ETLA ELINKEINOELÄMÄN TUTKIMUSLAITOS

Sami Napari

ESSAYS ON THE GENDER WAGE GAP IN FINLAND

A 44 Helsinki 2008

ETLA ELINKEINOELÄMÄN TUTKIMUSLAITOS
THE RESEARCH INSTITUTE OF THE FINNISH ECONOMY

Sarja A 44 Series

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ETLA, The Research Institute of the Finnish Economy
Publisher: Taloustieto Oy

Helsinki 2008

ISBN 978-951-628-475-3
ISSN 0356-7435

Published also as
Helsinki School of Economics Acta Universitatis Oeconomicae Helsingiensis A-328
ISSN 1237-556X; ISBN 978-952-488-243-9

Printed in: HSE Print, Helsinki 2008

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ESSAYS ON THE GENDER WAGE GAP IN FINLAND

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Essay I: Napari, S.: "The Early-Career Gender Wage Gap among University Graduates in the Finnish Private Sector", an earlier version of the essay titled "The Early Career Gender Wage Gap" is published in the CEP Discussion Papers, 2006, No. 738.

Essay II: Napari, S.: "Type of Education and the Gender Wage Gap", an earlier version of the essay is published in HECER Discussion Papers, 2006, No. 128.

Essay III: Napari, S.: "Gender Differences in Early-Career Wage Growth", an earlier version of the essay is published in ETLA Discussion Papers, 2007, No. 1093.

ACKNOWLEDGEMENTS

Most of this thesis was written at the Department of Economics at the Helsinki School of Economics. It is a very inspiring and great place to work. I would like to thank the whole department and especially my supervisor Professor Pekka Ilmakunnas for his support and help during this project.

I thank Professor Astrid Kunze and Docent Juhana Vartiainen for examining my thesis. I benefited a great deal from their insightful comments and knowledge of the economics of gender.

Part of my thesis was written during my visit at the Centre for Economic Performance (CEP) at the London School of Economics. Warm thanks go to the whole staff at CEP. Especially, I thank Professor Alan Manning for his guidance and support with the first essay in the thesis. Respect.

I would also like to thank the people at the Research Institute of the Finnish Economy where I both started and finished my thesis. Most of all, I thank Docent Rita Asplund. I have been fortunate enough to benefit from her expertise throughout my graduate studies. This thesis would not have been completed without her support and encouragement. Thank you. Big thanks go also to Pekka Vanhala, who has helped me a great deal with the data.

I also like to express my gratitude to all my fellow students at the Department of Economics. You conjured up an atmosphere that made it feel more like a fun than work to write the thesis.

I am deeply grateful to my parents Harriet and Risto and to my sister Susanna and her family for all their support and encouragement during these years. Thank you all.

The greatest thanks go to my life partner Riina. Her incessant support and understanding have been invaluable for the completion of this thesis. Thank you. And as our cat Leevi is part and parcel of our family, also he deserves to be mentioned. Let's say that Leevi has been an unbeatable stress-remover who by example reminded me to take it easy every now and then.

I thank Statistics Finland and the Confederation of Finnish Industries for providing the data. The financial support from the Finnish Doctoral Programme in Economics, the Yrjö Jahnsson Foundation, the Academy of Finland, the Finnish Cultural Foundation and Helsinki School of Economics is gratefully acknowledged.

Helsinki, April 2008
Sami Napari

ABSTRACT

This dissertation is an empirical study of the gender wage gap in Finland. Much of the dissertation focuses explicitly on the early career as it is found that the first years after labour market entry are of great importance with respect to the overall gender wage gap. The dissertation consists of three essays.

The first essay explores the early-career gender wage gap in the Finnish private sector. I find that the gender wage gap increases significantly during the first ten years after labour market entry accounting for most of the life-time increase in the gender wage gap. The more detailed analysis of the factors contributing to the early-career gender wage focuses on university graduates. This mitigates the problems caused by the most disturbing shortcoming of the data used in the essay, namely the lack of information on working hours and part-time status. In Finland, part-time rates among university graduates are very low as well as the gender difference in these rates. In the essay I consider several explanations for the gender wage gap based on the human capital theory, job mobility and labour market segregation. The results suggest that only about 20 to 26 per cent of the average early-career gender wage gap is explained by gender differences in qualifications considered. Of the investigated factors gender differences in the field of education and work experience matter most.

In the second essay, I investigate in more detail the role of university majors in explaining the gender wage gap. Using data from the Confederation of Finnish Industries, significant gender differences in majors among white-collar workers are found. These differences in education account for about 38 per cent of the gender wage gap among young white-collar workers with a bachelor-level degree after controlling for age, year, gender, region, industry and firm size. The corresponding number for young white-collar workers with a master-level degree is roughly 31 per cent. There are no considerable differences in the effects of majors between new entrants and white-collar workers having more work experience. Furthermore, similarity of the results between OLS and panel methods controlling for unobserved individual factors implies that the effect of university majors is unlikely to reflect unobserved heterogeneity. Finally, women's gains from equalizing educational distributions do not depend in any significant way on the price structures used.

Using data from the Finnish manufacturing sector, the last essay studies the factors contributing to the gender gap in early-career wage growth. The analysis shows that the size of the gender gap in wage growth varies with mobility status, the gap being much higher when changing employers compared to within-firm wage growth. Several explanations for the gender gap in wage growth based on human capital theory and theory of compensating wage differentials are considered. However, much of the gap in wage growth remains unexplained. Further analysis documents that the female penalty in wage growth increases significantly as we move along the conditional wage growth distribution with a sharp acceleration in the gap at the top of the distribution.

Keywords: gender wage gap, wage growth, early career, mobility, type of education
JEL classification: J6, J16, J24, J31, J71

I Introduction

1. Background

Although several measures have been taken to attack gender inequality in wages, the reality is that a substantial gender wage gap still exists in all labour markets, even in the most advanced countries in the world. A report by the European Commission (2007) shows that on the basis of the Structure of Earnings Survey 2002, the average gender pay gap is almost 25 per cent at the level of the EU-25. The report also documents that the gender pay gap in Europe has been fairly stable during the last ten years. Moreover, in some countries like Sweden and Denmark with a relatively small gender pay gap in 1994, the gap seems to have stagnated or even widened in recent years. The state of the gender equality outside the EU is not any better. On the contrary, as the results of the report by World Economic Forum (2005) indicate, for example the US has succeeded worse than many of the EU member states in achieving equality between men and women. It thus seems that even though much progress has been made over a period of 15 to 20 years in reducing gender wage differences (OECD 2002), there is still plenty of scope for improving women's labour market status.

It is, however, encouraging to notice that there has been heightened international awareness of gender issues in recent years. For example, reducing the gender gap in wages is an important topic on the European political agenda. It has been part of the European employment strategy since 1999 and new policies to attack the gender wage gap have been introduced over the years. In 2003, the member states of the European Union were asked to take measures to achieve a substantial decrease in the gender wage gap by 2010.

Also the document entitled *'A Roadmap for Equality between Women and Men 2006-2010'* launched by the European Commission (2006) aims to reduce the gender wage gap. It is interesting to debate about the reasons for this increasing interest towards gender issues. Perhaps decision makers have started to realize that equality between men and women is much more than just a matter of political correctness. As was pointed out in the report by World Economic Forum (2005), countries which do not capitalize on the full potential of one half of their societies are misallocating their human resources. This may have significant effects on their competitive ability. Therefore, promoting gender equality is nowadays more and more often seen as an important strategic issue.

Mere quantification of the gender wage gap is not a sufficient step towards implementing corrective policies, but we need to understand the factors contributing to the gender differences in wages as well. Among economists the interest towards the gender wage gap and the mechanisms behind it has increased hand-in-hand with the increase in women's labour market participation. Modern economic research has developed a number of different theories and models giving explanations for the existence of the gender wage gap. Also the empirical literature on the topic is substantial. Both the theoretical considerations and the empirical studies on the factors contributing to the gender wage are discussed in more detail below.

This dissertation is an empirical study on the gender wage gap in the Finnish labour market. Much of the dissertation focuses on the early part of the working career as it turns out that the first years after entry to the labour market are the primary cause of the overall gender wage gap. Equipped with remarkably rich data sets I investigate several potentially important factors affecting wages and gender differences in those respects. One example of the factors to be addressed is the type of education. Men's and women's choices concerning the type of schooling have received surprisingly little attention so far even though the type of education is potentially of considerable importance in determining wages. The uppermost goal of this dissertation is to provide policy-makers with new and better information to improve men's and women's equal treatment in the labour market.

Next I discuss about the theoretical models offering explanations for the existence of the gender wage gap. After that I describe some of the main findings of the empirical research on the gender wage gap. The introduction ends with a summary of the essays.

2. Theoretical Framework

Two main theories underlie most of the empirical research on the gender wage gap: the human capital theory and models of labour market discrimination. The human capital theory originally developed by Becker (1964) and Mincer (1974) basically explains the gender gap in wages on the basis of productivity differences between men and women. These productivity differences have their roots in the traditional division of labour within the family. Anticipating child-related career breaks women are less motivated to make investments in human capital than men. Intermittent labour market participation might not only affect current investments in human capital (e.g. on-the-job training) but it might have effects on women's pre-labour market investment behaviour (e.g. investments in the quantity and type of education) as well. And because of women's weaker labour market attachment, they also accumulate less work experience than men. Furthermore, the anticipation of future intermittence may affect women's occupational choices as they have incentives to choose jobs where penalties for career interruptions are smaller.

There are naturally also many other routes than those mentioned above by which traditional gender roles within the family may affect women's wage outcomes. One potentially important factor is job mobility and gender differences in this respect. The models of job mobility (e.g. Burdett 1978; Jovanovic 1979a, 1979b) point out that there is heterogeneity in the quality of worker-employer matches and through a process of job-shopping workers (especially the young ones) can experience substantial wage gains. Because of family commitments, women's choice set concerning potential jobs may be more constrained than men's. For the same reason, women's mobility might also be less motivated by money as they try to find "family-friendly" jobs. As a result, job mobility might be expected to be a less important determinant of wages for women than for men.

To the extent that the gender wage gap is not explained by gender differences in productivity, occupations and jobs driven by gender-based preference and skill differences, models of labour market discrimination offer an explanation. Economic theories of discrimination can be classified into two broad types of models. The first class of models initiated by Becker (1971) formalizes discrimination as a "taste" or prejudice by one group against another. Later on these taste-based models of discrimination have been extended, for example, to analyze the effects of customer or employer prejudice in the presence of costly labour market search (e.g. Borjas and Bronars 1989; Bowlus and Eckstein 2002).

The second group of models of discrimination has it roots in imperfect information about the skills or/and behaviour of a group of individuals. These models of statistical discrimination initiated by Phelps (1972) and Arrow (1973) emphasize that in a world of imperfect and asymmetric information employers have incentives to use easily observable characteristics such as gender to form expectations on the productivity of workers and to statistically discriminate among workers. Therefore, also women who are highly career-oriented might suffer from discrimination because they belong to a demographic group whose members are on *average* less attached to the labour market and as a result maybe less productive as well. Much of the theoretical work on discrimination over the last twenty years has its premise in imperfect information. One obvious reason for this is that models of statistical discrimination are consistent with the persistence of discrimination in the long run, whereas simpler models of taste-based discrimination typically predict the elimination of discrimination in the face of a competitive labour market.

Obviously, explanations based on the human capital theory and models of discrimination are not mutually exclusive sources of the gender wage gap. Both may play a role and there might exist feedback effects as well. Women may, for example, take into account the effects of discrimination on returns to their human capital when they make investment decisions. Examples of models indicating that discrimination might influence women's behaviour both before and after labour market entry are Blau (1984), Blau and Ferber (1992) and Coate and Loury (1993).

This dissertation considers several human capital-based explanations for the gender wage gap. For example, gender differences in the accumulation of experience are investigated. Also a detailed analysis of gender differences in educational choices is performed. Furthermore, the role of labour market mobility in contributing to the gender wage gap is investigated as well.

3. Empirical Research on the Gender Wage Gap

Over the last few decades a fairly large empirical literature on the gender wage gap has emerged. This section summarizes some of the main findings of this research. Most of the empirical studies on the gender wage gap have focused on the explanations provided by the human capital theory, and therefore, I will start with a discussion of this line of research.

The research on gender differences in pre-labour market human capital investments has mainly focused on differences in years of schooling between men and women. During the last few decades women's level of education has increased significantly and this convergence of years of education between genders has undoubtedly contributed to the narrowing of the gender wage gap as the results of Blau and Kahn (1997) show. Nowadays, however, as the gender differences in the quantity of education are in many countries practically nonexistent, the level of education does not play a role in explaining the gender wage gap. But men and women still differ in terms of the *type* of education. The existing studies on the topic show that the type of schooling matters when it comes to explaining the gender wage gap. For example, the results in Brown and Corcoran (1997) suggest that gender differences in college majors explain as much as 40-45 per cent of the gender wage gap among workers with several years of college in the US. A more recent study by Machin and Puhani (2003) documents that in the UK and Germany gender differences in university majors explain about 9-19 per cent of the gender wage gap after controlling for age, industry, part-time work and public sector employment.

Perhaps the most often presented critique against the studies on the gender wage gap is that these studies typically fail to control adequately for differences in the work histories of men and women. Recent studies show that the gender gap in actual levels of work experience is indeed an important determinant of the gender differences in wages. For example, Manning and Swaffield (2005) found that actual work experience explains about 30 per cent of the gender gap in early-career wage growth in the UK. And it is not only the total amount of experience that matters but also the timing of work experience. A study by Light and Ureta (1995) documents that gender differences in the frequency, duration and placement of non-work spells account for 12 per cent of the gender wage gap among workers with the same amount of experience. The bottom line from these studies is nevertheless that the gender gap in work experience is typically far too small to explain the size of the gender wage differences.

There has also been a lot of research on gender differences in labour market turnover. It has been argued that women quit jobs at a higher rate than men and because of this they receive less job training than men (which again contributes to the gender wage gap). However, the empirical evidence of gender differences in quit probability is not unanimous. There are studies (e.g. Becker and Lindsay 1994) that indicate that the probability for staying with an employer is lower for women than for men. In contrast, for example Light and Ureta (1992) show that once observable characteristics are controlled for it is as easy to predict a female stayer as a male stayer among the younger cohorts. Be that as it may, several authors have documented that women receive less job training than men and that this has effects on the gender wage gap (e.g. Hill 1995; Olsen and Sexton 1996).

The effects of mobility on wages are not clear, however, a priori. Mobility affects wages negatively to the extent it decreases investments in firm-specific human capital. On the other hand, through mobility workers can find better employer-employee matches, which leads to higher wages as workers change to jobs that are higher in the wage distribution. There are empirical studies indicating that men and women might differ in some important ways in their mobility behaviour. For example, women have been found to change employers more often than men because of family-related reasons whereas for men the biggest incentive to change jobs is typically money (e.g. Keith and McWilliams 1999; Manning 2003, ch7). However, the evidence of the importance of gender differences in mobility in explaining the wage gap between men and women suggests that mobility differences have relatively minor effects on the wage gap. For example, Manning and Swaffield (2005) found that mobility explains only about 6 per cent of the early-career gender gap in wage growth.

Among labour economists there has been some disagreement about whether or not measures of job characteristics should be used in a wage equation giving an *explanation* for the gender wage gap. On the one hand, differences in job characteristics might reflect gender differences in tastes for jobs. In this case, excluding them from the model leads to an overestimation of the unexplained gender wage gap. If, however, gender differences in the job characteristics are due to discriminatory factors, using them in the wage equations underestimates the magnitude of the residual wage difference. Without taking a stand on the matter, job characteristics have, nevertheless, proved to be important determinants of the gender wage gap. For example, the results by Blau and Kahn (1997) show that industry, occupation and collective bargaining variables reduce the residual wage gap from 22 per cent to 13 per cent.

The main conclusion to be drawn from the empirical studies focusing on the importance of gender differences in productivity-related characteristics is that these differences are far too small to explain the size of the wage gap. A substantial unexplained gap thus remains. Some researchers take this as evidence of labour market discrimination towards women whereas others argue that the residual wage gap results from researchers' inability to control for all the relevant worker characteristics.

Understandably, it is very difficult to provide direct empirical evidence of the potential relevance of discrimination with respect to men's and women's labour market outcomes. There are, however, some papers that have tried to explore this topic. One is a study by Hellerstein et al. (1999), who estimate marginal products of workers and compare these estimates to wages. Hellerstein et al. provide several estimates of marginal products but one of their more conservative estimates indicate that women are about 15 per cent less productive than men but are paid 32 per cent less. Their results thus suggest that at least in some cases the role of discrimination as a factor contributing to the gender wage gap might be substantial.

As mentioned above, the empirical literature on the gender wage gap is large. However, much of this research has focused on the US and the UK, the institutional settings of which differ in many respects from those of the continental Europe. The research on the effects of labour market institutions show that the different institutional arrangements may not only explain the variation of the overall gender gap across countries (Blau and Kahn 1996) but they may have effects on the relative importance of factors behind the sex-based wage gap as well (Albrect et al. 2003). Therefore it is important to provide information on the gender wage gap in different institutional set-ups. This improves our understanding of the mechanisms behind the gender wage and also serves as a useful guide for policy as we might learn from the experiences of countries that have succeeded better in promoting the gender equality in the labour market. This dissertation investigates the gender wage gap in the Finnish labour market and can be regarded as a detailed study of the gender wage differences in a labour market where the overall gender wage gap is relatively small, the wage-setting process is highly centralized and where women's labour market participation is supported by many institutional arrangements.

The existing body of research on the gender wage differences in Finland is fairly small. Examples of the most recent studies are Vartiainen (2001), Kangasniemi (2003) and Korkeamäki and Kyyrä (2006). Vartiainen analyzed gender wage gap using data from the period 1996-1998. He found that personal characteristics like age, education and years of employment play a fairly minor role in explaining the average gender wage gap on the magnitude of 21 per cent. A much more important issue is that men and women end up working at different industries and occupations. Also Korkeamäki and Kyyrä, who investigated full-time workers employed in the Finnish manufacturing sector in 2000, conclude that occupational segregation is of great importance in contributing to the gender wage differences.

Kangasniemi investigated the wage effects of tenure, job changes and occupation with special reference to gender differences. Also her data came from manufacturing covering the period 1980-1996. One of Kangasniemi's main findings is that men and women either behave or are treated in a very different manner in terms of job mobility and wage profiles. She concludes that institutions supporting gender equality have not been able to attain similar labour market outcomes for men and women.

This dissertation contributes in several ways to the existing literature on the gender wage gap in Finland. It also adds to the international research by focusing on topics which have received fairly little attention so far. One example of these topics is the development of the gender wage gap with work experience. Much of this dissertation focuses explicitly on the early career as it is highlighted that the first years after labour market entry are of crucial importance with respect to the gender wage gap. Another rather little investigated issue is the role of pre-labour market human capital investments in explaining the wage gap between men and women. This dissertation provides a detailed study of the gender differences in university majors. It turns out that educational choices and gender differences in this respect contribute significantly to the sex-based wage gap.

4. Summary of the Essays

4.1 The Early-Career Gender Wage Gap among University Graduates in the Finnish Private Sector

Using data from Statistics Finland covering the period 1996-2004, this paper investigates the gender wage gap in the Finnish private sector. The paper starts by documenting that the gender wage gap increases significantly during the first 10 years after labour market entry accounting for most of the life-time increase in the sex-based wage gap. The rest of the paper focuses on factors contributing to the early-career gender wage gap as it is necessary in order to understand the overall gender wage gap in Finland.

The detailed analysis of the early-career gender wage gap focuses on university graduates from 1996 and 1997. Concentrating on university graduates mitigates the problems caused by the most disturbing shortcoming of the data set, namely the lack of information on working hours and part-time status. In Finland, part-time rates among university graduates are very low as well as the gender differences in these rates.

The paper considers several explanations for the early-career gender wage gap. First of all, the paper examines gender differences in the accumulation of work experience. Also the effects of the type of education, family type and employer characteristics on the gender wage gap are discussed. Finally, I investigate differences in mobility between male and female university graduates.

The underlying factors behind the early-career gender wage differentials are investigated by applying the Oaxaca-Blinder type of decomposition analysis. The decomposition is executed by using three different sets of estimates (OLS, random and fixed effects) and three different price structures (male, female and pooled). The results suggest that only about 20 to 26 per cent of the early-career gender wage gap among university graduates can be explained by sex-based differences in qualifications considered. Of the investigated factors the field of education and work experience matter most. They both explain about 5 to 11 per cent of the average gender wage gap, the contribution varying in line with the estimation method and the price structure used.

Thus, most of the wage gap is due to gender differences in the estimated returns to characteristics. One of the most significant gender differences in this respect is the asymmetric effect of children on men's and women's wages. The estimation results show no child-penalty for men whereas women suffer substantial wage losses due to children. A more detailed analysis of the child-penalty shows that the gender wage gap increases significantly during the years immediately after the childbirth but that women catch up with men in wages as the child gets older. This pattern is in line with the hypothesis that women cut working hours when children are very young. Furthermore, this implies that my estimates of the child-penalty are probably upward biased due to my inability to control for actual working hours. However, the analysis also shows that women's wages are lower than men's already before the childbirth. This indicates that also other factors than child-related career breaks have a role in explaining the early-career gender wage gap. My results imply that among these other factors the type of schooling seems to be of particular importance.

4.2 Type of Education and the Gender Wage Gap

This paper focuses on a single question: how important is the type of education in explaining the gender wage gap among university graduates in the Finnish manufacturing sector. The data come from the Confederation of Finnish Industries covering the period 1998-2004 and they contain information on white-collar workers. The data set is very suitable for the analysis in question because it has exceptionally detailed information on education. The size of the data is large as well enabling me to utilize the detailed measure of education fully.

The results suggest that the type of education is a very important single factor behind the gender wage gap among university graduates. When only nine major categories are used, gender differences in majors explain about 15 per cent of the wage gap after controlling for age, gender, region, industry, firm size and year. As the number of major categories is increased up to 247, the contribution of majors to the wage gap rises to over 30 per cent. There is some variation in the estimated size of the contribution of majors with the level of university degree and with the stage of a career, but irrespective of the worker group considered, the choice of major matters a lot when it comes to explaining the gender wage gap.

The role played by unobserved individual factors is analyzed by comparing the decomposition results based on OLS and random and fixed effects estimates. The results of the different estimation methods differ fairly little. This suggests that the conclusions made concerning the importance of the type of education are probably not driven by unobserved individual heterogeneity.

Also the dependency of women's gains from equalizing educational distributions between genders on the price structure used is analyzed. This is done by applying the method presented by Brown and Corcoran (1997). No evidence is found that the change in wages experienced by women from steering them into male-dominated majors would depend on whether male or female prices are used.

