LUND UNIVERSITY
School of Economics and Management

Master programme in Economic History

Can Theories of Skill-Biased Technological Change Explain the Evolution of Wage Inequality in Finland since 1970?

Jessica Finnilä
jessica.finnila.415@student.lu.se

Abstract: Wage inequality has increased in many OECD countries since the 1970s. Many have explained this development in terms of skill-biased technological change. According to theories of skill-biased technological change, wage inequality is the result of a technology-induced increase in the demand for skills which has not been met by equal increases in the supply of skills. This paper explores the relationship between supply and demand for skills in Finland since 1970. The main finding is that changes in the supply of education can explain the bulk of changes in the skill premium and that technological change provides added explanatory power in periods when the simple supply-based framework falls short. The results also suggest an increasing within-group inequality of workers with equivalent educational levels. The cause of the within-group inequality is less clear, but both technological and institutional factors are likely to play roles in this development.

Key words: Skill premium, wage inequality, technological change

Website www.ehl.lu.se

Table of Contents

Acknowledgements

1 Introduction

1.1 Background and aim

Wage inequality has increased in many OECD countries since the 1970s. In the US and the UK, a large portion of the rising wage inequality has been caused by a rising skill premium, meaning that wages for workers with higher levels of educational attainment has risen more than wages for less educated workers (Magalhaes & Hellström, 2013). Many economists have blamed so called skill-biased technological change for this development. The idea behind this is that technological change in recent decades has been more complementary with skilled workers than unskilled workers, increasing the demand for skilled workers proportionally more. Economists like Goldin and Katz (2008) have talked about wage inequality being the result of a "race between education and technology" that has been lost by education, meaning that technological change has been not been met by an equal increase in the supply of skills.

Finland makes for a very interesting case study of this theory, since both levels of education and technology have increased tremendously in recent decades. Finland was late bloomer when it comes to industrialization and was still trying to catch up with the EU15 in 1970. The population was poorly educated and anything past basic schooling was available only to those who could afford it and happened to live in the right area. However, thirty years later Finland was topping international lists of competitiveness, R&D expenditure, student performance and educational equity, completing the transformation of Finland into a knowledge-based economy.

The main aim of the following paper is to find out how the skill premium in Finland has evolved since 1970 and whether the evolution can be explained in terms of the supply of skills and changes in technological development. I also want to find out whether the skill premium is a good indicator of wage inequality in Finland.

1.3 Method, data and scope

The main part of my analysis is going to be conducted using a dataset from Statistics Finland that covers wage and salary income of the whole working Finnish population, as well as data on R&D expenditure from Statistics Finland.

I am going to focus on a relatively small group of skilled workers, namely those with doctorate or higher-degree level tertiary educations. This is because I am especially interested in how well the supply and demand theory can explain changes at the upper end of the wage spectrum.

I will make use of both descriptive statistics and a formal analysis based on Vector Autoregression (VAR) models in my interpretation of the data. My results provide evidence that fluctuations in the supply of skills are able to explain a huge part of the variation in the skill premium, and that accelerations in the speed of technological change can explain changes in the skill premium where the supply explanation falls short. However, I also find that education has become an increasingly bad predictor of wage, since within-group inequality for workers with the same educational level has increased. I consider alternative explanations for this, and find that institutional factors are better at explaining this development. Additionally, I place the skill premium in a broader context of inequality by comparing it to both Gini coefficients and measures of top incomes. I find that the evolution of top incomes provides a better indicator of overall income changes than the skill premium.

1.3 Structure of thesis

I will begin with an exposition of theories and concepts relating to skill-biased technological change in Section 2. Section 3 will provide the historical context, focusing on chronological accounts of the Finnish education system and Finnish technological development in the period since 1970. Section 4 will describe the process and results of my quantitative analysis. In Section 5, I will relate my analysis, which focuses on the skill premium, to broader measures of wage inequality. Section 6 will finish with a conclusion.

2 Theory and previous research

Theories of skill-biased technological change have evolved over time and are strongly related to historical developments. Hence, it is elucidating to begin with a genealogy of the concept of skill-biased change. I will continue by discussing crucial aspects of the theory in detail, as well as look at criticism and alternatives. In addition, I will discuss previous research on skill-biased technological change in Finland.

2.1 A history of ideas of skill-biased technological change

The idea that technological development favours skilled workers is relatively new in the grand scheme of things and did not become popular until the twentieth century. In the nineteenth century skilled artisans instead feared that new weaving, spinning and treshing machines would render their skills unnecessary, which even resulted in the destruction of such machines during the Luddite and Captain Swing riots (Acemoglu, 2002). Indeed their fears were justified, since later the artisan shops were replaced by assembly lines. Thus these technological changes can be considered *skill-replacing* rather than *skill-biased*. However, Goldin and Katz (1998) have found that the beginning of the twentieth century brought technology-skill and capital-skill complementarities with the adoption of electric motors and other production methods.

The 1960s gave rise to a variety of literature on technology-skill complementarity. This has been called a decade of "human capital revolution" in economic theory since it gave birth to a burgeoning literature on the investment aspect of education, and ideas of technology-skill complementarity fitted well into this intellectual epoch. Examples include Nelson and Phelps (1966), who formalized models around the hypothesis that "educated people make good innovators, so that education speeds the process of technological diffusion", Griliches (1969), who found evidence for the hypothesis that skilled labour is more complementary with capital than unskilled labour, and Schultz (1975), who argued that ability to deal with economic disequilibria is enhanced by education. A pioneering contribution was made by Tinbergen (1975), who introduced a supply and demand framework in which wage inequality was the result of a "race between technological development and access to education" (Katz & Autor 1999, p. 1465).

In the 1980s and 1990s, the skill premium in the US and the UK increased dramatically. For example, in the US, wages of college graduates relative to wages of high-school graduates increased by over 25 percent between 1979 and 1995 (Acemoglu, 2002). This resulted in a wide array of literature attempting to connect the evolution of the wage structure to skill-biased technological change. Much of it investigated the specific role of computers and the Internet on the skill premium. One important contribution to the literature was made by Berman, Bound and Griliches (1994), who studied the composition of employment in US manufacturing from 1979 to 1987, finding that investments in R&D and computers was strongly correlated with the demand for white-collar workers. However, other possibilities for the wage inequality, such as trade liberalization, deunionization and immigration were discussed as well, although many pointed to technological change as the main cause. Bound and Johnson (1992) contributed to this debate, finding that skill-biased technological change was a greater cause of the increase of the relative wages of highly educated workers in the US in the 1980s than factors relating to trade, unions and cohort size.

In 2008, Goldin and Katz published an influential book whose title *The Race between Education and Technology* echoed Tinbergen's contribution in the 1970s. Goldin and Katz explored wage inequality in the US in the period 1915 to 2005. They focused on the skill premium, which they considered to be a good proxy for wage inequality in the period. The major finding of the book is that most of the educational wage differentials can be well explained by changes in the growth of the supply of educated workers. Acemoglu and Autor (2012) have suggested that the framework proposed by Goldin and Katz needs some amendment, since it cannot sufficiently account for the deceleration in the skill premium since the early 1990s, or the fact that earnings have grown relatively more at the top and the bottom than in the middle of the wage distribution. As a solution, they propose a "tasks framework" that is based on the possibility that technological change can cause some tasks previously performed by workers to be replaced by capital. According to them, this results in job polarization caused by growth of employment in high skill, high wage occupations and low skill, low wage occupations. Hence, they consider technological change to be only partially skill-biased.

2.2 Modelling skill-biased technological change

The traditional way to measure technological change on the macro level has been through measures of aggregate total factor productivity (TFP). This was the result of pioneering work by

Solow (1957), whose insight was that technological change could be estimated "residually" using a production function:

$$Y = AK^\alpha L^\beta$$

By inserting measures of aggregate output (Y), aggregate capital (K), and aggregate labour (L) from national accounts and an estimate of a and β (the two inputs' respective shares of output) it was possible to arrive at a change in technology (A), or total factor productivity as it is called, amounting to:

$$\Delta(TFP) = \Delta(Y) - \alpha\Delta(K) - \beta\Delta(L)$$

This concept of technological change has been widely used ever since. Solow defines an increase in TFP as a rise in output that leaves marginal rates of transformations unchanged for given inputs. In other words, a change in TFP is a form of *factor-neutral* technological change (Violante, 2008). However, since the end of the 1970s, the US and the UK have seen dramatic increases both in the relative supply of skilled workers, and the price of skilled labour relative to unskilled labour, called the skill premium. Since factor-neutral technological change does not take account of relative prices, the concept of *factor-biased* technological change was introduced to make sense of these historical developments (Violante, 2008). Following Violante (2008), this can be expressed by letting labour input be a constant elasticity of substitution function of skilled and unskilled labour, L_s and L_u, with factor-specific productivities A_s and A_u:

$$L = [(A_s L_s)^\sigma + (A_u L_u)^\sigma]^{\frac{1}{\sigma}} , \ \sigma \leq 1$$

This means that in a competitive market, the marginal rate of transformation between the two labour inputs – and hence the skill premium – can be written as follows:

$$\ln(MRT_{s,u}) = \sigma \ln\left(\frac{A_s}{A_u}\right) + (1 - \sigma)ln\left(\frac{L_u}{L_s}\right)$$

The above equation captures how the skill premium increases as the factor specific productivity of skilled labourers (A_s) increases relatively to the factor specific productivity of unskilled labourers (A_u), and furthermore, how the skill premium decreases as the supply of skilled labour (L_s) increases relative to the supply of unskilled labourers (L_u). Katz and Murphy (1992) were the

first to use this equation to estimate skill-biased technological change residually, finding that a trend favouring skilled workers combined with fluctuations in the supply of skilled workers could explain changes in the skill premium. Goldin and Katz (2008) also base their calculations on this equation. However, as argued by Hornstein, Krusell and Violante (2005), this approach leaves a lot of uncertainty about the specifics of skill-biased technological change since it is based on residually measured unobservables.

The above equation has been widely used as a basis for modelling skill premia. Some have called models based on it the "canonical model" because of its prominent status in the literature. However, others have attempted to model and measure the relationship between technology, education and wage inequality in very different ways. In a review of the literature on technological change and labour market inequalities, Hornstein et al. (2005) stress that a distinctive feature of the literature is that the ideas which it involves have been presented in a very wide variety of different theoretical frameworks. According to them the main reason for this diversity is the fact that that it's natural to depart from competitive models when studying labour markets, which means that many alternative frameworks to incorporate frictions exist. Hornstein et al. (2005) point out that the main drawback of this lack of a unified framework is that it makes structurally based quantitative comparisons between different mechanisms difficult to make.

2.3 The speed of technological change

The speed of technological change has been measured and proxied in a variety of different ways in addition to residual calculations of total factor productivity and factor specific productivity mentioned above. In the 1980s and the 1990s, the personal computer (PC) and related technologies, including the Internet, were the most popular measures of technological change (Card & DiNardo, 2002). One approach pioneered by Krueger (1993) was to measure technological change by the fraction of workers who use a computer on the job. An alternative indicator has been the relative size of the information technology (IT) sector in the overall economy (e.g. Jorgenson (2001)). As Card and DiNardo (2012) point out, there are many problems with such simplified measures. First of all, the IT sector includes many disparate products and services, which are characterized by rapid changes in quality, making simple comparisons difficult. Secondly, even though it would be possible to measure IT output accurately, the impact of IT-related technological change on the economy is not necessarily proportional to the size of the IT sector. Another measure of technological change that has been

used in many studies is R&D intensity (e.g. Berman et al., 2004). According to Huttunen (2002), the obvious drawback of this measure is that it only is an input, describing where the innovation is originated but not where it is used. In other words, unlike computer investments, R&D measures do not measure the use of new technology in production. However, Huttunen adds, there are many studies providing evidence that R&D activities clearly are complementary to a number of other changes in firms' production technology, for example the adoption of new machinery, and that it is a reasonably good proxy of outputs of innovative processes.

Some studies have taken the rate of technological change to be constant and explained changes in wage inequality in terms of changes in the supply of skills. Acemoglu (2002) calls this the *steady-demand hypothesis*. An example of this is found in Katz and Murphy (1992), where the evolution of the college premium in the US in 1963-1987 is argued to be a result of smooth trend demand growth in favour of more-educated workers combined with fluctuations in the relative supply of college graduates caused by baby boomers entering the labour market in the early 1970s. Another approach has been to consider the rate of technological change as accelerating, which Acemoglu (2002) calls the *acceleration hypothesis*. According to Aghion (2002), the first convincing evidence in favour of this hypothesis was provided by Krusell, Ohanian, Rios Rull & Violante (1994), who argued that the skill-biased technological change proxied by the decline of the relative price of production equipment goods since the mid-1970s could account for most of the variation in the college wage premium.

