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Ph.D. Thesis

Department of Economics

University of Copenhagen

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Contents

1 Preface

This thesis has become a collection of papers on occupational mobility. It did not start out this way and I can look back on my Ph.D. as a journey that has taken many turns before achieving the final product. I am incredibly indebted to a lot of people without whom these past years would not have been as rewarding. Most of all I would like to thank my supervisor Martin Browning for his guidance, motivation, and belief in me, which I can not imagine having been without. You have inspired me tremendously and for this I am grateful.

Mette Ejrnæs, my second supervisor, has been my everyday support and has offered me feedback and advice on small and large problems about both academics and life. For this I would like to thank you.

I would also like to extend thanks to my coauthors Philipp Kircher and Iourii Manovskii. It has been inspiring to work with you, I have learned a lot, and your coauthorship has greatly improved the quality of this thesis.

I am thankful to all my colleagues and friends at Centre for Applied Microeconometrics (CAM). I have had a great time with you all and will miss you at my new job at the Copenhagen Business School. I would especially like to thank my office mate throughout the most of my Ph.D. Helene Bie Lilleør for endless discussion about economics and life and introducing me to her husband Joao Ejarque. The two of you forever inspire me. I would also like to thank Karsten Albæk for introducing me to the Ph.D. program, Edith Madsen for being my role model and always helping me with econometrics and coffee companionship, John Kennes for discussions about economics and being who he is, and Bo Honoré for facilitating contact to University of Pennsylvania for me as as well as always checking up on me.

During my Ph.D. I visited the Economics Department at University of Pennsylvania and Petra Todd for 16 months. I am grateful to University of Pennsylvania to providing this opportunity and for their hospitality. Especially, I would like to thank Petra Todd for inviting me and discussing my research with me. I thank the Fulbright Commission for offering me a grant to make the stay possible, and I would also like to thank the Ph.D. students and other visiting students at Penn for always making me feel welcome. I would also like to extend a special gratitude to the Department of Economics at University of Copenhagen who made this project possible. You have given me the freedom and the time to develop my ideas, made it possible to visit other research environments, and supported me throughout the Ph.D.. I would also like to thank the Department of Economics at the Copenhagen Business School for providing me with the opportunity to finish this project on my own terms.

Finally, I would like to thank my family and friends for always being there; my brother for inspiring me to study a Ph.D., my parents for their full understanding, support, and encouragement during the course of my life and during this project and last but not least, I am forever thankful to my boyfriend and best friend Daniel Metz for always believing in me and being an incredible support in all aspects of my life. Thank you.

Fane Groes
Copenhagen, July 2009

2 Introduction and summary

This thesis consist of four self-contained chapters. The main focus of the thesis is on occupational mobility, both empirically and theoretically. Chapter 2 introduces a set of new patterns of occupational mobility, chapter 3 presents a model to match the observed patterns of chapter 2, and chapter 3 provides a more detailed analysis of the occupational mobility patterns from a group of people with the same education. Chapter 1, which is about the effect of welfare benefits on single mothers' participation in training, welfare, and the labor market, is not directly related to the last three chapters.

The second chapter is an empirical paper, which uses administrative panel data on 100% of the Danish population to document a new set of patterns about occupational mobility. The population data is used to find each workers' percentile in the wage distribution within his occupation. The paper presents two main patterns of occupational mobility. By following a sample of workers after they graduate from school and calculating their wage percentiles within their occupation in a given year, a very robust result is that workers' probability of switching occupations are U-shaped in their wages. It is the highest and the lowest paid workers who have the highest probability of switching occupation while the workers in the middle of the wage distribution have the lowest probability of switching occupation. The second new pattern of occupational mobility is that conditional on switching occupation, high wage workers have a higher probability of switching to occupations with higher average wages than the average wage of the occupation they switched out of. The opposite is true for low wage workers who, conditional on switching occupation, have higher probability of switching to new occupations where the average wage is lower than their original occupation.

The second chapter is the background paper of chapter 3, which is coauthored with Philipp Kircher and Iourii Manovskii. In this paper we present the main new patterns from chapter 2 and develop a general equilibrium model of occupational choice. We show analytically that the model is consistent with the patterns we find from the data on occupational mobility. In our theory, workers have different innate abilities and workers and employers learn about these abilities by observing the output realizations. The model further has scarce employment opportunities such that workers compete for jobs and it has complementarities in the production function between workers' ability and productivity of an occupation, which leaves the more able workers, in equilibrium, occupying the jobs in the more productive occupations. As agents learn that they are either too good or too bad for a given profession they switch to a more appropriate one, which induces the U-shapes. We further show that other predictions from the model on wage changes and shocks to occupations matches moments in the data and separates our model from other models of occupational mobility.

The forth chapter is an analysis of the occupational mobility of people who have finished an apprenticeship as a wall painter. On average close to 70 % of this group of educated painters are working as painters, 10 % work in other occupations and 20 % are not working. The first part of this chapter is an analysis of how occupational choices of these painters relate to the fact that they are educated as painters. Using a discrete dynamic choice model this paper presents a model of occupational choice that takes into account that most of the educated painters prefer to work as painters. The second part of this chapter analyzes how the year of graduation affects long run labor market outcomes for the painting apprentices. Painting apprentices who graduate when unemployment rate is high are less likely to work in painting right after graduation but the majority of workers return to the painting occupations, when unemployment rate falls. One advantage of the presented theory is that it makes it possible to know when the worker is not in the occupation he is trained for. It is therefore possible to perform counterfactual experiments on how workers who graduate during a recession will react if e.g. the government helps them to a job in their preferred occupation after they graduate. The model is not estimated but parameters are chosen to let the moments from the model somewhat fit the data. Using the chosen parameters, the paper shows a counterfactual experiment of letting the job offer probability in the painting occupation be 100 % during the first year after graduation. Results from this counterfactual experiment indicates that if there was 100 % probability of receiving a job offer in painting the first year after graduation, this will increase the probability of having a job as a painter by 7 percentage points 15 years after graduation for painters who graduated during high unemployment.

Chapter 2, 3, and 4 are the main chapters of this thesis but chapter 1 on the effect on training, welfare participation and participation in the labor market of increasing welfare benefit, is included and important as well. Chapter 1, which is the earliest paper in this thesis is related to the other chapters in the sense that all chapters build on empirical analyses using the Danish data however, chapter 1 is unrelated to the other chapters because it does not include anything on occupational choice. The focus of this chapter is to examine the effect on employment probabilities, welfare participation, and voluntary participation in training programs in Denmark of a reform from 1987, which increased welfare benefits of single parents by a minimum of 12 percent. Using a difference-in-difference approach to analyze participation in training programs this paper shows that single mothers on welfare choose a higher participation level in a labor market training program when their maximum level of attainable benefits increase. The results on welfare participation and labor market participation show considerable heterogeneity in the treatment effect for mothers with children of different ages. The mothers with older children do not show any significant changes in their employment probabilities from having increased welfare benefits but for mothers with young children the effect on employment probability is positive. The impact of the reform on welfare participation is indeterminate for mother with young children, but for mothers with older children the effect is negative, indicating a relatively higher exit rate out of welfare during the reform period relative to the period before the reform.

3 Summary in Danish

Denne afhandling består af fire kapitler. Fokus i denne afhandling er på erhvervsmobilitet, både empirisk og teoretisk, men der er også et kapitel om enlige mødre på kontanthjælp.

Andet kapitel i denne afhandling er et empirisk papir som bruger administrative register data fra 100 % af den danske population til at dokumentere et nyt set af mønstre vedrørende erhvervsmobilitet. Data fra populationen bruges til at finde hver arbejders percentil i lønfordelingen inden for deres eget erhverv. Papiret præsenterer to nye mønstre inden for erhvervsmobilitet. Ved at følge et sample af individer fra de bliver færdige med deres udannelse og udregne deres lønpercentiler inden for deres erhverv i et givet år, er et meget robust resultat fra papiret at arbejdernes sandsynlighed for at skifte erhverv er U-formet i deres lønninger. Det er de højest- og lavest betalte arbejdere indenfor et erhverv, som har den højeste sandsynlighed for at skifte erhverv mens arbejderne i midten af lønfordelingen har de laveste sandsynligheder for at skifte erhverv. Det andet nye mønster inden for erhvervsmobilitet viser, at betinget på at skifte erhverv, arbejdere med høj løn inden for deres erhverv har højest sandsynlighed for at skifte til nye erhverv, hvor gennemsnitslønnen er højere end det erhverv de kom fra. Modsat er det for arbejdere som skifter erhverv fra bunden af lønfordelingen, som har højest sandsynlighed for at skifte til nye erhverv, hvor gennemsnitslønnen er lavere end det erhverv de kom fra.

Tredje kapitel er skrevet sammen med Philipp Kircher og Iourii Manovskii på baggrund af resultaterne fra det andet kapitel. I dette kapitel præsenterer vi de nye mønstre om erhvervsmobilitet fra kapitel 2 og udvikler en generel ligevægtsmodel for valg af erhverv. Vi viser analytisk at modellen er i overensstemmelse med de mønstre vi finder fra data om erhvervsmobilitet. I vores teori har alle individer forskellige medfødte evner og arbejdere og arbejdsgivere lærer om disse evner ved at observere produktionsrealisationer. Modellen har også knappe ansættelsesmuligheder således at arbejdere konkurrerer om jobs, og den har komplementaritet i produktionsfunktionen mellem arbejdernes evner og erhvervets produktivitet, hvilket gør at arbejdere med højere evner, i ligevægt, besætter de jobs der er i de mere produktive erhverv. Når arbejderne erfarer at de enten er for gode eller for dårlige til et givet erhverv, skifter de til et mere passende et, hvilket medfører U-formerne. Vi viser endvidere at andre forudsigelser fra modellen om lønændringer og chok til erhverv også passer på momenter i data, og derved adskiller vores model fra andre modeller om erhvervsmobilitet.

Fjerde kapitel er en analyse af erhvervsmobilitet for folk som har færdiggjort en lærlingeuddannelse som malere. I gennemsnit arbejder tæt ved 70 % af denne gruppe uddannede malere som malere mens 10 % arbejder som noget andet end malere og omkring 20 % er arbejdsløse. Den første del af dette kapitel er en analyse af, hvordan disse maleres erhvervsvalg relaterer til, at de er uddannede malere. Ved at bruge en diskret dynamisk valg model, præsenterer dette kapitel en model vedrørende erhvervsvalg, som tager højde for at de fleste af dem som er uddannede malere foretrækker at arbejde som malere. Anden del af dette kapitel analyserer hvordan det år, hvor folk bliver færdige med deres uddannelse, har indflydelse på resultater på arbejdsmarkedet på lang sigt. Maler lærlinge som bliver færdige når arbejdsløsheden er høj er mindre tilbøjelige til at arbejde som malere lige efter de bliver færdige med deres uddannelse, men hovedparten af dem går tilbage til at arbejde som malere, når arbejdsløsheden bliver lavere. En fordel ved modellen i dette kapitel er, at den gør det muligt at foretage kontra-virkeligheds-eksperimenter med hvordan arbejdere som bliver færdige når arbejdsløsheden er høj vil reagere, hvis fx regeringen sørger for at alle kan have et arbejde første år efter endt uddannelse. Modellen er ikke estimeret men parametre er valgt til at lade momenter fra modellen passe rimeligt på data. Ved at bruge disse valgte parametre ses i kapitel 4 et kontra-virkeligheds-eksperiment, som lader alle malerlærlinge have 100 % chance for at få et job det første år efter de er færdige med deres uddannelse. Resultatet fra dette kontra-virkeligheds-eksperiment viser at hvis der var 100 % chance for at få et job som maler første år efter endt lærlingeuddannelse, ville dette øge sandsynligheden for at have et job som maler med 7 procentpoint for malere som bliver færdige under høj arbejdsløshed.

Kapitel 1, som er det først skrevne papir i denne afhandling, undersøger effekterne på arbejdsfrekvensen, sandsynligheden for at modtage kontanthjælp, og frivillig deltagelse i revalideringsprogrammer af en kontanthjælpsreform fra 1987, som øgede kontanthjælpen med minimum 12 % for enlige forældre. Ved at bruge en "differnce-in-differnce" estimationsprocedure til at analysere deltagelsen i revalideringsprogrammer viser dette papir at enlige mødre på kontanthjælp har højere sandsynlighed for at deltage i revalideringsprogrammer, når kontanthjælpssatsen øges. Endvidere ses at arbejdsfrekvensen og sandsynligheden for at modtage kontanthjælp afhænger af, hvor gamle de enlige mødres børn er. Mødre med ældre børn viser ingen signifikante ændringer i deres arbejdsfrekvens ved forhøjet kontanthjælpssats, men for mødre med børn under 7 år øger det arbejdsmarkedsfrekvensen når kontanthjælpen hæves. Effekten af reformen på sandsynligheden for at modtage kontanthjælp kan ikke bestemmes for mødre med yngre børn, men for mødre med ældre børn er effekten negativ, hvilket vidner om relativt højere sandsynlighed for at skifte væk fra kontanthjælp i tidsperioden under reformen i forhold til tidsperioden før reformen.

Welfare Benefits and Participation in Training, Welfare, and the Labor Market of Single Mothers *

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Abstract

This paper uses a reform from 1987, which increased welfare benefits of single parents by a minimum of 12 percent, to examine the effect on employment probabilities, welfare participation, and voluntary participation in training programs in Denmark. Using a difference-in-difference approach to analyze participation in training programs this paper shows that single mothers on welfare choose a higher participation level in a labor market training program when their maximum level of attainable benefits increase. The effects on both employment probabilities and welfare participation are positive for mothers with small children and the effect on welfare participation is negative for mothers with children older than seven years old.

Chapter 1 of PhD thesis

*I gratefully acknowledge the comments I have received from Martin Browning and Mette Ejrnæs. This paper has also benefited from helpful comment from participants at the Center for Applied Microeconometrics' Christmas Workshop and from participants at the COST conference in London.

1 Introduction

The purpose of this paper is an empirical analysis of how welfare benefit recipients in Denmark react to an increase in their benefits. Using a difference-in-difference methodology I will attempt to estimate the impact on welfare participation, training participation and employment probabilities of a Danish welfare reform that increased the welfare benefits of single mothers. The Danish welfare reform happened in 1987 and it increased the real disposable income of single parents on welfare by a minimum of 12 percent. I will use this to identify what the impacts of increased welfare benefits are on single mothers' employment probabilities and their welfare and training participation rates.

Using single mothers to estimate the impact of the Danish welfare reform follows a large literature that also has used difference-in-difference methods to isolate impacts of other reforms. Eissa and Liebman (1996), Blundell, Brewer, and Shephard (2005), and Francesconi and Van der Klaauw (2004) are some of the studies. Even though this paper also uses single mothers to identify an impact of a reform change, the reform and the outcome of this analysis are different than that of the studies mentioned above. I analyze an increase in welfare benefits, which was given unconditional on any work requirements. Furthermore, the Danish welfare system around the period of the reform allowed welfare recipients to voluntarily participate in a training program. This allows me not only to look at how labor supply and welfare participation are affected by an increase in welfare benefits but it also allows me to analyze how welfare recipients' incentives to participate in training are affected by the amount of benefits they can receive during training.

Denmark is an interesting country to analyze the effect of welfare benefits because it has one of the highest welfare benefit levels in the world. This means the incentive to work is small unless a certain earned income is possible. The 1987 reform changed the incentives to work for an unskilled mother with two children under 6 years old from being able to make, in 2006, what would be approximately \$20 extra per month to loosing about \$30 per month if she was working relative to what she would be able to receive on welfare.

The way out of welfare is to earn more money than the welfare benefits provide and one way to accomplish this is to build up human capital. Investment in human capital can be done through work experience or by taking an education. The training program analyzed in this paper allowed participants to build up their human capital by enrolling in a formal education or working in a subsidized job while receiving benefits. The increase in welfare benefits gave the poorest single parents a higher income and my motivation for this paper is to analyze if the benefit increase lead to any further positive effects, such as investment in human capital through the training program. In order to understand more about the impact of the reform, I also include an analysis of the higher welfare benefits' impact on single mothers' employment rates and their welfare participation rates.

There exist a large literature on welfare programs' effect on employment probabilities and welfare participation rates however, both the empirical and the theoretical literature on welfare programs' effect on human capital accumulation is extremely sparse. In an empirical analysis Miller and Sanders (1997) find that differences in welfare benefits have no impact on high school graduation rates. Kesselman (1976) and Moffitt(2003) have theoretical models of welfare programs' effect on training participation however, neither of these models can be fully applied to analyze the impact of increased benefits on voluntary training participation. The training program analyzed in this paper has been analyzed by Høgelund and Holm (2006). In a sample from 1995 they find that the training increased the participants job probabilities in low and medium paid jobs.

In my analysis I use two samples of welfare participants. The first sample is from 1986, which is the last full year before the welfare reform, and the individuals in the sample are followed to 1988, which is the first full year after the welfare reform. To find the effect of the increase in welfare benefits the estimation strategy is to compare the labor market participation, welfare participation, and training participation of single mothers to that of single women without children before and after the reform in 1987. Based on two structural assumptions and a comparison of the pre-reform and the post-reform outcomes for mothers relative to women without children it is possible to identify outcome changes, caused by the welfare reform. This is the two period difference-in-difference (DID) estimation method that I apply in this paper. One of the assumptions for the model to be identified is the "common time trend" assumption and to test for this, I also perform the same DID analysis on a sample of welfare participants from 1984 who I follow through to 1986.

The most robust result of my analysis is that the increase in welfare benefits increased the training participation rate of single mothers with children younger than seven years old relative to that of single women without children. Furthermore, the group of mothers with young children had a higher probability of staying on welfare but the increase in welfare participation was not as high as the increase in training participation. The same group of mothers with children younger than seven also had an increased employment rate after the reform. It is possible for the mothers to have a positive effect in all three outcome because the outcomes are not mutually exclusive. However, the positive results on employment rates cannot be explained by any economic theory that I present in this paper. The increased welfare benefits for mothers with children older than seven years old did not have a significant effect on either employment rates or training participation but it decreased the welfare participation rate. This last result can also not be explained by the theory I present in this paper.

The paper is organized in the following way. First I describe the institutional framework of the welfare system in Denmark during the 1980's and then I go into details in describing the training program that was offered as a part of the welfare system. In section 2.3 I describe the 1987 welfare reform and in section 3, I explain what other reforms occurred during the period of my analysis. Section 4 is an overview of some theoretical models of labor supply and welfare and training participation, which can be used for predicting the expected effects of the welfare benefit increase. In section 5 I describe the evaluation methodology, a section under which I explain why I have chosen to condition the sample on receiving welfare benefits in the year before the reform and I explain the setup of the difference-in-difference estimation method. Section 6 is a description of the data and section 7 is a presentation of the results. Finally, I will conclude in section 8.

2 The Danish Welfare Benefit System

In this introduction to the Danish welfare system from the 1980's I will first describe how a person becomes eligible for welfare and what the institutional framework of the welfare system was. After that I will explain in detail how a person qualified for the training program and what the program consisted of. Then I will explain the welfare reform that this paper revolves around and I will illustrate how large the welfare benefit increase was and what the level of benefits were relative to the lowest and average earned income for different educational groups.

2.1 Institutional Framework of Welfare Benefits

The main reason of receiving welfare benefits is unemployment. In Denmark unemployed individuals can receive either unemployment insurance (UI) benefits or welfare benefits. This division between the unemployment support has existed since 1976 where the first act on welfare benefits was passed.

To qualify for UI benefits a recipient must hold a voluntary membership to an unemployment insurance fund and must do so for at least one year prior to collecting UI benefits. From 1985 to 1991, which is the period analyzed in this paper, a person with an UI fund membership was eligible for UI benefits if she fulfilled what was called the "26 weeks rule". The rule conditioned the right to collect UI benefits on at least 26 weeks of full time employment within the previous three years. Exceptions were given when the member had finished an education of minimum 18 months length. In this case the member would receive a lower benefit level and earn the right to receive full UI benefits after 26 weeks of full time employment. An important feature of the 26 weeks rule was that the full time employment also includes participation in labor market programs, such as public salary support for employment in private firms or job training with employment at the local or regional municipality. (Ingerslev (1992)).

The unemployment insurance benefits were in general higher than the welfare benefits. The Social Welfare Act of 1987[1] stated that the total amount of welfare benefits were not allowed to exceed the maximum amount of unemployment insurance benefits. An exemption from this was if 90 percent of the welfare recipient's previous income was higher than the unemployment insurance benefits.

The people who were unemployed in the 1980's and who were not eligible for UI benefits had four different ways of ensuring themselves welfare benefits. The first way was to fulfill the conditions to receive temporary welfare benefits, the second was to fulfill the conditions in order to receive permanent welfare benefits, the third way was to fulfill conditions to receive welfare benefits to cover single expenses, and the last way was to commit to a training program defined under the Social Welfare Act. In my data it is only possible to determine the difference between receiving welfare benefits under a training program or not. This means that both permanent, temporary, and single expenses benefits are categorized the same. Following Thalow and Gamst (1987) about 60 percent of all single women on welfare received it in the form of temporary welfare. Another 20 percent received welfare benefits under the training conditions, another 16 percent received welfare benefits to cover single expenses, and the rest (4 percent) received permanent benefits.

[1] In Danish this is "Lov om Social Bistand"

A person was able to qualify for temporary welfare benefits if she met five core conditions. The first condition was that the individual must have been subjected to a social occurrence, which could be the loss of a job, illness, pregnancy, divorce, or other changes that temporarily prevented the individual from paying her necessary expenses. A core condition was also that the individual's expenses could not be covered by other means of public income support ie. unemployment insurance, student grants, or retirement benefits. Welfare benefits were means-tested and depended on the family income (except children under the age of 18 years), such that a third condition was, if the income of a spouse (or the joint income) was above the maximum attainable benefit level the unemployed individual would no longer be eligible for the welfare benefits. Furthermore, if the family had large savings that could cover their expenses these saving had to be exhausted before the unemployed individual was eligible for welfare benefits. Exceptions were given when the savings were related to housing or education. Finally the fifth core condition to receive welfare benefits was the requirement that the unemployed individual and her spouse had exhausted their employment possibilities, meaning that they were not able to find a suitable job, incapable of working because of illness or caretaking of a child, or because of participation in a public sponsored schooling program. (See Lov om social bistand 1987).

Welfare benefits to cover single expenses were given mostly to prevent or relieve problems with children in the household, but could also be given to the welfare recipient. This could be in the case of handicapped children, medicine or medical treatment for children or the welfare recipient, or cover travel expenses in order for the child to stay in contact with a parent who did not live in the household with the child.

In order to receive permanent welfare benefits the recipient had prove it would be impossible for her to hold a job. Individuals on permanent welfare would most often be transferred to other types of permanent income support schemes after a while. This could be either disability benefits or early retirement benefits. In the rest of this paper I will not pay any more attention to either individuals who received welfare benefits to cover single expenses or to individuals who received permanent welfare benefits.

The last way to receive welfare benefits was to participate in a training program. The training program consisted of the choice between any kind of education, internship, apprenticeship, a stay at an institution, or holding a job with a subsidized salary. A person who participated in the training program would receive the same amount of welfare benefits as if she was on temporary benefits, unless she held a job with a subsidized salary in which case she would receive the minimum wage. The eligibility to participate in the training program was stated in the Social Welfare Act. A person was eligible for training if this training was a necessary requirement for the person's ability to take care of her self or her family as long as there were no other public schemes/institutions that could help the person.[2] In theory this eligible group is

[2]This is §42 of the Danish Social Welafre Act. In Danish this paragraph goes under the name "revalidering" and directly translated into English this word means rehabilitation. These words are not good sustitutes because the meaning of the English "rehabilitation" is not the same as the Danish "revalidering". Rehabilitation is a concept that gained popularity in the US and the UK in 1950's where the purpose was to help war invalids to get an acceptable life and, if possible, be rehabilitated to work a new job. Rehabilitation included both steps toward restoring the participant's health as well as their working prospects.

In Denmark it was argued that rehabilitation should not include treatment of health related issues, because this was already financed by the state. As a result the semantic meaning of the Danish word "revalidering", which is similar to the English word rehabilitation, is different from the notion of rehabilitation in Denmark. The idea of rehabilitation in Denmark has only focused on work related issues, such as education, vocational very large, however in practice, the training program was aimed at six main groups that all had some form of weak labor force attachment. The main focus groups were single parents, young people with a low level of education, long time unemployed, persons receiving sickness benefits and who are unable to return to their prior work, immigrants and refugees, and persons with problematic social conditions. All these groups will be discussed in some detail in section 2.2 below however, all of them (except the long term unemployed) were able to enter the training program without experiencing a period of unemployment and all of them were able to receive welfare benefits until they finished their training program.

Once a person qualified to receive welfare benefits they received a basis amount and another amount, which depended on their housing expenses and whether or not they had any children. The welfare benefits were tax free and the total amount of received benefits was reduced dollar for dollar with the after tax earned income. This means that the welfare benefits were taxed at a 100 percent marginal tax rate until the after tax earned income exceeded the maximum welfare benefit amount. At the time around the reform, the enrollment in the welfare program did not have a time limit and there existed no mandatory work requirements, just as there was no duty to participate in the training program.

2.2 The training program

The training program analyzed in this paper was a part of the welfare program in the 1980's. If a person participated in the training program she would receive the same amount of welfare benefits as a person who received welfare benefits as a passive recipient. The training participants could receive benefits for five different types of training. In my data it is not possible to identify what type of training the participant was enrolled but Valbak and Wamsler (1986) has a survey, which gives the percentages of participants in each category.

Six percent of the participants in the training program received welfare benefits to be at what I call an institutional stay. This was a kind of workshop supported by the municipality where the training participant was evaluated to see if she was fit for work. The second type of training was enrollment in a formal education. Participants enrolled in a formal education had by far the largest share of the training participants. In total 71 percent of the training participants were enrolled in a formal education. This covered 24 percent in education up to 9th grade, 20 percent in vocational training that could be up to 18 months long, and 27 percent in vocational training that lasted longer time than 18 months. The last three types of training was internships, apprenticeships, and subsidized wage work, which together consisted of the last 23 percent of the training participants.

In the Social Welfare Act it was stated that all persons were eligible for training if the training was a necessary requirement for the person's ability to take care of her self in the future. However, certain focus groups were mentioned in the guidelines provided for the case workers who administered the funding for the training program in the municipalities. Before I describe the focus groups it is important to state that these guidelines originated in 1983 and

training, and job retraining. This is the reason why I, in this paper, have called the program a labor market training program rather than a rehabilitation program.

did not change during the period of the welfare reform analyzed in this paper. Furthermore, there was no right or duty to participate in the training program for either the focus groups or the welfare participants not included in the focus groups. Most of the decision was left up to the case workers in the municipalities and it is therefore important for my further analysis to emphasize that the case workers did not receive any official change in their guidelines from 1983 to 1988, which is the last year of my analysis.

The guidelines for the training program described six main focus groups. Valbak and Wamsler (1986) has, in their survey, divided the training participants into five groups dependent on reason for training. I will refer to some of their enrollment percentages because my data does not allow me to know what focus group the training participants in my sample fit under. The only focus group Valbak and Wamsler have not included is immigrants and refugees. This focus group is self explanatory however, in my analysis I have excluded these individuals in order to have a more homogenous group of welfare and training participants. The second focus group was people who received sickness or disability benefits and who could not return to their previous job. According to Valbak and Wamsler (1986) this group consisted of 29 percent of the training participants. The third focus group in the guidelines for the training program is the young people with low level of education. This group consisted of 10 percent of the training participants in Valbak and Wamsler's survey. I have also chosen to exclude this group of young individuals from the survey because if they received welfare benefits they could also be a part of another training program where they did not receive welfare benefits. The forth focus group were the people who had been long time unemployed. Valbak and Wamsler do not have this group as a separate category but together with the fifth focus group, who were the people with problematic social conditions, they make up 52 percent of the training participants. The sixth and last group was the single parents who are the ones I will use in my further analysis. This group consisted of 21 percent of the training participants. In the sample I use in this paper, it shows that 25 percent of the single mothers who received welfare benefits in 1986 was enrolled in a training program and for single women without children this number was 17 percent.

2.3 The 1987 welfare reform

On July 1st 1987 there was an increase in the amount paid out to the welfare recipients in Denmark, which especially benefited parents as can be seen in table 1 below. Both before and after 1987 the welfare benefits were divided into three sub categories. The first being the basis support, the second was additional child benefits, and the third was housing support. The basis support and the child support were both before and after the reform given in somewhat fixed levels of benefits whereas the housing support could be given to cover rent, water, heat, electricity etc. and had no fixed level of benefits attached. It was especially the amount of child support that changed in 1987 because the part of the welfare benefits given to support any children in the household close to doubled. The increase was such that a single parent with two children on welfare (and no additional income) would have had a real increase in overall benefits of about 16 percent, whereas the same single individual without children would have had a real increase in benefits of about 4 percent.[3][4][5]

Table 1. Changes in maximum nominal monthly welfare benefits for singles on July 1st 1987, in Danish Kroner

	Prior to July 1987 (1)	After July 1987 (2)	Percent increase (nominal) (3)	Percent increase (real) (4)
Basis Support:				
-singles	2,319	2,579	11%	7%
Child Support:				
-first child	582	1,196	105%	98%
-second or above child	582	997	71%	65%
Housing Support:				
-non-parents	2,115	2,200	4%	No change
-parents	3,076	3,199	4%	No change
Single, one child	5,977	6,974	16%	12%
Single, two children	6,559	7,872	20%	16%
Single w/o children	4,434	4,779	7%	4%

Sources: Lov om Social Bistand 1987, Børnetilskudsloven 1987, Jappe (1987), Bekendtgørelsen om størrelsen af ydelser efter børnetilskudsloven pr. 1 juli 1987

Both before and after the reform in 1987 the welfare benefits were regulated once a year to keep up with inflation. To get a feeling of the inflation at the time, the consumer price index rose 3.7 % in 1986, 4 % in 1987, and 4.5 % in 1988. This means the real value of the increase in the 1987 reform was as given in column 4. All the welfare benefits were tax free, which means the welfare benefits should be compared to otherwise possible earned income net of taxes.

In 1987 an unskilled individual's monthly gross minimum wage was about 9,500 Dkk per month and the wages of a newly educated grade school teacher was about 13,000 Dkk before tax. According to Thalow and Gamst (1987) a single mother on welfare with one child in daycare before the 1987 reform had to earn 9,000 Dkk before taxes in order to have a marginal tax rate less than 100 percent. This was such that the same single mother with one child in daycare would receive 50 Dkk extra in after tax income if she worked full time at the minimum wage for unskilled workers in stead of receiving welfare and she would receive an extra 750 Dkk net income if she worked full time as a newly educated teacher. This is approximately equivalent to an extra income of $20 dollars for the unskilled and $300 for the newly educated teacher if the Danish kroner from 1986 is calculated into dollar values in year 2006. The little

[3] This is only for individuals above 23 years of age.

[4] The basis amount was reduced for individuals with longer spells than 9 months but this reduction was the same for indivduals without training.

[5] This housing support originates from an example after the reform in 1987 of typical housing support for a single individual without children and is estimated for a single individual with children. The value is reduced by 4 percent to find the housing support prior to the 1987 reform, which was the increase in CPI. The average house payments for singles was in 1987 approxiamtely 2,260 dkk per month and approximately 3,250 dkk per month for single parents. These numbers includes both renting and owning where owning costs about the double of renting. (See Jappe (1987) and Statistisk Tiårsoversigt (1990))

extra disposable income was because welfare benefits were means tested and so were additional housing support and subsidy for daycare, which is described in more detail below.

The three major forms of additional income (or subsidies) for welfare recipients were subsidized housing, subsidized daycare, and other types of child support from the state, which were not included in the welfare benefits. The additional benefits are an important source of income for the welfare recipients, especially for the single providers. On average they contribute 20 percent of the total disposable income. The first source of additional income is a housing subsidy given to all persons who live in rental housing. In 1987 around 70 percent of the single mothers on welfare received this subsidy, which depended on household income and housing expenses and on average the welfare recipients received a rent subsidy of 1,200 Dkk per month. The subsidy was not dependent on receiving welfare such that a person on welfare with the same disposable income and housing expenses as a working person would receive the same amount of housing subsidy. However, since the housing subsidy is means tested it is one of the two major sources of high marginal tax rates facing individuals wishing to work.

The second means tested subsidy was the subsidy for child care. It is not possible from the data used in this paper to see how much the welfare recipient received in childcare subsidy but the maximum allowed monthly gross income was 11,250 Dkk in 1987, which was above the minimum wage for unskilled employees but below the income for a newly educated teacher. The Ministry of Social Affairs calculated that a single mother earning a minimum wage as an unskilled worker and who had one child in nursery care and another child in kindergarten got around a 1,000 Dkk subsidy. This is out of a nursery care payment of 1,115 Dkk and a kindergarten payment of 938 Dkk in 1987.

The last additional income source, which also only applies to parents are additional types of child support from the state and the municipality. These additional child benefits demand special attention since they have changed in levels in the analyzed period and therefore may cause an identification problem of the effect of increased welfare benefits for single parents. They will be described in the following section.

3 Other reforms in the 1980's

During the time period analyzed in this paper, there have been two other major reforms which potentially can affect the outcomes in my analysis. The first one is the reform in child support from the state and the municipality and the other one is what in Denmark is referred to as the "Potato Cure".

In the 1980's there existed five different kinds of child supports, where four of them were given whether or not the single mother received welfare benefits. In English I call these benefits; child-contribution, child-benefit, family-benefit, a child-check, and a special child-benefit. All these child benefits are transfer payments and are therefore not calculated as income (to go toward the means tested welfare benefits) when a person receives social welfare.

The child-check existed up to and including 1986 and was a check paid out to families with children under the age of 10 and the benefits were 800 DKK per year per child no matter if the parents received welfare benefits or not. In 1987 and 1988 the child-check was replaced by the family-benefit which was a tax free benefit worth 5.000 DKK per child per year, no matter what the children's ages were or the income of the family, however only half the amount was paid out in 1987.

The rules behind the administration of the child-benefit were also changed in 1987, such that it was no longer dependent on family income and it included children up to 18 years of age in stead of only up to 16 years before 1987. If a single mother had a higher income than 140.000 Dkk before 1987 then the benefits would gradually be reduced until the women earned around 200.000 Dkk in which case she would no longer receive child benefits. After 1987 all parent received the child benefits independent of income. To put the 140.000 into perspective a skilled worker earning minimum wage would receive what was around 114.000 DKK and the average income for a single mother who was a public servant was around 159.600 DKK per year. Not taking account for the means tested child benefits before 1987, a single mother would receive 443 DKK in child benefits for the first child before 1987. This included both the child benefits and the special child benefits. After the reform a single mother received 535 DKK for the first child.

The last kind of child- support is the child-contribution, which is the contribution from the father to the mother of the child if the child only lives with the mother. This amount was 5.028 DKK in 1986, which also makes it 582 Dkk per child per month and in 1987 this benefit also increased a little to about 598 DKK per month. This was paid by the father of the child and if the father did not pay then it was paid by the municipality. The child-support from the father was also given whether or not the mother received welfare benefits. In total a mother with one child would receive around 7.200 DKK more each year after 1987 than before and even more if she earned more than 140.000 before 1987.

The second reform was the "Potato Cure". This "cure" was a tax reform that happened in 1987 and the main goal was to reduce the Danish population's incentive to borrow money and force the house owners to have bigger savings. Summarizing from Christoffersen (1999) this was done by reducing the tax value of the interest deduction house owners could get, thus making the relative wealth in houses significantly less. In my empirical analyses I have therefore included a control variable for whether or not the individuals in the sample are house owners.

4 Theoretical models of labor supply and welfare and training participation

The welfare program analyzed in this paper is the largest welfare program in Denmark. Furthermore, the alternatives to the welfare are often not feasible for the welfare participant in the sense that the welfare recipients do not fulfill the requirements. This could be that the welfare recipients are not old enough to receive retirement benefits, are not sick enough to receive sickness benefits, or they have not worked enough to be a member of an unemployment insurance fund.

In this theoretical setup I only consider work as an alternative to welfare and in the next section I will divide the welfare recipients into two categories. One category with recipients who only receive passive welfare and another category where recipients receive welfare conditional on participation in a training program.

There exists a large literature on labor supply issues related to welfare reforms. Friedman (1962) and Tobin (1965) noted that welfare programs with 100 % marginal tax rate discouraged work compared to a negative income tax with tax rates less than 100 %. In this section I will show a model with 100 % marginal tax rate of welfare benefits because this is how the Danish welfare system looked in the 1980's. The theory discussed here follows Moffitt (2002). He has, in his handbook chapter, reviewed some of the theoretical models that combine labor supply and welfare participation and I will use this as my main reference.