4.3 Gender Differences in Early-Career Wage Growth

This essay also uses data from the registers of the Confederation of Finnish Industries. The period of investigation is 1995-2004. Using different data sources than the first paper in the dissertation, this paper finds significant gender differences in early-career wage growth as well. Female white-collar workers lag behind men in average hourly wages by ten log points immediately at entry into the labour market. After ten years the size of the gender wage gap has more than doubled. A more detailed analysis shows that the size of the gender gap in wage growth varies considerably with mobility status. Women's disadvantage in annual within-firm wage growth relative to men is 0.67 percentage points whereas they lag behind men in between-firms wage growth by 1.9 percentage points.

Potential explanations for gender differences in wage growth are numerous. This essay focuses mainly on the importance of gender differences in employer and job characteristics. Characteristics to be considered are among other things firm size, industry, occupation, and the complexity level of a job.

I find it difficult to explain the observed gender gap in early-career wage growth. Even after controlling for several employee and employer characteristics a substantial unexplained gender gap both in the between-firms and within-firm wage growth remains.

The analysis of the gender gap in average wage growth was extended to also to other parts of the wage growth distribution. By applying the quantile regression methods, I find that the female penalty increases throughout the conditional wage growth distribution with a sharp acceleration in the gap at the top of the distribution. This holds for both between-firms and within-firm wage growth. The finding of an increasing female-penalty along the wage growth distribution is an interesting extension to the previous studies of the quantile differences in wage *levels* between men and women. These studies have documented that the gender gap in wages tends to increase throughout the wage level distribution. Some researchers take this as evidence of the existence of glass ceilings hampering women's career and wage development.

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II The Early-Career Gender Wage Gap among University Graduates in the Finnish Private Sector*

Abstract

In the Finnish private sector, the gender wage gap increases significantly during the first ten years after labour market entry, accounting for most of the life-time increase in the gender wage differentials. This paper investigates the reasons for this gender difference in early-career wage development. By focusing on university graduates the paper considers several explanations based on the human capital theory, job mobility and labour market segregation. The results suggest that only about 20 to 26 per cent of the average early-career gender wage gap is explained by gender differences in qualifications considered. A substantial unexplained gap thus remains. Of the investigated factors gender differences in the field of education and work experience matter most.

Keywords: gender wage gap, early career
JEL Classification: J24, J31, J7

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* I thank Alan Manning, Pekka Ilmakunnas and Rita Asplund for helpful comments. I also thank the Centre for Economic Performance for hospitality during my stay in 2005-2006. I thank the Academy of Finland, FDPE, Helsinki School of Economics, and Yrjö Jahnsson Foundation for financial support. I thank Statistics Finland for the data.

1. Introduction

There is a large body of literature focusing on factors contributing to the average gender wage gap (see surveys by Altonji and Blank 1999; Kunze 2000). However, the variation of the gender wage differentials with work experience remains much less investigated. The existing evidence suggests that the male-female wage gap is typically fairly small on entry to the labour market but after a few years a significant wage gap has emerged (e.g. Manning and Swaffield 2005). This increase in the gender wage gap during the early careers accounts for much for the life-time increase in the gap. It thus seems that explaining the male-female wage gap essentially requires an understanding of the factors driving the gender differentials in early-career wage development.

This paper investigates gender wage differentials using data from the Finnish private sector covering the period 1996-2004. In line with the results from the U.S. and the U.K., also in Finland the male-female wage gap increases significantly during the first years in the labour market. It is this gender difference in early-career wage development that this paper focuses on.

The most frequently applied approach to explaining the gender differentials in wages is based on the human capital model. Although the human capital model provides several explanations for the gender wage gap, much of the empirical work has concentrated on the role played by work experience. Due to unequal division of housework between genders, women tend to spend more time outside the labour market than men and, as a result, women accumulate less work experience. The main finding from studies exploring the importance of work experience in accounting for the early-career gender wage differentials is that although women's lower level of work experience is an important single factor contributing to the early-career gender wage gap, a substantial unexplained wage gap remains even after controlling for actual work experience (Wellington 1993; Light and Ureta 1995; Kunze 2003; Manning and Swaffield 2005). In the end, as a result of women's increased participation in the labour market, the gap in work experience between men and women is simply too small to explain the size of the early-career gender wage gap.

Gender differences in mobility as a potential source of the early-career gender wage differentials have also received attention among researchers. Job mobility is often associated with rapid wage growth as workers move from low-paid to better-paying jobs (e.g. Topel and Ward 1992). However, there seems to be gender differences in the importance of mobility as a factor behind wage growth. In particular, women have been found to experience lower returns to mobility than men (e.g. Simpson 1990; Loprest 1992). Typically these studies fail, however, to account for the non-pecuniary aspects of jobs. One might argue that due to women's twin burden of domestic responsibilities and paid work, non-pecuniary features of jobs such as flexible working hours are more important for women. Indeed, there is evidence suggesting that the reasons behind mobility differ between genders. Men's mobility is typically motivated by money whereas for women non-market related reasons are also important. These differences in reasons behind mobility have been found to account for much of the gender gap in returns to mobility (e.g. Abbott and Beach 1994; Sicherman 1996; Keith and McWilliams 1997, 1999).

This paper investigates the early-career gender wage differentials using linked employer-employee panel data from Statistics Finland. The data can be considered to be of very high quality as they come directly from administrative registers. The data contain a large set of information both on employees and employers allowing me to examine several alternative hypotheses for the early-career gender wage gap. Starting from those based on the human capital theory, I investigate the role of gender differences in the accumulation of work experience and type of education in accounting for the early-career gender wage gap. Also the effects of children on the wage gap are explored. Secondly, I study gender differences in employer characteristics. It is well-known that the labour market is heavily segregated by gender. My data include information on many employer characteristics which have been shown to be related to wages (e.g. Brown and Medoff 1989; Aitken et al. 1996; Winter-Ebmer and Zweimuller 1999). This allows me to examine the importance of women's segregation into different types of firms than men with respect to the early-career gender wage differentials. Finally, I investigate men's and women's mobility behaviour and whether gender differences in early-career mobility account for the gender gap in wage development during the early careers.

This paper is interesting not only because it focuses on the early career and considers several alternative explanations for the gender wage gap, but also because it uses data from the Finnish labour market. Most of the previous studies on the topic have focused on the U.S. and the U.K. However, the institutional framework of the Finnish labour market differs in many respects from those in place in the Anglo-Saxon countries. For example, in Finland, like in the other Nordic countries, the wage-setting process is highly centralized and employment protection tighter than in the U.S. and in the U.K. Labour market institutions may have important effects on wages and gender differences in those respects (e.g. Blau and Kahn 1996; Albrecht et al. 2003). Therefore, one should be careful in applying the

U.S. and the U.K. evidence directly to Finland or to other countries with an institutional framework similar to that of the Finnish labour market. Finally, many of the existing studies on the early-career gender wage differentials use data that dates back to the 1980s. My data, on the other hand, come from the period 1996-2004 thus providing fresher information on the topic.

The more detailed analysis of the factors contributing to the early-career gender wage gap focuses on university graduates. This is to mitigate the most disturbing shortcoming of my data, namely the lack of information on working hours and part-time status. In Finland, part-time rates among university graduates are very low as well as the gender difference in these rates. According to the Working Conditions Study, the part-time rate among 20-34 year-olds is 7.6 per cent and 2.7 per cent for female and male university graduates respectively. Also information on working hours is not that crucial when the focus is on university graduates as most of them work in jobs that pay monthly wage, not according to the working hours.

In line with the evidence from the U.S. and the U.K., I find that the gender wage gap increases significantly during the first years in the labour market. This gap in early-career wage growth between men and women accounts for most of the life-time increase in the gender wage gap in the Finnish private sector. The results of the more detailed investigation of the reasons for the gender gap in early-career wage developments show that only a fairly small part of the wage gap among university graduates can be explained by gender differences in qualifications considered. The decomposition results imply that about 20 to 26 per cent of the average early-career gender wage gap is explained by differences in variables used in the wage model. Of the investigated factors the field of education and work experience matter most. They both account for about 5 to 11 per cent of the average gender wage gap. Men's and women's segregation into different industries and different types of employers matter as well, but less so compared to the field of education and work experience. Job mobility, on the other hand, proved to be irrelevant in accounting for the early-career gender wage differentials among university graduates.

The rest of the paper is structured as follows. In the next section, the theoretical background of the paper is discussed. Then I continue with presenting the data and by showing descriptive evidence of the gender differences in early-career wage development in the Finnish private sector. Section 4 presents the empirical model after which the results are shown. Section 6 gives a summary of the paper and presents the main conclusions.

2. Theoretical Framework

Theories of wage determination offer several possible explanations for the gender wage gap. The human capital model developed by Becker (1964) and Mincer (1974) is the most often applied theoretical framework in the gender wage gap literature. The human capital model explains women's lower wages by their lower level of human capital. Since human capital is composed of various elements, the model gives us plenty of explanations for the sex-based wage gap, all of which are in one way or another related to the fact that women are more likely than men to have intermittent labour market careers. Because of this, women accumulate less work experience than men, and as a result, have lower wages as well. Anticipation of career breaks may also lower women's motivation to do wage-enhancing investments in job training. Besides gender differences in human capital investment behaviour after the labour market entry, men and women may differ in pre-labour market human capital investments as well due to women's weaker labour market attachment. Although gender differences in terms of the quantity of education are small nowadays, men's and women's choices concerning the type of education still differ explaining a considerable portion of the observed gender wage gap (e.g. Machin and Puhani 2003; Napari 2006). Finally, as discussed by Becker (1985), due to women's greater domestic responsibilities, women might be less "energetic" than men in the labour market with negative effects on their productivity and wages.

Another explanation for the gender wage gap can be derived from the models of job mobility (e.g. Burdett 1978; Jovanovic 1979a, 1979b). These models point out that there is heterogeneity in the quality of employee-employer matches: some employee-employer matches are more productive than others. Therefore, one way to improve one's standing in the wage distribution is to find a better match and move between employers. This hypothesis has also received empirical support: several papers have shown that a considerable part of the early-career wage growth can be ascribed to job mobility (e.g. Barter and Borjas 1981; Topel and Ward 1992). However, there is also evidence that women gain less from mobility than men (e.g. Loprest 1992). Although the models of mobility are typically silent about gender differences in the process of mobility, it is easy to come up with reasons for why the returns on mobility might be lower for women than for men. For example, due to family responsibilities, women may be constrained to search for jobs near home or with flexible working hours. Indeed, there is evidence that women change jobs more often than men because of family or non-market related reasons and that these gender differences in the reasons behind mobility account for much of the gender gap in the gains from mobility (e.g. Sicherman 1996; Keith and McWilliams 1997, 1999; Manning 2003, ch7).

Gender differentials in wages can also be explained as a result of compensating wage differentials. The theory of compensating wage differentials states that in the competitive labour market worker's utility from all jobs should be equal when both pecuniary and non-pecuniary aspects of jobs are taken into account. Women might seek family-friendly jobs that are easy to combine with family requirements and forsake wages for these features.

Finally, it is possible that part of the gender wage differentials is due to discrimination. Economic theories of discrimination can be classified into two broad classes of models. Models in the first class formalize discrimination as a "taste" or prejudice by one group against another. Taste-based model of discrimination was first introduced by Becker (1971). Models in the second class are models of statistical discrimination. These models developed by Phelps (1972) and Arrow (1973) point out that in the world of imperfect and asymmetric information employers have incentives to use easily observable employee characteristics, like gender, in forming expectations of the productivity of workers. If women are on average less productive than men, then women who are highly career-oriented and productive may suffer from discrimination. This is because they belong to a group of workers who are on average fairly loosely attached to the labour market and who might therefore also be less productive.

Based on the discussion above, this paper considers several explanations for the gender differentials in the early-career wage development. Starting with the human capital model, I examine gender differences in the accumulation of work experience. I also study men's and women's choices concerning the type of education. As the last issue related to the human capital model, I analyze the effects of family type on the gender wage gap. Because of women's traditional role as the main provider of childcare in a household, children have undoubtedly bigger effects on women's earnings potential than on men's wages.

I also examine gender differences in employer characteristics. There is plenty of empirical evidence showing that women tend to work in different industries, firms and jobs than men and that labour market segregation accounts for much of the gender wage differentials (e.g. Groshen 1991; Carrington and Troske 1998; Bayard et al. 2003; Datta Gupta and Smith 2005). My data contain a rich set of employer characteristics enabling me to investigate whether young women work in different types of firms than young men and what role this plays in explaining the early-career gender wage differentials in the Finnish private sector.[1] I have information among other things on the field of industry, firm size, foreign ownership, average age and average level of schooling of the personnel, firm productivity and the female share of the personnel.

[1] Investigation of the reasons behind segregation is beyond the scope of this study. Segregation may be a result, for example, of gender differences in human capital investments or/and in preferences. Also discrimination against women may play a role.

Finally, I study gender differences in mobility between establishments.[2] Contrary to most of the earlier papers, I focus on cumulative mobility instead of a single mobility event. My aim is to investigate whether there are gender differences in early-career mobility history patterns and how much possible differences in mobility behaviour explain the early-career wage differentials between men and women.

3. Data and Descriptive Evidence of the Gender Gap in Early-Career Wages

3.1 Data

The empirical analysis is based on a panel data set from Statistics Finland that links information on individuals, establishments and firms. The data are constructed by linking information from various data sources: Business Register, Census of Manufacturing, Financial Statements Statistics, R&D survey, ICT survey, and Employment Statistics. The resulting data set is called the Finnish Longitudinal Employer-Employee Data (FLEED). The detailed version of FLEED is maintained at Statistics Finland and because of confidentiality concerns outside researchers (like me) get a limited version of the data. In my sample, the number of variables is somewhat smaller than in the original FLEED. Also, variables for establishments and firms are modified meaning basically that information on employers is

[2] I do not examine mobility between firms because of the problems related to the identification of a firm change. As discussed in Section 3, a mobility variable is based on comparisons of employer codes attached to employees between years. Due to business reorganizations, there might be cases where firm codes change even though workers do not actually change employers. However, these reorganizations do not typically affect establishment codes and therefore mobility between establishments can be fairly reliably identified.

in the form of classified variables and growth rates. For more about the data sources and the linking process see Ilmakunnas et al. (2001) and Maliranta (2003).

The period of investigation is 1996-2004. I concentrate on individuals who can be linked to employer information using firm and establishment identifiers. This practically restricts the sample to the private sector. I further restrict the sample by analyzing individuals who are 18-60 years old, have not been entrepreneurs in any year during the investigation period, have reliable wage information[3] and have no breaks in the panel[4]. These restrictions lead to a sample of 4,196,472 observations on 732,431 individuals of which 48.04 per cent are men. This sample is used in calculating wage profiles shown in figures 1 and 2 (section 3.2).

In the more detailed analysis of the factors contributing to the early-career gender wage gap I further restrict the sample on university graduates. As discussed in the introduction, this mitigates the potential problems caused by the most important shortcoming of the data, namely the lack of information on working hours and part-time status. The econometric analysis concentrates on individuals who finish their university degree in 1996/1997 and who stay in the data throughout the investigation period.[5] The career of the worker is defined to begin the year after to graduation, and all observations

[3] Monthly wages below/above the $1^{st}/99^{th}$ centile of the wage distribution calculated by year and the level of education are excluded from the analysis. Monthly wages are defined as annual wages divided by months in employment. Data on annual wages come from the tax records. Wages are converted into 2000 money by using the Cost-of-living index of Statistics Finland.
[4] Breaks in the panel are uncommon in my data: only about 0.4 per cent of individuals have breaks in the panel. This holds for both men and women.
[5] The restriction on including only graduates who are observed during all years of the investigation period is unlikely to present any sample selection problems since 96.9 per cent of male and 96.5 per cent of female university graduates from years 1996-1997 stay in the data over the whole investigation period.

preceding this date are excluded from the analysis. Furthermore, to exclude workers with a considerable working career already at the time of graduation, I impose a further restriction which excludes individuals who are over 30 years old when they complete their degree. After these restrictions, I am left with 13,532 male and 7,501 female observations. This corresponds to 2,340 men and 1,502 women.

Table 1 shows summary statistics for some of the variables used in the econometric analysis. The average gender wage gap among the university graduates from 1996/1997 during the investigation period is large, about 31 per cent. As expected, women accumulate less work experience than men, but gender differences in this respect are fairly small: by the end of the investigation period, women have accumulated an average 14.4 months less work experience than their male colleagues. Gender differences in the type of education are instead significant. Male graduates are heavily represented in technology whereas women tend to choose fields like humanities and arts and social sciences considerably more often than men. There seems to be some gender differences in terms of firm characteristics as well. For example, men work in larger and more productive firms than women. Men also work more often in firms with higher male shares of the personnel and in firms with more educated employees. Somewhat surprisingly, women seem to switch between establishments more often than men. Before investigating how much these gender differences in the background characteristics account for the early-career wage differentials between male and female university graduates, I explore in more detail the wage-experience profiles of men and women and the development of the gender wage gap with time spent in the labour market.

3.2 Descriptive Evidence of the Gender Differences in the Early-Career Wage Development

As discussed in the introduction, there is empirical evidence suggesting that the gender wage gap increases significantly during the first years after labour market entry and that this gap in the early-career wage growth between men and women accounts for most of the life-time increase in the sex-based wage gap. However, this evidence comes mainly from the US and the UK. In this section, I investigate whether these results concerning the importance of the first years in the labour market with respect to the gender wage gap holds also in the Finnish private sector.

Figure 1 shows the wage-experience profiles for men and women together with the gender wage gap. Wages are normalized to be zero for men with zero years of potential work experience. Interestingly, in contrast for example to Manning and Swaffield (2005) who used data from the UK, a considerable gender wage gap exists already at the entry to the labour market. However, in line with the earlier evidence, also in Finland the gender wage gap increases rapidly during the first ten years in the labour market. In fact, pretty much all of the life-time increase in the gender wage gap takes place during the first ten years of the working career.

One might suspect that at least part of the observed increase in the gender wage gap during the early-career is due to cohort effects. Figure 2 shows the gender wage gap profiles for different birth cohorts. As can be seen, it is true that the gender wage gap tends to be lower for younger birth cohorts, but that the gap increases significantly with experience also among them. Therefore, the observed pattern of increasing gender wage differences immediately after entry to the labour market cannot be explained simply by the cohort effects.

Finally, figure 3 shows the wage profiles for those who finished their university degree in 1996-1997 and upon whom the econometric analysis of the paper focuses. As can be seen, also among this group of workers the gender wage differences increase considerably during the first years in the labour market.

4. Empirical Model

Gender wage gap studies are often criticized for their failing to control fully for differences in the work histories of men and women. Standard measures of individuals' employment histories, potential and actual work experience, are considered to provide inadequate proxies for women's labour market skills because of their tendency to spend much time in non-work activities. Indeed, studies for example by Mincer and Polachek (1974) and Mincer and Ofek (1982) have shown that non-work spells do not only affect the level of accumulated work experience, but career interruptions might cause depreciation of human capital as well.

Light and Ureta (1995) present a so called work history model which includes an array of experience variables measuring the fraction of time spent in work each year from the beginning of the career to the present. The model also accounts for possible wage penalties from non-employment spells by including controls for periods out of work. The work history model thus provides a very detailed characterization of an individual's employment history regardless of how intermittent it has been. This may be particularly important when it comes to explaining the gender wage differentials. Indeed, the results of Light and Ureta show that the work history model may give us new insights into the factors behind the gender wage gap. They find that it is not only the amount of work experience that matters but also the timing of experience is important: in their data, gender differences in the timing of early-career work experience explain as much as 12 per cent of the gender wage gap. Another nice feature of the work history model is that it is much more flexible in the functional form than the standard quadratic specification of the wage-experience profile first introduced by Mincer (1974). Murphy and Welch (1990) and Light and Ureta (1995) show that the quadratic specification might provide a fairly poor approximation of the true wage-experience relationship and that a more flexible functional form may be warranted. This holds especially for the early careers.

I estimate a wage equation which draws heavily on the work history specification introduced by Light and Ureta (1995). I assume that wages are determined as follows:

$$\ln W_{it} = \beta_0 + \sum_{s=t}^{s=t-8} ex_{is}\beta_{1s} + \beta_2 X_{it} + \beta_3 Z_{it} + \beta_4 M_{it} + \beta_5 Y_{it} + u_{it}, \qquad (1)$$

where subscripts i and t refer to individual and year respectively. The dependent variable is logarithmic real monthly wage. An individual's work history is captured by variable ex_{is} which measures the fraction of time worked in the last year, two years ago, three years ago and so on back to the start of the career.[6] This specification is very flexible as it allows the returns to experience to vary depending on how recently the experience has been accumulated. It is plausible to

[6] Fraction of time worked is defined as months in work during a year divided by 12.

think that the more recent experience is more valuable than work experience accumulated further back in the past. Vector X_{it} contains information on other human capital-related factors than work experience. It includes dummy variables for the field of education (8 categories), a dummy indicating whether a worker has acquired a bachelor or master level degree, a dummy controlling for the year of graduation, dummy variables for marriage and children and a dummy indicating whether a worker has children below school age. Vector X_{it} also includes indicators which take a value of one if the individual did not work at all s years ago but his career was in progress, and zero otherwise. These indicators thus distinguish between the two reasons for why variable ex_{is} might take a value of zero, namely because the individual did not work at all during the year or, because his career was not yet started s years ago.[7] I allow the effects of career breaks to vary for up to two years into the past.[8]

Z_{it} is a vector of employer characteristics. It includes an array of dummies for industry (23 categories), firm size (7 categories), region (6 categories) and the gender structure of the personnel of the firm (3 categories)[9]. Z also contains controls for the personnel's average years of schooling, the average age of the personnel and its square, the log of a productivity measure of the firm[10] and a dummy for foreign ownership[11].

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[7] Just to illustrate this, for example in 1998, the career of an individual graduated in 1996 was not in progress 3 years ago, four years ago, ..., 8 years ago, in which case the variable ex_{is} takes a value of zero.

[8] Statistical tests suggest that the effects of career breaks further in the past do not typically vary significantly.

[9] A firm is classified as female-dominated if at least 60 per cent of its employment consists of women. Correspondingly, a firm is male-dominated if the male share of employment is at least 60 per cent. Otherwise, a firm is classified as balanced.

[10] The productivity measure used is firm's value added per worker.

[11] The foreign ownership variable takes a value of one if the foreign ownership of a firm is 20 per cent or more and zero otherwise.