Economists who agree on the acceleration hypothesis still have another question to answer, namely *why* the rate of technological change has accelerated. One option is to interpret the rate of technological change as *exogenous*, as is done in neoclassical models. The model by Krusell et al. (2000) has been interpreted as an exogenous technology model by Acemoglu (2002) since it assumes that the decline in the relative price of equipment capital is exogenous. However, the main debate in recent years has been between two different types of theories with an *endogenous* rate of technological change, both inspired by Schumpeterian growth theory (Malghaes & Hellström, 2013). The first is the *demand pull* hypothesis, which is the idea that an increase in the supply of skills in the 1970s changed the production incentives for firms and caused them to develop more machines that complemented these skills (Bogliacino & Lucchese, 2011). The effect of the increase skill suppy has been called the *market-size* effect by Acemoglu (2002), a proponent of the hypothesis. The second hypothesis is a *technology push* hypothesis, which stresses the non-linear diffusion of new technologies and has been advocated by e.g. Aghion (2002). This non-linear diffusion is a reference in particular to new General Purpose Technologies in

information and communications technology, which have diffused throughout industrialized economies in recent decades

2.4 Observed and unobservable skills

Modelling skill-biased technological change in terms of shifts in supply and demand for different types of labour is usually done by classifying workers into different observable skill categories. Most of the literature examining the impact of technological change on the demand for skill has used very crude measures of skill and has usually divided workers into only two or three groups (e.g. skilled, semi-skilled and unskilled workers) based on some educational level, or by dividing labour into production and non-production workers. Another common measure of skill is experience, often proxied by age (in which case it is referred to as "potential experience"). One complicating factor in simple age and education categories pointed out by Huttunen (2005) is that skilled workers of the same level of education but different ages might not be perfect substitutes if technological progress makes skills of an older vintage obsolete.

Education and age are both examples of observable skill categories. Wage inequality that is not captured by observed skill categories is called *residual wage inequality*. A difficult thing to measure is to what extent changes in wage inequality is a result of the relative price and quantity of observed worker attributes as opposed to changes in residual inequality. According to Katz and Autor (1999), a common approach to calculating the contributions of observable and unobservable components of wage dispersion to changes in overall wage inequality is a standard variance decomposition. The starting point is a Mincerian wage equation of the form:

$$Y_{it} = X_{it} B_t + u_{it}$$

where Y_{it} is the log wage of individual i in year t, X_{it} is a vector of observed individual characteristics (e.g. education and experience), B_t is the vector of estimated (OLS) returns to observable characteristics in t, and u_{it} is the log wage residual, which depends on the prices and quantities of unobserved skills, measurement error, and estimation error. The variance can be written as:

$$Var(Y_{it}) = Var(X_{it} B_t) + Var(u_{it})$$

Hence the variance of log wages can be decomposed into two components: one measures the contribution of observable prices and quantities, and the other measures the residual variance, which is a component measuring the effects of unobservables. These two components are usually called *between-group* and *within-group inequality* (Katz & Autor, 1999, p. 1489).

A puzzle often discussed in relation to theories of skill-biased technological change is that wage inequality has increased sharply, not only between groups, but within educational and age groups as well. According to Machin (1996), the residual standard deviation in hourly earnings increased by 23 percent in the UK and 14 percent in the US between 1979 and 1993, which is a substantial fraction of the overall increase in income inequality. This puzzle is further complicated by the discovery by Blundell and Preston (1999; cited in Aghion, 2002) that the increase in within-group inequality has been mainly transitory, whereas the increase in between-group inequality has been of a more permanent character.

One possible way to explain the rise in within-group inequality in terms of technological change is to say that within-group wage dispersion reflects differences in unobservable skills. The thought is that an increase in the demand for skills would increase both demand for observed and unobservable skills (Juhn, Murphy & Pierce, 1993). To some extent, the existence of unobservable skills seems to be difficult to avoid, since measuring skills is by no means an easy task. As Aghion (2002) points out, a PhD from a top university should be valued more than a PhD from a lesser place, even though they both may involve the same number of years of education. Similarly, he continues, an equivalent number of years spent at different jobs may lead to very different degrees of learning-by-doing and training. However, according to Aghion, a substantial amount of residual wage inequality remains even after these types of measurement problems are controlled for.

Aghion and Howitt (2002) argue that within-group inequality can be explained based on technological change raising the rewards to adaptability. According to them, within-group wage inequality arises because only a random fraction of *ex-ante* identical workers with the same educational background get the opportunity to learn and adapt to the most recent vintage(s) of machines. Aghion and Howitt present models based on these premises, highlighting that the key is that the speed with which a worker can adapt to working with new technology is only partly a matter of education and partly a matter of luck. According to this model, the skill premium stabilizes in the long run when technology diffuses and people become increasingly used to it.

2.5 Alternatives to technology-based explanations

Skill-biased technological change has not been the only suggestion for the rise in the skill premium. Another main argument has been that increased international trade between skill-scarce less-developed countries and skill-abundant rich economies decreased wages of low-skilled workers in the US (e.g. Wood (1994)). By the end of the 20th century, the consensus view among economists was that trade flows were too small to account for the changes in skill demands during the 1980s and 1990s. However, recently there have been some economists, such as Krugman, who have argued that in particular the trade integration between the US and China has reached such high levels that its role may have become more important, although this view is still controversial (Autor, 2010). In the twenty-first century the focus has shifted to the role of tasks trade, or offshoring (e.g. Bliner (2007)). As argued by Autor (2010), the distinction between technology and offshoring is in some sense moot, since information technology plays such a big role in enabling offshoring in the first place that a distinction between the effect of technology and the effect of offshoring is almost impossible to make.

Several others have blamed the rising skill premium on labour market institutions and pointed in particular to the changes that US labour unions have undergone since the 1970s. According to Katz and Autor (1999), many studies have found that differences in wage setting institutions (union and government roles in wage setting) seem to be strongly related to differences in wage inequality, especially in the lower half of the wage distribution and across different educational levels. A common assumption, sometimes called the Krugman hypothesis, maintains that inequality did not increase as much in Europe because of its labour market institutions that encourage wage compression and limit the extent of inequality (Acemoglu, 2002). According to this hypothesis, skill-biased change in Europe led to higher rates of unemployment instead of an increased skill premium because of the lack of flexibility in the wage structure. In a recent blockbuster book called *Capital in the Twenty-First Century*, Piketty (2014) argues that theories of skill-biased technological change fail to explain the explosion of very high salaries, and especially why they have developed only in some countries but not others. Piketty argues that the race between education and technology and its underlying idea of marginal productivity of skill cannot explain this. He writes that jobs at the top are unique and have a marginal productivity that is very hard, if not impossible, to define, which means that e.g. manager's individual marginal productivity becomes almost an ideological construct. Hence, according to Piketty, wages at the top are susceptible to hierarchical relationships, the individual's bargaining power, and social

norms reflecting "beliefs about the contributions that different individuals make to the firm's output and to economic growth in general" (Piketty, 2014, p. 236).

According to most economists, the change in the wage structure is not the consequence of one single cause but a combination of reasons. Acemoglu (2002) argues that the direct effects of changes in labour institutions, international trade and organizational factors on the US wage structure were limited. Instead he suggests that all three interacted with technological change in a way which amplified the direct effect of technological change on inequality.

2.6 Empirical studies on skill-biased technological change in Finland

The literature on skill-biased technological change in Finland is sparse, unanimous, and stems from the 1990s and the 2000s.

Vainiomäki (1999), following a method by Berman et al. (1994), analyses changes in amounts of skilled employment and wage premiums within and between plants in the period 1974 to 1994, based on the idea that skill upgrading within plants is considered to be a reflection of skill-biased technological change, whereas between-plant changes are thought to reflect trade and other demand explanations. He finds that skill upgrading is mostly due to increased demand for educated workers within plants, as opposed to between-plants, which he interprets as evidence of skill-biased technological change. He continues with a regression analysis in order to test the direct effects of technology, trade and other explanations, and finds that R&D intensity is positively correlated with changes in employment shares for educated workers, further strengthening the hypothesis of skill-biased technological change. He also discusses the effect of the supply of skills on the skill premium. He comes to the conclusion that the effects of higher demand for skilled workers seem to have been channelled into a higher demand for skilled employment rather than an increase in wages.

Huttunen (2002) also follows the method by Berman et al. (1994), distinguishing between young and old workers as well as skill levels focusing on changes in skill demand for private sector establishments in the period 1988 to 1998. She finds evidence that an increase in the level of R&D and export share significantly increases the demand for highly educated younger workers, while the impact is much less pronounced or insignificant for older workers.

In his study of changes in the wage structure in Finland between 1977 and 1995, Uusitalo (2002) provides an explanation based on the demand for and supply of skills. He finds that the model used is able to account for changes in relative wages between groups of different educational and experience levels, but not changes in within-group wage dispersion. Uusitalo also maintains that changes in the wage structure in the period do not indicate a change in relative productivity of skilled and unskilled workers.

Huttunen (2005) finds that employment has generally shifted towards highly educated and older workers reflecting the skill structure of the population, but finds no significant effect of R&D intensity and export share on the demand for skill within manufacturing sector plants in the period 1988 to 2001.

In contrast, Einiö (2013) examines the period 1976 to 2004 and finds a large increase in the demand for skills in the period 1976 to 2004. According to Einiö, the demand shift was the most intense from the mid-1970s to the end of the 1980s, which Einiö associates with the introduction of computer technologies. Einiö also finds a positive correlation between increases in industries' R&D intensity and their demand for skills. He argues that his findings add credence to the view that a sharp increase in the demand for skills driven by technological development has been a main cause of the rising wage inequality in developed economies.

3 A history of Finnish education and technology since 1970

In order to set the context for the analysis in Section 4 and facilitate the interpretation and analysis of results, I am now going to give an account of the historical developments in education and technology that have taken place in Finland since 1970.

## 3.1 A brief history of the Finnish education system

Before the 1970s, Finland was still poorly educated and the education system was rather elitist. Further education was accessible only those who could afford it and happened to live close to a grammar school and university (Sahlberg, 2011). The biggest promise of change came in 1963 when a decision for comprehensive school reform was reached by the Finnish Parliament. Sahlberg (2011, p. 24) calls this "perhaps the most important single consensus in the history of Finnish education". The new system was realized in 1970 and emphasized equity and equal access to good primary and secondary education for all (Sahlberg, 2011). Equity was also improved by a further regional expansion of the university system and the introduction of financial aid for students (Asplund & Maliranta, 2006).

In the 1980s, universities were becoming increasingly seen as engines of economic growth. Emphasis in the 1970s had been on social sciences and public services, but now focus shifted to subjects promoting technological and economic development (Asplund & Maliranta, 2006). Students' learning outcomes had begun to even out, but a gap was still maintained through the system of streaming pupils into different groupings in mathematics and languages according to ability. This system was abolished in the mid-1980s, after which the achievement gap decreased (Sahlberg, 2011). Upper secondary education was also restructured to increase access for all students, further increasing the level of equity in the education system (Sahlberg, 2011).

Sahlberg (2011) calls 1990 an important watershed in Finnish educational history. He bases this claim on the insight that the time before 1990s was characterized by the creation of institutions and frameworks for a welfare-based education system, whereas the time after 1990 has been more concerned with ideas and innovations (Sahlberg, 2011). Such ideas have included a decentralization of power through school-based curricula, and coordination between schools and municipalities for sharing ideas (Sahlberg, 2011). The 1990s onwards were also a time of expansion in the higher and adult education sectors. Sahlberg (2011) argues that part of the

motivation for developing the Finnish education system in this period came from Finland's accession process of becoming a member of the European Union, which was realized in 1995. According to Sahlberg, Finnish schools had a poor reputation in the fields of mathematics and sciences compared to other European nations in the 1970s and 1980s, and the EU membership functioned as an incentive to make sure that the Finnish educational performance was at a European level (Sahlberg, 2011).

In 2000, the first report by the Programme for International Student Assessment (PISA) was published, comparing the educational performance of 15 year olds. Finland was ranked as a top performer and maintained its top position in the three following reports in 2003, 2006, and 2009, making the country world famous in the educational arena. Although Finland's scores dropped in the last PISA Report of 2012, Finland remains a top European performer with one of the most equitable school systems in the world (Sahlberg, 2013). Finnish higher education has also reached a high international standard and participation rates. Summing up, it can be said that the increase in the educational level of the Finnish education and the quality of the education system has been very rapid. Figure 1 shows the evolution of the educational structure of the Finnish population.