The presented theory is meant to give an idea of the expected sign of the difference-in-difference estimator, which can be used to comment on the findings in the empirical section. The link between this theory section and the findings in the empirical results section is not structural and should this analysis be carried any further this link would be the place to start. Blundell and MaCurdy (1998) have a discussion of what kind of structural restrictions are needed for the difference-in-difference estimator to measure a meaningful behavioral parameter and in section 5.3 I will present these restrictions.

4.1 Labor supply and passive welfare participation

A simple theoretical framework that relates labor supply to welfare participation is a static model. The individuals in this model have well behaved preferences over consumption (C) and leisure (L) and have utility function $U(C, L)$. The budget constraint without welfare benefits is given by $N + (1-t)\,W\,(T-L) = PC$. Here N is exogenous unearned income, such as government child support, W is hourly wage rate, P is the price of consumption goods, t is the marginal tax rate on earned income, and T is the total time available in the interval. If a person receives welfare benefits she receives $B = G - (1-t)\,W\,(T-L)$ in welfare, where G is the maximum amount of attainable welfare benefits. The total amount of received benefits, B, is reduced dollar for dollar with the after tax earned income $(1-t)\,W\,(T-L)$. If $(1-t)\,W\,(T-L) > G$ then $B = 0$, meaning that the means tested welfare benefits is zero if earned income net of taxes is above the maximum attainable welfare benefits. If the after tax earned income is smaller than G, then the total income is G.

With hours worked defined as $H = T - L$ and the price of consumption goods, P, normalized to 1, the budget constraint can be rewritten as a piecewise linear budget constraint such that:

$$Y = G + N \qquad \text{if } G > (1-t)\,WH \text{ and}$$
$$Y = N + (1-t)\,W\,(T-L) \qquad \text{if } G < (1-t)\,WH.$$

Figure 1 illustrates the budget constraint where the vertical distance AB represents G before the welfare reform. The horizontal segment BC represents the welfare benefits which are taxed at a 100 % marginal tax rate and the segment AD is the non-welfare constraint. At the point C the earned income exceeds the welfare benefits and the slope of the segment CD is $-W\,(1-t)$. There is no exogenous unearned income in the illustration because N is set to zero.

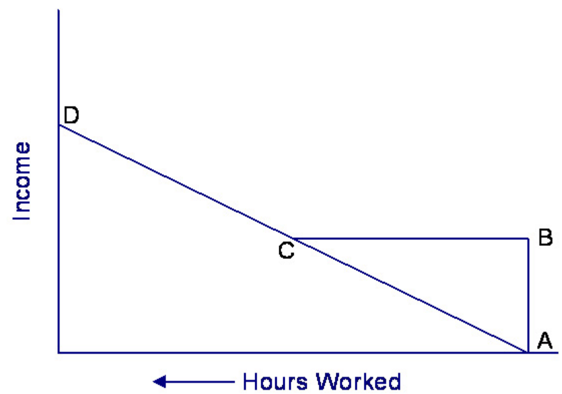

Figure 1: Budget constraint before the reform.

In this model, an individual with well behaved preferences will prefer to work when she is able to earn an income larger than the maximum welfare benefits. If her potential earned income is lower than the maximum benefit level she will prefer to receive the full amount of welfare benefits and not work. This is illustrated in figure 2 where a person who receives the full amount of welfare benefits has indifference curve 1 and a person who prefers to work without receiving benefits has indifference curve 2.

In the Danish data there exist individuals who do not receive welfare and have an earned income less than the maximum attainable welfare benefits thus, a person on the segment AC in figures. A reason for observing these eligible individuals may be that there exists disutility from receiving welfare that makes people want to work in stead. Moffitt (1983) has a theoretical model where he shows how the disutility could arise from stigma of being on welfare. In the sample used in my analyses I only look at people who received welfare in the year before the welfare reform thus I do not observe any individuals on the segment AC.

In the data I do observe welfare recipients from 1986 who also earned an income in the same year and therefore possibly lie on the horizontal segment BC. With well behaved preferences

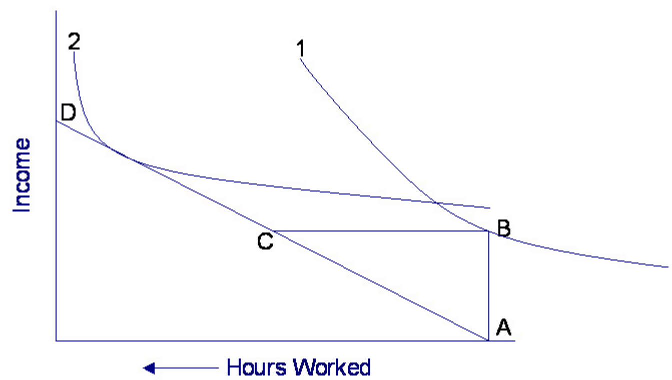

Figure 2: Budget constraint with indifference curves.

these individuals do not fit into the predictions presented in figure 2. There are several reasons why this can be the case and here I will present two of them.

The first reason for observing individuals who both work and receive welfare is that the data is annual data. In a given observed year this gives the individuals the possibility of convexify their budget constraints by moving on and off welfare over time periods, which are shorter than a year. Ignoring discounting, the women in the sample could in this way achieve higher utility than choosing a fixed amount of hours on the DC segment or zero hours at the point B. The data does not include dates on time spent on welfare but does provide information about amount of welfare benefits received. The movement on and off welfare is therefore an option that cannot be excluded. Blundell and MaCurdy (1998) describes this dynamic model, which uses a two stage budgeting technique and the labor supply, which is separable between all time periods.

The second reason why individuals would want to work, when they can receive welfare benefits, is because of wage growth possibilities related to work experience. Miller and Sanders (1997) have a theoretical model like this, which also is a dynamic model of labor supply rather than the static setup presented in figure 1 and 2.

Even though a dynamic model of labor supply can explain the observed data better, the static model can still be used to look at a change in welfare benefits. Figure 3 illustrates an increase in maximum attainable welfare benefits in the static model. The maximum attainable welfare benefits, G, has increased from B to B'. In the model where individuals either receive the full welfare amount or work without receiving any welfare, the increase in G has the effect as showed by the arrows in figure 3.

First of all, individuals who received full welfare before the increase continue to receive full welfare. They are strictly better off after the increase and have no incentives to deviate from the choice of receiving full welfare. This is illustrated by the arrow that goes from B to B'. The other arrow illustrates that some of the individuals who worked full time before the reform will choose to receive welfare after the reform. They will move from the segment DC to the point B' and be strictly better off.[6] In this simple model there is therefore an unambiguously negative

[6]It should be noted that these individuals are excluded from the sample, since the sample only includes

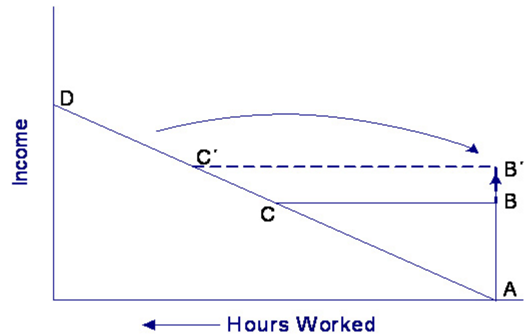

Figure 3: Budget constraint after increase in welfare benefits.

effect on labor supply and an equally unambiguously positive effect on welfare participation.

The unambiguous result of increased welfare benefits on labor supply and welfare participation does not change if the model allows individuals to both receive welfare benefits and work. In the two dynamic models mentioned above where work and welfare can be combined, an increase in welfare benefits also gives that fewer people will be willing to work and more people will want to receive welfare benefits.

If the individuals in the dynamic models receive full welfare in all periods before the reform they will continue to do so after the reform and be strictly better off. Among individuals who convexify their budget constraint there should be some who, after the welfare benefit increase, get strictly better off by receiving full welfare. These individuals will reduce their labor supply and stop working. In a model where people work in order to get experience, the labor supply effect of a welfare increase is also negative. As in the static model, the alternative income to work is now higher and for some individuals even with their potential wage growth they will not be able to earn more money than what they are able to receive from welfare after the reform. These people will make a career out of welfare.

The models presented above give an unambiguously prediction for the empirical section. This is that the individuals who experienced the welfare increase should reduce their labor supply and have a higher welfare participation rate after the reform relative to individuals measured over the same time period who did not receive the increase in welfare benefits.

4.2 Training Participation

There only exist few studies that have analyzed the theoretical effects of welfare programs on the decision of participating in a training program. To my knowledge, there are no studies

individuals who received welfare before the reform.

that analyze a setting where the welfare recipients voluntarily can participate in training and receive the same amount of welfare benefits as if they had been accepting passive welfare. In this section I will present the studies referred to by Moffitt (2002), which analyze theories about welfare and training programs and explain why my study differs from these. The three studies I will refer to are Kesselman (1976), Miller and Sanders (1997), and Moffitt (2003).

I analyze participation in a training program as a human capital investment because a high percentage of the Danish training participants are enrolled in school. Human capital investment models are analyzed in a dynamic setting and the static model presented above therefore falls a little short.

The basic setup in human capital models is that they require an investment of time (i.e. in education or job training) and then they yield some rate of return in form of higher future wages. The value to an individual participating in the training program is the present value of future wages and earnings gained minus the net present value of the cost of time and direct costs such as tuition fees etc. In this case, It is important to know whether the training program is voluntary or mandatory to determine when individuals will participate in training or not. No one will participate in a voluntary training program unless it has a positive net present value. However, if the training program is mandatory, participants can potentially be made worse off by participation. As noted by Moffitt (2003) the rate of return to the training program depends on whether it raises earnings sufficiently to induce the individual to go off welfare. This is because the marginal tax rate off welfare is lower than it is on welfare, which is the case in all three studies discussed below as well as in my analysis.

Miller and Sanders (1997) analyze two types of human capital accumulation, which is educational attainment and labor market experience. They set up a theoretical model for the joint decision of welfare participation and work but this model does not include a choice of schooling or training. They analyze educational attainment as a separate empirical analysis but do not include a theoretical model, which could explain their findings.

Kesselman (1976) analyzed individuals who would be on welfare both before and after a training period and he found that they had less incentive to participate in training if a welfare program existed. He looked at a welfare program where individuals on welfare worked at the same time as they received welfare and for each dollar they made there was a higher marginal tax rate than for people who did not receive welfare. Individuals could be in the welfare program up to a certain threshold earning, much like it is the case for the Danish welfare program. The reason why an individual on welfare both before and after the reform would have less incentive to participate in the training is because both their opportunity costs and their return to training is lower on welfare than off welfare. In Kesselman's analysis people off welfare received their entire wage, W, and people on welfare paid a marginal tax of their wage such that $(1-t)\,W$ was their net of tax wage.

In a two period model, individuals off welfare would have a net present value of training, which would be $PV_{off} = -W_1 + \beta W_2$ where W_1 is the wage before training, W_2 is the wage after training, and β is a time discount factor. Similarly for individuals on welfare who would have a net present value of $PV_{on} = -(1-t)\,W_1 + \beta\,(1-t)\,W_2 = (1-t)\,PV_{off}$. Individuals on welfare would therefore have a rate of return to the training, which would be $(1-t)$ of what it would be in absence of the program. This means that no individuals should participate in a voluntary training program if they intend to stay on welfare.

The effect of a training program is the opposite if it can move a person off welfare. The return at the margin will be higher because the marginal tax rate for work off welfare is lower than it is on welfare. The net present value for an individual on welfare during the training and off welfare after the training is $PV_{on} = -(1-t)W_1 + \beta W_2 > PV_{off}$. Therefore human capital investment is encouraged relative to what it would be in absence of the program.

Moffitt (2003) built on the model by Kesselman (1976). He also assumes that the opportunity cost of participating in a training program is in lost earnings rather than in leisure. However, he sets up a model where the welfare recipients have to undergo training as a condition for receiving welfare benefits such that the human capital investment becomes a type of work requirement. This is unlike the Danish welfare program during the 1980's, where there was "no right or duty" for the welfare participants to participate in the training program.

The settings in Kesselman (1976) and Moffitt (2003) are not the same as in my analysis but the results can be somewhat applied to what I want to analyze. In my analysis it should also be true that people who received full welfare before the reform would not want to participate in training after the reform. The marginal tax rate on welfare is 100 % in my analysis and the opportunity costs of training, according to Kesselman's setup is therefore zero. If I was comparing a situation with no welfare to one with a welfare program I could use Kesselman's setup. However, I want to analyze the effect of an increase in welfare benefits and not one of whether there is welfare or not. If I apply Kesselman's model to my analysis this would affect individuals who were on the margin of receiving welfare before the reform and received welfare after the increase. These individuals would have the same outcomes as in Kesselman's analysis where the people who could move off welfare after the training would have a higher incentive to participate in training with the increased welfare than without it. The incentive to take training for the person who worked before the reform is not a part of my analysis since I only include individuals who received welfare before the reform thus, who already had zero opportunity cost of training in Kesselman's model. These individuals should according to Kesselman (1976) and Moffitt (2003) not be expected to have higher incentives to participate in training.

My empirical analysis in section 7 show that the single mothers with young children who received higher welfare benefits also had a relatively high enrollment rate in the training programs during the period of the welfare increase. The models discussed above do not give this result however, the models are also very simple. One extension of the models above to reproduce my empirical finding could be to let the stigma of being on welfare be positively related to the amount of welfare benefits received. Then, if the stigma of being in training while receiving welfare benefits was less than the stigma of passive benefits, an increase in welfare benefits could make welfare recipients choose more training when welfare benefits increase.

More elaborate dynamic models like the ones in Keane and Wolpin (1997) and Cohen-Goldner and Eckstein (2006) include more choice variables and the individuals in their models are allowed to experience a difference in wage growth depending on time spent in the labor market, education, and their career choice. In dynamic model like these it would be possible to let welfare recipients be on welfare as a result of a bad shock thus some recipients would not be on welfare voluntarily. If this is the case then the marginal worker who would have worked in the period after the shock is the same type of marginal worker as explained above. If she would have worked the next period if the welfare increase had not occurred, her opportunity costs are no longer the lost benefits (which she does not experience) but her wage minus the benefits she is able to receive. She will be able to lift her self out of welfare after training and therefore an increase in welfare benefits will increase her incentive to participate in a training program. By including welfare benefits and training on welfare in a dynamic structural model like the ones mentioned above it is also possible that this would allow for individuals who work while they are on welfare to compare their wage profiles as an unskilled worker to a wage profile as a skilled worker. To become a skilled worker they would have to invest time in education and this would take time away from a potential wage growth they would have as an unskilled worker. If the wage growth as an unskilled worker could lead people out of welfare fast and becoming a skilled worker would take longer time on welfare (training) then the opportunity cost of training is no longer zero but the potential increase in wage from work experience. This is a setup very much like Coohen-Goldner and Eckstein (2006) where the opportunity costs of unemployment and training is accumulation of work experience, which they allow to affect future wages.

The ways of expanding these dynamic models are merely suggestive. I have in this paper not set up a formal model of welfare and training participation, which can be applied to my empirical analysis. As mentioned in the theory introduction, this analysis is primarily empirical. Should it be carried any further a theoretical model for joint labor market, welfare and training participation, which could give a structural interpretation to the parameters of an empirical analysis would be the place to start.

5 Evaluation Methodology

5.1 Identification Strategy

The empirical analysis in this paper aims at estimating the effects of increased welfare benefits on labor market participation, welfare participation and training participation. To find the effect of the increase in welfare benefits the estimation strategy is to compare the labor market participation, welfare participation and training participation of single mothers to that of single women without children before and after the reform in 1987. This is done by considering single mothers (who are the ones that receive the increased benefits) as the treatment group and women without children (who do not receive increased benefits) as the control group. This is done in order to isolate the effect of the increase in benefits from other policies or economic shocks that might have occurred in the time period, which have affected both groups similarly.

The difference in time between the change in labor market participation, training participation and welfare participation of single mothers to that of single women without children are the estimates of the 1987 reform. This is the difference-in-difference approach, which compares outcomes of the treated from before the reform in 1986 to outcomes of the treated after the reform in 1988 and at the same time taking account of the change in outcomes for the non-treated.

The pre-evaluation year of the reform is chosen as 1986 because this is the last year before the reform. The idea is that single women's decisions in 1986 are not affected by the 1987 reform. The law for the reform was passed in December 1986 and put into effect on July 1st 1987, which means that the welfare recipients in 1986 could potentially have anticipated the reform and made their choices in a forward looking manner. In my analyses I have not taken this forward looking behavior into account. I have carried all the analyses out assuming the law was unanticipated in 1986.

The post-evaluation year of the reform is chosen as 1988 because this is the first full year after the reform has been put into effect. I have not included observations from 1987 because the reform occurred in July and it is not clear if 1987 should be included as a pre- or post-reform year.

There exists a substantial literature that uses the outcomes of single mothers compared to outcomes of single women without children to estimate effects of tax or benefit reforms. Examples of these studies are Eissa and Liebman (1996), Meyer and Rosenbaum (2001), Blundell, Brewer, and Shephard (2005), and Francesconi and Van der Klaauw (2004). The reasons I have chosen outcomes of single mothers compared to outcomes of single women without children are the same as in the existing literature. The three main reasons why single mothers and single women without children are popular groups to compare are because of the reforms being analyzed, problems with joint labor market participation decisions, and data issues.

The analyzed reforms, in the mentioned papers, are all reforms that changed the benefits or the tax schedule for parents and not for people without children. In a difference-in-difference estimation this makes it obvious to compare people with children to those without any children. In the papers, the changes in taxes or benefits are also larger for single parents, which is one of the reasons for why single parents are used in the DID approach. The second reason why single parents are used is to avoid problems with joint labor market decisions in the household. Many of the analyzed benefits or tax credits are given conditional on household incomes, such that the endogenous income of the spouse (and the change in this income) would also have to be included in the analysis. To keep the analysis as simple as possible most studies therefore only look at changes in outcomes of single individuals. One of the main reasons why the outcomes of single women are more popular to analyze than the outcomes of single men is that there are more single mothers than single fathers. Single mothers often consist of the largest part of the reforms' target groups, which makes it possible to perform the DID with a larger data set.

In the data used in this paper single women consists of 51 percent of the welfare recipients in 1986 and single men consist of 49 percent. However, of all single women on welfare in 1986, 37 percent of them were single mothers, which makes the treatment group relatively large compared to the single men where only 3 percent of the single male welfare recipients were single fathers.

5.2 Selection Problem of training participant

The problem of analyzing the choice of participation in this type of training program is that in order to be eligible for participation in the training program the majority of individuals must receive welfare benefits, which in it self is an endogenous decision. To avoid the problem of individuals selecting into welfare, which is likely to be endogenous to the reform, the sample is taken to include individuals who received welfare in 1986. By conditioning on being a welfare recipient in 1986 and following these individuals to 1988 the selection into welfare is taken account for but the selection out of welfare is not dealt with.

Ideally I would like to compare those individuals who choose training participation because of the increase in benefits to those with similar characteristics, who did not receive the increase in benefits. The complication is that the reason for taking training is not fully known.

The first scenario for participating in training is that the participants in the training program choose to receive welfare benefits conditional on training in stead of receiving passive welfare benefits. The second scenario is that the training participants take training as a substitute for having a job with an earned income. The two reasons for participating in the training program have different policy implications and this is why I also look at the reforms' effect on welfare and participation and employment probabilities.

The increase in benefits could affect the 1986 welfare recipients such that mothers change their participation in the training program relative to non-parents and there is no change in exit rates out of total welfare for either group[7]. If this is the case the total welfare participation is unaffected by the reform and DID estimator will estimate the effect on training participation when the total welfare participation as constant. Thus, the women who take training substitute the passive welfare for the training. However, women with children should have a lower rate out of welfare, compared to the period before the reform, because their benefits are higher. This brings about the second possible effect the DID estimator on training can estimate. If the increase in total welfare is exactly like the increase in training then the single mothers would have substituted work for training. A last possible scenario is that single mothers and women without children on welfare have a fixed participation rate in the training program. Because exit rates out of welfare is not exogenous to the reform an estimation of the training participation effect could simply just pick up that parents stay longer on welfare after the reform and they have a fixed rate of the welfare participants in training.

The difference-in-difference estimator does not take the change in welfare participation into account and the reasons for selecting into training probably include elements of each of the illustrated cases above. From the data I cannot tell the reason for choosing training but I have argued earlier that the training program is a voluntary program for the women included in the sample. When I discuss the results in section 7, I will give my interpretation on how much of the increase in training could be due to an active selection into training from either welfare or work and how much can be due to a "forced" or fixed rate training participation of the welfare recipients. I will do this by comparing the DID estimator of the training participation with the DID estimator of the welfare and the labor market participation.

5.3 The Difference-in-Difference Estimator

To assess whether single female welfare recipients adjust their labor supply, welfare participation, and training participation in response to exogenous changes in welfare benefits I use a difference-in-difference approach. There exists a large literature on the difference-in-difference

[7]The total number of welfare recipients is here thought of as the total number of passive welfare recipients plus the total number of training participants.

estimation method and applications of this method starting with Ashenfelter (1978) and Heckman and Robb (1985). In this paper I follow Abadie (2005) and Blundell et.al. (2005) who both use ordinary least squares (OLS) to account for time-invariant unobservables that enter additively in the determination of labor market participation, welfare participation and training participation. The least squares, based on a linear probability model, is reported for simplicity of interpretation however, I have also estimated Chamberlain fixed-effects logit model, which provides estimates that give qualitatively similar results.

The 1987 reform increased the maximum attainable welfare benefits of single mothers relative to that of women without children. Based on two structural assumptions and a comparison of the pre-reform and the post-reform outcomes for mothers relative to women without children it is possible to identify outcome changes, caused by the welfare reform. This is the two period difference-in-difference (DID) estimation method. In this section I present a simple version of the DID method where all single mothers have one homogenous treatment effect. In the next section I expand the DID method in order to allow for the welfare benefits to have differential impacts on the outcomes of single mothers depending on the number and ages of their children.

Following Abadie (2005) and Ashenfelter and Card (1985) let $Y(i,t)$ be the outcome of interest for individual i at time period t. The three different estimations methods are set up similarly such that, in estimation 1, $Y(i,t) = 1$ for individuals who participate in the labor market in a given year and $Y(i,t) = 0$ otherwise. Similarly, in estimation 2, I let $Y(i,t) = 1$ if the single women participate in training and in estimation 3, $Y(i,t) = 1$ if the women receive welfare benefits. In both estimations $Y(i,t) = 0$ otherwise.

The pre-reform outcome is observed in 1986, which is classified as $t = 0$ and post reform outcome is observed in 1988, which is at $t = 1$. Between period $t = 0$ and $t = 1$ single mothers in the sample are exposed to treatment, because they receive higher welfare benefits. Letting $D(i,t) = 1$ if individual i has been exposed to treatment previous to period t and $D(i,t) = 0$ otherwise. Individuals with $D(i,1) = 1$ are called treated and individuals with $D(i,1) = 0$ are the controls, and since treatment only occurs after period $t = 0$ then $D(i,0) = 0$ for all i.

Having at least one child gives single mothers the right to higher welfare benefits in period $t = 1$ such that single mothers are defined as the treated and single women are the controls.

The conventional DID estimator is here derived by a linear probability model[8] where outcome variables are generated by the following process:

$$Y(i,t) = \delta(t) + \alpha \cdot D(i,t) + \eta(i) + \nu(i,t) \tag{1}$$

where $\delta(t)$ is a time specific component, α is the impact of treatment, $\eta(i)$ is an unobserved individual specific component, and $\nu(i,t)$ is an unobserved individual transitory shock with mean zero at both $t = 0, 1$. Notice that only $Y(i,t)$ and $D(i,t)$ are observed.

A sufficient condition for identifying α is that selection for treatment does not depend on the unobserved individual-transitory shocks, such that:

[8]The linear probability model is used for convenience and simplicity of interpretation. In derivation 2 in the appendix the Chamberlain fixed-effect logit is described and the results from this will be used for sensitivity analyses.

$$P\left(D\left(i,1\right)=1|\nu\left(i,t\right)\right)=P\left(D\left(i,1\right)=1\right) \tag{2}$$

for $t=0,1$. By applying equation 2 to equation 1 this gives the the following regression model[9]:

$$Y\left(i,t\right)=\mu+\tau\cdot D\left(i,1\right)+\delta\cdot t+\alpha\cdot D\left(i,t\right)+\varepsilon\left(i,t\right) \tag{3}$$

where $\varepsilon\left(i,t\right)=\eta\left(i\right)-E\left[\eta\left(i\right)|D\left(i,1\right)\right]+\nu\left(i,t\right)$.

Notice that the restriction in equation 2 for $t=0,1$ implies that $E\left[\left(1,D\left(i,1\right),t,D\left(i,t\right)\right)\cdot\varepsilon\left(i,t\right)\right]=0$ such that all parameters in equation 3 can be estimated by least squares. This also includes the treatment effect, α, and therefore the difference-in-difference estimator is estimable in a longitudinal sample by least squares regression of $Y\left(i,1\right)-Y\left(i,0\right)$ on $D\left(i,1\right)$ such that:

$$\alpha=E\left[Y\left(i,1\right)-Y\left(i,0\right)|D\left(i,1\right)=1\right]-E\left[Y\left(i,1\right)-Y\left(i,0\right)|D\left(i,1\right)=0\right] \tag{4}$$

which estimates the average effect of treatment on the treated between period $t=0$ and $t=1$.

Time invariant covariates and predetermined time variant covariates (age) can be introduced linearly into the DID model in equation 3 by interacting them with time. This is done by:

$$Y\left(i,t\right)=\mu+X\left(i\right)'\pi\left(t\right)+\tau\cdot D\left(i,1\right)+\delta\cdot t+\alpha\cdot D\left(i,t\right)+\varepsilon\left(i,t\right) \tag{5}$$

where $X\left(i\right)$ is assumed uncorrelated with $\varepsilon\left(i,t\right)$.

In this way the regression allows for heterogeneity in the outcome dynamics, such that not only parenthood can affect the change in outcome between period $t=0$ and $t=1$, but also other predetermined variables such as age, level of education, prior welfare experience, labor market experience, and additional prior income classifications.[10] Individuals' residence is included in a separate regression because not all municipalities have welfare recipients participating in training, such that municipalities with perfect prediction of people not in training are dropped in this regression. Notice that time-varying X's, which are not predetermined are not included in the regression because these are likely to be endogenous to the reform.

With repeated observation for the same individual differencing equation 5 with respect to t gives a useful alternative formulation of the difference in difference estimator, which becomes:

$$Y\left(i,1\right)-Y\left(i,0\right)=\delta+X\left(i\right)'\pi+\alpha\cdot D\left(i,1\right)+\varepsilon\left(i,1\right)-\varepsilon\left(i,0\right) \tag{6}$$

where $\pi=\pi\left(1\right)-\pi\left(0\right)$ and α is still the parameter that captures the treatment effect, i.e. the effect of mothers' higher welfare benefits on labor market participation, training participation and welfare participation.

[9] See derivation in appendix

[10] A full description of the covariates is given in section XX.

Equation 6 is the benchmark estimation that I will expand in the next section in order to allow for heterogeneity in the treatment effect depending on the number and age of the single mothers' children.

Before I go on expanding the DID estimator it is important to emphasize the two threats to the validity of the α parameter that captures the treatment effect. The threats give the two following identifying assumptions:

Assumption 1: *No compositional changes*

This states that composition of the treatment group and control group must not change between the pre-reform and post-reform periods. This is mainly an issue when cross-sectional data is used and can cause the estimated treatment effect, α, only to represent a change in the distribution of (D, X) between $t = 0$ and $t = 1$. If it is not the same individuals that make up each group both in the period before the reform and in the period after the reform then differencing does not eliminate the averages of the unobserved individual effects, $\eta(i)$. This problem is not a major concern in this paper since I use longitudinal data, but it is one of the reasons why I have chosen not to include women who change parent status between the two periods.

Assumption 2: *Common time effects*

This assumption states that in absence of treatment, the average outcomes for the treated and the controls would have experienced the same variation over time, thus have common time effects. An example, which could break this assumption, is a contemporaneous shock that affect the relative outcomes of the treatment and control groups.[11] If there exist some variation in the outcome dynamics between the two groups this can sometimes be explained by including covariates. However, if the dynamics depend on unobservables, the identification breaks down. To test the common time effect assumption I have performed the difference-in-difference estimation on the periods $t = -1, 0$ and tested whether α is equal to zero. To do this I have selected a sample from 1984 similarly to the way I selected the 1986 sample. The sample from 1984 is followed to 1986 and these two years are called $t = -1$ (for 1984) and $t = 0$ (for 1986).

As a second sensitivity analysis I also look at heterogeneous treatment effects. This allows the treatment and control group to vary their responses to the reform differently across a few observable characteristics. Following Blundell et. al. (2005a) I allow for this by estimating models that distinguish the single women by age and education, which are two observable characteristics that differ between the treatment and control groups. This allows for the treatment and control groups to experience different trends within the same age or education group. The results of this are discussed in section 7.

As a last comment to the DID estimator I should note that the estimated results cannot be used to simulate policy responses because of selection bias in the sample.

[11] Two other shocks that did occur in the 1986-1988 time period is a shock for house owners and a change in the general child benefits as described in section 3. When I write about the results I will comment further on this.

5.4 Effects by number of children and by children's ages

The 1987 welfare reform increased the welfare benefits for parents dependent on the number of children in the parent(s) had to support. This means that if there is any income effects from welfare benefits on labor market participation, welfare participation, and training participation these effects should depend on the number of children. I explore this possibility by including a linear effect of the number of children in the estimations[12]. That is, in equation 6 I interact the treatment status indicator $D(i,1)$ with the term $N(i,1)$, which is the number of children for woman i in period 1. This gives:

$$Y(i,1) - Y(i,0) = \delta + X(i)' \pi + \beta_1 \cdot N(i,1) \cdot D(i,1) + \varepsilon(i,1) - \varepsilon(i,0) \tag{7}$$

where $\pi = \pi(1) - \pi(0)$ and β_1 captures the treatment effect from the number of children.

A further analysis is carried out where I separate the treatment effect from the number of dependent children into two age intervals. The first is number of preschool children at ages 0-6 and the second is children of ages 7-17. In equation 8, $N(i,1)$ is split into two variables where $N^1(i,1)$ is number of children under 7 and $N^2(i,1)$ is number of children who are 7 years or older.

$$\begin{aligned} Y(i,1) - Y(i,0) &= \delta + X(i)' \pi + \\ &\quad \left(\beta_{21} \cdot N^1(i,1) + \beta_{22} \cdot N^2(i,1)\right) \cdot D(i,1) + \varepsilon(i,1) - \varepsilon(i,0) \end{aligned} \tag{8}$$

In equation 8 β_{21} indicate the treatment effect from the number of children under 7 years old and β_{22} is the treatment from number of children who are 7 years or older.

The last estimation is to check whether the estimated treatment effects β_{21} and β_{22} in equation 8 are coming from the number of children or if they have to do with an effect of having at least one child in the age category. This is done by extending equation 8 to include two dummy variables for at least one child under 7 and at least one child over 7. This gives equation 9:

$$\begin{aligned} Y(i,1) - Y(i,0) &= \delta + X(i)' \pi + \\ &\quad \left(\beta_{31} \cdot N^1(i,1) + \beta_{32} \cdot N^2(i,1)\right) \cdot D(i,1) + \\ &\quad \left(\beta_{41} \cdot I\left[N^1(i,1) > 0\right] + \beta_{42} \cdot I\left[N^2(i,1) > 0\right]\right) \cdot D(i,1) \\ &\quad + \varepsilon(i,1) - \varepsilon(i,0) \end{aligned} \tag{9}$$

[12] I have also tested for other than effects a linear however none of these other effects were significant and therefore not included in my analysis.

where $I[N^1(i,1) > 0]$ is an indicator function, which is equal to 1 if the number of children younger than 7 years old is greater than zero. Similarly for $I[N^2(i,1) > 0]$ which equals 1 if the number of children who are 7 years or older is greater than zero.

The results from the estimations of equation 7, 8, and 9 are given in section 7.

6 Data

The data used for this study is a 10 percent random sample of the Danish population covering the period from January 1st 1983 to December 31st 1988. It is administrative register data from the Integrated Database for Labor Market Research (IDA) and the Income Register, which are both longitudinal databases with annual observation.

The Income Register identify the nominal amount individuals receive in welfare benefits and includes a separate variable for individuals receiving welfare benefits while participating in some form of training program. It is not possible to know either the total time period spent on welfare or the time spent in the training program. Other than information on welfare, the Income Register also reveals information about earned income in the year and other benefits such as child support, housing support, pension and sickness benefits.

The Integrated Database for Labor Market Research contains information about age, education, marital status, number of children, residence, labor market history etc. Together the Income Register and the Integrated Database for Labor Market Research contain more than 200 variables of which I have used approximately 30.

For the difference-in-difference analyses I have conditioned the sample of single women on receiving welfare benefits at any time during 1986. In order to test for the common time effect assumption I have also performed similarly difference-in-difference analyses on a sample conditioned on being on welfare in 1984.

In the 10 percent sample of the Danish population there were 7.561 single women with or without children who received at least 1 Danish kroner in welfare benefits in 1986. This is 8.9 percent of the single women in the 10 percent sample. For the sample conditioned on receiving welfare in 1984 there were 8.183 single women, which is 9.8 percent of all the single women in 1984. I have only included women who were in the sample all three years in the two periods, 1984-1986 and 1986-1988. I have not allowed the single women to change marital status between 1986 and 1988 or between 1984 and 1986. This means that I have only included women who were single in all three years in the analyses, which reduces the sample to 5.583 single women followed through the 1986-1988 period and 5.932 single women from the 1984-1986 period.

The sample is reduced further because I have excluded all single women under 25 years of age in 1986. There are two main reasons why women under 23 are excluded from the sample and one reason why women who are 23 or 24 year old are excluded. The first reason why women under 23 are excluded from the sample is because the women under 23 who do not have any children received a decrease in their welfare benefits in 1987. However, this was only if they did not participate in a training program. If they participated in the training program they would receive the same benefits as the women older than 23 years of age. Single mothers younger than 23 also experienced the same increase in benefits as mothers older than 23. The second reason to exclude women under 23 and the reason why 23 and 24 years old women have been excluded is that individuals under 25 were a part of a different training program. This other training program did not give benefits through the welfare system and the women under 25 years of age would therefore not be expected to have any change in training offered by the welfare program.

I have also excluded people above 55 years of age because this group had a very low training participation rate and a high retirement rate compared to the rest of the sample. All immigrants are also excluded from the sample in order to get a more homogenous group. This makes the sample of single women on welfare in 1986 decrease to 2.660, which is divided into 924 single women without children and 1.736 single mothers.

The last group of women I have excluded from the sample are the women who changed status with respect to being a single mother in any of the two time periods. I have furthermore excluded women who got more or fewer children during the analyzed periods. This is done to avoid compositional changes between the single mothers and the single women without any children. This is also a way to try and avoid problems with endogenous fertility decisions and changing incentives due to change in the number of children. The final sample used in the analyses is 2.294 single women from 1986 who are followed to 1988 and 2.346 single women from 1984 who are followed to 1986.

The time-varying covariates used in the estimations are all measured in levels. For the DID estimator of the 1986-1988 period the covariates are measured either in 1985 or in 1986 or in both years. The same is the case for the estimation of the 1984-1986 period where all the covariates are from either 1983 or 1984. This is done to avoid that the covariates are affected by the increase in benefits and thereby potentially becomes endogenous to the reform.

Table A1 and A2 in the appendix presents some summary statistics from 1984 and 1986 of the single women without children and the single mothers.

Table A2 shows summary statistics for the sample conditioned on receiving welfare in 1986. The table show that the single mothers in the sample on average have 1.6 child form, which are divided into 0.57 children who are younger than seven years old and 1.03 children who are seven years and older. The other observable characteristics for the single women without children and single mothers mostly show significant differences. Women without children are on average older, than the single mothers but have almost the same average years of schooling. Within the group of mothers the difference in age and schooling is bigger than the differences across motherhood. The mothers with at least one child between zero and six are a lot younger and longer educated than the mothers with the older children. This is a difference that is both true for the sample conditioned on receiving welfare in 1986 and for the sample conditioned on receiving welfare in 1984, which is given in table A1.