Vector M_{it} contains information on mobility. It includes a cumulative measure of establishment changes and its square (to capture the potential diminishing returns to mobility). Furthermore, M_{it} also includes interactions between mobility variables and a dummy which equals one if the size of the personnel of the establishment decreases more than 20 per cent between years t-1 and t, and zero otherwise.[12] My data do not record reasons for job changes and the idea of the interactions is to try to distinguish between voluntary and involuntary job changes. This may be important as there is plenty of evidence documenting that voluntary job changes are associated with wage gains whereas involuntary mobility often results in wage losses (e.g. Jacobsen et al. 1993; Davia 2005). Finally, Y_{it} is an array of year dummies and u_{it} is the error term.

The error term u_{it} is defined as: $u_{it} = \alpha_i + \varepsilon_{it}$. Parameter α_i captures the effects of unobserved heterogeneity on wages that vary across individuals but are time-invariant. It can be thought to incorporate individual characteristics like innate ability or motivation and effort. The effects of unobserved factors that vary both across individuals and time are captured in ε_{it} (for example, luck). A large number of studies on gender wage differentials have made an assumption that α_i is random and used the ordinary least squares (OLS) estimator to obtain the parameter estimates of the wage model. Even if this assumption is not violated and the error term of the model is uncorrelated with the regressors, OLS is, however, inefficient with panel data because of the serial correlation caused by the presence of α_i for different observations on the same individual. In this setting the

[12] Identification of an establishment switch is based on comparing establishment codes between years. These codes are associated with workers who have jobs in the last week in a given year. This implies that I can observe at most one establishment change per worker in a year. Therefore, my measure of cumulative mobility is likely to underestimate the true level of mobility.

random effects (RE) estimator would provide a way to reduce the variance.

The uncorrelatedness of the error term with the regressors is a fairly strong assumption. For example, it is plausible that less motivated workers both accumulate less work experience and have lower wages. In this case, the OLS estimates of work experience capture the effects of motivation on wages rather than the real returns on experience. A standard way to deal with the heterogeneity bias caused by the correlation of α_i with the regressors is to apply fixed effects (FE) estimators, either the mean-deviation estimator or first-difference estimator. The mean-deviation estimator removes α_i by expressing all variables as deviations from individual means whereas the first-difference approach sweeps out α_i by subtracting variables with their lagged values. The FE estimator is consistent if the conditional expectation of the transformed ε_{it} is zero given the transformed regressors.[13]

An obvious shortcoming of the FE estimator is that it not only sweeps out the unobserved time-constant heterogeneity term, but also all other time-constant regressors. One way to deal with the endogeneity problems due to unobserved individual-specific effects and yet to get estimates for the time-constant regressors is to apply instrumental variable (IV) estimators. In this model one needs to find variable(s) (i.e. instrument(s)) that is (are) sufficiently correlated with the endogenous variables, but not with the error term of the model. The difficulty with the IV estimator is that in practice it is very

[13] In the case of the first-difference estimator, the transformed ε_{it} is defined as ε_{it} - ε_{it-1}. If the mean-deviator estimator is applied, the transformed ε_{it} is equal to ε_{it} - $\varepsilon_{i.}$ where $\varepsilon_{i.}$ is the individual mean of ε_{it}. Transformed regressors and the dependent variable are defined in a similar way.

hard to come up with instruments that satisfy both of these conditions.

There are naturally many other sources of endogeneity than that due to unobserved individual heterogeneity. One is non-random selection into the labour market. For example, women with low earnings potential might choose to drop out from the labour market and focus on raising children instead. In this case, ignoring sample selection would lead to underestimation of the true gender wage gap. Another potential source of selection bias is the choice of sector of employment. Women typically account for a much larger share of the public sector employment than men. One explanation for this is that the public sector is often seen as a family-friendly employer which offers better opportunities to combine work and family than private sector. Therefore it might be that women who are highly career-oriented and ambitious self-select into the private sector, in which case ignoring sample selection would again probably lead to underestimation of the gender wage differentials. If these selection processes are time dependent, FE estimators do not help to provide consistent estimates. One solution to correct for the selectivity bias would be Heckman's two-stage sample selection model (Heckman 1979).

In this paper, I use OLS, RE and FE estimation techniques to obtain the parameter estimates of the wage model (1) separately for male and female samples.[14] By applying different estimation techniques I get information on how sensitive my conclusions concerning the factors behind the early-career gender wage differentials are with respect to the identification assumptions made. This is important

[14] Of the FE estimators, the mean-deviation estimator is used.

since the credibility of the conclusions hinges on consistent estimation of the parameters of interest. Comparisons of OLS estimates and those obtained by RE and FE estimation shed light on the importance of unobserved time-invariant heterogeneity in my data. Furthermore, by comparing OLS and RE results to FE estimates I get information on the possible bias due to correlation of the unobserved characteristics with the regressors.

As discussed above, even though I deal with heterogeneity bias by employing FE estimators several potential sources of endogeneity problems remain. Of these the non-random selection of women into the labour market is of less concern since I use data from Finland, where the labour market participation rates of women are very high, and even more so among the highly educated women (e.g. Pissarides et al. 2005). It should also be noticed that my data are unlikely to suffer from the selection bias arising from gender differences regarding university education because the gender gap in this respect is small as well.[15] Instead the choice of the sector of employment might give rise to selection problems. In Finland, like in many other countries, women's share of the public sector employment is high compared to men. The evidence concerning the importance of the bias due to endogenous sector choice is somewhat mixed, the conclusions varying among other things with the countries being analyzed. The earlier results using different data sets suggest, however, that the non-random selection into the private and public sectors is probably not a serious problem in Finland (Asplund 1993).

Besides selectivity, additional sources of endogeneity arise if the error term is more complex than what I assume. It could well be that in

[15] The female share of the Finnish university graduates is about 53 per cent.

addition to the unobserved time-invariant individual heterogeneity effect the error term contains, for example, a match-value component capturing the value of the worker-firm match.[16] It is also plausible that the unobserved individual heterogeneity component is not time-invariant but has different effects at different stages of a career, in which case the FE estimator does not remove the heterogeneity bias. These considerations should be kept in mind when interpreting the results.

5. The Results

5.1 Estimation Results

Table 2 shows the estimation results separately for male and female university graduates. Starting with the work experience variables, the returns to work experience seem to be higher for men than for women. This is a fairly typical finding in the gender wage gap literature. For example, Light and Ureta (1995) conclude that the gender differences in the return to experience account much more for the gender wage gap than gender differences in the accumulation of experience. And although there are considerable differences in the parameter estimates for the work experience between the different estimation methods, the results in table 2 show that experience is more valuable for men than for women irrespective of the estimator. The returns to work experience are much higher for both men and women in the case of RE and FE estimators compared to OLS

[16] For example, the mobility variables in equation (1) are likely to be endogenous in the presence of a match-value component because low-value matches are more likely to be ended than high-value matches.

estimates. Again, this finding is consistent with earlier literature (e.g. Kim and Polachek 1994).

There also seem to be gender differences in the time effects of experience. For men I find that the most recent work experience is more valuable than experience acquired further back in the past. For women, however, this pattern is less pronounced.[17] This is in line with Light and Ureta (1995) as also in their paper the path of higher returns to more recent experience appears to be more evident among men. This may partly reflect the potential endogeneity problems with the work history variables used in the wage model. Furthermore, the results in table 2 shows that estimates for variables capturing the effects of time out of work are typically statistically insignificant and do not exhibit wage penalties from career breaks. This might be partly due to the fact that workers in my sample are highly attached to the labour market and periods with zero months in work during the year are fairly uncommon.[18]

Results for education variables offer few surprises. For example, getting a degree in social science and business or in technology seems to provide better earnings prospects for both genders than a degree in humanities. Estimates for the field of education are not, however, typically significant. On the other hand, male and female graduates with a master's degree both have about 20 per cent higher wages than graduates with a bachelor's degree. Instead the estimates for the family type variables differ significantly between men and women. Marriage seems to have positive wage effects for

[17] To check whether the standard results hold, I also estimated a wage model with (potential) experience and (potential) experience squared. Coefficients for experience variables show expected signs for both genders.
[18] Only about 5 per cent of male observations are from years with zero months in work. For women the corresponding figure is 9 per cent.

men but negative effects for women. This is in line with the earlier research (e.g. Dolton and Makepeace 1987; Schoeni 1990; Korenman and Neumark 1991, 1992). It is also well-established in the literature that children have asymmetric effects on men's and women's wages. A fairly typical finding has been a child-penalty of 10 to 15 per cent for women but no negative wage effects for men (e.g. Korenman and Neumark 1992; Jacobsen and Rayack 1996; Loh 1996). A similar conclusion can also be drawn from table 2: children do not have negative effects on men's wages but women appear to suffer a considerable child-penalty. OLS estimates suggest that this penalty is restricted to women with children below school age whereas the RE and FE results imply that not only women with small children suffer a wage penalty but women with children in general have lower wages than childless women. The estimates of the size of the penalty of small children vary between 22.1 per cent (FE estimate) and 33.4 per cent (OLS estimate), which are somewhat higher than what has been typically found in the literature. This is undoubtedly at least partly due to my inability to control for working hours and part-time work.

Results for employer characteristics are mostly what could be expected on the grounds of the earlier empirical evidence. For example, large firms pay higher wages than small firms. Wages are also higher in foreign-owned firms, in firms with highly educated personnel and in more productive firms. These conclusions hold for both men and women. Somewhat surprisingly, estimates for the gender structure of the firm are insignificant irrespective of the estimator used or gender.

Finally, mobility seems to be positively correlated with wages for both men and women. For women, however, the estimates for mobility variables are insignificant. I do not find evidence of decreasing returns to mobility and neither do I find that the estimates for interaction terms aiming to distinguish between voluntary and involuntary mobility are statistically significant.

Although the estimation results are interesting as such, it is, however, quite difficult to make conclusions about the factors driving the early-career gender wage gap among university graduates based on the estimates shown in table 2. To get more insight into the mechanisms giving rise to the gender wage gap, in the following section I apply a wage gap decomposition technique.

5.2 Wage Gap Decomposition

Researchers have suggested several different wage decomposition techniques in order to identify the most relevant factors underlying the gender wage differentials (see e.g. Altonji and Blank 1999; Kunze 2007). The standard approach used in the literature is the Blinder-Oaxaca decomposition (Blinder 1973; Oaxaca 1973), which is typically written as:

$$\underbrace{\overline{\ln W}^{M} - \overline{\ln W}^{F}}_{raw\ wage\ gap} = \underbrace{(\overline{X}^{M} - \overline{X}^{F})\hat{\beta}^{M}}_{explained\ part} + \underbrace{\overline{X}^{F}(\hat{\beta}^{M} - \hat{\beta}^{F})}_{unexplained\ part}, \qquad (2)$$

where upper bars refer to sample means, M and F stand for male and female respectively, and $\hat{\beta}^{M}$ and $\hat{\beta}^{F}$ results from estimation of wage regressions separately for men and women. The first term in the right-hand side of the equation describes the contribution of gender differences in characteristics to the wage gap, which in the literature is interpreted as the "explained part" of the wage gap. The second term is the "unexplained part" which measures gender differences in the parameter estimates. It is often used as a measure of discrimination in the labour market.

There are several problems related to the decomposition techniques such as that shown in (2).[19] One is the choice of the price structure used to weight gender differences in characteristics. In equation (2), male prices serve as proxies for competitive market prices, but there are also many other possibilities. For instance, one might as well use estimates from female-only sample or some weighted average of male and female samples. In the literature, however, male prices serve most often as a reference price structure. The justification for this is that men are unlikely to face discrimination in the labour market. However, many other weighting matrices have been suggested. For example, Reimers (1983) argue that in a non-discriminatory world neither the majority group's (men in my setting) nor the minority group's (women) wage distribution would exist but the non-discrimination wage distribution would probably lie somewhere between them. Therefore, Reimers chooses to use a weight of 0.5 in the decomposition analysis. Using a similar kind of argumentation, Cotton (1988) proposes a weight equal to the proportion of the group's share of employed work force. Since then, many more weighting matrices have been introduced (see e.g. Oaxaca and Ransom 1994).

Another important issue with the decomposition techniques concerns the consistency of the parameter estimates of the model. Inconsistent estimates might not only cause incorrect conclusions about the size of the unexplained part of the gap, but might also lead to over- or underestimation of the contribution due to gender

[19] These problems relate not only to the Blinder-Oaxaca decomposition, but concerns decomposition techniques in general.

differences in characteristics as these differences are weighted with inconsistently estimated prices. Finally, possible measurement errors in variables included in the model might also lead to inconsistent estimation both of the explained and unexplained parts of the decomposition.

A much less obvious problem with decompositions such as (2) is the identification problem related to estimation of the contribution of single factors to the wage gap. While for the explained part of the decomposition it is possible to separate the effects of a subset of variables, this is not the case for the unexplained part.[20] This identification problem might be particularly relevant if dummy variables are included in the vector of regressors. In this case, the effects of a subset of coefficients depend on the choice of the omitted group (see e.g. Jones 1983; Oaxaca and Ransom 1999; Horrace and Oaxaca 2001).

In the following, I focus on the explained part of the wage gap. The estimated wage model includes several categorical variables and therefore the unexplained component is of less interest due to the identification problem discussed. Although the economic interpretation is perhaps more evident for the explained part than for the unexplained term, it should be noticed that the explained part might not only reflect gender differences in human capital investments and preferences, but some of the gap in endowments might be a result of discriminatory factors. Therefore, the decomposition technique applied should be interpreted as a method which *mechanically* decomposes the average gender wage gap into more detailed factors contributing to the wage gap rather than a

[20] The contribution of the differences in parameter estimates is well-defined only when they are calculated over all coefficients, including the intercept.

technique which provides an estimate of the size of the gender wage gap not due to labour market discrimination.

The decomposition focus on the role of gender differences in experience, the field of education, industry, other employer characteristics and mobility in explaining the early-career gender gap in wages among university graduates. As discussed above, the credibility of the decomposition results depends critically on the consistency of the parameter estimates and the assumptions concerning the competitive price structure. To provide information on how sensitive my conclusions are in this respect, I show the decomposition results using three sets of estimates (OLS, RE and FE) and three different reference price structures (male, female and pooled).

Tables 3-5 show the decomposition results. The first row in the tables documents that the average gender wage gap during the observation period among those used in estimations is 31.1 log points. Of this gap, gender differences in characteristics used to explain wages in model (1) account only for a fairly small part. Decompositions based on OLS and RE estimates suggest that they explain 20 to 26 per cent of the average wage gap depending on the reference wage structure used. FE estimates show even lower contribution, which is partly due to the fact that the effect of the field of education drops out as the field of education is a time-invariant variable in the wage model. The most robust finding in the sense that it holds irrespective of the estimator and the price structure used is that the field of education matters with respect to the gender wage gap. Gender differences in the type of education account for 5 to 11 per cent of the average gender wage gap, which is a considerable amount of the total explained wage gap.

The gender gap in work experience is also an important single factor behind the sex-based wage differentials. Differences in experience account most when FE estimates are used, in which case experience explains 6 to 11 per cent of the average gender wage gap the contribution varying with the price structure applied: female prices produce the lowest and male prices the highest estimate of the importance of experience. OLS and RE estimates give somewhat lower estimate of the effects of work experience. If male prices or estimates from the pooled model are used, then OLS and RE estimators suggest that gender differences in experience account for 5 to 9 per cent of the average gender wage gap. On the other hand, if female prices are applied, the contribution of experience to the wage gap is between 2 and 4 per cent.

Gender differences in mobility seem to be irrelevant in accounting for the early-career gender wage gap. This is what one could expect on the grounds of table 1, which shows that gender differences in mobility are in fact fairly small in my data. On the other hand, the results concerning the importance of men's and women's segregation into different industries and different types of firms in explaining the gender wage gap differ between estimation methods. OLS and RE both suggest that gender segregation in these terms matters whereas the contributions of industry and other firm characteristics are insignificant when FE estimates are applied. This might be due to the fact that there is fairly little within-individual variation in employer characteristics resulting imprecise FE estimates.

Much of the early-career gender wage gap thus remains unexplained. For some reasons, there are considerable gender differences in the wage effects of certain characteristics contributing to different wage development between men and women. One of the most eyecatching gender difference in the parameter estimates presented in table 2 is the wage effects of children. Women suffer a considerable child-penalty whereas men's wages are not affected by children. As discussed above, this is a typical finding in the literature. The fact that there is a child-penalty for women but not for men suggests that the asymmetric effect of children is one potential explanation for the sex-based wage gap. Therefore, the last part of the paper investigates in more detail the issue of children behind the early-career gender wage gap.

5.3 Effects of Children on the Early-Career Gender Wage Gap

I examine the effects of children on the wage profiles by focusing on those who have no family at the entry to the labour market but who get children at some point during the investigation period. For these university graduates I calculate three different experience variables: experience before the first childbirth, experience after the last born child observed in the data is at least three years old, and finally, experience between the two periods.[21] This specification, which draws heavily on the paper by Datta Gupta and Smith (2003), is interesting for several reasons. First of all, it provides information on whether men and women differ in wage profiles already before childbirth or whether the widening of the gender wage gap takes place after the child-related career break. Secondly, this specification also sheds some light on the issue of to what extent the large estimated child-penalties are driven by my inability to control for working hours and part-time work. In this case I might expect to see a large increase in the gender wage gap following the years immediately after the

[21] Experience here refers to potential experience.

childbirth as the need for adjusting working hours is probably greatest during this period. The wage gap should, however, recover as children get older and the demand for part-time work decreases. On the other hand, if the child penalty has more to do with the differences in career development between men and women with children, then the gender wage gap might remain at high levels, or even increase, even though children get older.

The imposed restrictions cause a fairly large decrease in the number of observations. Therefore, I estimate a somewhat simpler model for this sample. Instead of using 23 different industry indicators as in the full model, the simplified specification includes 17 industry dummies. The number of controls for the field of education decreases from eight to three. The wage model is estimated by OLS and RE methods. Due to the small number of observations, the FE estimator provided very imprecise estimates and identification in this case required restricting the set of explanatory variables even further. Therefore, in the following I focus only on the OLS and RE results.

Table 6 presents the estimation results. The discussion of the results will focus on the experience variables as the main interest of this exercise is in the effects of children on the wage-experience profiles of men and women. As can be seen, both OLS and RE estimation results show that there are substantial gender differences in the wage-experience relationship. Men gain more from experience both before and between childbirths. However, after childbirths women seem to catch up with men in wages. Interestingly, between the childbirths the female estimates for the experience variables are of the "wrong" sign. This might reflect women's adjustments of their working hours when the child is very young.

To get a more precise picture of the effects of children on the gender wage gap tables 7 and 8 show predicted gender wage gaps based on the parameter estimates presented in table 6. The predicted gender wage differentials are calculated by multiplying the gender difference in the parameter estimates with a vector of average mean characteristics calculated from the pooled sample of those men and women used in the estimations shown in table 6. The results indicate that the gender wage gap is high already before the childbirth suggesting that also other factors than the child-related career breaks have a role in explaining the early-career gender wage differentials. Between childbirths there is a substantial increase in the gender wage gap, but after the last childbirth recorded in the data the wage gap recovers quickly and returns to the level preceding the births or falls even below that. This is consistent with the hypothesis that the large observed child-penalty for women is at least partly due to the fact that women tend to work less during the immediate years after childbirth. Again, the conclusions made are independent of the estimation method applied.

6. Conclusions

In this paper I have illustrated that understanding the gender wage gap in the Finnish private sector essentially requires identification of factors contributing to the gender gap in early-career wage development. Using data from Statistics Finland I showed that the gender wage gap increases significantly during the first years in the labour market accounting for most of the life-time increase in the gender wage gap.

The more detailed analysis of the early-career gender wage gap focused on university graduates from 1996 and 1997. Several different explanations for the wage gap were considered. For example, gender differences in the accumulation of work experience and the field of education were examined. Also the importance of women's segregation into different types of firms than men and gender differences in job mobility were investigated.

The results suggest that only a fairly small part of the early-career gender wage gap among university graduates can be explained by gender differences in qualifications considered. Decompositions based on OLS and RE estimates show that 20 to 26 per cent of the average early-career gender wage gap is explained by differences in variables used in the wage model. Of the investigated factors the field of education and work experience matter most. They both explain about 5 to 11 per cent of the average gender wage gap, the contribution varying depending on the estimation method and the price structure used in the decomposition. Men's and women's segregation into different industries and different types of employers matter as well, but not as much as the field of education and work experience. Job mobility, on the other hand, proved to be irrelevant in accounting for the early-career gender wage differentials.

Thus, most of the wage gap is accounted for by gender differences in the estimated returns to characteristics. One of the most notable gender differences in this respect is the asymmetric effect of children on men's and women's wages. The estimation results imply that children have no effects on men's wages whereas women suffer a substantial child-penalty. A more detailed analysis of the child-penalty shows that the gender wage gap increases significantly during the years immediately after the childbirth but that women catch up with men in wages as the child gets older. This pattern is consistent with the hypothesis that women tend to cut working hours when children are very young. Furthermore, this implies that my estimates of the child-penalty are probably upward biased due to my inability to control for hours in work. However, the analysis also shows that women's wages are significantly lower than men's already before the childbirth. This indicates that also other factors than child-related career breaks have a role in explaining the early-career gender wage gap. My results imply that among these other factors the type of schooling seems to be of particular importance.

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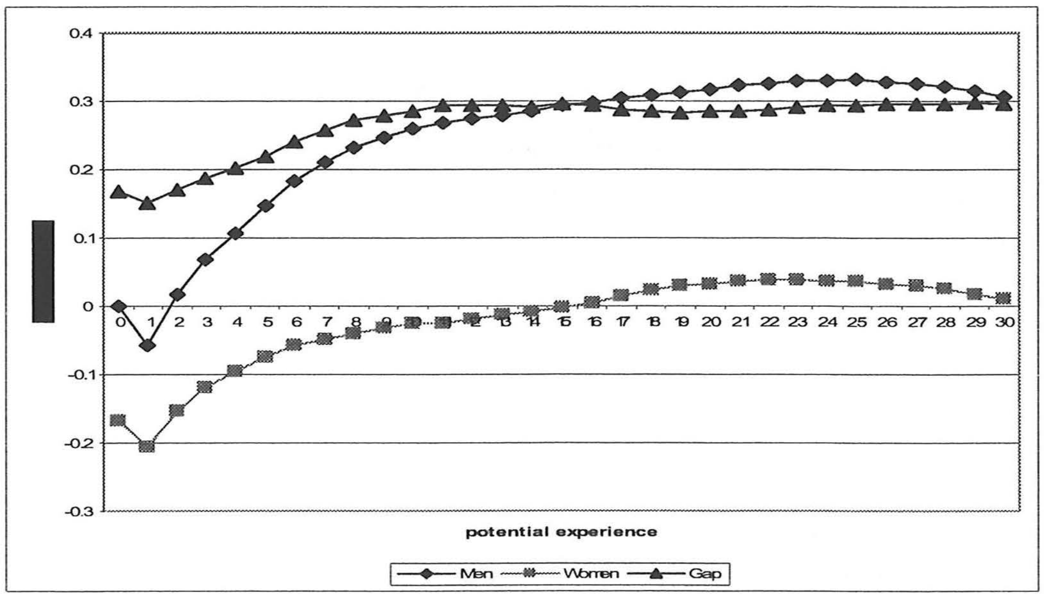
Figure 1: Wage-experience profiles for men and women in the Finnish private sector



Notes:
1. Wages are normalized to be zero for men with zero years of potential experience.

