Changes in Workplaces and Careers

Christina Håkanson
Abstract

Organizational Change and Productivity Growth - Evidence from Sweden This paper uses two different survey datasets together with matched employer-employee data to investigate both determinants and effects of different types of organizational change. Specifically, I look at indicators of delayering, layering, multitasking and span of control and use a two-step procedure to estimate the effects on productivity growth. The results support the competition hypothesis for inducing organizational change. Increased competition is associated with firms delayering whereas decreased competition is associated with firms adding layers in the following period. Among the four measures of organizational change investigated in this paper, only delayering shows significant effect on subsequent productivity growth, where firms that decrease the number of decision levels on average get a significantly higher productivity growth.

Firms and Skills: The Evolution of Worker Sorting Are workers increasingly being sorted into firms according to their skills? We investigate this issue using data on cognitive and non-cognitive skills for 28 cohorts of Swedish men. The skill measures are comparable over time and measured before men enter into the labor market. We document a significant increase in sorting by both cognitive and non-cognitive skill from 1986 to 2008: Skill differences within firms have fallen in all major industries while differences in skill between firms have increased. Two main factors drive the increase in sorting. First, workers in high-skilled occupations, such as engineers, have moved to the IT and telecom industries. Second, assortative matching of workers by skill has become more positive.
Trading Off or Having it All? Completed Fertility and Mid-Career Earnings of Swedish Men and Women

Earnings in mid-career and children are two fundamental outcomes of the life-choices of men and women. Both require time and other resources and reflect the accumulated priorities of individuals and couples. We explore how these outcomes have changed for Swedish men and women born 1945-1962 by documenting changes in education, assortative mating patterns, completed fertility and mid-career earnings. We find an overall increasing inequality in career and family outcomes of men, reflecting a rise in the family-career complementarity. For women, the family-career trade-off has become easier for non-professionals, and there appears to be a convergence in the life-choices of women across educational groups. Despite these different developments for men and women, we find that within-family specialization, measured by the average spousal earnings contribution, is remarkably stable throughout the period.

Solving the Puzzle – Hours constraints, Technical Change and Female Labor Supply

Women with small children have substantially increased their career commitment in terms of labor supply on the intensive margin in recent decades. Concurrently, these women have also entered into more complex jobs. This paper extends the standard theory of labor supply to incorporate an important ingredient in the labor supply decision of today’s women: the role of flexibility and time constraints. To describe and formalize this notion, I set up a life cycle model where labor supply depends on a family constraint (child rearing), requirement for minimum hours in different types of jobs and the variation in flexibility of organizational technology. I show that as technology allows jobs to become more flexible, time constrained individuals can supply more hours and may therefore find it attractive to opt for a more demanding career.
To my wonderful family
Acknowledgments

I have always been curious. Pursuing a PhD taught me to be patiently curious.

To start from the beginning, I was not going to be an economist. I was obsessed with anatomy and physiology and studied to become a physical therapist at Karolinska Institutet. During my second year I did an internship at a surgery clinic that were the frontier institution in plastic repair of the anterior cruciate ligament of the knee joint. I had a battery of questions for the senior physical therapists: How long does the rehab take in general? Are there different strategies? What are the success rates and how are you tracking this data? I was completely thrown off by her dismissal answer: “This is how we always have done it”. Conversation closed. Right then, I got serious doubts whether this occupation was going to make me happy in the end. After long discussions with Joakim on a sailboat in the Aegean Sea, I decided to take a semester off and do something more math-oriented at the university. I signed up for Economics 101 – and never looked back. This experience has been the exact opposite. In research, you constantly challenge your beliefs, carefully consider every assumption, every restriction to data. And yet best, if you miss something, you can be sure that the sharp minds of your colleagues will find it and point it out to you in a constructive way. This is the beauty of science, it is a dialogue, I love that.

Many thanks are in order. First of all, I would like to thank my advisor Per Krusell. His thoughtful comments were very valuable when I ran into obstacles along the way. I also very much appreciated that he let me pursue the projects that caught my interest. This while helping me stay focused, as I sometimes trended towards too many simultaneous research adventures. In particular during this last intense period, his advice and reassurance have been crucial to the completion of this thesis.

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As a PhD student, you learn the most from writing together with senior researches. I want to thank my other co-authors, Anne Boschini, Ulf Jakobsson, Satu Johanson, Assar Lindbeck, Erik Lindqvist, Åsa Rosén and Jonas Vlachos. I also benefited greatly from discussions with Philippe Aghion when he visited the IIES. Like no one else, he takes the time to listen to the work in progress of the PhD students at the Institute and generously shares his comments and thoughts. In addition, I owe much gratitude to Fabrizio Zilibotti for the early discussions on my research ideas and for supporting my application to the IIES.

The IIES is a fantastic research environment. I have benefited tremendously from the friendly and inspiring atmosphere, high level seminars and everyday discussions. I also want to express my gratitude to the Research Institute of Industrial Economics, where I spent important years after completing my master’s degree. Having the opportunity be in the midst of research was pivotal for the decision to apply for the PhD program. I also wish to acknowledge the support from my employer, Sveriges riksbank, both for support in the collection of data and for allowing me to take time to finish the final parts of the thesis during this winter.

The administrative staff at the IIES deserves a special thanks. Annika Andreasson, for great companionship in “the IIES running club”, therapeutic talks and the occasional ebay distraction. Åsa Storm, whose honesty greatly impresses me, Christina Lönnblad for excellent support in everything from parental leave issues to editorial assistance and to Karl Eriksson, for giving special care to the skill sorting project and allocating quotas way beyond normal on the computational server.
I also wish to thank my fellow graduate students at the IIES and the department of economics and in particular my office mates in the legendary office A814; Mema Perotta, Ettore Panetti and Pamela Campa. Thanks for many laughs, challenging discussions, tips and tricks in Stata and \textsc{\LaTeX}. Ettore, some day we need to write down the model on “To repent in sequence or in one-shot”. Looking back at the years in the PhD program, I only have one regret; In spite of sharing an office with not one, two, but three Italians at the IIES, I did not manage to become fluent in Italian – I will correct that mistake later on.

Special thanks goes to my friends outside academia; Åsa Ek and Zuhal Yamini for faithful friendship and to my singing friends in the Matteus Choir, the Soprano Lounge and the Tuesday wine society.

This thesis would never have been possible without the help to ease constraints and solve the puzzle of time. Karin, Henrik, Marianne and Stig, thank you for giving us extra sets of hands when we needed it the most.

To my fantastic parents, Karin and Henrik and my dearest brother Fredrik, thank you for your constant love and support! To Joakim, my life companion, thank you for initially inspiring me to embark on this journey and for standing by my side all this time. You have given me the greatest gift of all: our wonderful family! I love you very much! To Buster and Bianca, thank you for letting me be a part of your lives. Finally, to my beautiful boys, Kaspar and Gabriel. You are the joy of my life, I promise to leave the computer behind this summer!

Stockholm, February 2013

Christina Häkanson
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Chapter 1

Introduction

1.1 Introduction

“The promise of the Information Age is the unleashing of unprecedented productive capacity by the power of the mind. I think, therefore I produce. In so doing, we will have the leisure to experiment with spirituality, and the opportunity of reconciliation with nature, without sacrificing the material well-being of our children. The dream of the Enlightenment, that reason and science would solve the problems of humankind, is within reach.”

Manuel Castells

This thesis is really about technology. It consists of four self-contained papers that, broadly speaking, deal with different aspects of how workplaces, firms and individuals are affected by changes in technology. Chapters 2 and 3 take a firm perspective, while chapters 4 and 5 concentrate on individuals. This order also more or less represents the order in which the papers came about, although there has been a substantial overlap in the process.

I remember reading Manuel Castells’ book The Rise of the Network Economy back in the early 2000’s – it described a new paradigm and there was no end to the possibilities. During the dot-com era, newspapers and executives were starting to talk about new business models, some even claimed that the
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old laws of economics did not apply anymore and that new laws had taken
their place. Now, in the end, the old laws of economics did bite, and firms
had to comply. The arguments became more moderated and reconnected to
reality again. Still, it appears that many things did change. We gradually got
accustomed to new technology and seen over a longer period of time, these
changes in technology have arguably had a great deal of influence on how we
do business, how we communicate and organize work and, more generally,
the conditions both in the labor market and at home.

One aspect of this is the contemporary trend towards flatter hierarchies
and more decentralized decision making. A number of causes and conse-
quences of these developments have been proposed in the literature and in
almost all, the link to technology has a prominent role. Bresnahan et al.
(2002) point to the need for complementary investments in organizational
capital as more skilled labor and ICT are used in production and Aghion
et al. (1999) argue that skilled labor is complementary, not only to techni-
cal progress but also to contemporary reorganizations. Skilled employees are
assumed to cope better with multi-tasking and increased responsibility and
thus, there is an increase in the demand for this type of labor. Acemoglu et al.
(2007) suggest that the degree of decentralization/centralization is linked to
how far from the technology frontier a firm is located. The closer to the
frontier, the more valuable is the knowledge of local managers, which leads
firms to decentralize. This is the topic of Chapter 2 “Organizational Change
and Productivity Growth – Evidence from Sweden”, where I investigate the
determinants of organizational change and the subsequent effects on firm
productivity.

Related to this, technology may also affect how workers are sorted into
firms. If worker skills are complements (Kremer, 1993), or if worker skills are
complementary to technology (Caselli, 1999), changes in technology that in-
crease these complementarities will lead to increased sorting between firms.
This question is explored in the third chapter “Firms and Skills: The Evolu-
tion of Worker Sorting”. The difficulty in assessing changes in sorting stems
from a lack of skill measures that are comparable over time. Our contribution
is to systematically study sorting of skills using data on workers’ cognitive
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and non-cognitive skills from the Swedish military enlistment. These measures are strong predictors of labor market outcomes, comparable over time and, importantly, since the enlistment evaluations are administered at the age of 18, the skill measures are unaffected by the expansion of higher education and changes in later market conditions.

Technical changes have not only affected conditions in the market place. There has been a rapid development in the possibilities of a more flexible working life. The emergence and increasing use of email, remote access etc have decreased the need for face time and increased the possibilities of being productive in other locations than the office. Changing the way we work, making jobs more flexible, has thereby eased the family-career trade-off and altered the conditions for occupational choice. This is the focus of the last two chapters of the thesis. First, Chapter 4 “Trading off or Having it All: Completed Fertility and Mid-career Earnings of Swedish Men and Women” studies two fundamental life outcomes; earnings and children. Bertrand et al. (2010) show that there is still a sharp trade-off between career and family for US female top professionals. Evidence for other countries and other parts of the distribution of women shows weaker effects of children on careers. Using population-wide Swedish register data, we measure and document trends in completed fertility, mid-career earnings and contribution to joint spousal earnings by own and spousal education. Further, we analyze how the association between mid-career earnings and completed fertility for men and women has changed over time.

Goldin and Katz (2008) suggest that highly educated women in the US recently both have more children and work more. In addition, Olivetti (2006) shows that the returns to experience in the labor market have increased substantially for women relative to those of men and Black and Spitz-Oener (2010) document that women have witnessed an increase in non-routine analytical tasks, in particular within occupations where computers have made major headway. The last chapter of the thesis, “Solving the Puzzle – Hours Constraints, Technical Change and Female Labor Supply” extends the standard theory of labor supply to incorporate an important ingredient in the labor supply decision of today’s women: the role of flexibility and time con-
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straints. In this chapter, I formalize the notion that when technology allows jobs to become more flexible, individuals that are time constrained can supply more hours of work and may therefore find it attractive to opt for a more demanding career.

I now turn to a somewhat more detailed description of each chapter.

Chapter 2: “Effects of Organizational Change on Productivity Growth - Evidence from Sweden” combines results from two parts of a project on productivity at Sveriges riksbank, studying the relation between organizational change, IT and productivity growth. Data on organizational change was obtained by including a block of questions into two existing Swedish firm-level surveys. First, within the 2003 wave of the “Plan Survey”, a business cycle forecasting survey conducted by the Confederation of Swedish Enterprises, and second, within the survey “IT, Organization and Productivity” administered by Statistics Sweden in collaboration with Sveriges riksbank in 2006. In both these surveys, the firms were asked about the number of decision levels in the organization and whether they had increased, decreased or remained unchanged during the survey period. In addition, firms were asked whether, for a majority of the employees, the areas of responsibility and/or the number of tasks performed had increased, decreased or remained unchanged.

I investigate two hypotheses put forth in the literature that organizational change i) increases with competition (Crespi et al., 2007; Nickell et al., 2001; Van Reenen, 2011)) and ii) decreases in the distance to the technology frontier and increases in industry heterogeneity (Acemoglu et al., 2007)). The results show that delayering of the hierarchy is indeed related to increased competition, thus supporting the competition hypothesis. Layering, on the other hand, is significantly related to decreased competition. In that respect, an increase in competition does not only trigger any type of organizational change; rather organizational change toward flatter and more decentralization. I also find the distance to the technology frontier to be positively correlated with the number of layers in the firm hierarchy, i.e. the closer to
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the technology frontier, the fewer the number of layers conditional on firm size. Estimating the effects of organizational change on productivity growth, the results suggest that firms that invested above the median in IT at the same time as they did organizational change showed a significantly stronger productivity growth. For the second panel, analyzing organizational change in more detail, I find that only delayering shows positive effects, where firms that removed levels in their hierarchy had a significantly higher productivity growth afterwards. Since firms might self-select into organizational change, there is a concern that the OLS estimates are inconsistent. To address this issue, I use a selection model and instrumental variables, using the determinants of organizational change in the first step. In this analysis, my broad conclusions survive and the key qualitative results are stronger, but there are also indications that the instrumentation is weak.

Chapter 3: “Firms and Skills: The Evolution of Worker Sorting” is a collaboration with Erik Lindqvist and Jonas Vlachos. In this paper, we study sorting by skill in the Swedish economy between 1986 and 2008 using measures of cognitive and non-cognitive skills from the Swedish military enlistment. To the best of our knowledge, our paper is the first attempt at studying sorting by skill over time using a pre-market measure of skill which is comparable over time. Using the enlistment skill measures, we document a significant increase in sorting from 1986 to 2008.

There is a number of reasons to believe that technological change and globalization increase sorting. For example, the theoretical literature has stressed that firms investing in new technology face a higher return to hiring skilled workers (Acemoglu, 1999; Caselli, 1999). Another possibility is that more complex production processes strengthen the complementarity between workers’ skills, implying that unskilled workers constitute “weak links” in firms with skilled workers (Kremer, 1993). Globalization increases the scope for skill-sorting by narrowing the set of tasks that needs to be performed domestically (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008) and by allowing skilled workers in rich countries to match with workers in developing countries rather than with unskilled workers in their own
country (Kremer and Maskin, 2006).

We document a substantial increase in sorting from 1986 to 2008. During this period, workers became more similar within firms (falling within-firm variance of skills) and more dissimilar between firms (increasing between-firm variance) with respect to both cognitive and non-cognitive skills. The trend towards increased skill segregation is robust to assuming alternative distributions of skills and non-parametric ways of measuring sorting. Using data on male relatives to impute cognitive and non-cognitive skills for women, we find the same trend towards more sorting among female workers.

Why did sorting increase? Our results suggest that technological change is at the heart of the story. The expansion of a small set of high-tech industries (IT services and manufacturing of telecom products) lead to increasing differences across firms in terms of the skill-intensity of technology. In this respect, our results bear out a central prediction in models of skilled-biased technical change (e.g., Acemoglu 1999, Caselli 1999), that new technology will increase skill sorting in the labor market. We have also showed that assortative matching has become more positive over time. For cognitive (but not for non-cognitive) skill, the degree of assortative matching at the firm level is associated with skill upgrading, suggesting that technological change may play a role also in this case.

Chapter 4: “Trading off or Having it All? Completed Fertility and Mid-career Earnings of Swedish Men and Women” is a collaboration with Anne Boschini, Åsa Rosén and Anna Sjögren. In this chapter, we explore the trends in the family-career trade-off facing Swedish men and women born between 1945 and 1962 and their spouses. We document changes in education, assortative mating patterns, completed fertility and mid-career earnings. Several important patterns emerge. First, we find a rising trend in childlessness for men at all educational levels. For women, there is instead a pattern of convergence such that the gap in childlessness between women with low and high education has narrowed. Together with rising education for women, this implies that the relative supply of educated men participating in the family market has declined over time.
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These changes have appeared in parallel to other altered family formation patterns of Swedish men and women. We find that the increase in the age at first child is similar across educational groups. Furthermore, counter to the idea that spouses should have become more similar over time, we find an increase in the spousal age gap in all educational groups and an overall decline in educational assortative mating.

We document a negative association between educational level and average fertility for women. Although we find that fertility rises with education for men, this relation between average fertility and education is not very strong. The data show that the gender earnings gap for professionals actually grew wider, stabilizing at around 70 percent for the cohorts born after 1950. For the other educational categories, the earnings gap instead closed, stabilizing at around 72 percent.

Our starting point was that mid-career earnings and children are the outcomes of the life-choices of men and women. While high productivity on the labor market can generate high earnings, thereby making it possible to afford a large family, it also implies a high opportunity cost for the time it takes to have and raise children. In particular, if a higher opportunity cost for time and a higher income also induce individuals to substitute child quality for quantity, the well-know negative relation between income and the number of children may arise. For men, it seems clear that the income effect dominates. Increasing childlessness and the growing positive association between earnings and fertility suggest that an increased earnings inequality goes hand in hand with increased fertility inequality. For women, the pattern is more complex. If anything, we find a reduced earnings inequality (relative to the development of men) and a reduced fertility inequality across educational groups. One reason for this is that professional women appear to have traded-off some of their potential earnings gains for a (larger) family. There is an increased gender earnings gap and a lower fraction of childlessness for professional women, at the same time as the opposite pattern is true for less educated women. While men increasingly either have all or nothing, the life-choices of women have converged.
Chapter 5: “Solving the Puzzle – Hours Constraints, Technical Change and Female Labor Supply”  The theory outlined in this paper extends the standard theory of labor supply to incorporate an important ingredient in the labor supply decision of today’s women: the role of flexibility and time constraints. There has been a rapid development in the possibilities of a more flexible working life. The emergence and increasing use of email, remote access, video conferences etc have decreased the need for face time in working life, increased the possibility of being productive in other locations than the actual workplace, thus allowing individuals that are time constrained to supply more hours of work by shifting hours during the day to make room for necessary commitments at home, for instance by doing some work from home at night, early mornings, weekends etc. Hence, as technology makes jobs more flexible, time constrained individuals can supply more hours of work and may therefore find it attractive to opt for a more demanding career.

To describe and formalize this notion, I set up a life-cycle model where labor supply depends on a family constraint (child rearing), minimum hours requirements and variation of flexibility in different jobs. The basic intuition is simple: Having children requires parents to drop off and pick up at day care, provide meals, care, help with homework – in short: parenting. Assuming that these household activities can only be partially outsourced, this implies that parents face a binding time constraint. This is not only due to the actual time needed for child rearing, but also reflects the fact that these activities must be carried out at a certain point in time during the day, which infringes on the hours available for work. Moreover, if more complex jobs have a constraint on the hours of work that need to be supplied for the job to be productive, this will imply that individuals that are family constrained, taking the larger responsibly for child rearing, cannot choose these jobs - or can only choose them with large sacrifices as concerns other activities.

I find that for low levels of flexibility, the sacrifice of pursuing a more demanding career is too large, and family constrained individuals thus opt for the less demanding job. The labor supply profile of family constrained individuals exhibits the double peaked profile documented by Olivetti (2006).
for women in the 1970’s. However, when flexible technology becomes efficient enough, it becomes optimal for family constrained individuals to pursue a more career oriented occupation. However, this implies a large reallocation of time, where both leisure and home production decrease and flexible labor supply and market hours increase. Furthermore, adding skill accumulation to the model further strengthens the trade off. When the stakes are higher in the sense that current labor supply choices carry over into future periods in determining wages, it will be optimal to pursue the more demanding career at lower levels of flexible technology and, as a consequence, leisure is further depleted. Relaxing the minimum requirements in the career oriented job, I show that the skill accumulation (and depreciation) by itself sustains the basic patterns found. Family constrained individuals will now work less than those who are unconstrained, but more as compared to what they would in a less career oriented job. This implies that they will accumulate less skill over their working life and the cost of a career interruption is larger, the larger is the depreciation of human capital and the larger the forgone skill accumulation.

There are no unified conclusions from the four studies in my dissertation. If there is a broad message, it would rather be that we have only begun to scratch the surface of what the recent technology revolution has meant for workplaces and households. Many, many more studies are needed, and I would be very happy to contribute to some myself. My ongoing work is very much a continuation of the work presented in this dissertation. We are taking the skill sorting project one step further and look in more detail at skill sorting at the firm level and explore whether worker skills are substitutes or complements and whether such patterns hold between all types of occupational groups. The work on female labor supply is heading in two directions, first to take the model on hours constraints and flexibility to the data and do a proper calibration to also get quantitative results. The second avenue is to model the firm side and look at the adoption of flexible work practices both empirically and theoretically.
Bibliography


Chapter 2

Organizational Change and Productivity Growth - Evidence from Sweden*

2.1 Introduction

What are the determinants of organizational change and what are, if any, their effects on productivity? Over the last two decades, the main direction of organizational change has been towards flatter, more decentralized decision making. A number of causes and consequences of these developments have been proposed in the literature. However, there are relatively few empirical studies based on direct measures of organizational change. The present paper uses unique Swedish data enabling precise measurement of different kinds of organizational change, as well as an exploration of their determinants and their relation to firm-level productivity growth.

Swedish productivity has had a similar development to that in the US, i.e., quite different from that in the rest of Europe. Sweden differs from the

*Thanks to Mikael Carlsson, Vivek Ghosal, Per Krusell, Erik Mellander, Ettore Panetti, David Strömberg, seminar participants at the Riksbank, the IIES Macro group and the 10th annual conference of the Swedish Network for Economics and Business (SNEE) 2008 for helpful comments. An earlier version of this paper has been published as WP #232 at Sveriges riksbank
US in that, like the rest of Europe, Sweden has strict market regulations. Compared to a broad cross section of countries, Sweden scores high on efficient workplace practices and various measures of decentralization of the firm (Bloom et al., 2012). This study combines results from two parts of a project on productivity at Sveriges riksbank 2006, studying the relation between organizational change, IT and productivity growth. Data on organizational change was obtained by including a block of questions into two existing Swedish firm level surveys. First, within the 2003 wave of the “Plan Survey”, a business cycle forecasting survey conducted by the Confederation of Swedish Enterprises and the Research Institute of Industrial Economics, and second, within the survey “IT, work organization and productivity” administered by Statistics Sweden in collaboration with Sveriges riksbank in 2006. In both these surveys, the firms were asked about the number of decision levels in the organization and whether they had increased, decreased or remained unchanged during the survey period. In addition, firms were asked whether, for a majority of the employees, the areas of responsibility and/or the number of tasks performed had increased, decreased or remained unchanged.¹ To assess the effects on productivity growth, both surveys are matched with accounting data from the Structural Business Statistics and registry data on labor composition and wages, yielding two panels.

The first panel, based on the “Plan Survey”, is rich in data but very small, 120 firms followed over nine years. To take advantage of the data and, at the same time, economize on parameters, the approach taken is to calculate TFP using detailed measures on labor composition and employ a difference-in-difference estimator using organizational change as treatment to establish the effect on productivity growth. The empirical results suggest a sizable positive effect on TFP growth for firms that at the same time as they undertook changes in organization also invested more in IT than the median firm.

The second part of the project uses data from the survey “IT, work organization and productivity”. This sample is of an order of magnitude larger and thus allows for a two-step procedure, with the aim of looking at both

¹The questions were designed to match those used in Caroli and Van Reenen (2001).
the determinants and the effects of organizational change. Accordingly, I first investigate two hypotheses put forth in the literature that change i) increases with competition (Crespi et al., 2007; Nickell et al., 2001; Van Reenen, 2011) and ii) decreases in the distance to the technology frontier and increases in industry heterogeneity (Acemoglu et al., 2007). The results show that de-layering of the hierarchy is indeed related to increased competition, thus supporting the competition hypothesis. Layering, on the other hand, is significantly related to decreased competition. In that respect, an increase in competition appears to not only trigger any type of organizational change; rather organizational change in the direction of flatter and more decentralization. I also find the distance to the technology frontier to be positively correlated with the number of layers in the firm hierarchy, i.e. the closer to the technology frontier, the fewer the number of layers conditional on firm size. Estimating the effects of organizational change on productivity growth, only delayering shows positive effects, where firms that removed levels in their hierarchy had a significantly higher productivity growth afterwards. Since firms might self-select into organizational change, there is a concern that the OLS estimates are inconsistent. To address this, I use a selection model and instrumental variables, using the determinants of organizational changes in the first step. In this analysis, my broad conclusions survive and the key qualitative results are stronger, but there are also indications that the instrumentation is weak and that the exclusion restrictions are not fully adequate.

The remainder of this paper is organized as follows. In the next section, I discuss the literature with a focus on the empirical evidence. Section (2.3) presents the two surveys used in this study and the register data which is added to form the panels used in the analysis. The key variables on organizational change and IT are presented in some detail. Next, in section (2.4), I present the empirical implementation for the different parts of the study. The results are presented in section(2.5) and section (2.6) concludes the paper.
2.2 Literature

There is a number of academic papers accounting for the trend towards decentralization either emphasizing versions of the principal agent problem (Aghion and Tirole, 1997; Hart and Moore, 2005; Acemoglu et al., 2007) or the need for complementary investments in organizational capital as more skilled labor and ICT are used in production (Bresnahan et al., 2002; Caroli and Van Reenen, 2001; Lindbeck and Snower, 2000; Aghion et al., 1999). Lindbeck and Snower (2000) point to advances in information technology, increased versatility of capital equipment, widening of human capital across tasks and changes in workers’ preferences as the driving forces. Aghion et al. (1999) argue that skilled labor is complementary, not only to technical progress but also to contemporary reorganizations. Skilled employees are assumed to cope better with multi-tasking and increased responsibility and thus, there is an increase in the demand for this type of labor. In an endogenous growth model, Acemoglu et al. (2007) show that the closer a firm is to the technological frontier, the higher is the relative importance of innovation and therefore, the more likely is a firm to adopt a structure with decentralized decision making. Yet another reason for the delayering of organizations is found within the “high performance work organizations” literature. Firm performance and productivity can be improved through a continuous education of employees, delegation of authority and incentive pay, cf. (Kling, 1995). In a different approach, Garicano and Rossi-Hansberg (2006) model knowledge hierarchies and show that falling IT prices lead to flatter organizations, whereas falling prices for communication have the opposite effect. This is an interesting feature, since it creates a balanced relationship where the optimal organization hierarchy is determined by the technology mix, i.e., it is not only flattening that can boost productivity.

2.2.1 Empirical evidence

There is a small but growing body of empirical evidence on the productivity effect of organizational change. However, most studies employ organizational data from the mid 1980’s to the mid 1990’s. Bresnahan et al. (2002) argue
that higher levels of technology are associated with an increased delegation of authority to individuals and teams and higher levels of skill and education in the workforce. They find empirical support for complementarity between technology skill and organization of work on US data. Black and Lynch (2001) estimate augmented production functions on US firm-level data in 1987-1993 and relate the firm-specific residual to measures of workplace practices, human capital investments and computer usage. They find that the proportion of non-managerial workers using computers has a positive effect on productivity, as has the average educational level. They also find that firms with a larger share of younger capital have a higher average productivity. Concerning workplace practices, their results suggest that it is not whether an employer adopts a particular practice or not that plays a role, but rather how that workplace practice is implemented. In a companion paper from 2004, the same authors study two cross sections of US firms on later data (1993-1996), but they do not find any support for an interaction between workplace practice and IT. Caroli and Van Reenen (2001) examine the complementarity between skills and reorganization and find that reorganizations (in the direction of more decentralized decision making) lead to a lower demand for low skilled labor. They also find that a falling relative price on high-skilled labor increases the probability of a firm reorganizing and that the largest effects on productivity are in organizations with a large proportion of high-skilled labor. However, they find no evidence of an interaction between IT and organizational change.

In a different strand of the literature, the effect of organizational capital on productivity is instead indirectly studied via ownership. Bloom et al. (2012) find support for the complementarity between IT and organizational capital studying a large sample of British firms in 1995-2004. When comparing the returns for US multinationals and statistically similar UK firms, they find that US multinationals in the UK are more productive than similar UK firms. They argue that the reason for this productivity difference is that US multinationals also export their organizational capital to their foreign affiliates.²

²Similar results have been documented for Swedish firms. Karpaty (2007) finds an
The connection between competition and productivity is widely studied. Van Reenen (2011) surveys the link between competition, management practices and productivity growth and finds evidence that competition raises productivity and that quality of management is a key mechanism. Competition is found to affect productivity in two ways; first by fostering the adoption of better management practices and second through reallocation away from low productivity firms.

There is an inherent difficulty in assessing effects of organizational changes in that they are multi-faceted and thus difficult to compare. However, recently, major leaps have been taken in terms of collection of data. Bloom and Van Reenen (2007) developed a survey tool to directly quantify management practices across firms, sectors and countries covering three essential areas; monitoring, target setting and people management. Using these cross-country surveys on management practice, Bloom et al. (2010) document that firms with better management practices are associated with more decentralization.

When assessing the effects on productivity, the main obstacle is that the choice to implement organizational changes is likely to be endogenous, thus making it hard to credibly get at the true effects. This has raised the interest in the determinant of organizational change. Several variables have been found to be correlated with organizational change and many studies are pointing at different indicators of competitive pressure being important. For example, Nickell et al. (2001) find that financial market pressures (measured by lagged changes in market shares) make firms more likely to introduce organizational innovations. Bloom et al. (2010) also find a positive significant association between product market competition and decentralized organizational innovations. Bloom et al. (2010) also find a positive significant association between product market competition and decentralized organizational changes.

increase of 3-11% in productivity from foreign acquisitions of Swedish firms (1986-2002).

3See e.g. Holmes and Schmitz (2010) for an overview.

4Reallocation is studied in Holmes and Schmitz (2010). In a model where firms can enter two different locations and there are tariffs between the two locations, they show that increased competition, in the sense that tariffs are lowered, causes more efficient firms to also move into the other location as it is cheaper to move goods. This increase in competition will put a downward pressure on price cost margins and thus weed out less efficient firms. In equilibrium, this reallocation effect will increase industry productivity. There will also be fewer firms in total giving rise to a scale effect on productivity.
2.2. LITERATURE

Using data from the Community innovation survey for the UK, Crespi et al. (2007) find that a change in competition, again measured as lagged changes in market share, is negatively related to the probability of organizational change, i.e., firms that are losing market shares are more likely to reorganize in the following period. They also find that exporting firms have a significantly higher probability of organizational change, possibly due to their facing a higher competitive pressure compared to locally active firms. In addition, foreign ownership significantly increases the probability of reorganization. This is consistent with organizational knowledge and/or concepts being exported to the foreign affiliates as in Bloom et al. (2012). Another source for competition is via trade. Guadalupe and Wulf (2010) look at the effects of trade liberalization and find, using US panel data, that increased product market competition reduces the number of positions between the CEO and division managers. Caroli and Van Reenen (2001) also estimate the probability of organizational change and find that higher wage inequality, proxied by regional educational wage differentials, is associated with a significantly lower probability of organizational change. Their interpretation is that a short supply of skilled workers drives up the relative wages, thus making fewer organizational changes profitable. They also find that organizational changes are correlated with technology, but they do not look at competition. On a different note, Acemoglu et al. (2007) make the argument that firms operating closer to the technological frontier and in more heterogeneous environments are more prone to have a decentralized organization as the knowledge of the local managers is more valuable and they find empirical support in data on French firms in 1997.

Another way of addressing the endogeneity problem of organizational change is by using random experiments. To my knowledge, there is only one study that relies on experimental information. Bloom et al. (2012) run a management field experiment providing free management consulting to randomly chosen large Indian textile firms. They find that adopting new management practices raised productivity by 17% as compared to the control plants.
2.3 Data

2.3.1 Survey data

It is hard to find firm-level panel data on performance, inputs, IT and organizational change. The two panels used in this study were created by introducing a block of questions on organizational change into two existing surveys in Sweden. These surveys were then matched to firm level accounting data and individual level employee data.

The first survey is the 2003 wave of the “Plan Survey”. The “Plan Survey” is a yearly survey administered by the Confederation of Swedish Enterprises and the Research Institute of Industrial Economics since the beginning of the 1970’s. It is a rotating panel covering mainly large firms or, more precisely, large workplaces in the Swedish manufacturing sector, and from the year 2000 onwards, also firms within the service sector. The main purpose of this survey is to make business cycle forecasts. Firms are asked about the present situation (capacity usage, new orders, investments, employees etc.) but also the plans for the year ahead (hence, the name Plan Survey). For this reason, the survey is not representative, the aim has instead been to cover as much as possible of the Swedish business sector with a limited amount of observations. Accordingly, more than 90 percent of the firms covered have at least 100 employees.

The second survey is called “IT, work organization and productivity” and was administered by Statistics Sweden in the fall of 2006. This survey was the first in a new yearly series covering IT expenditures in Sweden. The main purpose of this survey is to collect detailed information on investments in and expenditures for IT, communication equipment and software, as well as leasing costs and expenditures for communication and data traffic. The wave of 2006 covers a representative sample of about 2000 Swedish firms.

I had the opportunity to include an additional block on organizational change in these surveys.5 Firms were asked questions regarding the general

5I was involved in the survey design and the data collection of the “Plan Survey” working as a research assistant at the Research Institute of Industrial Economics at the time. Based on the results of this small survey, and to get a larger data set, the same set
hierarchical structure of the firm, i.e., how many staffing and manning levels they currently had and whether the number of hierarchical levels had changed. In addition, questions indicating indirect organizational changes were asked: the companies were asked to state whether, for a majority of their employees, the number of tasks and/or the amount of responsibility had increased, decreased or remained unchanged. The questions on organizational change were designed to match those used in Caroli and Van Reenen (2001).

2.3.2 Register data

To get detailed information about the surveyed firms, the surveys were matched to register data from Statistics Sweden. First, employees are linked to their employers using the RAMS.\(^6\) This database contains information on all workers employed in a firm at some point in time each year. It also contains firm-level information such as ownership and industry. Second, information about labor composition was added from the register database LOUISE, a longitudinal database compiled by Statistics Sweden covering every Swedish resident aged above 15 over the years 1990 and onwards. Using information on educational attainment, employees are divided into three different categories depending on level of education: \(LS\), Low skilled labor, has nine years of compulsory school and \(IS\), Intermediate skilled labor, has attained secondary school or has less than three years of tertiary education. High skilled, \(HS\), is employees with at least three years of tertiary education or post graduate education. Third, firm level financial information is added.

\(^6\)Since the Plan Survey is conducted outside of Statistics Sweden, the matching of this survey to administrative records required the permission of each firm. Formal requests were sent out in the spring of 2007, followed by e-mail reminders. Finally, the remaining firms were contacted by phone. Out of the 192 firms, 75% gave their permission to match data and 5% had changed structures to the extent that they were not meaningful to track. Only 5 firms, or 2.5%, denied the request to match data. Despite large efforts, the remaining firms could not be reached. Out of the 144 firms that gave their permission, we were able to successfully match 136. The estimation sample is further reduced to 120 companies due to restrictions on data, as some firms lacked information on investments in IT.
from the Swedish Business Statistics which for the years included in this study covers all firms in Sweden. This database holds detailed accounting information, e.g. value added, turnover, number of employees, gross and net investments and book values for machinery & equipment and buildings.

2.3.3 Key variables

In what follows, the key variables of the analysis, Organizational Change, \( \Delta O \) and the different measures of the level/intensity of IT investment are presented. The remainder of the variables and controls is described in appendix.

**Organizational Change, \( \Delta O \)**

Organizational change is measured by three questions included in the 2003 wave of the “Plan Survey” and the survey “IT, work organization and productivity” from 2006. The questions were designed to parallel some of those in Caroli and Van Reenen (2001). Turning first to the “Plan Survey”, table 2.1 presents each of the questions along with the distributions of answers. As a reference, also the distribution of answers in Caroli and Van Reenen (2001), henceforth CVR, is reproduced. For about twenty percent of the companies, the number of staffing and manning levels had changed. Compared to CVR, much fewer companies indicated a reduced number of staffing and manning levels (only 9 % as compared to almost 35%). For the other two indicators, the distributions of answers were much more similar. The areas of responsibility connected to specific positions had increased in 55% of the cases. Only 2% reported a decrease (the figures were 46% and 3%, respectively, in CVR). This pattern also holds when looking at the range of tasks connected to specific positions. In 45% of the cases, the number of tasks had increased and in only 5%, the number of tasks had decreased (as compared to 63% and 6%, respectively, in CVR). Hence, the majority of organizational changes was

---

\(^7\)In CVR, these questions were asked for non-manual and manual workers separately. The comparison made here concerns the answers of non-manual workers. The corresponding figures for manual workers are 33% more and 6% less responsibility, 40% more and
in the direction of flatter, more decentralized decision making, even though
the actual delayering was less pronounced as compared to CVR.

An increased use of new technology, IT and communications opens up
opportunities for more efficient ways of organizing the firm (e.g. Bresnahan
et al. (2002)). In the empirical analysis of the first survey, the “Plan Survey”,
organizational change is therefore represented by a dummy variable which
takes the value of 1 if a company reported at least two instances of orga-
nizational change (regardless of direction) and 0 otherwise. The foremost
reason for this is the limited sample size. However, another motivation for
allowing all directions of organizational change can be found in Garicano
and Rossi-Hansberg (2006). They model knowledge hierarchies and show,
by making access to knowledge cheaper, that falling prices of IT lead to
flatter organizations, whereas falling prices of communication have the op-
posite effect as monitoring becomes relatively cheaper. Thus, the direction of
the organizational change might differ depending on the industry and firm-
specific technological mix. In the empirical analysis, experiments are also
made restricting the $\Delta O$ dummy to be 1 only if firms reported at least two
organizational changes that were in the direction of being flatter. This does
not lead to any notable change in the results. If anything, the effects are
stronger than when using the wider definition. With the wider definition,
organizational change occurs in 55 out of 120 firms. As it turns out, the
vast majority (69%) of these are indeed in a flattening direction. 27% had
mixed indicators and only 4% purely had changes that indicate an increase
in hierarchy.