The breakup of educational categories dependent on length of education also show similar trends in education between in two sample period. The percentages of women who have completed a short, middle and further education are almost exactly the same between the two samples. Women without children have on average one or two percentage points higher completion rate in long further educations. The short and middle length education have the same percentages of completion. An example of a long further education is a five year university degree, and a middle long education can be a bachelor's degree or a school teacher whereas an example of a short further education is an education such as a nursing degree, which takes around two and a half years.

The women without children have 39 percent who have not completed 9th grade in 1986. Among the mothers there are on average 34 percent who have not completed 9th grade however, the 9th grade non-completion rate is distributed as 23 percent of mothers with children younger than seven and 39 percent of mothers with children older than seven who has not completed 9th grade. The women without children have a relatively higher completion rate of 12th grade and a much lower percentage of people who have somewhere between 9th and 11th grade. This trend in the differences between mothers and non-mothers are also the same for the sample selected in 1984 even though there are bigger percentages of women with 9th grade in both categories. At last, mothers on average seem to have a little higher completion rate in a skilled education such as painter, carpenter or seamstress.

When I estimate the heterogeneous responses in labor market, welfare, and training participation I divide the sample in two for both age and education. I use the average age of women without children, which is 38 years, as the first sample division and under 12th grade as the second division of the sample.

The second page of the summary statistics show that mothers on average have higher gross income and receive more welfare benefits both for the sample from 1986 and the sample from 1984. The income and welfare benefits are not included in the difference-in-difference estimation since I consider them to be highly correlated with the number of children in the household. I have included whether or not the women were on welfare the year before the sample was selected and the percentages of women who received welfare benefits in the previous year were around 73 to 75 percent of the sample for both single women without children and for single mothers. The average outcome for single mothers covers a spread in welfare dependency where women with young children had a ten percentage point lower welfare participation rate in 1983 compared to mothers with a least one child between 7 and 17, and for the 1986 sample this difference was five percent.

The percentages of women in school and who held a job with a wage in the sample year and the year before the sample are relatively similar between the mother and the non-mothers. Notice that the variable "receiving a wage in 1986" is the first year of the dependent variable in the DID estimation on employment probabilities in the 1986 sample. It is similar for the sample from 1984.

Ownership shows a little higher percentage of women without children for whom there are five percent that owns a house relative to three percent among the mothers. I will use the ownership variable in the DID estimation to control for the effect of the "Potato Cure", which happened in 1987.

The distribution in the take up rate of other benefits than welfare show some significant differences between mothers and women without children. For sickness benefits the differences are more pronounced in the 1986 sample and for retirement benefits the differences are bigger in 1984. Overall the single mother have a higher percentage who receives sickness benefits and unemployment support whereas the women without have a higher tendency to receive retirement benefits. Women without children also seem to live in bigger cities because in 1986, 40 percent of the women without children lived in a city with more than 100.000 inhabitants where this number for the single mothers 26 percent.

The women's participation rates in the training program is what I use as the dependent variable in the DID estimation on training. The training participation rate is very different between mothers and women without children. In the sample from 1986 there were 17 percent of women without children who participated in the program and among mothers this was 25 percent. The distribution in the sample in 1984 looks similar where mothers had a training participation rate of 23 percent and women without children had 16 percent of their welfare participant who participated in a training program in 1984. Within the group of mothers there was almost no difference between women with young children and women with older children.

Finally, I would like to comment on the housing and child support. These two types of supports are not included in the difference-in-difference estimation because child support is practically proportional to the number of children in the household and housing support is also dependent on number of children in the household as well as household income. Both the house and the child support shown in the summary statistics are the two types of government support, which were given in addition to the welfare benefits. The last eight lines on the third page of table A1 and A2 describes the patterns in these support schemes.

The percentage of women who received housing support has increased during the periods of the two estimations. For the 1986 sample, mothers receiving housing support have increased 3 percentage point and women without children have increased 7 and the average amount of support in the two groups have also increased even though the numbers presented in the summary statistics are in nominal terms. In real terms the average amount is less and as a percentage of gross income this has not changed much.[13] The sample from 1984 shows similar trends thus when I compare the two periods in my DID estimation results, the changes in housing support are not a major concern.

The government child support does need some special attention. As I described in section 3 this support scheme was changed at the same time as the welfare reform and gave almost double support to the mothers in the sample. Table A1 and A2 show that for all years in both samples the percentage of mothers who received child support was almost 100 percent. The differences are in the amount of support that the mothers receive. In table A1 with the sample from 1984, the child support in 1984 is 8,380 Danish kroner and in 1986 this was 9,553 Danish kroner. This was an increase in nominal child support of 13 percent, which is less than what the gross nominal income increased by. The increase in the extra child support in 1987 shows in the summary statistics for the sample from 1986. The nominal amount of child benefits for the mothers in 1986 was 8,948 Danish kroner and in 1988 the same mothers received 17,232 Danish kroner. This is almost a doubling of child support which should be held up against an increase in nominal income (without the child support) of 16 percent.

[13] Nominal gross income is measured without child support and housing support from the state, but it does include welfare benefits.

The change in child support in the 1986 to 1988 period may cause problems in my empirical analysis because it may affect the relative outcomes of the mother and the women without children. When I describe the results of the estimations, I will comment further on the effect of this child support and suggest what kind of bias it can give the estimates.

7 Results

This section includes the results of equations 7, 8, and 9, which are the difference-in-difference estimations. Three estimations are reported, one for single women's employment status, another for their welfare status and a third for their training status. The employment status equals one for a given year if the women hold a job with a wage at any time throughout the year. Similarly for the welfare status and training status where welfare equals one if the women receive any benefits from welfare during the year and the training equals one if the women receive welfare conditional on training at any time in a given year. The status equals zero in all three categories if no wage was received for the employment status, if no welfare benefits were received for the welfare status, and if no benefits conditional on training were received for the training status.

For each of the three outcomes, three types of regressions are performed, each with different classification of the possible effects from the number of children living with the single mother. The 1987 reform increased welfare benefits for single mothers proportional to the number of children in the household between zero and 17 years old. In the first estimation the treatment indication is a variable for the number of children between zero and 17 in the household. The second estimation divides the number of children in the household between number of children who are six years or younger and number of children above six years old. This division is made to capture the effect of having children who are not yet in school and who requires daycare or kindergarten if the lone mother is working as opposed to the effect of having children above six years old who are attending school, at least for a period of the day. The last type of estimation includes the same division between number of children who are six years and younger and the number of children who are older than six but at the same time it includes two indicators of having at least one child who is six or younger or having at least one child who is older than six. These indicators are included to capture whether the effect on single mothers' labor market, welfare, and training participation is affected by the extra amount of welfare benefits (this is the number of children) or simply an effect of having at least one child. The effect of at least one child could be stronger than the effect of number of children if the single mother makes her decision based on having at least one child or not. This could be the case if the single mother is concerned with the freedom that comes with welfare or training participation. Finally estimations including fixed effects of municipality residence are performed for all three ways of reporting the effects of children.

The covariates I described in the data section are also included in the estimations. Age and year of schooling are included as a third order polynomial and being a recipient of other kinds of support are included as indicator variables. The covariates also include an indicator of owning a house, which is included to try and control for the change in taxation of houses that also occurred in the same year as the benefit reform. Finally, the covariates also include an indicator of what size city the women live in.

The crucial structural restriction of the DID estimator is the common trend. This restriction can be tested when a pre-treatment period exist. Without the treatment, the treated and the controls should follow a parallel path, which can be tested by applying the DID estimator for period $t = -1$ and period $t = 0$ and testing that α from equation 6 is equal to zero. These result are presented together with the results from the reform period.

The samples for the DID estimator from period $t = -1$ to $t = 0$ is created the same way as the 1986-1988 sample, just in stead of conditioning on receiving welfare in 1986, the pre-treatment sample conditions on receiving welfare in 1984 and the DID estimates the changes from 1984 to 1986.

A summary of the results are given in table 2, 3, and 4 and four of the full estimation results are presented in table A3, A4, A5, A6, A7, and A8 in the appendix.

7.1 Labor Market Participation[14]

The overall results from the difference-in-difference estimations of women's employment status show a small but insignificant increase in employment for mothers relative to single women without children. A summary of effect on single mothers' employment status is presented in table 2. This includes six different estimations for each period and four of the full estimations can be found in the appendix table A3 and A4. Comparing the reform period to the period before the reform the first regression shows a two percentage point increase in the employment probability per child a mother has. The effect of the number of children in the pre-reform period is almost exactly zero and in the period of the reform the estimate is significant at the 10 percent level when I do not control for municipality fixed effects. When I control for the municipality fixed effects the coefficient becomes insignificant and therefore it cannot be rejected that there is no effect from the number of children.

The results of dividing the children in the household up between children younger than seven years old and children between seven and 17 are given in line two and three. The estimates also show no significant differences between the two periods 1984-1986 and 1986-1988. The size of the estimates show that mothers with young children seem to have a larger increase in their employment probability relative to the mothers with older children. However, the standard errors are really large and it cannot be rejected that the two groups of mothers have the same change in employment rates.

The results of the last regression, which is equation 9 is reported in the last four lines of table 2. Comparing the two periods 84-86 and 86-88 the mothers with children younger than 7 and the mothers with older children show opposite patterns. There is a positive effect on employment probability of the number of young children when I take account of having at least one young child. This shows because the change in employment probability in number of children younger

[14]The labor market participation I refer to here is whether or not the women held a job with a paid wage during a given year. This will be used interchangeably with employment status.

than seven years is less negative in the 86-88 period than it is in the 84-86 period. In the 84-86 period mothers with young children experience a relative fall in employment probability of 14.7 percent. In the 86-88 period the fall is 6.3 percent but is not significantly different from zero. The positive effect on employment per child younger than seven is outweighed by a fall in the employment probability from 21.9 to 13.3 percent of mothers who have at least one young child. The change in employment probability of mothers with older children relative to the change of women without children show a fall in the number of children older than seven but an increase for having at least one child older than seven. However, none of the estimates are significantly different from zero.

Table 2.The effect of increased welfare benefits on single mothers' employment status in the reform period (1986-88) and the pre-reform period (1984-1986).

	84-86 (i)	86-88 (ii)	84-86 (iii)	86-88 (iv)
1.				
Number of children age 0-17	0.001	0.020*	-0.002	0.020
	(0.012)	(0.012)	(0.012)	(0.013)
2.				
Number of children age 0-6	0.013	0.037	0.018	0.036
	(0.024)	(0.023)	(0.025)	(0.024)
Number of children age 7-17	-0.003	0.015	-0.008	0.014
	(0.013)	(0.014)	(0.014)	(0.015)
3.				
Number of children age 0-6	-0.144**	-0.084	-0.147**	-0.063
	(0.062)	(0.060)	(0.065)	(0.063)
Number of children age 7-17	0.014	-0.014	0.004	-0.011
	(0.021)	(0.023)	(0.023)	(0.024)
Dummy for at least 1 child 0-6	0.208**	0.161**	0.219**	0.133*
	(0.076)	(0.074)	(0.079)	(0.077)
Dummy for at least 1 child 7-17	-0.037	0.061	-0.027	0.054
	(0.038)	(0.039)	(0.041)	(0.041)
Municipality fixed effects	no	no	yes	yes

*Significant at 10 percent level

**Significant at 5 percent level

Notes: Standard errors are given in parentheses below the estimates. All regressions include same explanatory variables as given in the appendix

The estimates from equation 7 and 8 of the linear probability model presented above show similar results in a Chamberlain fixed effect logit estimation. These results are given in table A9 in the appendix. Here mothers also have a positive increase in employment probability per child younger than 7 relative to women without children, and for mothers with older children there is no significant change.[15]

[15]I only present results from equation 7 and 8 because the small sample size when conditioning on a change

The estimates on employment probability of single mothers relative to single women without children can be affected by the increase in government child support, which occurred the same time as the reform. The increase in child support was independent of labor market or welfare status and in the static labor supply model presented in section 4, this child support can be thought of as unearned income, N. If leisure is a normal good, an increase in unearned income will give a negative income effect on labor supply. This means that the estimates on the employment effect of the number of children in the household are a lower bound for the actual effect of the welfare reform.

I would also like to comment on the covariate, which indicates whether the single women owns a house or not. Due to the "Potato Cure" the women who owned a house would have experienced an income fall in the period of the reform relative to the period before the reform. This is a fall in unearned income, which according to the static labor supply model should lead to an increase in employment if leisure is a normal good. Comparing the coefficient on ownership in the reform period with the coefficient on ownership in the period before the reform shows a positive effect on employment probability of ownership. Table A3 in the appendix shows that the coefficient on ownership in the reform period is significantly positive and a little higher than 9 percent. The same coefficient in the pre-reform period is presented in table A4 and is 4 percent and is not significantly different from zero. This positive effect on employment probability of a drop in unearned income supports my argument that an increase in unearned income from extra child support would have a negative effect on employment. Thus, there is more reason to think that the estimates on the number of children are a lower bound.

The positive employment effect of number of young children and the insignificant effect of older children cannot be explained by the labor supply models I presented in section 4. The results are also not in line with other studies on labor supply effects of welfare programs. Moffitt (1992) has a survey of the empirical effects of the Aid to Families with Dependent Children (AFDC), which was an American welfare program.[16] The AFDC guaranteed a minimum income much like the Danish welfare program analyzed in this paper. The empirical results of AFDC all show that the program reduced labor supply and induced greater participation in the program. For Denmark Toomet (2005) has found that an increase in welfare benefits for young females reduce their entry rate into employment corresponding to an income elasticity of -0.4.

7.1.1 Heterogeneous responses in employment

In this section I present row (iii) and (iv) from table 2 seperately for women younger and older than 38 and for women with more or less education than 12th grade.[17] The two regressions presented in table A11 in the appendix show that older women tend to be the ones who experience the increase in employment probability when they have younger children. However, these effects from the two years are neither significantly different from each other nor are any

in employment status in the fixed effect logit.

[16]AFDC is now replace by Temporary Assistance for Needy Families (TANF). TANF is a welfare program that has a work requirement and a time limit and is therefore not suited for comparison to the Danish welfare program from the 1980's.

[17]I only present results from equation 7 and 8 because small sample sizes.

of them significantly different from zero. The younger women show practically no change in employment probability between the periods.

Table A12 in the appendix presents the results from dividing the sample up into women with at most 11th grade and women who have 12th grade or higher. This shows that it is the higher educated women with the young children who experience the higher employment probability during the period of the reform. This group experienced a five percent (insignificant) increase in employment probability compared to women without children during the reform period.

Summarizing the overall impact of the welfare benefit reform on the employment probabilities of mothers compared to women without children is not significantly different from the period before the reform. Mothers who are divided into their childrens' age categories show no significant effect when I do not control for having at least one child in the age category. But the insignificant results show that women with children between zero and six years old have an increase in their employment probability that is dependent on the number of children they have. This increase seems to come from older and more educated women who are the ones that show the increase in employment probability between the two periods. Women with older children show practically no changes in their employment rates between the period before the reform and the period of the reform

7.2 Welfare Participation

The results from the difference-in-difference estimations are reported in table 3. If the welfare participants only have the choice of either welfare or work then the welfare participation should be a mirror image of the employment rates. However, this is only the case for regression 3, which comes from equation 9.

A summary of effect of the number of children on the mothers' welfare participation status is presented in table 3. As was the case for the DID estimations on the employment status, this summary table also includes six different estimations for each period and four of the full estimations can be found in the appendix table A5 and A6. The effect of the increase in benefits have a negative impact from the overall number of children on mothers' welfare participation rate. In regression 1 column (iii) and (iv) the relative change in mothers welfare participation rate has fallen from 4.8 percent to 2.9 percent.

The relative change in welfare participation from the period before the reform to the period of the reform is very different for mothers with young children and mothers with older children. This is seen from regression two, which divides mothers into mothers with young children and mothers with older children. The effect of the increase in benefit on welfare participation seems to have positively affected single mothers welfare participation through the number of their children who are six years old or younger and negatively affected single mothers from the number of children who are older than seven. However, in the regressions where I divide up the effect from the number of children even further this shows that the positive effect on welfare participation of the number of children younger than seven is more an effect of the mother having at least one child under seven years old in the household. Regression three shows a decrease in the welfare participation from the number of children younger than seven years old. In the period before the reform the mothers with young children had a 11.2 percent higher probability of staying on welfare throughout the period than women without children. In the reform period this had fallen to an insignificant 4.3 percent. The change in the effect of having at least one child younger than seven is positive but insignificant. Mothers with older children show no significant differences between the two periods but they do have an (insignificant) fall in their welfare participation. This effect is through having at least one child between seven and 17 and not through the number of children.

Table 3. The effect of increased welfare benefits on single mothers' welfare status in reform period (1986-88) and pre-reform period (1984-1986).

	84-86 (i)	86-88 (ii)	84-86 (iii)	86-88 (iv)
1.				
Number of children age 0-17	0.052**	0.035**	0.048**	0.029**
	(0.010)	(0.011)	(0.011)	(0.011)
2.				
Number of children age 0-6	0.049**	0.080**	0.051**	0.077**
	(0.020)	(0.021)	(0.021)	(0.022)
Number of children age 7-17	0.053**	0.021*	0.047**	0.014*
	(0.011)	(0.012)	(0.012)	(0.013)
3.				
Number of children age 0-6	0.107**	0.057	0.112**	0.043
	(0.053)	(0.053)	(0.055)	(0.056)
Number of children age 7-17	0.029	0.033	0.028	0.024
	(0.018)	(0.020)	(0.020)	(0.022)
Dummy for at least 1 child 0-6	-0.077	0.030	-0.081	0.046
	(0.065)	(0.066)	(0.068)	(0.069)
Dummy for at least 1 child 7-17	0.053	-0.026	0.042	-0.021
	(0.032)	(0.034)	(0.035)	(0.036)
Municipality fixed effects	no	no	yes	yes

*Significant at 10 percent level

**Significant at 5 percent level

Notes: Standard errors are given in parentheses below the estimates. All regressions include same explanatory variables as given in the appendix

Comparing the welfare participation results in regression 3 from equation 9 to the results of the employment probability from equation 9 the two regressions show results that are consistent with each other. In the previous section I described how mothers with young children had an increase in their employment probabilities during the reform and mothers with older children did not show any effects that were significantly different from zero. The results of the welfare participation mirror this result such that the women with young children who had an increase in employment probability had a decrease in welfare participation at the same time. Neither of these two results match the theory, which I described in section 4. This also does not match the literature presented in Moffitt (1992) where the impact of the benefit levels of the AFDC has a positive effect on enrollment in the program.

The same way as the estimates on employment should illustrate a lower bound the estimates on welfare participation should represent a higher bound if leisure is a normal good. This means that the negative effect on welfare participation of the number of children under seven potentially could be even more negative. However, in this case table A5 and A6, which show the regressions including covariates does not seem to support the theory that higher income makes people more likely to participate in welfare. Again I look at the coefficient on ownership, which in the 1984-86 period is 0.11 and is significant at the 5 percent level. In the 1986-88 period this coefficient has decreased and is insignificant and around 0.044. All other things equal, this means that the fall in income experienced by the house owners has caused more of them to participate in welfare. This does therefore not support the theory that lower income should give higher labor supply. It is therefore more uncertain whether the increase in the extra child benefits cause the coefficients on the number of children to be a higher bound.

7.2.1 Heterogeneous responses in welfare participation

The results from the heterogeneous responses in welfare participation caused by age and education are presented in table A13 and A14 in the appendix. The absolute change in the estimates between the two periods are relatively similar for the two age groups. They both show a decrease in welfare participation in response to the total number of children. Furthermore, the effects when the mothers are divided into mothers with young children and mothers with old children are also the same as when there was no division of the mothers' age.

Table A14 shows the welfare participation effects when the sample is divided into more or less educated women. Both samples show that mothers reduce their welfare participation with the numbers of children who are seven years or older. However, only the women with 12th grade or higher show the positive effect in welfare participation from the number of children under seven (when having at least one child under seven is not controlled for). The women with an education shorter than 12 years and children younger than seven have a fall in their relative welfare participation from the period before the reform to the period of the reform.

Summarizing the overall impact on welfare participation is highly dependent on which category the number of children is divided into. Mothers with older children have a fall in their welfare participation rate, which seems to be driven by the effect of having at least one child between seven and 17 and not from the number of children. The mothers with children between zero and six years old show a decrease in their welfare participation from the number of their children but a positive effect of having at least one child in the age category. The women with an education, which is shorter than 12 years all have a decrease in their welfare participation when the reform period is compared to the period before the reform. This is true even when I do not control for having at least one child in the two different age categories.

7.3 Training Participation

The last outcome I will analyze is the participation in training under the welfare program. The results on the training participation are to some extent clearer than those of welfare participation in the sense that they do not change signs depending how I categorize the children. In table 3 a comparable summary to that of the six regressions on welfare participation is reported, only in this section it is for training participation. The full estimations are reported in the appendix table A7 and A8. In table 3 it can be seen that there is a positive effect on training participation from the number of children a single mother has during the reform period. The effect is coming from the number of children who are six years old or younger. Single mothers have about 5 percentage points higher probability of entering training per child they have under seven years old compared to the period before the reform. The effect from the number of children between seven and 17 is also positive but small and not significantly different from zero. In regression 3 when I control for having at least one child younger or older than seven, the effect from the number of children between zero and six becomes even stronger. This is because the change in the coefficient of indicator for having at least one child between zero and six has decreased from the period before the reform to the reform period. The small positive (insignificant) effect of the number of children older than seven seems to come from an effect of just having at least one child older than seven, even though the coefficients are insignificant.

Table 4. The effect of increased welfare benefits on single mothers' training status in reform period (1986-88) and pre-reform period (1984-1986).

	84-86 (i)	86-88 (ii)	84-86 (iii)	86-88 (iv)
1.				
Number of children age 0-17	0.004	0.031**	-0.002	0.026**
	(0.010)	(0.010)	(0.010)	(0.011)
2.				
Number of children age 0-6	0.014	0.082**	0.006	0.071**
	(0.020)	(0.020)	(0.020)	(0.021)
Number of children age 7-17	0.001	0.016	-0.004	0.012
	(0.011)	(0.012)	(0.011)	(0.012)
3.				
Number of children age 0-6	-0.018	0.134**	-0.027	0.119**
	(0.051)	(0.051)	(0.053)	(0.054)
Number of children age 7-17	0.015	-0.000	0.017	-0.001
	(0.018)	(0.019)	(0.019)	(0.021)
Dummy for at least 1 child 0-6	0.043	-0.070	0.045	-0.064
	(0.063)	(0.063)	(0.065)	(0.066)
Dummy for at least 1 child 7-17	-0.032	0.034	-0.045	0.028
	(0.031)	(0.033)	(0.033)	(0.035)
Municipality fixed effects	no	no	yes	yes

*Significant at 10 percent level

**Significant at 5 percent level

Notes: Standard errors are given in parentheses below the estimates. All regressions include same explanatory variables as given in the appendix

The two first regressions in the linear probability model presented above are also estimated by the Chamberlain fixed effect logit model. The results of this are given in table A10 in the appendix. The results show the same overall trend of mothers having an increase in training per child they have between zero and six years old. Also the mothers with older children show an increase in training dependent on the number of children older than seven, even though this effect is not significantly different from zero.

There should not exist an effect on training participation of the extra child support, if the training is viewed as a human capital investment. Unearned income, which is provided to the single mothers whether or not they participate in the welfare program, training program or have a full time job should not affect the human capital investment. This means that in theory the coefficients on training should not be biased as an effect of the extra child benefits provided during the period of the reform. I again compare to coefficient on housing ownership from the period before the reform to the period of the reform To see if a change in unearned income affects the training participation. Table A7 and A8 shows that the ownership coefficient is around 0.05 and not significantly different from zero in both periods analyzed. This supports the theory of no income effect on training.

A last thing to notice from table A7 and A8 are the coefficients on health and welfare. The reason for looking specifically at these two coefficients is because both the people receiving sickness benefits (which is the health variable) and the people who are long time unemployed (illustrated by the variable of receiving welfare in the year previous the sample period) are focus groups of the training program. I have argued that no change in administration occurred during the period of the reform compared to the period before the reform. By comparing the results for sickness benefits receivers and the long time unemployed from the period before the reform to the period of the reform I can see how these two other focus groups have changed their participation rates. These two groups did not experience an increase in their benefits and they should therefore show no effect of the reform. Comparing the results from these two groups will give me an indication of whether or not there was any change in the administration of the focus groups' entry into the training program.

Overall the coefficients on both the health and welfare do not show any increase in participation rates of these two other focus groups. By looking at the two periods 86-88 and 84-86 and comparing the coefficients on health86 to health84 and health8586 to health8384 the coefficients differ by two or three percentage points. The health84 is positive and significantly different from zero whereas health86 is not. This indicates that people on sickness benefits take less training during the reform period compared to the period before the reform. The coefficient on welfare85 and welfare83 are both around -0.09 and significant. This means that women who have been unemployed in the years previous to the estimation periods had a fall in their training participation rates but the fall is the same for both periods. Together the two results indicate no changes in the administration of the focus groups' entry into the training program.

In section 5.2 I discussed some potential problems of selection into the training program. I am especially interested in finding out if the estimations can give some indication of where the positive effect in training participation comes from. For this purpose I will only compare women with children between zero and six years old. The second DID estimation of training shows a significantly positive increase in training from the number of children from the period before the reform to the period of the reform. In the 1984-86 period the estimate was 0.006 and in the period of the reform this estimate was 0.071. This is an increase in the change of training participation of mothers relative to non-mothers of 6.5 percentage points. The relative welfare participation of the same group was 0.051 in the 1984-86 period and 0.077 in 1986-88. This is an increase in welfare participation of 2.6 percentage points per child between zero and six. This means that the increase in training was larger than the increase in welfare and the ratio of training participants to passive welfare participants must have increased. This further means that mothers who stayed on welfare during the reform period have a relatively higher rate of training participation compared to mothers who stayed on welfare before the reform. I interpret this as the increase in training is at least party due to mothers substituting passive welfare with training.

Miller and Sanders (1997) is another paper, which analyzes the effect of higher welfare benefits on human capital investment. They compare the generosity of Aid to Dependent Families with Children (AFDC) across states in the US and look at the high school completion rate. They find that the high school completion rates are not significantly affected by the level of welfare support provided by the different states. This is comparable to my results for women with older children but not for mothers with young children who increase their training participation with the higher amount of welfare benefits.

7.3.1 Heterogeneous responses in welfare participation

The results from the heterogeneous responses in training participation caused by age and education are presented in table A15 and A16 in the appendix. The results are not heterogeneous with respect to either age or education. Table A15, which shows the DID estimation divided into women younger and older than 38, shows the same pattern as the overall results presented above. The only heterogeneous effect is that older mothers have a relative larger increase in the training participation during the reform than their younger counterparts. In table A16 there is no difference in the estimates for mothers with a short education compared to the mothers with a long education.

Summarizing the overall impact of higher welfare benefits on training shows a positive effect on training from the number of children between zero and six years old. These is also a positive effect from having at least one child older than seven but the effect is not significantly different from zero. There is very little heterogeneity in the training participation response across women of different age group and across women with different length of education. Finally, there is some evidence that the effect on training comes from the increase in welfare benefits and not from mothers being a focus group of the municipality case worker nor because mothers receive extra child benefits during the period of the reform.

8 Conclusion

In this paper I have estimated the effects of a Danish welfare reform on three outcomes, which are employment, welfare participation, and participation in a training program. The welfare reform occurred in 1987 and increased the maximum amount of attainable welfare benefits by 12 percent for mothers with one child and by 16 percent for mothers with two children. Using longitudinal data from 1983 to 1988 I use a difference-in-difference technique to estimate the reform's impact on the outcomes of single mothers. The results show considerable heterogeneity in the treatment effect for mothers with children of different ages.

The mothers with older children do not show any significant changes in their employment probabilities or their training participation rates when I compare the period around the reform to the period before the reform. The impact of the reform on welfare participation for mothers with older children is negative, indicating higher exit rates out of welfare during the reform period relative to the period before the reform. However, this effect is not an income effect driven by the number of older children but rather an effect of having at least one older child.

The most robust result of my analysis is a positive and significant impact of the reform on the training participation of mothers dependent on the number of their children between zero and six years old. The increase in training during the reform period is occurring both for younger and older mothers as well as for the more and less educated mothers. The result is also robust to estimating the impact by a fixed effect logit model rather than the linear probability model, which I have used to interpret the results from. The effects from the number of young children on their mothers' employment probability is positive, which is an effect that is driven by the older and more educated mothers. Finally the impact on welfare participation from the number of young children a mother has, is highly dependent on how the children are categorized. When I control for having at least one child between zero and six, the welfare participation of mothers is decreasing the number of young children during the reform period. If I do not control for having at least one child in the age category the welfare participation effect changes sign and becomes negative in the number of young children.

Estimations involving training, which compares single mothers to single women without children are often subjected to criticism because it is argued that case workers assigning training will always give priority to the single mothers. In this paper I have argued that the official guidelines of the training program issued to the case workers did not change during the period from 1983 to 1988. The guidelines mentioned six focus groups for the training program and I have showed that the two groups (other than single mothers), which I can identify did not change their training participation rates when I compare the period of the reform to the period before the reform. I interpret this as an indication that there has been no change in the administration of the entry requirements into the training program, which therefore makes my estimates on training participation more credible.

Another way to make the results more credible is to perform the estimations on a bigger sample. This way I can get more precise estimates and be able to allow for more heterogeneity in order to get a better understanding of what is driving the results. The full population of welfare recipients will soon be available to me and when this happens I expect to be able to divide the data into more narrowly defined groups. This will for instance allow me to include immigrants and refugees in my analysis.

In this paper I have primarily been interested in finding the impact of the reform on mothers' training participation rates. Analyzing welfare benefits' effect on training participation is something that I have not found analyzed in the literature and hopefully my results can shed some light on the subject. However, a more formal model is required in order to understand more about the decision to enter training programs and how this decision is affected by the amount of welfare benefits a participant can receive. Combining the existing theory on human capital accumulation with a possibility of welfare and training during welfare could be the next step to understanding more about the training participation decision and perhaps a way to give a better interpretation to my results.

9 References

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APPENDICES

A1 Appendix

Derivation 1: Derivation of equation 3:

Equation 1 is given by:

$$Y\left(i,t\right)=\delta\left(t\right)+\alpha\cdot D\left(i,t\right)+\eta\left(i\right)+\nu\left(i,t\right) \tag{1a}$$

and the sufficient condition is:

$$P\left(D\left(i,1\right)=1|\nu\left(i,t\right)\right)=P\left(D\left(i,1\right)=1\right) \tag{2a}$$

By subtracting and adding $E\left[\eta\left(i\right)|D\left(i,1\right)\right]$ in equation 1a:

$$Y\left(i,t\right)=\delta\left(t\right)+\alpha\cdot D\left(i,t\right)+E\left[\eta\left(i\right)|D\left(i,1\right)\right]+\left\{\eta\left(i\right)-E\left[\eta\left(i\right)|D\left(i,1\right)\right]+\nu\left(i,t\right)\right\}$$

which gives:

$$Y\left(i,t\right)=\delta\left(t\right)+\alpha\cdot D\left(i,t\right)+E\left[\eta\left(i\right)|D\left(i,1\right)\right]+\varepsilon\left(i,t\right) \tag{3a}$$

where $\varepsilon\left(i,t\right)=\eta\left(i\right)-E\left[\eta\left(i\right)|D\left(i,1\right)\right]+\nu\left(i,t\right)$
Because $\delta\left(t\right)=\delta\left(0\right)+\left(\delta\left(1\right)-\delta\left(0\right)\right)t$
and $E\left[\eta\left(i\right)|D\left(i,1\right)\right]=E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]+\left(E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]-E\left[\eta\left(i\right)|D\left(i,1\right)=0\right]\right)D\left(i,1\right)$
Then equation 3a can be rewritten as:

$$\begin{aligned}Y\left(i,t\right) \;=\;& \delta\left(0\right)+\left(\delta\left(1\right)-\delta\left(0\right)\right)t+\alpha\cdot D\left(i,t\right)+\\ & E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]+\left(E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]-E\left[\eta\left(i\right)|D\left(i,1\right)=0\right]\right)D\left(i,1\right)+\varepsilon\left(i,t\right)\end{aligned}$$

which rearranged look like:

$$\begin{aligned}Y(i,t)=&\,\delta(0)+E\left[\eta(i)|D(i,1)=1\right]\\ &+\left(E\left[\eta(i)|D(i,1)=1\right]-E\left[\eta(i)|D(i,1)=0\right]\right)D(i,1)\\ &+\left(\delta(1)-\delta(0)\right)t+\alpha\cdot D(i,t)+\varepsilon(i,t)\end{aligned} \tag{4a}$$

setting:
$\mu=\delta\left(0\right)+E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]$
$\tau=E\left[\eta\left(i\right)|D\left(i,1\right)=1\right]-E\left[\eta\left(i\right)|D\left(i,1\right)=0\right]$, and
$\delta=\delta\left(1\right)-\delta\left(0\right)$
then equation 4a can be written as:

$$Y\left(i,t\right)=\mu+\tau\cdot D\left(i,1\right)+\delta\cdot t+\alpha\cdot D\left(i,t\right)+\varepsilon\left(i,t\right)$$

which is exactly equation 3 that is derived

Derivation 2: The Chamberlain fixed effect logit model

In order to compare the results from this model to the linear probability, I have only allowed the covariates to enter in levels from the year of the sample periods' start. These level are interacting them with time the same way as was the case for the linear probability model showed in section 5. The idea behind the fixed effect logit is to condition the sample observations for which $Y(i,t)$ changes, such that:

$$Y(i,t) = 1\left\{X(i,t)'\pi + \eta(i) + \nu(i,t) > 0\right\}$$

where $X(i,t)$ is the same list of covarites as in regression 6 and includes an indicator for being a mother in period $t = 1$. Then it can be showed that :

$$\begin{aligned} & P\left(Y(i,0) = 0, Y(i,1) = 1 | Y(i,0) + Y(i,1) = 1, X(i,0), X(i,1), \eta(i)\right) \\ = & \frac{1}{1 + \exp\left(X(i,1) - X(i,0)\pi\right)} \\ = & \Lambda\left(\Delta X(i,1)\pi\right) \end{aligned}$$

Table A1: Summary Statistics 1984. Means and standard deviations.

	Without children	With children		
Covariates		at least 1 child	at least 1 child 0-6	at least 1 child 7-17
Observations in 1984	929	1417	667	1037
Number of children in 1984		1.68	1.82	1.82
		(.83)	(.87)	(.88)
Number of children <7 in 1984		.58	1.23	.32
		(.69)	(.45)	(.55)
Number of children >6 in 1984		1.10	.60	1.50
		(.91)	(.79)	(.73)
Age in 1984	38.99	33.90	30.43	35.68
	(9.59)	(6.25)	(4.50)	(5.93)
Years of schooling in 1984	9.25	9.41	9.61	9.20
	(3.31)	(2.90)	(2.87)	(2.90)
Under 9th grade	.45	.39	.29	.46
	(.50)	(.49)	(.45)	(.50)
9th to 11th grade	.18	.28	.38	.23
	(.38)	(.45)	(.49)	(.42)
12th grade	.10	.05	.08	.03
	(.31)	(.22)	(.27)	(.17)
Skilled	.13	.18	.15	.19
	(.34)	(.38)	(.35)	(.39)
Short further education	.01	.01	.02	.01
	(.12)	(.11)	(.13)	(.11)
Middle further education	.06	.06	.06	.05
	(.24)	(.23)	(.23)	(.21)
Long further education	.05	.03	.04	.03
	(.22)	(.17)	(.19)	(.17)

Continued on next page

Table A1: Summary Statistics 1984. Means and standard deviations, cont.

	Without children	With children		
Covariates		at least 1 child	at least 1 child 0-6	at least 1 child 7-17
Gross Income in 1984	64123	76817	75904	76954
	(31029)	(32678)	(32463)	(32390)
Welfare benefits in 1984	25200	25889	27973	26018
	(18692)	(21097)	(21823)	(20971)
Receiving welfare benefits in 1983	.75	.73	.66	.76
	(.44)	(.44)	(.48)	(.43)
Receiving sickness benefits in 1984	.12	.17	.19	.16
	(.33)	(.37)	(.39)	(.37)
Receiving sickness benefits in 1983	.16	.17	.19	.16
	(.36)	(.38)	(.39)	(.37)
Receiving sickness benefits in 1983 and 1984	.06	.08	.08	.08
	(.23)	(.27)	(.27)	(.27)
In school in 1983	.14	.12	.11	.12
	(.34)	(.33)	(.32)	(.33)
In school in 1984	.12	.14	.14	.13
	(.33)	(.34)	(.35)	(.34)
Receiving unemployment support in 1983	.12	.23	.22	.23
	(.33)	(.42)	(.42)	(.42)
Receiving unemployment support in 1984	.16	.27	.26	.26
	(.37)	(.44)	(.44)	(.44)
Training participation 1984	.16	.23	.24	.23
	(.37)	(.42)	(.43)	(.42)
Ownership	.06	.03	.03	.03
	(.24)	(.17)	(.16)	(.17)

Continued on next page

Table A1: Summary Statistics 1984. Means and standard deviations, cont.