Figure 1. Educational structure of population aged 15 or over
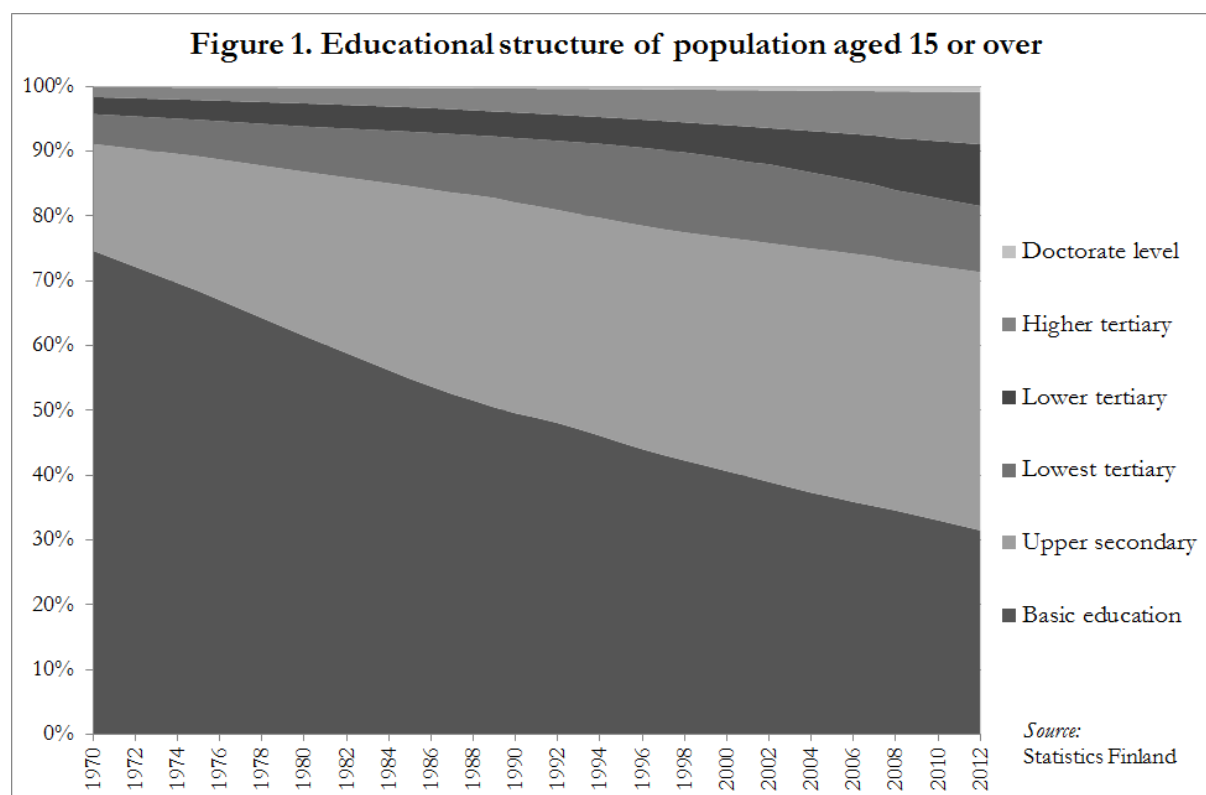
3.2 A brief history of Finnish technological development

The institutionalization of science and technology policy in Finland began in the early 1960s, which was later than for most developed OECD countries. The first actual science and technology policy programs were written in the early 1970s (Lemola, 2002). A reason for the new emphasis on technology was the growing internationalization and trade liberalization of the era, which put pressure on Finland's level of technology and the production structure, which still constituted to a large part of the forest industry (Lemola, 2002). Industrialization in Finland differed from that in many other Western European countries. First of all it was late: secondary production as a share of GDP peaked in 1974, later than in most Western European economies (Kokkinen, 2012). Additionally, production shifted from primary production to both secondary and tertiary production at the same time, which stands in contrast to the classical view of separate industrialisation and post-industrialisation phases (Kokkinen, 2012). In terms of GDP, Finland was able to catch up with the EU15 in the 1970s, exceeding their level in 1980 (Kokkinen, 2012). Growth in the 1970s was driven by high ratios of investment stemming from 1950s policies designed to accelerate Finland's industrialization (Bank of Finland, 2012). Hence, both growth in GDP and labour productivity were largely a result of growth in capital stock, although productivity was also improved through a catch-up effect as Finland was able to adopt technology from more advanced countries (Bank of Finland, 2012).

Technological and industrial R&D activities started to increase in the early 1980s reaching very high levels even in international comparison. Throughout the 1980s and 1990s industrial R&D spending grew faster in Finland than in any other OECD country (Kiander, 2004). This was partly a result of R&D enhancing policies. The current main executor of technology policy Tekes (The National Technology Agency) was established in 1983, launching the first national R&D programmes which were focused on stimulating collaboration between industry, universities and research institutes (Asplund & Maliranta, 2006). The principal aim was to accelerate the restructuring of industry from low-tech to high-tech sectors, a process in which information technology was regarded a key player (Asplund & Maliranta, 2006).

The 1990s was an important decade for Finnish technological development as well, although the decade started with the worst recession in Finnish history since the 1930s. Output and employment fell for three consecutive years from 1991 to 1993 resulting in an unemployment rate of 20 percent and a decline in GDP of 13 percent (Sahlberg, 2011). The government responded somewhat surprisingly by promoting innovation activities and diversifying production

away from traditional industries toward high-technology and mobile communication. R&D investments accelerated from 2 percent of GDP at the beginning of the decade to an excess of 3 percent before the end, hence reaching the millennium target set by the Science and Technology Policy Council ahead of schedule (Asplund & Maliranta, 2006). The growth of industrial production in 1992 to 2000 was record-high, averaging 7 percent per year, and labour productivity in manufacturing grew by an average of 6 percent a year, making Finland one of the countries with the highest productivity in the world (Kiander, 2004). The productivity growth was a result of vast structural change. Still in the beginning of the decade industrial production was dominated by paper, pulp, metal products and machinery, but by 2000 the electronics industry had outgrown them all, increasing its share from 8 to 27 percent (Kiander, 2004). Mainly this was due to the growth of mobile communications and Nokia, which by 2000 had become the world's biggest manufacturer of mobile phones with a global market share of 7 percent (Kiander, 2004). The electronics industry had a great impact on GDP growth. According to some estimates it contributed up to 3 percentage points of the total 5 percent growth of GDP in 2000 when the effect was the largest (Lehto & Lehmus, 2013). The effect on Finnish R&D spending in this year was also great, with Nokia accounting for approximately one-third of total R&D expenditure (Asplund & Maliranta, 2006).

Although the prime years of Nokia were over by 2000, the company continued to have a positive effect on Finnish growth rates until 2007, when the contribution to GDP was around 2.7 percentage points (Lehto & Lehmus, 2013). However, the effect of Nokia became clearly negative in 2008, and in 2009, at its largest, the electronics industry decreased GDP by 2 percentage points annually (Lehto & Lehmus, 2013). The effect was still negative in 2012. However, according to Lehto and Lehmus (2013), Finnish productivity in industry and construction from 2000 to 2012 has developed approximately in equal amounts as those of competing countries.

4 Analysis of skill-biased technological change in Finland

Now I am ready to begin my own analysis. I will start by discussing my dataset and continue by calculating skill premiums for different educational levels. Then I will proceed to test how well the steady-demand hypothesis and the acceleration hypothesis are at explaining the evolution of the skill premium. I will complete descriptive statistics of the relationships with a formal analysis based on Vector Autoregression (VAR) models. The role of within-group inequality will also be examined in detail.

4.1 Data and data processing

The calculations are based on a dataset from Statistics Finland which contains average and median yearly wage and salary income for employed members of the workforce between 18 and 64 years old as well as the number of people in these categories. According to Statistics Finland's definition, employed members of the workforce are people who were employed during the last week of the year when the statistics were gathered. The data from the years 1970, 1980 and 1985 are from the Population Censuses, and the data from 1987 to 2012, which is available annually, is from the Employment Statistics. Both databases are produced by Statistics Finland. The wage figures were nominal and have been transformed into real wages using the Consumer Price Index (2012 = '100') calculated by Statistics Finland.

A problem with the dataset is that there are many missing values before 1987. For the calculations of the skill premium, relative supply of skills, and within-group wage dispersion these values have been interpolated based on assumptions of either linear or exponential growth, depending on prior ocular inspection of the series.

Another point requiring awareness is that the dataset does not take account of the amount of time worked. There is no way of knowing how much the people worked during the year, a distinction is not even made between full-time and part-time employed. As such, the results should be interpreted with some caution.

The statistics are divided into six educational categories:

1) No education past basic schooling or unknown educational level (basic schooling in Finland is nine years);

2) Upper secondary level education (lasts 1-3 years, high shool ("gymnasium") or vocational school for e.g. nurses and electricians);

3) Lowest level tertiary education (lasts 2-3 years, is started after the upper secondary level education. E.g. degrees for technicians and agronomists);

4) Lower-degree level tertiary education (lasts 3-4 years, is started after the upper secondary level education. E.g. bachelor's degrees, engineering degrees. Qualifies candidate for higher-degree level tertiary education);

5) Higher-degree level tertiary education (lasts 1-2 years, master's degree from university or polytechnic),

6) Doctorate or equivalent level tertiary education.

The lack of knowledge about first category brings some uncertainty to the dataset. However, this is not likely to be a very big problem because based on an inspection of the data series the wages for category 1 are quite stable and are lower than for all the other groups (see Appendix). Hence it behaves in an expected way.
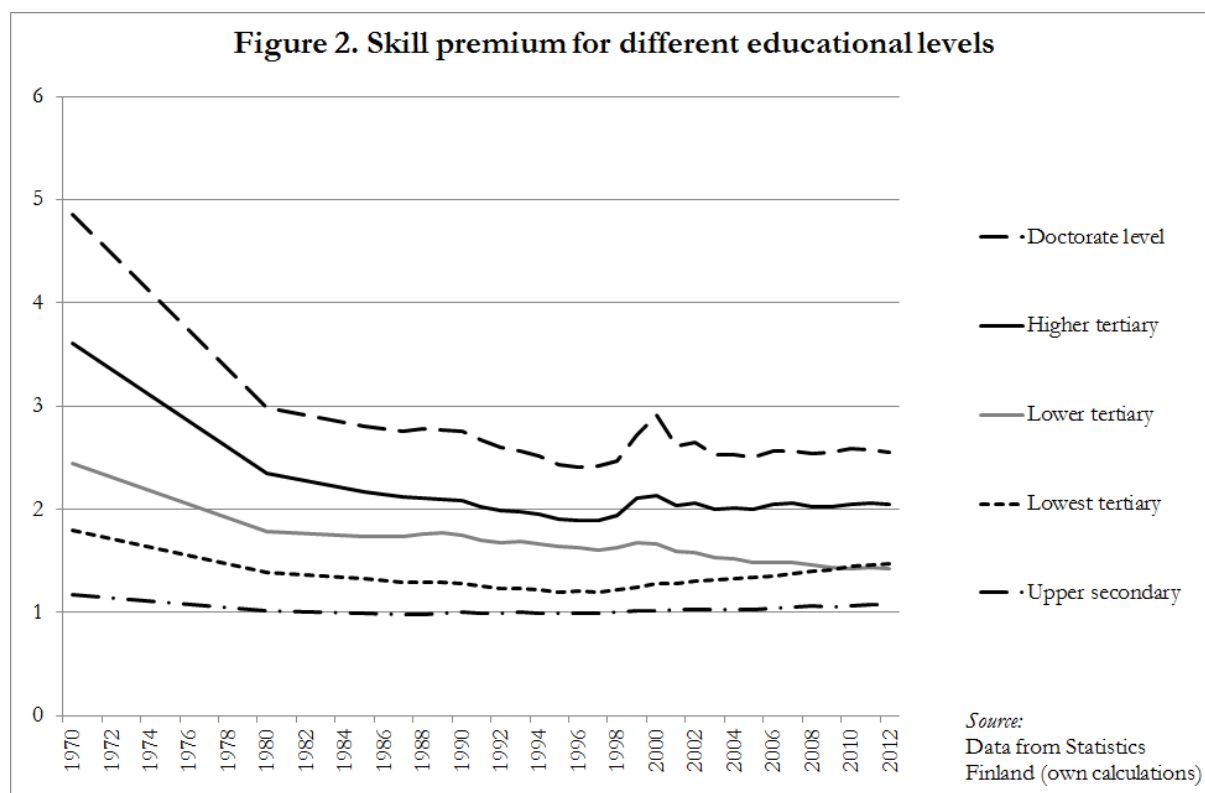
Overall it is a good dataset from a reliable source that benefits from its huge size. The dataset includes wages of between 1 562 121 and 2 227 447 people, i.e. all employed members of the workforce between ages 18 and 64 in the years 1970 to 2012.

4.2 Skill premiums for different educational levels

The skill premiums have been calculated simply by dividing each of the average yearly wages of educational categories 2-6 with that of category 1, i.e. those with no education past basic schooling. As can be seen from Figure 2, the skill premiums of tertiary and doctorate level educations were decreasing rapidly during the 1970s and at a slower pace in the 1980s.[1] The change has been particularly drastic at the higher educational levels. The skill premium for workers with a doctorate level education reaches a minimum value (2.409) in 1996, after which

---

[1] Data is available only for the years 1970, 1980, 1985 and annually from 1987 forward. However, in the graph all the data points have been connected with straight lines to add clarity.

the movement is of a more sporadic, and generally positive, character. The skill premium for workers with a higher tertiary education follows a similar, although less pronounced, pattern and reaches a minimum value (1.892) one year later in 1997. In the years preceding the year 2000 there are sudden increases in the skill premiums for workers with a doctorate level or higher tertiary level educations, although these increases are mirrored by rapid decreases, especially in the premium for doctors. In general the rank of the different curves has remained the same, although the skill premium for lowest level tertiary education has overtaken the skill premium for lower-degree level tertiary education in recent years. Much of this can probably be explained in terms of changes in the supply: since the end of the 1990s, the supply of the former has decreased while the supply of the latter has increased (see Figure 1).