Turning to the second survey, “IT, work organization and productivity”,
table 2.2 shows the distribution of answers for the same set of questions. Out
of 1789 firms, 3.4% indicated that they had decreased the number of layers
in their hierarchy, while 5.8% instead increased the number of layers in their
hierarchy. In that respect, the answers are different than in both CVR and the
“Plan Survey” as more firms indicate that they are increasing the number of
layers in the hierarchy relative to the number that does the opposite. A third
of the firms indicates that, for the majority of the employees, the number of

13% less tasks and 11% more and 46% fewer staffing and manning levels.
Table 2.1: Indicators of Organizational Change - The Plan Survey 2003

| Have the areas of responsibility connected to specific positions changed in the period 2000-2002? | CVR |
|---|---|---|
| All | non-manual workers | manual workers |
| yes, increased | 55% | 46% | 33% |
| no | 43% | 47% | 57% |
| yes, decreased | 2% | 3% | 6% |

| Has the range of tasks connected to positions changed in the period 2000-2002? |
|---|---|---|
| yes, increased | 45% | 63% | 40% |
| no | 50% | 28% | 45% |
| yes, decreased | 5% | 6% | 13% |

| Has the number of staffing and manning levels changed in the period 2000-2002? |
|---|---|---|
| yes, increased | 10% | 9% | 11% |
| no | 81% | 55% | 42% |
| yes, decreased | 9% | 35% | 46% |

tasks had increased. In a quarter of the firms, the areas of responsibility had increased for a majority of the employees.

Instead of using the combined measure used for the Plan Survey panel, four indicators of organizational change are formed here: delayering = 1 (layering) if the number of staffing and manning levels has decreased (increased), multitasking = 1 if the number of tasks attached to a specific position has increased and span of control = 1 if the areas of responsibility attached to a specific position have increased. delayering thus indicates that the organization is flatter. Note that, a priori, delayering does not imply that decision making is being decentralized. As pointed out by Guadalupe et al. (2012), fewer levels in the hierarchy can be the result both of centralizing and decentralizing the decision making. They show that an increase in size of the CEO executive team can be symptoms of both; on the one hand, an increased number of product related functional managers allows for more coordination across business units and the possibility of taking advantage of synergies - consistent with a centralization of certain functions. On the other hand, they find that as general managers move closer to the CEO, decentralization and delegation imply that they perform more activities which are
Table 2.2: Indicators of organizational change – IT, work organization and productivity

(a) Has the number of staffing and manning levels changed during 2004 and 2005?

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Per cent</th>
</tr>
</thead>
<tbody>
<tr>
<td>increased</td>
<td>104</td>
<td>6</td>
</tr>
<tr>
<td>decreased</td>
<td>60</td>
<td>3</td>
</tr>
<tr>
<td>unchanged</td>
<td>1,625</td>
<td>91</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>1,789</td>
<td>100</td>
</tr>
</tbody>
</table>

(b) In general, how did the range of tasks and areas of responsibility attached to a specific position develop during 2004 and 2005?

For a majority of the positions, the number of tasks performed has:

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Per cent</th>
</tr>
</thead>
<tbody>
<tr>
<td>decreased</td>
<td>34</td>
<td>2</td>
</tr>
<tr>
<td>increased</td>
<td>582</td>
<td>33</td>
</tr>
<tr>
<td>unchanged</td>
<td>1,173</td>
<td>66</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>1,789</td>
<td>100</td>
</tr>
</tbody>
</table>

For a majority of the positions, the areas of responsibility have:

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Per cent</th>
</tr>
</thead>
<tbody>
<tr>
<td>decreased</td>
<td>41</td>
<td>2</td>
</tr>
<tr>
<td>increased</td>
<td>461</td>
<td>26</td>
</tr>
<tr>
<td>unchanged</td>
<td>1,287</td>
<td>72</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>1,789</td>
<td>100</td>
</tr>
</tbody>
</table>

reflected in higher pay and a higher fraction of firm-performance related pay. Still, existing evidence indicates that delayering typically involves delegation of authority to lower levels of the hierarchy (Caroli and Van Reenen, 2001; Rajan and Wulf, 2006). Delegation may also be captured by the variable *span of control*. If the areas of responsibility attached to specific positions increase on average, this will imply that the span of control is moved out into the organization, as opposed to being focused at the top of the hierarchy.

**Technology, IT**

There is no information on investments in IT within the Structural Business Statistics. Hence, it is not possible to follow the evolution of the stock of IT capital.\(^8\) However, there is also information on investments in IT within

\(^8\)Statistics Sweden used to cover investments in IT, but the series was discontinued in 1994. A few years ago they decided to resume this data collection. The first survey is the
the first survey used in this study. The “Plan Survey” has information on investments in IT for the years 2001-2003.

It is not obvious how to measure IT investments. A classical procedure is to measure IT intensity as investments in IT relative to total investments. This would reveal the technology mix in a firm. But an argument for different measures can also be made. Consider a firm with very large investments in real capital, for instance in the paper and pulp industry. As an example, an installation of automatic computer surveillance in the production process can here give very large effects on productivity as the length of the production stops is significantly shortened. However, this investment will be minor relative to total investments. Here, IT investments relative to the number of employees might be a better measure. Moreover, it is natural to consider the investment in IT relative to the number of employees when looking at interactions with organizational change – since people define organizations. For the “Plan Survey”, I will make use of four different measures of the intensity of IT investments. The first two relate investments in IT to the number of employees and the last two to total investments. The main focus will be on the first measure (A) which categorizes firms into three different groups, $IT^{\text{zero}}$, $IT^{\text{low}}$ and $IT^{\text{high}}$, depending on their maximum investment in IT per employee during the period of organizational change. The $IT^{\text{zero}}$ firms reported zero investments in IT per employee for the period where organizational changes took place. $IT^{\text{low(\text{high})}}$ firms reported below (above) median investment in IT per employee.\textsuperscript{9} This division partitions both the sample as a whole and the sub-sample that carried through organizational changes into groups of a fairly equal size. As a sensitivity check, instead of using the maximum investment, the average investment in IT per employee and the maximum (mean) share of IT investments to total investments are considered, see section A.2.3 for details. The survey “IT, work organization and productivity” has access to more detailed information on investments in IT and communication equipment. In addition to investigating the role of

\textsuperscript{9}The cutoff value was set to the median of the firms that reported non zero investment levels in IT.
total investments, this allows for also letting IT and communications enter separately in the regressions. The main measure used is the (log of) total investments in IT and communication equipment per employee. In addition, to avoid dropping observations with zero investments in IT, I also construct the equivalent of measure (A) for this survey.

2.4 Framework

2.4.1 The production function

From a theoretical point of view, it is straightforward to consider the relationship between investments in IT, organizational changes and productivity in terms of embodied and disembodied technical change. More specifically, how is productivity growth affected by embodied and disembodied technical change, directly and via interaction effects? To benefit from embodied technical change, firms need to make physical investments – the new technology is in the machine. In this study, the embodied technical change will be represented by investments in IT capital. Disembodied technical change, on the other hand, is typically free and available for everyone. We can consider innovations in organizational technology as being disembodied technical change; as new organizational practices are introduced, they are, in principle, available free of charge. However, this does not mean that investments in organization are for free. On the contrary, organizational change typically induces large costs due to forgone production during the adjustment process.

Consider the following production:

\[ Y_{it} = Y(A_{it}, F(K_{IT}^{it}, O_{it}), K_{nit}^{IT}, L^n_{it}, X_{it}) \]

where \( K_{IT}^{it} \) is IT-capital, \( K_{nit}^{IT} \) is non-IT capital, \( O_{it} \) is organizational capital, \( L_{it} \) is a vector of labor inputs and \( X_{it} \) is a vector of other inputs, for firm \( i \) at time \( t \). Following Bresnahan et al. (2002) and Bloom et al. (2012), \( O \) and \( K_{IT}^{it} \) are assumed to be complementary in the production function. \( A_{it} \) is a Hicks neutral efficiency term.

Using lower case letters for variables in logs, the following simple pro-
duction function is assumed:

\[ y_{it} = \alpha_1 + \alpha_1 x_{it} + \alpha_2 l_{it} + \alpha_3 k_{IT}^{IT} + \alpha_4 k_{NIT}^{IT} + \alpha_5 O_{it} + \alpha_6 (k_{IT}^{IT} \times O_{it}) + \lambda_{ind} + \varepsilon_{it} \]

where \( \lambda_{ind} \) is an industry-fixed effect (i.e. an industry-specific intercept) and \( \varepsilon_{it} \) a stochastic error term (assumed iid and normal). Taking the first difference and rearranging equation 2.1 to get labor productivity growth on the left-hand side, the estimated equation is:

\[
\Delta(y_{it} - l_{it}) = \alpha_0 + \alpha_1 \Delta x_{it} + \alpha_2 \Delta l_{it} + \alpha_3 \Delta k_{IT}^{IT} + \alpha_4 \Delta k_{NIT}^{IT} + \
\alpha_5 \Delta O_{it} + \alpha_6 (\Delta k_{IT}^{IT} \times \Delta O_{it}) + \lambda_{ind} + \varepsilon_{it}
\]

### 2.4.2 The probability of organizational change

Several variables have been shown to be correlated with the incidence of organizational change. Besides introducing some relevant control variables, I look at two main hypotheses; (i) competition and (ii) distance to the technology frontier and industry heterogeneity. First, I explore the role of competition, suggested by e.g. Crespi et al. (2007); Nickell et al. (2001); Van Reenen (2011) and estimate the following equation:

\[
\Delta O = c + \kappa_1 \cdot HO_{t-1} + \kappa_2 \cdot \ln(L)_{t-1} + \kappa_3 \cdot \Delta SHARE_{t-1} + \lambda_{ind} + \nu_{it}
\]

(2.1)

where \( \Delta O \) is the 0/1 indicator for organizational change, \( \Delta SHARE \) is the lagged change in the four-digit industry market share, \( HO \) is a dummy variable indicating whether the firm has a foreign head office, \( \lambda_{ind} \) is the industry-fixed effect and \( \nu_{it} \) is the idiosyncratic error component.\(^{10}\) Acemoglu et al. (2007) make the argument that firms operating closer to the technological frontier and in more heterogeneous environments are more prone to have a decentralized organization as the local managers’ knowledge is more valuable.

\(^{10}\)The change in the market share is measured as the average change between 2003 and 2005.
To explore this, I estimate the following equation:

\[
\Delta O = c + \gamma_1 \ast HO_{t-1} + \gamma_2 \ast \ln(L)_{t-1} + \gamma_3 \ast H_{it-1} + \gamma_4 \ast DF_{it-1} + \lambda_{ind} + \nu_{it} \quad (2.2)
\]

where \(\Delta O\) is a dummy indicating organizational change and \(H_{it-1}\) is a measure of heterogeneity in the industry in which the firm is operating. I use the difference between the 90th and 10th percentile in the four-digit industry productivity growth distribution, which is the same measure as is suggested in Acemoglu et al. (2007). Moving on, \(DF_{it-1}\) is a measure of how far from the industry-specific productivity frontier the firm is (the difference between the firm’s own productivity and the productivity at the 99th percentile within the four-digit industry (once more, the same as in Acemoglu et al.). All right-hand side variables are lagged to mitigate the most obvious source of reverse causality.

In what follows I will now describe how the above setups can be used as guidance in confronting the available datasets.

2.4.3 Econometric implementation for the Plan Survey panel

Due to the small sample size in the Plan Survey, a different empirical strategy is used than what is described in the previous section. Instead, I use a difference-in-difference approach with organizational changes as treatment. The main outcome variable of interest is TFP-growth, but the results are also robust with respect to changing it to labor productivity growth.

I calculate TFP as the ratio of deflated value added and a Törnquist index of inputs, \(X_k\):

\[
TFP_t = \frac{Q_t}{f(X_{1,t}, X_{2,t}, ..., X_{k,t})}.
\]

The Törnquist index corresponds to the translog production function and allows for complementarity between inputs taking into account both direct and interaction effects of organizational change and other inputs of production. TFP growth is computed as the difference in the natural logarithm of
TFP according to:  

$$\Delta \ln TFP = \Delta \ln Q - \Delta \ln X_t,$$

where $\Delta \ln X_t$ is the growth of aggregated input, each input being weighted by its average cost share:

$$\Delta \ln X_t = \sum_k \omega_{k,t} \Delta \ln X_{k,t}.$$

$P_{k,t}$ is the price of input $k$ at time $t$ and $\omega_{k,t}$ is the average cost share of input $k$ at time $t$ according to:

$$\omega_{k,t} = \frac{1}{2} \left( \frac{P_{k,t-1}X_{k,t-1}}{\sum_k P_{k,t-1}X_{k,t-1}} + \frac{P_{k,t}X_{k,t}}{\sum_k P_{k,t}X_{k,t}} \right).$$

To capture the effect of organizational changes on productivity growth, one has to consider what would have happened, had the firms not undertaken organizational changes – the counterfactual situation. Since firms can only be observed in one state – they either did or did not make organizational changes – the counterfactual has to be constructed synthetically. The chosen strategy is to adopt a difference-in-differences approach using organizational changes as treatment. By comparing the change in outcomes for a group of treated firms (that made organizational changes) with that of control firms (that did not make any organizational changes), the aim is to isolate the effect. The difference-in-differences estimator is an unbiased estimate of the causal effect if, absent the treatment, the average change in TFP growth had been the same for the treatment and the control groups (the parallel underlying trend assumption). However, reorganizations are, in effect, not randomly assigned, so bias cannot be ruled out. Therefore, it is important to explicitly consider a potential bias due to nonrandom sampling, i.e., we would like firms to be, ex ante, as statistically similar as possible. One way of ensuring this is to first pair up treated and untreated (control) firms using...

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11See Christensen et al. (1973) on the translog production function.
a matching estimator. However, on this small panel, the observations are simply too few to make such matching. Instead, to evaluate the composition of the two groups, pretreatment characteristics are examined.

The basic difference-in-differences setup is:

$$\Delta f_{\text{p}it} = c + \theta_1 T_{it} + \theta_2 \Delta O_{it} + \theta_3 (T_{it} \times \Delta O_{it}) + \eta_i' \omega_{it} + \nu_i + \epsilon_{it} \quad (2.3)$$

where $T$ is the time effect, i.e. a dummy which takes the value of 0 in the years 1997-2001 (the years before the organizational change) and 1 after that. Note that in the survey data, there is no information on the exact date when the organizational changes took place; instead the data picks up organizational changes “in the last three years” (meaning 2000-2002). In the empirical analysis, organizational changes are placed in the middle of this interval, i.e., 2001.\(^{12}\) Continuing, $\Delta O$ is the group dummy indicating whether a firm is part of the treated group (i.e., undertook organizational changes). The coefficient of interest, the difference-in-differences estimator, is $\theta_3$ which captures the effect of being part of the treated group in the “after” period. $\omega_i$ is a vector of other controls such as industry, firm size, labor composition etc. These are included to reduce the compositional bias, i.e., to control for observable differences between the observations in the different groups. Finally, $\nu_i$ is a time invariant, firm-specific effect and $\epsilon_{it}$ is the idiosyncratic component of the error term.

To take the link with investments in IT into consideration, equation (2.3) is modified in the following way: both the group effect, $\theta_2$, and the difference-in-differences effect, $\theta_3$, are interacted with dummies indicating the intensity of IT investments, $IT^{\text{zero}} = 1$ if the firm had zero investments in IT, $IT^{\text{low}} = 1$ if the firm had, conditional on positive investments, below median investments in IT and finally $IT^{\text{high}} = 1$ if the firm had above median investments in IT. Changes in organizations can occur for all sorts of reasons and to focus on those made in connection with investments in IT, this interaction estimates the effect of organizational change separately.

\(^{12}\)Another way could be to simply eliminate the years 2000-2002 and apply the DiD estimator to that sample. The results are qualitatively robust to this. However, considering the limited amount of data that is available, the former approach is kept.
for firms with zero, low and high levels of IT investments. The estimated equation becomes:

\[
\Delta tfp = c + \theta_1 T + \theta_2^{zero} (\Delta O \times IT^{zero}) + \theta_2^{low} (\Delta O \times IT^{low}) + \theta_2^{high} (\Delta O \times IT^{high}) + \theta_3^{zero} (T \times \Delta O \times IT^{zero}) + \theta_3^{low} (T \times \Delta O \times IT^{low}) + \theta_3^{high} (T \times \Delta O \times IT^{high}) + \eta_i \omega + v_i + \varepsilon_{it} \tag{2.4}
\]

The key identifying assumptions are that the time effect \( T \) captures how both the treatment and the control group are influenced by time and that the fixed group effect \((\Delta O \times IT^j)\) captures any fixed unmeasured differences between the two groups, such that there is no interaction between the time effect and the treatment group effect, i.e., \(E(\varepsilon_{ij} \mid (T \times \Delta O \times IT^j)) = 0\). Given the structure of the data, it is not obvious that this condition is satisfied: the choice of both investing in organizational changes and in IT is likely to be endogenous. A weakness in this setup is thus that this choice is not modeled; organizational changes are treated as if they were exogenously given (as are investments in IT). Ideally, we would like to have some exogenous mechanism determining the choice, or use instruments for it.

### 2.5 Results

This section first presents the effects of organizational change on productivity growth using the difference-in-difference approach on the “Plan Survey” panel (2.5.1). After that, I move on to investigate determinants of organizational change using the “IT, work organization and productivity” survey (2.5.2.1). Section (2.5.2.2) presents the results from the OLS estimations and then addresses the selection into organizational change using a selection model and instrumental variables.
2.5. RESULTS

2.5.1 The “Plan Survey”

Recall that the ideal procedure here is to try to instrument for (the probability) of organizational change. However, for the “Plan Survey” panel, this is not a viable procedure: the estimated relations are all insignificant.\textsuperscript{13} However, reorganizations are, in effect, not randomly assigned. Therefore, it is important to explicitly consider any potential bias due to nonrandom sampling, i.e., we would like firms to be, ex ante, as statistically similar as possible. To evaluate the composition of the two groups, pretreatment characteristics are examined in A.2.1. All in all, the distributions of industry and employee characteristics are fairly similar. The treatment and control group also have a similar TFP pattern (and labor productivity) growth before organizational change took place. Together this gives some support for the parallel trend assumption.

I proceed to estimate equation (2.4) without a first step and the results are reported in table 2.3. The number of observations in the baseline estimation is 832, yielding an average of 6.9 observations (out of a maximum 8) per firm. All regressions have standard errors clustered at the firm level, a constant and control for the size of the firm (the number of employees). A full set of two-digit industry dummies is also included, unless a fixed-effect estimator is used. The first column reports the results from the baseline regression with no additional controls. The result is quite striking: the group of firms that both undertook organizational change and made large investments in IT had a 18.3 percentage point increase in TFP growth. The result is significant at the 1\% level. Interestingly, there were no significant effects for the firms with the other two groups of IT investment, thus supporting the hypothesis that it is indeed organizational changes combined with increased IT-capital that have an effect on productivity growth. A concern in the difference-in-differences setup is that there may be other interactions between the treatment group and time. One indication of this is that the regression shows a large time effect, $\theta_1$. Since $\theta_1$ picks up the effects of omitted variables and trends in the dependent variable, a large $\theta_1$ would suggest

\textsuperscript{13}The results are reported in Håkanson (2009).
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Number of observations: 832
Number of firms: 120
Adjusted R²: 0.082

IT measures: A max [investment in IT/employee]; B mean [investment in IT/employee]; C max [investment in IT/total investments]; D mean [investment in IT/total investments]
2.5. RESULTS

that the effects of these sources vary substantially between treatment and control group and that there are likely to be omitted variables. On the other hand, if the time effect, $\theta_1$, and the group effects, $\theta_{\text{zero}}$, $\theta_{\text{low}}$, $\theta_{\text{high}}$, are small and statistically insignificant, it is instead an indication that the treatment and control group indeed share the same trend prior to the policy change.

The time effect is significant in the first column. One possible reason can be that the timing of the treatment period incidentally coincided with a very sharp turn in the business cycle year 2001. Therefore, in column (2) and onwards, a third degree polynomial (TREND) is included to control for general business cycle movements. This renders the time effect insignificant, but leaves the other estimates unchanged. The group effects are in general insignificant, except for the group effect of low IT, which is significant at the 5% level, in the first two regressions. Column 3 repeats the baseline regression by using a fixed effect estimator. The point estimate for $\theta_{\text{high}}$ increases marginally whereas the significance is unchanged.

If selection into the treatment groups is correlated with the outcome, we will see changes in the estimates as a result of including more controls. In column 4, additional controls for employee composition are included: skill levels, field of study, age, share of females and the share of immigrants among the workers.\footnote{All additional controls are lagged one period.} Moreover, to rule out the possibility that large investments drive the result, net investments in machinery & equipment per employee are included. The inclusion of these controls does not affect the size or significance of the main estimate of interest; importantly, the group effect for the low IT group becomes insignificant.\footnote{In another set of regressions (not reported here), even more detailed labor composition was controlled for: field of education and age were controlled for at each educational level and the share of immigrants was also split into “new” and “old” immigrants, respectively. The results were unaffected by this.} Column 5 repeats the extended regression using the fixed effect estimator. The estimate of the effect of both investing above the median in IT and undertaking organizational change, $\theta_{\text{high}}^3$, is once more only marginally affected and is still significant at the 1% level.

In general, difference-in-differences estimators are regarded as more reli-
able when comparing outcomes just before and after a policy change. Yet, from a policy perspective, it is also of interest to look at medium- and long-term effects. The problem, however, is that as the time window increases, the treatment effect is likely to be confounded with the changes that occurred during the period. As another robustness check, the regressions are therefore re-estimated on a shorter panel only including the years 1999-2003, i.e., one year before and after the window for organizational change. Reassuringly, the estimates (columns 6 and 7) largely remain unchanged.\textsuperscript{16} Finally, instead of using TFP growth in the last two columns of table 2.3, the dependent variable is changed to labor productivity growth (log difference). The effect is now somewhat smaller, around 15-16 pp, but still highly significant. To sum up, the results are largely invariant to changes in specification, sample and the time period used.

To assess whether the use of different definitions of intensity in IT investment affects the result, the specifications in column 4 and 5 in table 2.3 are re-estimated using the three alternative measures of IT. The results, presented in appendix table A.7, are largely unchanged and remain significant.

\textbf{2.5.2 The “IT, work organization and productivity” survey}

In this section, I first show general patterns for productivity growth with respect to organizational change for the data from the second panel. Next, I look at the determinants of organizational change, investigating two hypotheses put forth in the literature; that the probability of organizational change i) increases with competition (Crespi et al., 2007; Nickell et al., 2001; Van Reenen, 2011) and ii) decreases in the distance to the technology frontier and increases in industry heterogeneity (Acemoglu et al., 2007). Thereafter, the results on productivity growth are presented, first, using OLS estimations and then, addressing the selection into organizational change using a selection model and instrumental variables.

\textsuperscript{16}Further experiments have been made removing e.g. very large/small firms, and firms with very high/low TFP growth to see if extreme observations seem to drive the results. This is not the case, however. When observations with very high/low TFP growth are deleted, the point estimate of the difference-in-difference for the high IT group is somewhat lower, but remains significant.
Figure 2.1: Productivity growth and organizational change

Figure 4.1 shows average, unconditional, labor productivity growth over time for the four indicators of organizational change, the horizontal line at 2005 representing the timing of organizational change. The left upward panel shows that the firms that decreased the number of layers in their hierarchy on average had a higher productivity growth after the delayering had taken place. On the other hand, firms that added layers to their hierarchy, if anything, show a tendency to decreased productivity growth after 2005. The remaining two indicators show no apparent different pattern compared to the firms that indicated no change.

2.5.2.1 Estimating probability of organizational change

Table 2.4 shows the first set of estimates for the probability of organizational change. I estimate equation 2.1 using a standard probit estimator. Marginal effects are reported along with robust standard errors, clustered at the two-digit industry level. Columns 1, 3, 5 and 7 show the main estimates including a full set of two-digit industry dummies. Since quite a few observations are lost due to some industry dummies completely predicting failure or success, the regressions are repeated grouping industries according to IT-use and
production. Column 1 relates the average change in market share two years before to the action of delayering. The effect is significant at the 1% level with a marginal effect of -0.71. This result is consistent with the findings in Crespi et al. (2007) and Nickell et al. (2001) - firms that lose market shares are more likely to reorganize in the next period. Having a foreign head office does not seem to increase the probability of delayering; the coefficient is positive, but insignificant. The grouped industry effects in column 2 suggest that delayering is more probable among manufacturing firms. The results for layering are presented in column 3. Interestingly, here the effect from the change in market share has the opposite sign, i.e. firms that gained market shares in previous periods are more likely to add layers in the following period. The marginal effect is 0.43 and it is also significant at the 1% level. The grouped industry effects in column 4 indicate that layering is more probable in ICT-producing service industries. Turning to multitasking and span of control (columns 5-8), the effect from a change in the market share is once more positive and significant, albeit smaller in size. In sum, changes to the number of layers in the hierarchy respond to changes in market shares in an expected way. The results for multitasking and span of control are harder to interpret. It can be that the indicators just pick up the demand effect. An increase in the market share in the previous period translates into the employees having more tasks and responsibilities at hand.

Acemoglu et al. (2007) model decentralization and show that firms operating closer to the technological frontier and in more heterogeneous environments are more prone to have a decentralized organization as the knowledge of the local managers is more valuable. They test their theory on data using information about whether firms are organized into profit centers as an indicator of decentralization and find support for the predictions of the model. In the present data, I have little information on actual delegation of authority. However, if one is willing to assume that delayering is associated with more decentralized decision making, the theory will predict that firms closer to the productivity frontier have a flatter organization (given their size). Moreover,

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17Industries are grouped according to production and use of IT following van Ark et al. (2003). Details given in Appendix
Table 2.4: Change in market shares

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</table>

Observations: 1,589 1,750 1,671 1,774 1,762 1,774 1,764 1,774
chi2: 47.60 32.12 34.25 17.35 138.8 106.7 117.3 82.57
Marginal effects are reported along with robust standard errors, clustered at the two-digit industry level.
Columns 1, 3, 5 and 7 include two-digit industry dummies.
$\Delta 4$ – digit market share is measured as the average change in the market share two years preceding the organizational change.
*** p<0.01, ** p<0.05, * p<0.1
firms operating in more heterogeneous industries would have less layers as the knowledge of local managers becomes more valuable.

In the first column of table 2.5, the number of layers in firms is related to the distance to the frontier. The coefficient is 0.10 and has the expected sign (significant at the 10%-level) indicating that as firms close the distance to the productivity frontier, they indeed tend to have fewer layers in the hierarchy. The second column instead relates the number of layers to the industry heterogeneity measured as the difference between the 90th and 10th percentile of the four-digit industry productivity growth distribution. Here the effect is insignificant and close to zero. If industry heterogeneity is instead measured as the 90/10 difference in productivity levels (column 3), the effect is opposite to the prediction of the theory; firms in more heterogeneous environments tend to have more layers in the hierarchy given their size.\textsuperscript{18}

Acemoglu et al. (2007) use a similar variable on delayering as that used in this study within one of their robustness checks. It is measured as the removal of one or more layers in the managerial hierarchy between 1996 and 1998. They argue that this measure is better than a general measure of number of levels in the hierarchy, as that would more likely also involve non-managerial workers. In the survey “IT, work organization and productivity”, there is no explicit focus on managerial levels only; the question is formulated to capture changes in the number of decision levels, but it is closely related. In table 2.6, the measures of industry heterogeneity and distance to the productivity frontier are instead related to the indicator \textit{delayering}.

In this specification, the coefficient on industry heterogeneity is insignificant throughout. Distance to frontier, however, is weakly significant and has the opposite sign from the expected. One interpretation is that this measure, which covers all levels in the hierarchy, not just the managerial levels, picks up effects of increasing competitive pressure. Firms loosing ground with respect to the technology frontier are more prone to delayering as a mean to regain their position. Another difference is that Acemoglu et al. (2007) have

\textsuperscript{18}Acemoglu et al. (2007) argue that the growth-based measure is likely to be better, as time-invariant omitted variables affecting the level of productivity (e.g. management quality and brand differences) are differenced out.
2.5. RESULTS

Table 2.5: Layers in hierarchy, distance to frontier and industry heterogeneity

<table>
<thead>
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</tr>
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<tbody>
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<td>Layers in hierarchy</td>
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</tr>
<tr>
<td>$HO_{t-1}$</td>
<td>0.19***</td>
<td>0.24***</td>
<td>0.22***</td>
</tr>
<tr>
<td></td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>$Multiplant_{t-1}$</td>
<td>0.14**</td>
<td>0.16**</td>
<td>0.13**</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
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<tr>
<td>$l_{t-1}$</td>
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<td>0.39***</td>
<td>0.40***</td>
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<tr>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>$DF_{t-1}$</td>
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<tr>
<td></td>
<td>(0.05)</td>
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<td></td>
</tr>
<tr>
<td>$H_{t-1}$ growth</td>
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</tr>
<tr>
<td></td>
<td></td>
<td>(0.06)</td>
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</tr>
<tr>
<td>$H_{t-1}$ level</td>
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<td></td>
<td>0.17*</td>
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<tr>
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<tr>
<td>Constant</td>
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<td>1.53***</td>
<td>1.21***</td>
</tr>
<tr>
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<td>(0.10)</td>
<td>(0.17)</td>
</tr>
<tr>
<td>Observations</td>
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<td>1,774</td>
<td>1,774</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.20</td>
<td>0.17</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
information on manufacturing firms only, while the present panel includes both service and manufacturing firms. Moreover, they find stronger results for IT intensive industries. Therefore, the last columns of table 2.6 first restrict the sample to manufacturing only and then to IT-intensive sectors only. However, the results remain. In sum, I find some support for the distance to the technology frontier to be related to the number of layers in the hierarchy, but not to the indicator of industry heterogeneity.

2.5.2.2 Effect of organizational change on productivity growth, OLS estimates

Table 2.7 shows the regular OLS estimations of equation (2.1). In addition to the reported variables, all regressions include two-digit industry dummies and five dummies controlling for firm size. Column 1 reports the result with respect to delayering. Firms that removed layers in the previous period on

\footnote{In the main specification, industry heterogeneity and distance to the frontier are calculated restricting the population of firms to those with at least one employee, i.e. self-employed are excluded. These measures have also been calculated on the population of firms with at least 10 employees and on a two- and three-digit industry level, with similar results.}
average have 14 percentage point higher productivity growth and the coefficient is significant at the 5%-level. Investments in IT are also positive and strongly significant, with a coefficient of 0.02. Increasing the share of high skilled is also significantly related to productivity growth. An increase of one standard deviation would imply an increase in productivity growth by 2.6\%.\textsuperscript{20} Next, in columns 2-4, the results for multitasking (2), span of control (3) and layering (4) are presented. For all three measures, the coefficients are close to zero and insignificant. The coefficients on change in high skilled and investments in IT are very similar with respect to column 1. Comparing domestic and foreign-owned firms, domestic firms show a higher productivity growth throughout. This is opposite to the results for UK firms in Bloom et al. (2012). However, the results may not be so surprising in the light of their results, where Swedish firms are among the top of the decentralization distribution across four different dimensions measuring plant manager autonomy on hiring, capital expenditure, marketing and product innovations.

A concern with the specification in table 2.7 is that firms with zero investments in IT are excluded as $\Delta k^{\text{ICT}}$ is measured in logs. Therefore, in addition to the main specification, productivity growth is also estimated with a different specification measuring ICT as in the Plan Survey. Instead of the (log of) investment in ICT, the two dummies $ICT^{\text{low}}$ and $ICT^{\text{high}}$ are included ($ICT^{\text{zero}}$ is the omitted category). $ICT^{\text{high}} = 1$ if the firm invested above the median (among the surveyed firms) in ICT per employee. Similarly, $ICT^{\text{low}} = 1$ for investments below the sample median and $ICT^{\text{zero}} = 1$ reported no investments in IT and communication. Last, to allow for complementarity between organizational change and ICT, there is an interaction between organizational change and $ICT^{\text{high}}$. The results are presented in table 2.8. The effect of delayering (column 1) becomes slightly smaller and is insignificant. However, an F-test of delayering and the interaction term $\text{delayering} \times IT^{\text{high}}$ being jointly zero is rejected (p-value 0.069). The coefficients on the change in the share of high skilled are still significant, although they are slightly smaller.

\textsuperscript{20}The standard deviation of change in the share of high skilled is 0.04 and the effect is obtained by calculating $0.66 \times 0.04 \times 100 \approx 2.6$. 
Table 2.7: OLS Productivity growth

<table>
<thead>
<tr>
<th></th>
<th>delayering</th>
<th>multitasking</th>
<th>span of control</th>
<th>layering</th>
</tr>
</thead>
<tbody>
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<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
</tr>
<tr>
<td>$HO_{t-1}$</td>
<td>-0.07***</td>
<td>-0.07***</td>
<td>-0.07***</td>
<td>-0.07***</td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
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</tr>
<tr>
<td>$Multiplant_{t-1}$</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>$\Delta l_{t-1}$</td>
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<td>0.08*</td>
<td>0.08*</td>
<td>0.08*</td>
</tr>
<tr>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
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</tr>
<tr>
<td>$\Delta l_{NICT}^{t-1}$</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td></td>
</tr>
<tr>
<td>$\Delta l_{ICT}^{t-1}$</td>
<td>0.02***</td>
<td>0.02***</td>
<td>0.02***</td>
<td>0.02***</td>
</tr>
<tr>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
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</tr>
<tr>
<td>$\Delta high skilled$</td>
<td>0.66**</td>
<td>0.64**</td>
<td>0.64**</td>
<td>0.65**</td>
</tr>
<tr>
<td>(0.26)</td>
<td>(0.27)</td>
<td>(0.27)</td>
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<td>$\Delta low skilled$</td>
<td>0.24</td>
<td>0.23</td>
<td>0.23</td>
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<tr>
<td>delayering$_{t-1}$</td>
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<td>(0.06)</td>
<td>(0.06)</td>
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<tr>
<td>$span of control_{t-1}$</td>
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<td>-0.00</td>
<td>-0.00</td>
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<td>(0.06)</td>
<td>(0.06)</td>
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<td>-0.14**</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>0.06</td>
<td>0.06</td>
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</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1
### Table 2.8: OLS Productivity growth, including zero ICT

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<tr>
<th>VARIABLES</th>
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<th>(3) span of control</th>
<th>(4) layering</th>
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<td>$H_0_{t-1}$</td>
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<td>-0.06**</td>
<td>-0.06**</td>
<td>-0.06**</td>
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<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
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<tr>
<td>$Multiplant_{t-1}$</td>
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<td>0.04</td>
<td>0.04*</td>
<td>0.04*</td>
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<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
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<tr>
<td>$\Delta ln(L)_{t-1}$</td>
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<td>0.11**</td>
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<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>$\Delta(ln(K^{NIT} - ln(L))_{t-1}$</td>
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<td>0.03</td>
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<td>0.02</td>
</tr>
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<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
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<tr>
<td>$\Delta$ high skilled</td>
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<td>0.50**</td>
<td>0.50**</td>
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<td>(0.25)</td>
<td>(0.25)</td>
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<tr>
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<td>(0.03)</td>
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<tr>
<td>$ICT_{1-1}^{high}$</td>
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<tr>
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</tr>
<tr>
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<tr>
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</tr>
<tr>
<td>layering * $ICT_{1-1}^{high}$</td>
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<td>(0.04)</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
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<td>1.548</td>
<td>1.548</td>
<td>1.548</td>
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<tr>
<td>R-squared</td>
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<td>0.06</td>
<td>0.06</td>
<td>0.06</td>
</tr>
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</table>

Robust standard errors clustered at industry in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
2.5.2.3 Selection into organizational change

The previous section established stable correlations between indicators of competitive pressure (lagged changes in market shares) and between delay-ering and distance to the technology frontier. In the OLS estimation of productivity growth, including delayering as an explanatory variable resulted in positive effects of delayering on productivity growth. However, since organizational change is likely to be endogenous, there is some concern that the OLS estimates are inconsistent.

The challenge in this case is that if there is self-selection into organizational change, the regressor variable will be correlated with the error term, which renders the OLS prediction inconsistent. In this section, I address this concern by using a selection model and instrumental variable (IV) techniques. I employ three different statistical methods, each with its pros and cons. The first two methods rely on the Stata procedure `treatreg`. This is an estimator for the special case when the endogenous regressor is binary. It uses either full information maximum likelihood or a two-step procedure to determine fits, and I employ both of these. The maximum likelihood syntax relies on the assumption that the errors are jointly normally distributed. If the assumption is satisfied (and the exclusion restrictions are met), then this estimator is consistent, efficient, and asymptotically normal. When instead using the two-step option, the estimator is consistent under somewhat weaker assumptions, with normality of the errors in the first stage (the treatment equation) only. Compared to a regular IV estimate, `treatreg` offers an increased precision, but has a greater chance of misspecification error. Finally, the third approach used is suggested by Wooldridge (2010): the first step is estimated using probit. The predicted probabilities are then used as instruments in an IV regression.\textsuperscript{21}

The results are presented in table 2.9. For reference, the first column of table 2.9 repeats the OLS estimate of table 2.7 for delayering. Using lagged changes in market share and lagged distance to the technology frontier as determinants of organizational change, column 2 shows the result from using

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treatreg and full information maximum likelihood. The effect on productivity growth of delayering becomes somewhat stronger compared to the OLS estimate and is still significant at the one percent level.\textsuperscript{22} The third column shows the first step used in the treatreg procedure. Here, the test for independent equations rejects the null that the equations are independent, suggesting that selection is indeed a problem.

The result using a two-step approach is presented in column 4 (the main equation) and 5 (the first step). Here, the coefficient on delayering is still significant but becomes very large. The estimate for the selection parameter $\lambda$ is 0.68 and it is significant at the one percent level, once more indicating that selection is indeed a relevant issue. To further examine this relationship, the predicted probabilities from a first-step profit (identical to column 5) are used as instruments for delayering in column 6. This renders the point estimate even larger (and still significant). As seen by the diagnostic statistics, the first stage has a very low $R^2$ in predicting delayering (0.04). The value of the F-test in the first stage is 9.8 which indicates that the instruments are rather weak: the critical values indicate that they are only valid if you accept a rejection rate of 10% of a nominal 5% Wald test. Moreover, the Hausman-Wu test for excludability is rejected.