Covariates	Without children	With children: at least 1 child	at least 1 child 0-6	at least 1 child 7-17
Receiving retirement benefits in 1983	.03	.01	.01	.01
	(.16)	(.09)	(.08)	(.08)
Receiving retirement benefits in 1984	.10	.02	.00	.03
	(.30)	(.16)	(.07)	(.16)
Receiving a wage in 1983	.49	.55	.53	.54
	(.50)	(.50)	(.50)	(.50)
Receiving a wage in 1984	.47	.57	.54	.56
	(.50)	(.50)	(.50)	(.50)
City w/ more than 100.000	.39	.32	.31	.30
	(.49)	(.47)	(.46)	(.46)
City b/t 50-100.000	.13	.12	.11	.12
	(.33)	(.33)	(.32)	(.32)
City b/t 20-50.000	.26	.28	.29	.28
	(.44)	(.45)	(.46)	(.45)
Receiving housing support in 1984	.39	.78	.78	.81
Receiving child benefits in 1984	.11	.98	.98	.99
Receiving housing support in 1986	.45	.81	.82	.83
Receiving child support in 1986	.00	.99	1.00	.99
Amount of housing support in 1984	1667	8606	8393	9209
Amount of child benefits in 1984	434	8380	8221	9188
Amount of housing support in 1986	2744	10345	10544	10698
Amount of child support in 1986	36	9554	9991	9960

Table A2: Summary Statistics 1986. Means and standard deviations

	Without children	With children		
Covariates		at least 1 child	at least 1 child 0-6	at least 1 child 7-17
Observations in 1986	878	1415	670	1026
Number of children in 1986		1.60	1.76	1.73
		(.77)	(.85)	(.81)
Number of children <7 in 1986		.57	1.20	.31
		(.68)	(.46)	(.54)
Number of children >6 in 1986		1.03	.55	1.42
		(.84)	(.77)	(.65)
Age in 1986	38.09	34.00	30.60	35.75
	(9.50)	(6.17)	(4.68)	(5.78)
Years of schooling in 1986	9.55	9.52	9.68	9.34
	(3.32)	(2.95)	(2.89)	(3.04)
Under 9th grade	.39	.34	.23	.39
	(.49)	(.47)	(.42)	(.49)
9th to 11th grade	.19	.33	.44	.28
	(.40)	(.47)	(.50)	(.45)
12th grade	.13	.05	.07	.04
	(.34)	(.22)	(.26)	(.19)
Skilled	.15	.17	.14	.18
	(.36)	(.37)	(.35)	(.38)
Short further education	.01	.01	.01	.01
	(.12)	(.11)	(.10)	(.12)
Middle further education	.06	.06	.06	.06
	(.24)	(.24)	(.24)	(.24)
Long further education	.05	.04	.04	.04
	(.23)	(.19)	(.20)	(.19)

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Table A2: Summary Statistics 1986. Means and Standard Deviations, cont.

	Without children	With children		
		at least 1	at least 1	at least 1
Covariates		child	child 0-6	child 7-17
Gross Income in 1986	75568	88365	85647	89450
	(37032)	(36804)	(34996)	(37464)
Welfare benefits in 1986	25684	27041	28349	27735
	(21257)	(23406)	(23923)	(23865)
Receiving welfare benefits in 1985	.73	.74	.71	.76
	(.44)	(.44)	(.45)	(.43)
Receiving sickness benefits in 1986	.15	.20	.27	.18
	(.36)	(.40)	(.44)	(.38)
Receiving sickness benefits in 1985	.14	.19	.25	.17
	(.34)	(.39)	(.43)	(.38)
Receiving sickness benefits in 1985 and 1986	.07	.10	.15	.09
	(.26)	(.31)	(.36)	(.29)
In school in 1985	.15	.13	.11	.12
	(.35)	(.33)	(.32)	(.33)
In school in 1986	.13	.13	.15	.12
	(.34)	(.34)	(.36)	(.32)
Receiving unemployment support in 1985	.15	.25	.27	.23
	(.36)	(.43)	(.45)	(.42)
Receiving unemployment support in 1986	.15	.22	.23	.22
	(.36)	(.42)	(.42)	(.41)
Training participation 1986	.17	.25	.27	.24
	(.38)	(.43)	(.44)	(.43)
Ownership	.05	.03	.03	.03
	(.22)	(.17)	(.17)	(.17)

Continued on next page

Table A2: Summary Statistics 1986. Means and Standard Deviations, cont.

	Without children	With children		
Covariates		at least 1 child	at least 1 child 0-6	at least 1 child 7-17
Receiving retirement benefits in 1985	.03	.01	.00	.01
	(.16)	(.11)	(.07)	(.11)
Receiving retirement benefits in 1986	.07	.03	.01	.04
	(.26)	(.17)	(.11)	(.17)
Receiving a wage in 1985	.54	.58	.57	.59
	(.50)	(.49)	(.50)	(.49)
Receiving a wage in 1986	.57	.61	.58	.61
	(.50)	(.49)	(.49)	(.49)
City w/ more than 100.000	.40	.26	.28	.28
	(.49)	(.47)	(.45)	(.45)
City b/t 50-100.000	.12	.12	.12	.12
	(.33)	(.33)	(.32)	(.33)
City b/t 20-50.000	.25	.29	.31	.29
	(.43)	(.45)	(.46)	(.45)
Receiving housing support in 1986	.42	.78	.77	.80
Receiving child benefits in 1986	.09	.99	.98	1.00
Receiving housing support in 1988	.49	.83	.87	.84
Receiving child support in 1988	.01	.99	1.00	.99
Amount of housing support in 1986	2052	9185	8710	9923
Amount of child benefits in 1986	374	8948	8952	9761
Amount of housing support in 1988	3333	11962	12627	12233
Amount of child support in 1988	52	17232	19007	17924

Table A3: Difference-in-difference estimation of labor market participation in the years 1986 to 1988, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.020*			
	(0.012)			
nbr of children <7		0.037	0.036	-0.063
		(0.023)	(0.024)	(0.063)
nbr of children >6		0.015	0.014	-0.011
		(0.014)	(0.015)	(0.024)
child <7 dummy				0.133*
				(0.077)
child >6 dummy				0.054
				(0.041)
year of school86	0.004	0.004	-0.006	-0.005
	(0.024)	(0.024)	(0.025)	(0.025)
year of school86^2	-0.001	-0.001	-0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)
year of school86^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age86	0.129	0.136	0.166*	0.162*
	(0.090)	(0.090)	(0.098)	(0.098)
age86^2	-0.003	-0.004	-0.004*	-0.004
	(0.002)	(0.002)	(0.003)	(0.003)
age86^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	0.094*	0.095*	0.092*	0.093*
	(0.052)	(0.052)	(0.054)	(0.054)
health85	0.016	0.014	-0.007	-0.005
	(0.039)	(0.039)	(0.042)	(0.042)
health86	-0.196**	-0.197**	-0.194**	-0.193**
	(0.031)	(0.031)	(0.033)	(0.033)
health8485	-0.051	-0.051	-0.016	-0.016
	(0.051)	(0.051)	(0.054)	(0.054)
welfare85	0.014	0.015	0.007	0.007
	(0.025)	(0.025)	(0.027)	(0.027)

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Table A3 continued: Difference-in-difference estimation of labor market participation in the years 1986 to 1988, part 2

	(1)	(2)	(3)	(4)
unemployment insurance85	-0.032	-0.032	-0.027	-0.029
	(0.032)	(0.032)	(0.035)	(0.035)
unemployment insurance86	0.034	0.035	0.026	0.023
	(0.033)	(0.033)	(0.035)	(0.035)
retirement85	-0.035	-0.036	-0.018	-0.015
	(0.097)	(0.097)	(0.101)	(0.101)
retirement86	0.027	0.028	0.019	0.019
	(0.059)	(0.059)	(0.062)	(0.062)
in school85	0.060	0.062	0.060	0.063
	(0.043)	(0.043)	(0.045)	(0.045)
in school86	0.099**	0.098**	0.085*	0.083*
	(0.043)	(0.043)	(0.045)	(0.045)
big municipality	0.003	0.003	0.098	0.025
	(0.028)	(0.028)	(0.506)	(0.507)
medium municipality	-0.002	-0.002	-0.083	-0.159
	(0.036)	(0.036)	(0.520)	(0.521)
small municipality	0.009	0.008	0.613	0.537
	(0.029)	(0.029)	(0.618)	(0.619)
municipality fixed effects	no	no	yes	yes
constant	-1.636	-1.749	-2.162*	-2.041
	(1.096)	(1.105)	(1.304)	(1.305)
Adjusted R^2	0.036	0.036	0.036	0.037

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A4: Difference-in-difference estimation of labor market participation in the years 1984 to 1986, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.001			
	(0.012)			
nbr of children <7		0.013	0.018	-0.147**
		(0.024)	(0.025)	(0.065)
nbr of children >6		-0.003	-0.008	0.004
		(0.013)	(0.014)	(0.023)
child <7 dummy				0.219**
				(0.079)
child >6 dummy				-0.027
				(0.041)
year of school84	0.012	0.012	0.029	0.027
	(0.024)	(0.024)	(0.025)	(0.025)
year of school84^2	-0.002	-0.002	-0.003	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)
year of school84^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age84	0.085	0.092	0.099	0.097
	(0.092)	(0.093)	(0.099)	(0.099)
age84^2	-0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)
age84^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	-0.043	-0.043	-0.040	-0.041
	(0.051)	(0.051)	(0.053)	(0.053)
health83	-0.038	-0.038	-0.034	-0.034
	(0.042)	(0.042)	(0.044)	(0.044)
health84	-0.188**	-0.188**	-0.177**	-0.182**
	(0.033)	(0.033)	(0.034)	(0.034)
health8283	0.004	0.003	0.009	0.013
	(0.052)	(0.052)	(0.055)	(0.055)
welfare83	0.079**	0.080**	0.082**	0.085**
	(0.025)	(0.025)	(0.027)	(0.027)

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Table A4 continued: Difference-in-difference estimation of labor market participation in the years 1984 to 1986, part 2

	(1)	(2)	(3)	(4)
unemployment insurance83	0.080**	0.080**	0.093**	0.093**
	(0.036)	(0.036)	(0.038)	(0.038)
unemployment insurance84	-0.035	-0.035	-0.039	-0.036
	(0.034)	(0.034)	(0.036)	(0.036)
retirement83	-0.062	-0.063	-0.061	-0.064
	(0.095)	(0.095)	(0.103)	(0.103)
retirement84	0.008	0.009	0.027	0.029
	(0.054)	(0.054)	(0.058)	(0.058)
employed83	0.093**	0.094**	0.096**	0.100**
	(0.046)	(0.046)	(0.049)	(0.049)
employed84	0.088*	0.088**	0.070	0.067
	(0.045)	(0.045)	(0.047)	(0.047)
in school83	-0.053	-0.051	-0.059	-0.057
	(0.038)	(0.038)	(0.040)	(0.040)
in school84	-0.167**	-0.166**	-0.159**	-0.160**
	(0.037)	(0.037)	(0.038)	(0.038)
big municipality	-0.036	-0.035	0.060	-1.148**
	(0.027)	(0.027)	(0.511)	(0.513)
medium municipality	-0.026	-0.026	0.022	-1.181**
	(0.036)	(0.036)	(0.523)	(0.524)
small municipality	-0.023	-0.023	-0.035	-1.213**
	(0.029)	(0.029)	(0.570)	(0.570)
municipality fixed effects	no	no	yes	yes
constant	-1.101	-1.210	-1.406	-0.189
	(1.133)	(1.148)	(1.321)	(1.330)
Adjusted R^2	0.047	0.046	0.043	0.045

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A5: Difference-in-difference estimation of Welfare Participation in the years 1986 to 1988, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.035^{**}			
	(0.011)			
nbr of children <7		0.080^{**}	0.077^{**}	0.043
		(0.021)	(0.022)	(0.056)
nbr of children >6		0.021^{*}	0.014^{*}	0.024
		(0.012)	(0.013)	(0.022)
child <7 dummy				0.046
				(0.069)
child >6 dummy				-0.021
				(0.036)
year of school86	-0.009	-0.008	-0.009	-0.009
	(0.021)	(0.021)	(0.022)	(0.022)
year of school86^2	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
year of school86^3	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age86	-0.042	-0.021	-0.007	-0.007
	(0.080)	(0.080)	(0.087)	(0.087)
age86^2	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
age86^3	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	-0.041	-0.037	-0.044	-0.044
	(0.046)	(0.046)	(0.048)	(0.048)
health85	0.070^{**}	0.064^{*}	0.051	0.052
	(0.035)	(0.035)	(0.037)	(0.037)
health86	0.055^{**}	0.049^{*}	0.047	0.046
	(0.028)	(0.028)	(0.029)	(0.029)
health8485	-0.020	-0.019	0.000	0.001
	(0.046)	(0.046)	(0.048)	(0.049)

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Table A5 continued: Difference-in-difference estimation of Welfare Participation in the years 1986 to 1988, part 2

	(1)	(2)	(3)	(4)
unemployment insurance85	-0.030	-0.031	-0.041	-0.042
	(0.029)	(0.029)	(0.031)	(0.031)
unemployment insurance86	-0.245**	-0.244**	-0.234**	-0.232**
	(0.029)	(0.029)	(0.031)	(0.031)
retirement85	0.005	0.002	0.008	0.008
	(0.085)	(0.085)	(0.089)	(0.089)
retirement86	-0.596**	-0.593**	-0.575**	-0.575**
	(0.053)	(0.053)	(0.055)	(0.055)
employed85	-0.095**	-0.093**	-0.096**	-0.095**
	(0.024)	(0.024)	(0.025)	(0.025)
employed86	-0.176**	-0.172**	-0.165**	-0.165**
	(0.024)	(0.024)	(0.025)	(0.025)
in school85	-0.098**	-0.091*	-0.106**	-0.104**
	(0.038)	(0.038)	(0.040)	(0.040)
in school86	0.096**	0.094*	0.102**	0.100**
	(0.038)	(0.038)	(0.040)	(0.040)
big municipality	0.014	0.013	-0.421	0.002
	(0.025)	(0.025)	(0.449)	(0.450)
medium municipality	-0.038	-0.037	-0.237	0.186
	(0.032)	(0.032)	(0.461)	(0.462)
small municipality	0.045*	0.042*	-0.843	-0.428
	(0.025)	(0.025)	(0.549)	(0.549)
municipality fixed effects	no	no	yes	yes
constant	1.330	1.012	1.233	0.804
	(0.975)	(0.982)	(1.146)	(1.161)
Adjusted R^2	0.209	0.211	0.211	0.211

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A6: Difference-in-difference estimation of Welfare Participation in the years 1984 to 1986, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.052**			
	(0.010)			
nbr of children <7		0.049**	0.051**	0.112**
		(0.020)	(0.021)	(0.055)
nbr of children >6		0.053**	0.047**	0.028
		(0.011)	(0.012)	(0.020)
child <7 dummy				-0.081
				(0.068)
child >6 dummy				0.042
				(0.035)
year of school84	-0.017	-0.017	-0.006	-0.006
	(0.020)	(0.020)	(0.021)	(0.021)
year of school84^2	0.002	0.002	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
year of school84^3	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age84	0.120	0.118	0.157*	0.154*
	(0.079)	(0.080)	(0.085)	(0.085)
age84^2	-0.003	-0.003	-0.004*	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
age84^3	0.000	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	-0.113**	-0.113**	-0.115**	-0.115**
	(0.044)	(0.044)	(0.045)	(0.045)
health83	0.043	0.043	0.044	0.043
	(0.036)	(0.036)	(0.038)	(0.038)
health84	0.094**	0.094**	0.084**	0.086**
	(0.028)	(0.028)	(0.029)	(0.030)
health8283	-0.036	-0.036	-0.043	-0.044
	(0.045)	(0.045)	(0.047)	(0.047)

Continued on next page

Table A6: Difference-in-difference estimation of Welfare Participation in the years 1984 to 1986, part 2

	(1)	(2)	(3)	(4)
unemployment insurance83	0.045	0.045	0.046	0.044
	(0.031)	(0.031)	(0.033)	(0.033)
unemployment insurance84	-0.260**	-0.260**	-0.278**	-0.279**
	(0.030)	(0.030)	(0.031)	(0.031)
retirement83	0.018	0.019	0.034	0.037
	(0.081)	(0.081)	(0.087)	(0.087)
retirement84	-0.585**	-0.585**	-0.583**	-0.585**
	(0.047)	(0.047)	(0.050)	(0.050)
employed83	-0.023	-0.023	-0.020	-0.020
	(0.022)	(0.022)	(0.023)	(0.023)
employed84	-0.207**	-0.207**	-0.205**	-0.207**
	(0.022)	(0.022)	(0.023)	(0.023)
in school83	-0.131**	-0.132**	-0.125**	-0.126**
	(0.040)	(0.040)	(0.042)	(0.042)
in school84	0.136**	0.136**	0.133**	0.135**
	(0.038)	(0.039)	(0.040)	(0.040)
big municipality	-0.003	-0.003	0.145	0.051
	(0.023)	(0.023)	(0.435)	(0.437)
medium municipality	0.039	0.039	0.122	0.023
	(0.031)	(0.031)	(0.445)	(0.447)
small municipality	0.031	0.031	0.089	-0.013
	(0.025)	(0.025)	(0.485)	(0.486)
municipality fixed effects	no	no	yes	yes
constant	-0.600	-0.569	-1.216	-1.076
	(0.973)	(0.987)	(1.127)	(1.136)
Adjusted R^2	0.234	0.233	0.240	0.240

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A7: Difference-in-difference estimation of Training Participation in the years 1986 to 1988, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.031**			
	(0.010)			
nbr of children <7		0.082**	0.071**	0.119**
		(0.020)	(0.021)	(0.054)
nbr of children >6		0.016	0.012	-0.001
		(0.012)	(0.012)	(0.021)
child <7 dummy				-0.064
				(0.066)
child >6 dummy				0.028
				(0.035)
year of school86	-0.013	-0.013	-0.012	-0.012
	(0.020)	(0.020)	(0.022)	(0.022)
year of school86^2	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
year of school86^3	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
age86	-0.160**	-0.136*	-0.131	-0.131
	(0.076)	(0.077)	(0.084)	(0.084)
age86^2	0.004*	0.003	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
age86^3	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	-0.055	-0.051	-0.053	-0.053
	(0.044)	(0.044)	(0.046)	(0.046)
health85	0.043	0.036	0.027	0.026
	(0.034)	(0.034)	(0.036)	(0.036)
health86	0.038	0.033	0.037	0.038
	(0.027)	(0.027)	(0.028)	(0.028)
health8485	-0.055	-0.054	-0.050	-0.050
	(0.044)	(0.044)	(0.047)	(0.047)
welfare85	-0.087**	-0.082**	-0.092**	-0.092**
	(0.022)	(0.022)	(0.023)	(0.023)

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Table A7 continued: Difference-in-difference estimation of Training Participation in the years 1986 to 1988, part 2

	(1)	(2)	(3)	(4)
unemployment insurance85	-0.034	0.034	0.038	0.038
	(0.028)	(0.028)	(0.030)	(0.030)
unemployment insurance86	-0.053*	-0.052*	-0.076**	-0.077**
	(0.028)	(0.028)	(0.030)	(0.030)
retirement85	-0.011	-0.013	-0.027	-0.028
	(0.082)	(0.082)	(0.087)	(0.087)
retirement86	-0.056	-0.053	-0.037	-0.036
	(0.051)	(0.051)	(0.053)	(0.053)
employed85	0.073**	0.076**	0.074**	0.072**
	(0.023)	(0.023)	(0.024)	(0.024)
employed86	-0.065**	-0.061**	-0.044*	-0.044*
	(0.023)	(0.023)	(0.024)	(0.024)
in school85	-0.164**	-0.156**	-0.158**	-0.161**
	(0.037)	(0.037)	(0.039)	(0.039)
in school86	-0.163**	-0.165**	-0.165**	-0.163**
	(0.036)	(0.036)	(0.038)	(0.038)
big municipality	0.024	0.022	0.850**	-0.763*
	(0.024)	(0.024)	(0.433)	(0.435)
medium municipality	0.025	0.027	1.012**	-0.600
	(0.031)	(0.030)	(0.444)	(0.447)
small municipality	-0.006	-0.010	0.873*	-0.728
	(0.024)	(0.024)	(0.530)	(0.531)
municipality fixed effects	no	no	yes	yes
constant	2.272**	1.907**	0.980	2.602**
	(0.935)	(0.941)	(1.107)	(1.120)
Adjusted R^2	0.078	0.082	0.067	0.066

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A8: Difference-in-difference estimation of Training Participation in the years 1984 to 1986, part 1

	(1)	(2)	(3)	(4)
nbr of children	0.004			
	(0.010)			
nbr of children <7		0.014	0.006	-0.027
		(0.020)	(0.020)	(0.053)
nbr of children >6		0.001	-0.004	0.017
		(0.011)	(0.011)	(0.019)
child <7 dummy				0.045
				(0.065)
child >6 dummy				-0.045
				(0.033)
year of school84	0.013	0.013	0.023	0.022
	(0.019)	(0.019)	(0.020)	(0.020)
year of school84^2	-0.003	-0.003	-0.005*	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
year of school84^3	0.000	0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
age84	-0.002	0.004	0.029	0.033
	(0.076)	(0.077)	(0.081)	(0.081)
age84^2	-0.000	-0.000	-0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
age84^3	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
ownership	-0.042	-0.042	-0.052	-0.052
	(0.042)	(0.042)	(0.043)	(0.043)
health83	-0.018	-0.018	-0.030	-0.029
	(0.035)	(0.035)	(0.036)	(0.036)
health84	0.052*	0.052*	0.066**	0.065**
	(0.027)	(0.027)	(0.028)	(0.028)
health8283	-0.076*	-0.076*	-0.063	-0.063
	(0.043)	(0.043)	(0.045)	(0.045)
welfare83	-0.091**	-0.090**	-0.094**	-0.093**
	(0.021)	(0.021)	(0.022)	(0.022)

Continued on next page

Table A8: Difference-in-difference estimation of Training Participation in the years 1984 to 1986, part 2

	(1)	(2)	(3)	(4)
unemployment insurance83	0.097**	0.097**	0.101**	0.103**
	(0.030)	(0.030)	(0.031)	(0.031)
unemployment insurance84	-0.093**	-0.093**	-0.099**	-0.099**
	(0.029)	(0.029)	(0.030)	(0.030)
retirement83	0.018	0.018	0.016	0.014
	(0.079)	(0.079)	(0.084)	(0.084)
retirement84	-0.027	-0.026	-0.010	-0.008
	(0.045)	(0.045)	(0.048)	(0.048)
employed83	0.089**	0.090**	0.102**	0.102**
	(0.021)	(0.021)	(0.022)	(0.022)
employed84	-0.057**	-0.056**	-0.068**	-0.066**
	(0.021)	(0.021)	(0.022)	(0.022)
in school83	-0.053	-0.051	-0.059	-0.057
	(0.038)	(0.038)	(0.040)	(0.040)
in school84	-0.167**	-0.166**	-0.159**	-0.160**
	(0.037)	(0.037)	(0.038)	(0.038)
big municipality	-0.040*	-0.040*	0.035	0.041
	(0.023)	(0.023)	(0.416)	(0.417)
medium municipality	-0.062**	-0.062**	0.172	0.182
	(0.030)	(0.030)	(0.425)	(0.427)
small municipality	-0.042*	-0.042*	0.164	0.172
	(0.024)	(0.024)	(0.464)	(0.464)
municipality fixed effects	no	no	yes	yes
constant	0.330	0.238	-0.168	-0.232
	(0.940)	(0.953)	(1.076)	(1.084)
Adjusted R^2	0.055	0.055	0.084	0.085

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates. Estimates are obtained from a linear probability model on a sample of single mothers and single women without children. See equation (7), (8), and (9).

Table A9: Employment, fixed effect logit, estimates are evaluated at mean of explanatory variables

	84-86 (i)	86-88 (ii)
1.		
Number of children age 0-17	-0.016	0.036
	(0.021)	(0.024)
2.		
Number of children age 0-6	0.016	0.072*
	(0.039)	(0.039)
Number of children age 7-17	-0.030	0.016
	(0.025)	(0.029)
Municipality fixed effects	no	no

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A10: Training, fixed effect logit, estimates are evaluated at mean of explanatory variables

	84-86 (i)	86-88 (ii)
1.		
Number of children age 0-17	0.028	0.089**
	(0.131)	(0.033)
2.		
Number of children age 0-6	0.106	0.153**
	(0.471)	(0.059)
Number of children age 7-17	-0.012	0.054
	(0.062)	(0.037)
Municipality fixed effects	no	no

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates

Table A11: Difference-in-difference estimation of employment divided on ages

	Younger than 38 years		38 years and older	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	0.003	0.013	-0.012	0.031
	(0.017)	(0.017)	(0.022)	(0.024)
2.				
Number of children age 0-6	0.021	0.017	-0.023	0.122
	(0.028)	(0.027)	(0.094)	(0.090)
Number of children age 7-17	-0.005	0.011	-0.011	0.024
	(0.019)	(0.019)	(0.023)	(0.025)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A12: Difference-in-difference estimation of employment divided on education

	Lower than 12^{th} grade		12^{th} grade and higher	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	-0.004	0.015	0.009	0.022
	(0.016)	(0.017)	(0.022)	(0.024)
2.				
Number of children age 0-6	0.033	0.010	-0.002	0.050
	(0.033)	(0.031)	(0.042)	(0.043)
Number of children age 7-17	-0.014	0.017	0.013	0.013
	(0.018)	(0.019)	(0.025)	(0.027)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A13: Difference-in-difference estimation of welfare divided on ages

	Younger than 38 years		38 years and older	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	0.052**	0.040**	0.054**	0.009
	(0.013)	(0.014)	(0.021)	(0.023)
2.				
Number of children age 0-6	0.044**	0.072**	0.121	0.154*
	(0.022)	(0.023)	(0.091)	(0.085)
Number of children age 7-17	0.055**	0.025	0.049**	-0.002
	(0.015)	(0.016)	(0.022)	(0.024)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A14: Difference-in-difference estimation of welfare divided on education

	Lower than 12^{th} grade		12^{th} grade and higher	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	0.050**	0.017	0.036*	0.034
	(0.013)	(0.015)	(0.020)	(0.021)
2.				
Number of children age 0-6	0.075**	0.060**	0.021	0.110**
	(0.027)	(0.028)	(0.038)	(0.038)
Number of children age 7-17	0.043**	0.003	0.042*	0.008
	(0.015)	(0.017)	(0.023)	(0.023)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A15: Difference-in-difference estimation of welfare divided on ages

	Younger than 38 years		38 years and older	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	-0.003	0.032**	-0.000	0.039**
	(0.014)	(0.015)	(0.017)	(0.019)
2.				
Number of children age 0-6	0.001	0.070**	-0.039	0.136*
	(0.024)	(0.024)	(0.072)	(0.071)
Number of children age 7-17	-0.005	0.014	0.002	0.031
	(0.016)	(0.018)	(0.017)	(0.020)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Table A16: Difference-in-difference estimation of welfare divided on education

	Lower than 12^{th} grade		12^{th} grade and higher	
	84-86	86-88	84-86	86-88
	(i)	(ii)	(iii)	(iv)
1.				
Number of children age 0-17	0.007	0.023*	-0.021	0.015
	(0.012)	(0.014)	(0.019)	(0.021)
2.				
Number of children age 0-6	0.012	0.062**	-0.005	0.068*
	(0.025)	(0.026)	(0.037)	(0.038)
Number of children age 7-17	0.005	0.011	-0.026	-0.002
	(0.014)	(0.016)	(0.022)	(0.023)
Municipality fixed effects	yes	yes	yes	yes

*Significant at 10 per cent level

**Significant at 5 per cent level

Notes: Standard errors are given in parentheses below the estimates.

Wages and Occupational Mobility
-patterns in the Danish data*

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Abstract

Using administrative panel data on 100% of the Danish population we document a new set of patterns about occupational mobility. The first new pattern of occupational mobility is that workers' probability of switching occupations are U-shaped in their wages. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. The second new pattern of occupational mobility is that, conditional on switching occupation, high wage workers have higher probability of switching to occupations with higher average wages than the average wage of the occupation they switched out of. The opposite is true for low wage workers who, conditional on switching occupation, have higher probability of switching to new occupations where the average wage is lower than the workers original occupation. The third new pattern about occupational mobility in Denmark is when the relative average wage of an occupation rises, the workers from the bottom of the wage distribution within the given occupation have the highest probability of leaving the occupation. For occupations where the average wage falls relative to other occupations it is the workers from the top of the wage distribution within the occupation who have the highest probability of leaving the occupation. These patterns are not implied by existing theories of occupational mobility.

Chapter 2 of PhD thesis

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1 Introduction

This paper analyzes the correlation between wage and occupational mobility of workers in Denmark. With the Danish data we reproduce findings from the U.S. about returns to occupational tenure and declining hazard rates out of an occupation when occupational tenure increases. We further exploit the fact that we have access to the full population in the Danish data and show three new patterns of occupational mobility based on a worker's percentile in the wage distribution within his occupation. The first new pattern of occupational mobility is that workers' probability of switching occupations are U-shaped in their wages. The U-shape implies that workers at the top and bottom end of the wage distribution within a given occupation has the highest probability of switching occupation, while the workers in the middle of the wage distribution have the lowest probability of switching occupation. The second new pattern of occupational mobility is that, conditional on switching occupation, high wage workers have higher probability of switching to occupations with higher average wages than the average wage of the occupation they switched out of. The opposite is true for low wage workers who, conditional on switching occupation, have higher probability of switching to new occupations where the average wage is lower than the workers original occupation. The last new pattern about occupational mobility in Denmark is when the relative average wage of an occupation rises, the workers from the bottom of the wage distribution within the given occupation have the highest probability of leaving the occupation. For occupations where the average wage falls relative to other occupations it is the workers from the top of the wage distribution within the occupation who have the highest probability of leaving the occupation.

The empirical results presented in this paper are part of a bigger project where we model the decision to change occupation. Our model of occupational mobility and a subset of the patterns from the data presented in this paper are presented in an accompanying paper (see Groes, Kircher, and Manovskii (2009)). That the workers' probability of switching occupation are U-shaped in their wages are not implied by any of the existing models of occupational mobility, which mostly thinks of occupations as a set of horizontally differentiated tasks. In our accompanying paper, we suggest that it might be productive to think of occupations as forming vertical hierarchies. The first part of the model we have in mind is a model where workers are unsure of their abilities but learn about them by observing their output realizations. As a second part of the model we have employment opportunities in each occupation, which are scarce such that it induces competition among workers for them. We also have complementarities in the production function between worker's ability and productivity of an occupation and this induces sorting of workers into occupations according to the workers' expected ability. Finally, the model is an equilibrium model of occupational choice including the above mentioned features.

In order to show where our new patterns of occupational mobility belongs in the literature we present a literature review, which is divided into three parts. The first part is a review of literature related to occupational tenure and wage growth and the second part is a review of the literature related to occupational mobility and tenure in an occupation. The third section of the literature review is about how existing models of occupational mobility relate to our new empirical finding that workers' probability of switching occupation are U-shaped in their wages.

The literature review is section 2 of the paper. In section 3 we present in detail the samples we use from the Danish data and the sample selections we perform. Section 4 gives an overview of the Danish occupational classifications and typical movements between occupations. In section 5 and in section 6 we present evidence of return to occupational tenure and declining probability of leaving an occupation with tenure in the occupation. In the last three sections we present our new patterns of occupational mobility, such that we in section 7 present the U-shapes of occupational mobility, in section 8 we show the direction of occupational mobility, conditional on changing occupation, and in section 9 we show what happens to individuals who work in occupations, which grow or fall in average wages. Finally in section 10 we conclude.

2 Literature review on occupational mobility and the return to occupation specific human capital

This literature review is divided into three parts. The first part addresses the correlation between wages and tenure in an occupation. The literature we present focusses on reduced form estimations and shows that wages within a given occupation increases with tenure in the occupation. The second part of this literature review is relating the probability of switching occupations to tenure in the given occupation. We mostly focus on presenting literature of reduced form estimations motivated by theoretical models, which shows a negative relationship between occupational tenure and the probability of leaving the occupation. A few structurally estimated models also produce the same negative relationship between tenure and the transition probability. The last part of the literature on occupational mobility is to show how existing models of occupational mobility relate to our new empirical findings.

The reason for the first two parts of this literature review is to show some common findings in the existing literature that we can show the Danish data matches. The two main finding we will show are; increasing wages within an occupation and decreasing probability of changing occupations with occupational tenure. Our new findings that workers' probability of switching occupation is U-shaped in their wages are therefore not, merely a fact of a different data set with different characteristics.

2.1 Literature on occupational tenure and wage growth

In the literature on return to occupation specific human capital it has been shown that tenure within an occupation generates wage growth, even after controlling for firm and industry tenure. The literature on the relation between tenure in an occupation and wage growth originated with Shaw (1984) and Shaw (1987) who argued that investment in occupation specific skills is important in determining earnings. The first to measure returns to occupation-specific human capital was Kambourov and Manovskii (2009b). They notice that occupational-specific human capital is distinct from employer-specific human capital because it is transferable across employers and thus accumulation of the occupational specific capital cannot be financed by the employers and should be thought more of as a type of general human capital. In data from the PSID Kambourov and Manovskii (2009b) find that wages on average grow by 12% to 20%

due to the first 5 years of experience in an occupation and this is the case when controlling for tenure in the industry and general experience.

Following Kambourov and Manovskii (2009b) more analyses have been done on the specificity of occupational human capital. Using Swedish data Kwon and Meyersson Milgrom (2004) find that firms prefer to hire workers with relevant occupational experience and they find that there is no return to firm tenure once tenure in an occupation is accounted for. Hagedorn, Kambourov, and Manovskii (2004) find substantial returns to occupational tenure in a large administrative German data set and using data from Canadian Adult Education and Training Survey, Kambourov, Manovskii, and Plesca (2005) find substantial losses in human capital when workers switch occupation. Sullivan (2006) supports the finding that human capital is primarily occupation specific using NLSY data however the results vary with the type of occupation a person has. Finally using British data, Zangelidis (2004) also finds support that occupational experience is a major contributor to wage growth whereas the evidence on industry specificity of wage growth is not supported. Zangelidis (2004) also finds lots of heterogeneity with respect to what occupations are analyzed. The specificity of occupational wage growth has not been analyzed using Danish data however, Bagger (2004) finds very low return to firm tenure in Danish data and high return to general human capital, which includes occupational human capital.

In conclusion, all the studies show that wages increase with occupational tenure. The majority of the papers estimate the return to occupational tenure by reduced form approach with both OLS regression and instrumental variable regression. In section 5 we show that there is also return to occupational tenure for the Danish sample we use in our analysis.

2.2 Literature on occupational mobility and tenure

The literature on occupational mobility has an unambiguous outcome from the data when analyzing the correlation between tenure and occupational mobility; the longer tenure a person has within an occupation the lower probability of separating from that occupation. In this section we present some literature on occupational mobility. The main focus will be results from the empirical literature, which links occupational tenure with occupational mobility. However, we will also review some of the models which have inspired the reduced form findings in the occupational mobility literature.

One of the earliest models of occupational mobility is Miller (1984) who developed a model of how young people straight out of their education choose their occupation in an optimal order. The model's outcome is that young people should first undertake occupations where success is rare and if they fail, switch out and try an occupation with the next highest probability of success. However, as McCall (1991) points out, there are two not very attractive implications of Miller's (1984) model. The first implication is that workers would sample all jobs in the riskiest occupation first before they would switch occupation, because matching is independent between jobs within an occupation. The second possible unattractive feature is that it is costless to switch both jobs and occupations. Two articles by McCall (1990) and McCall (1991) try to address the two shortcomings of Miller's (1984) model.