Figure 2: Gender wage gap for different birth cohorts

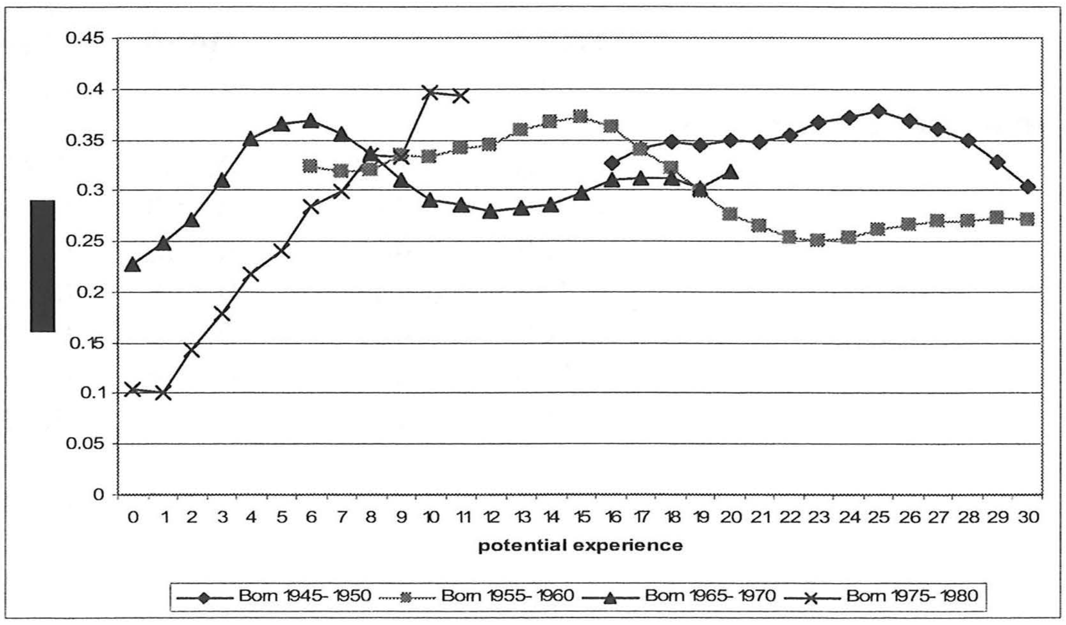
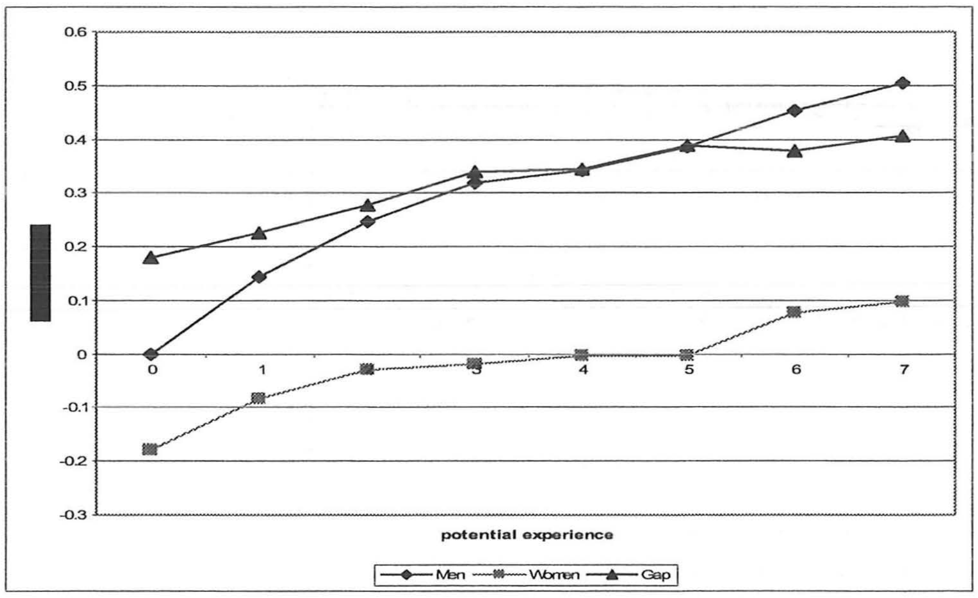


Figure 3: Wage-experience profiles for male and female university graduates from 1996-1997



Notes:
1. Wages are normalized to be zero for men with zero years of potential experience.

Table 1: Summary statistics

Variable	Men Mean	Men Std. Dev.	Women Mean	Women Std. Dev.
ln real monthly wage	8.011	0.384	7.700	0.479
fraction of the year spent in working:				
last year	0.828	0.357	0.796	0.371
two years ago	0.698	0.443	0.668	0.446
three years ago	0.568	0.481	0.538	0.477
four years ago	0.436	0.483	0.405	0.472
five years ago	0.308	0.451	0.280	0.433
six years ago	0.183	0.378	0.164	0.358
seven years ago	0.057	0.226	0.047	0.204
education:				
educational science	0.003	0.059	0.016	0.125
humanities and arts	0.016	0.126	0.115	0.319
social sciences and business	0.184	0.387	0.467	0.499
natural science	0.045	0.207	0.047	0.212
technology	0.718	0.450	0.209	0.407
agriculture and forestry	0.019	0.135	0.027	0.162
health and welfare	0.007	0.084	0.088	0.284
services	0.008	0.090	0.031	0.172
bachelor	0.544	0.498	0.464	0.499
family type:				
married	0.486	0.500	0.419	0.493
children (0/1)	0.404	0.491	0.327	0.469
children below school age (0/1)	0.385	0.487	0.313	0.464

(table 1 continues)

firm size:				
below 5 workers	0.011	0.104	0.017	0.128
5-9 workers	0.043	0.203	0.064	0.245
10-19 workers	0.057	0.232	0.094	0.292
20-49 workers	0.106	0.308	0.105	0.306
50-99 workers	0.085	0.278	0.090	0.286
100-299 workers	0.149	0.356	0.145	0.352
300 or more workers	0.549	0.498	0.486	0.500
gender structure of the personnel of the firm:				
female-dominated	0.059	0.235	0.316	0.465
male-dominated	0.809	0.393	0.454	0.498
balanced	0.133	0.339	0.230	0.421
other employer characteristics:				
foreign ownership (0/1)	0.194	0.396	0.208	0.406
personnel's average years of schooling	13.073	1.322	12.909	1.357
the average age of the personnel	37.593	4.332	37.424	4.383
log of value added per worker	11.163	0.726	11.006	0.748
mobility:				
cumulative mobility	0.742	0.987	0.784	1.002
contraction	0.065	0.246	0.069	0.253
Number of observations	13,532		7,501	

Notes:
1. Sample is that used in the estimations.

Table 2: Estimation results for male and female university graduates

Dependent variable: log of real monthly wages

	MEN			WOMEN		
	(1) OLS	**(2) RE**	**(3) FE**	**(4) OLS**	**(5) RE**	**(6) FE**
% of year spent working:						
last year	0.142	0.194	0.232	0.055	0.091	0.122
	(8.06)**	(10.91)**	(9.25)**	(2.49)*	(4.25)**	(4.21)**
2 years ago	0.107	0.157	0.196	0.007	0.047	0.094
	(6.40)**	(9.12)**	(8.05)**	(0.34)	(2.21)*	(3.26)**
3 years ago	0.107	0.151	0.189	0.006	0.042	0.087
	(6.36)**	(8.72)**	(7.73)**	(0.29)	(1.86)	(2.83)**
4 years ago	0.078	0.128	0.169	0.034	0.079	0.130
	(5.05)**	(7.62)**	(6.95)**	(1.60)	(3.79)**	(4.44)**
5 years ago	0.099	0.135	0.173	0.020	0.052	0.095
	(6.34)**	(8.31)**	(7.20)**	(0.84)	(2.17)*	(2.91)**
6 years ago	0.117	0.142	0.178	0.069	0.087	0.129
	(6.90)**	(8.46)**	(7.47)**	(2.60)**	(3.29)**	(3.71)**
7 years ago	0.086	0.120	0.156	0.003	0.035	0.081
	(4.46)**	(6.13)**	(6.03)**	(0.08)	(1.12)	(2.11)*

(table 2 continues)

1 if career in progress but did not work:						
last year	-0.003	0.058	0.074	0.020	0.058	0.079
	(0.08)	(1.38)	(1.12)	(0.48)	(1.41)	(1.52)
2 or more years ago	0.042	0.119	0.152	-0.054	0.000	0.074
	(1.39)	(3.38)**	(2.03)*	(1.66)	(0.01)	(1.21)
field of education:						
humanities	-0.038	0.013		-0.040	-0.047	
	(0.32)	(0.08)		(0.62)	(0.62)	
social science	0.114	0.196		0.099	0.099	
	(1.06)	(1.35)		(1.62)	(1.35)	
natural science	0.021	0.081		0.038	0.030	
	(0.20)	(0.56)		(0.56)	(0.37)	
technology	0.099	0.163		0.134	0.133	
	(0.92)	(1.13)		(2.16)*	(1.79)	
agriculture	-0.014	0.063		0.111	0.112	
	(0.12)	(0.42)		(1.56)	(1.34)	
health	-0.001	0.106		0.107	0.097	
	(0.01)	(0.69)		(1.62)	(1.24)	
services	0.031	0.133		0.032	0.027	
	(0.26)	(0.86)		(0.47)	(0.34)	
(omitted group: educational science)						
level of degree:						
bachelor	-0.199	-0.208		-0.210	-0.232	
	(20.01)**	(19.09)**		(13.18)**	(13.94)**	
(omitted group: master level)						
family type:						
married	0.027	0.018	0.006	-0.019	-0.030	-0.056
	(2.80)**	(2.19)*	(0.59)	(1.41)	(2.51)*	(3.62)**
children	0.040	0.011	0.003	-0.009	-0.094	-0.235
	(1.49)	(0.55)	(0.14)	(0.23)	(2.94)**	(4.33)**
children below school age	-0.014	-0.005	-0.009	-0.334	-0.295	-0.221
	(0.54)	(0.22)	(0.42)	(8.47)**	(8.85)**	(4.14)**
firm size (number of workers):						
5-9	0.080	0.017	-0.015	0.131	0.124	0.105
	(1.63)	(0.45)	(0.38)	(3.05)**	(2.76)**	(1.90)
10-19	0.167	0.082	0.033	0.208	0.179	0.134
	(3.33)**	(2.15)*	(0.83)	(4.67)**	(4.05)**	(2.40)*
20-49	0.214	0.122	0.062	0.199	0.183	0.141
	(4.35)**	(3.15)**	(1.50)	(4.43)**	(4.06)**	(2.35)*
50-99	0.249	0.148	0.081	0.230	0.203	0.167
	(5.00)**	(3.79)**	(1.95)	(5.13)**	(4.43)**	(2.74)**
100-299	0.251	0.149	0.076	0.225	0.209	0.164
	(5.12)**	(3.80)**	(1.77)	(5.15)**	(4.73)**	(2.72)**
300 or more	0.244	0.150	0.068	0.221	0.207	0.142
	(5.03)**	(3.88)**	(1.62)	(5.14)**	(4.72)**	(2.33)*
(omitted group: below 5 workers)						
other firm characteristics:						
foreign	0.063	0.033	0.013	0.057	0.023	-0.013
	(5.48)**	(3.05)**	(0.94)	(3.36)**	(1.42)	(0.59)
mean years of schooling	0.038	0.027	0.011	0.031	0.033	0.011
	(6.87)**	(5.63)**	(1.87)	(4.14)**	(4.82)**	(1.13)
mean age	-0.034	-0.010	0.003	-0.010	-0.020	-0.020
	(2.48)*	(0.79)	(0.21)	(0.46)	(1.04)	(0.85)

(table 2 continues)

mean age^2/10	0.004	0.001	-0.001	0.001	0.003	0.003
	(2.11)*	(0.51)	(0.31)	(0.51)	(1.13)	(0.94)
male dominated	-0.034	0.001	-0.000	0.033	0.033	0.007
	(1.63)	(0.07)	(0.02)	(1.58)	(1.66)	(0.27)
balanced	-0.011	0.000	-0.010	0.024	0.018	-0.006
	(0.48)	(0.01)	(0.43)	(1.21)	(1.00)	(0.28)
(omitted group: female dominated)						
ln(productivity)	0.052	0.024	0.010	0.060	0.027	-0.004
	(7.60)**	(4.65)**	(1.87)	(6.22)**	(3.14)**	(0.38)
mobility:						
cumulative mobility	0.028	0.030	0.032	0.028	0.024	0.019
	(2.78)**	(3.49)**	(3.46)**	(1.84)	(1.73)	(1.12)
cumulative mobility^2/10	0.004	-0.013	-0.027	-0.013	-0.026	-0.026
	(0.13)	(0.56)	(1.09)	(0.33)	(0.76)	(0.69)
cum.mob.* contraction	-0.011	0.012	0.018	-0.006	-0.024	-0.034
	(0.46)	(0.70)	(1.04)	(0.16)	(0.86)	(1.18)
cum.mob.^{2}/10 *contraction	0.060	-0.008	-0.023	-0.019	0.046	0.087
	(0.69)	(0.14)	(0.40)	(0.15)	(0.48)	(0.89)
constant	7.308	7.248	7.382	6.586	7.103	7.643
	(25.20)**	(25.88)**	(24.30)**	(16.54)**	(19.42)**	(18.00)**
observations	13,532	13,532	13,532	7,501	7,501	7,501
R-squared	0.39	0.36	0.37	0.34	0.18	0.19

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

Notes:
1. In addition to the variables presented above, all regressions also include industry dummies (23 categories), region dummies (6 categories) and year dummies. OLS and RE models further include a dummy controlling for the year of graduation.
2. Within R-squared are reported for RE and FE estimators.
3. t-statistics are in parentheses, and they are calculated using robust standard errors with clustering on the individual.

Table 3: Decomposition of the average gender wage gap based on OLS estimates

Sample used for coefficients	male	female	pooled
Average early-career gender wage gap	0.311	0.311	0.311
Contribution from gender differences in:			
experience	0.019	0.005	0.015
	(0.003)***	(0.003)**	(0.003)***
field of education	0.021	0.0336	0.021
	(0.009)**	(0.010)***	(0.006)***
industry	0.014	0.011	0.012
	(0.005)**	(0.006)*	(0.004)***
other firm character	0.009	0.027	0.017
	(0.006)	(0.007)***	(0.005)***
mobility	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Total contribution (%)	20.0	24.2	20.1

Notes:
1. See notes to table 5.

Table 4: Decomposition of the average gender wage gap based on RE estimates

Sample used for coefficients	male	female	pooled
Average early-career gender wage gap	0.311	0.311	0.311
Contribution from gender differences in:			
experience	0.027	0.011	0.022
	(0.004)***	(0.003)***	(0.003)***
field of education	0.014	0.035	0.019
	(0.009)	(0.010)***	(0.007)***
industry	0.007	0.011	0.008
	(0.005)	(0.006)*	(0.004)**
other firm character	0.014	0.023	0.017
	(0.005)**	(0.007)***	(0.004)***
mobility	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Total contribution (%)	19.6	25.8	21.0

Notes:
1. See notes to table 5.

Table 5: Decomposition of the average gender wage gap based on FE estimates

Sample used for coefficients	male	female	pooled
Average early-career gender wage gap	0.311	0.311	0.311
Contribution from gender differences in:			
experience	0.034 (0.006)***	0.019 (0.005)***	0.028 (0.005)***
field of education	- -	- -	- -
industry	0.006 (0.006)	0.003 (0.011)	0.001 (0.006)
other firm character	0.007 (0.006)	0.007 (0.009)	0.008 (0.005)
mobility	-0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)
Total contribution	14.7	9.2	11.7

Notes:
1. Decompositions in tables 3-5 are based on OLS, RE and FE estimates of wage model (1) respectively. Contribution of experience excludes the effects of career breaks variables. Other firm characteristics refer to the combined effects of gender differences in firm size, foreign ownership, personnel's average years of schooling, the average age of the personnel (and its square) and the productivity measure of the firm on the gender wage gap. The table only investigates gender differences in endowments.
2. Three reference price structures are used: male, female and pooled. Pooled refers to a wage model which combines male and female samples in which case a female-dummy is included as an additional variable in the regressions.
3. The standard errors of the components are in parenthesis. They are calculated using oaxaca-command in Stata 10.0 which computes the standard errors according to the method presented by Jann (2005).
4. *** significant at 1 %; ** significant at 5 %; * significant at 10 %.

Table 6: Estimation results for male and female university graduates who have no family at time of labour market entry but who get children during the observation period

Dependent variable: log of real monthly wages	MEN		WOMEN	
	(1) OLS	(2) RE	(3) OLS	(4) RE
experience:				
exp. before 1st childbirth	0.038	0.040	0.014	0.018
	(3.11)**	(4.01)**	(0.97)	(1.31)
exp. before 1st childbirth^2/10	-0.026	-0.029	-0.004	-0.008
	(2.52)*	(3.21)**	(0.33)	(0.68)
exp. between childbirths	0.014	0.014	-0.281	-0.265
	(1.02)	(1.15)	(12.25)**	(11.77)**
exp. between childbirths^2/10	-0.016	-0.016	0.443	0.403
	(0.79)	(0.89)	(11.61)**	(10.87)**
exp. after childbirths	0.018	0.017	0.404	0.445
	(1.00)	(1.15)	(9.66)**	(11.18)**
exp. after childbirths^2/10	0.024	-0.021	-0.715	-0.769
	(0.40)	(0.49)	(5.72)**	(6.72)**
field of education:				
technology	-0.020	-0.031	0.001	0.002
	(0.92)	(1.34)	(0.04)	(0.08)
other	-0.141	-0.152	-0.059	-0.059
	(4.55)**	(4.63)**	(2.04)*	(2.00)*
(omitted group: social science and business)				
level of degree:				
bachelor	-0.215	-0.228	-0.244	-0.250
	(13.43)**	(13.47)**	(9.51)**	(9.59)**
(omitted group: master level)				
family type:				
married	0.004	0.005	-0.053	-0.072
	(0.25)	(0.38)	(2.52)*	(3.58)**
firm size (number of workers):				
5-9	0.163	0.157	0.219	0.196
	(1.77)	(1.83)	(2.42)*	(2.22)*
10-19	0.154	0.142	0.278	0.245
	(1.67)	(1.65)	(2.93)**	(2.69)**
20-49	0.269	0.219	0.318	0.277
	(2.99)**	(2.58)**	(3.44)**	(3.17)**
50-99	0.333	0.260	0.354	0.289
	(3.67)**	(2.99)**	(3.73)**	(3.24)**
100-299	0.289	0.243	0.283	0.252
	(3.20)**	(2.75)**	(3.02)**	(2.86)**
300 or more	0.299	0.244	0.307	0.278
	(3.35)**	(2.84)**	(3.26)**	(3.12)**
(omitted group: below 5 workers)				
other firm characteristics:				
foreign	0.055	0.027	0.057	0.033
	(3.07)**	(1.65)	(2.06)*	(1.25)
mean years of schooling	0.035	0.030	0.041	0.043
	(4.36)**	(3.76)**	(3.31)**	(3.66)**
mean age	-0.030	-0.010	-0.025	-0.044
	(1.38)	(0.47)	(0.60)	(1.15)
mean age^2/10	0.003	0.001	0.004	0.006
	(1.13)	(0.33)	(0.67)	(1.20)
male dominated	-0.095	-0.039	0.038	0.038
	(3.04)**	(1.36)	(1.14)	(1.17)

(table 6 continues)

balanced	-0.081	-0.043	0.041	0.031
	(2.43)*	(1.45)	(1.33)	(1.08)
(omitted group: female dominated)				
ln(productivity)	0.059	0.034	0.071	0.046
	(5.45)**	(3.85)**	(4.43)**	(3.10)**
mobility:				
cumulative mobility	0.016	0.028	0.082	0.077
	(0.99)	(1.94)	(3.09)**	(3.09)**
cumulative mobility^2/10	0.017	-0.041	-0.132	-0.135
	(0.40)	(1.14)	(1.81)	(2.12)*
cum.mob.*contraction	0.019	0.023	-0.127	-0.140
	(0.49)	(0.78)	(1.68)	(1.93)
cum.mob. ^2/10*contraction	-0.042	-0.060	0.480	0.501
	(0.31)	(0.56)	(1.65)	(1.79)
constant	7.184	7.039	6.584	7.222
	(17.78)**	(17.39)**	(8.26)**	(10.04)**
observations	4,606	4,606	2,771	2,771
R-squared	0.38	0.34	0.29	0.17

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

Notes:
1. The sample is university graduates who have no children at time of labour market entry but who get children at some point during the observation period.
2. Definitions of the variables are discussed in Sections 4 and 5.
3. In addition to the variables presented above, all regressions also include industry dummies (17 categories), region dummies (6 categories), a dummy controlling for the year of graduation and year dummies.
4. Within R-squared are reported for RE estimator.
5. The t-statistics are in parentheses, and they are calculated using robust standard errors with clustering on the individual.
6. Wage information from one year before the childbirth is not used because the behavior of mothers-to-be may be affected by the future career break.
7. Field "other" includes educational science, humanities and arts, natural science, agriculture and forest, health and welfare and services.

Table 7: Predicted gender wage gap based on OLS estimates

	Predicted gender wage gap	Change in the predicted gender wage gap
experience before childbirth		
1	0.226	
2	0.244	0.018
experience between childbirths		
1	0.493	0.249
2	0.650	0.157
experience after childbirths		
1	0.339	-0.312
2	0.175	-0.164

Notes:
1. See notes to table 8.

Table 8: Predicted gender wage gap based on RE estimates

	Predicted gender wage gap	Change in the predicted gender wage gap
experience before childbirth		
1	0.244	
2	0.261	0.017
experience between childbirths		
1	0.499	0.238
2	0.652	0.154
experience after childbirths		
1	0.300	-0.353
2	0.097	-0.203

Notes:
1. The predicted gender wage gaps are based on the estimation results presented in Table 6. They are calculated by multiplying the gender difference in the parameter estimates with a vector of average mean characteristics calculated from the pooled sample of men and women.