To sum up, the results using the “IT, work organization and productivity” survey support the competition hypothesis, in that changes in competitive pressure increase the probability of organizational change, using lagged changes in firm market share as an indicator. The OLS estimates suggest that delayering is indeed associated with subsequent higher productivity growth. The results from the selection models indicate that selection is indeed an issue for the problem at hand. Using a full information maximum likelihood treatment regression supports the results from the OLS estimates. An important caveat, however, is that IV estimates suggest that the predictors of the probability of organizational change are weak instruments and that the exclusionary restriction is violated.\textsuperscript{23}

\textsuperscript{22}Robust standard errors clustered at the two-digit industry level.

\textsuperscript{23}Similar estimations have been made for the other measures of organizational change, but these results are less robust (recall that the OLS estimates indicated no effect on productivity growth from organizational change for the other measures). The selection
<table>
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<th></th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<td>treatreg FIML</td>
<td>first step</td>
<td>treatreg two step</td>
<td>first step</td>
<td>probit</td>
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<td>-0.01</td>
<td>-0.02</td>
<td>-0.02</td>
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<td></td>
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<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
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<td>(0.02)</td>
<td>(0.03)</td>
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<tr>
<td><strong>Δl_{t-1}</strong></td>
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<td>0.08*</td>
<td>0.11***</td>
<td>0.22***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.05)</td>
<td>(0.04)</td>
<td>(0.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>ΔNICT_{t-1}</strong></td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.03</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.03)</td>
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<td></td>
</tr>
<tr>
<td><strong>ΔICT_{t-1}</strong></td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>-0.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>ΔHS</strong></td>
<td>0.41***</td>
<td>0.42**</td>
<td>0.41*</td>
<td>0.83***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.20)</td>
<td>(0.22)</td>
<td>(0.37)</td>
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</tr>
<tr>
<td><strong>ΔLS</strong></td>
<td>-0.16</td>
<td>-0.15</td>
<td>-0.16</td>
<td>-0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.16)</td>
<td>(0.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>delayering_{t-1}</strong></td>
<td>0.11***</td>
<td>0.19***</td>
<td>1.64***</td>
<td>2.65***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.06)</td>
<td>(0.32)</td>
<td>(0.87)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Δl_{t-1}</strong></td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.03**</td>
<td>-0.04**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>l_{t-1}</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>market share_{t-1}</strong></td>
<td>0.18***</td>
<td></td>
<td>0.19***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Distance to frontier_{t-1}</strong></td>
<td>-0.59***</td>
<td>-0.51*</td>
<td>-0.51*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.22)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>hazard λ</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td><strong>athrho</strong></td>
<td>-0.19***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td></td>
<td>(0.05)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>lnsigma</strong></td>
<td>-1.68***</td>
<td></td>
<td>-1.68***</td>
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<td></td>
<td></td>
</tr>
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<td></td>
<td></td>
<td>(0.05)</td>
<td></td>
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</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.05***</td>
<td>-0.03*</td>
<td>-2.97***</td>
<td>0.00</td>
<td>-2.87***</td>
<td>0.02</td>
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<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.09)</td>
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</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1346</td>
<td>1344</td>
<td>1344</td>
<td>1344</td>
<td>1344</td>
<td>1344</td>
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<tr>
<td><strong>R-squared</strong></td>
<td>0.08</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Chi2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Chi2 indep eqn</strong></td>
<td>12.47</td>
<td>12.47</td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>p-value indep eqn</strong></td>
<td>0.000413</td>
<td>0.000413</td>
<td></td>
<td></td>
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<td><strong>chi2</strong></td>
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<tr>
<td><strong>first stage R2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>25.79</td>
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<tr>
<td><strong>first stage F-test</strong></td>
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<td></td>
<td></td>
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<td>0.0443</td>
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<td><strong>critical value 5</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td><strong>critical value 10</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>16.38</td>
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<tr>
<td><strong>critical value 15</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>8.960</td>
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<tr>
<td><strong>Hausman-Wu Chi2</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td>56.04</td>
</tr>
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</table>

Standard errors clustered at industry in parentheses

*** p<0.01, ** p<0.05, * p<0.1
2.6 Concluding remarks

This paper uses two different survey data sets matched to employer-employee data to estimate effects of organizational change on firm productivity growth. The first survey is analyzed using a difference-in-differences approach to assess the effects of organizational change on productivity growth around the year 2001. The data used is small but rich in detailed and firms that are followed over nine years: 1997-2005. The results show a sizable positive and significant effect on productivity growth for firms that both undertook organizational change and invested above the median in IT. No effects are found for firms that made reorganizations but had zero or low investments in IT. The results are quite robust to a variety of changes to the specification. The estimates are unaffected by shrinking the evaluation window and balancing the panel; also, they are qualitatively unaffected by the use of alternative measures of IT or the employment of a fixed-effect estimator. The main weakness, however, is that both organizational change and investments in IT are treated as exogenous while, in fact, they are likely to be endogenous through firm choice. I address this concern by using a selection model and instrumental variable (IV) techniques analyzing the same indicators of organizational change collected within the survey “IT organization and productivity”. In the first step, the probability of organizational change is estimated. I find support for the competition hypothesis; a lagged decrease in the firm market share increases the probability of delayering, while increasing market shares make firms more likely to add layers in the hierarchy. In the second step, only delayering has an effect on subsequent productivity growth. The OLS estimates suggest that delayering is associated with subsequent higher productivity growth. An increasing share of high skilled labor also has a significant effect on productivity growth, throughout the estimations. The results from the selection models indicate that selection is present. Using a full information maximum likelihood treatment regression supports the results from the OLS estimates. An important caveat, however, is that IV estimates suggest that the predictors of the probability of organi-

\[\text{models give zero effect in most cases, but the instruments here are even weaker.}\]
zational change are weak instruments and that the exclusionary restriction is violated.

Bibliography


A. APPENDIX

A Appendix

A.1 Definitions and computation of variables

Capital stocks
Capital stocks are calculated using a version of the Perpetual Inventory Method. For each firm and year, there is data on net investments for two types of capital: machinery and equipment and structures. Capital stocks are computed for the two types of capital according to:

\[ K_t^M = \max \{(1 - \delta^M)K_{t-1}^M, K_{t-1}^{bv,M} \} + I_{t-1}^M, \]

where \( K_t^M \) is the real capital stock of type \( M \) at the beginning of period \( t \), \( K_{t-1}^{bv,M} \) is real book value at the end of \( t-1 \), \( \delta^M \) is the time average depreciation rate at the two-digit industry level and \( I_t \) is real net investment (gross investment minus sales) in capital \( M \).

Capital rent prices are calculated separately for the two types of capital according to:

\[ P_{K,t}^M = P_{I,t-1}(1 + r - (1 - \delta_M) \frac{P_{I,t-2}}{P_{I,t-2}}), \]

where \( P_{I,t} \) is the investment price index and \( \delta_M \) is the time averaged depreciation rate at the two-digit industry level.\(^{24}\)

Labor composition
The panel has very detailed data on labor composition. First, the employees are divided into four different categories depending on level of education: \( L_1 \), Low skilled labor, has nine years of compulsory school and \( L_2 \), Intermediate skilled labor, has attained secondary school. High skilled labor is subdivided into two groups: \( L_3 \), with less than three years of tertiary education and, finally, \( L_4 \) labor with at least three years of tertiary education or post graduate education. All four levels are used in the TFP calculations, but when

\(^{24}\)Investment price indices are collected from the National Accounts of Statistics Sweden. Average depreciation rates are calculated using the population of firms in the Structural Business Statistics.
the level of education is also controlled for in regressions, only three levels are used to save on parameters, i.e. \( LS \) (low skilled), \( IS \) (intermediate skilled) and \( HS \) (high skilled), where the last group is the sum of \( L_3 \) and \( L_4 \).

For the Plan Survey Panel, additional detailed measures of labor composition were constructed; Within each educational level, the employees are further divided according to their field of study: the share of employees with a technical or engineering education \( (fos1) \), the share of employees with an education in the field of economics, business administration or law \( (fos2) \) and the share of employees with "other" education \( (fos3) \). Finally, within each educational level, there is also information on mean age \( (age1) \): share 16-29 year old, \( age2 \): share 30-49 years old and \( age3 \): share over 50 years old), gender composition \( (fem) \) and share of immigrants \( (imm) \).

**Market shares, distance to the technology frontier and industry heterogeneity**

The population of firms in the registers is restricted to those with at least one employee, i.e. self-employed are excluded before the remaining firms are used to form the measures of market shares, industry heterogeneity and distance to frontier. **Change in market share** is computed using four-digit industry level data on turnover from Statistics Sweden. Change in market share enters the estimations as the average change in market share in the two years preceding organizational change. The **distance to the technology frontier** is measured as the log difference between firm labor productivity and labor productivity at the 99th percentile in the same four-digit industry. **Industry heterogeneity** is measured as the log difference between the 90th and 10th percentile in the labor productivity growth distribution within the four-digit industry.\(^{25}\) For the surveyed firms, capital stocks are calculated using a version of the perpetual inventory method, see the appendix for details.

**Classification of industries**

Industries are classified according to intensity ICT in production/usage fol-

\(^{25}\)As a robustness check, these measures have also been calculated on the population of firms with at least 10 employees. The results are insensitive to this.
A. APPENDIX

Following van Ark et al. (2003). Table A.1 shows the industry codes included in the different groups. The Swedish industry classification SNI92 is equivalent to NACE rev 2 up to the four-digit level.

Table A.1: Classification of industries

<table>
<thead>
<tr>
<th>NACE Rev 2 Industry codes (SNI92)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICT producing manufacturing</td>
</tr>
<tr>
<td>ICT producing service</td>
</tr>
<tr>
<td>ICT using manufacturing</td>
</tr>
<tr>
<td>ICT using service</td>
</tr>
<tr>
<td>Non ICT manufacturing</td>
</tr>
<tr>
<td>Non ICT service</td>
</tr>
<tr>
<td>Non ICT other</td>
</tr>
</tbody>
</table>

A.2 Descriptive statistics

A.2.1 Comparison of pre treatment characteristics, The “Plan Survey”

In the analysis of the Plan Survey, organizational change is treated as exogenous. However, reorganizations are, in effect, not randomly assigned. To explicitly consider potential bias due to nonrandom sampling, this section examines the pretreatment characteristics to evaluate the composition of the two groups.

The data is first divided according to organizational change and the different measures for investments in IT. Although the final panel used is very small, it covers firms within many industries in the Swedish private sector. Out of the 120 companies, about 59% are from the manufacturing sector and 41% from the service sector. The distribution over industries does not vary substantially between treatment and control groups (see table A.3). Neither firm sizes does not differ to any large extent between firms that only reorganized or reorganized and invested above the median in IT, as compared to the total sample. The samples are quite similar with regard to employee composition and firm characteristics. Turning to the distribution over the three IT categories, quite a large fraction of firms report zero investment:
23% in the total sample and 27% among those that underwent organizational change. However, this does not imply that they are low tech-firms; rather, they simply did not make any IT investments in the time window where the organizational change was measured (see table A.4 in appendix).

To further compare the groups, in table A.2 the mean of the pre-treatment characteristic variables is compared for the control group, the group that undertook organizational change and the group that in addition to making organizational change also invested above the median in IT. T-tests with $H_0 : \mu_{\Delta O=0} = \mu_{\Delta O=1}$ and $\mu_{\Delta O=0} = \mu_{\Delta O \times IT_{A}^{high}=1}$, respectively, are included. In most aspects, the firms that made organizational changes are very similar to those that did not. Still, some differences are worth pointing out: firms that undertook organizational change on average had a higher share of employees with intermediate skills (significant at the 5% level) and were on average smaller (significant at the 10% level). On average, they also had a lower productivity growth; however, this difference is not significant. The group that made large investments in IT ($\Delta O \times IT_{A}^{high} = 1$) also had a lower productivity growth, the difference now being weakly significant. In addition, they were less represented among the largest firms (significant at the 5% level) and had a significantly lower share of immigrants among its employees (about three percentage points). To sum up, there are some statistically significant differences between the treatment and the control group. However, the distributions of industry and employee characteristics are fairly similar. The treatment and control group also have a similar TFP pattern (and labor productivity) growth before treatment. Together, this gives some support for the parallel trend assumption.
Table A.2: Comparison of means pretreatment

<table>
<thead>
<tr>
<th>variable</th>
<th>$\Delta O = 0$</th>
<th>$\Delta O = 1$</th>
<th>$\mu_{\Delta O=0} = \mu_{\Delta O=1}$</th>
<th>$\mu_{\Delta O=1} = \mu_{\Delta O \times IT_{A}^{high}=1}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ttp</td>
<td>5.67</td>
<td>5.90</td>
<td>(−1.00)</td>
<td>5.68</td>
</tr>
<tr>
<td>$\Delta ttp$</td>
<td>0.15</td>
<td>0.09</td>
<td>(1.15)</td>
<td>0.07</td>
</tr>
<tr>
<td>labor productivity (ln)</td>
<td>6.37</td>
<td>6.31</td>
<td>(0.81)</td>
<td>6.52</td>
</tr>
<tr>
<td>$\Delta$ labor productivity</td>
<td>0.004</td>
<td>-0.02</td>
<td>(0.69)</td>
<td>-0.06</td>
</tr>
<tr>
<td>share of employees:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>high skilled</td>
<td>0.23</td>
<td>0.21</td>
<td>(0.90)</td>
<td>0.23</td>
</tr>
<tr>
<td>intermediate skilled</td>
<td>0.47</td>
<td>0.51</td>
<td>(−2.29) * *</td>
<td>0.48</td>
</tr>
<tr>
<td>low skilled</td>
<td>0.30</td>
<td>0.28</td>
<td>(0.64)</td>
<td>0.29</td>
</tr>
<tr>
<td>edu. in engineering</td>
<td>0.40</td>
<td>0.37</td>
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<td>0.42</td>
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<tr>
<td>edu. in economics, business</td>
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<td>0.18</td>
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<td>0.45</td>
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<td>0.42</td>
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<td>other education</td>
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<td>(0.00)</td>
<td>0.42</td>
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<tr>
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<td>0.29</td>
<td>(−0.83)</td>
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<td>40-49</td>
<td>0.46</td>
<td>0.46</td>
<td>(0.29)</td>
<td>0.46</td>
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<tr>
<td>50-</td>
<td>0.28</td>
<td>0.27</td>
<td>(0.67)</td>
<td>0.31</td>
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<tr>
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<td>0.14</td>
<td>0.13</td>
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<td>0.11</td>
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<tr>
<td>number of employees</td>
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<td>376</td>
<td>(1.46) *</td>
<td>376</td>
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</table>

Pretreatment means are compared using observations for the years 1998 and 1999
Test for equal mean, t-statistics within parenthesis, *** p<0.01, ** p<0.05, * p<0.1
$\Delta O = 0$ refers to the group that did not make any organizational change
$\Delta O = 1$ refers to the group that made an organizational change
$\Delta O \times IT_{A}^{high} = 0$ refers to the group that made an organizational change and made large investments in IT
IT measure A: max [investment in IT / employee]
Table A.3: Descriptive statistics: distribution over industries, Plan Survey

<table>
<thead>
<tr>
<th>NACE</th>
<th>All</th>
<th>$\Delta O = 1$</th>
<th>$\Delta O \times IT_{A}^{high} = 1$</th>
<th>$\Delta O \times IT_{C}^{high} = 1$</th>
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</thead>
<tbody>
<tr>
<td>n = 120</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agriculture, fishing and forestry</td>
<td>1 – 2</td>
<td>1%</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td>Food products, textiles</td>
<td>15 – 19</td>
<td>6%</td>
<td>7%</td>
<td>9%</td>
</tr>
<tr>
<td>Pulp, paper and paper prod.</td>
<td>21</td>
<td>10%</td>
<td>9%</td>
<td>5%</td>
</tr>
<tr>
<td>Chemicals, non-metallic prod.</td>
<td>23 – 26</td>
<td>9%</td>
<td>9%</td>
<td>6%</td>
</tr>
<tr>
<td>Basic metal and metal products.</td>
<td>27 – 28</td>
<td>13%</td>
<td>13%</td>
<td>22%</td>
</tr>
<tr>
<td>Mach. and equip., instruments</td>
<td>29 – 36</td>
<td>21%</td>
<td>22%</td>
<td>23%</td>
</tr>
<tr>
<td>Constr., wholesale, retail, hotel.</td>
<td>45 – 55</td>
<td>6%</td>
<td>4%</td>
<td>0%</td>
</tr>
<tr>
<td>Transport storage and comm.</td>
<td>60 – 64</td>
<td>12%</td>
<td>9%</td>
<td>5%</td>
</tr>
<tr>
<td>Real estate, renting</td>
<td>70 – 71</td>
<td>8%</td>
<td>7%</td>
<td>9%</td>
</tr>
<tr>
<td>Business activities</td>
<td>72 – 74</td>
<td>16%</td>
<td>20%</td>
<td>27%</td>
</tr>
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</table>
Table A.4: Summary statistics, Plan Survey panel

| Variable                       | $\Delta O = 0, n = 449$ |      |      | $\Delta O = 1, n = 383$ |      |      | $\Delta O \times IT^\text{high} = 1, n = 148$ |      |      | $\Delta O \times IT^\text{low} = 1, n = 150$ |      |      |
|-------------------------------|--------------------------|------|------|--------------------------|------|------|-----------------------------------------------|------|------|
|                               | Mean         | Std. Dev. | Mean   | Std. Dev. | Mean   | Std. Dev. | Mean         | Std. Dev. | Mean         | Std. Dev. | Mean         | Std. Dev. |
| tftp                          | 5.911        | 1.499      | 6.075  | 1.258      | 6.029  | 1.701      | 6.480        | 0.561      |              |            |              |            |
| $\Delta tftp$                 | 0.067        | 0.364      | 0.035  | 0.373      | 0.070  | 0.359      | -0.016       | 0.376      |              |            |              |            |
| labor productivity (ln)       | 6.463        | 0.630      | 6.360  | 0.563      | 6.528  | 0.584      | 6.173        | 0.368      |              |            |              |            |
| $\Delta$ labor productivity   | 0.023        | 0.331      | 0.011  | 0.308      | 0.012  | 0.322      | -0.005       | 0.365      |              |            |              |            |
| $IT^c_A$                      | 0.300        | 0.342      | 0.340  | 0.377      | 0.519  | 0.367      | 0.746        | 0.266      |              |            |              |            |
| $IT^A_D$                      | 0.016        | 0.021      | 0.014  | 0.016      | 0.028  | 0.016      | 0.024        | 0.018      |              |            |              |            |
| $IT^D_D$                      | 0.211        | 0.276      | 0.262  | 0.332      | 0.400  | 0.329      | 0.589        | 0.304      |              |            |              |            |
| share of employees:           |              |            |        |            |        |            |              |            |              |            |              |            |
| high skilled                  | 0.249        | 0.195      | 0.245  | 0.192      | 0.288  | 0.211      | 0.306        | 0.231      |              |            |              |            |
| intermediate skilled          | 0.485        | 0.121      | 0.513  | 0.128      | 0.478  | 0.120      | 0.515        | 0.164      |              |            |              |            |
| low skilled                   | 0.267        | 0.137      | 0.242  | 0.119      | 0.233  | 0.129      | 0.179        | 0.115      |              |            |              |            |
| edu. in engineering           | 0.409        | 0.191      | 0.390  | 0.198      | 0.422  | 0.195      | 0.402        | 0.233      |              |            |              |            |
| edu. in economics, business adm., law | 0.135 | 0.105      | 0.156  | 0.097      | 0.163  | 0.086      | 0.190        | 0.122      |              |            |              |            |
| other education               | 0.456        | 0.178      | 0.454  | 0.159      | 0.415  | 0.144      | 0.408        | 0.153      |              |            |              |            |
| age -29                       | 0.254        | 0.159      | 0.262  | 0.149      | 0.219  | 0.128      | 0.285        | 0.192      |              |            |              |            |
| 40-49                         | 0.462        | 0.099      | 0.468  | 0.093      | 0.484  | 0.106      | 0.483        | 0.126      |              |            |              |            |
| 50-                            | 0.303        | 0.121      | 0.293  | 0.123      | 0.313  | 0.116      | 0.250        | 0.133      |              |            |              |            |
| immigrants                    | 0.140        | 0.105      | 0.139  | 0.105      | 0.126  | 0.075      | 0.166        | 0.069      |              |            |              |            |
| females                       | 0.278        | 0.172      | 0.305  | 0.198      | 0.277  | 0.165      | 0.329        | 0.229      |              |            |              |            |
| number of employees           | 862          | 2362       | 533    | 957        | 362    | 362        | 417          | 423.653    |              |            |              |            |
| share of companies in $IT_{A_{low}}^c$ | 0.194 | 0.396      | 0.272  | 0.445      |              |            |              |            |              |            |              |
| share of companies in $IT_{A_{high}}^c$ | 0.430 | 0.496      | 0.342  | 0.475      |              |            |              |            |              |            |              |
| share of companies in $IT_{A_{high}}^c$ | 0.376 | 0.485      | 0.386  | 0.488      |              |            |              |            |              |            |              |
A.2.2 Summary statistics, IT, work organization and productivity panel

Table A.5: Summary statistics, IT, work organization and productivity panel

<table>
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<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
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</thead>
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<tr>
<td>$\Delta(y - l)$</td>
<td>0.03</td>
<td>0.204</td>
<td>6590</td>
</tr>
<tr>
<td>$(y - l)$</td>
<td>6.309</td>
<td>0.527</td>
<td>6716</td>
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<td>$\Delta$market share</td>
<td>0.038</td>
<td>0.328</td>
<td>6597</td>
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<tr>
<td>$L$</td>
<td>195</td>
<td>1099</td>
<td>6730</td>
</tr>
<tr>
<td>investment in ICT/employee (ln)</td>
<td>5.325</td>
<td>1.882</td>
<td>1346</td>
</tr>
<tr>
<td>ICT$^{zero}$</td>
<td>0</td>
<td>0</td>
<td>1346</td>
</tr>
<tr>
<td>ICT$^{low}$</td>
<td>0.49</td>
<td>0.5</td>
<td>1346</td>
</tr>
<tr>
<td>ICT$^{high}$</td>
<td>0.51</td>
<td>0.5</td>
<td>1346</td>
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<td>Share of employees</td>
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<td></td>
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<tr>
<td>HS</td>
<td>0.114</td>
<td>0.16</td>
<td>6730</td>
</tr>
<tr>
<td>IS</td>
<td>0.388</td>
<td>0.142</td>
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<td>LS</td>
<td>0.498</td>
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<td>Foreign head office</td>
<td>0.201</td>
<td>0.401</td>
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<td>Multiplant</td>
<td>0.348</td>
<td>0.476</td>
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<tr>
<td>$\Delta k$</td>
<td>0.071</td>
<td>0.447</td>
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<tr>
<td>$\Delta k$</td>
<td>0.028</td>
<td>0.285</td>
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A.2.3 Alternative measures of IT

For the “Plan Survey” panel, different measures of IT are used as a sensitivity check. First, instead of using the maximum investment, the average investment (same period) in IT per employee is considered (B). This will decrease the impact of any one time large investment. Second, the focus is switched to the classical intensity of IT investments, looking at the maximum (mean) share of IT investments to total investments (measure C (D) ). Here, instead of having zero investment as a group, the cutoffs are set at the 33th and 67th percentile to get equal group sizes. Note that the same variable names will be used for all four measures in the estimations. The IT measures are indicated by the letters A, B, C and D in the results. Looking at the correlation between the different measures, it is worth pointing out that many of the firms in the IT$^{high}$ group change a great deal using the different measures: about 30% of the firms are exchanged going from measure A to measure C. The correlation is 0.45 in the total sample and 0.63 within the group that made...
organizational changes (see table A.6). The industry mix also changes the 
$IT^{high}$—group and the $IT^{high}$—group is more concentrated to the business 
services sector (i.e., consultants etc.) using measure C. Within this sector, 
IT is sometimes the only capital investment.

A.3 Results for the “Plan Survey” using different measures 
of IT

This appendix uses the different measures of IT presented in A.2.3 as a ro-

dustness check of the results in table 2.3. First, instead of looking at the 
maximum investment in IT per employee, the average over the period is 
considered. This will decrease the impact of any large investment and the 
estimated effect could therefore be expected to be smaller. This is indeed 
the case; $\theta^{high}_3$ is still significant, but it is lower in magnitude: 0.14. With 
the fixed-effect estimator, there is a slight increase in both point estimates. 
In columns (5-6), IT intensity is instead measured as the maximum share of 
IT investments in total investments. The results are largely unchanged and 
remain significant. Finally, in the last two columns, average investment in 
IT to total investments is considered. $\theta^{high}_3$ are once more lower when using 
the average. The results in table A.7 suggest that the interaction with orga-
nizational change is important both looking at IT investments per employee 
and IT investments to total investments. Recall also that about 30% of the
firms in the $IT^{high}$ group are exchanged, going from IT investments per employee (measure A) to IT investments to total investments (measure C) and the industry composition changes. This means that the effect on productivity of organizational change and IT investments is not confined to a certain industry or type of firm.
<table>
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<th>IT-measure dep. variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
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<td>IT</td>
<td>$\delta_1$</td>
<td>$-0.0195$</td>
<td>$-0.0263$</td>
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<td>$-0.0277$</td>
<td>$-0.0227$</td>
<td>$-0.0159$</td>
<td>$0.0404$</td>
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<tr>
<td>(O × IT&lt;sup&gt;zero&lt;/sup&gt;)</td>
<td>$\delta_2^{\text{zero}}$</td>
<td>$-0.0196$</td>
<td>$-0.0200$</td>
<td>$-0.0232$</td>
<td>$-0.0277$</td>
<td>$-0.0225$</td>
<td>$-0.0159$</td>
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<tr>
<td>(O × IT&lt;sup&gt;low&lt;/sup&gt;)</td>
<td>$\delta_2^{\text{low}}$</td>
<td>$-0.0502$</td>
<td>$-0.0742$</td>
<td>$0.0225$</td>
<td>$0.0225$</td>
<td>$-0.0812$</td>
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<tr>
<td>(O × IT&lt;sup&gt;high&lt;/sup&gt;)</td>
<td>$\delta_2^{\text{high}}$</td>
<td>$-0.0414$</td>
<td>$-0.0122$</td>
<td>$-0.8600$</td>
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<td>(T × O × IT&lt;sup&gt;zero&lt;/sup&gt;)</td>
<td>$\theta_1$</td>
<td>$0.0716$</td>
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<tr>
<td>(T × O × IT&lt;sup&gt;low&lt;/sup&gt;)</td>
<td>$\theta_2$</td>
<td>$0.0123$</td>
<td>$0.0334$</td>
<td>$0.0619$</td>
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<td>$0.0489$</td>
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<td>(T × O × IT&lt;sup&gt;high&lt;/sup&gt;)</td>
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<td>$-0.000581$</td>
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<td>intermediate skilled</td>
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<td>number of employees</td>
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<td>Adjusted $R^2$</td>
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<td>0.031</td>
<td>0.101</td>
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</tr>
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</table>

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

IT measures: A max [investment in IT /employee]; B mean [investment in IT /employee]; C max [investment in IT /total investments]; D mean [investment in IT /total investments]
Chapter 3

Firms and Skills: The Evolution of Worker Sorting*

3.1 Introduction

How has the sorting of workers by skill into firms evolved over recent decades? Previous empirical studies on this question have been constrained by a lack of measures of skill that are comparable over time. In this paper, we use data on cognitive and non-cognitive skills for a large, representative sample of Swedish men matched to employers in order to quantify changes in sorting. Our main result is that sorting by skill has increased since the mid 1980’s.

There are a number of reasons to believe that technological change and globalization increase sorting. For example, the theoretical literature has stressed that firms investing in new technology face a higher return to hiring skilled workers (Acemoglu, 1999; Caselli, 1999). Another possibility is that more complex production processes strengthen the complementarity between workers skills, implying that unskilled workers constitute “weak links” in

*We are thankful to David Cesarini, Jim Heckman, Fredrik Heyman, John Van Reenen, Valerie Smeets, Yoichi Sugita, Frederic Warzynski, seminar participants at Bena (Berlin), Gothenburg University, IFAU, the 2012 AEA meetings, EALE 2012 and the National Meeting of Swedish Economists 2012 for valuable comments. Financial support from the Jan Wallander and Tom Hedelius Foundation, IFAU, and Riksbankens Jubileumsfond is gratefully acknowledged.
firms with skilled workers (Kremer, 1993). Globalization increases the scope for skill-sorting by narrowing the set of tasks that needs to be performed domestically (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008) and by allowing skilled workers in rich countries to match with workers in developing countries rather than unskilled workers in their own country (Kremer and Maskin 2006). Relatedly, Grossman and Maggi (2000) argue that lower trade costs induce countries with a comparably low dispersion of skill, such as Sweden, to specialize in industries where it is optimal to match workers with similar skills. These proposed mechanisms all suggest that changes in the world economy in recent decades have resulted in firms becoming more different in terms of the skill level of their workforces. In other words, the economy might to an increasing extent be divided into Google-type firms that employ the most able workers and firms like McDonald’s that employ the least able.

An increase in the segregation by skill is likely to have substantial economic and social consequences. Wage inequality is increasing in skill segregation if worker skills are complements (e.g. Sattinger, 1975), or if fair wage considerations compress wage differences between low- and high-skilled workers within firms (Akerlof and Yellen, 1990; Bewley, 1999). Further, the extent of social interaction between different strata in society is reduced as workplaces become more internally homogeneous. This has potentially far-reaching consequences for the formation of social networks and for social cohesion in general.\footnote{See Jackson (2010) for an overview of social networks and their impact on economic behavior.}

Recent empirical evidence on labor markets in advanced economies is consistent with an increase in sorting. The increase in wage inequality witnessed in many advanced economies over recent decades is associated with increasing wage differences between firms.\footnote{This literature includes studies of Sweden plants 1986-2000 (Nordström-Skans, Edin and Holmlund 2010); Czech firms 1998-2006 (Eriksson, Pytlíková and Warzynski, 2009); the US manufacturing sector 1975-1992 (Dunne et al, 2004) and 1975-1986 (Davis and Haltiwanger, 1991) and UK firms 1984-2001 (Faggio et al, 2010).} Labor markets in advanced economies are also becoming increasingly polarized as routine jobs disappear while both
3.1. INTRODUCTION

high- and low-skilled non-routine jobs become more prevalent (Acemoglu and Autor, 2011; Adermon and Gustavsson, 2011). Yet, relatively little is still known about whether these changes in the structure of wages and jobs have been accompanied by an increase in segregation of workers by skill across firms.

The difficulty in assessing changes in sorting stems from a lack of skill measures that are comparable over time. Previous research on skill sorting has either focused on occupation (Kramarz, Lollivier and Pele, 1996; Kremer and Maskin, 1996; Dunne et al 1997, 2004), or skill measures derived from wage data (Iranzo, Schivardi and Tosetti, 2008). Each approach faces potential problems. For example, skilled-biased technological change may increase the dispersion of wages, even though the underlying distribution of skills remains unchanged. Relatedly, changes in the occupational structure could reflect changes in technology rather than changes in the composition of workers’ skills. Using educational attainment as a measure of skill does not solve the problems of comparability over time; higher education has expanded in most countries and students’ choices between different fields of education change in response to the economic environment.\footnote{Skill levels can change quite rapidly within fields of education: Grönqvist and Vlachos (2008) document that the average cognitive ability among entering teachers declined by more than half a standard deviation between 1992 and 2007.} Further, educational attainment, by construction, does not capture heterogeneity in skill within educational groups.\footnote{That income inequality within educational groups has increased suggests that within-group skill heterogeneities are becoming increasingly important (Machin, 1996; Katz and Autor, 1999). Altonji et al (2012) provide an overview of the returns to secondary and post-secondary education across different majors.}

In this paper, we study the evolution of skill sorting in the Swedish private sector between 1986 and 2008 using data on workers’ cognitive and non-cognitive skills from the military enlistment. The enlistment skill measures are strong predictors of future labor markets outcomes (Lindqvist and Vestman, 2011), comparable over time, and available for 28 cohorts of Swedish men. Since the enlistment evaluations were administered to Swedish men at the age of 18, the skill measures are unaffected by the expansion of higher
education and changes in labor market conditions.

Matching the enlistment skill measures for each worker with information about their employer in a given year, we document a substantial increase in sorting from 1986 to 2008. During this period, workers became more similar within firms (falling within-firm variance of skills) and more dissimilar between firms (increasing between-firm variance) with respect to both cognitive and non-cognitive skills. The trend towards increased skill segregation is robust to assuming alternative distributions of skills and non-parametric ways of measuring sorting. Using data on male relatives to impute cognitive and non-cognitive skills for women, we find the same trend towards more sorting among female workers. Throughout the time period we consider, between-firm differences are larger for cognitive than for non-cognitive skill.

Our data also allow us to decompose the covariance of cognitive and non-cognitive skills into between- and within-firm components. We show that the between-firm covariance in skills is positive and increasing during our study period. Consequently, firms that hire workers with high cognitive skills to an increasing extent also hire workers with high non-cognitive skills.

Why did sorting increase? A closer look at the data reveals that the increase in the between-firm variance of cognitive skill is mainly due to changes in the relative size and skill level of coarsely defined industries. In particular, the rapid growth of the IT-services industry, combined with skill upgrading in telecom manufacturing, are key factors behind the increase in sorting of cognitive skill. There is also evidence of skill-downgrading in low-tech service industries such as retail, construction, and transportation. The upshot is that the distribution of industry-averages of cognitive skill has become substantially more polarized over time. The increase in the between-industry variance in non-cognitive skill is mostly due to skill-upgrading in telecom manufacturing and financial intermediation.

The trend toward smaller differences in skills within firms is mostly due to a fall in the average within-firm variance in industries with an initially high variance. Consequently, while industries have become more different with respect to the average level of skill, they have become more similar with respect to the average variance of skill among workers in the same firm.
For example, in 1986 a number of manufacturing industries had an average within-firm variance of cognitive skill close to the population variance of 1. In 2008, only a couple of industries had an average within-firm variance of cognitive skill above 0.8. Yet the shift toward smaller skill differences within firms is present in all major industries, including industries with an initially low within-firm variance.

The final part of our analysis concerns the question whether the increase in sorting is due to larger technological differences between firms, or to stronger assortative matching of workers for a given technology. To this end, we use data on years of schooling and field of study for each worker as a proxy for occupation. Our analysis then proceeds in two steps. In the first step, we decompose the variance in cognitive and non-cognitive skills into their between- and within-occupation components. In the second step, we further decompose the between- and within-occupation variances into between- and within-firm components.

We argue that the share of the between-occupation variance explained by the between-firm component reflects the extent to which the skill-intensity of technology differs across firms. If firms either hire workers in high-skilled occupations (e.g., engineers) or low-skilled occupations (production workers), then the between-firm component will explain a large share of the between-occupation variance. If most firms instead encompass a rich variety of occupations, then most of the between-occupation variance will be within firms.

With respect to the within-occupation variance, we argue that the share explained by the between-firm component is a valid measure of assortative matching of worker skills. Assortative matching is positive, and the between-firm component large, if the highest skilled workers in each occupation tend to work in the same firms; for example if clever engineers work with clever secretaries.

As it turns out, the shares of the between- and within-occupation variances that are explained by sorting between firms are both increasing over time, suggesting that the increase in sorting is due both to larger differences in the skill-intensity of technology across firms and to assortative matching.

What forces drove these changes in sorting? Increasing differences in the
skill-intensity of technology across firms could be driven either by skill-biased technological change (Acemoglu, 1999; Caselli, 1999) or by outsourcing. Assortative matching could be affected by technological change, lower costs from matching skilled workers due to globalization (Kremer and Maskin, 2006), or by specialization between countries induced by lower trade costs (Grossman and Maggi, 2000). We are not able to provide conclusive evidence with respect to all of these mechanisms, but we do provide suggestive evidence that technological change is at heart of the story for cognitive skill. First, we show that the increasing differences in the skill-intensity of technology across firms can be explained by expansion of the IT-industry and skill-upgrading in telecom. Second, we look at which occupational groups drove the increase in sorting between firms and occupations and find that the allocation of engineers seems to be of particular importance. Taken together, the results for cognitive skill are broadly consistent with the models by Caselli (1999) and Acemoglu (1999): After the introduction of new technology (IT and telecom), high-skilled workers select into sectors intense in this technology. The results for non-cognitive skill are less conclusive regarding the exact mechanism.

We use variation within firms over time to analyze what factors correlate with a changes in assortative matching. For cognitive skill, we find that the variance of skill within occupations and firms is negatively associated with the firm skill level. This implies that assortative matching is strengthened in firms that experience skill upgrading, suggesting that technological change may play a role also in this case. In contrast, we find no association between skill upgrading and assortative matching for non-cognitive skills.

We discuss the previous literature on skill sorting in the next section and the construction of the data set in Section 3. Our approach for measuring sorting is discussed in Section 4 and the main results in Section 5. We analyze the mechanisms behind the observed changes in sorting in Section 6. Section 7 concludes the paper. We present additional material in three appendices denoted A (data description), B (additional results) and C (issues regarding how to quantify sorting).
3.2 Literature

The optimal allocation of skill across firms depends on the nature of the production function. Changes in sorting by skill is therefore either due to changes in the production function itself, or to changes in the constraints in the matching of workers to firms. With respect to the production function, economic theory either emphasize the interaction between workers with different levels of skill, or between skills and technology. In the former case, the sorting pattern depends on whether worker skills are substitutes or complements.

If skills are complements, the marginal value of increasing the skill level of one worker is increasing in the skill level of her co-workers. For example, in Kremer (1993), one weak link – in the sense of a low-skilled worker – reduces the value of the production by an otherwise highly skilled chain of workers. In such a setting, a competitive labor market without search frictions ensures that workers are perfectly sorted by skill, implying that high- and low-skilled workers work in different firms.

If skills are substitutes, the marginal value of a worker’s skill is lower the more skilled are the other workers in the firm. That is, productivity hinges on the skills of a few “superstars” (Rosen, 1981) rather than a high general level of skill. In order not to waste talent, optimal sorting then implies that the most skilled workers work in different firms. Consequently, skill differences will be large within firms, and small between firms, if skills are substitutes while the converse is true if skills are complements. If skills are neither substitutes nor complements the allocation of skill across firms does not affect output, implying that sorting of workers to firms is random.