Figure 2. Skill premium for different educational levels

Source: Data from Statistics Finland (own calculations)

4.3 Testing the steady-demand hypothesis

I am going to base the first part of my analysis on the canonical model that has been used by e.g. Goldin and Katz (2008). I am going to compare changes in the skill premium with changes in the relative supply of skills to see whether the supply of skills can explain the skill premium, as is theorized by believers in the steady-demand hypothesis. I am going to focus on a relatively small group of skilled workers, namely those with doctorate or higher-degree level tertiary educations.

This is because I am especially interested in the highest wages since the empirical literature has found these to be rising.

The skill premium has been calculated the following way. "Doctor" signifies an employed person between 18 and 64 with doctorate or equivalent level tertiary education and "master" signifies an employed person of the same age with a higher-degree level tertiary education.

$$skill\ premium = \frac{(average\ yearly\ wage\ of\ doctor) + (average\ yearly\ wage\ of\ master)}{2 * (average\ yearly\ wage\ of\ worker\ with\ no\ or\ unknown\ education)}$$

The relative supply of skills has been calculated according to the equation below. The total number employed refers to everyone between 18 and 64 who were employed during the collection of the statistics. Again "doctors" and "masters" refer to the same thing as above.

$$relative\ supply\ of\ skill = \frac{(no.of\ employed\ doctors) + (no.of\ employed\ masters)}{total\ number\ of\ employed}$$

The skill premium and the relative supply of skills have been calculated for all years for which there was available data. The missing values in the series for the skill premium have been interpolated based on an assumption of quadratically decelerating growth from 1970 to 1980 and from 1980 to 1985. This was because the original curve looked concave (see Figure 2). Similarly, the missing values in the supply series were interpolated, this time assuming arithmetic growth, based on the linear-looking growth of the series. All the interpolated values should be interpreted with caution. Next both series have been logged and then de-trended using a Hodrick-Prescott filter to facilitate comparison between the two series. The first procedure means that movements along the y-axis can be interpreted roughly as percentages, and the second procedure means that an upward movement can be interpreted as an acceleration and a downward movement can be interpreted as a deceleration in the measures of skill premium and skill supply.

As can be seen in Figure 3, there is a clear inverse relationship between the skill premium and the relative supply of skills. This gives weight to the steady-demand hypothesis which explains the evolution of the skill premium in terms of the relative supply of skills.

Figure 3. Relative supply of skills and skill premium
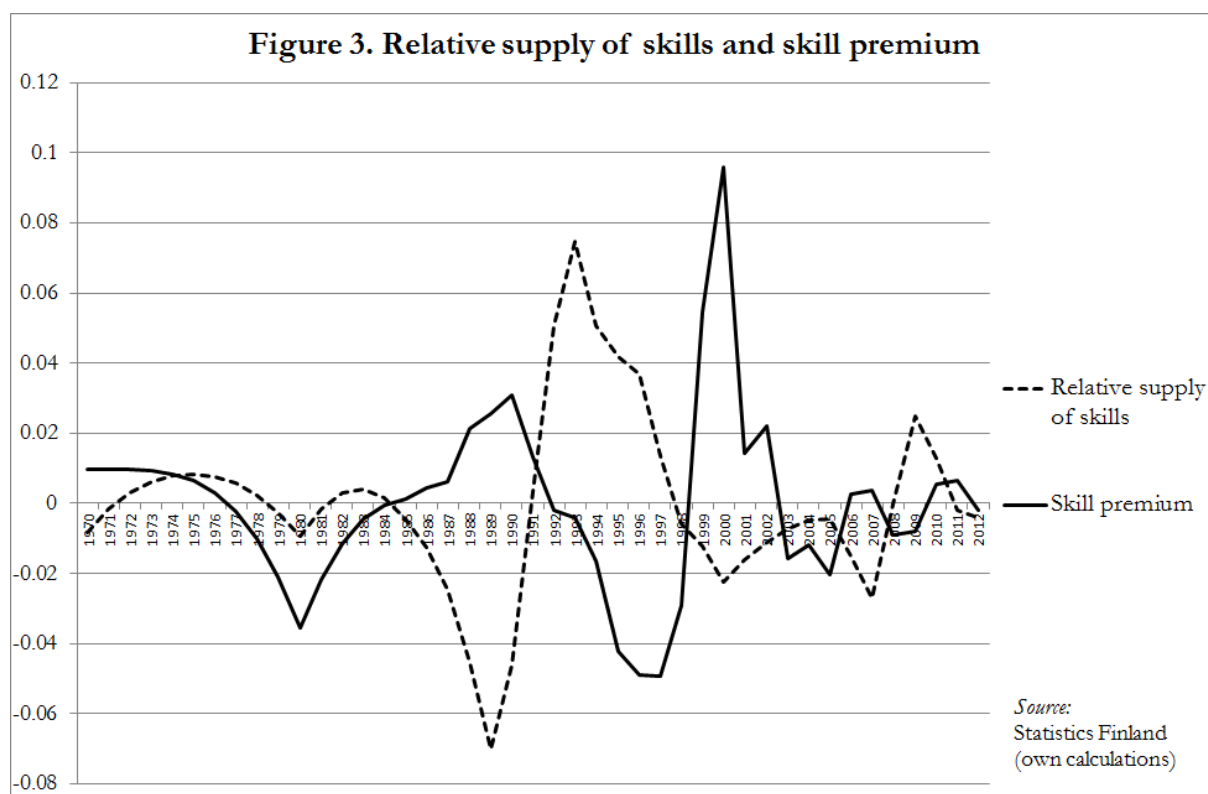
The curves before 1987 are more difficult to interpret since many of the values are missing. All that can be deduced is that the rate of growth of the supply of skills has been greater and more stable than the growth rate of the skill premium.

The most notable feature of the graph is that the rapid acceleration of the skill premium from 1997 to 2000 is not met by equal decelerations in the supply of skill. Hence, another explanation for the acceleration in the skill premium should be looked for. A likely cause is the success of Nokia. Furthermore, the skill premium does not decelerate in equal amounts as the supply of skills accelerates in the years 1990 to 1994. This is probably because of the recession which led to extreme levels of unemployment. If proportionally more unskilled workers became unemployed, it would increase the skill premium, since the dataset does not include unemployed people.

4.4 Within-group inequality

The steady-demand hypothesis is based on dividing workers into categories based on observable skills. However, not all inequality can be accounted for in terms of observable skills. In this section I will calculate and analyse the ratio of average-to-median wages which can be interpreted as a measure of within-group wage inequality. The median is the numerical value that would

separate everyone's wages into a lower and a higher half, if they were to be lined up in order of magnitude. If the average-to-median ratio is close to one, it means that the average is a good measure of what people in the middle are earning. If the ratio increases, it means that people at the top are earning increasingly more compared to people on the lower side of the median. Conversely, if the ratio decreases, it means that people below the median are earning increasingly less. As can be seen from Figure 4, the within-group inequality has been much less stable than the skill premiums.[2]

Figure 4. Ratio of average to median wage income
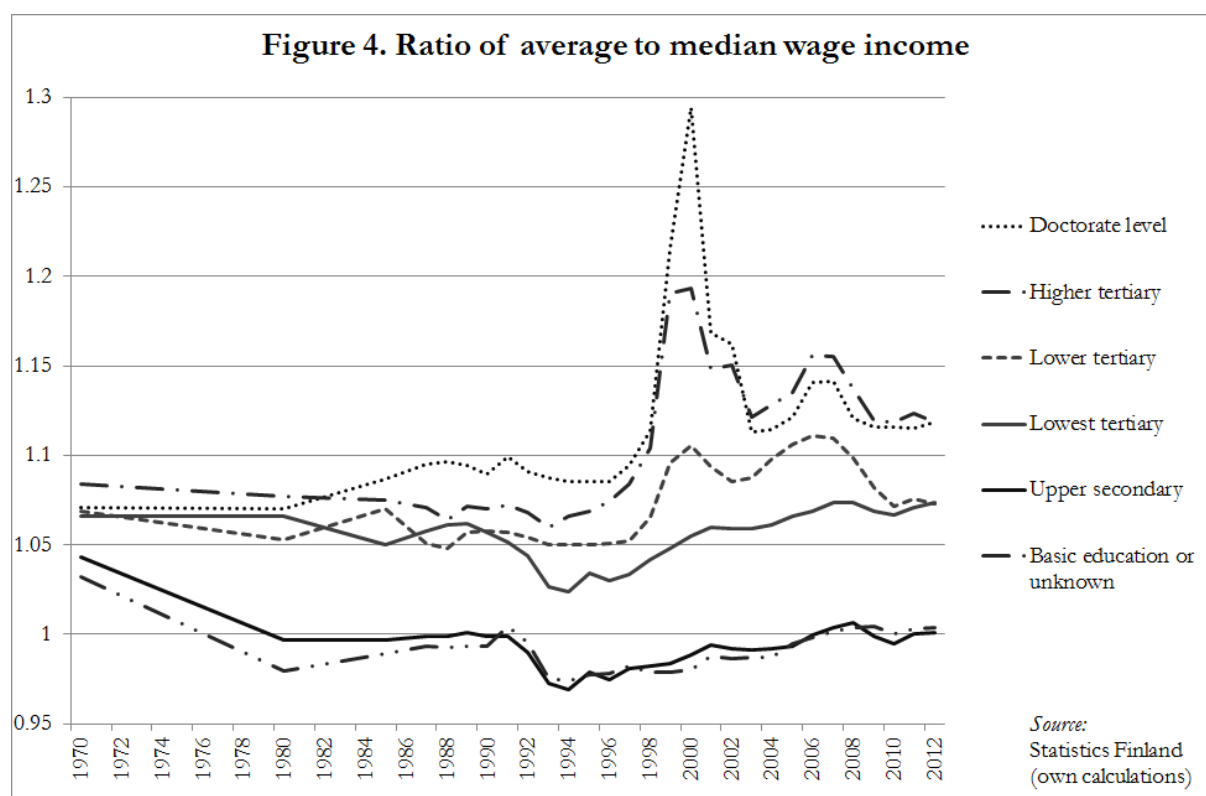
There are different patterns for the workers that hold tertiary degrees and those who hold only basic or upper secondary degrees. In the group of tertiary degree holders the average-to-median ratio seemed to be fairly stable, between 1.05 and 1.1, all the way from 1970 to around 1995. In 1996 they had all began to rise and continued rising until a peak in 2000, when all series except the measure for lowest-level tertiary education decreased markedly. This pattern was more pronounced at higher educational levels, especially so for holders of doctorate level degrees. The average-to-median ratio for all the tertiary level degree holders rose again from 2003 onwards,

---

[2] Data on average and median earnings is available only for the years 1970, 1980, 1985 and annually from 1987 forward. However, in the graph all the data points have been connected with straight lines to add clarity.

peaking around 2006-2007. In general, the average-to-median ratio has been higher at all tertiary levels after 1996 than before.

The pattern for those without tertiary degrees is notably different. Within-group inequality decreased in the 1970s, which could be a result of the rapid unionization in that period. It stabilized around 1 in the 1980s meaning that the average was a very good measure of what people in the middle were earning at that time. The ratio decreased below 1 from 1991 to 1994 during the recession, meaning that people below the median were earning increasingly less. Since 1994, the ratio has been slowly growing and has seemed to stabilize around 1 in recent years.

Overall, Figure 4 suggests that educational attainment has become an increasingly bad predictor of wage, and that inequality has been increasing especially within higher education groups. Moreover, the data in Figure 4 also indicates that within-group wage inequality is of a more transitory and fluctuating character than between-group wage inequality (Figure 1), which is in line with international evidence discussed in Section 2.4.


4.5 Testing the acceleration hypothesis

The steady-demand hypothesis seems to be quite good at explaining the movements of the skill premium since the 1970s. However, there are some exceptions that are more difficult to account for in terms of the supply of skills. Furthermore, as discussed in the previous section, within-group inequality seems to have been increasing, which makes the skill premium an increasingly bad predictor of wage inequality.

The canonical model is based on an assumption of constant speed of technological change. However, as discussed in Section 3.2, the technological development in Finland seems to have been somewhat uneven, with a large portion of the development taking place at the end of the 1990s. In this section I am going to assume that technological change is not necessarily steady and can be accelerating, and of course decelerating, as theorized by the acceleration hypothesis. I am going to let R&D spending, specifically the fraction of total R&D expenditure of GDP, indicate the level of technological change. As mentioned, this indicator of technological change is not without problems. However, R&D is a widely used measure of technological change and has proponents in e.g. Capron (2002) and Abramovitz (1986), who argue that levels and growth rates

of R&D expenditure are reliable indicators of technology diffusion because they are related to direct efforts toward innovation.