III Type of Education and the Gender Wage Gap*

Abstract

This paper investigates the role of university majors in explaining the gender wage gap. Using data from the Confederation of Finnish Industries, significant gender differences in majors among white-collar workers are found. These differences in education account for 37.6 per cent of the gender wage gap among young white-collar workers with a bachelor-level degree after controlling for age, year, gender, region, industry and firm size. The corresponding number for young white-collar workers with a master-level degree is 30.9 per cent. There are no considerable differences in the effects of majors between new entrants and white-collar workers having more work experience. Furthermore, the similarity of the results between OLS and random and fixed effects estimations implies that the effect of university majors is unlikely to reflect unobserved heterogeneity. Finally, women's gains from equalizing educational distributions do not depend in a significant way on the price structure used. In conclusion, the findings in this paper strongly support the idea that steering women toward male-dominated majors would significantly reduce the observed gender inequality in wages.

Keywords: gender wage gap, type of education
JEL Classification: J16, J31, J71

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* I thank Alan Manning, Pekka Ilmakunnas, Rita Asplund and Antti Kauhanen for valuable comments. The usual disclaimer applies. I thank the Academy of Finland, FDPE, the Helsinki School of Economics, and the Yrjö Jahnsson Foundation for financial support. I am also grateful to the Confederation of Finnish Industries for allowing me to use the data.

1. Introduction

A large amount of research has evolved exploring the question of why a substantial gender wage gap exists in practically all labour markets (see Altonji and Blank 1999; Blau and Kahn 2000; Kunze 2000, for a review). In terms of the methodological approach applied, studies in this line of research have commonly followed the example set by Blinder (1973) and Oaxaca (1973). Blinder and Oaxaca suggest an approach in which the gender wage gap is decomposed into one part explained by sex differences in qualifications and another part due to gender differences in the estimated rewards on those qualifications.[1] Studies differ with respect to the explanatory variables included in the wage equations, but despite using a wide variety of variables (e.g. work experience, job tenure, years of education, field of industry, occupation and so on), a sizeable unexplained gender wage gap typically remains. Some researchers interpret this as evidence of labour market discrimination towards women whereas others argue that the unexplained part of the wage gap results from researchers' inability to control for all the relevant productivity-related characteristics of workers.

One potentially important determinant of wages that has nevertheless received rather little attention so far is, somewhat surprisingly, education. Even though almost all studies of the gender wage gap include some measure of the *quantity* of education in the wage regressions, the *type* of schooling is typically controlled for only at a very general level. As is pointed out in Machin and Puhani (2003), this lack of attention to the type of education is probably partly due

[1] There are many other decomposition methods, like those suggested by Juhn, Murphy and Pierce (1993) and Brown, Moon and Zoloth (1980), but the Blinder-Oaxaca decomposition is by far the most often applied method in the gender wage gap literature.

to the fact that many standard data sets like the Current Population Survey, the Panel Survey of Income Dynamics, and the British Household Panel Study do not contain detailed information on education.

There are, however, a number of reasons to believe that the type of education is of considerable importance when it comes to explaining the gender-based wage gap. First of all, there are significant differences in wages between fields of education. For example, workers with a degree in technology have on average higher incomes than those who have completed a degree in humanities and arts. Secondly, it is well known that men and women differ with respect to their educational choices. Men are typically more heavily concentrated on technical education whereas women are 'overrepresented' in subjects like social sciences, education, and humanities and arts.

All the existing studies of the importance of the type of education in explaining the gender wage gap emphasize that the type of schooling matters.[2] The exact contribution of the type of education varies between 10 to 30 per cent of the overall gender wage gap depending among other things on the measure of education applied. There are, however, some important issues that have been explored only a little or not at all so far, and to which this paper tries to contribute. First of all, all the earlier studies in this particular line of research base their conclusions on parameter estimates drawn from the OLS wage regressions. However, it may be the case that differences in

[2] The existing literature on the role played by the type of education in explaining gender-based wage differentials is thin. One might mention Daymont and Andrisani (1984), Gerhart (1990), Brown and Corcoran (1997), Weinberger (1998), Machin and Puhani (2003), Black et al. (2004), and Liu (2006) as a fairly complete list of the studies on this particular topic.

education arise from differences in unobserved individual characteristics like preferences and abilities, and that these characteristics may contribute to higher wages as well. If this is true, then policies aiming at reducing the gender wage gap by steering women toward male-dominated majors will have only small effects. Studies applying OLS estimates have little to say about the role played by unobserved individual heterogeneity. I, on the other hand, have panel data enabling me to compare OLS and random and fixed effects estimation results and to examine whether time-constant unobserved heterogeneity accounts for the effects of majors on the gender wage gap.

Secondly, there is a lack of research investigating how the importance of the type of education as a determinant of wages differs by the stage of a working career. It is reasonable to assume that at the time of labour market entry when workers are still quite similar in terms of other individual background characteristics than education, the contribution of the type of education to the gender wage gap is likely to be particularly large. However, some question remains as to whether the type of education plays such an important role also among workers having more work experience. Many of the earlier studies focus exclusively on the early career and to my knowledge, only Gerhart (1990) has made comparative analysis between new entrants to the labour market and more experienced workers. Gerhart observes using data from a particular U.S. firm that the college major plays a key role in explaining the gender gap in starting wages but the college major is, however, much less important in explaining the wage gap between more experienced men and women. I also investigate new entrants to the labour market separately from more experienced workers to explore how the importance of the type of education in accounting for the gender-based wage gap differs by the stage of a career.

Thirdly, many of the earlier studies have been forced to settle for a fairly broad measure of education. This leaves open the question of how much information these broad educational categories hide that is valuable in explaining the gender wage gap. My data, however, have exceptionally detailed information on education: there are up to 247 majors represented in the data. Furthermore, my data set is also considerably larger compared to many of the earlier studies.[3] This enables me to get reasonably precise estimates of the effects of majors despite the use of detailed education variables.

Fourthly, with the exception of Machin and Puhani (2003), all the other earlier studies focus exclusively on the U.S. labour market. However, as is well known, there are many differences in the labour market institutions between the U.S. and those of the continental European countries. Differences in institutional arrangements may not only explain the variation in the size of the overall gender wage gap between the U.S. and Europe (Blau and Kahn 1996) but they

[3] To illustrate this, I present the number of observations and educational categories used in some of the previous papers. Daymont and Andrisani (1984) used 2,800 observations and ten different college majors. Brown and Corcoran (1997) have up to 20 different majors and 17,000 observations. (They also use another data set but it is smaller both in terms of education groups and observations). Examples of studies that use fairly detailed measures of education are Gerhart (1990), Machin and Puhani (2003), and Weinberger (1998). Gerhart has information on 65 college majors and the data used by Machin and Puhani report up to 124 different subject areas. Weinberger reports as many as 246 college majors. But in these three papers the number of observations is quite small. Gerhart estimates his model by using 4,600 observations, Machin and Puhani have 5,000 observations in their smaller data, and finally, Weinberger makes her analysis using information on about 6,000 workers. I have over 200,000 observations of workers with a bachelor-level degree and about 160,000 observations of workers who have completed a master-level degree. In the case of the bachelor level, there are 247 majors represented in my data. The corresponding figure for the master level is 176. See Table 2A for more detailed information about the number of education groups and number of observations.

may also have effects on the relative importance of different individual background characteristics with respect to the gender-based wage differentials (Albrecht et al. 2003). Therefore, to improve our understanding concerning the mechanisms (of which the type of education forms one part) behind the gender wage gap, it may be useful to do research in different institutional setups. In this respect there is a gap in the existing literature. This paper contributes to the filling of the gap by examining the role of the type of education in explaining the gender wage differentials in the Finnish labour market.

Finally, the data used in most of the existing studies dates back to the 1980s. Taking into account the considerable changes in the educational distributions during the past 15 years, most notably the significant increase in the fraction of workers with a college or higher education, research applying data from more recent years is needed. My data set extends up to 2004, thus providing fresh evidence of the effects of education on the gender wage gap.

In this paper, I examine the importance of the type of education in accounting for the gender gap in wages among white-collar workers with a university degree. The data set comes from the records of the Confederation of Finnish Industries (EK) covering the period 1998-2004. The overall degree of unionization is very high in the Finnish labour market, and EK is the largest organization on the employers' side. The EK data are very suitable for the analysis in question. First of all, they contain exceptionally detailed information on education. Secondly, the size of the data set is also large enabling me fully to utilize the detailed measures of education. Thirdly, it cannot be stressed enough that the EK data are of very high quality since the information comes from the employers' registers. As a result, there is virtually no response bias and information in the data is highly reliable. This is a clear advantage over the typically used surveys directed to employees. Finally, the panel structure of the EK data makes it possible to explore the question of whether the effects of university majors on the gender wage gap reflect unobserved heterogeneity.

One drawback with the EK data set is that it is not a representative sample of the whole Finnish economy. In the EK data, women are underrepresented and the gender wage gap is somewhat larger than in the Finnish labour market in general. I nevertheless apply the EK data in order to make use of the unusually detailed measures of education. Furthermore, it should be emphasized that my results are not without significance due to the use of somewhat more specialized data. First of all, the EK data set covers the Finnish manufacturing sector. The employment share of manufacturing was 20 per cent and its share of the total production was around 25 per cent during the period of investigation. The sector under study is thus an important part of the Finnish economy. Furthermore, as discussed in Korkeamäki and Kyyrä (2006), the EK data are rather similar in terms of many key characteristics to the other Nordic data sets on white-collar workers in the manufacturing sector. Therefore, the conclusions drawn in this study are not only of interest when the Finnish manufacturing sector or the Finnish labour market in general are considered, but also on a larger scale.

The rest of the paper is organized as follows. In the next section, I present the data and illustrate gender differences in the type of education among highly educated white-collar workers. Section 2 also explores wage differences between the fields of education. Section 3 starts with a discussion about the methodology used in the paper. Then I continue to show the basic results separately for the new entrants to the labour market and for workers having more work experience. I also examine the importance of unobserved factors with respect to the conclusions drawn from the basic analyses. Section 4 explores the question of how much women's wage changes caused by equalizing educational distributions between genders depend on the wage structure used. Section 5 gives a summary of the paper and reports the main conclusions.

2. The Data and some Descriptive Statistics

2.1 EK Data

The data used in the paper come from the records of the Confederation of Finnish Industries (EK). The Finnish labour market is highly unionized with comprehensive collective wage agreements. EK is the main organization of employers. There are member firms from construction, transportation, services, forest and energy industry, but the most important sector represented in the data is manufacturing. The firms that are affiliated with EK account for over two thirds of the value added of the Finnish manufacturing sector and a clear majority of the workers in manufacturing are employed in the member firms of EK.

The information in the EK data is gathered by sending surveys directed to the employers. Since the information comes directly from the administrative records of the member firms, the reliability of the EK data can be considered as exceptionally high. Also because it is compulsory for the member firms to provide the required information, the non-response bias is practically non-existent in the data.

EK gathers information on both white-collar and blue-collar workers, but in this paper I restrict myself exclusively to white-collar workers. Furthermore, only full-time workers (i.e. individuals who work at least 35 hours per week) aged between 17 and 65 are included in the analysis. I focus on university graduates because it is at this level of education where the information on the type of schooling is most detailed.[4] The resulting data cover the period 1998-2004 and contain over 360,000 observations. Summary statistics are shown in Table 1A. More about the advantages and drawbacks of the EK data are discussed in the introduction of this paper.

2.2 Gender Differences in University Majors

Figure 1 shows the distributions of fields of degrees by gender. For illustrative purposes, I use broad measures of education. As can be seen, white-collar men and women differ widely in their educational choices. Men are heavily represented in technology whereas over 40 per cent of women have obtained a degree in social sciences and business. White-collar women also have degrees in humanities and arts more often than their male colleagues.[5]

When the distributions reported in Figure 1 are compared to the corresponding distributions among university graduates in the Finnish labour market in general, the most notable difference is that workers with a degree in technology are clearly overrepresented in my data.

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[4] The university degrees in my data correspond to 5A-programmes in the ISCED 1997-classification.

[5] An important, although a very difficult question is what causes the educational distribution to differ between men and women? Is it the outcome of rational choices in competitive labour markets? Does labour market discrimination affect women's educational choices? This paper does not try to provide answers to these questions but takes the educational distribution as given and focuses on measuring the portion of the gender wage gap that is accounted for by the type of education.

This holds for both men and women. However, women's tendency to choose fields like social sciences and business or humanities and arts more often than men is a characteristic of the Finnish labour market in general, not just a feature of the EK data. Furthermore, the degree of gender segregation by fields of education does not seem to be particularly high in the EK data compared to the Finnish labour market as a whole. To illustrate this, I use another data source which comes from Statistics Finland and which is a representative sample of the Finnish private sector. Also this data contain information on the *broader* fields of education and the classification of fields is comparable between the two data sets. Using these data sources I compute the Duncan and Duncan segregation index (Duncan and Duncan 1955) for workers with a university degree in 2001.[6] The results are rather similar for both data sets: the value of the index is 0.53 for the EK data and 0.45 for the sample from Statistics Finland.

Table 1 examines gender differences in education within the broader fields of education. The purpose of Table 1 is to investigate whether the choices of majors differ between men and women who have obtained a degree in the same field of education. Again, this issue is explored by calculating the Duncan and Duncan segregation index. According to the results reported in Table 1, men's and women's educational choices differ even within the same field of education.

[6] The Duncan & Duncan segregation index is defined as $S = 0.5\sum_i |m_i - f_i|$ where m_i denotes the share of the male labour force in education field i, and f_i is similarly defined for women. The Duncan & Duncan index takes values between 0 and 1 indicating the proportion of men (women) that would have to be redistributed across fields of education in order to reach equal educational distributions between genders.

2.3 Wages and University Major

It is well known that there are wage differentials by field of education. For example, graduates in humanities typically earn less than workers with a degree in technology. Figure 2 illustrates this for my data. As can be seen, both at the bachelor and master level (BA and MA level respectively), fields like technology or business are associated with high incomes whereas workers who have specialized in humanities and arts must settle for lower incomes. These general conclusions hold for both genders, as can be noticed from Figure 3.

There is considerable wage variation also within the fields of education. To illustrate this, I have calculated wage profiles for three common majors in technology shown in Figure 4. As can be seen, graduates in computer sciences earn considerably more than graduates in mechanical engineering or in construction engineering. Similar kinds of wage differentials by major can be observed in other fields of education as well. Furthermore, these wage differentials remain even after I control for gender, so the observed wage differentials by major are not driven by differences in the proportion of women and men graduating in the majors in question.

It is these kinds of gender differences in educational choices and wage differentials between university majors that inspire me to investigate the role of sex-based differences in education in explaining the wage gap between men and women.

3. University Major and the Gender Wage Gap

3.1 Methodological Framework

The contribution of any productivity related characteristics X to the gender wage gap can be calculated as $(\overline{X}_m - \overline{X}_f)\hat{\beta}$ where $\overline{X}$ is the average of X, $\hat{\beta}$ denotes the estimated coefficient(s), and m and f refer to male and female workers respectively. One of the key decisions that a researcher must make concerns the sample from which $\hat{\beta}$ is estimated. There are various possibilities: one may estimate coefficients using male-only or female-only samples, or alternatively, some weighted average of male and female samples. Among researchers, there is plenty of debate about which reference wage structure one should prefer (e.g. Reimers 1983; Cotton 1988; Neumark 1988; Datta Gupta et al. 2003). In my case, however, there is one practical issue which strongly supports the use of the pooled sample (i.e. pooling men and women together). Because of the significant gender differences in educational choices, there are majors in the data in which there are only few men (women) but plenty of women (men). If wage equations are estimated separately for men and women, the standard errors for sex-atypical majors are typically high. Furthermore, these imprecisely estimated coefficients would be multiplied by large differences in the X's. To avoid this, I estimate wage equations using the pooled sample. I do realize, however, that the results may be sensitive to the choice of reference wage structure and therefore in Section 4, I investigate to what extent the possible wage gains experienced by women from equalizing major distributions depend on whether male or female prices are used.

I estimate three different wage regressions. Specification I is an augmented Mincerian wage equation including only age, age squared, and dummies for region, year and gender. In Specification II, industry and firm size dummies are added to the wage model. Finally, Specification III also includes occupation. Since a university major undoubtedly affects occupational determination, Specification III is likely to produce an underestimate of the 'true' wage effects of majors. It is, however, of some interest to compare the results of Specification III to the other specifications as it sheds light on the mechanisms through which the type of education affects wages. In all wage regressions, the log of hourly wage is the dependent variable. There is no direct information on hourly wages in the data, but they can be calculated using information on monthly wages and weekly working hours. Wages are converted into 2004 money using the cost-of-living index of Statistics Finland.

For each of the three wage specifications, I estimate two different versions: one that contains only broad measures of education (i.e. 9 different categories), and one that enters detailed controls for university majors (up to 247 different majors). The idea behind this is to investigate whether broad measures of education hide information that might be useful in explaining the gender wage gap. To give evidence that the wage regressions produce reasonable results, Table 3A in the appendix presents the regression results for the total data using a less detailed measure of education. Basically, the results are what one could expect based on economic theory and earlier empirical studies. For example, wages increase with age but at a decreasing rate. Furthermore, female white-collar workers earn significantly less than their male colleagues, and larger firms seem to pay higher wages than smaller firms which, again, is in line with earlier studies (e.g. Brown and Medoff 1989; Winter-Ebmer and Zweimuller 1999).

I experimented with several different wage models. To give some examples, I allowed the effects of industry and firm size to vary with the worker's age by including interaction terms in the wage model. The interaction terms proved to be mostly insignificant at the usual significance levels, and more importantly, they seemed to be of no importance with respect to the conclusions presented in the paper. I also investigated interactions between age and university majors. This was motivated by the often presented hypothesis according to which women's educational choices differ from those of men because women experience more career interruptions. As a result, women have lower incentives to school themselves for occupations and jobs that are associated with substantial investments in job-related training. If this is the case, and furthermore, if there are differences in the wage-experience profiles between jobs with different degrees of investment intensity, then a more appropriate way to model the effects of majors on wages is to use interactions between age (or experience) and majors besides major dummies. Although the joint significance of the interaction terms cannot be rejected, I decided not to include them in the wage regressions but use the approach applied in the earlier research instead, and enter educational variables into the wage model through dummy variables.[7] The main reason for this is that in order to reach identification for the interaction terms, I need to restrict the number of major categories rather heavily. The lack of identification with a detailed set of majors is partly due to the fact that there are many age-major cells with no or only a few observations. Furthermore, the differences in the slopes of the wage

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[7] Section 3.4, where I estimate a fixed effects model, forms an exception to this.

profiles between majors are actually quite small. [8] This can be seen already from Figures 2 and 3. Also the mean comparison tests concerning the average yearly wage growth by the field of education confirm that.[9] Therefore, the possible bias due to misspecification of the wage model resulting from the exclusion of the interaction terms is likely to be small.

3.2 Results for New Entrants to the Labour Market

The contribution of university majors to the gender wage gap is likely to be strongest at the time of labour market entry when workers are still quite similar in terms of other individual background characteristics than education. Therefore, I start my analysis by examining new entrants to the labour market. I define new entrant as a white-collar worker who has at most one year of (potential) experience when first observed in the data and who has completed a university degree at age 30 or younger. This results in 26,269 male and 9,966 female observations at the BA level and 19,649 male and 9,759 female observations at the MA level. By distinguishing new entrants from other workers I also facilitate comparison between my results and those of the earlier literature as many of the previous studies concentrate exclusively on workers in their early careers.

The OLS regression results for the new entries are fairly similar to those for the total sample presented in Table 3A. Therefore, they do

[8] The finding that differences in the wage profiles between majors are quite small is in some sense in line with Mincer's (1974) famous observation that the wage-experience profiles are similar for different educational levels.

[9] I executed the mean comparison tests for broad major categories using both average yearly wage growth calculated across the whole career (from age 24 to 60) and also across different stages of a career (age groups analyzed were 24-30, 31-40, and 41-50).

not need discussion. Regression tables for entries are available from the author upon request.

Table 2 shows the decomposition results for new entrants with less detailed controls for education. The first row presents the gender gap in log hourly wages. As can be seen, there exists a significant gender wage gap already on entry to the labour market: female entrants with a BA-level degree lag behind male entrants in average wages by 14 log points whereas the gender gap in average wages for entrants who have completed a MA-level degree is 10.3 log points. Row 2 shows that 22.8 per cent of the gender wage gap among entrants with a BA-level degree can be explained by differences in university major alone, controlling for age, year, region and gender. The corresponding figure for the MA-level entrants is 16.4 per cent. Adding controls for industry and firm size makes only a little difference in terms of the contribution of field of education to the gender wage differentials. As was expected, controlling for occupation decreases the size of the gender wage gap explained by education, but the type of education seems to matter even within occupations: in the case of BA workers the contribution of education amounts to 10.9 per cent of the gender wage gap after controlling for occupation and the corresponding figure for MA workers is somewhat higher, 12.9 per cent.

Table 3 is similar to Table 2 but instead of controlling for broad educational categories, Table 3 presents the decomposition results with a detailed measure of education. As can be seen, there are considerable gains to be achieved in terms of the proportion of the gender wage gap explained by using a more detailed measure of education. Considering Specification I, an additional 16.2 percentage points of the early career gender wage gap can be explained by detailed measures of education in the case of entrants with a BA-level degree. The corresponding figure for the other graduate group is 18.4 percentage points. These figures imply that after controlling for basic variables the proportion of the gender wage gap due to education amounts to 39 and 34.8 per cent among entrants with a BA-level and MA-level degree, respectively. This is a remarkably large contribution for a single factor. As before, also here employer characteristics (size and field of industry) have a relatively small impact on the results. Even after including controls for occupation the contribution of university majors to the gender wage gap is still huge, 20.7 and 27.4 per cent of the gender wage differentials among BA-level and MA-level graduates respectively.

My results thus suggest that university majors matter in accounting for the gender wage differentials among new entrants to the labour market. Furthermore, the estimated effects of the type of education on the gender wage gap roughly correspond to the results presented in earlier studies. For example, Daymont and Andrisani (1984) and Gerhart (1990) using data from the U.S. labour market conclude that college majors account for 20 to 40 per cent (depending on the specification) of the early career gender wage gap. This similarity between my results and those for the U.S. is itself of some interest taking into account the differences in the institutional setups between Finland and the United States.

As a robustness check, I made a similar analysis by restricting the size of education and occupation cells to at least 30 observations. The purpose of this exercise was to make sure that imprecisely estimated coefficients due to small numbers of observations in some education and occupation categories do not drive my conclusions in any way.

The decomposition results drawn from regressions using this restricted sample were practically identical to those discussed above.

3.3 Results for Experienced Workers

The previous section showed that the university major is an important factor behind the gender wage gap among new entrants to the labour market. In this section, using the total EK data excluding workers considered in Section 3.2, I investigate whether university majors play such a key role also among more experienced workers.