The extent to which worker skills are complements or substitutes is likely

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5 That skill complementarities can lead to positive assortative matching between workers with heterogenous skills and firms with heterogeneous skill demands goes back at least to Becker’s (1973) model of the marriage market. See also the literature on matching in labor markets with two-sided heterogeneity (Shimer and Smith, 2000 and Legros and Newman, 2002, 2007).

6 A more formalized argument of “weak links” and “superstars” in the production function is provided in Milgrom and Roberts (1990) with the concepts of “supermodularity” and “submodularity”.
to change when technology develops, although the direction of the change is not obvious a priori. For example, it could become more important to avoid “weak links” as production processes become more complex (Kremer, 1993), suggesting that technological change increases skill complementarities. Alternatively, improvement in information technology may imply that skilled workers can leverage their skills over a wider set of problems, thereby increasing the extent to which high-skilled workers substitute for low-skilled workers (Garicano and Rossi-Hansberg, 2006).

If skills interact with technology, workers will be sorted across firms by skill to the extent that technology differ across firms. Acemoglu (1999) and Caselli (1999) develop models where skilled-biased technological change (SBTC) may shift the economy from a pooling equilibrium where firms hire both skilled and unskilled workers to a separating equilibrium where unskilled and skilled workers are sorted into different firms. In these models, SBTC thus have the same effect on sorting as an increase in the complementarity between worker skills.

Apart from changes to the production function, sorting may be affected by changes in the scope for matching workers induced by globalization. Trade in tasks, or offshoring, allows for skill-sorting by narrowing the set of tasks that needs to be performed domestically (Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008). Globalization also opens up for the formation of international teams, allowing skilled workers in rich countries to match with workers in developing countries rather than unskilled workers in their own country (Kremer and Maskin 2006). Grossman and Maggi (2000) link standard trade theory with the organization of production by letting the distribution of skills differ between countries. These differences give rise to comparative advantages in sectors where skills are either complements (supermodular) or substitutes (submodular). For a country such as Sweden,

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7 There is a large literature on SBTC and its implications for the relationship between technology and skills. This literature does not, however, directly analyze worker sorting. See Acemoglu (2002), Hornstein et al (2005), and Acemoglu and Autor (2011) for surveys. Goldin and Katz (2008) provide a thorough analysis of the relation between technological change and worker skills.

8 There is a growing theoretical literature on international trade with heterogeneous
where the dispersion of skill among the workforce is low in an international comparison, the theory predicts that production of services where worker skills are complements will increase with trade, thereby increasing the optimal segregation by skill.\(^9\)


To the best of our knowledge, our study is the first to study sorting according to cognitive and non-cognitive skills. Our paper also differ from the previous literature in that we study a longer, and more recent, period (1986-2008). Finally, the fact that we have access to both cognitive and non-cognitive skills and data on years of schooling and field of study implies that we can answer questions about the underlying mechanism not possible in previous research.

\(^9\)Harrison, McLaren, and McMillan (2011) survey the literature on trade and inequality. The literature on trade and the organization of firms is surveyed by Antras and Rossi-Hansberg (2009). Trade and technological change are interrelated phenomena. See Bloom, Draca, and Van Reenen (2011) and references therein for theory and empirical evidence on how trade can induce technological change.

\(^10\)There are also a small set of papers that study sorting in the cross-section, e.g., Hellerstein and Neumark (2008).
3.3 Data

In order to analyze ability sorting over time, we match information on cognitive and non-cognitive skills from the Swedish military enlistment with employer-employee data. The first cohort for which we have enlistment data are men born in 1951, who were enlisted in 1969. Since it is possible to match individuals to firms in Sweden from 1986 and onwards, we can obtain a complete series of worker skill-firm matches at a given age for men at or below the age of 35. To obtain a sample of comparable individuals over time, we therefore restrict our sample in each year to men between the age of 30 and 35. We exclude men below the age of 30 from the sample to avoid a sample selection effect due to the expansion of higher education. The total sample consists of essentially all male Swedish citizens born between 1951 and 1978. Descriptive statistics for the data sets used in the analysis are available in Appendix A.

We link employees to their employers using the RAMS data base which contains information on all workers employed in a firm at some point in time each year. RAMS includes worker annual earnings by employer, the month employment started and ended, and firm level information such as ownership and industry. For workers who are recorded as having more than one employer during a given year, we retain only the employer that corresponds to the highest annual earnings. The majority of workers only receive earnings from one firm in a given year. For example, in 2006 71% of the workers in our data received earnings from one firm and 95% from no more than three firms. The industry classifications in RAMS have changed somewhat over time. In particular, the industry classification used from 1990 onwards (SNI92) is not perfectly comparable with earlier industry classification (SNI69). We impute industry backwards 1986-1989 for firms alive in 1990. For the subsample of firms not alive in 1990, we translate 2-digit industry codes from SNI69 to SNI92 using the official concordance (Statistics Sweden, 1992).

We make some further restrictions on the sample. First, we restrict our sample to firms where we observe at least three men with complete records from the military enlistment. The reason is that we are interested in studying
the variation in skills both within and between firms. Second, we restrict our
sample to firms in the private sector with at least 50 employees, excluding
firms controlled by the public sector and private non-profit organizations.\textsuperscript{11}
We include private firms registered in Sweden even if they are controlled
from outside of Sweden, for example subsidiaries to foreign firms. Finally,
we exclude men with zero or missing earnings in a given year. In 1986, the
average worker in our sample worked in a firm with 297 employees out of
which 22.8 were included in the sample. The corresponding figures for 2008
were 264 and 20.5, implying that there is a slight tendency for people to
work in smaller firms.

Information on basic demographics, including earnings, year of birth and
educational attainment, is taken from the data base LOUISE which covers
the entire Swedish population. We lack information about educational attai-
nement prior to 1989 for about 10 percent of the sample. For this group
we impute educational attainment between 1986 and 1989 using educational
attainment in 1990. We translate highest educational degree into years of
schooling, which we use as our measure of educational attainment.

For a subset of industries (mainly in manufacturing), we have rough data
on trade from which we construct two variables. $\text{Trade}_{kt}$ equals the total
value of exports and imports in industry $k$ divided by total turnover while
$\text{China\_import}_{kt}$ equals imports from China divided by turnover. We think
of $\text{China\_import}_{kt}$ as a proxy for competition from low-wage countries, and
also the scope for outsourcing production to other countries. Since not all
goods and services are traded, trade data is missing for several industries.
Rather than dropping these industries from the analysis, we in such cases
impute trade to be zero and check if the results are sensitive to this impu-
tation. See Appendix A for a detailed account regarding the construction of
these variables.

\textsuperscript{11}One reason for restricting attention to the private sector is that the definition of a
firm in the public sector is not restricted to companies owned by the public sector, but
also includes various types of government bodies. For example, each municipality is coded
as a separate “firm” in the data.
3.3.1 Enlistment skill measures

We obtain data on cognitive and non-cognitive skills from Swedish enlistment records. The enlistment usually takes place the year a Swedish man turns 18 or 19 and spans two days involving tests of health status, physical fitness, cognitive ability, and an interview with a certified psychologist. For the cohorts we consider, the military enlistment was mandatory for all Swedish men and exemptions were only granted to men with severe physical or mental handicaps. About 90 percent of the men in our sample were eventually enlisted to the military service. Lindqvist and Vestman (2011) provide a detailed account of the enlistment procedure, the tests of cognitive skill, and the enlistment interview.

Between 1969 and 1994, the enlistment test of cognitive ability consisted of four parts, testing verbal, logical, spatial and technical ability. The results of these tests were then transformed by the enlistment agency to the “stanine” scale – a discrete variable ranging from 1 to 9 that approximates a normal distribution. The basic structure of the test remained intact until 1994, although the actual test questions changed in 1980. There have also been slight changes in the mapping from the subtest scores to general cognitive ability over the years (see Grönqvist and Lindqvist, 2013). A new version of the test based on the stanine scale was introduced in 1994. The youngest cohort in our main sample (men born in 1978) did the enlistment in 1996 and 1997.

We percentile-rank the 1-9 cognitive score for each set of cohorts with the same test and mapping from raw to final scores. We then convert the percentile-rank to a normally distributed test score with zero mean and unit variance. A potential concern with this procedure is that standardization hides changes in the underlying distribution of abilities. As discussed in closer detail in Appendix A, there is evidence of a “Flynn effect” – a secular rise in results on cognitive test scores – but no trend in the dispersion of cognitive test scores over time. Also shown in Appendix A is that the average skill level in our sample is very close to the population mean of 0 throughout our study period.
3.3. DATA

At the enlistment, conscripts were also interviewed by a certified psychologist for about 25 minutes. The objective of the interview was to assess the conscript’s ability to cope with the psychological requirements of the military service and, in the extreme case, war. Each conscript was assigned a score in this respect from the same stanine scale as for cognitive ability. The instructions to the psychologists for how to evaluate conscripts was unchanged until 1995 when it was subject to slight revisions. The character traits considered beneficial by the enlistment agency include willingness to assume responsibility; independence; outgoing character; persistence; emotional stability, and power of initiative. Motivation for doing the military service was not considered beneficial for functioning in the military. We use the psychologists’ evaluation as a measure of non-cognitive skill and undertake the same normalization to zero mean and unit variance as for cognitive ability.

The measures of cognitive and non-cognitive ability have a modest positive correlation (0.39), suggesting that they capture different types of ability.\textsuperscript{12} Lindqvist and Vestman (2011) show that while both skill measures predict labor market outcomes, cognitive ability is relatively more important in skilled occupations while workers in unskilled occupations have a higher return to non-cognitive ability.

To motivate the use of the enlistment skill measures in a study of sorting, Figure 3.1 shows that industry wage differentials are strongly related to the average level of cognitive and non-cognitive skill. Table B.1 and B.2 shows that the enlistment skill measures outperform educational attainment as predictors of industry wage differentials.\textsuperscript{13}

\textsuperscript{12}The positive correlation between cognitive and non-cognitive ability could reflect an effect of cognitive skills on non-cognitive skills, or the other way around. Lindqvist and Vestman (2011) show that the result on the cognitive test score has a small positive effect on the psychologists evaluation of conscripts’ non-cognitive skills. On the other hand, noncognitive skills could affect the performance on the test of cognitive ability, as argued by Borghans, Meijers and ter Weel (2008) and Segal (2012). Moreover, noncognitive abilities could facilitate the acquisition of cognitive abilities over the life-cycle (Cunha and Heckman 2007; Cunha and Heckman 2008).

\textsuperscript{13}There is a long-standing debate about whether industry skill differentials reflect unobserved skill differences between workers or whether there are “true” wage differentials. See, for example, Gibbons and Katz (1992) and Gibbons, Katz, Lemieux and Parent (2005).
Figure 3.1: Enlistment skill measures and industry wage differentials

Note: Each circle gives the average level of log wages and the average cognitive or non-cognitive skill in a given industry. The size of each circle is proportional to the number of workers in the sample in each industry.
3.4 Measuring sorting

We quantify sorting by decomposing the variance of cognitive and non-cognitive skills. Let $C_{ij}$ denote the cognitive skill of worker $i$ in firm $j$. The sample variance of cognitive skill, $\sum_i \sum_j (C_{ij} - \bar{C})^2$, can be expressed as the sum of the variance within and between firms:

$$\frac{1}{N} \sum_j \sum_i (C_{ij} - C_j)^2 + \frac{1}{N} \sum_j N_j (C_j - \bar{C})^2,$$

where $C_j$ is the average level of cognitive skill in firm $j$, $N_j$ is the number of workers in firm $j$ and $N$ is the total number of workers in the economy. In an economy where firms either hire low-skilled ("McDonald’s") or high-skilled workers ("Google"), the within-firm component is low while the between-firm component is high. The other extreme is an economy where all firms have the same average level of skill. By studying the evolution of the within- and between-firm variances, we get an idea of whether sorting by skill has increased or decreased over time. The population variances of cognitive and non-cognitive skills are set to 1 by construction, but the sample variance may be either higher or lower than 1 depending on selection into the sample, i.e., private firms with at least 50 employees. Consequently, the within-firm variance may change even though the between-firm variance remains fixed, and vice versa, if the sample variance changes.

The between-firm variance of skill can be further decomposed into variance within firms in the same industry, and variance in skill between industries. Let $C_{jk}$ denote the average cognitive skills of firm $j$ in industry $k$ and $N_{jk}$ is the number of workers in this firm, while $C_k$ and $N_k$ are the corresponding variables at the industry level. The between-firm variance in cognitive skill can then be decomposed as:

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Our objective here is not to contribute to this literature, but simply to motivate the empirical relevance of the enlistment skill measures.
There are a number of issues to consider regarding the use of variance decompositions as a way to measure sorting of workers to firms. First, an implicit assumption in decomposition (3.1) and (3.2) is that we observe all workers in all firms. In fact, since we restrict attention to men between the age of 30 to 35, we observe $n_j$ out of $N_j$ workers in a given firm, where $n_j \leq N_j$. When $n_j < N_j$ we get a measurement error in the firm-level mean of skills, $C_j$, which inflates the between-firm variance and deflates the within-firm variance in (3.1). Using Bessel’s correction and adjusting for firm sample size implies that the decomposition in (3.1) becomes

$$
\frac{1}{N} \sum_j n_j \left( \frac{N_j - 1}{N_j} \right) \left( \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j)^2 + \frac{1}{N} \sum_k N_k (C_k - \bar{C})^2.
$$

(3.2)

All results presented in the paper are based on decompositions that adjust for sample size, but, to save on space, we show the expressions that take the adjustments into account in Appendix C.\textsuperscript{14} Note that we have chosen to weigh each firm by the number of observed workers ($n_j$) rather than the

\textsuperscript{14}The adjustment in (3.1’') implies that we view each firm as a population rather than a sample of random draws from a given distribution of worker skills. It is not obvious a priori which view is most accurate as sorting arguably both reflect random and deterministic factors. A potential concern with viewing the set of workers in a firm as a population rather than a sample is that a shift in the size distribution of firms could lead to changes in the estimated within- and between-firm components even if worker skills are drawn from the same underlying distribution. However, as discussed in the next paragraph, we simulate benchmark values of each component in that takes shifts in the size distribution of firms into account.
3.4. MEASURING SORTING

actual number of employees \((N_j)\) in \((3.1)\).\(^{15}\)

Second, since the number of workers at each firm is finite, the between-firm variance would be larger than zero also under random matching of workers to firms. To get a benchmark value of sorting, we randomly draw workers to firms without replacement from the set of workers in the sample and conduct the variance decomposition in \((3.1)\). Repeating this process 1,000 times provides a bootstrap-type test of sorting by comparing the true between-firm variance with the percentiles in the distribution of simulated variances.\(^{16}\) Comparing the actual and simulated between-firm variances is a first simple test of what forces drive sorting in the aggregate. If worker skills are complements, or if there is a complementarity between worker skills and technology (and technology differs across firms), then the actual between-firm variance should exceed the simulated variances. If, in contrast, there are no or weak complementarities between worker skills and technology and worker skills are substitutes, the observed level of sorting should be below the simulated level.

Third, the enlistment skill measures are likely affected by measurement error. Using data on monozygotic and dizygotic twins, Lindqvist and Vestman (2011) estimate a reliability ratio of 0.868 for cognitive and 0.703 for non-cognitive skills.\(^{17}\) As shown in Appendix C, measurement error inflates the within-firm variance relative to the between-firm variance. Since the effect of measurement error on the estimated firm mean of skills is smaller the larger are firms, a change in the size distribution of firms over time could affect the share of the measurement error variance that is attributed to within- and between-firm components. Assuming classical measurement

\(^{15}\)There are two reasons for this choice. First, weighting firms by the number of observed workers is more efficient. Weighting firms by the actual number of workers would imply that a number of firms with few observed workers would get a large weight, thus increasing random noise. Second, since our sample is restricted to men in the age of 30-35 in the first place, weighting firms by the actual number of workers would not be representative of the entire population of workers unless one is willing to assume that sorting patterns are exactly identical for 30-35 year old men compared to the population as a whole.

\(^{16}\)A similar approach is used by Ahlin (2010).

\(^{17}\)The lower reliability ratio of non-cognitive skills arguably reflects the additional error introduced by the fact that different psychologists evaluate different conscripts (Lindqvist and Vestman, 2011).
error, we derive a correction for measurement error. In essence, we use the estimated reliability ratios from Lindqvist and Vestman (2011) to simulate measurement errors for each worker in our data. We then use the simulated errors to estimate the share of the within- and between-firm variance which can be attributed to measurement error (see Appendix C for details). We report these results as a robustness check rather than as our main case.

Fourth, we assume that the enlistment skill measures follow a normal distribution. Although a reasonable benchmark case, there is no fundamental argument as to why skills should be normally distributed. It is thus fair to ask how robust our results are to monotone transformations of skills or non-parametric ways of quantifying sorting. To test the sensitivity to distributional assumptions, we transform the enlistment skill measures to alternative distributions (uniform and Beta distributions with different skewness) which we then decompose into between- and within firm components. To estimate sorting non-parametrically, we first rank all firms in each year according to the average level of skills. We then calculate the Kendall’s tau rank correlation between the rank of each firm and skill level of each individual.\(^\text{18}\)

Finally, our sample is restricted to men between 30 and 35. An advantage of this restriction is that the high mobility of young male workers implies that we are likely to detect changes in sorting patterns quickly. Still, the external validity would be stronger if the same sorting patterns are present for female workers and older male workers. We impute cognitive and non-cognitive skills for women using the draft records of close male relatives (see Appendix A). We then decompose the variance in skills for women between the age of 30 and 35 following the same procedure as for men. Since we have to impute cognitive and non-cognitive skills of females, measurement error in skill is an order of magnitude larger for this sample, leading to a spuriously low level of sorting across firms. To test the robustness of our results with respect to age, we study the sorting patterns from 1996 to 2008 for male workers between the age of 30 and 45.

The variance decompositions in (3.1) and (3.2) quantify sorting in each skill measure separately. However, the covariance of cognitive and non-cognitive

\(^{18}\)Our approach for quantifying sorting using Kendall’s tau is similar to Ahlin (2010).
skills can also be decomposed into between- and within-firm components. Let $C_{ij}$ and $NCS_{ij}$ denote cognitive and non-cognitive skills of worker $i$ in firm $j$ and $C_j$ and $NCS_j$ the corresponding averages for firm $j$. We can then decompose the covariance between cognitive and non-cognitive skill as

$$\frac{1}{n} \sum_j \sum_i (C_{ij} - C_j) (NCS_{ij} - NCS_j) + \frac{1}{n} \sum_j N_j (C_j - \bar{C}) (NCS_j - \bar{NCS})$$

The between-firm covariance tells us to what extent firms whose workers have high cognitive skills also have high non-cognitive skills. Since cognitive and non-cognitive skills are positively correlated at the level of the individual, the sum of the within- and between-firm components is positive. However, depending on how skills are valued across firms, the between-firm covariance could in principle be negative. For example, if cognitive and non-cognitive skills are substitutes in the firm-level production function, we expect firms to focus on hiring workers with either high cognitive or non-cognitive skill.\(^{19}\)

### 3.5 Sorting by skill 1986-2008

In this section, we document the evolution of skill sorting in the Swedish economy over the last 25 years. We begin with the most basic question: Has skill sorting increased or decreased?

Figure 3.2 shows the evolution of the within- and between-firm variance for the enlistment skill measures between 1986 and 2008. Panel A shows that the within-firm variance in cognitive skill fell from 0.802 in 1986 to 0.697 in 2008. At the same time, the between-firm variance increased from 0.134 to

\(^{19}\)In a future work, we plan to estimate production functions augmented with cognitive and non-cognitive skills, thereby allowing us to infer whether cognitive and non-cognitive skills are negative or positive complements, and whether returns to skills are positively or negatively correlated across different sectors of the economy. An alternative approach would be to estimate the production function that fits best with the observed sorting pattern along the lines suggested by Fox (2010). However, both of these exercises are beyond the scope of the present paper.
Figure 3.2: Between and within firm variance in skill

The results documented in Figure 3.2 are robust to a number of different specification tests, reported in Appendix B.

0.176. We can thus conclude that sorting has increased: people working in the same firm have become more similar while workers in different firms have grown more different in terms of their cognitive skills. The reason the fall in the within-firm variance is not fully reflected in a corresponding increase in the between-firm variance is that the variance of cognitive skills in our sample (private sector firms with 50 employees or more) fell somewhat during the study period. As shown in Panel B, the trend for non-cognitive skills is similar to that of cognitive skills, even though the between-firm variance is substantially lower.

Could the pattern in Figure 3.2 arise by chance? Table B.3 and B.4 show that the answer to this question is a clear “no”. For example, the 99th percentile of our simulated between-firm variances in cognitive skill is 0.006 both in 1986 and 2008. Consequently, there is substantially more sorting by skill in the data than would be expected if workers were randomly allocated to firms.
First, the trend toward an increase in sorting remains the same when we adjust for measurement error in skills. However, measurement error increases the level of the between-firm variance by 16-17% for cognitive skill and by about 50% for non-cognitive skill, depending on which year we consider (the within-firm variance falls by the same absolute amount as the between-firm variance increases). Measurement error thus leads us to understate the extent to which workers are sorted according to non-cognitive skill. While the unadjusted between-firm variance is about 80% higher for cognitive than for non-cognitive skill, the corresponding figure when we adjust for measurement error is approximately 40%.

Second, assuming that skills follow a uniform distribution, or a Beta distribution with positive or negative skew does not change the general trend toward more sorting. Relatedly, we also find evidence of an increase in sorting when we consider Kendall’s rank correlation.\(^{20}\)

Third, the sorting pattern for 1996-2008 is very similar regardless whether we consider men between age 30 and 45 or the main sample of men between 30 and 35. Similarly, we find that between-firm differences in cognitive and non-cognitive skills increased in the female sample along with a fall in the within-firm variance, although the trend toward increased sorting is not as dramatic as for the male sample.

We now turn to the covariance between cognitive and non-cognitive skill. Figure 3.3 shows the decomposed covariance over time. The between-firm covariance is positive throughout, implying that firms that hire workers with high cognitive skills also hire workers who are above average in terms of their non-cognitive skills, and much larger than predicted by random sorting. Figure 3.3 also shows that the between-firm covariance increased (while the within-firm covariance fell) from the mid 1980’s up to the mid 1990’s.\(^{21}\)

The fact that the between-firm covariance of cognitive and non-cognitive skill

\(^{20}\)Kendall’s tau-b coefficient increases from 0.285 in 1986 to 0.328 in 2008 for cognitive skill and from 0.199 to 0.240 for non-cognitive skill. Results for other years are available upon request.

\(^{21}\)The increase in the covariance holds also when we instead consider a non-parametric way of measuring sorting. Kendall’s tau-b coefficient increases from 0.375 in 1986 to 0.412 in 2008. Results for other years are available upon request.
skill is positive and increasing over our study period has important implications for the overall picture of sorting. In principle, an increase in between-firm differences in cognitive and non-cognitive skill could occur alongside a fall in the between-firm covariance. Such a pattern would indicate that firms to an increasing extent hire workers with a particular type of skill, rather than workers with a high general skill level. The fact that also the covariance increases suggests that this is not the case.

Having established that sorting by skill has increased during our study period, we now turn to a more detailed analysis of which industries drive this development. We start with taking a closer look at the between-firm variance, and then turn to the within-firm variance. Even though the increase in the between-firm variance is directly related to the fall in the within-firm variance (and vice versa), it is useful to analyze them separately in order to gain insight into the kind of mechanisms at play.
3.5. **SORTING BY SKILL 1986-2008**

Figure 3.4: Decomposing the between firm variance

![Graph showing decomposition of between firm variance](image)

Panel A: Cognitive skill

Panel B: Non-cognitive skill

Note: Sample men 30–35 years old, firms with at least 50 employees

3.5.1 **Decomposing the between firm variance**

We now turn to a more in-depth analysis of the between-firm variance of skill. Figure 3.4 shows the results from decomposition (3.2) where the between-firm variance in skills is decomposed into skill differences between industries, and differences in skill between firms within the same industry. We document a substantial increase, from 0.06 to 0.11, in the between-industry variance of cognitive skill from 1986 to 1995. The pattern is similar for non-cognitive skills up until the mid 1990’s when the between-industry variance fell somewhat. In general, sorting at the industry level appears to be more important for cognitive than for non-cognitive skills. This result is consistent with the finding in Lindqvist and Vestman (2011) that cognitive skills is a stronger predictor of selection into skilled or unskilled occupations than non-cognitive skills. Figure 3.5 also shows that the variance in skill between firms within the same industry increases from the mid 1990’s and onwards.

The fact that sorting at a relatively coarse industry level (about 50 industries) explains more than half of the between-firm variance in cognitive
skill suggests that broad differences in technology are important for sorting, and also have become more important over time. To get a more detailed picture, we test whether the change in the between-industry variance is due to changes in the relative skill level or relative size of industries. More precisely, we decompose the change in the between-industry variance into three parts:

\[
\sum_k \alpha_{k,08} \left( \left( \tilde{C}_{k,08} \right)^2 - \left( \tilde{C}_{k,86} \right)^2 \right) + \sum_k \Delta \alpha_k \left( \tilde{C}_{k,86} \right)^2 + \sum_k \Delta \alpha_k \left( \left( \tilde{C}_{k,08} \right)^2 - \left( \tilde{C}_{k,86} \right)^2 \right)
\]

where \( \alpha_{k,t} = n_{k,t}/n_t \) denotes the share of the sample employed in industry \( k \) in year \( t \), \( \tilde{C}_{k,t} = C_{k,t} - \bar{C}_t \) is the average cognitive skill in industry \( k \) centered by the sample average in year \( t \) and \( \Delta \alpha_k = \alpha_{k,08} - \alpha_{k,86} \) is the change in the employment share of industry \( k \).

Table 3.1 shows the results from decomposition (3.4). The bulk of the increase in between-firm variance of skill is due to an increase in the employment share of industries with values of skills away from the sample mean, while a smaller part is attributed to shifts in the mean values of skill away from the mean. The negative covariance term implies that industries which grew in size moved toward the sample mean of skills.\(^{22}\)

Which industries grew in size? Table 3.2 lists the mean values by industry for each skill measure, the change in mean between 1986 and 2008 and em-

\(^{22}\)Decomposition (3.4) can only be conducted for the 53 industries that are present in the data both in 1986 and 2008. In 1986 there were 55 industries and in 2008 54 industries in our data. Still, the 53 industries present in our data for the entire time period cover 99.98 % (1986) and 99.91 % (2008) of all the workers in our data.
Three facts stand out from Table 3.2. The first is the growth of the IT-industry (NACE 72). In 2008, 7.8% of 30-35 year old men worked in this industry, up from 1.2% in 1986. Despite the increase in size, the average cognitive skill of workers in the IT-sector remained constant at 0.70 standard deviations above average, the highest among the large industries in our data. Second, manufacturing of telecom products (32) increased the average level of cognitive skill from 0.46 to 0.60 standard deviations above average. Third, the average level of cognitive skills declined in a number of low-skilled service industries, including retail (52), construction (45), transportation (60), sales and repair of motor vehicles (50). In sum, the increase in sorting is due to an increase in the number of high-skilled firms (“Google”) and a fall in the skill level of the workers at low-skilled firms (“McDonald’s”). The growth of the IT industry and fall in the skill level in low-skilled industries also contribute to the increase in sorting of workers with respect to non-cognitive skill. However, the between-industry variance in non-cognitive skill is also caused by a substantial upgrading of skill in financial intermediation.

Figure 3.5 shows the distribution of industry mean values of cognitive skill in 1986 and 2008 with each industry weighted by its employment share. The increase in density at the high end of cognitive skill brought about by IT and telecom implies that the distribution is substantially more polarized in 2008.

As a final way to illustrate the importance of IT and manufacturing of telecom products for the increase in sorting, Figure 3.6 shows the evolution of the “counterfactual” between-firm variance when telecom and IT have been removed from the sample. As shown in the figure, skill differences between firms in other industries than telecom and did not change substantially during the study period.24 Since the skill levels in industries other than IT and telecom are not independent of sorting into IT and telecom, the results in

23The industry with the highest average level of cognitive skills - research and development - is not included in the Table 3.2 as it employs less than 2 percent of the workforce.  
24This result holds regardless of whether we include or exclude the IT and telecom industries from the sample when calculating the sample mean of skills.
Table 3.2. Mean values of skill by industry 1986 and 2008

<table>
<thead>
<tr>
<th>NACE Industry</th>
<th>Mean Skill 1986</th>
<th>∆ CS</th>
<th>Mean Skill 2008</th>
<th>∆ NCS</th>
<th>Mean Skill 2008</th>
<th>∆ α</th>
</tr>
</thead>
<tbody>
<tr>
<td>72 Computer and related activities</td>
<td>0.70</td>
<td>0.00</td>
<td>0.23</td>
<td>0.04</td>
<td>1.20</td>
<td>6.62</td>
</tr>
<tr>
<td>64 Post and telecommunications</td>
<td>0.56</td>
<td>-0.31</td>
<td>0.76</td>
<td>-0.65</td>
<td>0.02</td>
<td>2.15</td>
</tr>
<tr>
<td>32 Manufacture of radio, television and communication equip.</td>
<td>0.46</td>
<td>0.14</td>
<td>0.09</td>
<td>0.14</td>
<td>2.55</td>
<td>0.09</td>
</tr>
<tr>
<td>65 Financial intermediation, except insurance and pension funding</td>
<td>0.30</td>
<td>0.10</td>
<td>0.22</td>
<td>0.24</td>
<td>3.49</td>
<td>-0.62</td>
</tr>
<tr>
<td>74 Other business activities</td>
<td>0.22</td>
<td>0.04</td>
<td>0.10</td>
<td>0.04</td>
<td>8.41</td>
<td>4.10</td>
</tr>
<tr>
<td>51 Wholesale trade and commission</td>
<td>0.15</td>
<td>-0.21</td>
<td>0.12</td>
<td>-0.05</td>
<td>9.48</td>
<td>-2.48</td>
</tr>
<tr>
<td>22 Publishing, printing and reproduction of recorded media</td>
<td>0.12</td>
<td>0.04</td>
<td>-0.06</td>
<td>0.01</td>
<td>2.74</td>
<td>-1.39</td>
</tr>
<tr>
<td>24 Manufacture of chemicals and chemical products</td>
<td>0.11</td>
<td>0.05</td>
<td>0.01</td>
<td>0.12</td>
<td>2.13</td>
<td>-0.13</td>
</tr>
<tr>
<td>63 Supporting and auxiliary transport</td>
<td>0.08</td>
<td>-0.25</td>
<td>0.07</td>
<td>-0.14</td>
<td>1.66</td>
<td>0.58</td>
</tr>
<tr>
<td>34 Manufacture of motor vehicles</td>
<td>-0.03</td>
<td>-0.03</td>
<td>-0.07</td>
<td>-0.00</td>
<td>6.67</td>
<td>-0.26</td>
</tr>
<tr>
<td>29 Manufacture of machinery and equipment</td>
<td>-0.06</td>
<td>0.07</td>
<td>-0.06</td>
<td>0.06</td>
<td>7.92</td>
<td>-1.16</td>
</tr>
<tr>
<td>52 Sale, maintenance and repair of motor vehicles</td>
<td>-0.08</td>
<td>-0.06</td>
<td>-0.06</td>
<td>-0.00</td>
<td>2.10</td>
<td>2.06</td>
</tr>
<tr>
<td>45 Construction</td>
<td>-0.16</td>
<td>-0.03</td>
<td>0.01</td>
<td>0.03</td>
<td>8.89</td>
<td>-0.27</td>
</tr>
<tr>
<td>28 Manufacture of fabricated metal</td>
<td>-0.19</td>
<td>-0.05</td>
<td>-0.17</td>
<td>0.01</td>
<td>3.67</td>
<td>-1.12</td>
</tr>
<tr>
<td>21 Manufacture of paper and paper products</td>
<td>-0.20</td>
<td>0.06</td>
<td>-0.08</td>
<td>0.07</td>
<td>5.35</td>
<td>-3.61</td>
</tr>
<tr>
<td>15 Manufacture of food products and beverages</td>
<td>-0.22</td>
<td>-0.13</td>
<td>-0.15</td>
<td>-0.01</td>
<td>4.01</td>
<td>-1.35</td>
</tr>
<tr>
<td>60 Land transport; transport via pipelines</td>
<td>-0.27</td>
<td>-0.13</td>
<td>-0.28</td>
<td>-0.06</td>
<td>1.43</td>
<td>0.65</td>
</tr>
<tr>
<td>27 Manufacture of basic metals</td>
<td>-0.32</td>
<td>0.07</td>
<td>-0.18</td>
<td>0.07</td>
<td>2.38</td>
<td>-0.22</td>
</tr>
<tr>
<td>20 Manufacture of wood and of products of wood</td>
<td>-0.37</td>
<td>-0.00</td>
<td>-0.06</td>
<td>0.00</td>
<td>2.12</td>
<td>-0.28</td>
</tr>
<tr>
<td>26 Manufacture of tobacco</td>
<td>-0.41</td>
<td>0.09</td>
<td>-0.08</td>
<td>0.02</td>
<td>1.66</td>
<td>-1.03</td>
</tr>
</tbody>
</table>

Sample restricted to industries with at least 2% of the workforce in either 1986 or 2008.
Figure 3.5: Mean cognitive skill at the industry level

Note: Sample men 30–35 years old, firms with at least 50 employees
Figure 3.6 should be viewed with a grain of salt. Still, the pattern in the data is broadly consistent with the predictions from the models by Caselli (1999) and Acemoglu (1999): After the introduction of a new technology (IT and telecom), workers with high and low cognitive skills select into different sectors.

3.5.2 Decomposing the within firm variance

We now take a closer look at the within-firm variance. Given increasing differences in skill across industries, the within-firm variance has to fall (unless the sample variance increases, which it does not). However, such a fall in the within-firm variance can come about in different ways. Broadly speaking, the overall within-firm variance could fall because industries in which the average within-firm variance is small increase in relative size, because the average within-variance falls in all industries, or due to the interaction between these forces. In order to assess which factor is most important, we
3.5. SORTING BY SKILL 1986-2008

Table 3.3. Decomposing change in within-firm variance

<table>
<thead>
<tr>
<th>Skill measure</th>
<th>ΔWithin-firm variance</th>
<th>ΔSize of industries</th>
<th>Covariance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cognitive</td>
<td>-0.089</td>
<td>-0.029</td>
<td>0.012</td>
</tr>
<tr>
<td>Non-cognitive</td>
<td>-0.058</td>
<td>0.002</td>
<td>-0.007</td>
</tr>
</tbody>
</table>

decompose the change in the within-firm variance in three parts

\[
\sum_k \alpha_{k,86} \Delta \sigma_k^2 + \sum_k \Delta \alpha_k \sigma_{k,86}^2 + \sum_k \Delta \alpha_k \Delta \sigma_k^2, \tag{3.5}
\]

where \(\alpha_{k,t} = n_{k,t}/n_t\) denotes the share of the sample employed in industry \(k\) in year \(t\), \(\sigma_{k,t}^2\) is the average within-firm variance (weighted by firm size) in industry \(k\) in year \(t\), \(\Delta \sigma_k^2 = \sigma_{k,08}^2 - \sigma_{k,86}^2\) and \(\Delta \alpha_k = \alpha_{k,08} - \alpha_{k,86}\). The first term in (3.5) is the change in within-firm variance holding each industry’s share of total employment fixed at its 1986 level. This term should be negative if increasing complementarities between skills in the production function or diffusion of new technology makes it more profitable to match workers of a given skill level in the same firm. The second term is the change in within-firm variance due to changes in the relative size of industries. If, as suggested by Grossman and Maggi (2000), Sweden has a comparative advantage in goods and services where worker skills are complements, falling trade costs should lead to an increase in the relative size of industries where the initial within-firm variance \(\left(\sigma_{k,86}^2\right)\) is small and, consequently, a negative second term. The third term is the covariance between changes in the relative size of industries and changes in within-firm variance.

Table 3.3 displays decomposition (3.5) for each of our skill measures. The fall in the within-firm variance is mostly due to a fall in the within-firm variance for fixed industry shares. Industries with a low initial within-firm variance of cognitive did increase in size relative to other industries, but this effect can only explain a small share of the overall trend. In which industries did the within firm variance in skill fall the most? Table 3.4 lists the average within-firm variance (weighted by firm size) by industry for each skill measure, the change in within-firm variance between 1986 and 2008,
the relative size of the industry in 1986 and the change in relative size. We restrict the sample to industries with at least 2 percent of the workforce in either 1986 or 2008. The industries in the table are sorted according to average within-firm variance of cognitive skill (weighted by firm size) in 1986.

Table 3.4 shows that the average within-firm variance in 1986 was significantly higher in the manufacturing sector. In manufacturing of motor vehicles (NACE 34) and chemical products (24), the average variance of cognitive skill was close to the population variance, i.e., 1. Firms in high-skilled service sectors (financial intermediation and IT-services), had the lowest within-firm variances with an average around 0.6. However, Table 4 also shows that the within-firm variance in cognitive skill fell sharply in a range of manufacturing industries, including manufacture of telecom products (NACE 32); the chemical industry (24); pulp and paper (28); and the forest industry (20). Yet the fall in within-firm variance is a feature of almost all industries and holds for all skill measures. The main exception is the post- and telecom industry (64), but the diminutive size of this industry in 1986 implies that one should be cautious in interpreting this result. Table 3.4 also shows that the fall in within-firm variance is partly caused by the growth of the IT sector (72), which has the lowest within-firm variance of cognitive skill among the major industries.

The general trend toward smaller within firm variance is present also for non-cognitive skills, albeit not as dramatic as for cognitive skills. Unlike cognitive skills, large shifts in the within-firm variance of non-cognitive skills does not only pertain to manufacturing industries. The correlation between the changes in the average variances of cognitive and non-cognitive skills is 0.36, regardless of whether we weigh industries by the number of workers or not.