Figure 5 shows R&D, skill premium and the ratio of average-to-median wage for doctor or equivalent level workers. Again the series have been logged and de-trended to ease comparison so that an upwards (downwards) movement can be interpreted as an acceleration (deceleration) in the growth rates of the series. Again, there are some missing values in the series, which means that added caution in the interpretation is needed. R&D figures are available annually only from 1987 forward, before that they are available for every second year starting from 1971. The values for even years have been calculated by taking the average of the preceding and the succeeding year. The missing values for the skill premium have been dealt with as previously, and the missing values for the proxy for wage dispersion for skilled have been interpolated based on an assumption of linear growth between 1970, 1980, 1985 and 1987.

Figure 5. R&D spending, skill premium and skilled wage dispersion
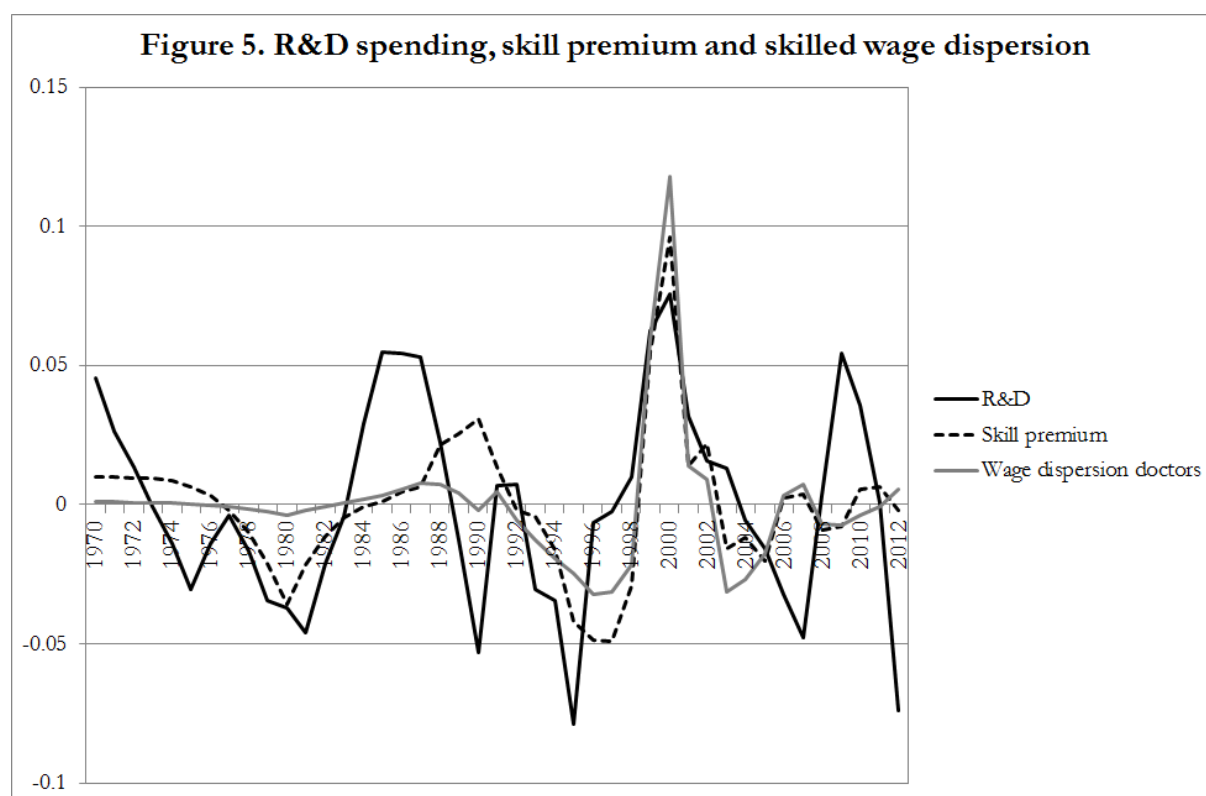
Based on Figure 5, there seems to be a positive relationship between R&D spending and skill premium. Both decelerate in the first decade and accelerate throughout most of the 1980s. There are rapid decelerations in both during the recession years, followed by the biggest and most rapid acceleration from 1995 to 2000. After this both series drop. The relationship between the series

seems to be gone from 2004 onwards, as the skill premium stabilizes and is not followed by the much larger fluctuations in R&D spending.

Skilled wage dispersion, on the other hand, seems to be much more independent of R&D spending in the first two decades, since it remains almost completely stable and does not react to the large changes in R&D. However, this changes in 1991 at the start of the recession, when skilled wage dispersion drops with R&D spending, after which they both grow, and then fall, rapidly.

The remarkable feature of Figure 5 is what happens in 2000 when all series peak together. It is hardly a coincidence that this value also is the maximum value of each series. As such, the (in this period) unprecedented acceleration of R&D investments, skill premium and within-group inequality for skilled workers take place together. This can be interpreted as a technology-driven boom.

As such, it appears that the speed of technological change can explain some of the asymmetries in that the steady-demand hypothesis gave rise to. As such, a combination of relative supply of skill and technological change succeeds in explaining a big part of the fluctuations in the skill premium. However, within-group inequality still remains to be explained.

4.6 Formal tests based on VAR models

There seems to be a clear relationship between the supply of skills and the skill premium, as well as a less constant relationship between R&D spending and skill premium. R&D expenditure seems to have affected wage dispersion for doctors only during the boom years. In this section I am going to test the relationships formally using Vector Autoregression (VAR) based models.

VAR models can be used to test for the direction of short-run causality using a Granger test, and also for how effects are distributed in the short run using Impulse Response Functions. It has to be pointed out that Granger causality is not equivalent to true causality, but is a statistical term that means that one series is useful in forecasting another. VAR models can be used in situations where several time series are interacting with each other, so that all the variables are potentially affecting each other and there are no clear-cut causal directions. In other words, it does not have to be decided in advance which variables are exogenous and which are endogenous.

I am going to use both a Granger test and Impulse Response Functions to investigate the relationships between the variables depicted in Figure 3 and Figure 5. In the first case, theory predicts that I should find a negative causality going from the relative supply of skills to the skill premium. However, it is not easy to tell from the graph whether this is really so. The series look like they are inversely related, but it is also conceivable that there is no causal relationship between them, or that causality goes from the skill premium to the supply of skills by motivating people to get an education or graduate quicker. In the second case theory predicts that R&D spending has a positive effect on the skill premium, but again, it is conceivable that the results could differ from the predictions if there is no causal relationship or if the skill premium actually affects R&D spending. Furthermore, I am going to include the wage dispersion for doctors, since it also seems to be connected to both series, especially the skill premium.

VAR models require that series are stationary. A stationary series is a series with a constant mean and variance over time. The series look like they could be stationary, but I will make a formal test using an Augmented Dickey-Fuller test to make sure. The results are presented in Table 1.

Table 1 *Results of the Augmented Dickey-Fuller test and the Breusch-Godfrey test*

Variable	Lags	Specification	Test statistic	5% critical value	Conclusion	Breusch-Godfrey test	No obs.
ln(supply) **detrended**	1	no intercept, no trend	-4.761	-1.950	Reject H0	0.2371	41
ln(skillpremium) **detrended**	1	no intercept, no trend	-3.943	-1.950	Reject H0	0.1554	41
ln(r&d) **detrended**	1	no intercept, no trend	-3.731	-1.950	Reject H0	0.3020	41
ln(dispersion) **detrended**	1	no intercept, no trend	-4.510	-2.901	Reject H0	0.1200	41

In all cases the null hypothesis of a unit root can be rejected, which means that the series are stationary and can be incorporated in a VAR model. Dickey-Fuller tests are biased towards finding a unit root, so these results should be very reliable. In addition I have tested my ADF-models for autocorrelation using the Breusch-Godfrey test. The null hypothesis of the Breusch-Godfrey test is that there is no autocorrelation of the lags in the ADF model, and the results

presented in Table 1 show that we cannot reject the null hypothesis in any of the cases, which means that none of the models suffer from autocorrelation.

Now that the series are known to be stationary, the VAR models can be specified. I choose two lags for both models based on recommendations by Akaike's information criterion. To investigate whether the VAR model is reliable I test it using several post-estimation diagnostic tests. The VAR model for skill premium and relative supply is stable based on a test of eigenvalues, and it does not suffer from autocorrelation according to the Lagrange multiplier test. However, the Jarque-Bera test finds skewness and kurtosis in the skill premium series that leads to the error residuals not being normally distributed. I perform the same diagnostic tests for my second VAR model of R&D, skill premium and wage dispersion for doctors. Again there are no problems with autocorrelation and the model is stable, but this time there are problems with non-normality caused by skewness and kurtosis in the series for wage dispersion. Hence the results should be interpreted with some caution. VAR models are difficult to interpret by themselves, hence a Granger causality test will be applied to the VAR model, the results of which are presented in Table 2.

As can be seen from Table 2a, we cannot reject the null hypothesis of no Granger causality at a 5% significance level in either case, although the p-value for Granger causality going from supply to skill premium is very low: 0.056. Since the 5% significance level is a more or less arbitrarily chosen level of statistical certainty, the null hypothesis should not be so quickly dismissed in this case. In fact, these Granger results provide strong evidence of Granger causality going from supply to skill premium. Hence, an acceleration in the relative supply of skills Granger causes a deceleration in the skill premium, just as predicted by the steady-demand hypothesis.

Table 2b displays the results from the Granger test for accelerations in R&D as a percentage of GDP, the skill premium and wage dispersion for workers with a doctoral level education. There is Granger causality going from the skill premium to wage dispersion, as well as from wage dispersion to the skill premium, indicating that these two are strongly connected. However, R&D only seems to affect the skill premium and not the wage dispersion for doctors. This can be interpreted as evidence of that technological change can explain some of the changes in the skill premium, but that it cannot explain changes in within-group wage dispersion for the highly skilled.

Table 2a *Results of Granger causality test*

Null hypothesis	*p* value	Conclusion
Skill premium does not Granger cause supply	0.490	Cannot reject H0
Supply does not Granger cause skill premium	0.056*	Cannot reject H0

Table 2b *Results of Granger causality test*

Null hypothesis	*p* value	Conclusion
W. dispersion does not Granger cause R&D	0.122	Cannot reject H0
SP does not Granger cause R&D	0.107	Cannot reject H0
R&D does not Granger cause w. dispersion	0.447	Cannot reject H0
SP does not Granger cause w. dispersion	0.020**	Reject H0
R&D does not Granger cause SP	0.080*	Cannot reject H0
W. dispersion does not Granger cause SP	0.033**	Reject H0

*,**,*** = Significant at the 10%, 5%, 1% significance level respectively.

To investigate these relationships in more detail, I use Impulse Response Functions. These can be used to plot the time path of shocks to dependent variables from the explanatory variables in a VAR model and help with interpretation of the results. It is important that the VAR model is stable for the IRFs to work, since a shock to the system should decline to zero after a few periods and this would not be the case in an unstable system. As seen earlier, both VAR models are stable so the Impulse Response Functions can be drawn. They are presented in Figure 6 and 7. All the variables have positive effects on themselves in the first 3-4 periods. This result is typical for Impulse Response Functions and not very interesting.

Figure 6 displays the relationship between skill premium and relative supply of skills. The interesting result in this table is in the bottom-left quadrant, which shows that the supply of skills has a negative effect on the skill premium. More specifically, a positive acceleration shock to the supply of skills is likely to cause a deceleration in the skill premium in the first four years. This effect is especially pronounced in year 3 when the whole area inside the 95% confidence interval is negative, meaning that the negative effect is statistically significant. As can be seen in the upper-right quadrant, there is no significant effect of the skill premium on the relative supply of skills. This is in accordance with theory.