The OLS regression results for this sample are in line with those for the total sample discussed in Section 3.1. Estimation results for the sample excluding entries are available from the author upon request.

Table 4 presents the decomposition results for the total data excluding entrants using a less detailed classification of education. As can be seen from the first row of the table, the gender gap in average log wages is considerably higher among more experienced university graduates compared to the new entrants to the labour market, especially for MA workers (0.14 vs. 0.18 among BA workers and 0.10 vs. 0.20 among MA workers). This difference in the gender wage gap between entrants and more experienced workers is undoubtedly partly due to cohort effects but several studies have shown that the gender wage differentials tend to grow with work experience (e.g. Loprest 1992; Manning and Swaffield 2005; Napari 2006). As could be expected, the university major accounts typically for a smaller portion of the overall gender wage gap among experienced workers compared to the new entrants but the differences in this respect are surprisingly small, at least when MA workers are considered. The

(table 1A continues)

Master level:

	Men			Women		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
ln hourly wage	109870	3.089	0.278	49957	2.907	0.269
age	109870	38.980	8.689	49957	36.931	7.932
age^2/10	109870	159.497	72.636	49957	142.684	63.733
Region:						
South Finland	109870	0.593	0.491	49957	0.651	0.477
West Finland	109870	0.299	0.458	49957	0.274	0.446
East Finland	109870	0.031	0.174	49957	0.025	0.157
the province of Oulu	109870	0.067	0.250	49957	0.044	0.204
Lapland	109870	0.010	0.100	49957	0.006	0.077
the Åland Islands	109870	0.000	0.005	49957	0.000	0.004
Field of industry:						
Manufacturing	109870	0.780	0.414	49957	0.742	0.438
Construction	109870	0.020	0.141	49957	0.013	0.115
Transportation	109870	0.036	0.187	49957	0.042	0.200
Services	109870	0.126	0.331	49957	0.127	0.332
Forest industry	109870	0.011	0.106	49957	0.009	0.096
Energy industry	109870	0.026	0.160	49957	0.067	0.251
Firm size (# of employees):						
No more than 50	109870	0.064	0.244	49957	0.070	0.255
51-100	109870	0.078	0.268	49957	0.084	0.277
101-200	109870	0.115	0.319	49957	0.121	0.327
201-500	109870	0.175	0.380	49957	0.165	0.371
501-1000	109870	0.126	0.332	49957	0.124	0.330
1001-2000	109870	0.067	0.249	49957	0.057	0.231
Over 2000	109870	0.376	0.484	49957	0.379	0.485
Field of education:						
Education	109870	0.003	0.058	49957	0.020	0.140
Humanities and arts	109870	0.022	0.146	49957	0.148	0.355
Social sciences and business	109870	0.148	0.355	49957	0.385	0.487
Natural science	109870	0.097	0.295	49957	0.128	0.334
Technology	109870	0.698	0.459	49957	0.255	0.436
Agriculture	109870	0.024	0.152	49957	0.040	0.196
Health and welfare	109870	0.007	0.081	49957	0.024	0.153
Service	109870	0.002	0.044	49957	0.001	0.028

Notes:
1. Occupational distributions are not presented in table 1A. Distributions of workers over educational categories are also shown only for the broad subject areas.

Table 2A: Number of subjects of degree and observations by the field of education

Number of different subjects:

Field of education	Bachelor level	Master level
Education science	22	12
Humanities and arts	56	57
Social science and business	59	47
Natural science	13	16
Technology	53	21
Agriculture and forestry	12	10
Health and welfare	16	8
Service	14	3
Unknown	2	2
Total	247	176

Number of male observations by education group:

Field of education	Bachelor level	Master level
Education science	167	373
Humanities and arts	1 311	2 394
Social science and business	8 730	16 288
Natural science	1 330	10 619
Technology	145 822	76 635
Agriculture and forestry	5 691	2 605
Health and welfare	230	731
Service	415	216
Unknown	10	9
Total	163 706	109 870

Number of female observations by education group:

Field of education	Bachelor level	Master level
Education science	536	1 004
Humanities and arts	4 962	7 376
Social science and business	18 920	19 234
Natural science	626	6 371
Technology	13 770	12 717
Agriculture and forestry	888	1 997
Health and welfare	1 405	1 195
Service	388	38
Unknown	18	25
Total	41 513	49 957

Table 3A: OLS estimation results for the total sample using a less detailed measure of education

Dependent variable: log of real hourly wage						
	Bachelor level			Master level		
Specification:	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
age	0.051	0.052	0.040	0.065	0.066	0.052
	(54.86)**	(58.25)**	(53.80)**	(54.01)**	(56.31)**	(51.04)**
$age^2/10$	-0.005	-0.005	-0.004	-0.006	-0.006	-0.005
	(39.52)**	(41.45)**	(38.68)**	(41.20)**	(42.53)*	(38.45)**
female	-0.145	-0.146	-0.100	-0.127	-0.127	-0.096
	(41.22)**	(42.82)**	(36.24)**	(42.05)**	(43.11)**	(38.56)**
Field of education:						
humanities	-0.006	0.001	-0.001	-0.116	-0.098	-0.024
	(0.26)	(0.03)	(0.07)	(7.47)**	(6.42)**	(1.90)
business	0.112	0.128	0.063	0.130	0.136	0.100
	(5.54)**	(6.58)**	(4.22)**	(8.69)**	(9.33)**	(8.29)**
natural science	0.162	0.163	0.103	0.049	0.031	0.046
	(6.81)**	(6.91)**	(5.69)**	(3.26)**	(2.11)*	(3.71)**
technology	0.119	0.143	0.074	0.122	0.112	0.104
	(5.92)**	(7.34)**	(4.87)**	(8.25)**	(7.73)**	(8.69)**
agriculture	-0.091	-0.018	-0.055	0.090	0.073	0.058
	(4.37)**	(0.82)	(3.18)**	(5.41)**	(4.46)**	(4.24)**
health	-0.036	-0.044	-0.052	0.201	0.168	0.108
	(1.62)	(2.04)*	(3.10)**	(10.56)**	(8.85)**	(7.05)**
service	0.065	0.088	0.045	0.011	0.024	0.005
	(2.39)*	(3.36)**	(2.04)*	(0.31)	(0.76)	(0.22)
other/unknown	0.071	0.087	0.056	-0.107	-0.135	-0.076
	(0.48)	(0.64)	(0.53)	(1.69)	(2.03)*	(1.72)
(omitted group: teacher education)						
Firm size:						
50 or less		-0.103	-0.113		-0.073	-0.107
		(28.70)**	(36.90)**		(14.89)**	(25.27)**
51-100		-0.091	-0.090		-0.056	-0.078
		(24.16)**	(28.82)**		(12.96)**	(21.35)**
101-200		-0.088	-0.084		-0.046	-0.069
		(27.76)**	(31.70)**		(12.69)**	(21.98)**
201-500		-0.074	-0.062		-0.037	-0.051
		(24.86)**	(24.83)**		(11.17)**	(18.22)**
501-1000		-0.053	-0.046		-0.017	-0.028
		(16.36)**	(17.35)**		(4.76)**	(9.23)**
1001-2000		-0.039	-0.030		-0.017	-0.025
		(10.40)**	(9.46)**		(4.15)**	(6.90)**
(omitted group: over 2000 workers)						
Indicators for:						
Year	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	Yes	Yes	No	Yes	Yes
Occapation	No	No	Yes	No	No	Yes
Constant	1.741	1.757	2.054	1.661	1.669	1.996
	(63.27)**	(66.23)**	(92.39)**	(59.97)**	(61.47)**	(84.33)**
Observations	205,219	205,219	205,219	159,827	159,827	159,827
R^2	0.35	0.40	0.56	0.36	0.38	0.53

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

Notes:
1. Six region and industry dummies are used in the estimations. Furthermore, there are 137 and 124 occupational dummies at the bachelor level and master level, respectively.
2. The t statistics are in parentheses, and they are calculated using robust standard errors with clustering on the individual.

Table 4A: OLS vs. fixed effects results: bachelor level

	OLS			FE		
Contribution evaluated at age:	25	35	45	25	35	45
Specification I						
% of the gender wage gap due to gender differences in education	39.5	47.3	50.5	45.5	50.4	47.6
Specification II						
% of the gender wage gap due to gender differences in education	39.2	47.7	52.1	45.0	49.9	47.2
Specification III						
% of the gender wage gap due to gender differences in education	23.8	28.7	30.9	47.5	52.5	49.5

Notes:
1. Specification I includes age, age^2/10, log of aggregate earnings index, region dummies, age*education, and age^2/10*education. Specification II adds industry and firm-size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm-size dummies are used in the estimations. The measure of education contains 37 categories and occupation 76 categories.
3. Gender wage gap refers to the same wage gap used in Table 6, it is not an age-specific gender wage gap.

Table 5A: OLS vs. fixed effects results: master level

	OLS			FE		
Contribution evaluated at age:	25	35	45	25	35	45
Specification I						
% of the gender wage gap due to gender differences in education	27.2	32.0	33.3	33.5	37.1	35.1
Specification II						
% of the gender wage gap due to gender differences in education	24.2	28.8	30.6	33.1	36.8	35.0
Specification III						
% of the gender wage gap due to gender differences in education	18.2	22.1	24.0	31.9	33.7	29.3

Notes:
1. Specification I includes age, age^2/10, log of aggregate earnings index, region dummies, age*education, and age^2/10*education. Specification II adds industry and firm-size dummies to Specification I, and finally, Specification III adds occupation dummies to the wage model.
2. Six region and industry dummies and seven firm-size dummies are used in the estimations. The measure of education contains 31 categories and occupation 69 categories.
3. Gender wage gap refers to the same wage gap used in Table 6, it is not an age-specific gender wage gap.

IV Gender Differences in Early-Career Wage Growth*

Abstract

In Finnish manufacturing, the gender wage gap more than doubles during the first ten years in the labour market. This paper studies the factors contributing to this gender gap in early-career wage growth. The analysis shows that the size of the gender gap in average wage growth varies with mobility status, the gap being higher with employer changes compared to wage growth within firms. Several explanations for the gender gap in wage growth based on human capital theory and theory of compensating wage differentials are considered. However, most of the gap in wage growth remains unexplained. The distributional analysis of the wage growth shows that the female-penalty increases significantly as we move along the conditional wage growth distribution with a sharp acceleration in the gap at the top of the distribution.

Keywords: gender wage gap, wage growth, mobility
JEL Classification: J24, J31, J6, J7

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* I would like to thank Rita Asplund, Pekka Ilmakunnas and workshop participants at the LoWER workshop in Annecy for valuable discussions and comments. The usual disclaimer applies. Financial support from the FDPE and the Yrjö Jahnsson Foundation is gratefully acknowledged. I am also grateful to the Confederation of Finnish Industries for allowing me to use the data. Thanks go also to Pekka Vanhala for research assistance.

1. Introduction

Although the existing literature on the gender wage gap is large, researchers have only relatively recently started paying more attention to how the size of the male-female wage difference varies with the stage of a career. A typical finding from these studies has been that the gender wage gap is fairly small at the entry into the labour market, but after a few years a considerable gender wage gap emerges (e.g. Loprest 1992; Manning and Swaffield 2005). This gender gap in early-career wage growth accounts for most of the life-time increase in the sex-based wage differentials. Therefore, in order to achieve a better understanding of the overall gender wage gap, it seems to be of crucial importance to understand the factors contributing to the gender differential in early-career wage growth.

This paper analyzes gender differences in wage growth during the first ten years after labour market entry among white-collar workers in the Finnish manufacturing sector. The data show that women earn less than men already upon entry to the labour market, but ten years later the entry-level gender wage gap has more than doubled. It is this increase in the wage gap between male and female white-collar workers that this paper focuses on.

Earlier studies of the early-career gender wage differentials can be classified roughly into two categories. First, there is a line of research exploring the role of accumulation of work experience and labour market participation in explaining gender differences in early-career wage development. Second, a number of studies have focused on the importance of job mobility with respect to the wage growth during the first years in the labour market. Studies related to the first category have found that women's tendency to spend more time outside the labour market than men has negative impacts on their wage growth and that women's lower level of labour market experience is an important factor behind the gender gap in early-career wage development (e.g. Mincer and Polachek 1974; Sandell and Shapiro 1980; Mincer and Ofek 1982; Light and Ureta 1995; Manning and Swaffield 2005). However, it should be noticed that gender differences in the early-career wage growth are not only due to differences in work experience of men and women: a substantial unexplained gap typically remains after controlling for labour market experience (e.g. Kunze 2003; Manning and Swaffield 2005). The bottom line is that as a result of women's increasing attachment to the labour market, the gender gap in work experience is simply far too small to explain the size of the early-career gender wage differentials.

Job mobility has proved to be an important way for young workers to move up in the wage distribution (e.g. Topel and Ward 1992). There is, however, evidence that mobility plays a less important role in terms of wage growth for young women. Not only are young women less likely to quit a job, but they also seem to receive lower returns to mobility than young men (e.g. Simpson 1990; Light and Ureta 1992; Loprest 1992). However, these studies do not account for the non-pecuniary aspects of jobs. For example, Altonji and Paxson (1988, 1992) found evidence that job movers forsake wages for non-pecuniary features of jobs. Taking into account women's twin burdens of domestic responsibilities and paid work, these non-pecuniary features might well be more important for women than for men. Results of the studies distinguishing between different reasons for mobility support this view. Women change jobs more often than men because of family or non-market related reasons, which explains part of the gender differential in the returns to job mobility (e.g. Abbott and Beach 1994; Sicherman 1996; Keith and McWilliams 1997, 1999; Manning 2003, ch7).

Motivated by the findings of the earlier literature about the gender differentials in the returns to mobility, this paper investigates gender gap both in wage growth with firm changes and in within-firm wage growth. My approach is somewhat similar to that of Loprest (1992), who used data from the U.S. labour market. Loprest, however, excluded the within-firm component from her more detailed analysis because she found it to be unimportant with respect to the overall gender gap in early-career wage growth. This is not the case in my data. By examining both the within-firm and between-firm wage growth, this paper adds to the existing literature on the gender wage differentials.

This paper is interesting also for other reasons. First of all, unlike the existing studies of the gender gap in early-career wage growth, this paper considers not only gender differences in average wage growth but also the variation of the gap across the wage growth distribution. Secondly, most of the existing studies on the topic use data that date back to the 1980s. My data, on the other hand, cover the period 1995-2004. This paper thus provides fresher evidence on the gender differences in the early-career wage growth. Finally, the previous studies have focused on the U.S. and the U.K. I, on the other hand, use data from the Finnish labour market. There are many differences in the institutional set-ups between the Finnish labour market and those of the Anglo-Saxon countries (e.g. Kangasniemi 2003). The institutional framework might have important effects on wages and labour market mobility and these effects are not necessarily gender neutral (Blau and Kahn 1996; Teulings and Hartog 1998; Albrecht et al. 2003). Therefore, one should exercise caution in applying the U.S. and the U.K. evidence to the Finnish labour market.

The main findings of the paper are: female white-collar workers experience significantly lower wage growth than their male colleagues during the first ten years after labour market entry. This gender difference in early-career wage growth accounts for most of the life-time growth in gender-based wage differentials among white-collar workers in Finnish manufacturing. The size of the gender gap in average wage growth varies considerably with mobility status, the gap being much higher with employer changes compared to within-firm wage growth. The observed gender differences in between-firm and within-firm wage growth are not easily explained by men's and women's different educational choices or by the characteristics of the jobs they hold. The distributional analysis of the wage growth reveals that the female-penalty increases throughout the conditional wage growth distribution with a sharp acceleration in the upper tail of the wage growth distribution. This applies to both between-firm and within-firm wage growth.

The plan of the paper is as follows. In the next section, I present the data and give evidence of gender differences in early-career wage growth in the Finnish manufacturing sector. In Section 3 the theoretical framework is discussed. Then I proceed with presenting the empirical model of the determinants of wage growth with firm changes after which the estimation results are shown. Section 5 follows the structure of Section 4, but focuses on within-firm wage growth instead. Section 6 gives a summary of the paper and discusses the main conclusions.

2. The Data and Gender Differences in Wage Growth

2.1 The Data

This paper uses data from the records of the Confederation of Finnish Industries (EK). The Finnish labour market is highly unionized with comprehensive collective wage agreements and EK is the main organization of employers. There are member firms from construction, transportation, services, forest and energy industry, but the most important sector represented in the data is manufacturing. The firms affiliated with EK account for over two thirds of the value added of the Finnish manufacturing sector and a clear majority of the workers in manufacturing are employed in the member firms of EK.

The information on wages and working hours in the EK data can be considered highly reliable as it comes directly from the administrative records of the member firms. Also, since it is compulsory for the firms affiliated with EK to provide the required information, the non-response bias is practically non-existing in the data. The EK data contain a fairly rich set of variables typically applied in wage equations like gender, the level and field of education, age, occupation, field of industry and firm size. The data also include information on firm identifiers on which the mobility variable used in the paper is based. Perhaps the most unfortunate aspect of the data with respect to the focus of this paper is the lack of information on marital status and dependent children. This implies that I cannot identify the potential impact of maternity leave spells on wage growth.

Most of the variables used in the analysis are conventionally defined, and therefore they do not demand much discussion. A short description of the variables used in the regression analysis is provided in Appendix A. Some words concerning the definitions of the wage measure and the mobility variable may, however, be in order here. The wage variable is the log of real hourly wages. Hourly wages are calculated by scaling the basic monthly salary by the normal weekly working time.[1] The wage measure thus excludes earnings from other components such as overtime, shift work, bonuses, and so forth. The main reason for this is that the data do not provide information on all of these other components for all years, and in order to get a consistent wage measure for the whole investigation period I decided to base the wage measure on the basic monthly salary. Although the other components of pay may be an important part of the total compensation for some individuals, the basic monthly salary is by far the most important component of total pay constituting nearly 95 per cent of the earned labour income in my data. This holds for both genders.

Employer changes are identified by comparing firm identifiers attached to white-collar workers between consecutive years.[2] Because EK collects information from the member firms only once in a year, this means that I can observe at most one employer change

[1] Monthly salary is converted into 2000 money using the cost-of-living index of Statistics Finland.

[2] There are some (rare) cases where firm codes change even though workers do not actually change employers. This is due to business reorganizations like mergers. To distinguish a real firm change from a false one, I set a further condition for an employer change: a white-collar worker is defined as switching employers if the firm code associated with a white-collar worker differs between years t and t-1, and if no more than 50 per cent of his/her fellow workers from year t-1 follow him/her to the new employer. This definition does not seem to be sensitive to the used percentage limit as other limits (e.g. 40) produced very similar results. Also some other robustness checks with alternative definitions of the firm change variable were made without any effects on conclusions. I thank Pekka Vanhala for constructing the mobility variable.

per white-collar worker each year. My mobility variable is thus likely to understate true mobility to the extent that white-collar workers may change employers several times during a year. No information is available for Finland in this respect. I focus on white-collar workers observed in the data between 1995 and 2004. The data set contains 1,481,065 observations on 282,807 white-collar workers in total. Some 62 per cent of them are men.

One might be concerned that the somewhat restricted coverage of my dataset affects the conclusions that can be made from my analysis. For example, gender differences in transitions from the firms included in the data into employers who are not affiliated with EK might bias my findings. To investigate this issue, I used information from Statistics Finland's Structure of Earnings data. It appears that the credibility of my conclusions is not at risk due to excluding certain job transitions. First of all, mobility from the member firms of EK to other firms in the Finnish private sector is very low, and more importantly, there are no gender differences in this respect. Calculated from the Structure of Earnings data, on average only about 0.9 per cent of white-collar workers employed in firms affiliated with EK in year t-1 are observed in non-member firms in year t during the period 1995-2004. This holds for both genders.[3] Secondly, the corresponding figure for the transitions from the member firms to the public sector is even lower, 0.4 per cent for male white-collar workers and 0.5 per cent for female white-collar workers.

[3] I made the calculations also by focusing on young white-collar workers with potential labour market experience ten years at most and the results were similar to this group of white-collar workers.

One might also wonder why I restrict myself exclusively to white-collar workers.[4] One reason is that the occupation classification system is much simpler in the white-collar data than in the blue-collar data. The system for white-collar workers is consistent across the fields of industries allowing me in a straightforward way to investigate the role of gender differences in occupations as one of the potential sources of the gender gap in wage growth. On the other hand, the occupation classification system in the blue-collar data is more complex with significant differences between industries. Also the sex composition is more equal among white-collar workers: during the investigation period, on average 37 per cent of white-collar workers in the EK data are women whereas the corresponding figure among blue-collar workers is only 25 per cent. And it must be noticed that even if blue-collar workers are excluded from the analysis, the workers under investigation form a significant part of the member firms' employees: about 40 per cent of them work in white-collar jobs.

2.2 Gender Differences in Wage Growth

As discussed in the introduction, there is empirical evidence showing that women lag behind men in wage growth during the first years after labour market entry, and that this gap in early-career wage growth accounts for much of the life-time increase in the gender wage gap. However, this evidence comes mainly from the U.S. and the U.K. Therefore, I start my analysis by investigating whether the early career is such an important stage of a career with respect to the gender wage gap also in the Finnish labour market.

[4] The possible movements between white-collar and blue-collar positions are not a problem: 99.3 per cent of the workers who had a white-collar job in year t-1 had a white-collar job also in year t.

Figure 1 shows the wage-experience profiles for male and female white-collar workers together with the gender wage gap. Wages are normalized so that the average log real hourly wages for men are zero at the time of labour market entry. At least two interesting issues emerge from the figure. First, a considerable entry gender wage gap exists: women lag behind men in average hourly wages by 10 log points immediately after entry into the labour market. Secondly, the gender wage gap more than doubles during the first ten years in the labour market, exactly the same pattern that has been found for the U.S. and the U.K. It is true that cohort effects may account for some of the observed widening of the gender-based wage gap with experience. However, Figure 2, which presents the gender wage gap profiles for two different birth cohorts, suggests that cohort effects are not the explanation for the pattern presented in Figure 1.