Finally, Table 3.5 lists the results when we regress the change between 1986 and 2008 in the average within firm variance at the industry level on different sets of covariates.25 The aim of these regressions is purely de-

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25 Due to missing values, the regressions in Table 3.5 only cover 49 out of the 55 industries present in our data in 1986. Together, these 49 industries cover 96.65% of our sample of workers in 1986.
### Table 3.4: Within-firm variance in skills 1986 and 2008

<table>
<thead>
<tr>
<th>NACE</th>
<th>Industry</th>
<th>Cognitive</th>
<th>Non-cognitive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\sigma^2_{86}$</td>
<td>$\Delta \sigma^2$</td>
</tr>
<tr>
<td>34</td>
<td>Manufacture of motor vehicles, trailers and semitrailers</td>
<td>0.97</td>
<td>-0.11</td>
</tr>
<tr>
<td>24</td>
<td>Manufacture of chemicals and chemical products</td>
<td>0.96</td>
<td>-0.15</td>
</tr>
<tr>
<td>32</td>
<td>Manufacture of radio, television and communication equipment</td>
<td>0.93</td>
<td>-0.25</td>
</tr>
<tr>
<td>15</td>
<td>Manufacture of food products and beverages</td>
<td>0.89</td>
<td>-0.09</td>
</tr>
<tr>
<td>29</td>
<td>Manufacture of machinery and equipment n.e.c</td>
<td>0.88</td>
<td>-0.08</td>
</tr>
<tr>
<td>20</td>
<td>Manufacture of wood and of products of wood and core</td>
<td>0.86</td>
<td>-0.13</td>
</tr>
<tr>
<td>27</td>
<td>Manufacture of basic metals</td>
<td>0.85</td>
<td>-0.08</td>
</tr>
<tr>
<td>21</td>
<td>Manufacture of fabricated metal</td>
<td>0.85</td>
<td>-0.14</td>
</tr>
<tr>
<td>28</td>
<td>Manufacture of paper and paper products</td>
<td>0.85</td>
<td>-0.09</td>
</tr>
<tr>
<td>22</td>
<td>Publishing, printing and reproduction of recorded media</td>
<td>0.79</td>
<td>-0.10</td>
</tr>
<tr>
<td>74</td>
<td>Other business activities</td>
<td>0.77</td>
<td>-0.12</td>
</tr>
<tr>
<td>60</td>
<td>Land transport; transport via pipeline</td>
<td>0.75</td>
<td>0.03</td>
</tr>
<tr>
<td>51</td>
<td>Wholesale trade</td>
<td>0.75</td>
<td>-0.11</td>
</tr>
<tr>
<td>52</td>
<td>Retail trade, except of motor vehicles</td>
<td>0.73</td>
<td>-0.01</td>
</tr>
<tr>
<td>63</td>
<td>Supporting and auxiliary transportation activities</td>
<td>0.72</td>
<td>0.01</td>
</tr>
<tr>
<td>45</td>
<td>Construction</td>
<td>0.70</td>
<td>-0.09</td>
</tr>
<tr>
<td>50</td>
<td>Sale, maintenance and repair of motor vehicles</td>
<td>0.66</td>
<td>-0.03</td>
</tr>
<tr>
<td>65</td>
<td>Financial intermediation, except insurance and pension funding</td>
<td>0.59</td>
<td>-0.03</td>
</tr>
<tr>
<td>72</td>
<td>Computer and related activities</td>
<td>0.59</td>
<td>-0.03</td>
</tr>
<tr>
<td>64</td>
<td>Post and telecommunications</td>
<td>0.49</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Sample restricted to industries with at least 2 % of the workforce in either 1986 or 2008.
The main result in Table 3.5 is that there was a converge in the average within-firm variance across industries. Notably, firms in the manufacturing sector did not experience a sharper fall in the within-firm variance once the initial within-firm variance is controlled for. Using our admittedly rough data on trade, there is some indication in the data that the average within-firm variance fell less in the industries where world trade increased the most, suggesting that trade does not explain the shift toward firms with more homogeneous labor forces.
### Table 3.5. Changes in Average Within Firm Variance at the Industry Level 1986-2008

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>CS</td>
<td>CS</td>
<td>CS</td>
<td>NCS</td>
<td>NCS</td>
<td>NCS</td>
<td>NCS</td>
<td>NCS</td>
</tr>
<tr>
<td>$CS_{1986}$</td>
<td>-0.00897</td>
<td>-0.0526</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0413)</td>
<td>(0.0445)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Within firm variance CS_{1986}$</td>
<td>-0.507***</td>
<td>-0.473***</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.157)</td>
<td>(0.155)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$ln(Capital)_{1986}$</td>
<td>0.0186</td>
<td>0.00215</td>
<td>0.0290</td>
<td></td>
<td>0.0277*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0218)</td>
<td>(0.0214)</td>
<td>(0.0190)</td>
<td></td>
<td>(0.0163)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$Trade world_{1986}$</td>
<td>0.00163</td>
<td>0.0141*</td>
<td>-0.00432</td>
<td>-0.000993</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00546)</td>
<td>(0.00737)</td>
<td>(0.00538)</td>
<td>(0.00924)</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
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<td>0.365</td>
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</table>

Robust standard errors that allows for clustering at the industry level in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Dependent variable is the change in within firm skills sorting between 1986 and 2008. Constant included but not reported.  
$\Delta$ refers to changes between 1986 and 2008 in the reported variable.  
Regressions are weighted by the number of observed individuals in each industry in 1986.
3.6 Mechanisms

So far, we have documented two basic facts about changes in sorting over time in the Swedish labor market. First, following the expansion and skill upgrading of a few high-tech industries, differences in cognitive skill between firms have increased. Second, differences in cognitive skill among workers in the same firm have fallen in all major industries. The fall is larger for industries where the within-firm differences in skill were large to begin with, implying converge in the average within-firm variance across industries.

In this final section, we consider the question whether the increase in sorting is due to larger technological differences between firms, or to stronger assortative matching of workers for a given technology. To this end, we first decompose the variance in cognitive and non-cognitive skill into the variance between and within occupations. We then further decompose the between- and within-occupation variances into between- and within-firm components. The main idea behind this two-step procedure is that a firm’s occupational structure is reasonable proxy for the skill-intensity of its technology, allowing us to assess whether sorting is driven by technological differences between firms or assortative matching of workers for a given technology. As we will see, our results suggest that both technology and assortative matching explain the increase in sorting.

3.6.1 Framework

Our analysis proceeds in two steps. In the first step, we decompose the overall variance in skill into between- and within-occupation variance. Let $\hat{C}_{ij}$ denote the average cognitive skill in the occupation held by individual $i$ while $C_{ij}$ denotes worker $i$’s actual skill level. Consequently, $C_{ij} - \hat{C}_{ij}$ equals worker $i$’s residual from a regression of actual skills ($C_{ij}$) on occupation fixed effects. Then the sample variance in cognitive skill can be decomposed as
3.6. MECHANISMS

\[ \frac{1}{n} \sum_j \sum_i \left[ \frac{1}{n_j} \left( \hat{C}_{ij} - \bar{C} \right)^2 + \frac{1}{n_j} \left( C_{ij} - \hat{C}_{ij} \right)^2 \right] \]  

(3.6)

Since occupational data is missing for blue-collar workers between 1986 and 1995, we use the combination of field of study and years of schooling as a proxy for occupation. For example, workers with a five-year tertiary degree in engineering are coded as belonging to the same “occupation”. Since we use data on educational attainment to infer occupation, the between- and within occupation components are determined already at the time when the men in our sample enter the labor market. Consequently, changes sorting between occupations are not explained by sorting of workers to firms.

In the second step, we decompose the between- and within-occupation variance into between- and within-firm components. Let \( \hat{C}_j \) denote the expected firm-level mean of cognitive skills in firm \( j \) conditional on the firm’s occupational structure. We argue that \( \hat{C}_j \) can be thought of as a proxy for the skill-intensity of technology in a firm. For example, a firm that hires many engineers, who are high-skilled on average, will have a high value of \( \hat{C}_j \). The between-occupation variance in cognitive skill can then be decomposed as

\[ \frac{1}{n} \sum_j n_j \left( \bar{C}_j - \bar{C} \right)^2 + \frac{1}{n} \sum_j \sum_i \left( \hat{C}_{ij} - \bar{C}_j \right)^2 \]  

(3.7)

The between-firm component in (3.7) is the variance in cognitive skill attributable to differences in the occupational structure across firms. For example, this component is large if some firms hire a large fraction of workers in high-skilled occupations (e.g., engineers) while other firms mostly hire

\[ \text{Data on occupation for all sectors of the economy are available from 1996 onwards, but we nevertheless choose to stick to our proxy for consistency over time. The results come out in a similar fashion for the 1996-2008 period when we use actual occupations instead of the proxy based on education.} \]
workers in low-skilled occupations (e.g., production workers). We argue that we can think of the between-firm component as a measure of the differences in the skill-intensity of technology across firms.

The within-firm component in (3.7) reflects the variance explained by the fact that each firm may encompass workers from many different occupations, with different levels of skill. For example, the within-firm component is large for a firm which employs both engineers and production workers, but low for a firm that employ only engineers or only production workers. This component thus reflects the extent to which firms concentrate on a set of tasks with similar skill requirements.

An increase in the first (between-firm) component relative to the second (within-firm) component could arise due to skilled-biased technological change. For example, in the model by Caselli (1999), all workers work in the same type of firm and use the same technology in the pooling equilibrium. Skilled-biased technological change leads to a separating equilibrium where workers sort by skill to different firms and work with different technology. However, a change in the relative size of the between-firm component could also be due to outsourcing. For example, consider a firm which both develops new products (skill-intensive) and manufactures them (not skill intensive). If product development and manufacturing is instead split into two different firms, differences in the skill-intensity of technology between firms would increase.

We now turn to the within-occupation variance. Keeping with the same terminology as above, the within-occupation variance can be decomposed into between- and within-firm components:

\[
\frac{1}{n} \sum_j n_j \left( C_j - \hat{C}_j \right)^2 + \frac{1}{n} \sum_j \sum_i \left( \left( C_{ij} - \hat{C}_{ij} \right) - \left( C_j - \hat{C}_j \right) \right)^2
\]

(3.8)

The between-firm component in (3.8) is the variance in the difference between firms’ actual and predicted average level of cognitive skills. This
component is large if the best workers in a given occupation work in the same firms, i.e., the more positive is assortative matching. For example, assortative matching is positive if particularly clever engineers work in the same firm, and if the most clever engineers work with the most clever secretaries.

The within-firm component in (3.8) is large if there is a high variance of skill within firms given the general skill level. For example, the second term would be high if a firm both employs particularly skilled and particularly unskilled engineers. Alternatively, the second term would be high for a firm where all engineers are particularly skilled compared to the average engineer whereas all production workers are particularly unskilled compared to the average production worker.

Stronger (positive) assortative matching of workers for a given technology is associated with an increase in the relative size of the first (between-firm) component relative to the second (within-firm) component in (3.8). An increase in assortative matching could arise because complementarities between workers skills become more positive (for example due to technological change), or because of lower costs from matching workers with similar levels of skill (for example due to liberalization of trade).

Before we turn to the results, let us comment on the relationship between (3.7) and (3.8), and the between- and within-firm variances in decomposition (3.1). The total between-firm variance in cognitive skill is given by the sum of the between-firm components in (3.7) and (3.8) and a third component, 

$$2 \left( C_j - \hat{C}_j \right) \left( \hat{C}_j - \bar{C} \right),$$

i.e., the covariance between $C_j - \hat{C}_j$ and $\hat{C}_j - \bar{C}$. A positive covariance means that firms that hire workers in high-skilled occupations also hire workers who are more skilled than the average in their respective occupations. The total within-firm variance is given by the sum of the within-firm components in (3.7) and (3.8) plus the covariance multiplied by $-1$. The covariance thus cancels out when we sum up the total sample variance. In results available upon request, we show that a smaller part of the increase in the between-firm variance documented in Section 5 is explained by the covariance becoming more positive.
3.6.2 Results

Figure 3.7 shows the decomposition of the between-occupation variance in (3.7) between 1986 and 2008. The figure shows the absolute level of each component. There are three facts worth noting from this figure. First, the between-occupation variance (i.e., the sum of the between- and within-firm components) is much larger for cognitive and than for non-cognitive skill. This results fits well with the finding in Lindqvist and Vestman (2011) that cognitive skill is a stronger predictor of occupational choice. Second, most of the variance in skill between occupations is reflected in the within-firm component. In short, this means that technological differences within firms are larger than differences between firms. Third, the share of the variance explained by the between-firm component is increasing over time. For cognitive skill, the between-firm share increases from 25 % to 34 %, while the increase is from 24 % to 29 % for non-cognitive skill. These results suggest that differences between firms in terms of the skill-intensity of technology are increasing over time.
Figure 3.8: Decomposing the variance within occupations

Figure 3.8 shows the decomposition of the within-occupation variance in (3.8) between 1986 and 2008. As shown by the figure, sorting of workers between firms only account for a small share of the total variance in skill within occupations. However, the between-firm share is significantly larger than predicted by random sorting at all points in time, suggesting that worker skills are complements. Moreover, the fall in the within-firm components combined with the slight increase in the between-firm components imply that the between-firm share is increasing over time. The increase is from 3.3 % to 4.2 % for cognitive skill and from 2.7 % to 4.1 % for non-cognitive skill. Figure 3.8 thus suggests that assortative matching has become more positive over time, albeit from a low level.

Before we conclude, we provide suggestive evidence regarding the mechanisms at play. We begin with the between-occupation variance.

As argued above, an increase in the between-firm component in (3.7) could be due either to skilled-biased technological change or to outsourcing. We argue based on two pieces of evidence that technological change is at heart of the story. First, we showed in Figure 3.6 that the IT industry and
manufacturing of telecom products could explain a large fraction of the overall increase in the between-firm variance with respect to cognitive skill. In Figure B.3, we show that we obtain similar results if we conduct the same exercise for the between-firm component in (3.7), i.e., the variance between occupations and between firms. Second, we calculate “counterfactuals” for the between-firm component in (3.7) removing either “civil engineers” (defined as a four-year degree in engineering) or workers with at least a three-year degree in business administration or law. These two groups of workers are of roughly the same size and each constitute a small share of the overall sample. Figure 3.9 shows that removing workers with a degree in business or law does not change the level or trend for the skill-intensity of technology. In contrast, removing civil engineers has a strong negative effect both on the level and the trend for cognitive skills.\footnote{The variances in Figure 3.9 are calculated using the sample mean of skill when each occupational group is removed from the data. However, using the mean for the full sample does not change our results appreciably.}

The increase in the between-firm component of the within-occupation...
3.6. MECHANISMS

variance could be explained by stronger complementarities between worker skills or lower costs from matching workers. Skill complementarities are a function of technology while matching costs are affected by globalization, among other things. In order to investigate which forces drive assortative matching, we regress the within-firm component in (3.8) on different sets of covariates. Specifically, let $\sigma_{WOWF,jkt}^2$ denote the second component from decomposition (3.8) for firm $j$ in industry $k$ at time $t$. We estimate regressions of the following generic form

$$
\sigma_{WOWF,jkt}^2 = \beta_0 + \beta_1 \log(Capital)_{jkt} + \beta_2 \log(Size)_{jkt}
+ \beta_3 (C_{jkt} - \hat{C}_{jkt}) + \beta_4 \hat{C}_{jkt} + \beta_5 Trade_{kt}
+ \beta_6 China_{\text{import}}_{kt} + \gamma_{jk} + \epsilon_{jkt}
$$

(3.9)

where $Capital_j$ is capital intensity, $Size_j$ is the number of employees, $(C_{jkt} - \hat{C}_{jkt})$ is the difference between the actual and predicted skill level of firm $j$ and $\hat{C}_{jkt}$ is the predicted skill level of firm $j$ based upon its occupational structure. We include a firm-level fixed effect, $\gamma_{jk}$, in all regressions. $Trade_{kt}$ equals the total value of exports and imports in industry $k$ divided by total turnover while $China_{\text{import}}_{kt}$ are the same variables as in Table 3.5 above. Since we only have trade data for a subset of industries (mainly in the manufacturing sector), we estimate all versions of (9) using both this subset and the whole sample with imputed values for the trade variables. Each firm or industry is weighted with the number of workers observed in our sample.

Our main interest in regression (9) are the variables related to technology and trade. If more complex production processes are associated with stronger complementarities (as in Kremer 1993), then we should observe a negative association between $\sigma_{WOWF,jkt}^2$ and the predicted skill level, $\hat{C}_{jkt}$. We also expect a negative sign of $\beta_3$ if “star” firms, with unexpectedly high skills given their technology, display stronger assortative matching. The sum of $\beta_3$ and $\beta_4$ gives the total correlation between the firm-level average of cognitive
skill at time $t$ ($C_{jkt}$) and $\sigma_{WOWF,jkt}^2$.\footnote{The regression analysis laid above does not allow us to obtain conclusive evidence behind the general strengthening of assortative matching. Apart from concerns regarding endogeneity and omitted variables, the fundamental problem is that, since we can only study variation within and between firms or industries, we cannot identify the effect of factors that affect the entire economy in the same fashion. It is an open question whether our findings can be extrapolated to the economy as a whole.}

We show the results from different versions of regression (9) in Table 3.6. Our first finding is that firms that increase in size also tend to see an increase in $\sigma_{WOWF,jkt}^2$. Since assortative matching is stronger the smaller is $\sigma_{WOWF,jkt}^2$, this implies that expanding firms have weaker assortative matching. Regarding trade, there is no statistically significant relation between aggregate trade and assortative matching. There is, however, a tendency for assortative matching in cognitive skill to become more positive in industries that experience an increase in imports from China.

We also see that an increase in cognitive skills is strongly associated with more positive assortative matching. Interestingly, the results for assortative matching with respect to non-cognitive skills look quite different. Here, we find that upgrading of non-cognitive skill is associated with less positive assortative matching, and we find no correlation between changes in firm size and assortative matching.

Taken together, for cognitive skill we find some evidence in support of an “O-ring”-type story along the lines suggested by Kremer (1993). That is, more complex production processes due to, say, technological change, increase complementarities between workers, inducing firms to match workers who are particularly good (or particularly bad) in the same firm.
### Table 3.6. Variance within occupation within firm

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<td>0.356</td>
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</table>

Robust standard errors clustered at the 2-digit industry level reported in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1

Dependent variables are within firm assortative matching for the respective skill.

Regressions include firm and year fixed effects and are weighted by the number of observed individuals in each firm-year.
3.7 Concluding remarks

We have studied sorting by skill in the Swedish economy between 1986 and 2008 using measures of cognitive and non-cognitive skills from the Swedish military enlistment. To the best of our knowledge, our paper marks the first attempt to study sorting by skill over time using a pre-market measure of skill. Using the enlistment skill measures, we document a significant increase in sorting from 1986 to 2008.

Why did sorting increase? Our results suggest that technological change is at heart of the story. The expansion of a small set of high-tech industries (IT services and manufacturing of telecom products) lead to increasing differences across firms in terms of the skill-intensity of technology. In this respect, our results bear out a central prediction in models of skilled-biased technical change (e.g., Acemoglu 1999, Caselli 1999), that new technology will increase skill sorting in the labor market. We have also showed that assortative matching have become more positive over time. For cognitive (but not for non-cognitive) skill, the degree of assortative matching at the firm level is associated with skill upgrading, suggesting that technological change may play a role also in this case.

Before we conclude, let us mention two avenues for future research. First, a priority for future research is to study the effect of trade on sorting using better data and a more credible identification strategy. Second, our analysis of assortative matching did not answer the question for what types of workers assortative matching is strongest. We will return to this question in future work.

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A Appendix: Description of data

A.1 Data on occupations

Since occupation data is only available from 1996 and onwards, we construct proxies for occupation by combining level and fields of education. Specifically, five level groups are created: at most compulsory schooling; two years of secondary education; three years of secondary education; some post-secondary education; at least three years of post-secondary education. Field of study is based on the 26 detailed categories available in the Swedish SUN classification. In total, this procedure results in 80 “occupations”. When comparing the results using these imputed “occupations” with the results based on actual occupations, we make use of 3-digit SSYK codes (113 occupations).

A.2 Wage data

We obtain information on wages from the Structural Wage Statistics (SWS) which is based on annual surveys on a subsample of firms.\(^29\) When wages are missing from the SWS, we impute wages using the SWS from other years within the same employer-employee match and index up by general industry wage increase. For matches where no SWS wage is available, we set the wage equal to the predicted value from a regression of (observed and imputed) wages from the SWS on a high-order polynomial in the average monthly

\(^{29}\)There is some variation across years in terms of the exact sampling procedure and in the number of sampled firms, but small firms are less likely to be sampled throughout our study period.
pay from RAMS. The exact details regarding our construction of wages is available in Appendix A.

A.3 Industry codes

The industry classifications in RAMS have changed somewhat over time. In particular, the industry classification used from 1990 onwards (SNI92) is not perfectly comparable with earlier industry classification (SNI69). We impute industry backwards 1986-1989 for firms alive in 1990. For the subsample of firms not alive in 1990, we translate 2-digit industry codes from SNI69 to SNI92 using the official concordance (Statistics Sweden, 1992).

A.4 Imputing enlistment data for women

Since women in general have not gone through the Swedish enlistment procedure, data on cognitive and non-cognitive abilities is lacking for half of the population. To get an idea if the patterns found for men are also applicable to women, we impute values for women using the conscription records of their close relatives. We judge this to be a reasonable approach as previous research has found the ability correlations between close family members to be substantial: After correcting for measurement error, Grönqvist et al (2012) find that the father-son ability correlations fall between 0.4 and 0.5 for non-cognitive and cognitive abilities. The same study also reports sibling correlations of 0.45 for cognitive and 0.3 for non-cognitive abilities, without adjusting for measurement error. The reliability ratios they report suggest that the true sibling correlations are approximately 0.6 for both types of abilities. Assortative mating is also substantial; Boschini et al (2011) find the correlation in educational attainment between Swedish spouses to be around 0.5.

To find close relatives, we make use of the Multi Generation Register (Flergenerationsregistret), which contains information on ties between parents and their children for all individuals who have ever resided in Sweden since 1961 and who are born after 1932. When we impute values for a woman, we give priority to the evaluation results for her oldest brother with a con-
scription record. If such a record is not available, we use her fathers’ record and if that is missing, we turn to her sons (in age order). If none of these records can be found, we impute values using the woman’s spouse, defined as the father of her first born child. Using this algorithm, 40 percent of values are imputed using brothers, 14 percent using fathers, 29 percent using sons, and 16 percent using spouses. Using an algorithm that instead first pulls the records of the oldest brother, thereafter the spouse, then the father, and finally the son gives alternative cognitive and non-cognitive measures highly correlated (0.96) with the baseline imputations. Table A.2 reports correlations and descriptive statistics for the full sample of women for which imputed conscription records is available.

A.5 Trends in Cognitive Abilities

The analysis in this paper makes use of skill measures that are standardized by enlistment year. Standardization ensures that individuals at the same position in the overall skill distribution are compared over time, but may hide changes in the underlying distribution of skills. In this Appendix, we analyze if such changes are likely to be a concern for cognitive skills. This is possible since raw test scores are available for a subset of the years analyzed. For non-cognitive skills, no such raw scores are available and a similar analysis is thus not possible to undertake.

Between the enlistment years 1969 and 1994, the cognitive ability test consisted of four parts, testing verbal, logical, spatial and technical ability. The raw scores on these tests are transformed by the enlistment agency to a 1 to 9 “stanine” scale for each subtest. The resulting four stanine scores are then transformed into the aggregate 1 to 9 scales used for the main analysis of cognitive skills in this paper. In this Appendix, we instead make use of the raw scores. For some individuals, data on raw subscores is missing and we then only have data on the 1 to 9 scale for each subtest. In such cases, we impute the average raw score for those with the same subtest score on the 1 to 9 scale. In order to account for differences in maximum scores between subtests and test periods, we divide the raw scores by the maximum score
possible for each subtest. The sum of the score on the four subtests is our measure of raw cognitive ability.

Figure A.1 depicts the mean and standard deviation of raw cognitive abilities by enlistment year. In 1980 the test underwent minor revisions and apart from a jump in the standard deviation in connection to this, the dispersion of skills is stable throughout the time period. There is, however, a slight increase in mean cognitive skills. Taking the average of skills during the first four years and comparing it to the last four years, this increase amounts to 13 percent of a standard deviation.\textsuperscript{30} We conclude from this exercise that standardization is unlikely to have any substantive impact on the analysis in this paper.

\textsuperscript{30}The mean over the years 1969-72 is 2.37 and over 1991-94 2.45.
A.6 Trade data

In order to account for the relation between international trade and skill sorting, we use data on trade (scaled by total turnover) at the industry level. Two variables are created: total trade and imports from China. The first variable is intended to capture the general degree of internationalization of an industry and the second is a proxy for low-wage trade competition. The main limitation when constructing consistent series is that industry trade data do not map well over time. The reason is that industry classification underwent a major change in 1995 when reporting moved from the SNI69 to the SNI92 system. SNI69 was based on ISIC Rev.2 while SNI92 is based on NACE Rev.1 and the differences are documented in Statistics Sweden (1992).

For these reasons we can only construct trade data for 30 industries (mainly in manufacturing) but in most of the remaining industries trade is likely to be limited. We therefore impute trade to be zero (0) in industries without trade data. As mentioned in the main text, the results are not sensitive to the inclusion or exclusion of these industries. Trade data are collected from Statistics Sweden’s Statistical Database (Statistikdatabasen) and the series are “Varuimport och varuexport efter Varu-SNI69 och handelspartner” for the period 1986-94, "Varuimport och varuexport efter produktgrupp Prod-SNI97 och handelspartner" for the years 1995-97, and “Varuimport och varuexport efter produktgrupp SPIN 2002 och handelspartner” for years 1998-2008. Data on turnover is from the Firm Register (Företagsdatabasen), the same source as capital intensity and other firm level variables used in this paper.

A.7 The final samples

Table A.2 shows basic samples that we will be working with. The first column shows the total number of firms with at least 50 employees in the RAMS database. The next two columns show the share and the number of private firms in RAMS. The fourth column shows the number of 30 to 35 year old individuals with complete enlistment records that we observe employed at
private firms with at least 50 employees and at least three 30 to 35 year old men with enlistment records among their employees, and the fifth column shows the number of firms in the sample that fulfills these conditions. The following two columns shows the corresponding numbers for individuals and firms with at least three 30 to 45 year old males with enlistment records, and the final four columns shows the coverage when we add women with imputed enlistment records to the sample.
### Table A.2 Summary statistics for basic samples

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<th>RAMS data base</th>
<th>Male sample</th>
<th>Including females</th>
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<td>211907</td>
<td>82.59</td>
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</tr>
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<td>2008</td>
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B. APPENDIX: ADDITIONAL RESULTS

B  Appendix: Additional results
### Table B.1 Cross industry wage differentials

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<tr>
<td>CS</td>
<td>0.244***</td>
<td>0.178*</td>
<td>0.268***</td>
<td>0.294***</td>
<td>0.294***</td>
<td>0.294***</td>
<td>0.294***</td>
<td>0.294***</td>
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<td></td>
<td>(0.0268)</td>
<td>(0.105)</td>
<td>(0.0304)</td>
<td>(0.0864)</td>
<td>(0.0864)</td>
<td>(0.0864)</td>
<td>(0.0864)</td>
<td>(0.0864)</td>
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<tr>
<td>NCS</td>
<td>0.429***</td>
<td>0.194**</td>
<td>0.520***</td>
<td>0.418***</td>
<td>0.418***</td>
<td>0.418***</td>
<td>0.418***</td>
<td>0.418***</td>
</tr>
<tr>
<td></td>
<td>(0.0514)</td>
<td>(0.0843)</td>
<td>(0.0539)</td>
<td>(0.0990)</td>
<td>(0.0990)</td>
<td>(0.0990)</td>
<td>(0.0990)</td>
<td>(0.0990)</td>
</tr>
<tr>
<td>ED</td>
<td>0.0792***</td>
<td>-0.00795</td>
<td>0.0920***</td>
<td>-0.0851***</td>
<td>0.0920***</td>
<td>-0.0851***</td>
<td>0.0920***</td>
<td>-0.0851***</td>
</tr>
<tr>
<td></td>
<td>(0.00970)</td>
<td>(0.0332)</td>
<td>(0.0127)</td>
<td>(0.0338)</td>
<td>(0.0127)</td>
<td>(0.0338)</td>
<td>(0.0127)</td>
<td>(0.0338)</td>
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<td>(0.00678)</td>
<td>(0.109)</td>
<td>(0.371)</td>
<td>(0.00969)</td>
<td>(0.00948)</td>
<td>(0.165)</td>
<td>(0.431)</td>
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<td>Observations</td>
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<td>55</td>
<td>55</td>
<td>55</td>
<td>54</td>
<td>54</td>
<td>54</td>
<td>54</td>
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<tr>
<td>Adjusted R-squared</td>
<td>0.602</td>
<td>0.560</td>
<td>0.549</td>
<td>0.626</td>
<td>0.591</td>
<td>0.635</td>
<td>0.492</td>
<td>0.693</td>
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Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
industries weighted by number of observation

---

### Table B.2 Cross industry wage differentials, long differences

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<td></td>
<td>Δw_{1986−2008}</td>
<td>Δw_{1986−2008}</td>
<td>Δw_{1986−2008}</td>
<td>Δw_{1986−2008}</td>
</tr>
<tr>
<td>Change in average CS</td>
<td>0.263***</td>
<td>0.151</td>
<td>(0.0567)</td>
<td>(0.102)</td>
</tr>
<tr>
<td>Change in average NCS</td>
<td>0.280***</td>
<td>0.208**</td>
<td>(0.0526)</td>
<td>(0.0869)</td>
</tr>
<tr>
<td>Change in average ED</td>
<td>0.0788***</td>
<td>-0.00250</td>
<td>(0.0167)</td>
<td>(0.0332)</td>
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<tr>
<td>ED</td>
<td>-0.0125</td>
<td>(0.0104)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.366***</td>
<td>0.353***</td>
<td>0.242***</td>
<td>0.524***</td>
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<tr>
<td></td>
<td>(0.00760)</td>
<td>(0.00723)</td>
<td>(0.0258)</td>
<td>(0.164)</td>
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<tr>
<td>Observations</td>
<td>53</td>
<td>53</td>
<td>53</td>
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<tr>
<td>Adjusted R-squared</td>
<td>0.283</td>
<td>0.344</td>
<td>0.290</td>
<td>0.360</td>
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</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
industries weighted by number of observation
Figure B.1: Between and within firm variance in skill. Sample of 30-45 year old men 1996-2008

Note: Sample men 30–45 years old, firms with at least 50 employees. Sample corrected variances.

Figure B.2: Between and within firm variance in skill. Sample of 30-35 year old women

Note: Sample men 30–35 years old, firms with at least 50 employees. Sample corrected variances.
Figure B.3: Counterfactual sorting, between occupation between firm

Panel A: Cognitive skill
Panel B: Non-cognitive skill

Note: Sample men 30−35 years old, firms with at least 50 employees

Figure B.4: Alternative distribution: Beta (2,4)
Figure B.5: Alternative distribution: Beta (4,2)

Figure B.6: Alternative distribution: Uniform
Table B.3 Simulated variances 1986

<table>
<thead>
<tr>
<th>Cognitive Skill</th>
<th>Sample</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P1</td>
<td>P50</td>
</tr>
<tr>
<td>Within firm total</td>
<td>0.8021</td>
<td>0.9303</td>
</tr>
<tr>
<td>Between occupation, within firm</td>
<td>0.2200</td>
<td>0.2921</td>
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<tr>
<td>Within occupation, within firm</td>
<td>0.6209</td>
<td>0.6382</td>
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<tr>
<td>Covariance</td>
<td>-0.0387</td>
<td>-0.0016</td>
</tr>
<tr>
<td>Between firm total</td>
<td>0.1340</td>
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<tr>
<td>Between occupation, between firm</td>
<td>0.0739</td>
<td>0.0004</td>
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<tr>
<td>Within occupation, between firm</td>
<td>0.0213</td>
<td>0.0009</td>
</tr>
<tr>
<td>Covariance</td>
<td>0.0387</td>
<td>-0.0014</td>
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</table>

<table>
<thead>
<tr>
<th>Non-cognitive Skill</th>
<th>Sample</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P1</td>
<td>P50</td>
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<tr>
<td>Within firm total</td>
<td>0.8167</td>
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<tr>
<td>Between occupation, within firm</td>
<td>0.0676</td>
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<td>Within occupation, within firm</td>
<td>0.7596</td>
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<td>Covariance</td>
<td>-0.0105</td>
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<td>Between firm total</td>
<td>0.0531</td>
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<td>Between occupation, between firm</td>
<td>0.0218</td>
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<tr>
<td>BF assortative</td>
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<td>Covariance</td>
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<table>
<thead>
<tr>
<th>Skill Covariance</th>
<th>Sample</th>
<th>Simulated</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>P1</td>
<td>P50</td>
</tr>
<tr>
<td>Within firm</td>
<td>0.2471</td>
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### Table B.4 Simulated variances 2008

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<th>P50</th>
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<tr>
<td>Within firm total</td>
<td>0.6971</td>
<td>0.8668</td>
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<tr>
<td>Between occupation, within firm</td>
<td>0.1961</td>
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<td>Within occupation, within firm</td>
<td>0.5526</td>
<td>0.5726</td>
<td>0.5742</td>
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<tr>
<td>Covariance</td>
<td>-0.0517</td>
<td>-0.0015</td>
<td>0.0000</td>
</tr>
<tr>
<td>Between firm total</td>
<td>0.1757</td>
<td>0.0018</td>
<td>0.0036</td>
</tr>
<tr>
<td>Between occupation, between firm</td>
<td>0.1000</td>
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<td>0.0013</td>
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<td>Within occupation, between firm</td>
<td>0.0240</td>
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<td>Covariance</td>
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<td>-0.0014</td>
<td>0.0000</td>
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<thead>
<tr>
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<th>P1</th>
<th>P50</th>
<th>P99</th>
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<tbody>
<tr>
<td>Within firm total</td>
<td>0.7549</td>
<td>0.8299</td>
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<td>Between occupation, within firm</td>
<td>0.0844</td>
<td>0.1176</td>
<td>0.1178</td>
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<td>Within occupation, within firm</td>
<td>0.6878</td>
<td>0.7123</td>
<td>0.7140</td>
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<tr>
<td>Covariance</td>
<td>-0.0173</td>
<td>-0.0010</td>
<td>0.0000</td>
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<tr>
<td>Between firm total</td>
<td>0.0805</td>
<td>0.0015</td>
<td>0.0036</td>
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<td>Between occupation, between firm</td>
<td>0.0339</td>
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<th>P99</th>
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<td>Within</td>
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<td>Between</td>
<td>0.0921</td>
<td>-0.0002</td>
<td>0.0014</td>
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Figure B.7: Variances corrected for measurement error
C. Appendix: Measuring sorting

C.1 Sample size corrections

The fact that we do not observe all workers in all firms implies that we need to adjust the variance decomposition. First, we show how we get from the unadjusted variance decomposition in (3.1) to the adjusted variance decomposition in (3.1’). When we have a sample of \( n_j \) workers from firm \( j \) with \( N_j \) workers in total, then an unbiased estimator of the skill variance in firm \( j \) is

\[
\left( \frac{N_j - 1}{N_j} \right) \left( \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j)^2
\]

For every firm in the sample, we know \( N_j \) (number of employees) and \( n_j \) (number of employees for which we observe skill).\(^{31}\) In order to estimate the true between-firm variance, we need to tease out the share of the between-firm variance which is due to measurement error in the mean skill at the firm level. This measurement error variance amounts to

\[ \frac{N-n}{Nn} S^2 = \frac{N_j - n_j}{N_j n_j} \left( \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j)^2 \]

Using the expression and dividing each term by \( n = \sum_j n_j \) (total number of observations in the sample) gives the decomposed variances

\[
\underbrace{\frac{1}{n} \sum_j n_j \left( \frac{N_j - 1}{N_j} \right) \left( \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j)^2}_{\text{within-firm variance}}
\]

\[+ \frac{1}{n} \sum_j n_j \left[ (C_j - \overline{C})^2 - \frac{N_j - n_j}{N_j n_j} \left( \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j)^2 \right] \]

\[\text{between-firm variance}\]

\(^{31}\)In principle, the \( n_j \) workers whose skills we observe need to be a random sample of all the \( N_j \) workers in the firm for us to make an inference about the within-firm variance of firm \( j \). This is not the case for us, since we focus on men between the age of 30 and 35 for the most part.
We now turn to the further decomposition of the between-firm variance in (3.2). By analogy of the between-firm component, the between-industry variance $VAR_{BI}$ is

$$
\frac{1}{n} \sum_k n_k \left( (C_k - \overline{C})^2 - \frac{N_k - n_k}{N_k n_k} \sum_i (C_{ijk} - C_k)^2 \right)
$$

The between-firm variance within industries $VAR_{BFWI}$ is just the difference between the between-firm and the between-industry variance, i.e.,

$$VAR_{BFWI} = VAR_{BF} - VAR_{BI}.$$

We now turn to the covariance between cognitive and non-cognitive skills. Let $N_j$ denote the number of workers in firm $j$ and $n_j$ the number of observations in the same firm. The adjustment for sample size is the same as in the case of standard variance. That is, we get

$$
\frac{1}{n} \sum_j n_j \left( \frac{N_j - 1}{N_j} - \frac{1}{n_j - 1} \right) \sum_i (C_{ij} - C_j) (NC_{ij} - NC_j) + \text{within-firm covariance weighted by } n_j
$$

$$
\frac{1}{n} \sum_k \sum_j n_j \left[ (C_j - \overline{C}) (NC_j - \overline{NC}) \right] - \frac{N_j - n_j}{N_j n_j} \sum_i (C_{ij} - C_j) (NC_{ij} - NC_j) \right]
$$

Finally, we consider the decompositions of the between-firm and within-firm variances in Section 6. We begin with the decomposition of the between-firm variance in (3.6). The basic problem here is exactly the same as above: The fact that we only observe a subsample of the workers in each firm implies that we get measurement error in the firm averages, leading to between-firm differences in skills. We thus get a too large between–firm variance that we decompose into the part we can explain by occupational mix. We know the extent of the measurement error and how to decompose the “aggregate” variance. The fact that we only study a small set of workers thus gives measurement error in the observed mean $C_j$, but also in the predicted mean skill, $\widehat{C}_j$. The predicted mean also suffers from an additional measurement error as we do not observe all workers within a given occupation. Also adjusting
for this error is beyond the scope of the paper. Let \( \hat{C}_{ij} \) denote the average skill of the occupation individual \( i \) belongs to. The adjusted variance due to occupational mix (component 1) equals

\[
\frac{1}{n} \sum_j n_j \left[ (\hat{C}_j - \bar{C})^2 - \frac{N_j - n_j}{N_j n_j} \left( \frac{1}{n_j - 1} \right) \sum_i (\hat{C}_{ij} - \hat{C}_j)^2 \right]
\]

while the variance due to deviations from the predicted mean (component 2) equals:

\[
\frac{1}{n} \sum_j n_j \left[ (C_j - \hat{C}_j)^2 - \frac{N_j - n_j}{N_j n_j} \left( \frac{1}{n_j - 1} \right) \sum_i ((C_{ij} - \hat{C}_{ij}) - (C_j - \hat{C}_j))^2 \right]
\]

Finally, the adjusted interaction term (component 3) equals

\[
\frac{2}{n} \sum_j n_j \left[ \frac{(C_j - \hat{C}_j)}{N_j n_j} \left( \frac{1}{n_j - 1} \right) \sum_i ((C_{ij} - \hat{C}_{ij}) - (C_j - \hat{C}_j)) (\hat{C}_{ij} - \hat{C}_j) \right]
\]

Now consider the decomposition of the within-firm variance in (3.7). Since we view \( \hat{C}_{ij} \) as error-free, no adjustment except for multiplying each term by

\[
\left( \frac{N_j - 1}{N_j} \right) \left( \frac{1}{n_j - 1} \right)
\]

is needed.