Besides Miller (1984) most other models of occupational mobility show declining probability of switching out of an occupation (sometimes career) as tenure in the occupation (career) increases. McCall (1990) derives a theory for occupational matching and shows by estimating a proportional hazard function that given tenure in a firm, the probability of changing job is negatively related to tenure in an occupation. Also using young people straight after graduation, he shows this by comparing two groups of job switchers, those who switched jobs without switching occupation and those who switched job and occupation. Conditional on having switched job once, the probability of switching job again is negatively related to the time spent in the first job and this effect is stronger for those who did not switch occupation in their first recorded switch. The reason why McCall (1990) does not structurally estimate his model is because the empirical results of his model "suggest that a more complex occupation-specific matching process would be necessary". This is one place where our empirical results can shed more light in order to find out what else is important when considering occupational matching and mobility.

McCall (1990) also sets up a dynamic occupational choice model where information about the occupational match is revealed with time spent in the occupation and the model includes training cost or entry cost of switching occupations. He finds that workers only sample the occupations with the most match uncertainty first (straight after graduation) if the training/entry costs are low. Finally, McCall (1990) notices that his model does not include employer behavior. He conjectures that in equilibrium where employers (at least partially) would compensate workers for higher training costs and when workers are identical then they would choose their initial occupation at random. However, this would not be true if there is heterogeneity among workers with respect to their comparative advantage.

Building on McCall (1990), Neal (1999), (and an extension from Pavan (2005)), also introduces a model of employer and career choices with match uncertainty. Conceptually Neal (1999) defines a career as performing the same skill, which is closely related to occupational category. However in the empirical work, due to measurement error in the NLSY, a career switch (conditional on switching employer) relies primarily on changes in industry codes.

Neal (1999) builds on McCall's (1990) result, which predicted that the hazard rate of leaving a second job should be a decreasing function of tenure on the previous job, if a person did not change occupation in their first job transition. Neal (1999) develops a model with employer- and career matches and finds an optimal job search strategy where workers search over career first and then once they find their career they will search for an employer. This outcome relates to McCall (1990) in the sense that in McCall (1990) a worker will not change employer within an occupation if he has learned that the career match is not a good one. Neal (1999) tests his model empirically and finds no evidence that the model can be rejected.

Pavan (2005) and Sullivan (2006) extends Neal's (1999) model and estimate their models structurally. Pavan (2005) gives evidence of career specific matches by showing his model can reproduce reduced form findings. His model reproduces that conditional on firm tenure the probability of switching out of a career declines with tenure in the career. The reduced form analysis is done by a multinomial logit where a worker has three choices; not switching job, a firm switch but stay in the career, and a career and firm switch. This is all conditional on being full time in the work force in all years after first time observed as a full time worker. Pavan (2005) extends Neal's (1999) model to include firm-specific and career-specific matches to evolve stochastically over time (rather than being constant as in Neal (1999)).

In McCall (1990), and Neal (1999) the structural relation between occupational/career tenure and the probability of separating from a job is negative and they have various ways of showing that this also is what the data shows. Pavan (2005) extends these results by showing that the probability of switching out of a career is also negatively related to tenure in the career. In Miller (1984) there is no clear result of the sign of this relationship.

Borrowing from the literature on firm switching (i.e. Abraham and Farber (1987), Farber (1998), Parent (2000)), Munch (2006) uses Danish data and a competing risk hazard model to show the relationship between probability of leaving an occupation and tenure in the occupation. He finds the probability of exiting a career is declining with tenure in the career however the probability of exiting an occupation, conditional on the probability of exiting either their firms or their industries is flat and so does not decline with tenure in an occupation. Munch (2006) looks at the population (meaning not people coming straight from school) and for people in all types of jobs. We look at people who we can follow straight from graduation and we look at people both in the private and public sector.

2.3 Literature on occupational mobility relating to our empirical findings

In this section we will present some models of occupational mobility and describe how they relate to our findings that workers' probabilities of switching occupation are U-shaped in their wages.

There are three classes of models of occupational mobility we would like to relate to our empirical findings. The first one, described in, e.g., McCall (1990) and Neal (1999), is based on match-specific occupational sorting. Occupations are perceived as identical (e.g., not different with respect to skill requirements), but workers find out the quality of their specific match to an occupation over time. Match-specific sorting occurs when workers realize that their match-specific shock is bad and abandon the match in favor of (the search for) a better one. The predictions from this theory are based on selection: Since those workers that are content with their match stay in their occupation, this theory predicts that the probability of switching occupation declines with tenure in that occupation, which is consistent with the data. Moreover, since good matches survive longer, wages and tenure are positively correlated in the cross-section of workers - an observation that is also consistent with the data. However, the fundamental selection mechanism in these match-specific sorting models is not consistent with the data. Virtually any model in which productivities are drawn independently for each worker-occupation-match rather than representing a permanent trait of either the occupation or the worker would predict that the probability of switching occupation is negatively related to wages which indicate match quality. Instead, we find a strong evidence that the probability of switching occupation is U-shaped in wages: not only is it people with wages lower than the occupational average, but also those with wages above the average that are more likely to switch.

A second class of existing models focuses on net mobility, which is explained by fluctuating demands for services of different occupations. They generally also imply that it is either only the people on the lower part of wage distribution within an occupation or only in the upper part of the distribution that tend to switch in response to a change in demand conditions, rather than workers on both ends of the spectrum. This is the property of the classic Roy (1951) model (and its extensions in, e.g., Moscarini (2001)). The models in Kambourov and Manovskii (2005, 2009a) generically have a similar prediction. They represent a version of the island economy model of Lucas and Prescott (1974) where islands are interpreted as occupations and workers accumulate occupation-specific human capital. Human capital is destroyed upon switching occupations which implies that, if workers with different levels of human capital are perfectly substitutable in the occupational production function, it is the low human capital, and hence, low wage, workers that switch first if occupational demand declines. If occupational demand rises, no one leaves the occupation.

The last model we would like to mention are models of career progressions. Jovanovic and Nyarko (1997) and Sichernam and Galor (1990) suggest that some occupations form rungs of a career ladder. Workers spend time on the lower rungs accumulating skills that allow them to perform effectively at higher rungs. Our setup and these theories share the idea that occupations may be vertically ranked. However, while their models describe why high wage workers move to occupations with higher average wages than the occupation they came from, we show that the occupational mobility goes in both directions; high wage people move to higher paying occupations and low wage people move to lower paying occupations.

3 Data

We use the administrative Danish register data covering 100% of the population in the years 1980 to 2002. The first part of the data is from the Integrated Database for Labor Market Research (IDA), which contains annual information on socioeconomic variables (e.g., age, gender, education, etc.) and characteristics of employment (e.g., private sector or government, occupations, industries, etc.) of the population. Information on wages is extracted from the Income Registers and consists of the hourly wage in the job held in the last week in November of each year. Wage information is not available for workers who are not employed in the last week of November. The wages are deflated to the 1995 wage level using Statistics Denmark's consumer price index and trimmed from above and below at the 0.99 and 0.01 percentile for each year of the selected sample described below.

We use the Danish rather than the U.S. data for two reasons. First, the sample size is much larger. One of our objectives is to document the patterns of occupational mobility depending on the position of the individual in the wage distribution within her occupation. A sample sufficiently large to be representative *in each occupation* is essential for this purpose. Second, the administrative data minimizes the amount of measurement error in occupational coding that plagues the available US data (see Kambourov and Manovskii (2009b)). Nevertheless, as we show in section 5 and 6 the features of occupational mobility that can be compared between the U.S. and Denmark are quite similar. This leads us to expect that the patterns of occupational mobility that we describe using Danish data generalize to, e.g., the U.S.

3.0.1 Sample selection

While the Danish register data dates back to 1980, because information on firm tenure is available only after 1995 and because of a change in the occupational classification in 1995, we study the data spanning the 1995-2002 period (the latter cut-off was dictated by the data availability at the time we performed the analysis). We use the pre-1995 data in constructing some of the variables. For example, in 1995 the two occupational classifications used in the Danish register data are linked to the worker's job which allows us to construct measures of occupational tenure. For example, a worker will be considered to have 5 years of occupational experience in 1996 if he is observed in the same occupation in 1995 and 1996 according to the new occupational classification and at the same time has the same occupational classification from 1992 to 1995 according to the old occupational classification.

We only select male workers in order to minimize the impact of the fertility decision on labor market transitions. To construct experience and tenure variables we need to observe each individual's entire labor market history. Thus, our sample includes all individuals completing their education in or after 1980 if they remain in the sample at least until 1995. The sample includes graduates from all types of education from 7th grade to a graduate degree conditional on observing the individual not going back to school for at least three years after graduation (for people graduating in 2000 we use educational information from 2003). Thus, a worker who completed high school, worked for three years, then obtained a college degree and went back to full time work will have two spells in our sample: first, the three years between high school and college, and second, after graduating from college. If he worked for less than three years between high school and college, he joins our sample only after graduating from college.

We show our results hold for two different ways of further selecting the sample; one very restrictive way where we only include full time privately employed workers and another less restrictive sample where we allow workers to work in both public and private employment and have spells of non-employment in between. In the most restrictive sample, we truncate the workers' labor market histories the first time we observe them in part-time employment, public employment, and self employment. We allow workers to have a non-employment spell after their graduation, but we truncate their work spell the first time they are observed with missing wage data (including non-employment) after they have worked in full time private employment.

The sample with full time privately employed workers consists of 486,612 observations from 122,000 individuals graduating in the years 1980-2000. The workers do not go back to school within 3 years after graduation, their spells are truncated according to the description above, and they have at least 2 consecutive years of full time private employment after 1995. This sample is a very restrictive sample since most individuals graduating in the early sample period are not included in the analysis because they experience a spell of non-fulltime private employment before 1995. Table 1 shows where the people in the restrictive sample come from. Column 1 in table 1 shows how many graduates there are in each year from 1980 to 2000 and column 2 shows how many observations between 1995 and 2002 each graduation year give. Column 3 in table 1 shows how many workers we use in our main sample and how they are distributed over the sample years from 1995-2001. Notice, this sample only goes to 2001 since for workers in 2002 we do not know if they change occupation the year after. [1] Since the full time privately employed workers sample excludes a lot of individuals and observations we have selected a less restrictive sample where we show the results also hold.

For both samples we always select a sample of graduates from 1980 to 2000 who do not

[1]the sample presented in table Table 1 includes people from the years where they are not employed, if this spell of non-employment directly follows their graduation.

Table 1: Fulltime private work. Main sample by workers graduation year and calendar year in the sample.

t	graduates each year	observations in 1995-2001 sample by graduation year	observations in 1995-2001 sample by calendar year
	(1)	(2)	(3)
1980	3350	18027	-
1981	3572	19354	-
1982	4024	21791	-
1983	4213	22249	-
1984	4210	22018	-
1985	4514	23719	-
1986	4941	25118	-
1987	5108	25918	-
1988	5187	25896	-
1989	5246	25950	-
1990	4729	22765	-
1991	5547	25849	-
1992	6417	28946	-
1993	7137	31062	-
1994	7308	30245	-
1995	9183	33314	72682
1996	8807	27647	73781
1997	8517	22912	75038
1998	7990	17641	73559
1999	6536	10325	66529
2000	5866	5866	63882
2001	-	-	61141
Total	122402	486612	486612

return to school for at least three years after graduation and whom we observe employed full time for at least one year in the data from 1995-2002. Their individual working spell for each educational degree received is truncated the first time we observe them in a new education (either in school or with a new graduation year). This sample consists of 6.5 million individuals and table A-1 column 1 shows how many graduated in each year. Column 2 from table A-1 shows how many from each graduation year are in the sample from 1981-2002 and column 3 shows how many there are in the sample from 1995-2002 by graduation year.

The most restrictive sample, which we will refer to as the full time privately employed sample, is further restricted to never include workers in part time employment (defined as having less than 20 hours of work per week in either public or private sector). The part time employed people are excluded from the sample because they do not have reliable hourly wage information and they do not have any occupational codes, which makes it impossible to calculate tenure in their occupations. We truncate all spells the first time we observe the individual in part time employment. We further delete spells, which do not have any observations with full time employment after 1995 because of the part time truncation. Table A-2 column 1, 2, and 3 show how many people are in full time employment, non-employment, and part time employment each year. After truncating the workers spells the first time they are in part time employment table A-2 column 4 and 5 show how many are left in full time employment and non employment.

The third sample restriction is a truncation of all spells the first time they have a missing occupational data while working full time. We do this to be able to calculate the workers occupational tenure for all years in the sample. Table A-3 shows the number of non-employment and full private and public employment with and without missing occupational data each year. Table A-4 column 4 shows how many of the total observations are truncated because of missing occupational codes and column 5 shows how many observations we further drop by restricting the sample to include one year of full time employment between 1995 and 2002. Column 1, 2, and 3 in table A-4 are the number of observations each year left in the overall sample divided into non-employment, private full time employment, and public full time employment. Table A-3 shows that it is around 20 percent of the full time private employment observations, which have missing occupational data and it is also around 20 percent of the full time public employment spells. However, as table 4 shows these 20 percent forces us to drop 45 percent of the observations from the time period 1980-2002 by truncating the spells and making sure we have at least one observation from each spell after 1995.

To create our full time privately employed sample we further restrict the sample to only include those workers who have two consecutive years of full time private work in the period 1995-2002. This procedure drops 800,000 of the 2.5 million observations of the entire 1981-2002 period and leaves 965,000 observations in the period 1995-2002. Since we only look at privately employed people we truncate the workers spells first time they are observed in public employment. Table A-5 column 3 shows how many from each year we drop because of the public employment truncation. Column 4 in table A-5 shows how many observations we drop afterwards in order to only include workers who have two consecutive years of full time private employment after the public employment truncation. Column 1 and 2 in table A-5 show how many people are left in non-employment and private employment each year. The above truncations give a sample of workers who are either in full time private employment or not working each period. We restrict our main sample to include only those years where people are full time privately employed. Workers are allowed to enter non-employment after graduation but once they have entered private employment they are truncated the first time we observe them entering non-employment after their initial private employment spell. Table A-6 column 3 shows how many observations we truncate with this procedure and column 4 shows how many we further delete because they do not have two consecutive years in private employment after the truncation. This leaves a sample of 1.22 million observations in the period 1981-2002 and 730.000 observations from 1995-2002.

The final truncation we do for our main sample is to truncate those spells which have missing firm codes. The firm codes are available from 1995. Table A-7 column 3 shows how many observations we truncate each year due to missing firm codes and column 4 shows how many observations we further drop from the sample due to the restriction of having at least 2 consecutive years of full time private employment without missing firm codes in the period 1995-2002. Column 1 and 2 in table A-7 show how many of the observations are in non-employment and in private employment each year. The dataset, which we create the main sample from, there are 1.08 million observations from 1981 to 2002 and 630,000 in the period 1995 to 2002.

For our analyses we use only people while they are working and each calendar year, for each graduation cohort, we drop the workers with the highest and lowest 0.1 percent of real wages. Furthermore, to create the U-shapes with our main sample we only use the workers last year to determine what occupation they are in, thus for the U-shape graphs we do not use the workers' last year in the sample. Descriptive statistics for the final main sample of all workers in the years 1995 to 2002 are given in table 2 column 1. Column 2 from table 2 is descriptive statistics of the sample where we have excluded workers in their final year in the sample. Column 3 is for the same sample as in column 2 where there is at least 10 workers in each occupation in each year. Column 4 is for the sample with at least 10 workers in each occupation, year, and years after graduation category and column 5 is for the sample with at least 100 workers in each occupation and year. These samples, which includes only full time privately employed workers, we call our main sample and they will be used in the analysis below. [2]

Table A-11 in the appendix show the descriptive statistics of the less restrictive sample. In this sample we use both full time private and full time public employees. We do not have information on firms for the public sector employees and we therefore choose to define the entire public sector as one firm. The workers are allowed to switch in and out of employment but since we do not have reliable data on part time workers, these workers are treated as if they were unemployed for the duration of their part time work. This means that while they are working part time they will not be included in our analyses and they will not generate general experience or tenure in any occupation, firm, or industry. However, once we observe the worker in any full time employment, he is part of the sample we use for the analyses again. As mentioned during the description of the full time privately employed sample, some workers have missing occupation or firm codes while they are full time employed. If a worker has missing occupational data we cannot calculate his his occupational tenure. We therefore exclude the workers observations while he has missing occupation-codes or missing firm-codes. It is possible for the worker to re-enter the sample if he is observed switching occupation or firm after his spell of missing data. When a worker switches occupation, firm, or industry his tenure will be reset to zero in the new occupation. This means that a worker who is a cook in period t, has missing occupation in period t+1, is a cook in period t+2, and a truck driver in period t+3, will be included in the sample in period t and again in period t+3 where his tenure as a truck driver is 1. As in the sample with full time privately employed workers, a worker is defined as switching occupation if he works in two different occupations in two consecutive years. For this least restrictive sample we further allow workers to switch occupation through unemployment, non-employment or through part time work, if this stage last for no more than one year. This means that a worker who is a cook in period t, is part time employed in period t+1, and is a cook in period t+2, is in the sample in period t and t+2, and in period t+2 he has one more year of experience and occupational tenure than he had in period t. If the worker was a truck driver in period t+2 he would have an indicator for switching occupation in the period t. In both cases the worker would be in the sample in period t and he would be in the sample in period t+2 depending on what he did in period t+3 and t+4 because we do not include

[2] table 1 shows how many graduate each year from this sample from column 2 in table 2, and how many of them are in the sample each year.

people in their last work year. However, if the worker was a cook in period t, part time in period t+1 and t+2, and a cook again in period t+3, he would not be included in the sample in period t. Only workers who work in two consecutive years or who at most have one year in non-employment between two employment spells are included in the sample.

Table 2: Summary statistics for the full time privately employed samples.

	Full Sample	Without last year and trimmed at 0.1 pct	Over 10 per occupation and year	Over 10 per occupation year and experience	Over 100 per per occupation and year
Number of observations	609014	486612	483969	440448	455401
Number of occupations	355	353	236	146	109
Age	31.14	30.92	30.92	30.69	30.84
Occ. tenure	2.91	2.80	2.81	2.80	2.81
Occ. spell number	2.33	2.29	2.28	2.24	2.27
Occ. switchers	0.14	0.18	0.18	0.17	0.17
Empl. tenure	2.77	2.57	2.57	2.54	2.57
Firm switchers	0.14	0.18	0.18	0.18	0.18
Occ. and firm switchers	0.05	0.06	0.06	0.06	0.06
Occ. but not firm switchers	0.09	0.12	0.12	0.11	0.11
Ind. tenure	3.87	3.71	3.71	3.67	3.72
Years after graduation	8.05	7.90	7.90	7.74	7.88
Less than 12 years of school	0.06	0.05	0.05	0.04	0.05
Apprenticeship education	0.74	0.70	0.70	0.71	0.71
2 year university	0.11	0.10	0.10	0.10	0.10
Bachelor	0.11	0.09	0.09	0.09	0.09
Masters degree or above	0.08	0.06	0.06	0.06	0.06
Hourly wage in DKK in 1995	175.71	173.84	173.83	172.27	173.15
Married	0.36	0.35	0.35	0.34	0.35
Union	0.94	0.94	0.94	0.94	0.94
Number of children	0.82	0.82	0.82	0.80	0.81

Table A-8 shows how the workers in the least restrictive sample are distributed each year from 1980-2002 on different labor market states and A-9 shows who has missing occupation and firm data. Column 4 in table A-9 workers who do not either have two consecutive years of full time employment in the period 1995-2002 or workers who have two years of employment in the period 1995-2002 separated by at most one year of non-employment or part time work. From this sample we further define workers as out of the sample if they have missing occupation codes or missing firm codes and have not been observed with a switch after their missing observation. Table A-10 column 4 shows how many workers are not in the sample each year due to only having missing occupation codes, column 5 shows how many have missing firm codes, and column 6 shows how many have both missing firm and occupation codes. Notice that we only observe firm data from 1995 thus no one are missing from the sample due to missing firm data before 1995. Column 7 of table A-10 shows how many observations we completely remove from the sample because the worker do not have any valid employment data after 1995. From the sample of full time workers from column 1 in table A-10 we use those who we can observe what occupation they are in the year after we use them in the sample and we only selcet observation in the period 1995 to 2002. This gives a total 1.3 million observations. Table A-11 column 1 shows the summary statistics of these workers. Column 2 in table A-11 shows summary statistics for those workers who are in occupations with at least 10 workers every year and column 3 shows summary statistics for those workers who are in occupations with at least 10 workers ever year and year after graduation. Column 4 from table A-11 shows summary statistics for workers who are in occupations with at least 100 workers during the period 1995-2002.

4 Wage Determination and Occupational Classification

The hourly wages from the Danish data are calculated as the sum of total labor market income and mandatory pension fund payments of the job held in the last week in November in a given year divided by the total number of hours worked in the job held in November in the given year. The labor income and the pension contributions are from the tax authorities and are considered to be highly reliable - see **?** for a further description of the Danish wage data. Job protection is low in Denmark and the wages are compressed, which is partly due to high benefit levels and partly due to a high degree of unionization where wage bargaining historically has been centralized. In 2000, 74 % of workers were members of a union and more than 80 % were covered by a collective agreement. The centralized wage bargaining structure has however, been decreasing during the 1980's and the 1990's and these are described in more detail in **?**.

There exists four different wage setting systems in Denmark. The first is a *standard-rate system*, where wages of workers are by the industry collective agreements and wages are not modified at the firm. The standard-rate system covers around 13 % of workers in the private sector over the period 1995 to 1999. In two of the four wage setting systems, covering around 56 % of the workers, the wage rates set at the industry level are set as a floor and are only paid to very inexperienced workers. The rest of the workers can negotiate higher wages at the firm level. The last wage setting system is the *firm-level bargaining* where the collective bargaining states that workers wages are negotiated at the plant or firm level. This covers the rest of the 11 % of workers covered by collective agreements.

The Occupational code in the Danish data is based on the DISCO code, which is the Danish version of the ISCO-88 classification (International Standard Classification of Occupations). For the main part of our analysis we have chosen the most disaggregate definition of the occupational classification, which is at the 4-digit level. This aggregation level is chosen partly to capture all occupational mobility and partly because we look at the wage distributions within occupations. Some of the occupations at the 4-digit level have significantly different wage distributions compared to their 3-digit counterparts. At the 1-digit level there are 10 different occupational classification, where one of them is the military. There are 27 major occupational groups at the 2-digit level and 111 occupational groups at the 3-digit level. For the 4-digit level of occupations there are 372 possible occupations and in our least exclusive sample we observe workers in 368 of the occupations. In the appendix section A2 we show the occupational classifications and how they are grouped from the first to the forth digit level.

In Denmark it is the employers' responsibility to collect and report the DISCO codes to Statistics Denmark. The validity is considered to be high and is used for information on economics implications of proposals for the workers and employers of two wage bargaining parties at the national level; The Danish Confederation of Trade Unions (LO) and The Confederation of Danish Employers (DA). Furthermore, Statistics **?** assess that the DISCO code is a useful tool to group workers according to occupations.

One of the reasons for including occupations at the 4-digit level is because the wage distribution is different for occupations at the 4-digit level than at the 3-digit level. An example of this is economists who have the 4-digit code 2441 and who, among others, are in the same 3-digit group as sociologist, philosophers, and historians. Since we look at a worker's place in the wage distribution within his occupation by aggregating to the 3-digit level we compare the wages of economists to, for example, historians. The economist in the lowest decile of the wage distribution of all economist with same number of years after their graduation and in the same calendar year are not all in the lowest wage decile in their 3-digit occupational group. In the 3-digit occupational group only 28 percent of the workers who are in the lowest decile of the economists are in the lowest decile of their related 3-digit occupational distribution. Another 67 percent are in the second decile and 5 percent are in the third decile of their 3-digit occupational classification. The pattern is similar for chemical engineer where 39 percent of the chemical engineers from the lowest wage decile of chemical engineers are in the lowest decile of their 3-digit occupational group. For the chemical engineers from the lowest decile another 19 percent are in the second lowest decile, 24 percent are in the third lowest decile, 11 percent are in the forth lowest decile, 6 percent are in the fifth lowest decile, and 1 percent is in the 7th lowest decile in their 3-digit occupational group. If we include the public sector workers in the occupational distribution, the above results become even more significant and we also observe the same patterns for medical doctors, where 54 percent of the lowest decile from the medical doctor distribution are in the lowest decile in their related 3-digit distribution.

A second reason for keeping the 4-digit level occupations is that occupational switching at the 4-digit level, where the occupations are in the same 3-digit level occupational classification, in some cases are associated with significantly change in occupational specific human capital. This is true for switches between the occupations mentioned above as well as other occupational switches, where the 4-digit occupations belong to the same 3-digit occupations. Examples of such occupations are; plumbers and electricians, bricklayers and carpenters, gardeners and field crop growers, fire-fighters and prison guards, hair-dressers and undertakers, travel guides and travel stewards, radio-announcers and circus clowns, and medical assistants and pharmaceutical assistants.

In appendix A3 we show the occupational switching patterns of full time employees from the private sectors. We have excluded occupations with less than 500 observations over the 1995-2002 period and we have excluded those occupations the workers enter if the occupation accounts for less than 2 percent of the overall switchers from the original occupation. Deleting switches to occupations, which accounts for less than 2 percent of the total switches from the original occupation leaves 54.000 total switches. This is 67 percent of all switches when we condition on occupations with at least 500 employees during the period 1995-2002. Appendix A3 shows that the 4-digit occupational switches associated with significantly different tasks in their original occupation and their new occupation, which are in the same 3-digit occupational groups, are limited. This result speaks in favor of performing our analyzes at a more aggregated occupational level. We therefore show our main results for different occupational classification levels. [3]

In order to get a better understanding of which occupations people switch between we have included table A4, A5, A6, and A7. Table A4 through A6 show pairs of occupations that workers switches between. Table A4 show those occupations where at least 5 percent of the switchers from the original occupation switches to *and* where at least 5 percent of the switchers from the new occupation switches to the original occupation. In the sample of private sector employees there are 38.000 switches between occupations when we condition on occupations receiving at least 5 percent of the total switches from an occupation. Out of these 38.000 occupational switches there are 29.000 switches where workers switches back and forth between the same two occupations. Examples of occupations that are joined by one such link are; Department managers in construction and civil engineers, department managers in wholesales and shop sales persons, supply and distribution managers and buyers, chemist and chemical engineers, computer system designers and computer assistants, all kinds of engineers to engineering technicians, accountants and administration managers, accountants to bookkeepers, electrical engineering technician and electricians, electronic engineering assistant and computer assistant, cooks and waiters, cooks and truck drivers, carpenters and wood-product machine operators, welders and tool-makers, blacksmiths and plumbers, dairy product machine operators and dairy product makers, and building construction laborers and road construction laborers.

The occupational pairs, which have high percentage of workers switching between them are occupations of similar nature as the pairs of occupations from table A4 indicates. A similar pattern is the case for occupations which are linked by two occupational switches, even though occupational switches, which comes back to the original occupation after two other occupations have larger differences between the occupations than if the link is only through one other occupation. Table A5 shows what occupations these are. There are 2.597 switches, which are linked by occupational triple pair. A few examples are that conditional on switching occupation, 8 percent of the managers in construction switch to civil engineering technicians from which 11 percent switch to civil engineering where again 5 percent switches back to managers in construction. Another example is that of the people who switches occupation, 24 percent of shop and sales persons demonstrator switches to office clerks where 5 percent switches to freight transport handlers from where another 12 percent switches back to sales persons demonstrators. A last example is 25 percent of electrical mechanics switches to buildings electricians where another 10 percent switches to electrical engineering technicians from which 11 percent switches back to electrical mechanics. The last example illustrate a vast amount of the type of changes in table A5. As other examples, many engineering technicians switches between types of engineering technicians and engineers as well as computer programmers switches between different types of computer programming analyst, computer designer, and computer assistant.

Table A6 in the appendix is like table A4 and A5, only in table A6 we allow three occupational changes before the occupational switch comes back to the original occupation. This accounts for 2.577 switches where the occupations are three-way linked occupational groups. One example of occupations, which maps back to the original occupation after 4 occupational

[3] Note also that the 4-digit occupations that ends with the number 9, are the occupations which are not elsewhere classified. We perform robustness analyzes where these occupations are excluded.

switches (with more than 5 percent of switchers from an occupation) are; Department managers in wholesales, commercial sales representatives, office clerks, and shop sales persons. Another example is computer programmers, electronics engineers, electronics engineering technicians, and computer assistants. A third example which creates a loop in occupational switches is carpenters, cabinet makers, wood production machine operators, and transport laborers.

Finally, there are occupational switches, which are not represented by the switches between occupations that loop back to the same occupation. Table A7 shows what occupations workers switches between, where their switch does does bring them back to their original occupation after 3 switches or less. These type of switches we classify as one-way switches and there are 5.648 of them in the sample. Examples of these type of occupational switches, which do not loop back around are: sales department managers to sales representatives, mechanical engineers to sales representatives, primary education teachers to handicrafts workers in wood related materials, computer assistants to office clerks, buyers to office clerks, production clerk to sales representative, metal molder to tool-maker, and meat- and fish processing operator to manufacturing laborer.

The one way occupational switches from table A7 represents mostly workers who switches between more different occupation than in table A4 to A6. This gives us an indication that vertical occupational switches are the most likely switches that occur, and when we observe switches between occupation that do not go both ways these switches are more likely to be horizontal switches.

5 Returns to Occupational Tenure

In this section we show that the return to occupational tenure is higher than the return to firm or industry tenure, when controlling for other explanatory factors.

5.1 Econometric Model for Wage Regression

We show the return to occupational tenure for our two samples following the approach by Kambourov and Manovskii (2009b) who show that there exist return to occupational tenure in the U.S. data. The returns to tenure can be measured from the linear estimation model:

$$\begin{aligned} \ln w_{ijmnt} = &\beta_0 Emp\_Ten_{ijt} + \beta_1 OJ_{ijt} + \beta_2 OCC\_Ten_{imt} + \beta_3 OCC\_Spell\_nb_{imt} \\ &+ \beta_4 Ind\_Ten_{int} + \beta_5 Work\_Exp_{it} + \theta_{ijmnt} \end{aligned} \tag{1}$$

where w_{ijmnt} is the real hourly wage of person i working in period t with employer j in occupation m and industry n. Emp_Ten_{ijt}, OCC_Ten_{imt}, and Ind_Ten are tenure with an employer, an occupation, and the industry and all three terms are included linearly, squared, and cubed for occupation and industry tenure. The term $OCC\_Spell\_nb_{imt}$ are dummy variables indicating occupational what spell the individual is in. We are able to include the spell number because we follow individuals from the time they graduate from school. $Work\_Exp_{it}$ denotes overall work experience and is also included with a linear, square, and cubed term. OJ_{ijt} is a dummy variable, which equals one if in the worker is past his his year at a firm. Other covariates in the regression model are a dummy variable if the workers in member of a union, number of children of the worker, a dummy variable if the worker is married, lagged unemployment rate in county of residence, year dummies, dummies for 1-digit occupations, and dummies for 1-digit industries.

Following the literature on measuring return to tenure we use an estimation model by Altonji and Shakotko (1987). The estimates on tenure are likely to be biased from unobserved individual and match heterogeneity. This is because workers with a better employer match would be expected to have higher employer tenure and receive higher wages. Also, a worker in a good match is more likely to receive higher wages and accumulate more tenure in that occupation. This will bias the estimate on tenure from the OLS regression upward.

The OLS can be biased because the error component can be decomposed as:

$$\theta_{ijmnt} = \mu_i + \lambda_{ij} + \xi_{im} + \upsilon_{in} + \varepsilon_{it} \tag{2}$$

where μ_i is a fixed individual specific error component, λ_{ij} is a fixed job match-specific error component, ξ_{im} is a fixed occupation match-specific error component, υ_{in} is a fixed industry match-specific error component, and ε_{it} is a time-varying person specific error term in the wage, which affects wages of all employees.

To deal with this problem we follow the literature started by Altonji and Shakotko (1987) and used by Parent (2000) and Kambourov and Manovskii (2009b) and use an instrumental variable procedure. This is done by instrumenting the three types of tenure, general experience, and OJ with deviations from their sample means. If X_{imt} is occupational tenure of individual i who is working in occupation m in period t, then $\overline{X_{im}}$ denotes the sample mean of tenure period individual i worked in occupation m and the instrumental variable is $\widetilde{X}_{imt} = X_{imt} - \overline{X_{im}}$. The squared and cubed terms are similarly $\left(\widetilde{X}_{imt}\right)^2 = (X_{imt})^2 - \left(\overline{X^2_{im}}\right)$ and $\left(\widetilde{X}_{imt}\right)^3 = (X_{imt})^3 - \left(\overline{X^3_{im}}\right)$.

Furthermore, since the analysis is done by panel data we also follow the literature and estimate the instrumented model using generalized least squares (here called IV-GLS). We show results for regression 1 by OLS, Random effects GLS, IV-OLS, and IV-GLS.

5.2 Wage Regression Results

The first estimates from the wage regression are from the sample of full time privately employed workers. Table 3 below shows the returns to 2, 5, and 8 years of occupational tenure, industry tenure, and firm tenure estimated by OLS and IV-GLS of model 1. The returns are somewhat lower than they are for the U.S. reported in Kambourov and Manovskii (2009b), who have 20 percent return for 5 years of occupational tenure estimated by OLS and 12 % return to tenure estimated by IV-GLS on a random sample of the US population. Also Sullivan (2006) has high returns for young people after they graduate from school. The coefficients of the three tenure variables and general experience from model 1 of the OLS and IV-GLS (and the GLS and IV-OLS) are reported in the appendix, table A-12 .

Table 3 shows that for the sample of full time privately employed workers, there are higher returns to occupational tenure than there are to industry or firm tenure in both the OLS and the IV random effects estimation. This matches the findings in both Kambourov and Manovskii

Table 3: Returns to 2, 5, and 8 years of tenure, private worker sample

	2 years	5 years	8 years
OLS			
Occupation	0.048	0.079	0.074
	(0.0015)	(0.002)	(0.002)
Industry	0.009	0.005	-0.014
	(0.002)	(0.002)	(0.002)
Employer	0.014	0.013	-0.015
	(0.003)	(0.004)	(0.004)
IV_GLS			
Occupation	0.043	0.086	0.108
	(0.002)	(0.003)	(0.004)
Industry	0.002	0.002	-0.001
	(0.002)	(0.002)	(0.003)
Employer	-0.023	-0.051	-0.067
	(0.003)	(0.004)	(0.003)

Note: Standard errors in parentheses

(2009b) and Sullivan (2006) who found the same patterns respectively for the U.S. and the U.K. Both their samples were also privately employed workers and in Sullivan (2006) the workers are also observed since they leave school. However, there is a problem in our dataset with firm tenure because we only observe firms from 1995. In table 4 we show the returns on a subsample of people who graduated after 1994 and who did not have more than 3 years of general experience by the time they graduated.

Table 4 shows that for the smaller sample of graduates after 1994 the results are qualitatively similar but the return to firm tenure, as expected is relatively higher than in the sample of graduates from 1980 to 2000. The coefficients of the four estimations on the smaller sample is presented in the appendix, table A-13.

As a robustness analysis we show in the appendix table A-15 that if we include full time public sector workers and allow the workers to have spells of unemployment, non-employment, and part time work the results on the returns to tenure becomes smaller. Table A-14 shows the coefficients for the four regressions, OLS, GLS, IV-OLS, and IV-GLS for our larger sample including public sector employees and table A-15 shows the returns to 2, 5, and 8 years of tenure when including public sector employees.

6 Occupational mobility and tenure - duration

Our aim when analyzing the tenure and occupational mobility relationship is to analyze the sign of this relationship. Furthermore, we are also interested in reproducing some of the facts from the literature in order to understand whether the Danish data shows similar characteristics in

Table 4: Returns to 2, 5, and 8 years of tenure, private worker sample

	2 years	5 years	8 years
OLS			
Occupation	0.0917	0.151	0.230
	(0.009)	(0.008)	(0.022)
Industry	-0.019	-0.014	0.020
	(0.011)	(0.009)	(0.023)
Employer	0.051	0.059	-0.013
	(0.010)	(0.014)	(0.013)
IV_GLS			
Occupation	0.066	0.077	0.112
	(0.010)	(0.012)	(0.022)
Industry	-0.026	-0.012	-0.007
	(0.011)	(0.010)	(0.022)
Employer	0.005	-0.006	-0.041
	(0.013)	(0.018)	(0.012)

Note: Standard errors in parentheses

term of the relationship between tenure and occupational mobility as is found in the U.S. data.

6.1 Econometric model of occupational mobility and tenure

With the duration models we want to show the correlation between tenure in an occupation and probability of separating from the given occupation. This section draws on literature from Wooldridge (2002), Cameron and Trivedi (2005), Jenkins (2005), and Chen and Manatunga (2007).

