033)	(.054)	(.028)
Age_19	-.180***	-.122***	-.140*	-.048	-.175	-.069	.072	.041
	(.048)	(.035)	(.084)	(.044)	(.117)	(.054)	(.115)	(.093)
Age_20	-.119**	-.066**	-.146*	-.071	-.170	-.040	.096	.076
	(.053)	(.031)	(.076)	(.046)	(.138)	(.052)	(.112)	(.094)
Age_23	-.122***	-.095***	-.125*	-.053	-.175*	-.074	-.044	-.014
	(.041)	(.029)	(.067)	(.043)	(.099)	(.046)	(.100)	(.084)
Ability_low	-.048	-.072**	.033	-.047	.151	.027	-.127	-.129
	(.055)	(.036)	(.070)	(.041)	(.124)	(.057)	(.103)	(.084)
Ability_aver	.042	-.027	.020	-.069	.124	-.018	-.218**	-.198**
	(.048)	(.029)	(.075)	(.043)	(.125)	(.056)	(.111)	(.082)
Ability_high	.033	-.018	-.015	-.066	.112	-.026	-.289*	-.215**
	(.050)	(. 031)	(.083)	(.043)	(.139)	(.061)	(.155)	(.109)
Shift Study	-.012	.005	.035	.035	-.076**	-.044	.028	-.013
	(.023)	(.020)	(.038)	(.029)	(.038)	(.034)	(.068)	(.043)
Relocate	.039**	.050***	.041*	.026	.054	.014	-.051	-.032
	(.020)	(.014)	(.025)	(.018)	(.038)	(.026)	(.044)	(.036)
Post-graduate	.171***	.203***	.093*	.132***	-.001	.042	.043	.003
	(.042)	(.032)	(.051)	(.035)	(.065)	(.056)	(.102)	(.080)
Manager	.522***	.490***	.485***	. 438***	.838***	.790***	.830***	.815***
	(.067)	(.066)	(.059)	(.053)	(.199)	(.200)	(.281)	(.286)
Scientist	.343***	.292***	.299***	.231***	.561***	.525***	.641**	.621**
	(.072)	(.071)	(.063)	(.054)	(.192)	(.194)	(.263)	(.267)
Medical Doctor	.491***	.482***	.516***	.497***	.944***	.930***	1.063***	1.058***
	(.067)	(.068)	(.063)	(.062)	(.174)	(.177)	(.282)	(.288)
Engineer	.312***	.278***	.378***	.324***	.701***	.654***	.803***	.787***
	(.070)	(.070)	(.059)	(.052)	(.196)	(.197)	(.271)	(.275)
Legal/Business	.448***	.407***	.306***	.239***	.610***	.562***	.810***	.794**
	(.067)	(.066)	(.072)	(.064)	(.198)	(.199)	(.305)	(.310)
Teacher	.096	.058	.157***	.129***	.599***	.549***	.615**	.621**
	(.066)	(.065)	(.053)	(.049)	(.186)	(.187)	(.284)	(.290)
Public Service	.047	.006	.046	-.010	.442**	.387**	.493*	.488
	(.068)	(.067)	(.059)	(.051)	(.189)	(.189)	(.293)	(.299)
Other Profess.	.150**	.110	.152*	.098	.436**	.410**	.493	.431
	(.074)	(.073)	(.081)	(.073)	(.190)	(.192)	(.339)	(.325)
Medium-skill Jobs	.314***	.268***	.244***	.185***	.515***	.464**	.693**	.680**
	(.067)	(.066)	(.058)	(.050)	(.191)	(.191)	(.273)	(.277)
Low-skill Jobs	.036	-.011	-.230**	-.312***	.161	.112	.257	.211
	(.085)	(.084)	(.095)	(.086)	(.205)	(.204)	(.291)	(.291)
Match	.121***	.033	.154***	.029	.137**	.066	.156*	.102
	(.038)	(.022)	(.057)	(.022)	(.066)	(.047)	(.091)	(.081)
Constant	7.271***	7.615***	7.413***	7.641***	7.684***	7.374***	7.540***	7.353***
	(.147)	(.066)	(.161)	(.061)	(.211)	(.169)	(.294)	(.245)
Observations	3354	3183	1998	1846	1189	1115	664	622
R-squared	.17	.22	.14	.24	.14	.21	.21	.27

Table 5: Post-graduate wage premium, Intra-Region

Robust Standard Errors in brackets; * significant at 10%; ** 5%; *** 1%

Appendix

List of Variables

	MALE	1=Male; 0=Female
	EMPL	1=Employed; 0=Otherwise
	Relocate	1=Moved to other city after studying; 0=Otherwise
Education	Vocational Degree	1=Upper Secondary, Vocational, Tertiary; 0=Otherwise
Ref: No Degree	Master’s Degree	1=Master's Degree; 0=Otherwise
	PhD	1=PhD; 0=Otherwise
	Graduate	1 = Bachelor’s Degree or higher; 0=Otherwise
	Postgarduate	1=Master´s Degree or higher; 0=Otherwise
	Shift Study	1=Completes studies (no change, no dropout); 0=Otherwise
	Years of Education	Average Number of Schooling Years weighted by expected graduation time per university and per field of study
Age	Age_19	
Ref: >25 years	Age_20	
	Age_23	
Abilities	Ability_low	
Ref: Blanks	Ability_ aver	
	Ability_high	
Profession	Manager	1=Manager; 0=Otherwise
Ref: Low-Skill Job	Scientist	1=Scientist; 0=Otherwise
	Medical Doctor	1=Medical Doctor; 0=Otherwise
	Engineer	1=Engineer; 0=Otherwise
	Teacher	1=Teacher; 0=Otherwise
	Legal /Business	1=Legal/Business Professionals; 0=Otherwise
	Public Service Professionals	1=Social Scientists, Administrators; 0=Otherwise
	Other Professionals	1=Artists, Clergy, Public Serv; 0=Otherwise
	Medium-Skill Jobs	1=Medium-Skilled Job; 0=Otherwise
Mismatch	Match	1=Perfect Match between occupation and qualification; 0 otherwise
Helsinki	Helsinki	1=Lives in Helsinki in 2005; 0=Otherwise
Field of study	Education	1=Works in Education; 0=Otherwise
Ref: Agriculture	Humanities	1=Studies Humanities and Arts; 0=Otherwise
	Business/Social Sciences	1=Studied Business, Social Sciences; 0=Otherwise
	Information Science	1= Information Sciences/Hard Sciences; 0=Otherwise
	Engineering	1=Technical Studies, Engineering, Architecture; 0=Otherwise
	Medicine	1=Studied Medicine, Health-Care; 0=Otherwise
	Service	1=Studied Services; 0=Otherwise

Data Treatment

The original sample consists of 9713 observations. Observations with missing earnings were dropped after having checked that missing earnings were not correlated with individual characteristics (i.e. gender, education attainment). Observations with missing earnings also missed working months: when we had data on earnings we imputed the average number of working months of the income class to which the individual belongs. We excluded from the final sample 146 individuals with missing working months and zero earnings. For observations with ‘zero’ value for working months we assigned a fictitious 0.1 whereas we dropped those with positive income since working is not their main source of earning and they can distort our model specification. Moreover, we create a specific category for those with missing job code. Finally, we also drop individuals with missing degrees. The sample of 8880 observations is further reduced to 8787 after the exclusion of earners above the 99% percentile.