**C.2 Measurement error correction**

We derive the measurement error correction for cognitive skill, but the procedure is exactly the same for non-cognitive skill. Suppose observed cognitive skill \( (C) \) is a function of true skill \( (C^*) \) and measurement error \( (\varepsilon) \), so that

\[
C_i = C^*_i + \varepsilon_{C,i}
\]

We assume that the measurement error is orthogonal to true skill and that both true skill and the error term are normally distributed. The total error
variance equals

\[
\frac{1}{n} \sum_j \sum_i (\varepsilon_{C,ij} - \bar{\varepsilon})^2
\]

As for the skill measures, the error variance can be decomposed into between- and within-firm components. Let \( VI_{WF} \) denote the within-firm error variance and \( VI_{BF} \) the between-firm error variance. We get

\[
VI_{WF,CS} = \frac{1}{n} \sum_j \sum_i \varepsilon_{C,ij}^2 - \frac{1}{n} \sum_j (\varepsilon_{C,j} - \bar{\varepsilon})^2
\]

and

\[
VI_{BF,CS} = \frac{1}{n} \sum_j (\varepsilon_{C,j} - \bar{\varepsilon})^2.
\]

Since the expected covariance between true skill and the measurement error is zero, \( VI_{WF} \) and \( VI_{BF} \) equal the expected inflation of the within- and between-firm variance in cognitive skill which is due to measurement error. To quantify the effect of the measurement error, we do a simulation where \( \varepsilon_{C,ij} \) is drawn randomly for each individual from the distribution \( N \left( 0, \sigma_{\varepsilon_C}^2 \right) \). Using the simulated data, we then calculate \( VI_{WF} \) and \( VI_{BF} \). We use the estimated measurement error variances based on twin data reported by Lindqvist and Vestman (2011) in these simulations. Lindqvist and Vestman find that the error term variance is substantially higher for non-cognitive \( (\sigma_{\varepsilon_N}^2 = 0.297) \) than for cognitive skill \( (\sigma_{\varepsilon_C}^2 = 0.1325) \). Subtracting the simulated inflated variances from the between- and within-firm variances in (3.1) gives us an unbiased estimate of the variance in true skill. However, since our skill measures have no natural metric, the statement that “measurement error inflates the between- and within firm variances” is misleading. To get an estimate which is comparable to the standard decomposition (under the assumption of no measurement error in skill), we normalize the measurement-adjusted variances so that the total adjusted sample variance equals the total unadjusted sample variance. Thus, only the relative size of the between- and within-firm components change.
The adjusted components are:

\[
\begin{align*}
BF_{VAR-CS_{ADJ,t}} &= \frac{BF_{VAR-CS_{UNADJ,t}} - VI_{BF,CS}}{1 - (0.1325/(BF_{VAR-CS_{UNADJ,t}} + WF_{VAR-CS_{UNADJ,t}}))} \\
WF_{VAR-CS_{ADJ,t}} &= \frac{WF_{VAR-CS_{UNADJ,t}} - VI_{WF,CS}}{1 - (0.1325/(BF_{VAR-CS_{UNADJ,t}} + WF_{VAR-CS_{UNADJ,t}}))} \\
BF_{VAR-NCS_{ADJ,t}} &= \frac{BF_{VAR-NCS_{UNADJ,t}} - VI_{BF,NCS}}{1 - (0.297/(BF_{VAR-NCS_{UNADJ,t}} + WF_{VAR-NCS_{UNADJ,t}}))} \\
WF_{VAR-NCS_{ADJ,t}} &= \frac{WF_{VAR-NCS_{UNADJ,t}} - VI_{WF,NCS}}{1 - (0.297/(BF_{VAR-NCS_{UNADJ,t}} + WF_{VAR-NCS_{UNADJ,t}}))}
\end{align*}
\]

Note that the error term corrections should be adjusted for the same firm-sample-size multiplicator as used when deriving the unadjusted between- and within-firm variances, even though the these terms are not included in the expressions above. Since we randomize the error terms, the results come out slightly different in different simulations. Therefore, we use the average value from 200 simulations, and also plot the 98 % “confidence interval” (the 1st and 99th percentiles for each year).
Chapter 4

Trading Off or Having it All?
Completed Fertility and Mid-career Earnings of Swedish Men and Women*

4.1 Introduction

Increased female labor force participation, the expansion of higher education, and the emergence of a female dominance among the highly educated have changed the conditions for family formation, fertility decisions and careers of men and women over the past decades. Bertrand et al (2010) show that there is still a sharp trade-off between career and family for US female top professionals.

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professionals. Evidence for other countries and other parts of the distribution of women shows weaker effects of children on careers.¹ Shang and Weinberg (2009) and Goldin and Katz (2008) suggest that highly educated women in the US recently both have more children and work more, which is consistent with the reversal of a previous negative correlation between female participation rates and fertility rates in cross-country comparisons found in Ahn and Mira (2002). In Sweden, active policy promotion of gender equality through the introduction of individual taxation, the expansion of subsidized childcare and generous parental leave has aimed at easing the family-work trade-off. It is debated whether the policies have been successful or not (Albrecht et al 2003; Boschini 2004; Henrekson and Stenkula 2009; Economist 2009).

This paper aims at uncovering what has happened to the family-career trade-off for Swedish men and women by presenting how long-run trends in completed fertility and mid-career earnings relate to education and partner choices. Our starting point is that earnings in mid-career and children are two fundamental outcomes of the life-choices of men and women. Both require time and other resources and reflect the accumulated priorities of individuals. Competition for time may result in a trade-off between career and children, but to the extent that own time can be substituted by spousal or market provided time, some individuals manage to have it all.

Rich and universal Swedish register data from Statistics Sweden allow us to document trends in educational assortative mating, family formation patterns and labor market outcomes for the cohorts born 1945-1962. We measure and document changes in completed fertility, mid-career earnings and contributions to joint spousal earnings by own and spousal education. Further, we analyze how the association between mid-career earnings and completed fertility for men and women has developed over time. We have chosen total annual earnings, not wages, as our outcome measure, since we are interested in the accumulated career effects of the long-run allocation of time towards family and career, rather than wage penalties for work inter-

ruptions or part-time work. The main analysis focuses on three educational groups, non-university educated, university educated and the select group of university educated holding professional degrees. We also explicitly account for compositional changes by categorizing individuals according to their position in the distribution of years of education.

Becker (1981) emphasized the family as a production unit where the spouses specialize according to their comparative advantage in doing market or household work and rearing children. Modern families are less specialized, at least in the sense that it is more common for both spouses to engage in market work. Stevenson and Wolfers (2007) argue that this is the result of a number of forces that have reduced the importance of family production complementarities.

Technological advances in household production, e.g. dishwashers, washing machines etc, and the expansion of the markets for services that allow modern families to outsource a number of household and child related activities have drastically lowered the returns to household specialization. Increased female wages, higher returns to education and, in the case of Sweden, the introduction of individual taxation, high marginal tax rates and substantial child care subsidies, have further decreased the returns to traditional household specialization. It may be the case that if the family used to be a production unit with specialized tasks, the modern family has developed into a partnership, where the returns are potentially high for equal and similar partners to engage in multi-skilling and multi-tasking and where utility is derived both from joint consumption and the fruits of teamwork. A consequence would be more equal spousal contributions to family earnings and increased positive assortative mating.

A pattern of increased educational assortative mating was indeed documented in the US in the seminal paper by Mare (1991). Moreover, the trend is found to mainly be driven by the university educated marrying each other – see Schwartz and Mare (2005) for updated references. However, Liu and Lu (2006) find evidence that this trend was reversed in the 1980’s. There is surprisingly little research on Swedish data. Henz and Jonsson (2004) find decreasing assortative mating in Sweden when comparing cohorts born be-
tween 1919 and 1935 with those born between 1955 and 1973, accounting for changes in the education structure of men and women. Sweden experienced a significant expansion of higher education during the second half of the 20th century. The expansion was more rapid among women than among men (Björklund et al, 2010), causing women to face an increasing relative scarcity of educated spouses.

The developments of the Swedish labor market have been subject to more study and some important facts relevant to this paper have been uncovered. Importantly, the labor force participation of Swedish mothers increased rapidly from below 40% to around 80% from the early 1960’s to the early 1980’s (Gustafsson and Jacobsson, 1985) when the oldest cohorts studied in this paper were in their mid-thirties. Since then, changes in participation rates have slowed down. In addition, the closing of the Swedish gender wage gap stagnated already in the early 1980’s (Edin and Richardson, 2002) and Albrecht et al (2003) argue that a glass-ceiling emerged for women on the Swedish labor market in the 1990’s. We believe that uncovering the changes in family formation patterns and fertility choices can shed some useful light on the developments of gender differences in the Swedish labor market.

There are several reasons to believe that the incentives for fertility and career decisions facing Swedish men and women have changed between the cohorts born in the mid 1940’s and those born in the 1960’s. While the individual taxation of spouses introduced in 1971 created an incentive for reduced household specialization, major cuts in marginal tax rates following the 1991 tax reform potentially had an effect in the opposite direction. Family policy, such as the introduction of parental leave in 1974 and successive extensions during the 1980’s and 1990’s and the introduction of quotas for fathers and the expansion of child care coverage from some 20 percent of the 3-6 year olds in the mid 1970’s to around 60 percent in the mid 1990’s are also important for family and career choices.

Björklund (2006) and Andersson et al (2009) document that the over-

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2 Figure 17 in the Appendix shows the raw gender wage gap between 1992 and 2007.
3 Various Swedish reforms are discussed in e.g. Selin (2009), Björklund (2006), Mörk et al (2008) and Edlund and Machado (2009).
all cohort fertility of Swedish women was rather stable around replacement throughout the period of rapid expansion of female labor force participation. Björklund argues that family policy has played an important role in allowing women to combine family and work, and hence to maintained fertility levels. Moreover, this stability over time is present also when considering the fertility of women with different levels of education, although the last cohorts studied suggested a slight fanning out of the distribution of fertility such that fertility increased among lower skilled women and decreased among the highly educated. Such a development could suggest that highly educated women are forced to trade off career and family and that this trade off favored an increased career orientation at the cost of fertility. However, much less is known about the fertility patterns of men, but while there appears to be an inverse relation between education and fertility for women, the reverse is true for men (Statistics Sweden, 2002).

Our contribution is to uncover long-run trends in assortative mating, completed fertility and mid-career earnings in a uniform framework for the universe of Swedish men and women born 1945-1962. Several important patterns emerge in the data. First, it is evident that for the cohorts studied, there was a slowdown in the education expansion, in particular for men. While women continued to get more education, men did not. Furthermore, there is a rising trend in childlessness for men at all educational levels. For women, there is instead a pattern of convergence; the gap in childlessness between women with low and high education has narrowed. As a result, the relative supply of educated men participating in the family market has declined over time.

These changes have come in parallel to altered family formation patterns of Swedish men and women. We find that the increase in the age at first parenthood has taken place in a similar way within all educational groups for men. For women, however, the increase is less pronounced for university non-professionals than for less educated women, which is somewhat at odds with the idea of a rising delay premium for the high skilled (Buckles, 2008). Furthermore, counter to the idea that spouses should have become more similar over time, we find an increase in the spousal age gap in all educational
groups. Using population wide register data, we can also confirm the overall decline in educational assortative mating found in Swedish survey data in Henz and Jonson (2004).

We replicate the pattern found in Björklund (2006) showing a negative association between educational level and average fertility for women. Although we find that fertility rises with education for men, the relation between average fertility and education is weaker than for women.

Over the cohorts studied, the mid-career earnings have grown rapidly for professional men born after 1950, causing a fanning out of the earnings distribution. The gender earnings gap for professionals actually grew wider, stabilizing around 70 percent for the cohorts born after 1950. For the other educational categories, the earnings gap instead closed, stabilizing at around 72 percent. We find that the association between mid-career earnings and fertility is stronger for men than for women. The mid-career earnings of childless men are significantly lower than the earnings of fathers for all education categories. Also among non-professional women do childless women earn less than mothers. An interesting contrast to the idea of a child wage penalty for high skilled women is that childless professional women never show up at the top of the female mid-career earnings league, and in the most recent cohorts, they earn the least also among professional women.

In spite of changes in mating patterns, fertility and earnings, when we explore the change in the contribution of women to joint spousal earnings, a notable stability emerges. The spousal mid-career earnings-gap has remained stable over the period regardless of education and spouse’s education. Hence, it would appear as if little had changed over time at the household level. However, when we investigate the changes in the association of mid-career earnings and completed fertility, it is clear that there is a positive association for men, which has grown stronger over time. For less educated women, there is on average a negative association between the number of children and mid-career earnings. This trade-off has remained stable. However, over time, the association between motherhood per se and mid-career earnings has turned positive for this group. The latter is true also for university non-

\[^4\text{Non-professionals = non-university educated + university non-professionals.}\]
professionals, for whom the negative trade-off between the number of children and mid-career earnings has disappeared over time. Interestingly, for professional women, we find no significant positive or negative association between mid-career earnings and fertility.

After describing our data sources and definitions, we proceed, in section 3, to describe the changes in the supply of men and women with different levels of education and show that the 1945-1962 cohorts experienced a relative slowdown in the expansion of higher education, in particular for men. We move on to document a rising fraction of childless men in all education categories and a convergence in childlessness for women. We also document an overall downward trend in assortative mating. Next, in Section 4, we explore the developments of fertility and how it varies by own education and spouse’s education. Section 5 focuses on changes in mid-career earnings and shows how the association between mid-career earnings and completed fertility has changed for men and women depending on the educational level. Section 6 concludes the paper.

4.2 Data and definitions

We use population wide register data from Statistics Sweden. Linking vital statistics from the multi-generation register and population wide labor market statistics from LOUISE for the years 1990-2007, we can construct a dataset containing complete fertility measures, education, mid-career (age 45) earnings and spouse characteristics for the population of Swedish men and women born between 1945 and 1962.

There are several reasons for measuring characteristics in mid-career. First we want to measure completed fertility. At the age of 45, for women and for a vast majority of men, fertility is complete.\(^5\) We measure fertility by counting the individual’s total number of live biological (or adopted) children.

\(^5\)In Figure 18 in the Appendix, we plot the ratio of male fertility measured at the age of 45 to male fertility measured as late in life as possible, i.e. in 2007, for the analyzed cohorts. It is clear that male fertility is completed in the early fifties and that, for men, only some 2.5 percent of all children are born after age 45. In addition, this fraction has been stable over time.
born by the time the individual is 45.\footnote{We have verified that the patterns in the data do not change if we account for male fertility at older age for the cohorts where this is possible.}

Second, a measure of earnings at mid-career is arguably a reasonable measure of the quality of an individual’s career.\footnote{Böhlmark and Lindquist (2006) argue that the life-time earnings of Swedish men can be reasonably captured in the mid-thirties, while women’s earnings at a higher age are more representative of life time earnings.} Moreover, it has been argued that the intertemporal earnings variability is small in the mid-forties (Baker and Solon, 2003). We measure annual earnings from employment and self-employment at the age of 45. The resulting dataset includes rich labor market data, such as annual earnings, complete fertility histories, and educational attainment for all individuals and their spouses. Detailed definitions of all variables and sources are presented in Table 3 in the Appendix.

We define educational level based on the highest degree attained at the age of 45 according to the education register. In order to avoid misclassifications due to a major revision of the education classification system in the year 2000, we use the education register from 2001 to classify education for all cohorts born 1945-1950. Hence, for these cohorts education is measured when they are older than 45. This poses little problem since very few individuals pursue education beyond the age of 45. Measuring educational attainment and degrees late in life, rather than at the time of first parenthood, is consistent with Björklund (2006). This gives a correct account of the number of children of 45-year olds by educational level, but calls for caution in making causal interpretations of the effect of education on children or the other way around.

We define three educational levels, non-university educated, university graduates and professionals. We strive to have a comparable set of degrees over time and we have chosen a restrictive definition of university educated. As university educated we define those having completed at least a three-year bachelor’s degree, i.e. with at least 15 years of education. Individuals with less than a university degree are defined as non-university educated. Within the group of university educated, we define the sub-group holding professional degrees. These are degrees that traditionally have been the most conducive
to lucrative and prestigious careers. We have singled out four specific professional degrees; business administration, law, medicine and engineering.

Because this classification is sensitive to changes in the education distribution, we also use an alternative education classification based on the individuals' position in the gender and cohort specific percentile distribution of years of education. We do this to explore the extent to which the patterns found are driven by changes in selection or behavior and report the results of the alternative measure when they contribute to the understanding of the patterns found.

We characterize how fertility and earnings relate to own education, but we are also interested in the importance of spousal characteristics and how family formation has changed over time. Hence, we need to identify the individual's spouse. In the assortative mating literature, it is common to take marriage as the indicator of whether two people have formed a family or not (Mare, 1991). As argued in Henz and Jonsson (2004), cohabitation is an important phenomenon in Sweden and the marriage rates are relatively low. Importantly, a high fraction of firstborns are born out of wedlock. Yet a high fraction of children live with both their parents. Our approach is to identify an individual's spouse as the other parent of the individual's first born. Although a non-negligible fraction have a new spouse by the time they are 45, the other parent of the individual's first child is likely to be influential in shaping the conditions for both family and career choices. Swedish register data allow us to identify cohabiting couples only when they have common children. Our definition of spouse, based on parenthood rather than marriage or cohabitation, unfortunately precludes an analysis of the influence of spouse characteristics on the extensive fertility margin and on the earnings of those couples that do not have children. In this paper, the analysis of the extensive fertility margin is thus only based on individual characteristics.

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8 As a robustness check, the analysis is also carried out using the individual's current spouse. The results are insensitive to the definition of spouse.
4.3 Supply of educated spouses and assortative mating

In this section, we study the evolution of the family market, i.e., the market for mates or spouses. In particular, we examine how the expansion of higher education has increased the supply of university-educated spouses. We also consider how the supply of spouses has been affected by changes in the degree to which men and women participate in the family market, i.e., the extensive fertility margin, by studying the evolution of childlessness in the different educational groups.

4.3.1 Education

It is well documented that higher education has expanded dramatically in Sweden over the last 50 years (Björklund et al, 2010). The first major expansion took place in the 1960’s and 1970’s when the university system was reformed. The second major expansion took place during the 1990’s. Some reforms have aimed at increasing the enrollment within traditional educational fields; other reforms have integrated training programs for professions, such as nurses, police officers and elementary and pre-school teachers into the university system.

Figure 4.1 shows the percentage of men and women, respectively, with a university degree, equivalent to at least three years of university studies, for the cohorts that constitute the focus of this paper. Within the group of university educated we also study professionals. Overall, the figure shows that the period we study is one of rather slow education expansion. In the early cohorts, the fraction of university educated is similar for men and women, but throughout the cohorts studied, women become increasingly more educated than men. The divergence starts already for the cohorts born in the mid 1940’s, with a slow but steady increase in the share of professionals. The increase in the share of female university graduates levels off somewhat during the first half of the 1950’s, due to a slight fall in the share of university non-professionals. It is interesting to note that while women born in the 1950’s
4.3. SUPPLY OF EDUCATED SPOUSES AND ASSORTATIVE MATING

Figure 4.1: The expansion of higher education

![Graph showing the expansion of higher education for men and women from 1945 to 1960.

continued to get more educated, the fraction of university-educated men remained rather stable. Similar to the pattern for women, the share of men with a professional degree increased steadily over the period. However, this increase is totally offset by the decline in the share with a non-professional university degree, leaving the total rather stable.

4.3.2 Childlessness – rise and convergence

In order to understand how the supply of men and women at different educational levels influences family formation patterns, we need to recognize that not all men and women participate in the family market and have children. Figure 4.2 shows the fraction of childless individuals by gender and cohort for our education categories.

An interesting pattern emerges where it is clear that the fraction of men that do not have children, and hence stay out of the family market, has risen over time in all educational categories. For the least educated in the 1962-cohort, well over one in five men never have children as compared to
around 18 percent in the 1945 cohort. In accordance with Statistics Sweden (2002), childlessness is less frequent among professional men and the time trend is similar across the education spectrum. This pattern is also found for Norwegian men born 1940-1964 (Kravdal and Rinfuss, 2008).

Women show a quite different pattern. Overall, fewer women than men are childless, but interestingly the differences between educational groups have declined over time. There is a downward trend in childlessness among professionals, who are still more likely to be childless compared to those who are less educated. Consistent with Anderson et al (2009), we also find an upward trend in childlessness among the non-university educated. Thus, the overall pattern for women is one of convergence in childlessness between the educational categories studied here.

However, as shown in Figure 4.1, the education distribution has changed over time. In particular, the fraction of professional women has grown. Thus, it is interesting to understand to what extent the decline in childlessness for this group is driven by changes in behavior or by the changing selection of
women choosing a professional career. Figure A.4 in the Appendix shows the development of childlessness when we instead categorize individuals according to their position in the education distribution. The share of childless women among the top five percent in the education distribution of women does not decline over time, suggesting that the pattern found for professionals could be due to selection changes.

### 4.3.3 Assortative mating and family formation patterns

Rising education for women and stagnation for men at the same time as childlessness declines among female professionals while fewer men in all educational groups participate in the family market, voluntarily or not, has implications for family formation patterns. One consequence is that the supply of educated men falls relative to the supply of educated women.

We first explore how the general pattern of educational assortative mating has changed over time. Measuring changes in assortative mating is complicated for several reasons. Education distributions are discrete and have changed in different ways for men and women over time. Moreover, using years of education as a cardinal measure is questionable. Therefore, we take two different approaches. First, we have computed the correlation in the percentile rank position in the distribution of years of education for individual \( i \) in cohort \( t \) with \( i \)'s spouse's percentile rank in the distribution of years of education of the spouse’s cohort and gender (where the spouse is the other parent of person \( i \)'s first child) for each cohort, separately for men and women. We also compute the corresponding correlation for the subsamples of men and women that constitute the top quartile of the education distribution of their respective cohorts. Note that the spouses can be older or younger. The results are presented in Figure 4.3.\(^9\)

First, the solid lines (showing the cohort-specific correlation coefficient of own education with spouse’s education for all men and women) depict downward trends. Over time, spouses’ education has become less or strongly correlated. This is consistent with the findings in Henz and Jonsson (2004)

\(^9\)The trends in assortative mating are very similar if we instead estimate the correlation in years of education or compute Kendall’s rank correlation coefficient.
and while different from the early US findings (Mare, 1991) it is also consistent with Liu and Lu (2006) for the US after 1980. Interestingly, the downward trend in assortative mating is present also at the top of the education distribution. The revealed pattern is thus at odds with the hypothesis of increasing assortative mating driven by consumption complementarities and reduced returns to intra-household specialization at higher educational levels.

Our second approach is to explore changes in how different educational groups are matched over time. In Table 4.1, we present the distribution of spousal matches by own and spouse’s education category at the beginning and end of the time period studied, i.e. for cohorts 1945-1946 (top panel) and 1961-1962 (bottom panel) for women (left-hand panel) and men (right-hand panel). The table reveals a clear over-representation of matches on the main diagonal. Consistent with the previous analysis of assortative mating, this over-representation has not grown any stronger over time.

As an example, 84.53 percent of women’s spouses do not have a univer-
Table 4.1: The distribution of matches by own and spouse’s education

<table>
<thead>
<tr>
<th>Cohorts born</th>
<th>Own education</th>
<th>Women Education of spouse</th>
<th>Men Education of spouse</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No university</td>
<td>University</td>
</tr>
<tr>
<td></td>
<td></td>
<td>non professional</td>
<td></td>
</tr>
<tr>
<td>1945-1946</td>
<td>No university</td>
<td>79153</td>
<td>4960</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>91.56</td>
<td>5.74</td>
</tr>
<tr>
<td></td>
<td>University np</td>
<td>7705</td>
<td>5167</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>49.99</td>
<td>33.52</td>
</tr>
<tr>
<td></td>
<td>Professionals</td>
<td>459</td>
<td>381</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>32.1</td>
<td>26.64</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>87317</td>
<td>10508</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>84.53</td>
<td>10.17</td>
</tr>
<tr>
<td>1961-1962</td>
<td>No university</td>
<td>6777</td>
<td>4306</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>90.16</td>
<td>5.73</td>
</tr>
<tr>
<td></td>
<td>University np</td>
<td>10221</td>
<td>3503</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>64.53</td>
<td>22.12</td>
</tr>
<tr>
<td></td>
<td>Professionals</td>
<td>1601</td>
<td>660</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>40.64</td>
<td>16.76</td>
</tr>
<tr>
<td></td>
<td>All</td>
<td>79592</td>
<td>8469</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>83.83</td>
<td>8.92</td>
</tr>
</tbody>
</table>
sity degree, yet a higher share, 91.56 percent, of the non-university educated women born 1945-1946 have a non-university educated spouse. Only 32 percent of the professional women in the early cohorts had a non-university educated spouse. Instead, 41.26 percent had a professional spouse although they constitute only 5.29 percent of all spouses in the early cohorts. In the later cohorts, the patterns are very similar, but while the share of professional spouses available to women has increased to 7.25, there was only a marginal increase in the fraction of professional women with a professional spouse.

In Table 4.2, we summarize the pattern in Table 4.1 by computing the change in the odds ratio over time, i.e. in the case of professional women with a professional spouse, the odds ratio was 7.8 (41.26/5.29) in 1944-1945 and 5.9 (42.6/7.25) in 1961-1962, which implies that the odds ratio has declined over time. Comparing the recent cohorts to the earliest cohorts analyzed, the relative ratio declined to 0.8 (5.9/7.8). The emerging pattern again suggests that there has been decreased assortative mating over time, in particular among the highly educated where the main diagonal elements are well below 1. Although we find that educational assortative mating has declined over time, it is still possible that societal changes promoting less household spe-
specialization lead to increased assortative mating on other dimensions. Figure 4.4 shows the spousal age gap (male age – female age) for the cohorts in our sample. Note that the age gap for all educational groups grows until the cohorts born in the mid 1950’s. After that, the age gap flattens out for both women and men overall. Only for non-university educated men and for professional women is there a reversal of the trend. Hence, over time, spouses become more different both in terms of education and in terms of age.

The difference in levels when considering men and women is puzzling at first. It cannot be reconciled by comparing the patterns for men and women adjusting for an age lag corresponding to the size of the age gap. However, an explanation can be found in gender differences in the probability of forming new families and their different behaviors when finding a new spouse. First, over the time period studied, there is an increase in the share of men and women that also have children with a new spouse.¹⁰ For men, their new

¹⁰ The increase is about 4 percentage points both for men and women, starting at 36% for men born in 1945 to 40.4%
spouse is more often a first time parent, than for women. Second, when men form a new union, on average they do so with a younger woman than their first spouse. The new union is thus more unequal in terms of age. This is not true for women. While a new union is, on average, also with a younger spouse than the former, in the case of women, this means that the age difference becomes smaller.\footnote{For men, the average age difference increases from 2.97 years in the first match to 4.85 years in the new match. For women, the age gap instead decreases from 2.63 years to only 1.42 years in the new match.} Figure 4.4 includes spouses with children in a previous union. In Figure A.5 in the Appendix, we have restricted the sample to only include unions where both spouses had their first child. The rising trend in the age gap persists, but it is no longer the case that the age gap is larger for first time mothers, compared to first time fathers.

### 4.4 Trends in parenthood and fertility

The increase in average age at first parenthood is well documented. Moreover, it is well known that highly educated women delay fertility. It is often hypothesized that these trends may contribute to rising levels of childlessness and lower completed fertility.

Anderson et al (2009) show that the age at which 50% of a cohort of Swedish women have become mothers has risen across educational groups over time, suggesting that the increase in age at first child is not necessarily only a consequence of a rising trend in education. In Figure 4.5, we explore the trends in age at first child for Swedish men and women. Professional women have their first child about four and a half years later than women without a university education. For men the difference is somewhat smaller, just less than four years later.

In line with the findings in Dribe and Stanfors (2009), the age at first child has increased for both men and women. Comparing the first and last cohort, men and women on average now have their first child about two years later. However, what is interesting to note is that while parenthood is further delayed for both men and women over time, we also find, in line with...
with Statistics Sweden (2002), that the magnitudes are similar for all educational groups studied here. This pattern is somewhat at odds with the idea that rising returns to experience and increasing skill premia should have lead to particularly large increases in the premia for delaying child birth for the highly educated.\footnote{Buckles (2008) shows, for the US, that the returns from delaying childbearing is higher for high-skilled women.} The pattern found here suggests that, overall, the premium for delayed child birth has increased independently of education for both men and women.

As documented by e.g. Björklund (2006) and Andersson et al (2009), the cohort fertility of Swedish women has been rather stable throughout the period of rapid expansion of female labor force participation. Less is known about the trends in fertility of Swedish men.\footnote{One exception is Dribe and Stanfors (2009). They study the determinants of entering into parenthood for Swedish men and women for the cohorts born 1949, 1959 and 1964.} Figure 4.6 shows the fertility trends among Swedish men and women, plotting average completed fertility (at the age of 45) by cohort and education. Some things are worth
pointing out. Men with a professional degree do, on average, have more children than other men. For women, on the other hand, the least educated have the most children (around two) and those with a professional degree have the fewest. For all educational groups, female fertility, as previously documented, is rather stable.

Figure 4.7 instead shows the development of fertility on the intensive margin. Recall that in Figure 4.2, we showed that childlessness, i.e. the extensive fertility margin, has risen over time for men and that there has been a convergence for women. Interestingly, male fertility does not depend strongly on education, once differences in childlessness have been accounted for. For women, however, the converging pattern on the extensive margin and the stability of educational gradients in total average fertility are reconciled once the diverging pattern on the intensive margin has been taken into account. Over time, the negative education gradient has grown on the intensive fertility margin. For the cohorts studied, mothers with a professional degree on average have had around 2.1 children throughout the time period. Mothers without a university degree have increased their number of children from some 2.2 to 2.4 over the studied cohorts.

4.4.1 The fertility distribution

The studied fertility trends have implications for changes in the distribution of fertility. An interesting conclusion that can be drawn on the basis of the analysis of childlessness is that fatherhood has become more unequally distributed within educational groups over time due to increased childlessness. Motherhood has become more evenly distributed among professional women, and more unequally distributed for women with less than university. In order to further understand the changing fertility distributions, we take a closer look at parity in Figure 4.8, i.e. we explore how the fractions of men and women who are childless, have a single child, two children, three or four or more have evolved.

For both men and women, the two children norm is rather strong. Around 40% of university non-professionals have two children and the fraction is in-
Figure 4.6: Total average fertility of men and women

Figure 4.7: Fertility by educational group, intensive margin only
creasing over time. After 1955, having three or four (or more) children becomes less common in favor of instead having two children. Also in this figure the rising share of childless men is present. Turning to professionals, the pattern is similar. However, the increase in the share of professional women with two children is even stronger than for university non-professionals, reaching almost 50% for the most recent cohorts. It is also interesting to note that as the fraction of professional women with two children increases, the fractions at all other family sizes decline.

Women without university education display a different development. The two-child norm weakens over time and fewer have a single child. In this group, however, the fraction of childless women is rising, but so do the fractions of women having three children, and four or more children. In this group of women, there is hence an increasing tendency of choosing to have a large family or no family at all, a behavior that has often been associated with highly educated women. It appears that these women increasingly face a trade-off between work and family. One can speculate as to why. The jobs of these women are likely to be low paying with low flexibility of working hours and it is possible that they have become increasingly so.

Next we consider how average fertility has evolved for the different educational groups when we take into account the education of the spouse. Figure 4.9 displays the development of fertility by educational group and education of the spouse. Note that this implies that we study the intensive margin, i.e. average fertility conditional on having children. The two top panels show the trends for non-university educated men and women. For men, average fertility has a somewhat upward trend at the beginning of the

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14Studies of fertility by education in a couple perspective are rare. For Sweden, two exceptions are Dribe and Stanfors (2010) and Stanfors (2009). Both papers study the fertility of couples with at least one child when controlling for a number of variables including civil status and age for the period 1991-2005. Dribe and Stanfors (2010) find that power-couples are more likely to have two or more children, where power couples are identified by level and field of education and sector of employment. Stanfors (2009) finds that among females with a law or medical degree or with a PhD, the relative chance of having more than one child increases with the partner’s educational status. Another study on Swedish data is Andersson and Duvander (2003). They find that higher income of both men and women increases the propensity to have a second child. Fertility in a couple perspective with German data is studied in Bauer and Jacob (2009).
Figure 4.8: Parity by educational group
sample but it falls from the 1955 cohort and onwards regardless of the education of the spouse. For non-university educated women the decline starts later, except for those with a non-university educated spouse, their fertility continues to rise further and then levels off.

We consider the trends for university non-professionals in the middle panel. It is interesting to note than non-professionals matched with a similar spouse get fewer and fewer children throughout the cohorts we are studying; the decline is about -0.25 children comparing the first and last cohorts. On the other hand, university educated non-professional men with a professional spouse increased their average fertility at the beginning of the sample, but from the cohorts born in the early 1950’s and onward, the trend has been reversed. A possible explanation is that this coincides with women putting more weight on career and thus opting for fewer children.

The bottom two panels display the trends for university-educated professionals. For professional men, the fertility is decreasing regardless of their spouses’ education. However, it is interesting to note that while there was quite a large fertility difference between those with a professional spouse and those with a non-university spouse at the beginning of the sample period, fertility has converged and at the end of the sample, the gap has been completely closed. The trends for professional women confirm this pattern. Those with a university-educated spouse display stable fertility through the mid 1950’s cohorts and after that fertility has declined. Professional women with a non-university educated spouse on average have fewer children than those with a professional or non-professional university educated spouse. Their fertility has been rather stable throughout the cohorts studied. Overall, the emerging pattern shows that the importance of spousal education for fertility decreases with education for men, while the reverse is true for women.
Figure 4.9: Fertility by educational group and education of the spouse
4.5 Labor market outcomes and the family-career trade-off

In this section, we explore how the labor market outcomes of men and women with different educations relate to their spouse’s education, and to their spouse’s earnings as well as to their number of children. By measuring earnings at the age of 45, well beyond the child bearing years, we focus on the association between children and the success of one’s career rather than on short-term trade-offs. We explore the extent to which there is a trade-off between family and career and how this has evolved over time.

4.5.1 Trends in mid-career earnings for different educational groups

We start by studying the evolution of mid-career earnings across cohorts – adjusted for changes in CPI. As expected, women on average earn much less than men over the entire period as shown in Figure 4.10. Female professionals have experienced a considerable increase in earnings across cohorts, but the corresponding development for men has been even stronger. In 2007, female 45-year-old professionals earn as much as male professionals at 45 years of age earned back in 1990. The deep recession of the early 1990’s is likely to be part of the explanation for the stagnating and falling real earnings for the 1945-1950 cohorts. The recovery of the economy and skill biased technical change are likely to be the reasons for the rapid growth of professional earnings from the cohorts born in the early and mid 1950’s and onwards.

Figure 4.11 shows the development of the gender earnings gap by educational group. The figure displays female average annual earnings as a fraction of male average annual earnings. Note that we consider the average annual earnings of all men and women, including those that do not have any earnings and including individuals working part time. While the ratio of female to male wages has been stable at around 80 percent during the time period studied here (1990-2007), the ratio of female to male earnings at 45 shows
Figure 4.10: Annual earnings at 45, by education and gender (SEK thousand)

![Graph showing annual earnings at 45 by education and gender](image)

4.5. LABOR MARKET OUTCOMES

For non-university educated and university non-professionals, female earnings caught up with male earnings for the cohorts born in the late 1940's and leveled off at around 0.72. The relative earnings of female professionals show the reverse development and actually declined for the early cohorts and then leveled off at a lower level than for the less educated groups, all changes being statistically significant. This development is consistent with the emergence of a glass ceiling (Albrecht et al, 2003).

4.5.2 The earnings of singles and by spouse’s education

To what extent do mid-career earnings differ between those who do not have children and by the education of the spouse for those who do?\textsuperscript{16} In Figure

\textsuperscript{15}See Figure A.2 in the Appendix which shows the ratio of female to male wages for the entire economy for the years 1992-2007.

\textsuperscript{16}There are few studies on earnings as a function of the characteristics of the spouse. One exception is Aström (2009). She studies Swedish married couples in the late 1990’s and finds a positive spousal education gradient in earnings for all men and for university educated women.
Figure 4.11: Gender earnings gap, by education
4.5. LABOR MARKET OUTCOMES

4.12, the average mid-career earnings are plotted by own education for those who do not have children, i.e. singles, and by spouse’s education for those who have children. A first striking observation is that single men have the lowest mid-career earnings, regardless of education category. With the exception of professionals, this is also true for women.

When we consider that university, and in particular, professional degrees to a higher extent lead to more career oriented occupations, Figure 4.12 shows interesting evidence of a presence of returns to household specialization for both men and women. For men, both university non-professionals and professionals on average have higher earnings when matched to a university non-professional spouse compared to when they have a spouse with a professional degree. For women, this is the case only for professionals.

Another observation from Figure 4.12 is the extent of earnings compression for women relative to men. For women, the difference between the highest and lowest paid group is less than SEK 100,000. For men, the difference ranges between SEK 150,000 (non-professionals) and SEK 300,000 (professionals).

We also see the increasing returns to education, primarily for men. Mid-life earnings grow faster across cohorts for those with a university degree than for those without. Men with children (i.e. with a spouse) have a particularly strong earnings growth. For women, the effect of the spouse’s education is less pronounced.