The observed transition times from one occupation to another are grouped in years and it is assumed that the hazard within the yearly interval is constant. This means the duration in an occupation is measured as an interval and we have to take account of this by estimating a discrete-time hazard function. The probability of transition at discrete time t_j of a person i, given survival up to time t_j, is defined as the discrete-time hazard function, where the hazard h_{ij} is given as:

$$\lambda(t) = \Pr\left[T = t | T \geq t\right] \tag{3}$$

In the first part of the duration analysis we specify a proportional hazard model (Cox (1972)), which is given by

$$\lambda(t; x) = \exp(\beta' x)\lambda_0(t) \tag{4}$$

where $\lambda_0(t)$ is an unspecified baseline hazard function and β is a vector of regression coefficients associated with x and together $\exp(\beta' x)$ serves as a scaling function. Because the survival is discrete we use a proportional odds model (Cox (1972)). The proportional odds model assumes that the relative odds of making a transition in year t, given survival up to the end of the previous year is summarized by the expression:

$$\frac{\lambda_t(x)}{1-\lambda_t(x)} = \left[\frac{\lambda_t(x_0)}{1-\lambda_t(x_0)}\right] \exp(\beta'(x-x_0)) \tag{5}$$

where $\lambda_t(x)$ is the discrete time hazard rate for year t and $\lambda_t(x_0)$ is the discrete time hazard rate where x_0 is some arbitrary known baseline covariate value (most often this is taken where $x_0 = 0$). By taking logs on both sides of equation it follows that:

$$logit[\lambda_t(x)] = \log\left[\frac{\lambda_t(x)}{1-\lambda_t(x)}\right] = \alpha_t + \beta'(x-x_0) \tag{6}$$

where $\alpha_t = \log it\,[\lambda_t(x_0)]$.

The hazard of switching occupation in period t can alternatively be written as:

$$\lambda_t(x) = \frac{1}{1+\exp\left(-\alpha_j - \beta'(x-x_0)\right)} \tag{7}$$

which has a proportional odds interpretation of its derivatives.

In our analysis we set the baseline hazard to be piece-wise constant and we do this by defining $\alpha_j = \gamma_1 D_1 + \gamma_2 D_2 + ... + \gamma_J D_J$, where D_J is a binary variable equal to 1 if $t = l$ and equal to zero otherwise. When estimating the model we will not include an intercept in the hazard of switching occupation β.

Occupational spells that do not end within the eight years of the sample period are treated as right censored. These spells all have occupational transition equal to zero for all periods of the spell and their contribution to the likelihood function is the probability of having worked in the same occupation for at least the observed number of years.

The literature on occupational and career mobility often tries to separate between an occupational transition, which happens at the same time as a firm transition, or at the same time as an industry transition. To address this issue we have also estimated a multinomial logit model, which can be seen as a proportional odds model in a competing risk framework.

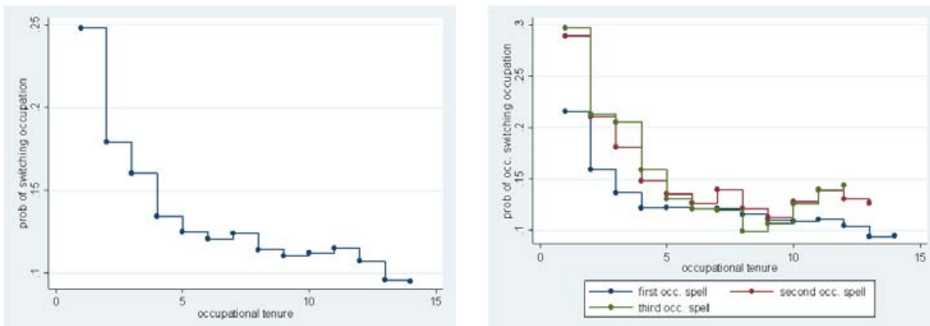
Rather than having two states (observed switching occupation or not) as above in the logit regression, we allow for five states in our multinomial logit model. The hazard of transiting into state k in this model is now defined as:

$$\lambda_{k,t}(x) = \frac{\exp\left(-\alpha_{k,t} - \beta'_k(x-x_0)\right)}{1+\exp\left(-\alpha_{k,t} - \beta'_k(x-x_0)\right)} \tag{8}$$

where k takes on the values (0) no observed transition, (1) transition into new occupation within same firm and industry, (2) transition into new occupation and new firm, but stay in the same industry, (4) transition into a new occupation and a new industry, but staying at the same firm, and (5) transition into new occupation, new firm, and new industry.

6.2 Duration Results

Figure 1(a) shows the pointwise estimates of the hazard rate form model 7 at the mean of the fulltime privately working sample and table A-16 column 1 in the appendix shows the coefficients from the regression. Figure 1(a) shows the probability of switching occupation decreases over the first 15 years of occupational tenure. The decrease in probability of switching occupation is largest in the first 4 years whereafter it flattens out. A second feature of the data is shown in table 1(b), where the hazard rate out of an occupation is given for different occupational spell number. Figure 1(b) shows that the probability of leaving an occupation is lowest if it is the first occupation the worker has ever been in and the probability of switching occupation is higher for the second and third occupation the worker is in. This means that conditional on switching occupation, the probability of switching again is higher than if the workers never switches occupation.



(a) Probability of switching occupation by occupational tenure

(b) Probability of switching occupation by occupational spell number and occupational tenure

Figure 1: Hazard rate out of occupations by occupational tenure, over all and by occupational spell number.

If there is return to occupational tenure then we should expect a negative duration dependence like the one we observe. However, in the literature it has been argued that the negative duration dependence should be with respect to career changes (both occupation and industry change) and not purely with respect to occupation. I test this by estimating model 8, which is a multinomial logit. The point estimates are given in table A-17 and the predicted hazard rates at the mean of the sample are shown in figure 2. For table A-17 the reference category is to stay in the occupation. Column 1 gives point estimates of switching only occupation, column 2 is switching occupation and firm, column 3 is switching occupation and industry, and column 4 is switching occupation, firm, and industry.

Figure 2 shows that the hazard rate of occupational switches occurring alone, with firm-switches, and with firm and industry switches all exhibits a declining hazard. The highest probability of switching occupation is occurring for people switching occupation but not firm or industry. These have around 14 % probability of switching occupation after 1 year of work compared to firm and occupation switches, which happens with 7 % and occupation, firm, and industry switches, which happens for 2 % of the sample with 1 year of occupational tenure. All three types of occupational switches fall with tenure in the occupation.

The probability of switching occupation alone falls more in the first couple of years than the probability of switching firm and occupation, or firm, industry, and occupation. This can be taken as a sign that the workers try out more occupations than occupation-firm pairs.

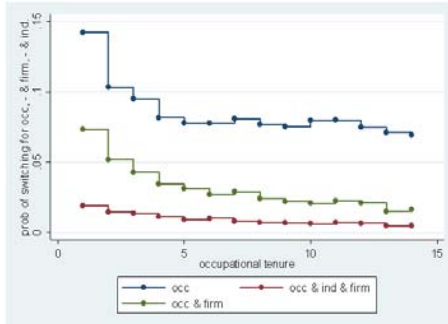


Figure 2: Hazard rate out of occupations by occupational tenure, over all and by occupational spell number.

This is opposite the occupation, firm, and industry switching, which only falls very little with occupational tenure. Together with statistics from our chapter on U-shapes in the data we get the picture that workers are mobile in the beginning of their occupational spell (and from the U-shapes we get that the most mobile are the ones at the ends of the wage distributions). In Groes, Kircher, and Manovskii (2009) we argue that people learn about their ability and sort them self according to their expected ability in different occupations. This sorting it not as prevalent in firm choices, and is non-existing in industry choices.

In the appendix we show in figure A-1 and A-2 similar to figure 1 and 2, only for our larger sample where we include public employees and allow people to return to the sample after spells of non-employment and part-time work. Table A-16 column 2 shows the coefficient from the regression behind figure 1(a) and table A-18 in the appendix shows the regression coefficients behind figure 2. As was the case for the return to occupational tenure, figure 1(a) shows, that the decrease in hazard rate with occupational tenure is also slightly lower for the first few years of tenure than for the sample of full time private employees. The workers' probability of changing occupation decreases from 25 % one year after graduation to 12 % five years after graduation. Figure 1(b) shows that the difference in effect on switching occupations from different occupational spells is also smaller for the sample including all workers, than it is for the sample including only full time private employees. Finally figure 2 shows that it is still occupational switching alone, which has the highest hazard, followed by firm and occupational switching. Switching occupation, firm, and industry is again for this larger sample changing very little over the years of occupational tenure [4].

7 U-shapes in occupational mobility

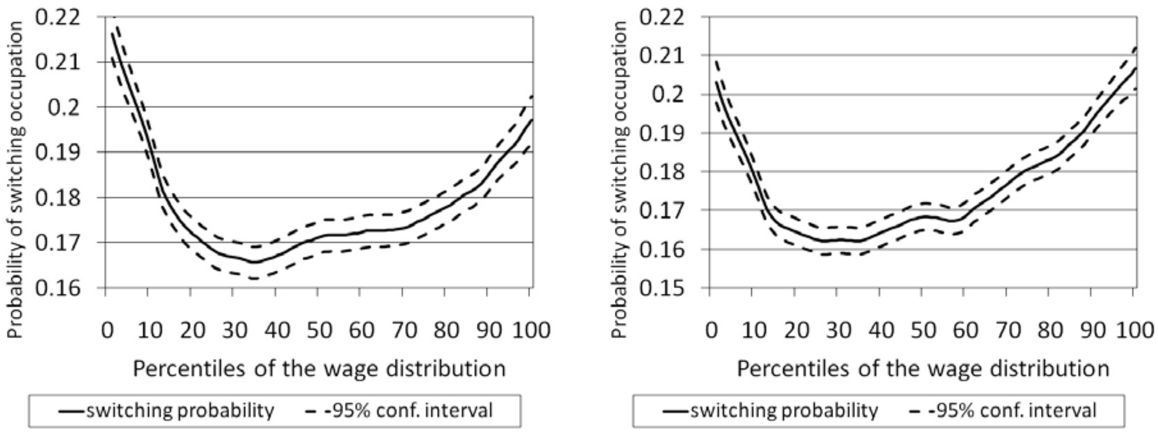
The previous two sections of our data analysis have shown that workers in Denmark behave similarly to workers, especially from the US, who have been analyzed in the existing literature. The workers have wage return to occupational tenure and their occupational mobility decreases with longer tenure and with more general experience. In this section we combine

[4] We should keep in mind that in this sample we artificially lower the firm transition rates because we classify all public sector employment as working for the same firm.

the occupational mobility of workers with their wages. We show that doing this produces a wage-occupational mobility relationship, which is U-shaped.

Our results that the probability of switching occupation is U-shaped in workers wages are presented in two parts. The first part is an aggregation of all occupations to show how a worker's wage within his occupation relates to his probability of switching out of that occupation. The second part shows that most occupations separately exhibits U-shapes in the probability of switching occupation. We will show the results for both of our two samples, the full time privately employed workers, and the sample allowing for public employees and spells of non-employment and part-time work.

Figure 3(a) is a non-parametric plot (from a kernel smoothed local linear regression with bandwidth 5) of the probability of switching out of an occupation as a function of a worker's position in the wage distribution *in that occupation* in a given year. The probability of switching occupation is clearly U-shaped in wages. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. The workers in the middle wage deciles have the lowest probability of switching occupations.



(a) wage distribution of raw wages within occupation and year

(b) wage distribution of wage residuals

Figure 3: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution.

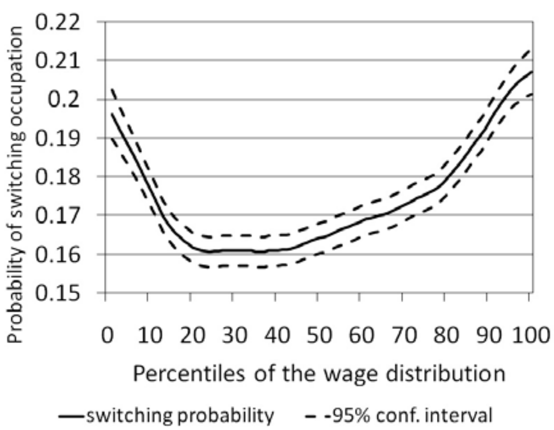
Figure 3(a) is based on raw wage data. Figure 3(b) indicates that we also observe a U-shaped pattern of occupational mobility in the position of the worker in the distribution of residual wages in his occupation in a given year. We generate residual wages by estimating a standard wage regression

$$lnw_{ijt} = X_{ijt}\beta + \epsilon_{ijt}, \tag{9}$$

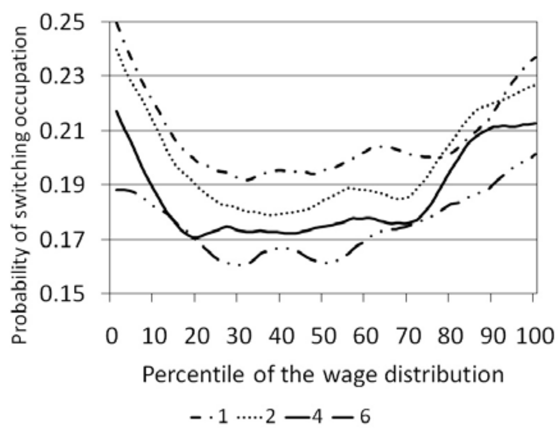
where w_{ijt} is real hourly wage of an individual i working in occupation j in period t. The explanatory variables in X include dummies for calendar years, third degree polynomials in general experience, occupational tenure, industry tenure, a second degree polynomial in firm tenure, number of occupational spells, education, marital status, union membership, and regional dummies. These wage regressions are estimated separately for each occupation.[5]

[5]Figure A-3 in Appendix A10 shows that excluding the regressors firm and industry tenure or excluding

The U-shapes further hold if we look at wage percentiles within occupation, year, and years after graduation. Figure 4(a) plots the probability of switching occupation as a function of worker's position in the wage distribution of workers in the same occupation, calendar year, and years after graduation. Figure 4(b) separately graphs occupational mobility for 1, 2, 4, and 6 years after graduation. The figure shows U-shapes in occupational mobility for all years after graduation and shows that the level of mobility decreases with years after graduation for almost all percentiles of the within occupation, calendar year, and years since graduation wage distribution. In the appendix figure A-7 we show the U-shapes for 1, 2, 4, and 6 years after graduation for 2.5 % and 10 % bandwidths.



(a) wage distribution of raw wages within occupation, year, and years after graduation



(b) wage distribution of raw wages within occupation, year, and years after graduation for different years after graduation

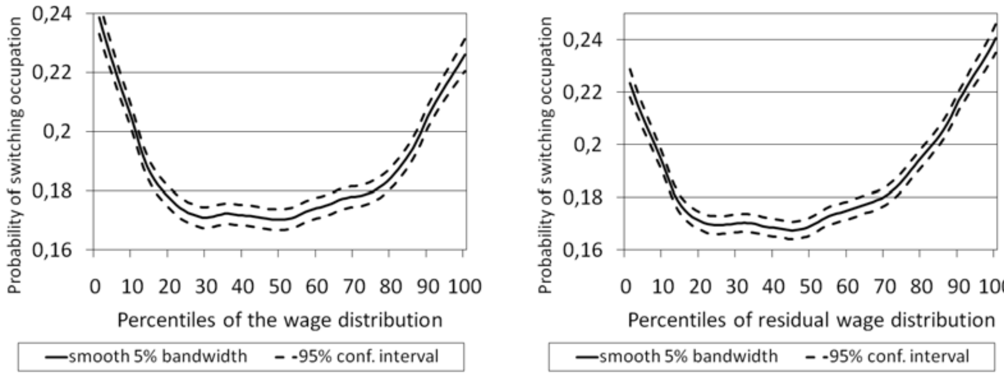
Figure 4: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation, year, and years after graduation.

The same way we showed the hazard rates for combinations of switching occupation and firm we also show the U-shapes for occupation and firm switchers in figure A-8 in the appendix. Figure A-8 shows that the U-shapes are not as pronounced when we look at firm and occupational switchers as when we only look at occupational switchers. However, when percentiles are generated from the residuals and when percentiles are found within occupations, calendar year, and years after graduation, the U-shapes are the most pronounced, which are the graphs, where we control for the most.

Above we show there exists U-shapes in the probability of switching occupation for the sample of full time privately employed workers. The same U-shapes exist for our sample allowing for public employment and spells of non-employment and part time work. Figure 5 shows, for the larger sample including public sector workers, that also here do the highest and lowest people in the wage distribution have the highest probability of switching occupation, while the workers in the middle of the wage distribution have the lowest occupational switching

dummies for the occupational spell number in the wage regression does not change the qualitative result of the U-shape in occupational mobility. In the Appendix Figures A-4 to A-7 we show that the U-shapes hold for bandwidths which are half and double of what we use in Figures 3 and 4.

probability. Figure 5(a) shows there exist U-shapes when we look at workers percentile in their raw wage distribution within occupation and year, and figure 5(b) shows that there also exist U-shapes when we look at percentiles in the residual wage distribution from model 9.



(a) wage distribution of raw wages within occupation and year

(b) Risidual wage distribution within occupation and year

Figure 5: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution or residual wage distribution.

In the appendix we have included several different robustness checks of the U-shapes for the larger sample, which includes public sector employees. Figure A-9 in the appendix shows, in column 1, variations of the U-shapes for workers switching both occupation and firm or workers switching occupation but not firm. Column 2 shows the same U-shapes for occupations groups to a three digit level. The graphs in figure A-9 shows that workers at the three digit level occupations have an overall lower probability of switching three digit occupations, than they had in their four digit level occupations. Besides this obvious feature, there are no qualitative differences in the U-shapes between the three and four digit level occupations when we create percentile within occupation and year. Figure A-10 shows a similar picture when we create percentiles from the wage residuals. In figure A-10 the results from the smaller private sample appears again in the larger sample including public sector employees. The U-shapes are more pronounced for occupation and firm switchers when we create residual distributions rather than percentiles from the raw wage distribution. The figures A-11, A-12, and A-13 in the appendix show the U-shapes when we create percentiles within occupation, calendar year, and years after graduation. Column 1 in the three graphs shows the probability of switching 4-digit occupation and column 2 shows the probability of switching 3-digit level occupation. Figure A-11 shows that creating percentiles within occupation, year, and years after graduation creates almost the same U-shapes as in figure A-9 and figure A-10. Figure A-12 and A-13 in the appendix show the probability of switching occupation, switching occupation and firm, or switching occupation but not firm for different years after graduation. Unlike the hazard rate out of an occupation as a function of tenure, workers from the larger sample have smaller differences in the probability of switching occupation in the U-shapes when we look at the first 6 years after graduation. For the first 6 years after graduation the probability of switching occupation is falling very little as shown in the top line in figure A-12. However, if we look at the probability of switching occupation over the first 15 years after graduation in figure A-13 the trend is clear; occupational mobility is falling for all parts of the wage distribution with years after graduation.

There is a possibility of errors in occupational coding. People at the extremes of occupational wage distribution seem more likely to be miscoded in a given year and it may not be surprising to see them switch in the following year. The fact that we see U-shapes for people many years after graduation is comforting in this respect. Moreover, as figure A-14 in the appendix shows there is persistence in wages. People with high (low) wages in their occupation in a given year also have higher probability of switching occupation two years after their wages in the end of the wage distribution is observed. This is both true in figure 14(a) for workers who stay in the same occupation in the two periods prior to a possible switch and also true if we allow people to change occupation before the year in which we look at the probability of switching occupation as shown in figure 14(b).

An additional informative statistic is the percentage of occupation-year pairs that exhibit U-shapes. Computing these statistics requires enough workers in each occupation in each year to accurately predict a probability of changing occupation in different parts of the wage distribution of that occupation. Thus, we restrict the sample to occupations that include at least 100 workers in a given year and we divide the wage distribution of each occupation into quintiles. We define U-shapes in each occupation-year pair in two ways. First, we count an occupation in a given year as having a U-shape if the quintile with the highest probability of changing occupation is either quintile 1 or quintile 5. Second, we count an occupation in a given year as having a U-shape if, in addition, the quintile with the lowest probability of changing occupation is in the interior, i.e., quintile 2, 3, or 4. There are 598 occupation-year observations with at least 100 workers in the sample of full time privately employed workers. 95 Percent of workers in these 598 occupation-year pairs are in occupations that have a maximum probability of switching occupation in one of the extreme quintiles when the quintiles are based on raw wages. When the quintiles are defined on the wage residuals, 98% of workers are in occupations which exhibit U-shapes according to this definition. In addition, 66% of the these occupations have a global minimum in the interior of the distribution of raw wages and 77% of the these occupations have a global minimum in the interior of the distribution of wage residuals.

A different way of examining whether individuals occupations exhibits U-shapes is to keep the percentiles within occupation and year and use these percentiles as a continues explanatory variable in a probit regression where the dependent variable is probability of switching occupation. We run the Probit regression separately for each occupation with at least 100 workers in it and include the percentiles as a 2^{nd} degree polynomial, such that $Pr(switch) = \Phi\left[\alpha + \beta * perc + \gamma * perc^2\right]$. From each regression we check the sign and significance of the β coefficient and the sign and significance of $\beta + 2 * \gamma$. We want the derivative of the 2^{nd} order polynomial to be falling at the beginning (where $perc = 0$) and, since the derivative is $\beta + 2 * \gamma * perc$, we check whether the β coefficient is negative and significant. We also want the curve to be increasing at the high end (where $perc = 1$), and we therefore also check the sign and significance of $\beta + 2 * \gamma$. There are 1.26 million workers when we calculate percentiles from the residual wage distribution and of these 78 % are in occupations, where both β and $\beta + 2 * \gamma$ have the correct sign and are significantly different from zero. When we create percentile in the raw wage distribution within each occupation and year, there are 77 %

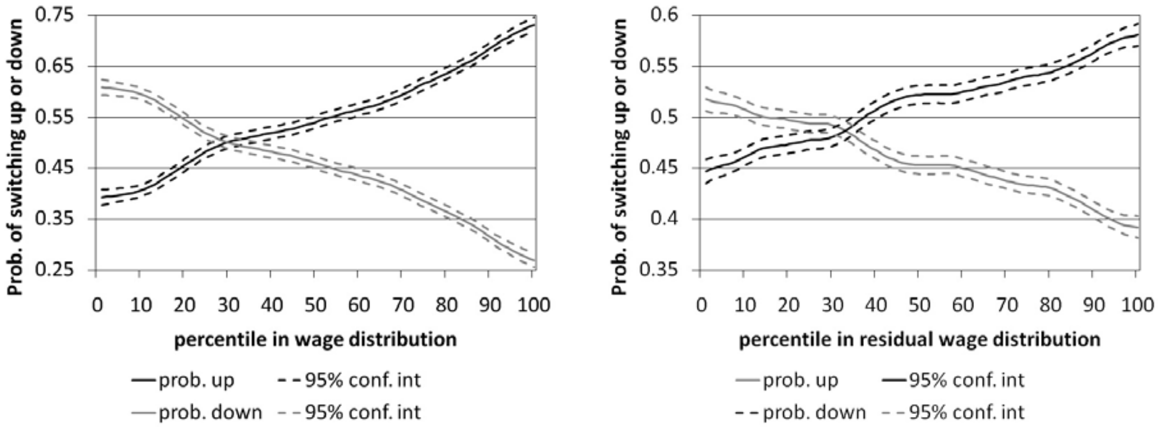
of workers in occupation that exhibit U-shapes. For occupations at the 3-digit level there are 86 % of workers from both the residual distribution and the raw wage distribution who are in occupations that show U-shapes. It is primarily the larger occupation that show the U-shapes therefore if we increase the number in an occupation to be 1000 before we include it, there are 77 and 84 % of workers in occupations at the 4-digit level which exhibit significant U-shapes. If we only count occupations with the correct sign and do not condition on the coefficient being significantly different from zero there are 85 and 91 % of workers in occupations with at least 100 workers that have U-shapes at the four digit level. For occupation with at least 1000 workers these percentages increase to 91 and 94 % of workers who are in occupations that exhibit U-shapes.

8 Direction of occupational mobility

In this section we document another prominent feature of the data: conditional on changing occupation, workers with higher (lower) relative wage *within* their occupation tend to switch to occupations with higher (lower) *average* wages. We first find the average wage of the occupations in a given year in order to determine the ranking between occupations. Similarly to our analysis of probability of occupational switching, we rank occupations based on their raw wages or residual wages adjusted for worker characteristics. To obtain the ranking based on raw wages, we find the average real wage of all full time private sector workers in a given occupation in a given year when we look at private sector employees. For private and public sector employees we generate ranking on occupations based on both public and private sector workers in the given occupation.[6] To obtain the ranking based on residual wages, we use our two different selected samples to run similar wage regressions as in equation 9 for each occupation where we include time dummies in the regression (without the intercept). We interpret the coefficients on these time dummies as the average occupational wage in a given year, adjusted for human capital accumulation of workers in the occupation as well as other worker characteristics such as education, regional dummies, and marital status. For this wage regression we include only occupations which have more than 100 observations in total over the 8 year period 1995-2002.

Figure 6(a) plots the probability of switching to an occupation with a higher or lower average wage as a function of the worker's position in the wage distribution of the occupation he or she is leaving. The sample on which the figure is based consists of all workers from the private sector sample who switched occupation in a given year and occupations are ranked based on the raw average wages. Figure 6(b) presents corresponding evidence when occupations are ranked based on residual wages and the direction of occupational mobility is plotted against the percentile in the distribution of residual wages within an occupation the worker is switching from. The evidence contained in these figures suggest that, conditional on switching occupation, the higher wage a person had in his occupation before the switch the higher is the probability that the worker will switch to an occupation with a higher average wage. Similarly, the lower wage a worker has in his occupation the higher is the probability that he will switch to an

[6] Note that both these samples are bigger than our selected samples, which only consists of workers who graduated after 1980. In the fulltime private employee sample the workers who never worked in the public sector, worked part time, etc. The results are, however, robust to only looking at the average wages in our selected sample.



(a) wage distribution of raw wages within occupation and year. Average wage in occupation from population.

(b) wage distribution of wage residuals. Average wage in occupation from time constants in wage regression

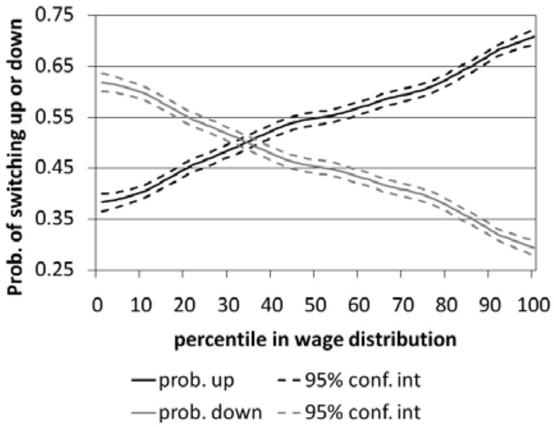
Figure 6: Non-parametric plot of direction of occupational mobility, conditional on switching occupation.

occupation with a lower average wage than in the occupation he switches from.

Figure 7(a) illustrates that similar results hold if we further condition the private sector workers on their position in the distribution of wages in their occupation in a given year *and* among other workers with the same number of years since graduation. This figure is comparable to figure 6(a) in that occupational average wages are calculated from raw wages of the population in the occupation in a given year. Finally, Figure 7(b) shows that the direction of occupational mobility is similar for individuals who graduated 1, 2, 4, or 6 years prior.

The direction of occupational mobility is a very robust feature of the data. In our large sample, which includes the public sector workers and allow people to have spells of non-employment and part time work, we find the same pattern in the direction of occupational mobility as we did in the smaller sample, only including public sector workers. Conditional on changing occupation, the high wage workers have high probability of switching to new occupations, which have higher average wage than the occupation they originate from. The opposite is true for low wage workers who have a high probability of switching to occupations with lower average wages than the occupation they switch out of. In the appendix we show graphs for the direction of occupational mobility from the sample of both public and private sector workers. Figure 6(a) shows the direction of occupational mobility when workers' wage percentiles are calculated from within occupation and year. In column 1 the occupations are from the 4-digit level and in column 2 the occupations are from the 3-digit level. The first row represents all occupational switchers, the second row are occupation and firm switchers, and the third row are occupations switchers who did not switch firm. The six graphs in figure 6(a) show that the patterns of directional mobility are true for both the 3 and 4 digit occupations as well as for occupation switchers and occupation and firm switchers.

Figure A-16 shows that the patterns are the same when we use workers percentiles in the



(a) wage distribution of raw wages within occupation, year, and year after graduation. Average wage in occupation from population.

(b) wage distribution of raw wages within occupation, year, and year after graduation for individual years after graduation. Average wage in occupation from population.

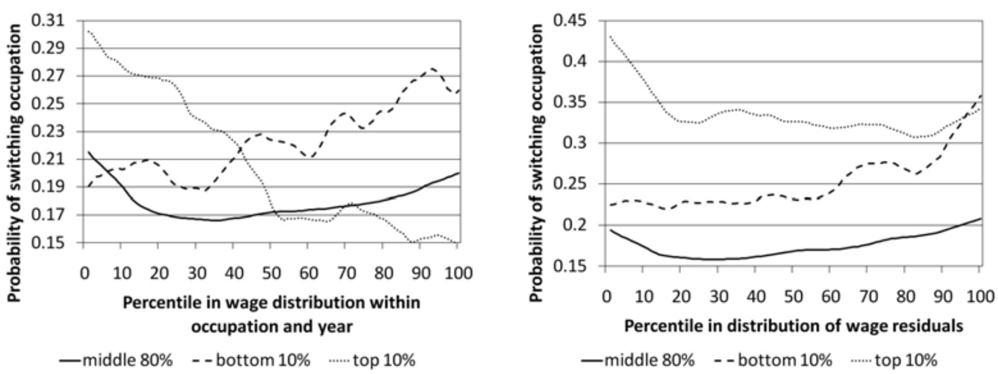
Figure 7: Non-parametric plot of direction of occupational mobility, conditional on switching occupation.

residual wage distribution and at the same time calculate the average wages of their occupations from the time dummies in the wage regressions, which run separately for each occupation. Again the direction of occupational mobility is robust to looking at occupations at the 4-digit level as shown in column 1 and to the 3-digit occupations as shown in column 1. The direction of occupational mobility is also robust to calculating workers wage percentile within their occupation, calendar year, and years after graduation as figure A-17 shows. Figure A-18 shows the probability of moving to occupations with higher average wage than the average wage of the occupation the worker was in before his switch. As figure A-18 shows the probability of moving to higher paying occupations, conditional on switching occupation, are close to the same for 1, 2, 4, and 6 years after graduation. Figure A-19 shows similar probabilities of switching to higher paying occupations for workers with 1, 5, 10, and 15 years after graduation, conditional on switching occupation and conditional on being in the same original wage percentile calculated within the worker's occupation, year, and year after graduation.

9 Occupational mobility in occupations changing rank

In section 7 we show that workers' probability of switching occupation is U-shaped in their wages and in section 8 we show that we can rank occupations by calculating the population average wages in each occupation. We calculate the average wage of all occupations separately for each year in our sample period 1995 to 2002, which means that we end up with eight different averages per occupation. This section examines what happens to workers' occupational mobility when they are in occupations, which have high fluctuations in the average wages. More specifically, we want to see if workers' probabilities of switching occupations still are U-shaped in their wages when they are in occupations that have slow growing average wages or when they are in occupations with the high growing average wages. In the model of occupational mobility in Groes, Kircher, and Manovskii (2009) each occupation has a specific productivity that can be mapped into workers' wages. When the average wage of an occupation falls relative to other occupations this can therefore be a signal of falling relative productivity of the given occupation. From the data we find that lower paid workers tend to leave their occupation when the relative average wage of the given occupation rises. In the other end of the wage distribution, higher paid workers are more likely to leave their occupation when the relative average wage of the given occupation declines.

We calculate the average growth rates of the occupations in two different ways. The first way is from the raw data where we calculate the occupational average wages each year from the population and find the growth rates between the year to year average wages. Alternatively, we find the average wage of an occupation in a given year by using our selected sample to run a wage regression for each occupation where we include time dummies in the regression. We use the coefficients on the time dummies in the regression as the average residual occupational wage in a given year and calculate growth rate of the yearly residuals. We calculate the growth rates by the percent increase between two consecutive years from 1995 to 2002 of all individual occupations. We use coefficients on time dummies from the wage regression in order to find occupations' growth rates after correcting for changes in compositional effects from year to year in the occupation and across occupations. An example of the correction is if an occupation's average wage grows purely due to the people in it accumulating more tenure or if they become higher educated, this will be controlled for by the wage regression and should therefore not affect the ranking of the occupation from one year to another.



(a) wage distribution of raw wages within occupation and year. Growth rates of average wage in occupation from population.

(b) wage distribution of wages residuals. Growth rates of average wage in occupation from time constants in wage regression.

Figure 8: Non-parametric plot of direction of occupational mobility of the private worker sample for occupations growing at different rates.

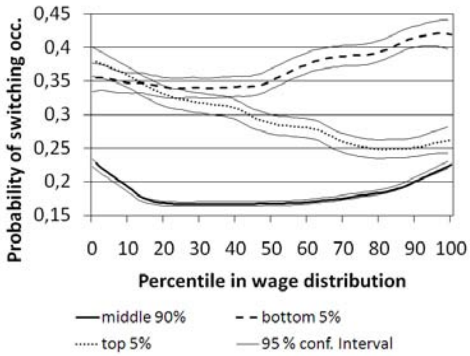
Figure 8(a) plots three groups of occupations, separated by the growth rates in raw average wages between years t and $t + 1$ for our sample of full time privately employed workers. The first group consists of the 10 percent of occupations with the lowest growth rates, the second group is the 10 percent of occupations with the highest growth rates, and the third group is the occupations with growth rates in average occupational wages in the middle 80 percent.

For the three different occupational groups we plot the probabilities of switching occupation as function of the workers' position in wage distribution in their occupation in year t. Figures 8(a) and 8(b) show that workers in the lowest growing occupations between t and $t+1$ have higher probability of leaving their occupation between t and $t+1$ if they are from the upper end of the occupational wage distribution in year t. Workers in the fast growing occupations have higher probability of changing occupation if they are in the low end of the wage distribution in their occupation. Workers in occupation, which grows faster than the slowest 10 percent but slower than the fastest 10 percent, have a probability of changing occupation that is U-shaped in their wage percentile.[7]

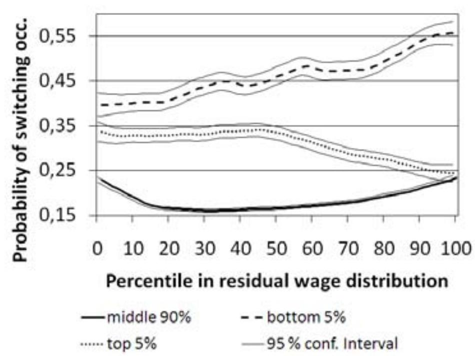
The above results are from the sample of privately employed workers who never worked in the public sector or worked part time. The results for the sample of both public and private sector workers look similar to the results from the private sector workers. The growth rates in average occupational wages are found by only including the wages of workers who stay in a given occupation between two years. Figure 9 shows the occupational mobility of people in the larger sample. Figure 9(a) shows the mobility pattern for workers in the 5 % lowest and 5 % highest growing occupations when average wage is calculated from population raw wages. Figure 9(b) shows the mobility pattern when the occupation growth is taken from the time coefficient of the wage regression. Both Figure 9(a) and 9(b) show that in the occupations growing the 5 % slowest, high wage workers have higher probability of leaving the occupation than low wage workers. For the highest 5 % of growing occupations the picture is reverse, here it is the lowest wage workers who have higher probability of leaving the occupation. Figure 9(a) and 9(b) further show that workers in the low and high growing occupations have higher mobility than in the average growing occupation. The average worker mobility of the highest and lowest growing occupations decrease when we look at the 10 % highest and lowest growing occupations rather than the extreme 5 %. Figure 9(c) and 9(d) show the workers' probabilities of changing occupations when they are in the highest or lowest 10 % growing occupations. In figure 9(c) the occupational growth rates are calculated from the average wage of stayers in the occupations and in figure 9(d) the growth rates are from the time dummies in a wage regression done separately for each occupation. When a worker is in an occupation that is among the 10 % slowest growing occupations his probability of switching occupation is still highest if he is among the highest paid or the highest wage residual workers. The opposite is again true for the highest growing occupations where it is the workers at the bottom of the wage distribution who have the highest probability of switching occupation.