To provide more evidence on the gender differences in early-career wage growth, I estimate a simple wage growth model of the following form:

$$\Delta w_{it} = \alpha_0 + \alpha_1 x_{it} + \alpha_2 x_{it}^2 + \alpha_3 x_{it}^3 + \alpha_4 x_{it}^4 + \varepsilon_{it} \,, \qquad (1)$$

where $\Delta w = w_t - w_{t-1}$, w is log real hourly wage, x is years of potential experience and ε is the error term. I estimate this model for those who have at most ten years of potential experience and who have completed their education at age 30 or younger. Furthermore, the model is estimated separately for men and women. Table 1 shows the implied wage growth derived from the results for equation (1). The results in columns 1 and 2 confirm the conclusion made from Figure 1: women experience lower wage growth during the first years in the labour market. For men the average predicted yearly wage growth over the first ten years after labour market entry is 9.8 per cent whereas the corresponding figure for women is 9.0 per cent. Of course, men and women may differ in some important ways in terms of individual characteristics that give rise to this 0.8 percentage point gender gap in annual wage growth. One way to investigate this possibility is to account for individual fixed effects in the wage growth model. Results for the fixed effects regressions are shown in columns 3 and 4 in Table 1. As can be seen, accounting for individual fixed effects does not affect the predicted average gender gap in annual wage growth.

Thus, my results so far confirm the earlier findings from the U.S. and the U.K.: the size of the gender wage gap more than doubles during the first ten years in the labour market and this gap in early-career wage growth accounts for much of the life-time increase in the gender-based wage differentials. Therefore, the rest of this paper focuses exclusively on the early career (defined above). After this restriction, the data contain 166,823 male and 82,626 female observations.

2.3 Decomposition of the Early-Career Wage Growth

Table 2 presents a simple wage decomposition shedding light on the factors driving the gender gap in early-career wage growth. I decompose the average annual wage growth into two parts: one that is associated with employer changes and another that is related to wage careers within firms. The first row shows that young female white-collar workers lag behind their male colleagues in average annual wage growth by 0.74 percentage points. However, the size of the gap seems to vary significantly with mobility status: the gender gap in average within-firm wage growth is 0.67 percentage points whereas there is a striking 1.92 percentage point difference in wage growth with employer changes. This result corresponds well with the findings of Loprest (1992). Also similar to Loprest, there are no gender differences in overall rates of mobility.

Table 2 implies that the gap in early-career wage growth between male and female white-collar workers has not that much to do with gender differences in rates of employer changes but more with the fact that women lag behind men both in between-firm and within-firm wage growth. Therefore, this paper excludes the analysis of factors affecting workers' propensity to switch firms. To retain the focus of the paper, I also ignore the important question of what contributes to the entry-level gender wage gap.

3. Theoretical Considerations

Theories of wage determination offer several explanations for the gender gap in early-career wage growth. The most common approach is based on the human capital theory developed by Becker (1964) and Mincer (1974). According to the human capital theory, gender wage differentials are due to gender differences in human capital accumulation. First of all, because of women's weaker labour market attachment, they tend to accumulate less labour market experience than men. Since labour market experience is an important factor contributing to wage growth, differences in experience between men and women are likely to explain at least some of the gender gap in the early-career wage growth. Secondly, it is plausible that anticipation of future career breaks affects women's motivation to do wage-enhancing investments in job training. For the same reason, there might be gender differences in pre-labour market human capital investments – men might invest more in education or/and in different types of education than women. And finally, as Becker (1985) pointed out, it might well be that due to women's greater domestic responsibilities, they bring less energy to the labour market with adverse effects on their productivity and wages.

Another explanation for women's lower wage growth can be derived from the theory of compensating wage differentials. This theory states that in the competitive labour market all jobs are equally attractive to the worker in the equilibrium when both pecuniary and non-pecuniary aspects of jobs are taken into account. It might well be that women are more likely than men to seek jobs that are easier to combine with family requirements and forsake wages and wage growth for these features.

Models of job mobility point out that there is heterogeneity in the quality of employee-employer matches. By searching for better matches and jobs, workers can experience wage gains through job mobility. Although standard models of mobility (e.g. Burdett 1978; Jovanovic 1979a, 1979b) are silent about gender differences in the process of mobility, it is easy to come up with reasons for why we might see women's mobility behaviour differ from that of men's. For example, due to family requirements women might face constraints in terms of how many hours they can work or how long they can travel to work. As a result, there might be gender differences in returns to mobility contributing to the gender gap in early-career wage growth.

Finally, theories of discrimination offer yet another explanation for the gender differences in wage development. There are two broad types of economic models of discrimination. The first class of models, developed by Becker (1971), formalizes discrimination as a taste or prejudice by one group against another. The second group of models of discrimination has its roots in imperfect information about the skills and behaviour of a group of individuals. These models of statistical discrimination, initiated by Phelps (1972) and Arrow (1973), emphasize that in a world of imperfect and asymmetric information employers have incentives to use easily observable characteristics, such as gender, in forming expectations on the productivity of workers and to discriminate among workers. For example, if women are on average less productive than men, then women who are highly career-oriented and productive may suffer from discrimination. This is because they belong to a group whose members are on average fairly loosely attached to the labour market and as a result less productive as well.

This paper considers several explanations for the gender gap in early-career wage growth. Starting with the human capital theory, I consider gender differences in human capital investments before labour market entry. My data contain information on both the quantity and the type of education. Controlling for the type of education might be particularly important because nowadays men and women are fairly similar in terms of the amount of schooling but their choices concerning the type of education still differ significantly (e.g. Machin and Puhani 2003; Napari 2006). I also investigate gender differences in employment histories. Due to the unequal division of labour within households, women are likely to experience more and longer career breaks than men. These differences in patterns of job history breaks might explain part of the gender gap in early-career wage growth. I also examine labour market segregation. It is well known that genders tend to segregate into different industries, firms and occupations. This may be due to many factors, such as discrimination or gender differences in human capital or in preferences. Without taking any stand on the reasons behind differences in employer characteristics between men and women, I investigate the role of industry, firm size and occupation in explaining the gender gap in early-career wages. Since the factors contributing to the gender gap in wage growth may differ depending on the mobility status, I examine between-firms and within-firm wage growth separately.

4. Gender Differences in Wage Growth with Firm Changes

4.1 Some Descriptive Analysis

Before discussing the empirical model of wage growth with firm changes and its results, I provide some descriptive evidence of gender differences in the type of mobility. Table 3 investigates changes in industry, firm size and occupation associated with employer changes. As can be seen, there are some differences between men and women in this respect. Men seem to move between industries and occupations more often than women. On the other hand, in terms of changes in firm size there are no statistically significant differences between men and women.

In the EK data, occupations are classified into four complexity categories. Although the classification system is broad and hence hides much variation in the actual complexity between occupations, it is interesting to examine movements across the complexity ladder with employer changes. Table 4 provides information on this. The upper part of the table does not control for initial job assignment.

However, men tend to start their careers from higher complexity ladders than women, which obviously affects transitions between complexity ladders. Therefore, the lower part of the table focuses exclusively on those who are at the lowest complexity ladder at the time of a firm change. As expected, controlling for initial job assignment is important. Without taking into account initial job assignment gender differences in movements along the complexity ladder are small. But when we focus on those who are at the lowest complexity level in year t-1, clear gender differences emerge: nearly 90 per cent of men's employer changes that are also associated with a change in occupation are movements to a higher complexity level whereas for women the corresponding figure is 70 per cent.

Similar to Loprest (1992), also I investigated whether men and women differ in probability to switch between full-time and part-time work with employer changes. In my data, however, practically all white-collar workers work full-time and there are only a few transitions between full-time and part-time statuses with firm switches.[5] This excludes the possibility that gender differences in trade-offs between wages and fewer working hours would explain the observed gender gap in returns to mobility in the EK data. Besides changes in full-time / part-time statutes, I also explored transitions between shift work and non-shift work. Also in this respect men and women turned out to be very similar.

[5] I used several different definitions for part-time work (weekly working hours less than 20, 30, and 35 hours), but in all cases about 99 % of firm changes for both genders were transitions between full-time jobs.

4.2 An Empirical Model of Wage Growth with Firm Changes

To investigate the factors behind the gender gap in wage growth with firm changes, the following wage growth model using the pooled sample of male and female white-collar workers is estimated:

$$\Delta w_{it} = \alpha_0 + \alpha_1 F_i + X_{it}\beta_1 + Z_{it}\beta_2 + Y_{it}\beta_3 + \varepsilon_{it}, \tag{2}$$

where $\Delta w_{it} = w_{it} - w_{it-1}$ is the difference in log real hourly wages between year t and t-1, F_i is the female dummy, X_{it} is a set of worker characteristics, Z_{it} is a vector of employer/job characteristics, and Y_{it} comprises year dummies. Equation (2) is estimated for the sample of white-collar workers who change employers between years t and t-1. The first-differencing eliminates the correlation of error terms across observations that is due to the unobserved time-constant individual characteristics. However, a shock at one time period may still cause the error terms to be correlated because a shock in period t is part of two successive observations. Therefore, to get robust standard errors I use clustering on the individual.

I estimate four different specifications of the wage growth model (2). The first specification includes controls for (potential) experience, the level and field of education[6] and region for periods t and t-1.[7] Female dummy and year indicators are included in all specifications. The purpose of this specification is to examine whether a female penalty in wage growth is observed once basic human capital and labour

[6] I use four dummies for the level of education and nine dummies for the field of education.

[7] I decided not to include the regional variables in a difference form but use levels instead. This is because the region variable is in practice fairly time-invariant. Whether we use a difference or level specification is not important with respect to my conclusions.

market characteristics are controlled for. Specification 2 adds dummies for changes in industry and firm size with employer changes. To capture the effects of movements between occupations with firm changes, specification 3 includes four indicators for firm-to-firm mobility: i) a firm change without a change in occupation, ii) a firm change with a change in occupation but no change in the complexity level, iii) a firm change with an upwards move in the complexity ladder, and iv) a firm change with a downwards move in the complexity ladder. The last specification tries to take labour market segregation by gender into account by including a set of dummies for the industry, firm size, and occupation in period t-1.

In 2002, a new occupational classification system was introduced in the EK data. This makes it practically impossible to get reliable information on occupational changes around the break year. Therefore, I do not use wage growth observations between 2001 and 2002 in the regressions. This does not have any effects on my conclusions, but it facilitates comparison between specifications as the underlying population is the same in all cases.

I experimented with many other wage growth model specifications as well. To give some examples, I investigated the effects of cumulative mobility on wage growth, but this had no impact on my conclusions. Secondly, I explored the possibility that previous breaks in the panel may be related to the wage gains from mobility. This was motivated by the perception that individuals who have intermittent employment may differ in their mobility behaviour from workers who are more strongly attached to the labour market. However, I did not observe any significant effects of previous breaks on the results.

Thirdly, although my data set does not contain information on the reasons behind employer changes, I tried to distinguish between voluntary and involuntary movements by constructing a dummy-variable which equals one if the firm disappears from the data between t-1 and t or if the number of white-collar workers at the firm decreases by more than 15 per cent during the corresponding time period. This variable, however, was found to have insignificant effects on the wage growth with employer changes.

Finally, one explanation for men's higher returns to mobility observed in the data is related to firm-specific human capital. Due to men's stronger attachment to the labour market, the completed tenure at the previous employer may be higher for men than for women. This together with the fact that workers who switch employers suffer a loss of firm-specific human capital for which they must be compensated in order to induce them to move to a new job might explain some of the gender gap in returns to mobility. I investigated this by constructing a firm tenure variable based on the starting year of the current employment contract. Replacing potential experience with firm tenure produced, however, very similar results. Furthermore, there were no statistically significant gender differences in tenure at the previous employer among the employer changers. It should be mentioned that there are certain problems associated with the variable indicating the starting year of the current employment. First of all, in some cases this variable produces tenure values that are suspiciously large. Secondly, sometimes white-collar workers are employed by using repeated contracts. Therefore, the time since the starting of the current contract does not in all cases reflect the true firm tenure. Moreover, this practice of repeated contracts became more common during my investigation period, increasing this source of bias in the tenure variable (Kangasniemi 2003). Because of these problems together with the fact that my results are not sensitive to whether I apply experience or the tenure variable (or both), I decided to use experience in the wage growth equations.

I estimate wage growth model (2) by using a pooled sample of men and women. Although a test of whether the wage growth equation for men and women differed only by a constant was typically rejected, the conclusions derived from the analysis based on separate wage growth equations were similar to those of the pooled regressions. I prefer the pooled specification mainly for expositional reasons. One might also be concerned about my decision to define wage growth as a difference in wages between two consecutive years. This approach has the potential disadvantage that it may under-sample women as they typically have more intermittent employment compared to men. This, however, seems not to be of particular concern in my case: the share of female observations is 34.0 per cent before I restrict the data to those who have wage observations from consecutive years compared to 33.1 per cent after the restriction.

4.3 Results

Table 5 shows the OLS estimation results for wage growth model (2). From the first column we see that there is a gender gap in wage growth with employer changes also after basic human capital and labour market characteristics have been controlled for. Taking into account that there are significant educational differences between male and female white-collar workers and that education is typically considered as an important factor affecting career paths, the large female penalty after including controls for education is somewhat surprising. In column 2, controls for changes in industry and firm size are added to the model, but those account fairly little for the female-penalty in wage growth. The third column includes indicators for changes in occupation, but also this has only minor effects on the gender gap in wage growth. Finally, adding controls for job characteristics in period t-1 decreases the female-penalty leaving it, however, still highly significant.

So far I have concentrated on the gender gap in average wage growth. However, it might be interesting to examine also other parts of the wage growth distribution. There has recently been increasing interest in the gender wage gap literature regarding the question of how gender affects both the location and the shape of the wage distribution. Several studies from many different countries have found that the gender gap in wage levels tends to increase throughout the conditional wage distribution with an acceleration in the upper tail of the wage distribution (e.g. Albrecht et al. 2003; Arulampalam et al. 2007). This has been interpreted as evidence of the glass ceiling preventing women from entering the most demanding and high-paying jobs. I extend the distributional analysis to cover gender differences in wage growth. If there exists a glass-ceiling hampering women's career progress, we could expect to see gender gaps increase not only throughout the wage level distribution but also across the wage growth distribution. This is because wage growth is likely to be strongest in movements from less demanding jobs to high-demanding managerial jobs.

To execute the distributional analysis I utilize the quantile regression techniques for the wage growth model (2). The model is estimated by the bootstrap method using 500 repetitions. Table 6 presents the results for this exercise. Due to a lack of space, only estimates for the female-dummy together with standard errors at various percentiles of the wage growth distribution are reported. Interestingly, at the lower tail of the conditional wage growth distribution there appears to be no female-penalty in returns to mobility. However, the female-penalty increases throughout the conditional wage growth distribution and at the top of the distribution women fall substantially behind men. This pattern holds for all four model specifications.

5. Gender Differences in Within-Firm Wage Growth

5.1 Some Descriptive Analysis

Following the structure of section 4, the examination of gender differences in within-firm wage growth starts with a descriptive analysis. As discussed in section 3, the labour market is heavily segregated by gender. To the extent there are differences in wage profiles between industries, firms and occupations, labour market segregation offers one potential explanation for the gender gap in wage growth. Table 7 provides information on segregation among firm-stayers. As can be seen, gender differences in industry and firm size distributions are relatively small, but in terms of occupation men and women differ substantially. For instance, men work considerable more often than women in jobs related to product design whereas sales or assistant office jobs are examples of typical female-jobs.

Table 8 examines occupational mobility within firms. Men seem to move more often than women to more demanding jobs, but gender differences in this respect are quite small. However, as was the case in the between-firms wage growth, also here it is important to control for initial job assignment. To illustrate this, the lower part of the table focuses on those who are at the lowest demand level in year t-1.

Among these white-collar workers, 16.5 per cent of the men move to a higher complexity level whereas the corresponding figure for women is only 8.4 per cent.

Finally, I also investigated gender differences in breaks in the panel. As expected, women experience breaks more often than men. However, gender differences in this respect are fairly small. Of female firm-stayers 7.8 per cent have experienced a break in the panel at some point during the investigation period. The corresponding figure for men is 6.2 per cent.

5.2 An Empirical Model of Within-Firm Wage Growth

The model to be estimated here is in many respects similar to the wage growth model analyzed in the previous section. The dependent variable is the change in log real hourly wages between years t and t-1 among those who stayed in the same firm. Based on the theoretical discussion in Chapter 3, five different model specifications are estimated. In specification 1, the set of explanatory variables is similar to the corresponding specification in Chapter 4, but regional dummies for period t-1 are excluded (because for firm-stayers the region in period t-1 is the same as in period t). To account for the effects of career breaks on within-firm wage growth, specification 2 adds a cumulative break variable and its interaction with the female-dummy to the model. Specification 3 also controls for industry and firm size. To capture the effects of within-firm mobility on wage growth, specification 4 adds four indicators for internal mobility: i) a change in occupation without a change in the complexity level, ii) movement into a more demanding occupation, iii) movement into a less demanding occupation, iv) no change in occupation. Finally, specification 5 includes dummies for the occupation in period t-1. Similar to the Chapter 4, the model is estimated using a pooled sample of male and female white-collar workers and information on wage growth between 2001 and 2002 is not used because of the change in the occupational classification system.

As a robustness check, I experimented with many other model specifications. To give some examples, I first of all estimated models with controls for changes in firm size. This was motivated by the well-known empirical fact according to which the rate of internal mobility is correlated with the rate of firm growth (e.g. Rosenbaum 1979). Therefore, firm growth may have effects on wage growth as well. Indeed, I found a positive correlation between the change in firm size and wage growth. But controlling for firm growth did not affect the size of the female-penalty in within-firm wage growth, and therefore I decided to exclude it from the model.

Secondly, standard models of job matching highlight the importance of job mobility in sorting workers into the jobs and firms where their productivity is highest (e.g Jovanovic 1979b). This implies that workers' mobility history might have effects on their wage development with their current employer. To the extent there are gender differences in mobility behaviour, controlling for previous mobility might be important in explaining the gender gap in within-firm wage growth. I investigated this issue by controlling for the number of previous employer changes, but it did not help explain the gender gap in wage growth within firms.

Thirdly, human capital theory suggests that controlling for past career breaks may not be enough in accounting for the effects of career interruptions on wage growth, but that one should take future career interruptions into account as well. This is because expectations about the future career interruptions might well affect decisions concerning current investments in human capital. To investigate whether future career breaks explain the gender gap in within-firm wage growth, I added a dummy to the model taking a value of one if a worker experiences a break in the panel in any of the years t+1, t+2 and t+3 and zero otherwise. As expected, the coefficient on this variable is negative, and it is statistically significant at the 5 % level. However, controlling for future breaks did not have any effects on the female-penalty in within-firm wage growth.

One might also wonder whether the effects of breaks are sufficiently captured by controlling for the number of breaks. It might be important to account also for the length of the break and how recent the break occurred is. It turned out that exploiting information on these issues does not make any difference compared to the case where I only control for the number of observed breaks.

Finally, I also estimated the within-firm wage growth regressions using information on firm tenure without significant changes in the results.

5.3 Results

The results of the within-firm wage growth regressions are presented in Table 9. The first column documents that women lag behind men in within-firm wage growth also after gender differences in educational background are controlled for. Also accounting for career breaks does not help to explain the gender gap in wage growth as can be seen from column 2. The results in column 3 show that there are some differences in wage growth between industries and firms of different size, but neither do these employer characteristics explain the female-penalty in within-firm wage growth. Column 4 adds controls for occupational mobility. The results imply that within-firm mobility pays off especially when one is changing to more demanding jobs. Internal mobility does not, however, account for the gender gap in within-firm wage growth. The final column presents the results for the full wage growth model including controls for occupation. This decreases the female-penalty from -0.012 to -0.010 leaving it still strongly significant.

The results presented in tables 5 and 9 are in line with those of Loprest (1992), who used data from the U.S. labour market. She concluded that "differences in job characteristics play only a limited role" and that "the source of much of the substantial difference between men's and women's wage growth with job changes still remains to be explained". My results show that Loprest's conclusion holds also in the Finnish manufacturing sector. Furthermore, the results in tables 5 and 9 indicate that gender differences in employer and job characteristics and in basic human capital variables explain poorly not only the gender gap in wage growth with employer changes but they fail also to account for much of the gender differences in within-firm wage growth.

To provide information on the variation of the female-penalty throughout the conditional wage growth distribution, Table 10 presents estimates for the female-dummy at various percentiles. The quantile regression model is estimated for the same five specifications presented in table 9. Similar to Chapter 4, the quantile regression model is estimated by bootstrapping using 500 repetitions. However, due to the large number of within-firm wage growth observations the estimation by bootstrapping becomes fairly burdensome and time-consuming. Therefore, I take a 5 per cent random sample from the within-firm wage growth observations resulting in 9,948 observations.

The results in table 10 show that there is no female-penalty in within-firm wage growth at the bottom of the wage growth distribution. However, when the top of the conditional wage growth distribution is investigated, women fall substantially behind men. For example in the case of specification 1, the estimated female-penalty is -1.1 at the median. After the 75^{th} percentile there is a substantial acceleration in the penalty and at the 95^{th} percentile the estimate for the female-dummy is -3.3. Although the disparity in the gender gap in wage growth between the lower and upper tails of the within-firm wage growth distribution decreases as I add explanatory variables to the model, the finding of an increasing female-penalty throughout the conditional wage growth distribution with a considerable acceleration at the top holds for all specifications.

6. Conclusions

This paper started with an illustration of the gender differences in early-career wage growth among white-collar workers employed in Finnish manufacturing. Using data from the Confederation of Finnish Industries covering the years 1995-2004 I showed that there are significant disparities in wage development between genders during the first ten years in the labour market. Female white-collar workers lag behind their male colleagues in average hourly wages by ten log points immediately after entry into the labour market. After ten years the size of the gender wage gap has more than doubled, accounting for most of the life-time increase in the gender wage gap among white-collar workers employed in the Finnish manufacturing sector. The rest of the paper focused on investigating this gender gap in early-career wage growth.

The decomposition of the average early-career wage growth into one part associated with employer changes and another part due to wage growth within firms revealed that the size of the gender gap in average wage growth varies considerably with mobility status. The female-penalty in average annual within-firm wage growth is 0.67 percentage points whereas the penalty is as high as 1.9 percentage points with employer changes. Several explanations for this gender gap in early-career wage growth were considered, but even after controlling for many background characteristics a significant unexplained gender gap both in the between-firms and within-firm wage growth remains.

The distributional analysis of the gender differentials in wage growth shows that the female penalty increases throughout the conditional wage growth distribution with a sharp acceleration in the gap at the top of the distribution. This holds for both between-firms and within-firm wage growth. The finding of an increasing female-penalty along the wage growth distribution is an interesting extension to the previous studies of the quantile differences in wage levels between men and women. These studies have documented that the gender gap in wages tends to increase throughout the wage level distribution. Some researchers interpret this as evidence of glass ceilings hampering women's career and wage development.