Figure 6. Impulse Response Function of skill premium and relative supply of skills
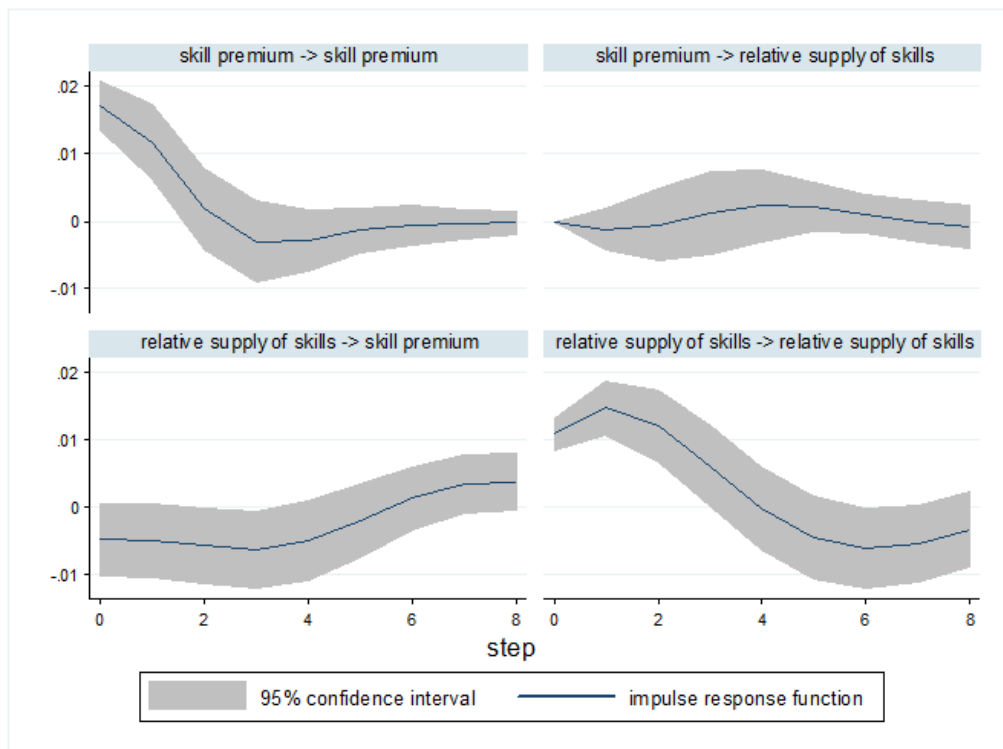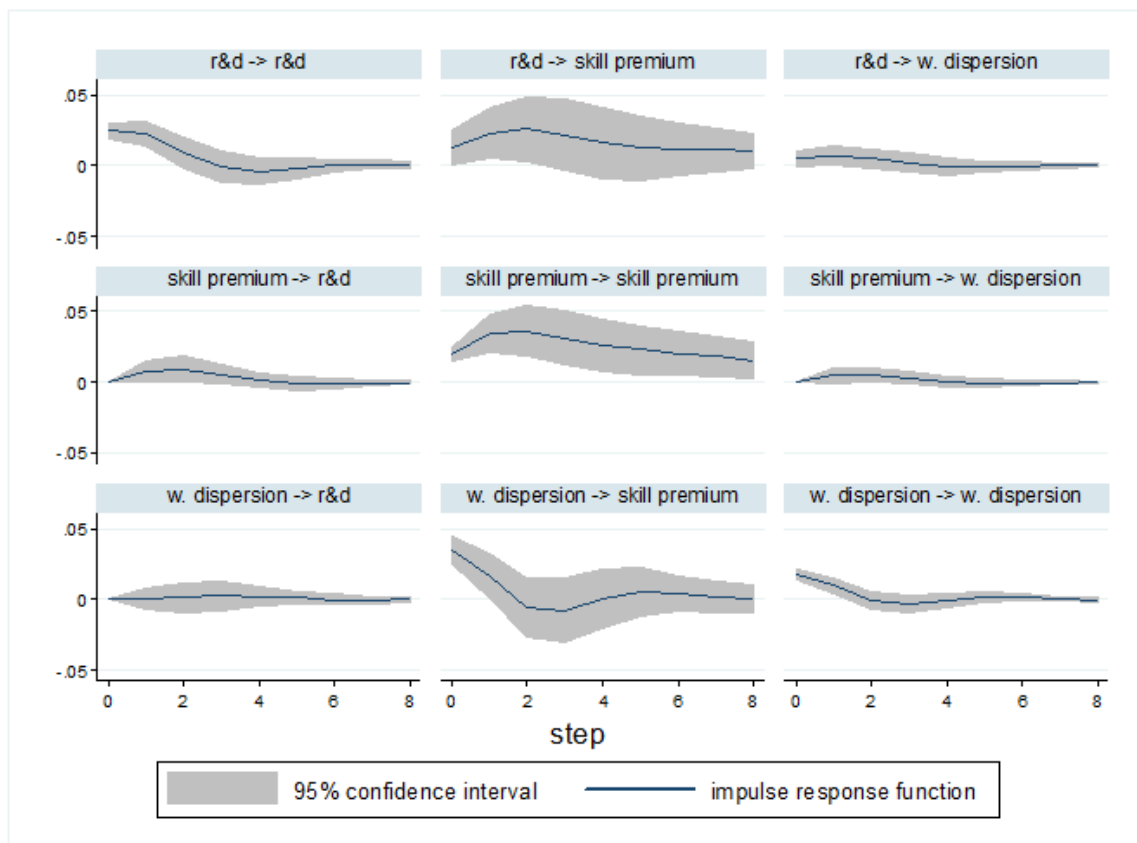

Figure 7. Impulse Response Function of R&D, skill premium and wage dispersion

The Impulse Response Functions in Figure 7 show the effects that shocks in R&D as a percentage of GDP, skill premium and wage dispersion for doctors (proxied by the average-to-median earnings ratio) have on each other. The interesting result here is in the first row in the second and third quadrant. As can be seen, a positive shock to R&D has a significant positive effect on the skill premium in the first two years, whereas R&D seems to have no or a very minor effect on wage dispersion for doctors. This is despite the fact that the skill premium and wage dispersion for doctors seem clearly related to each other, although more so based on the Granger test than the Impulse Response Function, which does not show a clear effect of skill premium on wage dispersion for doctors but shows a greater effect in the other direction.

To summarize the results it can be said that there seems to be a clear inverse short-run relationship between skill premium and supply of skills with the direction of causality going from the supply of skills to skill premium and the effect being the clearest three years after a shock to the supply of skills. Furthermore, the skill premium seems to be clearly related to the skilled wage dispersion and the causality appears to go in both directions. However, of the two, only the skill premium is affected by R&D spending, which suggests that the skill premium is affected by technology but the wage dispersion for doctors is not. This result is in line with much of the theoretical and empirical literature, which argues that skill-biased technological change can explain the evolution of the skill premium, but is not as good at explaining the evolution of within-group inequality.

4.7 A closer look at within-group inequality

R&D expenditure does not seem to be a very good predictor of within-group inequality for doctors. Also in general many argue that skill-biased technological change is not a very good explanation of within-group inequality. So what could alternative explanations for this phenomenon be?
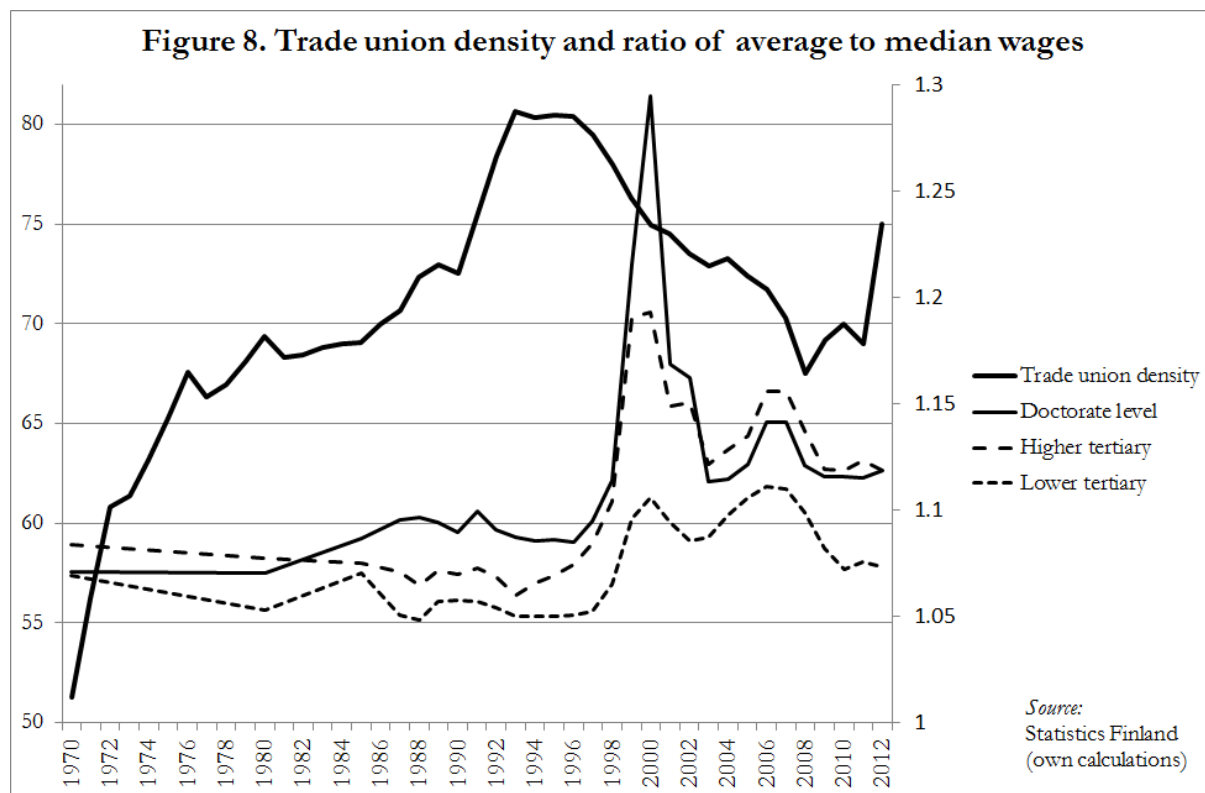
Eriksson and Jäntti (1997) study wage inequality in the period 1971 to 1990. They find a large increase in earnings inequality at the end of the 1980s, which stems largely from within-group inequality. Eriksson and Jäntti point out that this is a new phenomenon, since earlier shifts in inequality could be accounted for in terms of observed characteristics. They consider supply and demand related explanations, but argue that these are insufficient, suggesting instead that labour market institutions have been responsible for the changes. They point out that the compression

of wages during the 1970s coincided with highly centralized wage-bargaining and solidarity wage policies, and that the later increase in dispersion occurred at the same time as steps towards a more decentralized wage setting were taken. However, according to Eriksson and Jäntti, the large magnitude of the changes in the late 1980s is still somewhat puzzling, since the changes in wage bargaining were more gradual than changes in within-group inequality.

The explanation based on unionization is supported by Uusitalo (2002). He studies wage dispersion in the period 1977 to 1995 and argues that a supply-demand framework succeeds in explaining variation in between-group earnings sufficiently well, but also believes that it cannot account for changes within skill groups. He finds a strong relationship between the proportion of union members and the 90-10 wage gap (the ratio between those in the 90th percentile and those in the 10th percentile). Uusitalo thinks this suggests that the growth in within-group wage dispersion at the end of the 1980s might be related to decentralization. He also points out that the early 1990s were a time of both contraction of the wage distribution and four successive rounds of nationwide wage negotiations, and that wage differences in the latter half of the 1990s are likely to have increased as a result of industry-level bargains.

Indeed, as can be seen in Figure 8, trade unions seem to play a big role also after the early 1990s. There is a rapid decrease in the degree of unionization starting in 1996 and reaching a minimum in 2008. This is also a period of a rapid increase in the ratio of average to median earnings for the three highest educational levels, which I use as an indicator of within-group inequality for skilled workers. Although the two seem to be connected, the curve of trade union density is a lot smoother than the curves for within-group inequality, suggesting that that the former can only explain part of the latter.

Another possible explanation for within-group inequality, which is likely to be highly related to patterns of unionization, is that performance-based pay has become more prevalent. Kangasniemi and Kauhanen (2010a, 2010b) investigate this phenomenon, focusing on industrial firms in the period 1998 to 2007 and service-based firms in 1990 to 2005. They find that performance-based pay has increased in both cases, especially among white-collar workers. This has increased wage dispersion of white-collar workers in general. Kangasniemi and Asplund further find that the main part of the increase in wage dispersion in this group is due to unobservable qualities and cannot be explained in terms of e.g. education or age.

Figure 8. Trade union density and ratio of average to median wages

Source: Statistics Finland (own calculations)

Institutional factors like deunionization and the increase in performance-based pay seem to be likely candidates for the increase in within-group inequality. Does that mean that technology has no place in explaining within-group inequality? Most probably not. First of all, it is not clear that patterns of unionization and performance-based pay can be isolated from technological development (Acemoglu, 2002). Second, if technological change increases the proportion of jobs requiring expert level skills, it is likely to raise within-group inequality proportionally more among highly educated workers. The reason for this is that it is not only the level of education but the type of education that matters. For example, a person who holds a master's degree in Philosophy is likely to not be as well prepared for the diffusion of new technology as a person with a master's degree in Computer Engineering. As such, if the need for technology-based expertise increases, it is likely to benefit highly educated workers more – but only those who possess the right kind of knowledge, leading to a higher wage dispersion among higher levels of education. Indeed, there is recent evidence that expert-level employment has increased more than other kinds of employment in Finland. Maliranta (2010) studies the transformation of employment structures from 1990 to 2004. He finds that employment has increased most for "specialists". This is the group with the highest level of education (15.3 years on average). Maliranta finds that there has been a decrease in mid-skill-level employment and a slight increase in low-skill-level employment, which gives some evidence of job polarization, i.e. a suggestion that technological change has been simultaneously skill-biased and skill-replacing (although skill-biased to a much larger extent).

5 Relating the skill premium to other types of inequality

In *The Race between Education and Technology*, Goldin and Katz (2008) write that they are confident that changes in the skill premium is a reasonable proxy for wage inequality in the period 1915 to 2005. Is this the case for Finland since 1970? The answer is not so straightforward, because it depends on what is meant by wage inequality. However, the fact that within-group inequality has increased so much since the late 1980s is a sign that the skill premiums have become increasingly bad predictors of overall wage inequality.