Comparing figures 9(a) and 9(b) to figures 9(c) and 9(d) it is noticeable that the level of occupational mobility falls when we include more occupations in the extreme occupation-growing categories. Furthermore, when more occupations are included in the top and bottom growing occupations the pattern of high wage people leaving low growing occupation and low wage people leaving high growing occupations becomes less clear and the workers tend to behave a little more like the previous studied U-shapes. To further illustrate this point figure A-20 in the appendix shows mobility patterns of workers from the highest 15 % growing occupations and the lowest 15 % growing occupations. For workers in these 15 % extreme occupations the mobility patterns are almost showing the original U-shapes.

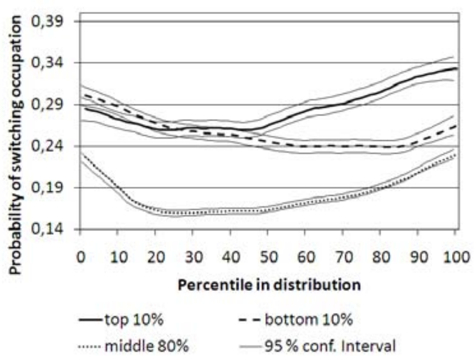
[7] The results are robust to calculating average wage change of the occupation only from workers who stay in the occupation between t and $t+1$.



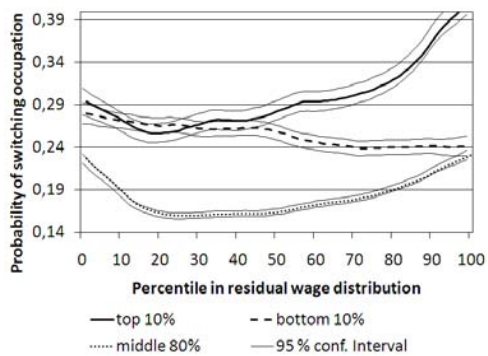
(a) wage distribution of raw wages within occupation and year. Average wage in occupation from population.



(b) wage distribution of wages residuals. Growth rates of average wage in occupation from time constants in wage regression.



(c) wage distribution of raw wages within occupation and year. Average wage in occupation from population.



(d) wage distribution of wages residuals. Growth rates of average wage in occupation from time constants in wage regression.

Figure 9: Non-parametric plot of direction of occupational mobility of the public and private worker sample for occupations growing at different rates.

The two last robustness checks of workers mobilities in fast or slow growing occupations are presented in figures A-21 and A-22 in the appendix. In figure A-21 we find workers' wage percentiles within their occupation, year, and year after graduation and keep the population average occupational wages of stayers between two consecutive years in the occupation. Figure A-21 shows the same patterns as figure 9; when we include more occupations in the extreme growing occupations the workers in the extreme occupations get closer to having their probability of switching occupation being U-shaped in their wages. In the top graph in figure A-21 with the 5 % extreme occupation the patterns of low wage people leaving high growing occupations and high wage people leaving low growing occupations are very clear. In the bottom graph in figure A-21 where we include top and bottom 15 % of the growing occupations the workers' probability of switching occupation is U-shaped in their wages. The last figure in the appendix, figure A-22, shows the occupational mobility for workers who are in different years after their graduation and who are in the middle 80 % of the occupations, or in the lowest 10 % growing occupations, or in the fast 10 % growing occupations. The top graph in figure A-22 shows that workers of the middle 80 % occupations have U-shapes in their probability of switching occupation, independent of their years after graduation. The middle graph and the bottom graph in figure A-22 show the lowest 10 % growing occupations and the highest 10 % of growing occupations by groups of different years after graduation. Workers are divided into three groups according to their years after graduation where the first group includes workers who are 1 to 3 years after graduation, the second group is workers in 4 to 6 years after graduation, and the last group is workers 7 to 10 years after graduation. The middle graph shows that for all years after graduation, the high wage workers have higher probability of leaving the occupations, which are among the 10 % slowest growing. The bottom graph shows that low wage workers who are between 1 and 3 years after graduation do not have a higher probability of leaving the high growing occupations. However, for workers later than 3 years after graduation the patterns from the overall sample arises again. Low wage workers have higher probability of leaving occupations with fast growing average wages relative to the high wage workers in the same occupations.

10 Conclusion

In this paper we present three new patterns of occupational mobility. The first new pattern of occupational mobility is that workers' probability of switching occupations are U-shaped in their wages. We follow a set of workers after they graduate from school and calculate their wage percentiles within their occupation in a given year - or we use their residual wage percentile. We find that workers who are high in the wage distribution and workers who are in the bottom of the wage distribution have the highest probability of switching occupations whereas workers in the middle of the wage distribution have the lowest probability of switching occupations.

The second new pattern of occupational mobility is that, conditional on switching occupation, high wage workers have a higher probability of switching to occupations with higher average wages than the average wage of the occupation they switched out of. The opposite is true for low wage workers who, conditional on switching occupation, have higher probability of switching to new occupations where the average wage is lower than their original occupation. We rank occupations by including workers from the entire population and not just people who we follow since they graduated from school, which we use as our sample. Each occupation is ranked by the population-workers' average wages in the given occupation and we use this ranking to find that, conditional on switching occupation, high wage workers move to higher average wage occupations and low wage workers move to lower average wage occupations.

The third pattern we find is that when the average wage of an occupation changes this relates to different mobility patterns of workers in the given occupation than for the occupation that does not have a movement in average wages. For occupations where the average wage of the occupation increases relative to other occupations, workers at the bottom of the wage distribution in that given occupation have the highest probability of leaving the occupation. In occupations that have relative falling average wages it is the workers from the top of the wage distribution who have the highest probability of leaving the occupation.

We show our results hold for two different samples of workers whom we follow after they graduate from school. The first sample is workers who always only worked full time in the private sector and the second sample includes both public and private sector workers who are allowed to have spells on non-employment and part time work. We also show that our two samples have similar characteristics as the sample from the U.S. in terms of return to occupational tenure and declining probability of switching occupation with tenure in an occupation.

Our results cannot be explained by existing models of occupational mobility and therefore, in Groes, Kircher, and Manovskii (2009) we develop a model which is consistent with the new patterns of occupational mobility that we find.

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A1 Appendix Sample Summary Statistics

Table A-1: Initial sample selection. Includes men who graduates in 1980-2000 who do not return to school for at least 3 years and who works at least one year full time during the period 1995-2002

		people in the sample by year of graduation	
grad. year	graduates each year	sample 1980-2002	sample 1995-2002
	(1)	(2)	(3)
1980	22748	558543	200993
1981	22692	534923	201779
1982	23683	531651	210407
1983	23803	500995	208462
1984	22708	453096	199295
1985	22505	427633	199096
1986	23612	427822	211892
1987	24720	415338	219108
1988	23302	371728	210396
1989	23925	346348	210899
1990	22083	292160	192488
1991	24282	287488	206742
1992	24694	267261	213051
1993	23974	235447	211473
1994	22728	194274	194274
1995	23210	180390	180390
1996	22398	151908	151908
1997	22526	127596	127596
1998	23609	106029	106029
1999	19965	68415	68415
2000	21113	42226	42226

Table A-2: Sample 2 selection -excluding part time workers and truncating spells first time part time work is observed. Conditional on observing least 1 year of full time work in 1995-2002.

	Before part time truncation			After part time truncation	
t	full time (1)	non-employment (2)	part time (3)	full time (4)	non-employment (5)
1981	15892	4983	1873	11626	2940
1982	35979	9313	3154	25742	5467
1983	57960	13073	4275	41317	7431
1984	82959	13790	5730	58947	7733
1985	108086	13256	6915	76944	7258
1986	130726	15610	7395	93527	8519
1987	152989	18938	8665	110816	10306
1988	171988	27026	10160	126659	14660
1989	194910	29278	12153	144510	16011
1990	212719	36176	15675	160115	20341
1991	231833	41854	16922	175277	23886
1992	254320	47852	16499	192226	27943
1993	277707	53333	16275	210511	32291
1994	309902	48306	17903	237463	29487
1995	343342	43680	16901	265566	25987
1996	363182	44619	18516	277924	27687
1997	383951	44192	18751	291233	27286
1998	402322	44145	20120	303621	26971
1999	417667	47764	21515	314103	28715
2000	432477	48746	22064	322373	28776
2001	448168	50539	22082	331889	29056
2002	436029	56190	19957	315543	31045
Total	5465108	752663	303500	4087932	439796

Table A-3: Sample selection 3. Showing all full time private and public observations with missing occupational codes.

t	non-employment (1)	private (2)	private, no occ-code (3)	public (4)	public, no occ-code (5)
1981	294	7188	849	3367	222
1982	5467	16794	1558	6911	479
1983	7431	27391	2563	10475	888
1984	7733	40442	3782	13647	1076
1985	7258	53495	5523	16676	1250
1986	8519	65454	6941	19735	1397
1987	10306	78254	731	23704	1548
1988	14660	88670	8676	27611	1702
1989	16011	103181	8206	31082	2041
1990	20341	115164	10368	32757	1826
1991	23886	128810	8997	35756	1714
1992	27943	140444	10719	38703	2360
1993	32291	132520	14209	58687	5095
1994	29487	152005	17369	63155	4934
1995	25987	133989	56022	50129	25426
1996	27687	160221	38338	57333	22032
1997	27286	172806	35605	62333	20489
1998	26971	179837	37234	65357	21193
1999	28715	184317	39374	76583	13829
2000	28776	176512	53138	74888	17835
2001	29056	178667	56174	78511	18537
2002	31045	167699	54261	76607	16976
total	439796	2503860	477216	924007	182849

Table A-4: Sample selection 3. Excluding full time observations with no occupational codes and truncating spells first time missing occupation is observed. Conditional on observing least 1 year of full time work in 1995-2002.

t	non-employment (1)	private (2)	public (3)	occ.-truncation (4)	no fulltime obs in 1995-2002 (5)
1981	1291	4946	2264	1554	4511
1982	2340	11393	4703	3683	9090
1983	3048	18725	7026	6575	13374
1984	2840	27396	9077	10056	17311
1985	2118	36253	11126	14483	20222
1986	2265	44557	12971	19224	23029
1987	2698	53002	15253	23781	26388
1988	4553	60541	17500	28556	30169
1989	4915	69445	19396	33242	33523
1990	6491	78427	20670	38618	36250
1991	8286	85822	22209	43607	39239
1992	10260	94039	24037	49566	42267
1993	12351	91194	37720	57909	43628
1994	10708	104268	39972	65246	46756
1995	10088	115555	44030	117478	4402
1996	10140	118442	44260	130090	2679
1997	9197	122605	45253	139460	2004
1998	8557	125723	47351	147460	1501
1999	9028	126806	50902	154741	1341
2000	8422	115043	50617	176091	976
2001	7602	113623	53094	186042	584
2002	8013	98129	49537	190909	0
total	145211	1715934	628968	1638371	399244

Table A-5: Sample selection 4. Excluding full time observations from the public sector and truncating spells first time work in public sector is observed. Conditional on observing least 2 consecutive years of full time private work in 1995-2002.

	Public employment truncation			
t	non-employment	private	public truncation	2 consecutive private fulltime obs in 1995-2002
	(1)	(2)	(3)	(4)
1981	688	333	502	622
1982	1215	7741	1186	1171
1983	1572	12824	2057	1499
1984	1270	18857	2879	1743
1985	802	24938	3685	1999
1986	880	30719	4378	2260
1987	1146	36882	5179	2527
1988	2208	42730	6036	2719
1989	2198	49537	6998	2771
1990	3004	56030	7778	2906
1991	3686	61684	8540	2925
1992	4762	67644	9432	2881
1993	6194	73776	11863	1324
1994	4223	84105	12888	935
1995	4035	93422	13744	566
1996	3395	104271	14513	231
1997	3461	108016	15262	142
1998	3336	110999	15887	79
1999	3939	111370	16460	34
2000	3385	101379	14805	5
2001	2777	100225	14464	7
2002	3511	87537	13822	2
Total	61687	1388016	202358	29348

Table A-6: Sample selection 5. Excluding observations not in full time private employment after the workers have been observed in an initial spell of full time private employment. Conditional on observing least 2 consecutive years of full time private work in 1995-2002.

	Truncation after initial spell in private full time work			
t	non-employment	private	non-private truncation	2 consecutive private fulltime obs in 1995-2002
	(1)	(2)	(3)	(4)
1981	444	2581	0	993
1982	669	6182	227	1878
1983	687	10514	701	2494
1984	461	15405	1118	3143
1985	239	20234	1441	3826
1986	222	25094	1807	4476
1987	277	30295	2319	5137
1988	469	35777	3451	5241
1989	521	41305	4314	5595
1990	707	47062	5568	5697
1991	962	52195	7055	5158
1992	1353	57922	8854	4277
1993	1949	64299	10987	2735
1994	1706	72424	12085	2113
1995	1576	81445	13361	1075
1996	1331	91728	14349	258
1997	1043	95247	14985	202
1998	809	98194	15105	227
1999	748	99149	15269	143
2000	417	90503	13840	4
2001	4	89704	13283	11
2002	0	78167	12880	1
Total	16594	1205426	172999	54684

Table A-7: Sample selection 6. Truncating observations with missing firm codes.

	Missing firm code truncation			
t	non-employment	private	firm-code truncation	2 consecutive private fulltime obs in 1995-2002
	(1)	(2)	(3)	(4)
1981	417	2420	0	188
1982	627	5808	0	416
1983	656	9877	0	668
1984	431	14509	0	926
1985	222	19047	0	1204
1986	201	23577	0	1538
1987	251	28421	0	1900
1988	435	33542	0	2269
1989	484	38703	0	2639
1990	652	44034	0	3083
1991	871	48797	0	3489
1992	1230	54045	0	4000
1993	1780	59908	0	4560
1994	1546	67303	0	5281
1995	1408	75355	609	168
1996	1209	82577	9151	122
1997	968	83847	11400	75
1998	730	85139	13051	83
1999	677	82971	16174	75
2000	384	74415	16087	34
2001	3	72468	17234	3
2002	0	6144	16726	1
Total	15182	1068203	105913	32722

Table A-8: Sample selection 1 for least restrictive sample, part 1.

t	Full time employment (1)	part time (2)	non-employment (3)
1981	12,333	1,502	2,990
1982	28,439	2,467	5,716
1983	45,551	3,287	7,963
1984	65,234	4,417	7,783
1985	84,443	5,202	6,554
1986	102,211	5,531	7,089
1987	121,035	6,403	8,405
1988	135,933	7,483	13,576
1989	155,653	9,046	14,210
1990	169,516	11,424	17,955
1991	187,784	12,150	21,188
1992	203,818	11,508	24,313
1993	217,363	10,916	27,026
1994	241,336	12,402	21,717
1995	207,329	10,511	18,838
1996	252,277	10,583	15,490
1997	276,412	10,259	13,713
1998	296,602	10,682	12,326
1999	312,557	11,306	13,622
2000	302,132	11,589	12,835
2001	309,319	10,955	12,665
2002	289,494	10,956	17,740
total	4,016,771	190,579	303,714

Table A-9: Sample selection 1 for least restrictive sample, part 2.

t	missing occ. (1)	missing firm (2)	missing occ. and firm (3)	no fulltime obs in 1995-2002 (4)
1981	1,223	0	0	356
1982	2,389	0	0	691
1983	4,090	0	0	1,077
1984	5,651	0	0	1,328
1985	7,742	0	0	1,890
1986	9,361	0	0	2,627
1987	9,570	0	0	3,449
1988	11,018	0	0	3,780
1989	10,580	0	0	4,319
1990	12,424	0	0	4,564
1991	10,179	0	0	5,303
1992	12,386	0	0	5,673
1993	17,786	0	0	5,696
1994	19,310	0	0	5,550
1995	62,890	12,232	4,652	5,673
1996	41,128	13,565	2,908	5,390
1997	34,233	15,904	2,645	5,887
1998	36,071	10,581	1,969	6,569
1999	29,223	13,286	1,457	7,371
2000	47,843	12,811	2,210	8,812
2001	48,029	12,086	2,454	10,252
2002	56,254	11,563	2,723	11,839
total	489,380	102,028	21,018	108,096

Table A-10: Sample selection 2 for least restrictive sample. Excluding observations with no information on occupation or firm tenure

t	Full time employment (1)	part time (2)	non -employment (3)	missing occ (4)	missing firm (5)	missing occ and firm (6)	no fulltime obs in 1995-2002 (7)
1981	9,544	1,044	2,372	825	0	0	5,139
1982	21,628	1,606	4,150	2,029	0	0	10,950
1983	34,435	2,071	5,579	3,612	0	0	17,005
1984	48,590	2,779	5,225	5,352	0	0	23,218
1985	62,580	3,233	4,110	7,358	0	0	29,238
1986	75,573	3,275	4,308	9,251	0	0	35,078
1987	88,676	3,798	4,800	10,959	0	0	41,231
1988	99,796	4,404	7,975	12,669	0	0	47,851
1989	113,270	5,321	8,023	13,701	0	0	54,208
1990	124,163	6,711	10,320	15,182	0	0	60,745
1991	136,221	7,123	12,265	14,858	0	0	66,821
1992	148,968	6,757	14,482	15,116	0	0	73,140
1993	161,528	6,212	16,251	16,551	0	0	79,223
1994	177,918	7,488	12,961	17,220	0	0	85,482
1995	181,187	6,431	11,419	26,443	3,297	1,867	91,486
1996	197,686	5,984	8,819	25,085	5,030	2,670	96,072
1997	207,218	6,000	8,358	24,616	8,580	4,383	99,899
1998	215,670	6,321	7,792	24,748	11,194	6,162	102,913
1999	220,382	6,853	8,743	24,653	15,347	8,020	104,824
2000	209,363	6,863	8,097	41,709	15,399	11,818	104,983
2001	210,880	5,753	7,263	46,565	16,102	15,481	103,716
2002	189,268	5,243	9,244	57,603	17,312	19,630	102,269
total	2,934,544	111,270	182,556	416,105	92,261	70,031	1,435,491

Table A-11: Summary statistics of least restrictive sample. For workers in full time employment in 1995-2001.

	Full Sample	Over 10 per occupation and year	Over 10 per occupation, year, and experience	Over 100 per occupation and year
Number of observations	1294468	1292932	1229339	1291602
Number of occupations	368	324	242	295
Occupational tenure	4.53	4.54	4.57	4.54
Occupational switchers	0.19	0.19	0.18	0.19
Firm tenure	2.78	2.78	2.77	2.78
Firm switchers	0.15	0.15	0.15	0.15
Industry tenure	3.78	3.78	3.79	2.80
Years after graduation	9.56	9.56	9.54	9.56
Less than 12 years of school	0.10	0.10	0.10	0.10
Apprenticeship education	0.55	0.55	0.56	0.55
2 year university	0.08	0.08	0.08	0.08
Bachelor	0.15	0.15	0.15	0.15
Masters degree or above	0.11	0.11	0.11	0.11
Hourly wage in DKK in 1995	172.65	172.66	172.29	172.68
Married	0.42	0.42	0.42	0.42
Union	0.90	0.90	0.90	0.90

A2 Appendix Occupational Classification

A2.1 1, 2, 3, and 4-digit Occupational Classification

MAJOR GROUP 1
LEGISLATORS, SENIOR OFFICIALS AND MANAGERS
11 LEGISLATORS AND SENIOR OFFICIALS
111 LEGISLATORS
1110 Legislators
114 SENIOR OFFICIALS OF SPECIAL-INTEREST ORGANISATIONS
1141 Senior officials of political-party organisations
1142 Senior officials of employers', workers' and other economic-interest organisations
1143 Senior officials of humanitarian and other special-interest organisations
12 CORPORATE MANAGERS (This group is intended to include persons who - as directors, chief executives or department managers - manage enterprises or organisations, or departments, requiring a total of three or more managers.)
121 DIRECTORS AND CHIEF EXECUTIVES
1210 Directors and chief executives
122 PRODUCTION AND OPERATIONS DEPARTMENT MANAGERS
1221 Production and operations department managers in agriculture, hunting, forestry and fishing
1222 Production and operations department managers in manufacturing
1223 Production and operations department managers in construction
1224 Production and operations department managers in wholesale and retail trade
1225 Production and operations department managers in restaurants and hotels
1226 Production and operations department managers in transport, storage and communications
1227 Production and operations department managers in business services
1228 Production and operations department managers in personal care, cleaning and related services
1229 Production and operations department managers not elsewhere classified
123 OTHER DEPARTMENT MANAGERS
1231 Finance and administration department managers
1232 Personnel and industrial relations department managers
1233 Sales and marketing department managers
1234 Advertising and public relations department managers
1235 Supply and distribution department managers
1236 Computing services department managers
1237 Research and development department managers
1239 Other department managers not elsewhere classified
13 GENERAL MANAGERS (This group is intended to include persons who manage enterprises, or in some cases organisations, on their own behalf, or on behalf of the proprietor, with some non-managerial help and the assistance of no more than one other manager who should also be classified in this sub- major group as, in most cases, the tasks will be broader than those of a specialised manager in a larger enterpriseor organisation. Non-managerial staff should be classified according to their specific tasks.
131 GENERAL MANAGERS
1311 General managers in agriculture, hunting, forestry/ and fishing
1312 General managers in manufacturing
1313 General managers in construction
1314 General managers in wholesale and retail trade
1315 General managers of restaurants and hotels
1316 General managers in transport, storage and communications
1317 General managers of business services
1318 General managers in personal care, cleaning and related services
1319 General managers not elsewhere classified

MAJOR GROUP 2
PROFESSIONALS
21 PHYSICAL, MATHEMATICAL AND ENGINEERING SCIENCE PROFESSIONALS
211 PHYSICISTS, CHEMISTS AND RELATED PROFESSIONALS
2111 Physicists and astronomers
2112 Meteorologists
2113 Chemists
2114 Geologists and geophysicists
212 MATHEMATICIANS, STATISTICIANS AND RELATED PROFESSIONALS
2121 Mathematicians and related professionals
2122 Statisticians
213 COMPUTING PROFESSIONALS
2131 Computer systems designers and analysts
2132 Computer programmers
2139 Computing professionals not elsewhere classified
214 ARCHITECTS, ENGINEERS AND RELATED PROFESSIONALS
2141 Architects, town and traffic planners
2142 Civil engineers
2143 Electrical engineers
2144 Electronics and telecommunications engineers
2145 Mechanical engineers
2146 Chemical engineers
2147 Mining engineers, metallurgists and related professionals
2148 Cartographers and surveyors
2149 Architects, engineers and related professionals not elsewhere classified
22 LIFE SCIENCE AND HEALTH PROFESSIONALS
221 LIFE SCIENCE PROFESSIONALS
2211 Biologists, botanists, zoologists and related professionals
2212 Pharmacologists, pathologists and related professionals
2213 Agronomists and related professionals
222 HEALTH PROFESSIONALS (except nursing)
2221 Medical doctors
2222 Dentists
2223 Veterinarians
2224 Pharmacists
2229 Health professionals (except nursing) not elsewhere classified
223 NURSING AND MIDWIFERY PROFESSIONALS
2230 Nursing and midwifery professionals
23 TEACHING PROFESSIONALS
231 COLLEGE, UNIVERSITY AND HIGHER EDUCATION TEACHING PROFESSIONALS
2310 College, university and higher education teaching professionals
232 SECONDARY EDUCATION TEACHING PROFESSIONALS
2320 Secondary education teaching professionals
233 PRIMARY AND PRE-PRIMARY EDUCATION TEACHING PROFESSIONALS
2331 Primary education teaching professionals
234 SPECIAL EDUCATION TEACHING PROFESSIONALS
2340 Special education teaching professionals
235 OTHER TEACHING PROFESSIONALS
2351 Education methods specialists
2352 School inspectors
2359 Other teaching professionals not elsewhere classified
24 OTHER PROFESSIONALS
241 BUSINESS PROFESSIONALS
2411 Accountants
2412 Personnel and careers professionals
2419 Business professionals not elsewhere classified
242 LEGAL PROFESSIONALS
2421 Lawyers
2422 Judges
2429 Legal professionals not elsewhere classified
243 ARCHIVISTS, LIBRARIANS AND RELATED INFORMATION PROFESSIONALS
2431 Archivists and curators
2432 Librarians and related information professionals
244 SOCIAL SCIENCE AND RELATED PROFESSIONALS
2441 Economists
2442 Sociologists, anthropologists and related professionals
2443 Philosophers, historians and political scientists
2444 Philologists, translators and interpreters
2445 Psychologists
2446 Social work professionals
245 WRITERS AND CREATIVE OR PERFORMING ARTISTS
2451 Authors, journalists and other writers
2452 Sculptors, painters and related artists
2453 Composers, musicians and singers
2454 Choreographers and dancers
2455 Film, stage and related actors and directors
246 RELIGIOUS PROFESSIONALS
2460 Religious professionals
2470: working with administration of legislation in the public sector

MAJOR GROUP 3
TECHNICIANS AND ASSOCIATE PROFESSIONALS
31 PHYSICAL AND ENGINEERING SCIENCE ASSOCIATE PROFESSIONALS
311 PHYSICAL AND ENGINEERING SCIENCE TECHNICIANS
3111 Chemical and physical science technicians
3112 Civil engineering technicians
3113 Electrical engineering technicians
3114 Electronics and telecommunications engineering technicians
3115 Mechanical engineering technicians
3116 Chemical engineering technicians
3117 Mining and metallurgical technicians
3118 Draughtspersons
3119 Physical and engineering science technicians not elsewhere classified
312 COMPUTER ASSOCIATE PROFESSIONALS

3121 Computer assistants
3122 Computer equipment operators
3123 Industrial robot controllers
313 OPTICAL AND ELECTRONIC EQUIPMENT OPERATORS
3131 Photographers and image and sound recording equipment operators
3132 Broadcasting and telecommunications equipment operators
3133 Medical equipment operators
3139 Optical and electronic equipment operators not elsewhere classified
314 SHIP AND AIRCRAFT CONTROLLERS AND TECHNICIANS
3141 Ships' engineers
3142 Ships' deck officers and pilots
3143 Aircraft pilots and related associate professionals
3144 Air traffic controllers
3145 Air traffic safety technicians
315 SAFETY AND QUALITY INSPECTORS
3151 Building and fire inspectors 3152 Safety, health and quality inspectors
32 LIFE SCIENCE AND HEALTH ASSOCIATE PROFESSIONALS
321 LIFE SCIENCE TECHNICIANS AND RELATED ASSOCIATE PROFESSIONALS
3211 Life science technicians
3212 Agronomy and forestry technicians
3213 Farming and forestry advisers
322 MODERN HEALTH ASSOCIATE PROFESSIONALS (except nursing)
3221 Medical assistants
3222 Sanitarians
3223 Dieticians and nutritionists
3224 Optometrists and opticians
3225 Dental assistants
3226 Physiotherapists and related associate professionals
3227 Veterinary assistants
3228 Pharmaceutical assistants
3229 Modern health associate professionals (except nursing) not elsewhere classified
323 NURSING AND MIDWIFERY ASSOCIATE PROFESSIONALS
3231 Nursing associate professionals
33 TEACHING ASSOCIATE PROFESSIONALS
331 PRIMARY EDUCATION TEACHING ASSOCIATE PROFESSIONALS
3310 Primary education teaching associate professionals
332 PRE-PRIMARY EDUCATION TEACHING ASSOCIATE PROFESSIONALS
3320 Pre-primary education teaching associate professionals
333 SPECIAL EDUCATION TEACHING ASSOCIATE PROFESSIONALS
3330 Special education teaching associate professionals
334 OTHER TEACHING ASSOCIATE PROFESSIONALS
3340 Other teaching associate professionals
34 OTHER ASSOCIATE PROFESSIONALS
341 FINANCE AND SALES ASSOCIATE PROFESSIONALS
3411 Securities and finance dealers and brokers
3412 Insurance representatives
3413 Estate agents
3414 Travel consultants and organizers
3415 Technical and commercial sales representatives
3416 Buyers
3417 Appraisers, valuers and auctioneers
3419 Finance and sales associate professionals not elsewhere classified
342 BUSINESS SERVICES AGENTS AND TRADE BROKERS
3421 Trade brokers
3422 Clearing and forwarding agents
3423 Employment agents and labor contractors
3429 Business services agents and trade brokers not elsewhere classified
343 ADMINISTRATIVE ASSOCIATE PROFESSIONALS
3431 Administrative secretaries and related associate professionals
3432 Legal and related business associate professionals
3433 Bookkeepers
3434 Statistical, mathematical and related associate professionals
3439 Administrative associate professionals not elsewhere classified
344 CUSTOMS, TAX AND RELATED GOVERNMENT ASSOCIATE PROFESSIONALS
3441 Customs and border inspectors
3442 Government tax and excise officials
3443 Government social benefits officials
3444 Government licensing officials
3449 Customs, tax and related government associate professionals not elsewhere classified
345 POLICE INSPECTORS AND DETECTIVES
3450 Police inspectors and detectives
346 SOCIAL WORK ASSOCIATE PROFESSIONALS
3460 Social work associate professionals
347 ARTISTIC, ENTERTAINMENT AND SPORTS ASSOCIATE PROFESSIONALS
3471 Decorators and commercial designers
3472 Radio, television and other announcers
3473 Street, night-club and related musicians, singers and dancers
3474 Clowns, magicians, acrobats and related associate professionals
3475 Athletes, sportspersons and related associate professionals
348 RELIGIOUS ASSOCIATE PROFESSIONALS
3480 Religious associate professionals

MAJOR GROUP 4
CLERKS
41 OFFICE CLERKS
411 SECRETARIES AND KEYBOARD-OPERATING CLERKS
4111 Stenographers and typists
4112 Word-processor and related operators
4113 Data entry operators
4114 Calculating-machine operators
4115 Secretaries
412 NUMERICAL CLERKS
4121 Accounting and bookkeeping clerks
4122 Statistical and finance clerks
413 MATERIAL-RECORDING AND TRANSPORT CLERKS
4131 Stock clerks
4132 Production clerks
4133 Transport clerks
414 LIBRARY, MAIL AND RELATED CLERKS
4141 Library and filing clerks
4142 Mail carriers and sorting clerks
4143 Coding, proof-reading and related clerks
419 OTHER OFFICE CLERKS
4190 Other office clerks
42 CUSTOMER SERVICES CLERKS
421 CASHIERS, TELLERS AND RELATED CLERKS
4211 Cashiers and ticket clerks
4212 Tellers and other counter clerks
4213 Bookmakers and croupiers
4214 Pawnbrokers and money-lenders
4215 Debt-collectors and related workers
422 CLIENT INFORMATION CLERKS
4221 Travel agency and related clerks
4222 Receptionists and information clerks
4223 Telephone switchboard operators

MAJOR GROUP 5
SERVICE WORKERS AND SHOP AND MARKET SALES WORKERS
51 PERSONAL AND PROTECTIVE SERVICES WORKERS
511 TRAVEL ATTENDANTS AND RELATED WORKERS
5111 Travel attendants and travel stewards
5112 Transport conductors
5113 Travel guides
512 HOUSEKEEPING AND RESTAURANT SERVICES WORKERS
5121 Housekeepers and related workers
5122 Cooks
5123 Waiters, waitresses and bartenders
513 PERSONAL CARE AND RELATED WORKERS
5131 Child-care workers
5132 Institution-based personal care workers
5133 Home-based personal care workers
5139 Personal care and related workers not elsewhere classified
514 OTHER PERSONAL SERVICES WORKERS
5141 Hairdressers, barbers, beauticians and related workers
5142 Companions and valets
5143 Undertakers and embalmers
5149 Other personal services workers not elsewhere classified
515 ASTROLOGERS, FORTUNE-TELLERS AND RELATED WORKERS
5151 Astrologers and related workers
5152 Fortune-tellers, palmists and related workers
516 PROTECTIVE SERVICES WORKERS
5161 Fire-fighters
5162 Police officers
5163 Prison guards
5169 Protective services workers not elsewhere classified
52 MODELS, SALESPERSONS AND DEMONSTRATORS
521 FASHION AND OTHER MODELS
5210 Fashion and other models
522 SHOP SALESPERSONS AND DEMONSTRATORS
5220 Shop salespersons and demonstrators
523 STALL AND MARKET SALESPERSONS
5230 Stall and market salespersons

MAJOR GROUP 6
SKILLED AGRICULTURAL AND FISHERY WORKERS
61 MARKET-ORIENTED SKILLED AGRICULTURAL AND FISHERY WORKERS
611 MARKET GARDENERS AND CROP GROWERS
6111 Field crop and vegetable growers
6112 Tree and shrub crop growers
612 MARKET-ORIENTED ANIMAL PRODUCERS AND RELATED WORKERS
6121 Dairy and livestock producers
6122 Poultry producers
6129 Market-oriented animal producers and related workers not elsewhere classified
613 MARKET-ORIENTED CROP AND ANIMAL PRODUCERS
6130 Market-oriented crop and animal producers
614 FORESTRY AND RELATED WORKERS
6141 Forestry workers and loggers
6142 Charcoal burners and related workers
615 FISHERY WORKERS, HUNTERS AND TRAPPERS
6151 Aquatic-life cultivation workers

6152 Inland and coastal waters fishery workers
6153 Deep-sea fishery workers
6154 Hunters and trappers

MAJOR GROUP 7
CRAFT AND RELATED TRADES WORKERS
71 EXTRACTION AND BUILDING TRADES WORKERS
711 MINERS, SHOTFIRERS, STONE CUTTERS AND CARVERS
7111 Miners and quarry workers
7112 Shotfirers and blasters
7113 Stone splitters, cutters and carvers
712 BUILDING FRAME AND RELATED TRADES WORKERS
7121 Builders, traditional materials
7122 Bricklayers and stonemasons
7123 Concrete placers, concrete finishers and related workers
7124 Carpenters and joiners
7129 Building frame and related trades workers not elsewhere classified
713 BUILDING FINISHERS AND RELATED TRADES WORKERS
7131 Roofers
7132 Floor layers and tile setters
7133 Plasterers
7134 Insulation workers
7135 Glaziers
7136 Plumbers and pipe fitters
7137 Building and related electricians
7139: buildingswork elsewhere
714 PAINTERS, BUILDING STRUCTURE CLEANERS AND RELATED TRADES WORKERS
7141 Painters and related workers
7142 Varnishers and related painters
7143 Building structure cleaners
72 METAL, MACHINERY AND RELATED TRADES WORKERS
721 METAL MOULDERS, WELDERS, SHEET-METAL WORKERS, STRUCTURAL- METAL PREPARERS, ANDRELATED TRADES WORKERS
7211 Metal moulders and coremakers
7212 Welders and flamecutters
7213 Sheet metal workers
7214 Structural-metal preparers and erectors
7215 Riggers and cable splicers
7216 Underwater workers
722 BLACKSMITHS, TOOL-MAKERS AND RELATED TRADES WORKERS
7221 Blacksmiths, hammer-smiths and forging-press workers
7222 Tool-makers and related workers
7223 Machine-tool setters and setter-operators
7224 Metal wheel-grinders, polishers and tool sharpeners
723 MACHINERY MECHANICS AND FITTERS
7231 Motor vehicle mechanics and fitters
7232 Aircraft engine mechanics and fitters
7233 Agricultural- or industrial-machinery mechanics and fitters
724 ELECTRICAL AND ELECTRONIC EQUIPMENT MECHANICS AND FITTERS
7241 Electrical mechanics and fitters
7242 Electronics fitters
7243 Electronics mechanics and servicers
7244 Telegraph and telephone installers and servicers
7245 Electrical line installers, repairers and cable jointers
73 PRECISION, HANDICRAFT, PRINTING AND RELATED TRADES WORKERS
731 PRECISION WORKERS IN METAL AND RELATED MATERIALS
7311 Precision-instrument makers and repairers
7312 Musical instrument makers and tuners
7313 Jewellery and precious-metal workers
732 POTTERS, GLASS-MAKERS AND RELATED TRADES WORKERS
7321 Abrasive wheel formers, potters and related workers
7322 Glass makers, cutters, grinders and finishers
7323 Glass engravers and etchers
7324 Glass, ceramics and related decorative painters
733 HANDICRAFT WORKERS IN WOOD,TEXTILE, LEATHER AND RELATED MATERIALS
7331 Handicraft workers in wood and related materials
7332 Handicraft workers in textile, leather and related materials
734 PRINTING AND RELATED TRADES WORKERS
7341 Compositors, typesetters and related workers
7342 Stereotypers and electrotypers
7343 Printing engravers and etchers
7344 Photographic and related workers
7345 Bookbinders and related workers
7346 Silk-screen, block and textile printers
74 OTHER CRAFT AND RELATED TRADES WORKERS
741 FOOD PROCESSING AND RELATED TRADES WORKERS
7411 Butchers, fishmongers and related food preparers
7412 Bakers, pastry-cooks and confectionery makers
7413 Dairy-products makers
7414 Fruit, vegetable and related preservers
7415 Food and beverage tasters and graders
7416 Tobacco preparers and tobacco products makers
742 WOOD TREATERS, CABINET-MAKERS AND RELATED TRADES WORKERS
7421 Wood treaters
7422 Cabinet makers and related workers
7423 Woodworking machine setters and setter-operators
7424 Basketry weavers, brush makers and related workers
743 TEXTILE, GARMENT AND RELATED TRADES WORKERS
7431 Fibre preparers
7432 Weavers, knitters and related workers
7433 Tailors, dressmakers and hatters
7434 Furriers and related workers
7435 Textile, leather and related pattern-makers and cutters
7436 Sewers, embroiderers and related workers
7437 Upholsterers and related workers
744 PELT, LEATHER AND SHOEMAKING TRADES WORKERS
7441 Pelt dressers, tanners and fellmongers
7442 Shoe-makers and related workers