4.5.3 Changes in household specialization?

In Figure 4.12, we saw that highly educated men and women matched to university non-professionals had higher earnings. In this section, we consider what has happened to the spouses’ contributions to their joint spousal earnings. As women have become relatively more educated also compared to their spouses over time, one can expect that within a couple, the spousal earnings gap (male-female) has decreased.\footnote{While there exist several cross-countries studies of the female share of family income (see e.g. Harkness, 2010, and Cancian and Schoeni, 1998) and studies with Swedish data on trends in spousal earnings correlations (see eg Henz and Sundström, 2001) as well as...} Figure 4.13 plots the development...
Figure 4.12: Annual earnings, by cohort and spouses education (SEK thousand)
over time of the women’s share of spousal earnings at mid-career. When we consider the households of men born between 1945 and 1962, their spouses’ contribution ranges between slightly over 40 percent for non-university educated men to somewhat above 30 percent for professional men throughout the sample period. Note that the spouses can be younger (or older) and can also have a different educational level.

If we consider the households of women in the studied cohorts, the non-university educated women contribute somewhat over 40 percent of the joint spousal earnings at mid-career. Professional women contribute almost 50 percent. However, the contributions are remarkably stable over time. We showed earlier that the spousal age gap has increased over the period. Hence, women’s earnings are compared to the earnings of an increasingly older spouse. We have verified that the pattern remains as flat when we account for the changing age gap. Neither is there an overall trend if all educational groups are analyzed together.

In Figure 4.14, we further explore the female share of total spousal earnings for our different educational groups by spousal education. In line with the results in Figure 4.13, remarkably little has happened even within match types. We have also explored whether there are trends in the female share of total spousal earnings by the number of children, using education categories based on percentile ranks in the education distribution and when using current spouse instead of the other parent of one’s children. The absence of a trend is robust to all these alternatives. It is tempting to put forth the idea of a societal norm regarding how spouses with different educations should contribute to household earnings.

4.5.4 Trading-off or having it all?

To further explore how the family-career trade off has changed over time, we run regressions estimating how the association between children and earnings studies on the impact of wives’ earnings on inequalities in earnings in households (see e.g. Björklund, 1992), we are not aware of any other studies on Swedish data on trends in the female share of family income. For Norway, Mastekaasa and Birkelund (2011) report that the wives’ share of household earnings increased from 17% to 36% between 1974 and 2004. These results are available upon request.
Figure 4.13: Female contribution to total spousal earnings

has changed over time. We estimate regressions of the following form:

\[ Y_{it}^{45} = \alpha + \sum_{t=1945}^{1962} \beta_t \times \text{children}_{it}^{45} + \text{cohort}_t + \varepsilon_{it} \quad (4.1) \]

where \( Y_{it}^{45} \) is annual earnings at the age of 45 of individual \( i \) in cohort \( t \), and \( \text{children}_{it}^{45} \) is a) the number of children at the age of 45 and b) an indicator variable taking the value of 1 if the individual has any children at the age of 45 and 0 otherwise of individual \( i \) of cohort \( t \). We also include cohort-fixed effects.\(^{19}\) We estimate cohort-specific coefficients on fertility, i.e. the \( \beta_t \) for cohorts born 1945 through 1962. The regression is estimated separately for men and women and the three educational groups, non-university educated, university non-professionals and professionals. Since \( \beta_t \) is allowed to vary over time, it will capture how the strength of the association between mid-career earnings and completed fertility has varied over time. It needs to

\(^{19}\)The qualitative results remain unchanged when controlling for education and spouse’s education.
Figure 4.14: Female contribution to total spousal earnings by educational group and spouse’s education
be stressed that the relationship is not causal – earnings and fertility at 45 are outcomes of a joint decision. The results are presented in Figure 4.15, where the $\beta_t$'s are plotted with a standard 95% confidence interval. Panel a) displays the results when the number of children is included linearly. Panel b) displays the results when earnings are regressed on a dummy variable for having children or not, i.e. the extensive fertility margin.

The results in panel a) show that women without university education face a clear trade-off between mid-career earnings and fertility throughout the time period (all $\beta_t$'s are negative). For university non-professional women, it is noteworthy that the initial negative association between earnings and children decreases over time and even turns positive for the last cohorts, although it is not statistically significant. For professional women, the coefficients are imprecisely estimated and show no clear association between earnings and the number of children. For men in all educational groups, fertility is positively associated with earnings, and increasingly so. For professional men, the coefficient triples in magnitude over the time period. Compared to average earnings (in Figure 4.10) the coefficients correspond to 5 percent of annual earnings for the early cohorts and 10 percent for the last cohorts.

Panel b) instead shows the association between earnings and being a parent. For men, there is an increasingly positive association between fatherhood and earnings. It appears as if men are increasingly facing an all or nothing situation with a strong complementarity between earnings and children. When considering women, while we saw a trade-off between the number of children and earnings for the early cohorts except professional women, there is no trade-off between earnings and motherhood per se. Moreover, there is an upward trend in the association and for the late cohorts, there is actually a statistically significant positive association between mid-career earnings and motherhood. For these groups, which constitute the vast majority of women, the association now resembles that of men and they can now have it all. The development for professional women deviates in that there is no upward trend in the association between family and career. Instead, for this group the relation displays a high variability over time, and it is not obvious that these women face a trade-off at all.
Figure 4.15: Changes over time in the association between mid-career earnings and fertility

(a) Total number of children

(b) Total number of children

Note: Y-axis scale in SEK thousand
4.6 Conclusions

We have explored the trends in the family-career trade-off facing Swedish men and women born between 1945 and 1962 and their spouses. Several important patterns emerge. First, we find a rising trend in childlessness for men at all educational levels. For women, there is instead a pattern of convergence such that the gap in childlessness between women with low and high education has narrowed. Together with rising education for women, this implies that the relative supply of educated men participating in the family market has declined over time.

These changes have appeared parallel to other altered family formation patterns of Swedish men and women. We find that the increase in the age at first child is similar across educational groups. Furthermore, counter to the idea that spouses should have become more similar over time, we find an increase in the spousal age gap in all educational groups and an overall decline in educational assortative mating. Yet, these developments can be reconciled with increased assortative mating on some underlying productivity dimension and with the hypothesis of reduced returns to household specialization. Increased residual variation in earnings making education a worse predictor of future earnings capacity could make young individuals, in particular women, more inclined to wait until the earnings capacity is revealed.

We document a negative association between educational level and average fertility for women. Although we find that fertility rises with education for men, this relation between average fertility and education is not very strong. The data show that the gender earnings gap for professionals actually grew wider, stabilizing at around 70 percent for the cohorts born after 1950. For the other educational categories, the earnings gap instead closed, stabilizing at around 72 percent. In spite of changes in mating patterns and fertility, we find that women’s contribution to spousal earnings has remained stable regardless of education and the spouse's education. It would appear as if little had changed over time. However, when we investigate the changes in the association of mid-career earnings and completed fertility, it is clear that this association, which has always been positive, has grown stronger for
4.6. CONCLUSIONS

men over time. Moreover, we find that the association between mid-career earnings and fertility is stronger for men than for women.

For less educated women, there is on average a negative association between the number of children and mid-career earnings, suggesting that the trade-off facing these women has not changed to any considerable extent during the time period studied. However, over time, the association between motherhood per se and mid-career earnings has turned positive for this group. Increasing childlessness for those with poor earnings is likely to drive the result. The development of a positive association between motherhood and earnings is present also for university non-professionals. For this group, it is also the case that the initial negative trade-off between the number of children and mid-career earnings has disappeared over time. Interestingly, for professional women, we find no significant positive or negative association between mid-career earnings and fertility.

Our starting point was that mid-career earnings and children are the outcomes of the life-choices of men and women. While high productivity on the labor market can generate high earnings, thereby making it possible to afford a large family, it also implies a high opportunity cost for the time it takes to have and raise children. In particular, if a higher opportunity cost for time and a higher income also induce individuals to substitute child quality for quantity, the well-know negative relation between income and the number of children may arise. For men, it seems clear that the income effect dominates. Increasing childlessness and the growing positive association between earnings and fertility suggests that increased earnings inequality goes hand in hand with increased fertility inequality. For women, the pattern is more complex. If anything, we find a reduced earnings inequality (relative to the development of men) and a reduced fertility inequality across educational groups. One reason for this is that professional women appear to have traded-off some of their potential earnings gains for a (larger) family. There is an increased gender earnings gap and a lower fraction of childlessness for professional women, at the same time as the opposite pattern is true for less educated women. While men increasingly either have all or nothing, the life-choices of women have converged.
Bibliography


## Appendix

**Table A.1: Variable definitions and sources**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition and data source</th>
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<tbody>
<tr>
<td>Spouse</td>
<td>Other parent of individual’s first born child. FlerGen</td>
</tr>
<tr>
<td>Earnings at 45</td>
<td>Sum of annual earnings from employment and own business activity. Lonelnk+Fink, 2007 prices. LOUISE.</td>
</tr>
<tr>
<td>Education</td>
<td>Highest education according to education registers HSUN, HSUN2000. LOUISE.</td>
</tr>
<tr>
<td>University Professional</td>
<td>15+ years of education. Law (in 380), Engineering (in 547), Medicine (in 720), Business Administration (in 340) Other fields At most 14 years of education</td>
</tr>
<tr>
<td>University non-professional</td>
<td>HSUN, HSUN2000, (Sun2000in, Sun2000ni) LOUISE.</td>
</tr>
<tr>
<td>Non University</td>
<td></td>
</tr>
<tr>
<td>Children at 45</td>
<td>Number of biological or adopted children at the age of 45. FlerGen</td>
</tr>
</tbody>
</table>
Figure A.1: The proportion of children enrolled in subsidized childcare by age, 1976-2004

Figure A.2: The gender wage gap

Source: National Board of Education

Note: Monthly wage weighted with respect to age, education, hours worked and sector
Fraction women/men
Source: Statistics Sweden
Figure A.3: Ratio of fertility at 45 to fertility measured as late as possible, i.e. in 2007

![Graph showing the ratio of fertility at 45 to fertility measured as late as possible.](image)

Figure A.4: Childlessness across the educational distribution

![Graph showing childlessness across the educational distribution.](image)
Figure A.5: Age gap to spouse, for first unions for both spouses
TRADING OFF OR HAVING IT ALL?
Chapter 5

Solving the Puzzle - Hours Constraints, Technical Change and Female Labor Supply*

5.1 Introduction

“Having control over your schedule is the only way that women who want to have a career and a family can make it work”

Anne-Marie Slaughter, The Atlantic

The theory outlined in this paper extends the standard theory of labor supply to incorporate an important ingredient in the labor supply decision of today’s women: the role of flexibility and time constraints. There has been a rapid development in the possibilities of a more flexible working life. The emergence and increasing use of email, remote access, video conferences etc. has decreased the need for face time in working life and increased the possibility of being productive in other locations than the actual workplace, thus

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allowing individuals that are time constrained to supply more hours of work by shifting hours during the day to make room for necessary commitments at home, for instance by doing some work at night, early mornings, weekends etc from home. Hence, as technology makes jobs more flexible, time constrained individuals can supply more hours of work and may therefore find it attractive to opt for a more demanding career.

To describe and formalize this notion, I set up a life cycle model where labor supply depends on a family constraint (child rearing), minimum hours requirements and variation of flexibility in different jobs. The basic intuition is simple: Having children requires parents to drop off and pick up at day care, provide meals, care, help with homework – in short: parenting. Assuming that these household activities can only be partially outsourced, this implies that parents face a binding time constraint. Not only due to the actual time needed for child rearing, but also reflecting the fact that these activities must be carried out at a certain point in time during the day, which infringes on the hours available for work. Moreover, if more complex jobs have a constraint on the hours of work that need to be supplied for the job to be productive, this will imply that individuals that are family constrained, taking the larger responsibility for child rearing, cannot choose these jobs - or can only choose them with large sacrifices as concerns other activities.

Although the role of flexibility has been discussed in the literature (Goldin and Katz, 2011; Flabbi and Moro, 2012), the focus has been on selection into different occupations. The link to labor supply on the intensive margin (and its consequences for occupational choice) has not been considered so far. I formalize the notion that as technology makes jobs more flexible, time constrained individuals can supply more hours and may therefore find it attractive to opt for a more demanding career. The model thus offers a possible mechanism to explain recent changes in female labor supply, where women today both work more on the intensive margin and to a larger extent take on more demanding jobs.

There has been an increase in female labor supply since the beginning of the 1970’s and today, women participate in the labor market almost to the
same extent as men. In Sweden, female labor force participation increased rapidly from below 40 percent in the 1960’s to over 80 percent already in the 1980’s (Gustafsson and Jacobsson, 1985), but it has leveled off since then. The rise in female labor supply is widely studied in the literature, in particular the extensive margin, where the major shifts have occurred. Several papers have documented that this increase was primarily driven by a surge in the labor supply of married women e.g. (Attanasio et al., 2008; Olivetti, 2006; Goldin and Olivetti, 2013). This is the case also in Sweden where by the mid 1980’s, there was virtually no difference between the participation rates of married and unmarried women (Selin, 2009).

The intensive labor supply margin, which constitutes the main focus of studies of male labor supply, is much less studied for women. With participation now being so high, it arguably becomes important to also study the conditions forming female behavior at the intensive margin. Clearly, men and women to some extent face different conditions, the most obvious being the consequences of having a family, leading to a natural career break for women when the children are newborns, but also affecting women’s working conditions for many years after that. The reason is that there is a time constraint associated with having a family. This family constraint consists of two parts. First, it is the actual time needed for child rearing. The second part is related to timing: some of these activities must be carried out at certain points in time during the day (e.g. picking up from day care) and even if there is no actual activity together with the child, it is still a restriction on being at home.

The family constraint may also affect what types of occupations an individual can choose. In particular, many more complex and career oriented jobs are likely to be associated with a requirement on the minimum hours that need to be supplied for the job to be productive and lead to a successful

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1In 2007, 14 OECD countries had a female labor force participation over 80 percent with the highest participation in the Nordic countries with Sweden at the top at 87.1 percent.
2See figure A.1 in appendix
3See e.g. Heckman and Macurdy (1980); Altonji and Paxson (1988); Imai and Keane (2004); Killingsworth and Heckman (1986) and, recently, Keane (2011) for an overview.
career. This might, for instance, be the case for many management jobs and professional occupations where labor cannot be easily divided. Such jobs will thus be characterized by a tied hours-wage package, i.e. a career constraint on the hours supplied. Altonji and Paxson (1988) study the trade-off between working hours and wages in the labor market where employers place restrictions on the hours required for the job and show that individuals that currently work more than what they find optimal would be willing to forgo some pay in order to adjust their hours. Similarly, individuals who work less than they prefer would be willing to sacrifice wage gains for additional hours. For a family constrained individual, such restrictions on minimum hours could thus mean that it is optimal to choose a job at a lower level than what the individual is qualified for.⁴

Empirically, men work full-time. For women, entering the labor market has arguably created a trade off between family and career.⁵ To meet the family constraint, some women may choose less career oriented occupations and/or part time jobs. The different patterns for female and male labor supply may thus be due to time constraints, rather than differences in preferences.

In Sweden, active policy promotion of gender equality through the introduction of individual taxation, subsidized childcare and generous parental leave schemes has aimed at facilitating the family-career trade off.⁶ In spite

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⁴Relatedly, Albanesi and Olivetti (2009) show that an equilibrium where women have higher home hours and lower earnings can arise even if there are no ex ante gender differences. They employ a principal agent framework, where the cost of effort at work increases with home hours and both home hours and effort are private information and show that it is enough that firms believe that the distribution of home hours differs by gender for a gendered equilibrium to arise. Incentive compatible contracts will generate a self-fulfilling prophecy where women will be offered contracts with lower earnings, effort and performance pay relative to men, which in turn gives them a lower relative opportunity cost of home hours. Women will thus allocate more time for home hours which confirms the beliefs of the firm.

⁵Goldin (2004) studies the career-family choices for five generations of American women during the twentieth century. She describes how the conditions have changed from “family or career” for the cohort that graduated from college at the beginning of the twentieth century, via “job then family”, “family then job”, “career then family”, for the following generations, to “career and family” being the goal of the most recent generation that graduated between 1980 to 1990.

⁶Selin argues that the tax reform in 1971, when individual taxation was introduced,
of these policies, the gender wage gap stagnated already in the 1980's (Edin and Richardson, 2002). Studying US top professionals, Bertrand et al. (2010) show that there is still a sharp career penalty to having a family, finding that male MBA earnings outperform those of women by 60 log points a decade after graduation. They identify differences in career interruptions and weekly hours, both largely associated with motherhood, to be two of the main explanatory factors. For Sweden, Angelov et al. (2013) find that the spousal income and wage gaps increase by 35 and 10 percent fifteen years after the birth of the first child.

Goldin and Katz (2011) explore how flexibility affects occupational sorting. They discuss the flexibility of different occupations in a compensating differentials framework and study how the career costs of having a family vary between different high-end occupations and also across time. If women value flexible work hours more than men, they will disproportionally sort into occupations where this flexibility comes at a lower price.\(^7\) When the firms' cost of providing flexibility decreases and with an influx of women demanding this amenity, more employers will adopt such practices. They provide empirical evidence showing that many high-end professions have experienced an increased workplace flexibility and that some, in particular within the corporate and financial sector, have lagged behind. The contribution of this paper is to analyze how the ability to flexibly shift hours between activities during the day may loosen the career constraint and thereby affect not only occupational choice, but also women's labor supply on the intensive margin in a given occupation.

The remainder of the paper is organized as follows: In the next section, I motivate the paper by looking at patterns for labor supply and occupational choice using micro data for Sweden. Then, in section 5.3, I first present a

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\(^7\) Flabbi and Moro (2012) find that college graduates place a higher value on having flexible jobs compared to high school graduates. They also find that jobs requiring a college education can provide flexibility at a lower cost.

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played a major role in this rapid increase in the labor force participation of married women. The tax reform implied large cuts in marginal taxes. For example, if both spouses worked in an average blue collar job, the marginal tax rate fell from 55 percent to 32.5 percent in 1971 (Sundström, 1991).
simplified version of the model, using a static set up with standard Cobb-Douglas utility. It delivers straightforward analytical solutions and illustrates the mechanism of the model in a transparent way. Labor supply is affected by the flexibility of the job and time constraint associated with the family constraint. This implies that time constrained individuals will choose the career oriented job only if they are willing to deplete leisure, or if the job is flexible enough. Hence, I show that i) as technology allows more flexibility in jobs, it becomes optimal for family constrained individuals to pursue more career oriented occupations, and ii) when pursuing the more demanding career, there is a large reallocation of time, where both leisure and home production decrease and flexible working hours and market hours increase.

Next, in section 5.4, I reformulate the model in a life cycle setting to include two additional important features: First, working life is long and the period when individuals are constrained by having small children is relatively short. Thus, the family constraint does not bind in every period. Second, as shown in e.g. Angelov et al. (2013); Bertrand et al. (2010); Datta Gupta and Smith (2002), there is evidence of penalties associated with taking time off the labor market or working shorter hours. Thus, it is important to take the possible effects of returns to market experience into account. Following Imai and Keane (2004); Olivetti (2006); Wallenius (2011), this is done by making the wage (skill) in the next period dependent on the hours worked (and the type of job) in the previous period. The results show that when flexibility is low, the labor supply profile of family constrained individuals exhibits the double peaked profile documented by Olivetti (2006) for women in the 1970's. As technology improves, the lifecycle profile gradually becomes more similar to the single peaked profile of the unconstrained individuals. Taking the lifecycle into account also further strengthens the incentives to trade off; As the stakes are higher in the sense that current labor supply choices carry over into future periods in terms of wages, it will be optimal to pursue the more demanding career at lower levels of flexible technology. As a consequence, leisure is further depleted to make the more demanding career feasible. Comparing period utility, this trade-off results in family constrained individuals having lower utility in the more demanding career as compared to
the simpler career in the period when the family constraint binds. Although not modeled, this has implications for women opting out or shifting to a less demanding job when the requirements from home are most demanding. Relaxing the career constraint in the life cycle model gives some additional insights. When the more demanding job is characterized by accumulation and depreciation of skill, the career cost of less working hours during child bearing years is substantial. In the model, the decrease in hours worked translates into a wage difference where the wage of the family constrained individual is about 70 percent of that of the unconstrained individual at the end of working life. This wage difference decreases as technology improves and when technology is fully flexible, the gap to the unconstrained individual closes (almost) completely as the total efficient labor supply increases. Section 5.5 concludes the paper.

5.2 Patterns in data

An empirical observation among Swedish working women constitutes the starting point: Although the participation levels in Sweden flattened out, female labor supply has continued to increase along the intensive margin. For women with small children, the career commitment in terms of the share of full-time has increased substantially over the last fifteen years. Moreover, this movement on the intensive margin came in parallel with these women entering into more complex jobs.

The family constraint can be expected be most severe when the children are relatively small. I use the presence of children aged below seven to identify potentially family constrained individuals. In figure 5.1, I use data from the Swedish structural wage statistics and plot the average labor supply of women with children of preschool age over the years 1996-2009 for the private and the public sector, respectively.\(^8\) Individual labor supply is measured as fractions of full-time. Each employee has a supply of between 1 percent

\(^8\)The Swedish structural wage statistics covers about 50 percent of the employees in the private sector and all employees in the public sector. To get information about the number of children, the structural wage statistics is matched to population-wide registers rich in demographic variables; see appendix A for details.
SOLVING THE PUZZLE

and 100 percent (full-time), i.e. it only measures supply on the intensive margin. Data is aggregated into four groups of occupations: Higher-level managers and professionals, lower-level managers/professionals and higher-level supervisors and technicians, intermediate and lower level sales, service and routine.\(^9\) Figure 5.1 shows that women with small children working as higher-level or lower-level managers or professionals in the private sector (the solid black line) have, on average, increased their labor supply by about four percentage points between 1996 and 2009. Of these women, higher-level managers and professionals work the most, on average 95.4 percent of full-time in 2009, and are now closing the gap to men. Comparing the public to the private sector, labor supply is lower in the public sector. The increase in labor supply on the intensive margin is qualitatively similar, but the increase is smaller among higher-level managers/professionals.\(^10\) The labor supply for lower-level sales occupations, service and routine jobs (the dash-dotted line in figure 5.1), on the other hand, has remained relatively unchanged during the period with an average value of 84 percent.

At the same time as there has been an increase in labor supply, there seems to have been a remarkable change in the work of these women. Figure 5.2 shows how the employment shares for the four different occupational groups have evolved over time. An interesting pattern emerges where the share of women with small children in employment being higher-level managers and professionals doubled and lower-level managers and professionals increased by 70 percent within the private sector. The public sector experienced a similar change in employment shares, but women with small children are less represented among higher-level managers and professionals and more among lower-level managers and professionals as compared to the private sector. During the same period, the employment share in lower-level sales occupations, service and routine jobs has decreased by 13 and 15 percentage

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\(^9\)The groups are formed aggregating ISCO88 occupational codes to an aggregated version of European Socio-economic Classification (ESoC). See appendix A for details.

\(^10\)This picture is confirmed in the latest Swedish Time Use Survey (Sweden, 2012) where the difference in hours worked for men and women with children of preschool age has declined from 17 in 1990 to just under 10 in 2011, i.e. a decline by 42 percent. Almost all of this change has occurred since the beginning of the 2000’s.
5.2. PATTERNS IN DATA

Figure 5.1: Intensive margin labor supply, women with children of preschool age, by sector.

Tables 5.1 and 5.2 summarize the corresponding figures for men and women, with and without children of preschool age, in the private and public sector, respectively. It is evident from table 5.1 that almost all men in the private sector work full-time, regardless of whether they have small children at home or not. Men in the public sector work less, but once more, there is little difference in labor supply based on having children of preschool age or not. It is interesting to note, though, that, if anything, the trend among men is to work slightly less, comparing 2009 to 1996, in particular within the public sector.

The increase in the skill content of women’s work is studied in Black and Spitz-Oener (2010) using data from Germany 1979-1999. They document that women have witnessed an increase in non-routine analytical tasks and an even more pronounced decrease in routine tasks, relative to men. Moreover, they find that the task content has changed most rapidly in occupations where computers have made major headway. In that perspective, it is inter-
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Table 5.1: Employment shares and labor supply 1996 and 2009, private sector.
Table 5.2: Employment shares and labor supply 1996 and 2009, public sector

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Figure 5.2: Employment shares, women with children of preschool age, by sector.

It is interesting to see how the trends in employment shares differ between different industries with different IT profiles. For this purpose, I use the classification of industries in van Ark et al. (2003) grouping industries according to ICT intensity. In figure 5.3, the employment shares for women with small children are plotted for the four different occupation groups. Interestingly, the large increase in the employment share of higher managers and professionals is driven by changes within ICT-producing manufacturing and service industries supporting the results in Black and Spitz-Oener (2010).

The patterns described in this section are just unconditional trends. Over the period studied, there have been significant compositional changes in the group of women with small children. In particular, women are becoming increasingly more educated than men and also become mothers later in life (Boschini et al., 2011). This can probably explain part of the trends. Fully

\[\text{Seven groups are formed: ICT producing manufacturing, ICT using manufacturing, ICT producing service, ICT using service, Non-ICT service, Non-ICT manufacturing and Non-ICT other. Details are given in appendix A.}\]
Figure 5.3: Employment shares by industry and occupation, women with children aged below 7.
sorting these patterns out is beyond the scope of this paper. However, as a first-order check, I do the same tabulation holding education constant and restricting the ages observed. Looking only at women with a university degree (minimum 15 years of education) of ages 30-45, the share working as higher-level managers/professional increased by 5 percentage points between 1996 and 2009 among women with children aged below seven and labor supply increased on the intensive margin by 2.5 percentage points. A similar figure is found by restricting the sample to women with at least some tertiary education and shrinking the age span to ages 30-35. For this group, the share of managers/professionals increases by 4 percentage points and labor supply by 5.2 percentage points.  

5.3 A model of labor supply and hours constraints

The key trade off in this model comes from two assumptions regarding the labor market. First, more complex, better paid jobs require a minimum number of hours of labor supply to be productive. Second, workplace flexibility determines the degree to which labor can be shifted during the day so that some hours of labor can be supplied from home. This will create the basic mechanism in the model where time constrained individuals will only find it attractive to access the career oriented job if there is a high degree of workplace flexibility.

The model is presented in two steps. First, to build the intuition, I formulate a simple static version of the model with a standard Cobb-Douglas utility function. It delivers simple analytical solutions and gives a transparent view of the mechanism. Second, I reformulate the model into a life-cycle model taking the basic structure of Olivetti (2006) who analyzes the role of returns to experience in explaining women’s labor supply. By adding time restrictions to occupations and individuals and the possibility of workplace flexibility, I provide a mechanism to help explain recent changes in female intensive margin labor supply and also why women today take on more demanding jobs to a larger extent.

12The results are available upon request.
5.3. A MODEL OF LABOR SUPPLY AND HOURS CONSTRAINTS

Consider a standard Cobb Douglas utility function for an individual working in occupation \( s \):

\[
\ln(U) = a_1 \ln(c) + a_2 \ln(h) + a_3 \ln(1 - n - h)
\]

(5.1)

where \( c \) is individual consumption, \( h \) is hours spent in home production (child rearing) and \( l = 1 - n - h \) is leisure. It is assumed that consumption comes from the individual salary alone; adding an exogenous spousal transfer (positive or negative) would somewhat complicate the analysis, but not add much essence. This model adds three features that create the mechanism in the model; a career constraint (\( CC \)), a family constraint (\( FC \)) and the possibility of flexible work, \( f \).

Suppose that there are two jobs; one analytic, more complex job, \( A \), and one simpler, routine job, \( R \). The analytical job pays more, \( w_A > w_R \) but in return, has a minimum requirement, \( N \), for how many hours of labor supply that are needed for the job to be productive. Assuming that the minimum hours required are higher than what an individual would choose under unconstrained optimization, I will call this the career constraint, \( CC \).

In order to hold the complex job, the individual will have to make a sacrifice in terms of household production and/or leisure. The routine job, on the other hand, pays less but carries no restriction on the number of hours. An individual is equally productive working part time as full time.\(^\text{13}\)

Suppose further that individuals are heterogeneous with respect to the time constraint they face at home, the family constraint (\( FC \)). The family constraint does not only reflect the actual time needed for child rearing, but also that these hours must be carried out at a certain point in time during the day, which might infringe on the hours available for work. To formalize the family constraint, let there be a time cost \( x = X(children) \) associated with having children. \( x_j \in (0, 1) \) and \( X \) is increasing concave (\( X' > 0, X'' < 0 \)) with a population average \( \bar{x} \). The time constraint for mothers is assumed to be \( H^m = \xi x \) and \( H^f = (1 - \xi)x \) for fathers, where \( \xi \) is a distribution

---

\(^{13}\text{This implies that the routine job is fully dividable. Two individuals working at 50 percent are equivalent to one full-time employee.}\)
parameter. The size of an individuals’ $H$ thus captures family size, spouse characteristics etc., but may also reflect institutional features such as the cost and availability of childcare, which arguably is important for participation and potentially also for labor supply on the intensive margin.\footnote{An increasing public provision of childcare can be seen as affecting the entire distribution of $X$: for every family size, the time cost decreases. Domeij and Klein (2012) find that subsidized child care can have a large impact on female labor force participation. Calibrating their model to Germany, they find that subsidizing childcare to a level of 50 percent almost doubles the labor supply for women with small children. In Sweden, most women work, have children and use childcare. In the mid 1970’s, about 20 percent of the children aged 1-5 were enrolled in subsidized childcare. The share has increased steadily to reach 73 percent in 1998 and 86 percent by 2010. Lundin et al. (2008) study the impact of a nation-wide reform of the price of childcare in Sweden. They find no or economically insignificant effects on mothers’ labor supply. One explanation put forth by the authors is that in countries with a well-developed and highly subsidized childcare system, further reductions in the price of childcare seem to have small effects on mothers’ labor supply. Cortes and Tessada (2011) however, find positive effects on female labor supply, especially on highly educated mothers who worked longer hours.}

Let $h_{UR}$ represent the unconstrained choice of home production. Then, $FC$ binds for all individuals with $H > h_{UR}$ and all individuals with $H < h_{UR}$ are unconstrained. For $\xi = 1$, this implies that fathers are unconstrained and mothers on average have a time constraint $H = \bar{x}$. A perfectly equal division of the time cost, $\xi = 0.5$, would imply that both mothers and fathers on average have a time constraint $H = 0.5\bar{x}$, i.e more individuals may be constrained, but to a lesser extent.

The focus of this paper is how the consequences of the family constraint are affected by improvements to technology enabling flexibility in work. I capture this idea by introducing the possibility of performing some work from home – flexible work. Then, I assume that the family constraint can be met in two ways; either by home production only, or by a combination of home production and flexible work (from home), $f$, such that:

$$h + f \geq H \quad (FC)$$

In this way, as flexibility increases, individuals can supply more hours of labor and still meet the family constraint. The intuition is simple; many activities with children are tied to specific points in time during the day, i.e
dropping of at and picking up from day care, providing food and parenting etc. This imposes a restriction on the actual hours spent at work - unless the job is flexible in the sense that individuals are able to continue working once the family requirements are met. It is the possibility of distributing hours across time and location that is going to be the key for family constrained individuals.

I assume that only the A job has some degree of flexibility \( \theta \in [0, 1) \). \( \theta \) thus measures productivity working from home relative to working at the work place. Let \( n \) denote the share of time spent in the workplace (market hours) and \( f \) work supplied from home, then the individuals’ total effective labor supply is \( n + \theta f \). For simplicity, the R job is assumed to have zero flexibility. This will produce a clear cut off for which different careers are optimal.\(^{15}\) Note that since \( \theta \in [0, 1) \), an individual unconstrained by FC in the A job will also choose zero flexible hours as these are less productive. Once more, this is a simplification; one can easily make the argument for situations where work carried out from home is more productive, e.g. by shutting down distractions, interruptions etc. Allowing for this possibility would complicate the analysis, but also make it less focused so it is left for future examination.

### 5.3.1 The individual problem

Individuals choose career \( \{A, R\} \) so as to maximize utility. Individuals are endowed with one unit of time that is allocated to market work, \( n \), flexible work from home, \( f \), home production, child rearing, \( h \) and leisure, \( l \). Incorporating the possibility of flexible working hours, the individuals’ decision problem becomes:

\[
\max_{\{c, h, n, f\}} U = a_1 \ln(c) + a_2 \ln(h) + a_3 \ln(1 - n - h - f)
\]

\(^{15}\)It is straightforward to allow flexibility to vary also in the R job. The main differences are that there is a set of pairs \( \{\theta_R, \theta_A\} \) for which the preferred choice of career changes.
subject to:

\[(BC) \quad w_s(n + \theta f) - c = 0\]

\[(FC) \quad h + f - H \geq 0\]

\[(CC) \quad n + \theta f - N \geq 0\]

\[1 - h - n - f \geq 0 \quad n, h, f \in [0, 1]\]

in any A job; in an R job the wage is \(w_R, N = 0\) and \(f = 0\). The individual then chooses between A and R to maximize utility. Given the two different jobs and the different time constraints, you can identify four different cases; i) the unrestricted case where an individual works at the R job and is unrestricted by family, ii) having the R job and being restricted by the family constraint, iii) working at the A job, being subject to the career requirements, but unrestricted by family, and finally iv) working the A job and being restricted by both the career requirements and the family constraint. Which of the cases an individual ends up in depends on the parameter values. In what follows, I solve for the four different cases separately and then discuss the implications of changes in technology.\(^{16}\)

**i) Unrestricted case**

The unrestricted allocation delivers the standard Cobb Douglas weights. The individual optimizes over \(n\) and \(h\):

\[
\max_{\{n, h\}} a_1 \ln(w_Rn) + a_2 \ln(h) + a_3 \ln(1 - n - h)
\]

The first-order conditions are:

\[
h : \quad \frac{1}{h (h + n - 1)} (ha_2 - a_2 + ha_3 + na_2) = 0
\]

\[
n : \quad \frac{1}{n (h + n - 1)} (ha_1 - a_1 + na_1 + na_3) = 0
\]

\(^{16}\)Here it is assumed that CC always binds in the A job. Section 5.4.5 relaxes this assumption and explores the case where there are no formal requirements for minimum hours in the A job.
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The optimal solution is:

\[ h = \frac{a_2}{a_1 + a_2 + a_3} \]
\[ n = \frac{a_1}{a_1 + a_2 + a_3} \]

ii) R job when only the family constraint binds

Once more, there is only one decision variable. Since there is no flexibility in the R job and the FC binds such that \( h = H \), the individual can only decide over \( n \). The objective function now reads:

\[ \max_{\{n\}} a_1 \ln(w_R n) + a_2 \ln(H) + a_3 \ln(1 - n - H) \]

The first-order condition with respect to \( n \):

\[ \frac{1}{n(H + n - 1)} (Ha_1 - a_1 + na_1 + na_3) = 0 \]

The optimal solution is:

\[ n = \frac{a_1(1 - H)}{a_1 + a_3} \]
\[ h = H \]
\[ l = \frac{a_3(1 - H)}{a_1 + a_3} \]

Thus, with logarithmic utility, we obtain a time allocation which is independent of the wage; the substitution effect from a higher wage (working more) cancels the income effect (enjoying more leisure and home production).

iii) A job when only the career constraint binds

Since \( \theta < 1 \), it is assumed that one hour in \( f \) can never be as productive as one hour of market work, \( n \). Thus, an individual unconstrained by family will under optimization always choose \( f = 0 \). Once more, substituting the remainder of the constraints into the objective function:

\[ \max_{\{f\}} a_1 \ln(w_A N) + a_2 \ln(h) + a_3 \ln(1 - N - h) \]
The first-order condition with respect to $h$:

$$\frac{a_2(N - 1 + h) + a_3h}{h(N + h - 1)} = 0$$

and the optimal allocation of time is:

$$h = \frac{a_2(1 - N)}{a_2 + a_3}$$

$$n = \frac{a_3(1 - N)}{a_2 + a_3}$$

Thus, as the career constraint is tightened, individuals substitute away leisure and home production according to their relative weights ($\frac{\partial h^*}{\partial N}, \frac{\partial n^*}{\partial N} < 0.$)

iv) A job when both family and career constraint bind

For the family constrained individual working in the A job, there is only one decision variable, the choice of the amount of flexible work, $f$. To see this, substitute the constraints $BC$, $FC$ and $CC$ into the objective function. The problem reduces to:

$$\max_{\{f\}} \{a_1 \ln(w_A(N)) + a_2 \ln(H - f) + a_3 \ln(1 - N - H + \theta f)\}$$

The first-order condition with respect to $f$ delivers:

$$f = \max \left\{ \frac{(a_2(H + N - 1) + H\theta a_3)}{\theta(a_2 + a_3)}, 0 \right\}$$

For sufficiently low levels of $\theta$, the amount of flexible hours will be zero. The utility cost from the lower productivity is just too large, so all adjustments to the allocation of time will occur on leisure. Taking the partial derivatives with respect to $H$ and $N$, $f$ is increasing in both arguments. The response to an increase in $H$ is larger.$^{17}$

$^{17} \frac{\partial f}{\partial H} = \frac{a_2}{\theta(a_2 + a_3)} + \frac{a_3}{a_2 + a_3} > \frac{\partial f}{\partial N} = \frac{a_2}{\theta(a_2 + a_3)} > 0.$
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5.3.2 Static solution - an illustration

To illustrate the mechanism, the weights on consumption ($a_1$), home production ($a_2$) and leisure ($a_3$), are set to 0.3, 0.1 and 0.6, respectively. The family constraint $H$ is set to 0.3 and the career constraint $N$ to 0.45. The parameter values are chosen so as to allow an easy illustration and are not an attempt at calibration. $w_A$ is set to 1 and $w_R$ to 0.7 to reflect the earnings difference between the two jobs. The model is then solved over a grid of different $\theta$ going from zero flexibility to (near) full flexibility.

Throughout the remainder of the paper, in the figures the results for unrestricted individuals in the two different jobs are labeled $A$ and $R$ respectively. Results for family constrained individuals are instead labeled $FC,A$ and $FC,R$. Results for the $A$ job are in red lines and the $R$ job is drawn in blue. Optimal paths are in dashed black.