Figure 9. Gini coefficients, share of factor income of top 1%, and skill premium
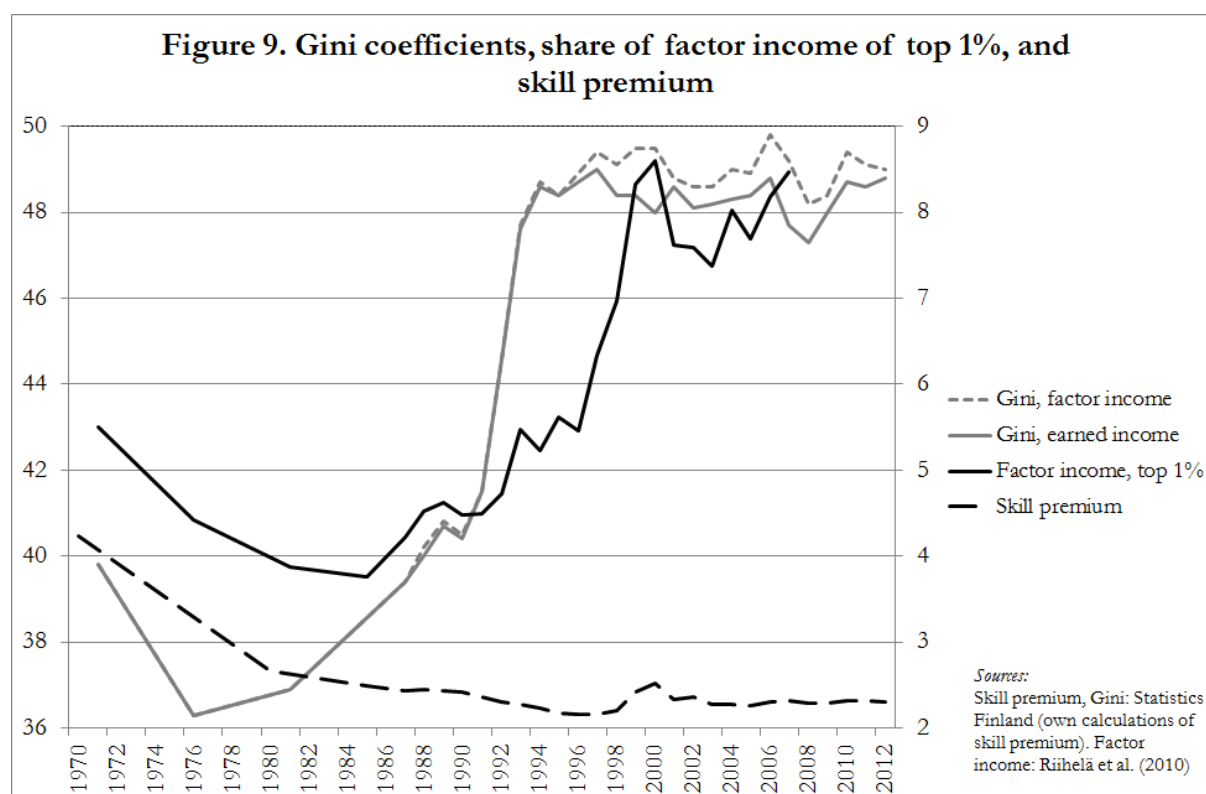
In Figure 9 some common measures of inequality are plotted next to the skill premium.[3] One of the most common measures of inequality is the Gini coefficient. The Gini coefficient takes account of the whole income distribution by dividing a Lorenz curve (the cumulative percentages of total income received against the cumulative number of recipients) with a hypothetical line of perfect equality. Thus, a Gini coefficient of 0 represents perfect equality and a coefficient of 100 represent maximum inequality. In Figure 9 the Gini coefficient measures the factor income of households. Two different Gini curves are plotted: that for *earned income* and that for *factor income*.

---

[3] The Gini coefficient and data on the top 1% income share is available only for the years 1971, 1976, 1981 and yearly from 1987 forward. Data for the skill premium is available only for the years 1970, 1980, 1985 and annually
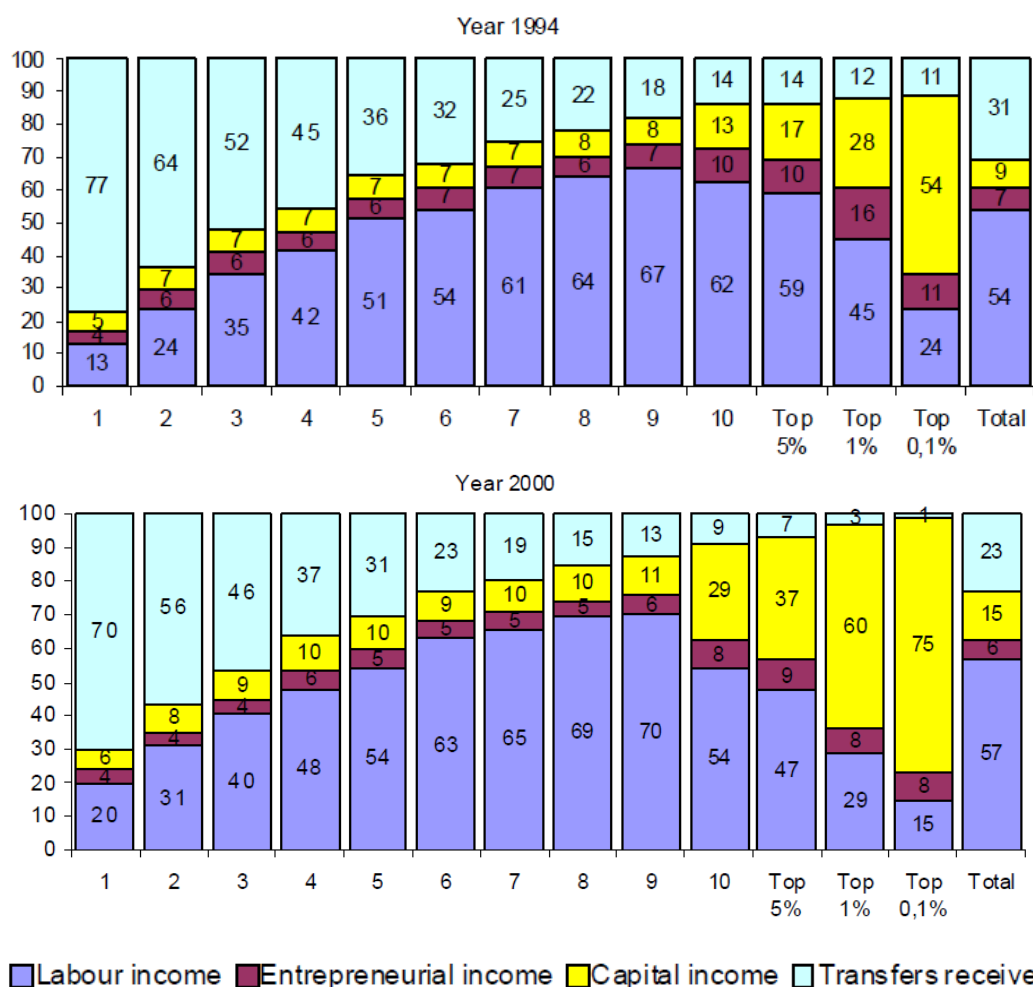
The former includes wages and entrepreneurial income. The latter includes wages, entrepreneurial income plus capital income. The Gini coefficient and figures for the top 1 percentile are not available only for wage income, which is why I have used these measures to get an understanding of overall inequality.

As can be seen in Figure 9, the skill premium is not a good indicator of income inequality measured by the Gini coefficients. The skill premium has mostly been decreasing, whereas the Gini coefficients have been increasing since 1976. The increase was especially steep from 1990 to 1994, which is probably because of the very high unemployment figures during the recession years. Since 1995, capital income has played a more important role in contributing to income inequality, which can be seen from the difference between the Gini coefficient for factor income and earned income.

The factor income share of the top 1 percent seems to be a better indicator of overall earnings inequality. (Again, this measure was not available only for wage and salary income.) As can be seen, this curve has been rising since 1985, and especially rapidly from 1996 to 2000. These were years when the share of R&D expenditure increased rapidly, which could be a sign that the increase in the factor income share of the top 1 percent was technology-driven.

However, since the measure of factor income includes other components in addition to wage and salary income, it is illuminating to look at whether the structure of those components changed in the period of the rapid rise in the share of the top one percent. Figure 10 shows that there was a dramatic change in the structure of income between 1994 and 2000. The capital income share of the top one percent more than doubled from 28 to 60 percent. This is a sign that wage inequality became a worse proxy for overall income inequality in the period.

---

from 1987 forward. However, in the graph all the data points have been connected with straight lines for best possible readability.

**Figure 10. Structure of income in 1994 vs 2000**

Source: Riihelä et al. (2010)

The decreased importance of the share of labour income is in line with global trends. According to Böckerman and Maliranta (2010), the share of employment compensation (largely gross wages and salaries) in national income has been decreasing in most developed countries in the last decades. Furthermore, the decrease has been steeper in Europe than the US, and has been especially steep in Finland. As can be seen in Figure 11, this development was especially rapid in the 1990s. According to Böckerman and Maliranta, this decline can be explained by increased globalization leading to wage moderation and a higher productivity caused by structural change. However, Böckerman and Maliranta argue that these globalization forces have not affected the wage structure itself.

Figure 11. Breakdown of national income

Source: Data from Statistics Finland
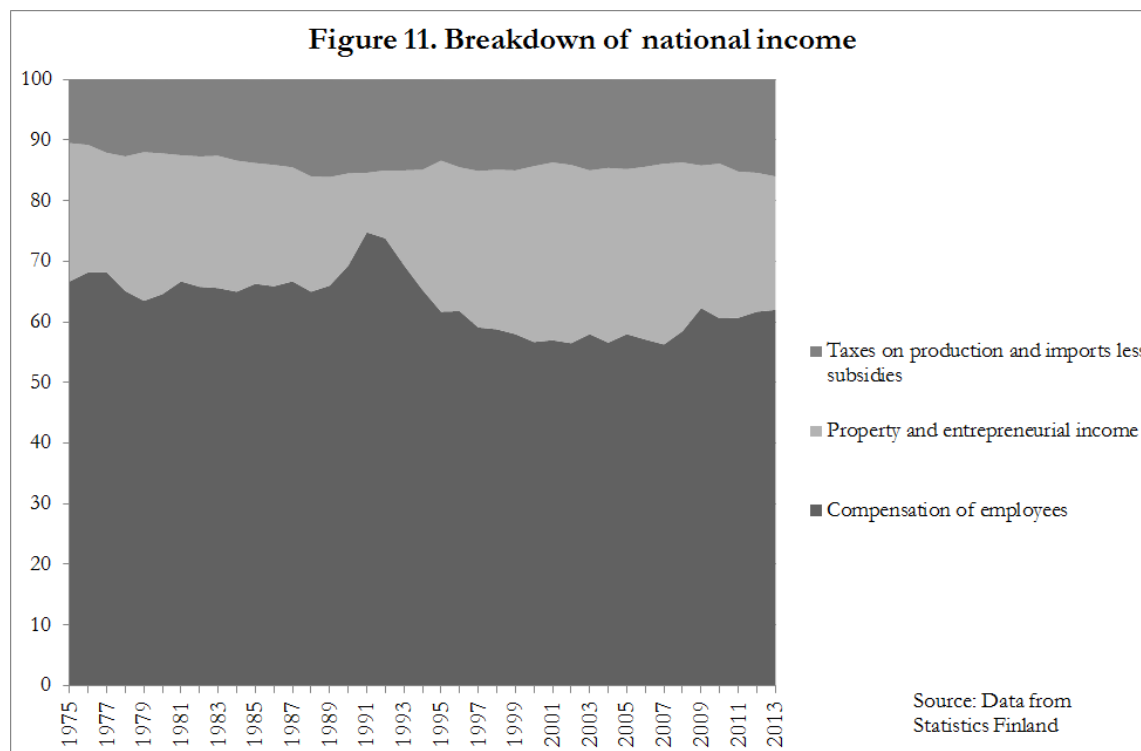
Another way to measure the inequality of wages that is focused on the distribution of top wages is to look at the Pareto-Lorenz coefficient. Figure 12 shows the Pareto-Lorenz coefficient for wages in Finland between 1987 and 2007.