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Figure 1: Wage-experience profiles

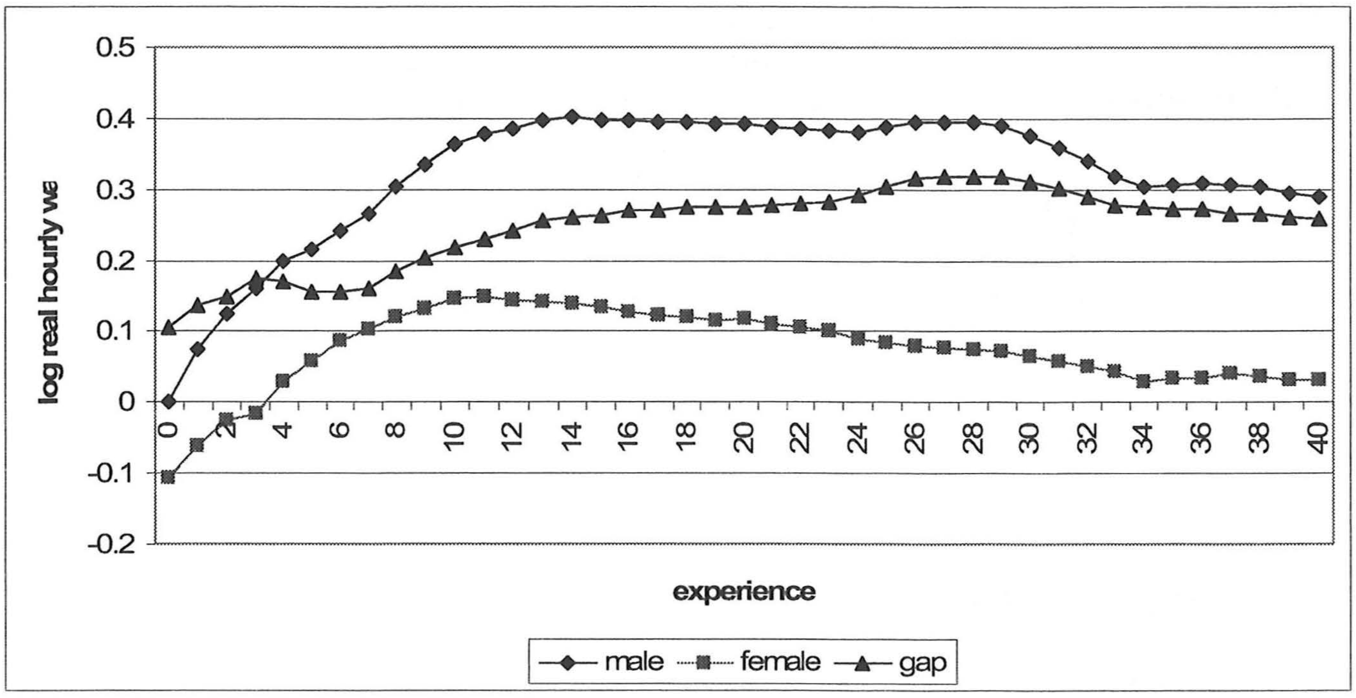

Figure 2: Wage-experience profiles by birth cohorts

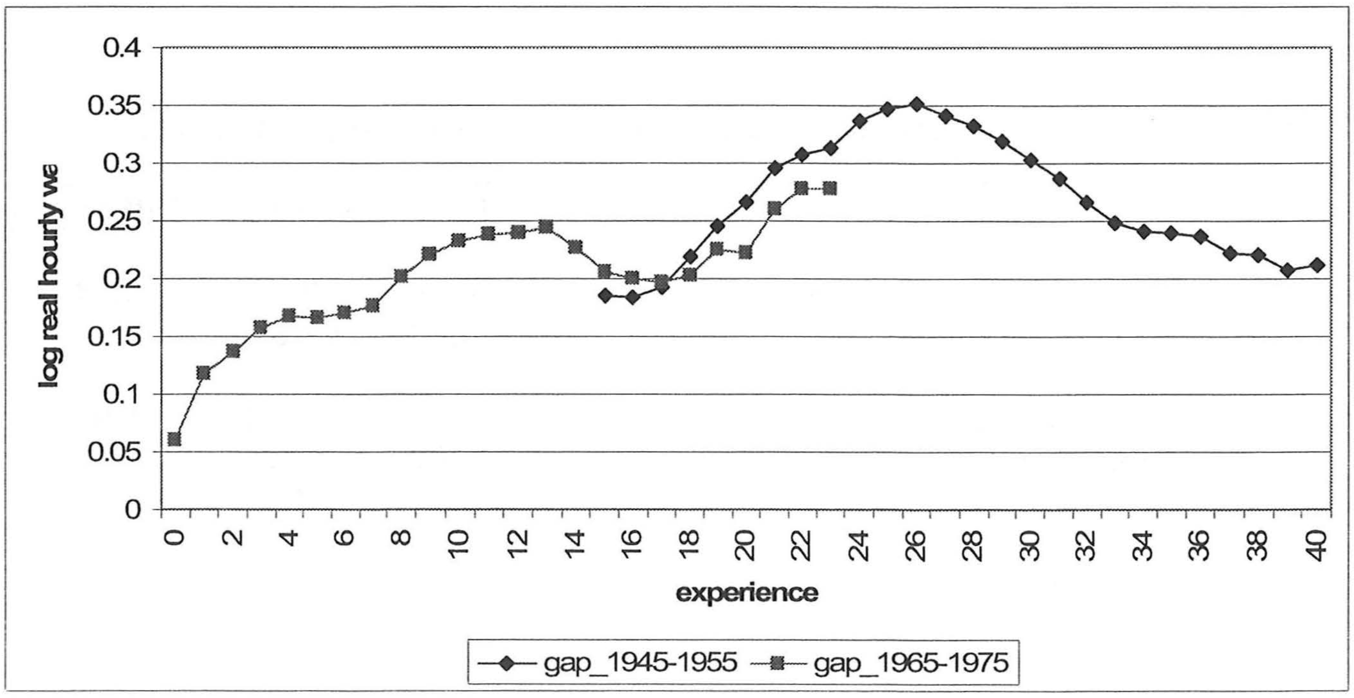

Table 1: Implied early-career wage growth

	Implied wage growth			
	Men	Women	Men	Women
Experience	(1)	(2)	(3)	(4)
1	0.132	0.120	0.147	0.139
2	0.112	0.104	0.130	0.124
3	0.101	0.095	0.118	0.111
4	0.097	0.091	0.110	0.102
5	0.096	0.089	0.103	0.094
6	0.095	0.087	0.097	0.087
7	0.094	0.084	0.091	0.080
8	0.090	0.080	0.084	0.074
9	0.086	0.077	0.078	0.070
10	0.080	0.075	0.073	0.067
Average	0.098	0.090	0.103	0.095
Fixed effects	No	No	Yes	Yes
No. of obs.	166,823	82,626	166,823	82,626
R^2	0.010	0.010	0.347	0.388

Notes:
1. Sample is those with no more than ten years of potential experience.
2. The implied wage growth is based on the estimated parameters of (1).

Table 2: Decomposition of the early-career wage growth

	Men	Women	Difference
Average annual wage growth (%)	9.20	8.46	0.74**
Number of observations	166,823	82,626	
Average annual wage growth with firm changes	14.23	12.31	1.92**
Number of observations	8,207	3,773	
% of total observations	4.9	4.6	
Average annual within-firm wage growth	8.94	8.27	0.67**
Number of observations	158,616	78,853	
% of total observations	95.1	95.4	

Notes:
1. Sample is those with no more than ten years of potential experience.
2. Wage growth is defined similar to Table 1, i.e. as a difference in wages between two consecutive years.
3. **: Difference significant at 1 % level.

Table 3: Gender differences in the type of mobility

Type of mobility	Men (%)	Women (%)
Change in:		
industry	20.5	17.1
firm size	82.4	83.7
occupation	54.9	50.1

Notes:
1. Sample is those who change employer between years t and t-1.

Table 4: Gender differences in mobility across complexity ladders of occupations

Type of occupation change	Men (%)	Women (%)
No controls for initial job assignment:		
upward movement	41.5	40.4
no change in complexity level	36.2	36.6
downward movement	22.3	23.1
Individuals initially at the lowest complexity level:		
upward movement	89.5	69.3

Notes:
1. Sample is those who change employer and occupation between years t and t-1.

Table 5: OLS wage growth regressions with employer change

Dependent variable: w_t - w_{t-1}

	(1)	(2)	(3)	(4)
Female	-0.024	-0.023	-0.022	-0.020
	(7.50)**	(7.09)**	(7.14)**	(5.84)**
Experience	-0.003	-0.003	-0.003	-0.003
	(6.56)**	(6.21)**	(5.96)**	(6.42)**
Level of education:				
Lowest tertiary	-0.000	-0.002	-0.006	-0.008
	(0.06)	(0.26)	(1.03)	(1.38)
Bachelor	0.019	0.017	0.011	0.007
	(3.37)**	(2.99)**	(1.97)*	(1.17)
Master	0.028	0.026	0.018	0.012
	(4.76)**	(4.50)**	(3.19)**	(1.85)
(Omitted group: secondary level)				
Field of education:				
Humanities	-0.053	-0.050	-0.045	-0.047
	(3.87)**	(3.72)**	(3.45)**	(3.41)**
Social Sciences	-0.044	-0.043	-0.037	-0.038
	(5.31)**	(5.15)**	(4.59)**	(4.59)**
Natural Sciences	-0.066	-0.065	-0.057	-0.055
	(6.84)**	(6.71)**	(6.04)**	(5.73)**
Technology	-0.061	-0.059	-0.055	-0.057
	(7.90)**	(7.71)**	(7.44)**	(7.42)**
Agriculture	-0.068	-0.066	-0.056	-0.056
	(5.20)**	(5.06)**	(4.43)**	(3.99)**
Health	-0.079	-0.073	-0.060	-0.058
	(5.64)**	(5.19)**	(4.39)**	(3.82)**
Services	-0.058	-0.055	-0.048	-0.050
	(4.43)**	(4.20)**	(3.78)**	(3.79)**
Other	-0.094	-0.088	-0.084	-0.081
	(2.69)**	(2.56)*	(2.46)*	(2.37)*
(Omitted group: General)				
Change in employer and job characteristics:				
Change in industry (0/1)		0.018	0.011	0.013
		(5.19)**	(3.01)**	(3.36)**
To a smaller firm		-0.020	-0.011	-0.011
		(5.85)**	(3.16)**	(2.95)**
To a larger firm		-0.005	-0.005	-0.006
		(1.24)	(1.35)	(1.44)
(Omitted group: same firm size)				
Same occupation			-0.065	-0.066
			(18.66)**	(17.84)**
Change in occupation, same complexity level			-0.033	-0.035
			(7.79)**	(8.13)**
Change in occupation, lower complexity level			-0.042	-0.048
			(8.57)**	(8.90)**
(Omitted group: change in occupation, higher complexity level)				

(Table 5 continues)

Indicators for:				
Region	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes
Firm size	No	No	No	Yes
Occupation	No	No	No	Yes
Constant	0.182	0.189	0.230	0.233
	(23.18)**	(22.59)**	(26.86)**	(15.62)**
Observations	10,282	10,282	10,282	10,280
R-squared	0.07	0.07	0.11	0.12

Robust t statistics in parentheses
* significant at 5%; ** significant at 1%

Notes:
1. Wage growth model is estimated for those changing employer and having no more than ten years of potential experience.
2. t statistics are in parenthesis, and they are calculated using robust standard errors with clustering on the individual.

Table 6: Quantile wage growth regressions with employer changes

	Specification			
	I	II	III	IV
5th percentile				
Female	0.007	0.004	0.003	0.006
	(0.007)	(0.005)	(0.003)	(0.004)
10th percentile				
Female	-0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
25th percentile				
Female	-0.009	-0.007	-0.006	-0.006
	(0.002)**	(0.002)**	(0.002)**	(0.002)*
Median				
Female	-0.020	-0.019	-0.020	-0.019
	(0.003)**	(0.003)**	(0.003)**	(0.003)**
75th percentile				
Female	-0.030	-0.029	-0.026	-0.023
	(0.005)**	(0.005)**	(0.005)**	(0.005)**
90th percentile				
Female	-0.048	-0.049	-0.042	-0.032
	(0.008)**	(0.007)**	(0.007)**	(0.007)**
95th percentile				
Female	-0.060	-0.061	-0.050	-0.037
	(0.010)**	(0.010)**	(0.010)**	(0.010)**

Notes:
1. Wage growth model is estimated for those changing employer and having no more than ten years of potential experience.
2. Standard errors are in parenthesis. The model is estimated by bootstrapping using 500 repetitions.
3. ** indicates that the coefficient on female-dummy is significant at 1 % level. * refers to significance at 5 % level.
4. Specifications I-IV refer to the specifications estimated in Table 5.

Table 7: Distributions across industries, firm sizes and occupation groups

Industry	Men (%)	Women (%)
manufacturing	73.5	72.5
construction	4.8	1.9
transportation	7.8	10.8
services	11.3	11.1
forest industry	1.5	1.0
energy industry	1.1	2.7

Firm size	Men (%)	Women (%)
no more than 50 employees	7.7	7.9
51-100 employees	6.6	8.1
101-200 employees	11.4	11.3
201-500 employees	15.6	16.7
501-1000 employees	12.0	10.4
1001-2000 employees	6.4	5.5
more than 2000 employees	40.2	40.1

Occupation group	Men (%)	Women (%)
product design	41.1	17.0
quality control	2.7	5.2
research	5.1	6.0
production, assembly and maintenance management	16.2	4.1
production support	9.3	3.3
material handling and transportation	2.0	1.7
purchasing	1.7	2.6
sales	9.0	16.4
marketing	1.4	3.6
coordination	0.8	1.0
PR	0.8	3.8
data processing	2.8	2.5
cashier	0.2	2.5
accounting	0.5	3.9
pricing and budgeting	0.8	2.3
secretary	0.1	10.1
office services	0.2	2.6
other	5.2	11.7

Notes:
1. Sample is those who stay in the same employer between years t and t-1.

Table 8: Gender differences in internal mobility

	Men (%)	Women (%)
No controls for initial job assignment:		
same occupation	88.1	87.8
change in occupation, same complexity level	4.1	4.8
change in occupation, higher complexity level	6.1	5.4
change in occupation, lower complexity level	1.7	2.0
White-collars initially at the lowest complexity level:		
change in occupation, higher complexity level	16.5	8.4

Notes:
1. Sample is those who stay in the same employer between years t and t-1.

Table 9: OLS within-firm wage growth regressions

Dependent variable: $w_t - w_{t-1}$

	(1)	(2)	(3)	(4)	(5)
Female	-0.011	-0.012	-0.012	-0.012	-0.010
	(24.41)**	(24.39)**	(25.05)**	(24.99)**	(21.20)**
Experience	-0.003	-0.003	-0.003	-0.003	-0.003
	(43.69)**	(43.05)**	(43.58)**	(43.20)**	(42.88)**
Level of education:					
Lowest tertiary	-0.005	-0.005	-0.005	-0.005	-0.005
	(6.89)**	(6.79)**	(6.35)**	(6.91)**	(6.68)**
Bachelor	0.004	0.005	0.004	0.003	0.001
	(6.46)**	(6.54)**	(5.37)**	(4.17)**	(0.98)
Master	0.006	0.006	0.005	0.004	0.002
	(8.32)**	(8.49)**	(6.68)**	(5.27)**	(2.16)*
(Omitted group: Secondary level)					
Field of education:					
Humanities	-0.036	-0.036	-0.036	-0.034	-0.029
	(19.61)**	(19.64)**	(19.48)**	(18.60)**	(15.76)**
Social sciences	-0.025	-0.025	-0.024	-0.023	-0.023
	(19.09)**	(19.06)**	(18.48)**	(17.92)**	(17.75)**
Natural sciences	-0.034	-0.034	-0.035	-0.033	-0.034
	(23.19)**	(23.17)**	(24.00)**	(23.12)**	(23.70)**
Technology	-0.037	-0.037	-0.036	-0.034	-0.034
	(29.64)**	(29.59)**	(29.09)**	(28.01)**	(27.33)**
Agriculture	-0.044	-0.044	-0.039	-0.038	-0.036
	(25.96)**	(26.01)**	(20.31)**	(19.80)**	(18.94)**
Health	-0.041	-0.041	-0.042	-0.038	-0.036
	(22.29)**	(22.31)**	(22.40)**	(21.24)**	(18.82)**
Services	-0.028	-0.028	-0.028	-0.026	-0.024
	(12.89)**	(12.87)**	(12.69)**	(12.02)**	(11.36)**
Other	-0.030	-0.030	-0.030	-0.029	-0.027
	(5.26)**	(5.26)**	(5.29)**	(5.14)**	(4.78)**
(Omitted group: General)					

(Table 9 continues)

Career breaks:					
Cumulative breaks		-0.006	-0.005	-0.006	-0.005
		(6.77)**	(6.19)**	(6.77)**	(6.45)**
Cumulative breaks*female		0.004	0.005	0.005	0.004
		(3.41)**	(3.47)**	(3.72)**	(3.45)**
Field of industry:					
Construction			0.001	-0.001	0.003
			(0.75)	(1.01)	(3.41)**
Transportation			-0.002	-0.001	0.001
			(3.00)**	(1.86)	(0.85)
Services			-0.003	-0.003	-0.005
			(4.06)**	(4.78)**	(6.29)**
Forestry			-0.007	-0.007	-0.004
			(4.27)**	(4.27)**	(2.43)*
Energy			0.003	0.004	0.008
			(1.89)	(2.34)*	(4.24)**
(Omitted group: Manufacturing)					
Firm size:					
51-100			0.000	0.001	0.001
			(0.33)	(0.79)	(1.06)
101-200			0.001	0.001	0.001
			(0.70)	(1.20)	(1.22)
201-500			0.003	0.003	0.003
			(3.77)**	(4.01)**	(4.15)**
501-1000			0.005	0.005	0.006
			(5.89)**	(6.08)**	(6.70)**
1001-2000			0.004	0.003	0.003
			(4.22)**	(3.60)**	(3.61)**
Over 2000			0.013	0.010	0.009
			(17.15)**	(13.80)**	(12.76)**
(Omitted group: no more than 50)					
Changes in job characteristics:					
Change in occupation, same complexity level				0.022	0.022
				(22.84)**	(22.53)**
Change in occupation, higher complexity level				0.049	0.049
				(49.87)**	(49.26)**
Change in occupation, lower complexity level				0.012	0.013
				(7.43)**	(7.72)**
(Omitted group: same occupation)					
Indicators for:					
Region	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Occupation	No	No	No	No	Yes
Constant	0.121	0.120	0.115	0.111	0.112
	(91.64)**	(91.23)**	(78.20)**	(76.51)**	(55.71)**
Observations	198,891	198,891	198,891	198,891	198,842
R-squared	0.10	0.10	0.10	0.12	0.13

Robust t statistics in parentheses
significant at 5%; ** significant at 1%

Notes:
1. Wage growth model is estimated using within-firm wage growth observations for those with no more than ten years of potential experience.
2. t statistics are in parentheses, and they are calculated using robust standard errors with clustering on the individual.

Table 10: Quantile within-firm wage growth regressions

	Specification				
	I	II	III	IV	V
5th percentile Female	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
10th percentile Female	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
25th percentile Female	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Median Female	-0.011 (0.002)**	-0.012 (0.002)**	-0.011 (0.002)**	-0.011 (0.002)**	-0.010 (0.002)**
75th percentile Female	-0.014 (0.002)**	-0.013 (0.003)**	-0.014 (0.002)**	-0.013 (0.003)**	-0.011 (0.003)**
90th percentile Female	-0.023 (0.004)**	-0.021 (0.005)**	-0.020 (0.004)**	-0.017 (0.004)**	-0.018 (0.004)**
95th percentile Female	-0.033 (0.007)**	-0.032 (0.007)**	-0.029 (0.008)**	-0.026 (0.007)**	-0.020 (0.007)**

Notes:
1. Standard errors are in parenthesis. The model is estimated by bootstrapping using 500 repetitions.
2. ** indicates that the coefficient on female-dummy is significant at 1 % level. * refers to significance at 5 % level.
3. Specifications I-V refer to the specifications estimated in Table 9.
4. Model is estimated for a 5 % random sample of within-firm wage growth observations.

Appendix A: Definitions of the variables used in the wage growth regressions

Log real hourly wage: The EK data do not contain direct information on hourly wages but they can be calculated using data on monthly wages and weekly working hours. The wage measure used in this study is based on the basic monthly salary, which does not include earnings from overtime, shift work, bonuses, and so forth. Wages are converted into 2000 money using the cost-of-living index of Statistics Finland.

Experience: Experience refers to potential experience calculated as age - years of schooling – 7.

Level of education: Four categories: i) basic or secondary level education, ii) lowest level tertiary education, iii) lower-degree level tertiary education and iv) higher-degree level tertiary education or doctorate level education.

Field of education: Nine categories: i) general education, ii) humanities and arts, iii) social science and business, iv) natural science, v) technology, vi) agriculture and forestry, vii) health and welfare, viii) services and ix) other.

Region: Five dummies for the location of firm: i) Southern Finland, ii) Western Finland, iii) Eastern Finland, iv) Oulu and v) Lapland.

Industry: Six industry dummies: i) manufacturing, ii) construction, iii) transportation, iv) services, v) forestry and vi) energy.

Firm size: Seven firm size categories: i) no more than 50 employees, ii) 51-100 employees, iii) 101-200 employees, iv) 201-500 employees, v) 501-1000 employees, vi) 1001-2000 employees and vii) over 2000 employees.

Occupation complexity level: Occupations are categorized into four complexity levels: i) management, ii) senior expert, iii) expert and iv) care taker. Information on complexity levels is included in the new occupation variable (see below) as such, but in the case of the old occupation variable, one must apply an occupation key provided by EK.

Occupation: Before 2002, the occupation code is a two-digit number containing 75 different codes. In 2002, a new six-digit occupation code is introduced, and as a result the number of different occupation codes increases substantially. EK provides an occupation key, which makes it possible to translate the new occupation codes into the old codes fairly reliably. This key is applied in constructing indicators for the previous period's occupation. Dummies for occupational changes are defined by comparing occupational codes between consecutive years. However, because it is impossible to get reliable information on occupational changes around 2002 (because of the change in the occupation code), occupational changes are not defined between 2001 and 2002.

Firm change: Firm changes are identified by comparing firm identifiers attached to white-collar workers between consecutive years. To avoid some rare cases where the firms code changes even though a white-collar worker does not actually change firm a further condition for an employer change is introduced: a white-collar worker is defined as switching firms if the firm code associated with a white-collar worker differs between years t and t-1, and if no more than 50 per cent of his/her fellow workers from year t-1 follow him/her to the new employer.

Cumulative breaks: First a dummy variable is calculated which takes a value of one if the gap between two observations for an individual is greater than one, and zero otherwise. The cumulative breaks variable is then defined as a cumulative sum of the dummy-variable in question.

ISBN 978-951-628-475-3 ISSN 0356-7435