5.3.2.1 Optimal career and labor supply

Figure 5.4 shows the utility for the two different careers as a function of the key object of interest; the technology parameter $\theta$. The dashed red and blue lines show the level of utility for the case of having an $A$ and $R$ job, respectively, when $FC$ does not bind. The solid thick blue and red lines show the utility of the corresponding family constrained individual. When flexibility is low, i.e. when work can be performed from home only with very low productivity, choosing the $R$ job clearly dominates choosing the $A$ job. The penalty from sacrificing family and leisure if choosing the career oriented job is simply too high. When firms adopt a workplace organization and technologies that enable flexible work such that productivity at home becomes high enough, $U^{A,FC} > U^{R,FC}$, and it becomes optimal to instead pursue the more demanding career (indicated by $\theta^*$ in the figure).\textsuperscript{18}

Market hours are plotted in panel A of figure 5.5. The optimal supply of hours if there is no restriction on minimum time is just the Cobb-Douglas weight on consumption, 0.3. $FC$ individuals in the routine job work less

\textsuperscript{18}If you allow $\theta$ to vary also for the $R$ job, a substitution of hours into flexible hours will also occur in the $R$ job, which will improve the utility from holding the $R$ job.
than unrestricted individuals in the same job (0.23 vs 0.30). For low levels of flexible technology, holding the A job, the CC implies that labor supply increases by 50 percent for unrestricted individuals and almost double for family constrained individuals. When \( \theta \geq \theta^* \) the optimal career shifts to the A job.\(^{19}\) To accomplish the shift to the A job, the FC individual increases the market hours dramatically from 0.23 to 0.40 and increases the flexible hours from 0 to 0.09. Hence, total time devoted to work \((n + f)\) is larger than for unconstrained individuals to compensate for the lower productivity at home, as seen in panel C. In case of further increases to flexibility, FC individuals in the A job can decrease their market hours and substitute using more flexible hours. Near full efficiency working from home implies that time constrained individuals supply almost a quarter of their total labor supply from home (0.11 of 0.45). The magnitudes described are, of course, a product of the parameters chosen but the broad picture remain also for different weights

\(^{19}\)If \( \theta_R \) is allowed to vary, improvements to the flexible technology will decrease the market hours but increase total labor supply as flexible hours are used. However, compared to the A job, the use of flexible hours starts at higher levels of technology.
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Figure 5.5: Labor supply

in the utility function. A higher level on the family or career constraint will increase the use of flexible hours. Sections 5.3.2.3 and 5.3.2.4 explore how the optimal choice of career and allocation of time varies with the magnitude of the time constraint.

5.3.2.2 Solving the puzzle - home production and leisure

The implications for home production and leisure are shown in figure 5.6. The dashed black line once more represents the optimal choice between the two jobs for different levels of technology. From figure 5.6, the trade-off between career, family and leisure becomes very clear. The consequences for an FC individual of pursuing the more demanding career is large for low levels of flexible technology. To meet the requirements of the A job, leisure would be
depleted by 45 percent (from 0.46 to 0.25). This sacrifice is simply too high in terms of utility and it is optimal to instead choose the less demanding $R$ job.

The optimal career choice changes at $\theta^*$. This involves a large reallocation of time for the $FC$-individual. Home production drops from 0.30 to 0.21 and leisure from 0.47 to 0.30 to meet family and career constraints. By comparison, individuals unconstrained by family decrease home production to 0.08 (0.10) and leisure to 0.47 (0.60) to hold the $A$ job.

### 5.3.2.3 Changing the career requirements, $N$.

How does the optimal allocation vary with the magnitude of the career requirements? Start at the labor supply chosen by the family constrained individual in the $R$ job ($n_{FC,R} = \frac{a_1(1−H)}{(a_1+a_3)}$) and increase the constraint step by step. For each level of the career requirement, the minimum level of flexible
technology needed to still pursue the A job is solved for and then, given that level of technology, also the optimal allocation of time. This process is continued until there is no value for $\theta$, for which it is still optimal to choose the A job. The results are presented in figure 5.7, with career requirement $N$ on the x axis.

The top left panel shows the minimum level of flexible technology needed to still pursue the A job. For quite a large range of the career requirement ($N \leq 0.4$), the FC-individual will choose the A job regardless of the level of $\theta$. To meet the increasing career constraint, leisure is substituted for market hours (mid left and bottom right panel) and the utility decreases towards that in the R job. As shown in the mid-right panel, it is only beyond that the FC-individual begins utilizing flexible work. Since productivity is lower in flexible work, that option is only executed when further sacrifice in terms of leisure is costly enough. With the parameters used, for $N > 0.53$ it will no longer be optimal to choose the A job, even if technology is fully flexible. At the maximum level of the career requirement, the FC-individual supplies 25 percent of total labor supply by flexible working hours.
Figure 5.7: Minimum technology and optimal allocation for different levels of the career constraint
Next, holding \( N \) fixed at 0.45, \( H \) is gradually increased, starting at the level of home production chosen by the family constrained individual in the \( R \) job \( (h_{FC,R} = \frac{a_2(1-N)}{(a_2+a_3)}) \) and again solving for the minimum level of technology needed to still prefer the \( A \) job. As in the previous experiment, given that level of technology, I solve for the optimal allocation of time. The first thing to note is that, as seen in the top left panel of figure 5.8, technology almost immediately becomes an important factor. At \( H=0.22 \), the minimum level of flexible technology \( \theta^* \) jumps up and increases rather steeply to reach its maximum. To be able to meet the requirements of both constraints, in principle all work carried out from home (see the two mid panels). This level of the family requirements would reflect a situation with no limited access to child care and a very unequal division of the requirement for family time between spouses. Consequently, almost all of the time is spent around the children (actively or passively).

Consider again the basic case with \( H = 0.30 \) and \( N = 0.45 \). The minimum level of technology needed to pursue the more demanding career is \( \theta^* \). Now, suppose that technology improves further. As the model abstracts from the fertility choice and \( H \) is taken as exogenous (and fixed), the response of the \( FC \)-constrained individuals is to improve on their time allocation by using more flexible hours, spending more time on leisure and less time on market hours and home production (see figure 5.5 and 5.6). In reality, however, it could be that you can see other kinds of behavior. In particular, if you endogenize \( H \), it may well be that the “slack” created by improved technology is used to instead choose a higher \( H \). If having a demanding career previously meant that you had to abstain from having a family, or were limited to one child only, an improvement in flexibility might open up the opportunity to also have a second child. Boschini et al. (2011) find that it becomes more and more common for professional women in Sweden to have a second child. They find that the share of professional women having two children has increased from about 38 percent in the cohort born in 1945 to almost 50 percent in the cohorts born at the beginning of the 1960’s. More-
Figure 5.8: Minimum technology and optimal allocation for different levels of the family constraint
over, for these women, there was a decrease in childlessness over time. One
interpretation of this development is that professional women have traded
off some of the increased possibilities in terms of technology, i.e. the possi-
bility of using more flexible hours and getting more leisure to instead having
a larger family and thus “choosing” a higher $H$. This is a natural extension
which I intend to explore further in future work.

5.4 Returns to experience - the lifecycle model

Next, following Olivetti (2006), the model is reformulated and extended into
during periods, each representing ten years of working life. The family con-
straint $FC$ is assumed to bind only in the second period (and, as before,
not for everyone). There is no uncertainty, individuals have perfect foresight.
The key difference from the static model is the returns to experience. In par-
ticular, the wage in the next period is determined by the current wage but
also total labor supply in the current period, to be specified in greater detail
below. This makes the stakes higher in the family constrained period since
choosing less hours and/or a less demanding job has consequences for the
entire span of working life.\textsuperscript{20} In this section, the utility function is slightly
modified compared to the static version. In particular, I use a similar func-
tional form to that of Olivetti, but introduce the same time restrictions and
different career paths as those presented in the static case. In addition, home
production is simplified compared to Olivetti’s treatment: she models $h$
as a CES aggregate of parents’ time and purchased services. I abstract from
explicitly modeling the purchase of childcare services. However, as discussed
in section 5.3, the price and availability of childcare are reflected in the fam-
ily constraint, $H$. As before, individuals have preferences over consumption,
home production and leisure and are assumed to have the following utility
function:

\[ U(c_t, h_t, n_t, f_t) = \ln(c_t) + b \ln(h_t) - B \frac{(n_t + h_t + f_t)^\alpha}{\alpha} \]

\textsuperscript{20} The model abstracts from saving.
where \( c \) is consumption and \( b \) represents the weight that individuals put on home production (family). \( B\left(\frac{(n_{t}+h_{t}+f_{t})}{\alpha}\right) \) is the disutility of work, \( B \) and \( \alpha \) are positive. Notice that this is a slightly different formulation than in the static case, where \(-B\left(\frac{(n_{t}+h_{t}+f_{t})}{\alpha}\right) \) represents \( \ln(1 - n - h - f) \). As in the static model, it is assumed that the disutility of work is equally large for home production, market work, and flexible work from home. This can be relaxed but does not qualitatively change the implications of the model.

Many studies suggest that there are (large) career penalties to having a family. For example, Bertrand et al. (2010) find that male MBA earnings outperform those of women by 60 log points a decade after graduation and identify differences in career interruptions and weekly hours, both largely associated with motherhood, to be two of the main explanatory factors. The cost of a career interruption is larger the larger the depreciation of human capital and the larger the forgone skill accumulation. Hence, the cost of a career interruption would be higher the more skill intensive the job is. For that reason, family constrained individuals may self-select into occupations where the penalties are lower (Goldin and Katz, 2011). To incorporate this feature, I introduce skill accumulation into the \( A \) job. In particular, assuming that the wage equals the individual’s productivity and modeling the wage in the next period, \( w_{t+1}^{A} \) is a function of a depreciation rate, \( \delta \), labor supply in the current period, \( n_{t} + \theta f_{t} \) and the current wage:
\[
\begin{align*}
\frac{w_{t+1}^{A}}{w_{t}^{A}} &= G^{A}(n_{t}, f_{t}, w_{t}^{A}) = (1 - \delta)w_{t}^{A} + \varphi w_{t}^{A}(n_{t} + \theta f_{t})^{\gamma} \\
(5.2)
\end{align*}
\]

This way, the labor supply decision in one period does not only affect current earnings, but also determines future wages.

In the \( R \) job, skills are assumed not to depreciate, but there is also no potential for accumulating skill. Wages are instead assumed to grow exogenously at a rate \( g \). Hence, the career cost of reducing the working hours during intensive child rearing years will be lower in this job, which is why family constrained individuals might find it preferable and self-select. Thus,\footnote{The functional form is similar to that used in Olivetti (2006) and Wallenius (2011).}
for the $R$ job, we have:

$$w_{t+1}^R = G^R(g^R) = w_t^R(1 + g)^{10} \quad (5.3)$$

The occupational choice between $A$ and $R$ is assumed to be permanent; thus the individual chooses careers in period one only. This is a simplification although arguably many careers are difficult, if not impossible, to pursue if started later in life. However, this is an area which it is interesting to explore further. There is evidence of women opting out and shifting down, i.e. leaving the workforce or choosing a less demanding job, once family enters the picture (Boushey, 2008), but also of resuming a career after the intensive childbearing years. Allowing for a career shift is especially interesting in view of the accumulation and depreciation of skills. However, this is left to future work.

Adding the wage(skill) accumulation, the individual’s decision problem in the $A$ job becomes:

$$\max_{\{c_t, h_t, n_t, f_t, w_{t+1}^A\}} \sum_{t=0}^T \beta^t \{U(c_t, h_t, n_t, f_t)\}$$

subject to:

\begin{align*}
(BC) & \quad w_t^A(n_t + \theta f_t) - c_t = 0 \quad (\lambda_t) \\
& \quad w_{t+1}^A = G_t^A \quad (\eta_t) \\
(FC) & \quad h_t + f_t - H \geq 0 \quad \text{if } t = 2 \quad (\mu_{1,t=2}) \\
(CC) & \quad n_t + \theta_s f_t - N \geq 0 \quad \text{if } s = A \quad (\mu_{2,t})
\end{align*}

and for the $R$ job, the individual’s decision problem is:

$$\max_{\{c_t, h_t, n_t, f_t, w_{t+1}^R\}} \sum_{t=0}^T \beta^t \{U(c_t, h_t, n_t)\}$$
subject to:

\[(BC) \quad w_t^A n_t - c_t = 0 \quad (\lambda_t)\]
\[w_{t+1}^R = G_t^R \quad (\eta_t)\]
\[(FC) \quad h_t + f_t - H \geq 0 \quad \text{if } t = 2 \quad (\mu_{1,t=2})\]

\[(5.5)\]

Let \(\lambda_t\) be the multiplier on the time \(t\) budget constraint (\(BC\)), \(\eta_t\) the multiplier on the human capital accumulation constraint, \(\mu_{1,t=2}\) the multiplier on the family constraint (\(FC\)) and \(\mu_{2,t}\) the multiplier on the career constraint (\(CC\)) if holding the \(A\) job. In what follows, the different cases are solved for, starting with the unrestricted case in the \(R\) job and ending in the \(A\) job where both time restrictions bind. In the cases where the family constraint binds, the second period is solved for separately to make clear the key components of the model.

5.4.1 The \(R\) job

i) Unrestricted case

In this case, none of the time restrictions bind. The individual optimizes over consumption, home production and hours worked using no flexible hours. Wages grow exogenously at a rate \(g\). The first-order conditions are:

\[c_t : \quad \beta^{t-1} U_{c_t} - \lambda_t = 0 \quad (5.6)\]
\[h_t : \quad \beta^{t-1} U_{h_t} = 0 \quad (5.7)\]
\[n_t : \quad \beta^{t-1} U_{n_t} = \lambda_t w_t^R \quad (5.8)\]
\[\lambda_t : \quad w_t^R n_t - c_t = 0 \quad (5.9)\]

Dividing equation 5.8 by 5.6, we get the usual relationship between the marginal utility of work and consumption, \(\frac{U_{n_t}}{U_{c_t}} = c_t B(n_t + h_t)^{\alpha-1} = w_t^R\). By equation 5.7 we have that the marginal utility of home production is equal to the disutility of work, \(\frac{h_t}{h_t} = B(n + h)^{\alpha-1}\). Combining these, the optimal relationship between market hours and home production is \(n_t = \frac{1}{g} h_t\).
ii) Family constrained
The problem of the family constrained individual in the $R$ job is very similar. The first, third and fourth period are the same as the problem described above. In the second period, $h_2 = H$ since there is no flexibility in the $R$ job. Substituting $H$ into the expression of the MRS between work and consumption, $n$ is now the solution to $B(n_t + H_t)^{a-1} = \frac{1}{n}$. 

5.4.2 The $A$ job

iii) Unrestricted case
An individual working the $A$ job who is unconstrained by family is only deciding on one variable, i.e. the amount of home production. To see this, remember that $\theta < 1$ so no flexible hours will be used, $f_t = 0$. Moreover, since the career constraint binds, the amount of market work is predetermined, $n_t = N$. Looking at equation 5.11, the optimal amount of home production is given by the solution to $\frac{b}{n_t} = B(N + h_t)^{a-1}$.

The first-order conditions for the individual problem with respect to $c$, $h$, $n$ and $w_{t+1}$ are:

$$
c_t : \quad \beta^{t-1}U_{c_t} - \lambda_t = 0 \tag{5.10}
$$

$$
h_t : \quad \beta^{t-1}U_{h_t} = 0 \tag{5.11}
$$

$$
n_t : \quad \beta^{t-1}U_{n_t} = \lambda_t w^A_t + \eta_t G^A_{n_t} + \mu_{2,t} \tag{5.12}
$$

$$
w_{t+1} : \quad \eta_t = \lambda_{t+1} n_{t+1} + \eta_{t+1} G^A_{w_{t+1}} \tag{5.13}
$$

In period II, the family constraint binds and the individual may find it optimal to also use flexible hours, which is why the first-order condition
changes to:

**Period II**:

\[
\begin{align*}
    c_t &: \quad \beta^{t-1}U_{c_t} - \lambda_t = 0 \quad (5.14) \\
    h_t &: \quad \beta^{t-1}U_{h_t} + \mu_{1,t} = 0 \quad (5.15) \\
    n_t &: \quad \beta^{t-1}U_{n_t} = \lambda_t w^A_t + \eta_t G_{n_t} + \mu_{2,t} \quad (5.16) \\
    f_t &: \quad \beta^{t-1}U_{f_t} = \lambda_t w^A_t \theta + \eta_t G_{n_t} + \mu_{1,t} + \mu_{2,t} \theta \quad (5.17) \\
    w_{t+1} &: \quad \eta_t = \lambda_{t+1} (n_{t+1} + \theta f_{t+1}) + \eta_{t+1} G_{w^A_{t+1}} \quad (5.18)
\end{align*}
\]

Equations 5.14 and 5.15 are typical first-order conditions for consumption and home production, respectively. In the second period, when the family constraint binds, the (net) marginal utility of home production is equal to the shadow cost of the family constraint. Dividing 5.15 by 5.14, we get:

\[
\frac{U_{h_t}}{U_{c_t}} = \frac{\mu_{1,t}}{\lambda_t} \quad (5.19)
\]

So the marginal rate of substitution between home production and consumption equals the ratio of the shadow cost of the constraint to the marginal utility of wealth. In periods where the family constraint does not bind, the right-hand side is equal to zero, and the net marginal utility of home production equals the marginal utility of consumption.

Equation 5.16 is the first-order condition with respect to market hours. The first term on the right-hand side is the wage multiplied by the marginal utility of wealth. The second term captures the effect of human capital accumulation from working. It is clear from 5.16 that additional hours of work do not only result in the benefit of additional income but also in the benefit of higher wages in the future. Both these effects must be weighed against the disutility of working another hour and the shadow value of the career constraint. As in Wallenius (2011), this implies that the opportunity cost of time is flatter than the observed wage schedule, (in this case even more due to $\frac{\mu_{2,t}}{\lambda_t}$). The first-order condition with respect to flexible hours is very similar to that of market hours. The key difference is that both the bene-
5.4. RETURNS TO EXPERIENCE - THE LIFECYCLE MODEL

fit from income and from higher future wages is scaled down by $\theta$ as the flexible hours are less productive. Moreover, the shadow cost of the family constraint and the shadow cost of the career constraint (scaled by $\theta$) enter on the right-hand side. Equation 5.18 is the law of motion for wage (skill).

Dividing 5.16 and 5.17 by 5.14 gives the MRS between market work and consumption and flexible work and consumption, respectively:

$$\frac{U_{nt}}{U_{ct}} = w_t^A + \frac{\eta_t}{\lambda_t} G^A_{nt} + \frac{\mu_{2,t}}{\lambda_t}$$

$$\frac{U_{ft}}{U_{ct}} = w_t^A \theta_t + \frac{\eta_t}{\lambda_t} G^A_{ft} + \frac{\mu_{1,t}}{\lambda_t} + \frac{\mu_{2,t}}{\lambda_t}$$

Combining 5.20 and 5.21, we see that the shadow cost of the family constraint is equal to the difference in income generated by supplying $f$ instead of $n$ plus the difference in marginal human capital accumulation for $n$ compared to $f$, multiplied by the shadow value of skill. The last term $\mu_{2,t}(1-\theta)$ reflects the shadow cost of the career constraint, weighted by the productivity loss of using flexible hours:

$$\mu_{1,t} = \lambda_t w_t^A (1 - \theta) + \eta_t (G^A_{nt} - G^A_{ft}) + \mu_{2,t}(1 - \theta)$$

5.4.3 Parameters

The parameters $\{\alpha, b, B, w_{A,0}, w_{R,0}, D_t, \gamma, \beta, \varphi_t, g, N and H\}$ need to be calibrated. Taking the model to the data and doing a full quantitative assessment is beyond the scope of this paper. The aim here is to develop a framework that in a structured way incorporates an important feature of the conditions forming labor supply for women today. To this end, I therefore calibrate the model drawing on the results of other authors. The parameters of the utility function are from Olivetti (2006), unless otherwise stated. The weight on home production, $b$, is set to 0.35. The parameters that govern the disutility of work, $A$ and $\alpha$, are set to 25 and 3.02, respectively. Olivetti estimates $\alpha$ to be 2.88 for women and 3.02 for men. The higher value is chosen as there

---

22 As a robustness check I use the parameters in Wallenius (2011). The qualitative results remain unchanged.
are no differences in preferences between individuals in the model, only differences in the constraints they face. The discount factor $\beta = 1/(1 - 0.05)^{10}$ is set to 0.62 based on an annual interest rate of 5 percent. The wage in the initial period for the more complex analytical job, $w_{A,0}$, is normalized to 1. The corresponding wage for the routine job, $w_{R,0}$, is set to 0.8 to reflect the initial wage difference between complex and routine jobs. As we will see, over the life cycle, wage inequality grows as wages increase faster in the $A$ job.

The career constraint $N$ is set to 0.45, as in the static case. Wallenius (2011) created an average supply of life cycle hours using PSID data and found hours to be on average 0.40 over the life cycle, peaking just over 0.41. Choosing 0.45 is thus not too high and results in a binding $CC$. Moreover, this is very close to the average share of hours men devoted to work in the 1990’s as documented by Olivetti (2006) using PSID data.\footnote{Assuming a total endowment of 5000 hours, the average share devoted to work is 0.44 in ages 20-29 and 0.46 for the remaining three 10 year periods.} As in the static model, I assume $H$ to be 0.3. This is the same order of magnitude as in Olivetti (2006) who finds that women spend 32 percent of their time in the second ten-year period on childcare.

In the literature, a wide range of values has been documented for the learning parameter $\gamma$. Imai and Keane (2004) estimate $\gamma$ to be 0.23, Huggett et al. (2006) find a value around 0.7. Wallenius (2011) evaluates her model at $\gamma = 0.5$ which is close to Olivetti (2006) who sets $\gamma$ to be 0.4. Once more, I here follow the parameter values of Olivetti. Finally, the parameter values for $\varphi_t$ are set using the estimated parameters of the human capital production function for men in 1970 in Olivetti.\footnote{Since these parameter estimates are obtained using yearly data, I follow the procedure in Olivetti (2006) and iterate the law of motion for wages (skill) over the ten-year period assuming constant hours of work.} The parameter values are summarized in table 5.3.

5.4.4 Results

As in the static version, the model is solved over a grid of technology for the average constrained individual with $\xi = 1$ and $\xi = 0$, respectively (translating into a $FC$-individual with $H=0.3$ and an unconstrained individual)
Table 5.3: Parameter values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Comment</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$</td>
<td>0.35</td>
<td>Weight on home production</td>
</tr>
<tr>
<td>$B$</td>
<td>25</td>
<td>Disutility of work</td>
</tr>
<tr>
<td>$\phi_{t-1}$</td>
<td>0.0136</td>
<td>Returns to experience</td>
</tr>
<tr>
<td>$\phi_{t-2}$</td>
<td>0.0118</td>
<td>Returns to experience</td>
</tr>
<tr>
<td>$\phi_{t-3}$</td>
<td>0.0100</td>
<td>Returns to experience</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>3.02</td>
<td>Frisch elasticity= $e^{\alpha}$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.4</td>
<td>Learning parameter</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.62 (over 10 years)</td>
<td>Discounting</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.2</td>
<td>Depreciation</td>
</tr>
<tr>
<td>$w_*^A$</td>
<td>1</td>
<td>Initial wage $A$ job</td>
</tr>
<tr>
<td>$w_*^R$</td>
<td>0.8</td>
<td>Initial wage $R$ job</td>
</tr>
<tr>
<td>$H$</td>
<td>0.3</td>
<td>Family constraint $FC$</td>
</tr>
<tr>
<td>$N$</td>
<td>0.45</td>
<td>Career constraint $CC$</td>
</tr>
<tr>
<td>$g$</td>
<td>0.03</td>
<td>Exogenous wage growth</td>
</tr>
</tbody>
</table>

for the two different careers.\footnote{\(\theta\) is varied from 0.001 in steps of 0.001 to 0.999.} In figure 5.9, the life-time utility for an $FC$-individual is shown for the different careers. The blue solid line represents the utility in the $R$ job and the red solid line that in the $A$ job. To illustrate the impact of returns to experience, dashed lines represent the utility when returns to experience are shut down. In that case, the wages in the $A$ and $R$ job are assumed to grow exogenously. As seen in figure 5.9, adding returns to experience makes it optimal to pursue the $A$ job at lower levels of flexible technology. The reason is that more skill is accumulated in the $A$ job compared to the $R$ job as a result of more hours of work. In this setting, since $A$ is career constrained, hours of work do not change as a result of skill accumulation.\footnote{If there is skill accumulation also in the $R$ job, the hours profile will change in that job. Compared to exogenous wage growth, individuals will then find it optimal to work more in the early periods to accumulate a higher wage.}

Olivetti (2006) documents that the lifecycle profile of married women in the 1970’s was double peaked, i.e that labor supply is high at the beginning of working life, substantially lower during the child bearing years, and then high again as the children grow older. She also documents a distinct difference for
married women in the 1990’s, who instead had a single peaked profile, more similar to that of men. Comparing the two periods, Olivetti estimates that women’s returns to experience had increased by 25 percent and those of men only by 6 percent and finds that the change in returns to experience could explain almost the entire increase in labor supply. However, Olivetti’s model is silent on why the returns to experience had increased. The mechanism suggested by the present model is that it does not only involve more hours, but also more complex jobs.

In figure 5.10, market hours and flexible hours are plotted for low levels of technology, $\theta = 0.01$, near full flexibility, $\theta = 0.99$ and the point $\theta = \theta^*$ where utility in the $A$ job just dominates that in the $R$ job. First, the blue solid line is the lifecycle profile of an FC-individual in the $R$ job. Since there is no flexibility in the $R$ job, market hours drop substantially in the second period when the family constraint binds and the profile is double peaked as in Olivetti. The red solid lines show the market hours (panel A) and flexible hours (panel B) in the $A$ job. For very low levels of technology, the market
hours would equal what is demanded by the career requirements $N$, but since the sacrifice on home production and leisure would be so large, the less demanding job is chosen. Once more, as flexibility improves sufficiently, the $A$ job becomes optimal. The new allocation of time involves substituting market hours for flexible hours and the total time devoted to work is larger than for the unconstrained individual to compensate for lower productivity at home. Interestingly, when flexible hours can be used, the change in choice of careers implies that the dip in job the life cycle profile of labor supply (as seen in the blue solid line of panel A) disappears, the profile effective labor supply $n + \theta f$ of the $A$ is flat to meet the career requirements. A fully flexible technology implies that the $FC$-individual decreased the total time devoted to work to that of the unconstrained individual, supplying about one third of total labor supply from home.

Turning to home production, we saw in section 5.3.2.2 that changing careers implied a large reallocation of time. Here, the fact that $FC$ only binds in one period and that returns to experience increase the opportunity cost of working less is larger make the reallocation even larger in the second period compared to the static case, since it now becomes optimal to pursue the $A$ job at less efficient levels of technology. Consequently, comparing $\theta = \theta^*$ going from $R$ to $A$ implies a drop in home production from 0.20 to 0.08, and in leisure from 0.56 to 0.41. Compared to the unconstrained individuals, a $FC$-individual in the $A$ job has about 30 percent less time for leisure. The trade off is thus substantial both in terms of home production and leisure.

Although, for $\theta \geq \theta^*$, it is optimal to choose the $A$ job from a lifetime utility perspective, the results are mixed when utility for $R$ and $A$ is compared period by period. The blue dashed line in figure 5.12 is discounted utility for a family constrained individual in the $R$ job and the red line the corresponding utility in the $A$ job. Utility is evaluated at $\theta^*$, i.e. where it just becomes optimal to choose the more demanding career. As seen in figure 5.12, the trade off in terms of leisure and home production that is involved with choosing the more demanding career makes the period utility for the family constrained individual in the $A$ job utility in the second period lower than that in the $R$ job.
Figure 5.10: Labor supply
Figure 5.11: Home production and leisure
This result is connected to a recent literature studying female happiness. Stevenson and Wolfers (2009) document a decline in female happiness, both in absolute terms and relative to men. A possible hypothesis is that the source of women’s declining happiness is the "second" shift associated with pursuing both career and family. However, Stevenson and Wolfers (2009) find no evidence that the decline in happiness is more pronounced among working mothers as compared to non-working mothers, when comparing single to married mothers, prime age women to other age-groups or highly educated to less educated. Hence, although they document a decline in overall female happiness, they find no evidence that working the second shift is the underlying cause. However, as pointed out by the authors, there are large compositional changes within these groups over the period studied. Women have become more educated, they participate in the labor market to a larger extent and have children later in life. On the other hand Mencarini (2012) do find negative effects on happiness for working women. Using data from the European Social Survey between 2002 and 2008, they find that in particular for women employed more than 30 hours per week, happiness is negatively
affected by a large share of housework compared to other groups.

5.4.5 Relaxing the minimum requirement on an $A$ job

So far, the trade-off between the $A$ and the $R$ job has been created by imposing a minimum requirement with respect to hours worked in the $A$ job. This assumption is relaxed in this section. There is, however, still a 'natural' minimum requirement in place since skills depreciate in the $A$ job. The cost of a career interruption is larger, the larger the depreciation of human capital and the larger the forgone skill accumulation. This means that if labor supply is too low, skills depreciate on net, thus making the $A$ job less attractive than the $R$ job. Remember, the $R$ job neither has skill accumulation nor depreciation and the wage growth is thus unaffected by career interruptions or lower hours during childbearing years.

Returning to the problem in section 5.4.2 and removing the career requirements, the first-order condition with respect to $n$ becomes:

$$n_t: \quad \beta^{t-1} U_{n_t} = \lambda_t w_t^A + \eta_t G_{n_t}^A + \mu_{2,t}$$
$$w_{t+1}: \quad \eta_t = \lambda_{t+1} n_{t+1} + \eta_{t+1} G_{w_{t+1}}^A$$

and in the second period, for the family constrained individual, the first-order condition with respect to $f$ changes to:

$$f_t: \quad \beta^{t-1} U_{f_t} = \lambda_t w_t^A \theta_t + \eta_t G_{n_t} + \mu_{1,t} + \mu_{2,t} \theta$$

Redoing the manipulations in 5.4.2, the MRS between market work and consumption and flexible work and consumption looks almost as before, only without the terms in $\mu_{2,t}$:

$$\frac{U_{n_t}}{U_{c_t}} = w_t^A + \frac{\eta_t}{\lambda_t} G_{n_t}^A$$

$$\frac{U_{f_t}}{U_{c_t}} = w_t^A \theta_t + \frac{\eta_t}{\lambda_t} G_{f_t}^A + \frac{\mu_{1,t}}{\lambda_t} + \frac{\mu_{2,t}}{\lambda_t}$$

Combining 5.26 and 5.27, the shadow cost of the family constraint is equal
to the difference in income generated by supplying \( f \) instead of \( n \) plus the
difference in marginal human capital accumulation for \( n \) compared to \( f \),
multiplied by the shadow value of skill.

\[
\mu_{1,t} = \lambda_t w_t^A (1 - \theta) + \eta_t (G_{n,t}^A - G_{n,t}^f) 
\]  

(5.28)

How are the time allocations affected? Qualitatively, the same patterns
remain.\(^{27}\) As seen in figure 5.13, the skill accumulation creates an incentive
to work more early in working life and less toward the end, compared to the
constrained case. At \( \theta = \theta^* \), the double peak is still present in the \( A \) job,
although to a lesser extent than in the \( R \) job. This implies that the individual
working in the \( A \) job will accumulate less skill over the career and the fact
that the loss of hours happens early in the lifecycle makes the consequences
larger.

The effects of forgone skill accumulation are illustrated in figure 5.15.
First, compare the wage profile of a family constrained individual when it
just becomes optimal to pursue the \( A \) job (red dashed line) to the wage
profile when technology is nearly fully flexible in the same job (the red solid
line). The decrease in hours worked in the second period translates into a
wage difference where the wage of the family constrained individual is 71
percent of that of the unconstrained individual in the fourth period. This
wage difference decreases as technology improves; at \( \theta = 0.7 \), only a ten
percent difference remains and when technology is fully flexible, the gap to
the unconstrained individual closes (almost) completely.

\(^{27}\)Note that when the minimum requirements on the \( A \) job are relaxed, the utility from
this job increases and the life time utility shifts upwards. To give the \( R \) job a fair chance,
set the initial wages to be equal in the two jobs and just let the different processes for
wage(skill) accumulation play a role.
Figure 5.13: Labor supply - no minimum requirements on the A job
Figure 5.14: Home production and leisure - no minimum requirements on the A job

Figure 5.15: Wage profiles - no minimum requirements on the A job
5.5 Discussion and concluding remarks

Clearly men and women to some extent face different conditions on the labor market. The most obvious is the consequences of having a family, which does not only imply a career break (short or long), but also affects women’s working conditions during the years the children are young. One reason is that there is a time constraint associated with having a family, one that traditionally has largely been imposed on the mothers. Yet, women today do not only work more (Attanasio et al., 2008; Olivetti, 2006), they do so in jobs with a larger skill content (Black and Spitz-Oener, 2010) and have higher returns to experience Olivetti (2006). In Sweden, although the participation levels have flattened out, female labor supply along the intensive margin has continued to increase. For women with small children, the career commitment in terms of share of full-time has increased substantially over the last fifteen years. Moreover, this movement on the intensive margin came in parallel with these women entering more complex jobs.

In this paper, I suggest a mechanism to help explain recent changes. The key components are two assumptions regarding the labor market. First, more complex (and therefore) higher paying jobs require a minimum number of hours of labor supply to be productive and lead to a successful career. Second, workplace flexibility determines the degree to which labor can be shifted during the day so that some hours of labor can be supplied from home. This implies that time constrained individuals will choose the career oriented job only if they are willing to deplete leisure, or if the job is flexible enough.

I find that for low levels of flexibility, the sacrifice of pursuing a more demanding career is too large, and family constrained individuals thus opt for the routine job. The labor supply profile of family constrained individuals exhibits the double peaked profile documented by Olivetti (2006) for women in the 1970’s. When flexible technology becomes efficient enough, also family constrained individuals will find it attractive to pursue a more career oriented occupation. However, this implies a large reallocation of time, where both leisure and home production decrease and flexible labor supply and market
hours increase.

Adding skill accumulation to the model further strengthens the trade-off. When the stakes are higher in the sense that current labor supply choices carry over into future periods in determining wages, it will be optimal to pursue the more demanding career at lower levels of flexible technology and as a consequence, leisure is further depleted. Comparing period utility, this trade-off results in family constrained individuals having lower utility holding the analytic job, compared to the routine job in the period when the family constraint binds. Although not modeled, this has implications for women opting out or shifting down when the requirements from home are most demanding.

Relaxing the minimum requirements on the career oriented $A$ job, I show that the skill accumulation (and depreciation) by itself sustains the basic patterns found. Family constrained individuals in the $A$ job will work less than those who are unconstrained, but more as compared to what they would in the routine job. Lower labor supply implies that the individual working on the $A$ job will accumulate less skill over her working life. The cost of a career interruption is larger the larger the depreciation of human capital and the larger the forgone skill accumulation. Evaluating at the level of flexible technology where it just becomes optimal to choose the more demanding career, the decrease in hours worked translates into a rather large difference in wage, where the wage of the family constrained individual is 71 percent of that of the unconstrained individual in the last period.

The relatively simple setup in the model presented here leaves some questions open for future work. The next obvious step is to take the model to the data and make a more careful calibration. In doing so, extending the model to endogenize the fertility choice and thus the size of the family constraint would shed some light on recent trends not only in working life, but also on their interaction with trends in family formation. Another aspect that needs to be addressed is how patterns differ by educational groups. Clearly, the concept of flexibility applies to many high-skilled occupations, but may also be relevant in some low-skilled occupations that rely on the use of ICT. In addition, for some occupations, the relevant concept of flexibility is to have
To conclude, this paper focuses on the supply side of the story. One consequence of women becoming increasingly more educated than men is that also the share of highly skilled labor with a high demand for flexibility increases. To compete for talent, this may increase the incentives for firms to adopt such practices. In an ongoing project, we thus turn to the firm side and aim at modeling the adoption of flexible work practices.

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**A Appendix**

From the Swedish population wide register data LOUISE, I collect basic demographic variables such as education, sex, age and number of children aged below seven for the years 1996-2009. Employees are then linked to their employers using the RAMS data base which contains information on all workers employed in a firm at some point in time each year. RAMS includes worker annual earnings by employer, the month the employment started and ended, and firm-level information such as ownership and industry. For workers who are recorded as having more than one employer during a given year, only the employer that corresponds to the highest annual earnings is retained. I obtain information on wages and occupations from the Structural Wage Statistics (SWS) which is based on annual surveys covering about 50 percent of the private sector and the entire public sector.

Industries are classified according to intensity ICT in production/usage following van Ark et al. (2003). Table A.1 shows the industry codes included in the different groups. The Swedish industry classification SNI92 is equivalent to NACE rev 2 up to the four-digit level.

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28The year 1996 is is chosen as a starting year as it is the earliest year for which there is a consistent occupation classification.
Table A.1: Classification of industries

<table>
<thead>
<tr>
<th>NACE Rev 2 Industry codes (SNI92)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICT producing manufacturing</td>
</tr>
<tr>
<td>ICT producing service</td>
</tr>
<tr>
<td>ICT using manufacturing</td>
</tr>
<tr>
<td>ICT using service</td>
</tr>
<tr>
<td>Non ICT manufacturing</td>
</tr>
<tr>
<td>Non ICT service</td>
</tr>
<tr>
<td>Non ICT other</td>
</tr>
</tbody>
</table>

The occupational groups are formed aggregating ISCO88 occupational codes in the SWS to an aggregated version of European Socio-economic Classification (ESeC), see table A.2 (see https://www.iser.essex.ac.uk/archives/esec and Harrison and Rose (2006) for details on ESeC). The correspondence code to the ISCO 88 was kindly provided by Erik Bihagen, Swedish Institute for Social Research, Stockholm University.

Table A.2: Occupational groups

<table>
<thead>
<tr>
<th>EsEc code</th>
<th>Higher-level managers/professionals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Lower-level managers/professionals, higher-level supervisors and technicians</td>
</tr>
<tr>
<td>3</td>
<td>Intermediate</td>
</tr>
<tr>
<td>5, 7, 8, 9</td>
<td>Lower sales, service and routine</td>
</tr>
</tbody>
</table>
Figure A.1: Female labor force participation in 2007

Source: OECD, rates in 2007 for women aged 25 to 54
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