Figure 12. The Pareto-Lorenz coefficient
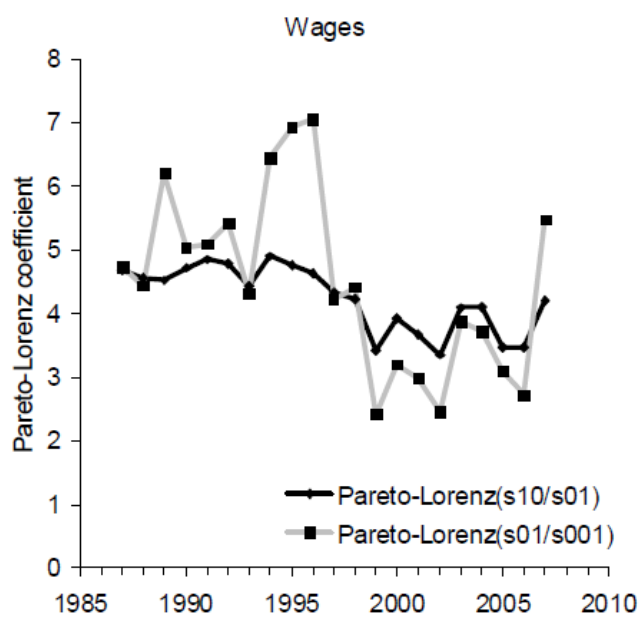
Source: Riihelä et al. (2010)

The Pareto-Lorenz coefficient measures the wage share of the top 1% within the top 10% (black line) and the wage share of the top 0.1% within the top 1% (light grey line). The smaller the coefficient, the larger is the within-group share of the top earners and the more unequal is the distribution at the top (Riihelä et al., 2010). Hence a falling coefficient means that inequality at the top has increased. Figure 12 shows that even without considering the tremendous effect of capital income, wage inequality at the top increased. In both groups, the increase in inequality was particularly rapid in the years 1996 and 1999, which coincides with both a rapid rise in R&D expenditure and a fall in union density. Figure 12 strengthens the results from Section 4.4 according to which within-group inequality increased the most in groups of higher educational attainment, since these are precisely the groups with the highest earnings (see Appendix).

Summing up, this section has shown how the skill premium fits into broader measures of inequality. Comparing the skill premium with Gini coefficients gives further weight to the results suggesting that the skill premium has become a worse indicator of overall earnings inequality. The Pareto-Lorenz coefficients indicate that wage inequality has increased most at the top end of the distribution, further corroborating the results from the analysis of within-group inequality. The factor income share of the top one percent seems to be a better indicator of overall inequality (proxied by Gini coefficients) than the skill premium. However, the increasing factor income share of the top one percent is not only driven by increases in top wages, but also by increases in top capital shares. Overall, a breakdown of national income shows that wage and salary income does not constitute as big a part of national income as it did in the 1970s. Hence, wage and salary income is able to explain a smaller part of overall income inequality than it could four decades ago. A thorough discussion of reasons for this lies without the scope of the paper, but is of interest with regards to further research on income inequality in Finland.

6 Conclusion

The aim of this paper has been to investigate how the skill premium in Finland has evolved since 1970 and whether the evolution can be explained in terms of the supply of skills and technology-induced demand for skills. The results showed that the relative supply of educated workers indeed can account for most of the changes in the skill premium, which is in accordance with the canonical steady-demand model. Technological change, proxied by R&D expenditure, also had an effect on the skill premium and added explanatory power where the simple supply-based framework did not do so well at explaining the skill premium. Additionally, the results suggest that within-group wage dispersion has increased, particularly for workers with the highest levels of educational attainment. These results fit well with the findings in Section 5, according to which most measures of inequality have increased, particularly at the top end of the income distribution, even though the skill premium has decreased. Within-group inequality for workers with equivalent educational attainment cannot be as easily explained by theories of skill-biased technological change as the skill premium. The increase in within-group inequality is an excellent area for future research, and here it would be very beneficial to complete this kind of macro-level approach with micro-level analyses of the nature and causes of within-group inequality. It has already been discussed that deunionization and increased occurrence of performance-based pay are two likely explanations, but it would be favourable to study these and other possible causes in more detail. The implications for policy makers depend partially on to what extent within-group inequality is found to be a consequence of hitherto unobservable skills. Wage inequality is likely to be more accepted if it is connected to observable skills and productivity, since wage inequality can then be justified on the basis of meritocratic ideals. In Finland a seeming development of the wage structure in an unmeritocratic direction has been taking place since the 1970s, since the connection between wages and skills, proxied by education, has weakened. However, it is possible that further, more detailed research could reveal the existence of previously unobservable skills that could help explain, and perhaps to an extent justify, the evolution of the Finnish wage inequality.

Bibliography

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind, *Journal of Economic History*, no. 46, pp. 386-406

Acemoglu, D. & Autor, D. (2012). What Does Human Capital Do? A Review of Goldin and Katz's The Race between Education and Technology, *Journal of Economic Literature*, vol. 50, no. 2, pp. 426-463

Acemoglu, D. (2002). Technical Change, Inequality, and the Labor Market, *Journal of Economic Literature*, vol. 40, no. 1, pp. 7-72

Aghion, P. & Howitt, P. (2002). Wage Inequality and the New Economy, *Oxford Review of Economic Policy*, vol. 18, no. 3, pp. 306-323

Aghion, P. (2002). Schumpeterian Growth Theory and the Dynamics of Income Inequality, *Econometrica*, vol. 70, no. 3, pp. 855-882

Asplund, R. & Maliranta, M. (2006). Productivity growth: The Role of Human Capital and Technology, in J. Ojala, J. Eloranta & J. Jalava (eds), The Road to Prosperity: An Economic History of Finland, pp. 263-284

Bank of Finland (2012). Long-term growth forecast for the Finnish economy, Bank of Finland Bulletin, no. 3

Berman, E., Bound, J. & Griliches, Z. (1994). Changes in the Demand for Skilled Labor within US Manufacturing: Evidence from the Annual Survey of Manufactures, *The Quarterly Journal of Economics*, vol. 109, no. 2, pp. 367-397

Blinder, A. (2007). How Many U.S. Jobs Might Be Offshorable?, Working Paper no. 142, Princeton University Center for Economic Policy Studies

Blundell, R. & Preston, I. (1999). Inequality and Uncertainty: Short-Run Uncertainty and Permanent Inequality in the US and Britain, mimeo UCL

Bogliacino, F. & Lucchese, M. (2011). Endogenous Skill Biased Technical Change: Testing for Demand Pull Effect, Gini Discussion Papers, no. 26

Bound, J. & Johnson, G. (1992). Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations, *The American Economic Review*, vol. 82, no. 3, pp. 371-392

Böckerman, P. & Maliranta, M. (2010). Palkkojen muutos, työn tulo-osuus ja globalisaatio, in Suomalainen palkkarakenne, Elinkeinoelämän Tutkimuslaitos ETLA, pp. 51-61

Capron, H. (2002). Transition towards the knowledge-based economy: growth potential and learning regions, Belgian Federal Office of Scientific, Technical and Cultural Affairs

Card, D. & DiNardo, J. (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles, *Journal of Labor Economics*, vol. 20, no. 4

Einiö, E. (2013). Trade, Technology, and the Sector-Specific Demand for Skills: Evidence from Plant-Level Data, 1976-2004, Government Institute for Economic Research (VATT), Helsinki

Eriksson, T. & Jäntti, M. (2007). The Distribution of Earnings in Finland 1971-1990, *European Economic Review*, no. 41, pp. 1763-1779

Goldin, C. & Katz, L. F. (1998). The Origins of Technology-Skill Complementarity, *The Quarterly Journal of Economics*, vol. 113, no. 3, p. 693-732

Goldin, C. & Katz, L. F. (2008). The Race Between Education and Technology, Cambridge, MA: Harvard University Press

Griliches, Z. (1969). Capital-Skill Complementarity, *The Review of Economics and Statistics*, vol. 51, no. 4, pp. 465-468

Hornstein, A., Krusell, P. & Violante, G. L. (2005). The Effects of Technical Change on Labor Market Inequalities, CEPS Working Paper, no. 113

Huttunen, K. (2002). Trade, Technology and the Skill Structure of Labour Demand in Finland, Available Online: http://www.eea-esem.com/papers/eea-esem/eea2002/1070/papereea2.pdf [Accessed 22 May 2014]

Huttunen, K. (2005). R&D Activity, Exports, and Changes in Skill Demand in Finland, Finnish Economic Papers, no. 2/2005

Jorgenson, D. W. (2001). Information Technology and the U.S. Economy, *American Economic Review*, no. 91, pp. 1-32

Juhn,C., Murphy, K. M. & Pierce, B. (1993). Wage Inequality and the Rise in Returns to Skill, *The Journal of Political Economy*, vol. 101, no. 3, pp. 410-442

Katz, L. F. & Autor, D. H. (1999). Changes in the Wage Structure and Earnings Inequality, in O. Ashenfelter & D. Card (eds), Handbook of Labor Economics, vol. 3A, pp. 1463-1555

Kangasniemi, M. & Kauhanen, A. (2010a). Tulospalkkaus ja palkkahajonta yksityisillä palvelualoilla, in Suomalainen palkkarakenne, Elinkeinoelämän Tutkimuslaitos ETLA, pp. 107-122

Kangasniemi, M. & Kauhanen, A. (2010b). Työmarkkinaliikkuvuuden ja urakatkojen vaikutus palkkakehitykseen ja palkkaeroihin, in Suomalainen palkkarakenne, Elinkeinoelämän Tutkimuslaitos ETLA, pp. 123-139

Katz, L. F. & Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors, *The Quarterly Journal of Economics*, vol. 107, no. 1, pp. 35-78

Kiander, J. (2004). The Evolution of the Finnish Model in the 1990s: From Depression to High-Tech Boom, VATT Discussion Papers, no. 344, Government Institute for Economic Research (VATT), Helsinki

Kokkinen, A. (2012). On Finland's Economic Growth and Convergence with Sweden and the EU15 in the 20th Century, Research Reports, no. 258, Statistics Finland

Krueger, A. B. (1993). How Computers Have Changed the Wage Structure: Evidence from Microdata, 1984–1989, *Quarterly Journal of Economics*, no. 108, pp. 33-60

Krusell, P., Ohanian, L. E., Rios-Rull, J. V. & Violante, G. L. (1994). Capital-Skill Complementarity and Inequality: A Macroeconomic Analysis, *Econometrica*, vol. 68, no. 5, pp. 1029-1053

Lehto, E. & Lehmus, M. (2013). Suomen teollisuuden kilpailukyky ja rakenteet: Toivoa ei ole vielä menetetty, Talous ja yhteiskunta, no. 4, pp. 2-10

Lemola, T. (2002). Convergence of national science and technology policies: the case of Finland, Research Policy, no. 31, pp. 1481-1490

Machin, S. (1996). Wage Inequality in the UK, *Oxford Review of Economic Policy*, vol. 12, no. 1, pp. 47-64

Malghaes, M. & Hellström, C. (2013). Technology diffusion and its effect on social inequalities, *Journal of Macroeconomics*, vol. 37, pp. 299-313

Maliranta, M. (2010). Tehtävärakenteiden muutos palkkojen ja tuottavuuden kasvun lähteenä, in Suomalainen palkkarakenne, Elinkeinoelämän Tutkimuslaitos ETLA, pp. 63-82

Nelson, R. R. & Phelps, E. S. (1966). Investment in Humans, Technological Diffusion, and Economic Growth, *The American Economic Review*, vol. 56, no. 1/2, pp. 69-75

Piketty, T. (2014). Capital in the Twenty-First Century, Cambridge, MA: The Belknap Press of Harvard University Press

Sahlberg, P. (2011). Finnish Lessons: What can the world learn from educational change in Finland? New York: Columbia University

Sahlberg, P. (2013). PISA 2012 Reinforces the Key Elements of the Finnish Way, Pasi Sahlberg Blog, Available Online: http://pasisahlberg.com/pisa-2012-reinforces-the-key-elements-of-the-finnish-way/ [Accessed: 22 May 2014]

Schultz, T. W. (1975). The Value of the Ability to Deal with Disequilibria, *Journal of Economic Literature*, vol. 13, no. 3, pp. 827-864

Solow, R. (1957). Technical Change and the Aggregate Production Function, *The Review of Economics and Statistics*, vol. 39, no. 3, pp. 312-320

Tinbergen, J. (1975) Income differences: recent research, Amsterdam: North-Holland Publishing Company

Uusitalo, R. (2002). Changes in the Finnish Wage Structure: Will Demand and Supply Do?, *Scandinavian Journal of Economics*, vol. 104, no. 1, pp. 69-85

Vainiomäki, J. (1999). Technology and skill-upgrading: Results from linked worker-plant data for Finnish manufacturing, Munich Personal RePEc Archive, paper no. 44662

Violante, G. R. (2008). Skill-Biased Technical Change, prepared for The New Palgrave Dictionary of Economics, 2nd ed,

Available Online: http://www.econ.nyu.edu/user/violante/Books/sbtc_january16.pdf [Accessed 20 May 2014]

Wood, A. (1994). How Trade Hurt Unskilled Workers, *Journal of Economic Perspectives*, vol. 9, no. 3, pp. 57-80

Appendix

Appendix. Average yearly wage and salary income (2012 prices)

Legend:
- Doctorate or equivalent level tertiary education
- Higher-degree level tertiary education
- Lower-degree level tertiary education
- Lowest level tertiary education
- Upper secondary level education
- No education past basic schooling or unknown level

Source: Statistics Finland