MAJOR GROUP 8
PLANT AND MACHINE OPERATORS AND ASSEMBLERS
81 STATIONARY-PLANT AND RELATED OPERATORS
811 MINING- AND MINERAL-PROCESSING-PLANT OPERATORS
8111 Mining-plant operators
8112 Mineral-ore- and stone-processing-plant operators
8113 Well drillers and borers and related workers
812 METAL-PROCESSING-PLANT OPERATORS
8121 Ore and metal furnace operators
8122 Metal melters, casters and rolling-mill operators
8123 Metal-heat-treating-plant operators
8124 Metal drawers and extruders
813 GLASS, CERAMICS AND RELATED PLANT OPERATORS
8131 Glass and ceramics kiln and related machine operators
8139 Glass, ceramics and related plant operators not elsewhere classified
814 WOOD-PROCESSING- AND PAPERMAKING-PLANT OPERATORS
8141 Wood-processing-plant operators
8142 Paper-pulp plant operators
8143 Papermaking-plant operators
815 CHEMICAL-PROCESSING-PLANT OPERATORS
8151 Crushing-, grinding- and chemical-mixing-machinery operators
8152 Chemical-heat-treating-plant operators
8153 Chemical-filtering- and separating-equipment operators
8154 Chemical-still and reactor operators (except petroleum and natural gas)
8155 Petroleum- and natural-gas-refining-plant operators
8159 Chemical-processing-plant operators not elsewhere classified
816 POWER-PRODUCTION AND RELATED PLANT OPERATORS
8161 Power-production plant operators
8162 Steam-engine and boiler operators
8163 Incinerator, water-treatment and related plant operators
817 AUTOMATED-ASSEMBLY-LINE AND INDUSTRIAL-ROBOT OPERATORS
82 MACHINE OPERATORS AND ASSEMBLERS
821 METAL- AND MINERAL-PRODUCTS MACHINE OPERATORS
8211 Machine-tool operators
8212 Cement and other mineral products machine operators
822 CHEMICAL-PRODUCTS MACHINE OPERATORS
8221 Pharmaceutical- and toiletry-products machine operators
8222 Ammunition- and explosive-products machine operators
8223 Metal finishing-, plating- and coating-machine operators
8224 Photographic-products machine operators
8229 Chemical-products machine operators not elsewhere classified
823 RUBBER- AND PLASTIC-PRODUCTS MACHINE OPERATORS
8231 Rubber-products machine operators
8232 Plastic-products machine operators
824 WOOD-PRODUCTS MACHINE OPERATORS
8240 Wood-products machine operators
825 PRINTING-, BINDING- AND PAPER-PRODUCTS MACHINE OPERATORS
8251 Printing-machine operators
8252 Bookbinding-machine operators
8253 Paper-products machine operators
826 TEXTILE-, FUR- AND LEATHER-PRODUCTS MACHINE OPERATORS
8261 Fibre-preparing-, spinning- and winding-machine operators
8262 Weaving- and knitting-machine operators
8263 Sewing-machine operators
8264 Bleaching-, dyeing- and cleaning-machine operators
8265 Fur and leather-preparing-machine operators
8266 Shoemaking- and related machine operators
8269 Textile-, fur- and leather-products machine operators not elsewhere classified
827 FOOD AND RELATED PRODUCTS MACHINE OPERATORS
8271 Meat- and fish-processing-machine operators
8272 Dairy-products machine operators
8273 Grain- and spice-milling-machine operators
8274 Baked-goods, cereal and chocolate-products machine operators
8275 Fruit-, vegetable- and nut-processing-machine operators
8276 Sugar production machine operators
8277 Tea-, coffee-, and cocoa-processing-machine operators
8278 Brewers, wine and other beverage machine operators
8279 Tobacco production machine operators
828 ASSEMBLERS
8281 Mechanical-machinery assemblers
8282 Electrical-equipment assemblers

8283 Electronic-equipment assemblers
8284 Metal-, rubber- and plastic-products assemblers
8285 Wood and related products assemblers
8286 Paperboard, textile and related products assemblers
8287: Assembly line and assembler elsewhere
829 OTHER MACHINE OPERATORS AND ASSEMBLERS
8290 Other machine operators and assemblers
83 DRIVERS AND MOBILE-PLANT OPERATORS
831 LOCOMOTIVE-ENGINE DRIVERS AND RELATED WORKERS
8311 Locomotive-engine drivers
8312 Railway brakers, signallers and shunters
832 MOTOR-VEHICLE DRIVERS
8321 Motor-cycle drivers
8322 Car, taxi and van drivers
8323 Bus and tram drivers
8324 Heavy-truck and lorry drivers
833 AGRICULTURAL AND OTHER MOBILE-PLANT OPERATORS
8331 Motorized farm and forestry plant operators
8332 Earth-moving- and related plant operators
8333 Crane, hoist and related plant operators
8334 Lifting-truck operators
834 SHIPS' DECK CREWS AND RELATED WORKERS
8340 Ships' deck crews and related workers

MAJOR GROUP 9
ELEMENTARY OCCUPATIONS
91 SALES AND SERVICES ELEMENTARY OCCUPATIONS
911 STREET VENDORS AND RELATED WORKERS
9113 Door-to-door and telephone salespersons
912 SHOE CLEANING AND OTHER STREET SERVICES ELEMENTARY OCCUPATIONS
9120 Shoe cleaning and other street services elementary occupations
913 DOMESTIC AND RELATED HELPERS, CLEANERS AND LAUNDERERS
9131 Domestic helpers and cleaners
9132 Helpers and cleaners in offices, hotels and other establishments
9133 Hand-launderers and pressers
914 BUILDING CARETAKERS, WINDOW AND RELATED CLEANERS
9141 Building caretakers
9142 Vehicle, window and related cleaners
915 MESSENGERS, PORTERS, DOORKEEPERS AND RELATED WORKERS
9151 Messengers, package and luggage porters and deliverers
9152 Doorkeepers, watchpersons and related workers
9153 Vending-machine money collectors, meter readers and related workers
916 GARBAGE COLLECTORS AND RELATED LABOURERS
9161 Garbage collectors
9162 Sweepers and related labourers
92 AGRICULTURAL, FISHERY AND RELATED LABOURERS
921 AGRICULTURAL, FISHERY AND RELATED LABOURERS
9211 Farm-hands and labourers
9212 Forestry labourers
9213 Fishery, hunting and trapping labourers
93 LABOURERS IN MINING, CONSTRUCTION, MANUFACTURING AND TRANSPORT
931 MINING AND CONSTRUCTION LABOURERS
9311 Mining and quarrying labourers
9312 Construction and maintenance labourers: roads, dams and similar constructions
9313 Building construction labourers
932 MANUFACTURING LABOURERS
933 TRANSPORT LABOURERS AND FREIGHT HANDLERS

MAJOR GROUP 0
ARMED FORCES
01 ARMED FORCES
011 ARMED FORCES
0110 Armed forces

A3 Most Common Occupational Switches For Private Sector Employees

From Occ. (1)	To Occ. (2)	Nb. switch (3)	Switch total (4)	Pct switch (5)
1210	1222	5	240	0,021
1210	1224	11	240	0,046
1210	1229	6	240	0,025
1210	1231	16	240	0,067
1210	1233	11	240	0,046
1210	1239	12	240	0,050
1210	1317	9	240	0,038
1210	2145	5	240	0,021
1210	2411	11	240	0,046
1210	3112	5	240	0,021
1210	3115	9	240	0,038
1210	3415	23	240	0,096
1210	3419	6	240	0,025
1210	5220	9	240	0,038
1210	7124	7	240	0,029
1210	7223	5	240	0,021
1222	1210	17	448	0,038
1222	1239	22	448	0,049
1222	1312	29	448	0,065
1222	2145	17	448	0,038
1222	2149	17	448	0,038
1222	3115	25	448	0,056
1222	3119	21	448	0,047
1222	3415	10	448	0,022
1222	3439	10	448	0,022
1222	4132	10	448	0,022
1222	7124	13	448	0,029
1222	7222	14	448	0,031
1222	7223	30	448	0,067
1222	7231	19	448	0,042
1222	7423	11	448	0,025
1222	8240	11	448	0,025
1223	1222	6	76	0,079
1223	1233	2	76	0,026
1223	1235	2	76	0,026
1223	1239	3	76	0,039
1223	1313	10	76	0,132
1223	2142	11	76	0,145
1223	2149	5	76	0,066
1223	3112	6	76	0,079
1223	3439	2	76	0,026
1223	7124	5	76	0,066
1223	7137	2	76	0,026
1223	7241	3	76	0,039
1224	1210	37	479	0,077
1224	1233	13	479	0,027
1224	1239	22	479	0,046
1224	1314	112	479	0,234
1224	3415	62	479	0,129
1224	3416	12	479	0,025
1224	3419	17	479	0,035
1224	4190	27	479	0,056
1224	5220	89	479	0,186
1229	1210	8	117	0,068
1229	1222	3	117	0,026
1229	1233	8	117	0,068
1229	1234	3	117	0,026
1229	1237	7	117	0,060
1229	1319	8	117	0,068
1229	2131	3	117	0,026
1229	2142	4	117	0,034
1229	3112	4	117	0,034
1229	3115	3	117	0,026
1229	3415	4	117	0,034
1229	3419	3	117	0,026
1229	4115	3	117	0,026
1229	7423	5	117	0,043
1231	1210	24	279	0,086
1231	1222	6	279	0,022
1231	1239	13	279	0,047
1231	2144	8	279	0,029
1231	2411	43	279	0,154
1231	2419	11	279	0,039
1231	2441	11	279	0,039
1231	3415	20	279	0,072
1231	3419	30	279	0,108
1231	3433	36	279	0,129
1231	4190	11	279	0,039
1233	1210	28	316	0,089
1233	1224	14	316	0,044
1233	1234	11	316	0,035
1233	1239	11	316	0,035
1233	3415	109	316	0,345
1233	3419	33	316	0,104
1233	5220	7	316	0,022
1234	1210	5	92	0,054
1234	1233	5	92	0,054
1234	1237	3	92	0,033
1234	1317	3	92	0,033
1234	2224	2	92	0,022
1234	2419	5	92	0,054
1234	2441	2	92	0,022
1234	2451	2	92	0,022
1234	3121	5	92	0,054
1234	3415	15	92	0,163
1234	3419	17	92	0,185
1234	3429	5	92	0,054
1234	3439	3	92	0,033
1234	4131	2	92	0,022
1235	1210	4	139	0,029
1235	1222	3	139	0,022
1235	1224	6	139	0,043
1235	1239	9	139	0,065
1235	2131	3	139	0,022
1235	2145	3	139	0,022
1235	2149	3	139	0,022
1235	3115	3	139	0,022
1235	3415	18	139	0,129
1235	3416	11	139	0,079
1235	3419	8	139	0,058
1235	3422	3	139	0,022
1235	3439	3	139	0,022
1235	4131	5	139	0,036
1235	4132	6	139	0,043
1235	4190	3	139	0,022
1235	5220	5	139	0,036
1235	7223	3	139	0,022
1235	7411	7	139	0,050
1235	9330	4	139	0,029
1237	1222	6	82	0,073
1237	1239	6	82	0,073
1237	2113	2	82	0,024
1237	2139	3	82	0,037
1237	2144	6	82	0,073
1237	2146	2	82	0,024
1237	2149	8	82	0,098
1237	2213	2	82	0,024
1237	2419	5	82	0,061
1237	3111	3	82	0,037
1237	3115	4	82	0,049
1237	3121	2	82	0,024
1237	3152	6	82	0,073
1239	1210	16	633	0,025
1239	1222	18	633	0,028
1239	1224	30	633	0,047
1239	1314	14	633	0,022
1239	2149	13	633	0,021
1239	3115	20	633	0,032
1239	3415	36	633	0,057
1239	3419	15	633	0,024
1239	4190	28	633	0,044
1239	5220	50	633	0,079
1239	7231	16	633	0,025
1314	1224	38	669	0,057
1314	1239	25	669	0,037
1314	3114	15	669	0,022
1314	3415	64	669	0,096
1314	4190	20	669	0,030
1314	5220	74	669	0,111
1314	7124	14	669	0,021
1314	7137	21	669	0,031
1314	7223	28	669	0,042
1314	7231	37	669	0,055
1314	7233	16	669	0,024
1314	7411	20	669	0,030
1314	8211	14	669	0,021
1314	8271	26	669	0,039
2113	1237	5	125	0,040
2113	1239	5	125	0,040
2113	2111	3	125	0,024
2113	2139	3	125	0,024
2113	2142	5	125	0,040
2113	2145	8	125	0,064
2113	2146	19	125	0,152
2113	2149	13	125	0,104
2113	2211	9	125	0,072
2113	2213	4	125	0,032
2113	2224	8	125	0,064
2113	2419	4	125	0,032
2113	3111	4	125	0,032
2113	3114	3	125	0,024
2131	2132	61	641	0,095
2131	2139	145	641	0,226
2131	2144	28	641	0,044
2131	2419	23	641	0,036
2131	3114	13	641	0,020
2131	3121	101	641	0,158
2131	3122	32	641	0,050
2131	3415	33	641	0,051
2131	3419	31	641	0,048
2131	4190	21	641	0,033
2132	2131	51	322	0,158
2132	2139	49	322	0,152
2132	2144	20	322	0,062
2132	2149	10	322	0,031
2132	3114	11	322	0,034
2132	3121	78	322	0,242
2132	3122	7	322	0,022
2132	3419	8	322	0,025
2132	4190	20	322	0,062
2139	2131	120	755	0,159
2139	2132	64	755	0,085
2139	2144	37	755	0,049
2139	2149	16	755	0,021
2139	2419	18	755	0,024
2139	3114	34	755	0,045
2139	3121	130	755	0,172
2139	3122	23	755	0,030
2139	3415	30	755	0,040
2139	3419	26	755	0,034
2139	4190	30	755	0,040
2139	7243	21	755	0,028
2141	1210	15	146	0,103
2141	1317	8	146	0,055
2141	2142	21	146	0,144
2141	2149	11	146	0,075
2141	2213	3	146	0,021
2141	2310	4	146	0,027
2141	3112	23	146	0,158
2141	3118	7	146	0,048
2141	3415	3	146	0,021
2141	3471	4	146	0,027
2141	7124	6	146	0,041
2142	1223	21	401	0,052
2142	1239	13	401	0,032
2142	2141	31	401	0,077
2142	2143	16	401	0,040
2142	2145	24	401	0,060
2142	2149	84	401	0,209
2142	3112	54	401	0,135
2142	3115	9	401	0,022
2142	3415	21	401	0,052
2142	7124	11	401	0,027
2143	1239	5	233	0,021
2143	2142	13	233	0,056
2143	2144	14	233	0,060
2143	2145	22	233	0,094
2143	2149	40	233	0,172
2143	3113	12	233	0,052
2143	3114	14	233	0,060
2143	3115	7	233	0,030
2143	3119	10	233	0,043
2143	3415	18	233	0,077
2143	7137	17	233	0,073
2143	7241	5	233	0,021
2144	2131	19	252	0,075
2144	2132	12	252	0,048
2144	2139	33	252	0,131
2144	2143	12	252	0,048
2144	2145	13	252	0,052
2144	2149	24	252	0,095
2144	3114	33	252	0,131
2144	3119	7	252	0,028
2144	3121	15	252	0,060
2144	3415	7	252	0,028

2144	7137	6	252	0,024
2144	7243	11	252	0,044
2145	1222	20	718	0,028
2145	1239	22	718	0,031
2145	2139	16	718	0,022
2145	2142	17	718	0,024
2145	2143	34	718	0,047
2145	2144	31	718	0,043
2145	2146	19	718	0,026
2145	2149	152	718	0,212
2145	2419	34	718	0,047
2145	3113	16	718	0,022
2145	3115	78	718	0,109
2145	3119	30	718	0,042
2145	3415	40	718	0,056
2145	7223	18	718	0,025
2146	1222	3	142	0,021
2146	1239	8	142	0,056
2146	2113	10	142	0,070
2146	2143	6	142	0,042
2146	2144	3	142	0,021
2146	2145	11	142	0,077
2146	2149	28	142	0,197
2146	2224	6	142	0,042
2146	2419	4	142	0,028
2146	3114	3	142	0,021
2146	3115	4	142	0,028
2146	3116	3	142	0,021
2146	3119	5	142	0,035
2146	3121	3	142	0,021
2146	3152	5	142	0,035
2146	3211	3	142	0,021
2146	3415	6	142	0,042
2149	1222	47	964	0,049
2149	1239	34	964	0,035
2149	2139	26	964	0,027
2149	2142	103	964	0,107
2149	2143	31	964	0,032
2149	2144	84	964	0,087
2149	2145	118	964	0,122
2149	2146	34	964	0,035
2149	3114	32	964	0,033
2149	3115	47	964	0,049
2149	3415	35	964	0,036
2224	1210	4	73	0,055
2224	1222	3	73	0,041
2224	1237	7	73	0,096
2224	1239	3	73	0,041
2224	2139	3	73	0,041
2224	2146	11	73	0,151
2224	2149	4	73	0,055
2224	2211	4	73	0,055
2224	2221	3	73	0,041
2224	2229	6	73	0,082
2224	2419	6	73	0,082
2224	3152	2	73	0,027
2224	3415	7	73	0,096
2331	3114	7	231	0,030
2331	3115	5	231	0,022
2331	3415	9	231	0,039
2331	4190	14	231	0,061
2331	5220	11	231	0,048
2331	7124	8	231	0,035
2331	7136	7	231	0,030
2331	7137	5	231	0,022
2331	7213	8	231	0,035
2331	7222	5	231	0,022
2331	7223	6	231	0,026
2331	7231	34	231	0,147
2331	7233	7	231	0,030
2331	7243	9	231	0,039
2411	1210	28	663	0,042
2411	1231	104	663	0,157
2411	1239	14	663	0,021
2411	2419	33	663	0,050
2411	3419	84	663	0,127
2411	3433	150	663	0,226
2411	3439	16	663	0,024
2411	4121	51	663	0,077
2411	4190	52	663	0,078
2419	1210	11	430	0,026
2419	1233	9	430	0,021
2419	1239	12	430	0,028
2419	2131	20	430	0,047
2419	2139	34	430	0,079
2419	2146	14	430	0,033
2419	2149	11	430	0,026
2419	2411	21	430	0,049
2419	2441	12	430	0,028
2419	3121	10	430	0,023
2419	3415	45	430	0,105
2419	3419	44	430	0,102
2419	3429	9	430	0,021
2419	3433	10	430	0,023
2421	1210	2	22	0,091
2421	1317	1	22	0,045
2421	2310	1	22	0,045
2421	2411	3	22	0,136
2421	2419	1	22	0,045
2421	2429	7	22	0,318
2421	3121	1	22	0,045
2421	3419	1	22	0,045
2421	4115	1	22	0,045
2421	4190	1	22	0,045
2421	4212	1	22	0,045
2421	5162	1	22	0,045
2421	9330	1	22	0,045
2451	1239	5	105	0,048
2451	1317	4	105	0,038
2451	2131	3	105	0,029
2451	2139	4	105	0,038
2451	2419	5	105	0,048
2451	2442	3	105	0,029
2451	2443	9	105	0,086
2451	3121	3	105	0,029
2451	3131	16	105	0,152
2451	3415	3	105	0,029
2451	3419	4	105	0,038
2451	3429	6	105	0,057
2451	3471	5	105	0,048
2451	4115	5	105	0,048
3111	2113	6	138	0,043
3111	2146	3	138	0,022
3111	2149	4	138	0,029
3111	3114	5	138	0,036
3111	3116	5	138	0,036
3111	3119	10	138	0,072
3111	3152	6	138	0,043
3111	3211	30	138	0,217
3111	3415	5	138	0,036
3111	4190	23	138	0,167
3112	1222	12	564	0,021
3112	1223	23	564	0,041
3112	2141	41	564	0,073
3112	2142	63	564	0,112
3112	2149	22	564	0,039
3112	3115	47	564	0,083
3112	3118	37	564	0,066
3112	3119	33	564	0,059
3112	3415	32	564	0,057
3112	7124	44	564	0,078
3112	7136	24	564	0,043
3113	2139	11	463	0,024
3113	2143	24	463	0,052
3113	2144	13	463	0,028
3113	2145	15	463	0,032
3113	2149	19	463	0,041
3113	3114	58	463	0,125
3113	3115	33	463	0,071
3113	3119	18	463	0,039
3113	3415	21	463	0,045
3113	7137	68	463	0,147
3113	7223	12	463	0,026
3113	7241	52	463	0,112
3113	7243	17	463	0,037
3114	2131	31	1218	0,025
3114	2139	59	1218	0,048
3114	2144	105	1218	0,086
3114	2145	27	1218	0,022
3114	2149	49	1218	0,040
3114	3113	65	1218	0,053
3114	3115	34	1218	0,028
3114	3119	52	1218	0,043
3114	3121	86	1218	0,071
3114	3122	37	1218	0,030
3114	3415	46	1218	0,038
3114	7137	39	1218	0,032
3114	7241	39	1218	0,032
3114	7242	78	1218	0,064
3114	7243	131	1218	0,108
3115	1222	54	1431	0,038
3115	1239	33	1431	0,023
3115	2145	129	1431	0,090
3115	2149	56	1431	0,039
3115	3112	45	1431	0,031
3115	3113	51	1431	0,036
3115	3114	42	1431	0,029
3115	3118	101	1431	0,071
3115	3119	143	1431	0,100
3115	3415	121	1431	0,085
3115	4132	29	1431	0,020
3115	7222	31	1431	0,022
3115	7223	54	1431	0,038
3115	7233	41	1431	0,029
3116	1239	2	88	0,023
3116	2146	4	88	0,045
3116	2149	4	88	0,045
3116	3111	5	88	0,057
3116	3114	4	88	0,045
3116	3115	7	88	0,080
3116	3118	3	88	0,034
3116	3119	7	88	0,080
3116	3211	6	88	0,068
3116	3415	4	88	0,045
3116	7136	9	88	0,102
3116	7137	3	88	0,034
3116	7223	2	88	0,023
3116	8141	3	88	0,034
3116	8159	2	88	0,023
3118	2145	14	356	0,039
3118	2149	9	356	0,025
3118	3112	41	356	0,115
3118	3114	10	356	0,028
3118	3115	81	356	0,228
3118	3119	44	356	0,124
3118	3415	15	356	0,042
3119	1222	42	1148	0,037
3119	2145	35	1148	0,030
3119	2149	39	1148	0,034
3119	3112	44	1148	0,038
3119	3113	33	1148	0,029
3119	3114	59	1148	0,051
3119	3115	141	1148	0,123
3119	3118	50	1148	0,044
3119	3121	23	1148	0,020
3119	3415	58	1148	0,051
3119	4132	27	1148	0,024
3119	7223	32	1148	0,028
3119	7243	31	1148	0,027
3121	2131	158	1057	0,149
3121	2132	86	1057	0,081
3121	2139	199	1057	0,188
3121	3114	60	1057	0,057
3121	3122	63	1057	0,060
3121	3415	40	1057	0,038
3121	3419	38	1057	0,036
3121	4190	111	1057	0,105
3121	7243	25	1057	0,024
3122	1312	8	397	0,020
3122	2131	59	397	0,149
3122	2132	14	397	0,035
3122	2139	35	397	0,088
3122	3114	28	397	0,071
3122	3121	92	397	0,232
3122	3415	14	397	0,035
3122	4190	26	397	0,065
3122	7243	17	397	0,043
3141	2145	2	68	0,029
3141	3113	2	68	0,029
3141	3115	22	68	0,324
3141	3142	2	68	0,029
3141	3415	5	68	0,074
3141	7212	2	68	0,029
3141	7222	3	68	0,044
3141	7231	2	68	0,029
3141	7233	8	68	0,118
3141	7243	2	68	0,029
3141	8253	2	68	0,029
3141	8340	3	68	0,044
3142	1223	1	37	0,027
3142	2444	1	37	0,027
3142	2452	1	37	0,027
3142	3121	2	37	0,054
3142	3122	1	37	0,027
3142	3141	5	37	0,135
3142	3152	1	37	0,027
3142	3415	1	37	0,027
3142	3439	8	37	0,216
3142	4115	1	37	0,027
3142	4133	2	37	0,054
3142	4190	1	37	0,027
3142	6130	1	37	0,027
3142	6152	2	37	0,054
3142	7214	1	37	0,027
3142	7222	1	37	0,027
3142	8113	2	37	0,054
3142	8271	1	37	0,027
3142	8278	1	37	0,027
3142	8334	1	37	0,027
3142	8340	1	37	0,027
3142	9330	1	37	0,027
3152	1222	7	205	0,034
3152	1239	9	205	0,044

3152	2145	6	205	0,029
3152	2146	7	205	0,034
3152	2149	12	205	0,059
3152	3114	10	205	0,049
3152	3115	20	205	0,098
3152	3119	13	205	0,063
3152	3121	5	205	0,024
3152	4190	6	205	0,029
3152	7124	5	205	0,024
3152	7223	11	205	0,054
3152	7231	6	205	0,029
3211	1239	6	108	0,056
3211	3111	22	108	0,204
3211	3116	6	108	0,056
3211	3119	13	108	0,120
3211	3415	3	108	0,028
3211	4190	15	108	0,139
3211	8159	7	108	0,065
3224	1210	1	23	0,043
3224	1224	3	23	0,130
3224	1239	16	23	0,696
3224	3415	2	23	0,087
3224	9151	1	23	0,043
3415	1224	92	3223	0,029
3415	1233	151	3223	0,047
3415	3115	93	3223	0,029
3415	3416	71	3223	0,022
3415	3419	360	3223	0,112
3415	4131	100	3223	0,031
3415	4132	75	3223	0,023
3415	4190	326	3223	0,101
3415	5220	385	3223	0,119
3416	1235	33	450	0,073
3416	2419	13	450	0,029
3416	3115	23	450	0,051
3416	3415	65	450	0,144
3416	3419	28	450	0,062
3416	3422	10	450	0,022
3416	3439	10	450	0,022
3416	4131	13	450	0,029
3416	4132	35	450	0,078
3416	4190	53	450	0,118
3416	5220	26	450	0,058
3419	1231	58	1680	0,035
3419	1233	47	1680	0,028
3419	1234	37	1680	0,022
3419	2131	54	1680	0,032
3419	2139	58	1680	0,035
3419	2411	117	1680	0,070
3419	2419	63	1680	0,038
3419	3121	58	1680	0,035
3419	3415	395	1680	0,235
3419	3429	60	1680	0,036
3419	3433	68	1680	0,040
3419	4115	39	1680	0,023
3419	4190	45	1680	0,027
3419	5220	60	1680	0,036
3422	3415	61	398	0,153
3422	3416	16	398	0,040
3422	3429	18	398	0,045
3422	4115	13	398	0,033
3422	4131	8	398	0,020
3422	4132	13	398	0,033
3422	4133	40	398	0,101
3422	4190	115	398	0,289
3422	9330	13	398	0,033
3429	1233	7	213	0,033
3429	2419	7	213	0,033
3429	3114	5	213	0,023
3429	3415	38	213	0,178
3429	3416	6	213	0,028
3429	3419	40	213	0,188
3429	3422	13	213	0,061
3429	4190	10	213	0,047
3429	7137	6	213	0,028
3431	1239	7	188	0,037
3431	2411	4	188	0,021
3431	3115	4	188	0,021
3431	3415	23	188	0,122
3431	3416	4	188	0,021
3431	3419	20	188	0,106
3431	3433	8	188	0,043
3431	3439	9	188	0,048
3431	4115	11	188	0,059
3431	4132	4	188	0,021
3431	4133	4	188	0,021
3431	4190	16	188	0,085
3431	5220	4	188	0,021
3433	1231	42	393	0,107
3433	1239	9	393	0,023
3433	2139	8	393	0,020
3433	2411	108	393	0,275
3433	2419	9	393	0,023
3433	3121	11	393	0,028
3433	3415	11	393	0,028
3433	3419	46	393	0,117
3433	3439	14	393	0,036
3433	4121	21	393	0,053
3433	4122	8	393	0,020
3433	4190	29	393	0,074
3439	1222	13	642	0,020
3439	1224	17	642	0,026
3439	1239	21	642	0,033
3439	3115	13	642	0,020
3439	3119	14	642	0,022
3439	3415	62	642	0,097
3439	3416	21	642	0,033
3439	3419	45	642	0,070
3439	3433	21	642	0,033
3439	4190	39	642	0,061
3439	5220	21	642	0,033
3471	1312	2	77	0,026
3471	1317	5	77	0,065
3471	2141	5	77	0,065
3471	2149	2	77	0,026
3471	2451	4	77	0,052
3471	2452	7	77	0,091
3471	3114	2	77	0,026
3471	3118	3	77	0,039
3471	3119	2	77	0,026
3471	3121	2	77	0,026
3471	3415	6	77	0,078
3471	3429	2	77	0,026
3471	3439	2	77	0,026
3471	4190	4	77	0,052
3471	5220	5	77	0,065
3471	7124	2	77	0,026
3471	7341	5	77	0,065
3471	8251	3	77	0,039
4115	3415	53	563	0,094
4115	3416	20	563	0,036
4115	3419	42	563	0,075
4115	3422	13	563	0,023
4115	3433	17	563	0,030
4115	3439	14	563	0,025
4115	4132	19	563	0,034
4115	4190	103	563	0,183
4115	5220	20	563	0,036
4121	1231	13	265	0,049
4121	2411	45	265	0,170
4121	3121	6	265	0,023
4121	3419	15	265	0,057
4121	3433	42	265	0,158
4121	3439	7	265	0,026
4121	4115	7	265	0,026
4121	4122	7	265	0,026
4121	4190	51	265	0,192
4131	3415	153	923	0,166
4131	3419	21	923	0,023
4131	4132	43	923	0,047
4131	4190	107	923	0,116
4131	5220	156	923	0,169
4131	9320	19	923	0,021
4131	9330	96	923	0,104
4132	1222	20	589	0,034
4132	3115	21	589	0,036
4132	3119	24	589	0,041
4132	3415	108	589	0,183
4132	3416	40	589	0,068
4132	3419	28	589	0,048
4132	4131	23	589	0,039
4132	4190	80	589	0,136
4132	5220	36	589	0,061
4132	7231	15	589	0,025
4133	3415	11	146	0,075
4133	3416	6	146	0,041
4133	3421	3	146	0,021
4133	3422	49	146	0,336
4133	3429	5	146	0,034
4133	3439	4	146	0,027
4133	4115	4	146	0,027
4133	4190	18	146	0,123
4133	5220	5	146	0,034
4133	7231	4	146	0,027
4133	8324	5	146	0,034
4190	3121	171	4901	0,035
4190	3415	776	4901	0,158
4190	3416	112	4901	0,023
4190	3422	165	4901	0,034
4190	4115	155	4901	0,032
4190	4131	132	4901	0,027
4190	4132	172	4901	0,035
4190	5220	1369	4901	0,279
4190	9330	261	4901	0,053
5122	1314	10	286	0,035
5122	3415	20	286	0,070
5122	3439	6	286	0,021
5122	5123	39	286	0,136
5122	5220	13	286	0,045
5122	8271	13	286	0,045
5122	8278	24	286	0,084
5122	8324	45	286	0,157
5122	9132	13	286	0,045
5122	9320	6	286	0,021
5123	4115	2	79	0,025
5123	4190	3	79	0,038
5123	5122	20	79	0,253
5123	5169	2	79	0,025
5123	5220	6	79	0,076
5123	7124	4	79	0,051
5123	7141	2	79	0,025
5123	7212	2	79	0,025
5123	7214	2	79	0,025
5123	7222	3	79	0,038
5123	8271	2	79	0,025
5123	8284	2	79	0,025
5123	9320	2	79	0,025
5220	1224	249	4020	0,062
5220	1239	123	4020	0,031
5220	1314	179	4020	0,045
5220	3415	871	4020	0,217
5220	4131	132	4020	0,033
5220	4190	982	4020	0,244
5220	9330	183	4020	0,046
6130	3415	18	879	0,020
6130	7124	70	879	0,080
6130	7212	25	879	0,028
6130	7214	18	879	0,020
6130	7221	37	879	0,042
6130	7222	21	879	0,024
6130	7223	34	879	0,039
6130	7231	59	879	0,067
6130	7233	82	879	0,093
6130	7241	18	879	0,020
6130	8240	22	879	0,025
6130	8271	49	879	0,056
6130	8324	21	879	0,024
6130	9312	23	879	0,026
6130	9320	18	879	0,020
7122	2142	8	184	0,043
7122	2149	12	184	0,065
7122	3112	17	184	0,092
7122	3415	6	184	0,033
7122	6130	8	184	0,043
7122	7124	15	184	0,082
7122	8232	5	184	0,027
7122	9132	4	184	0,022
7122	9211	5	184	0,027
7122	9312	6	184	0,033
7122	9313	12	184	0,065
7122	9320	5	184	0,027
7122	9330	4	184	0,022
7124	3112	91	2759	0,033
7124	6130	58	2759	0,021
7124	7132	61	2759	0,022
7124	7135	101	2759	0,037
7124	7139	57	2759	0,021
7124	7422	219	2759	0,079
7124	7423	423	2759	0,153
7124	8240	358	2759	0,130
7124	8285	85	2759	0,031
7124	9313	58	2759	0,021
7124	9320	122	2759	0,044
7124	9330	63	2759	0,023
7129	3112	4	135	0,030
7129	3415	3	135	0,022
7129	5220	5	135	0,037
7129	6130	3	135	0,022
7129	7124	27	135	0,200
7129	7214	5	135	0,037
7129	7221	9	135	0,067
7129	7222	23	135	0,170
7129	7223	3	135	0,022
7129	7231	4	135	0,030
7129	7422	3	135	0,022
7129	8271	3	135	0,022
7129	9313	5	135	0,037
7129	9320	3	135	0,022
7135	1239	2	90	0,022
7135	1312	3	90	0,033
7135	7124	53	90	0,589
7135	7231	3	90	0,033
7135	8240	2	90	0,022

7135	9132	2	90	0,022
7135	9312	2	90	0,022
7135	9330	3	90	0,033
7136	3112	54	1143	0,047
7136	3115	62	1143	0,054
7136	3415	25	1143	0,022
7136	7143	56	1143	0,049
7136	7212	84	1143	0,073
7136	7213	37	1143	0,032
7136	7214	47	1143	0,041
7136	7221	83	1143	0,073
7136	7222	46	1143	0,040
7136	7223	34	1143	0,030
7136	7233	132	1143	0,115
7137	2143	29	1325	0,022
7137	3113	132	1325	0,100
7137	3114	68	1325	0,051
7137	3415	44	1325	0,033
7137	7233	109	1325	0,082
7137	7241	318	1325	0,240
7137	7243	63	1325	0,048
7139	7124	44	152	0,289
7139	7129	4	152	0,026
7139	7136	13	152	0,086
7139	7137	4	152	0,026
7139	7213	4	152	0,026
7139	7221	6	152	0,039
7139	7222	7	152	0,046
7139	7223	9	152	0,059
7139	7231	10	152	0,066
7139	7233	4	152	0,026
7139	9313	4	152	0,026
7141	7142	124	431	0,288
7141	7242	99	431	0,230
7141	9320	20	431	0,046
7141	9330	11	431	0,026
7142	3415	4	151	0,026
7142	7141	79	151	0,523
7142	7231	4	151	0,026
7142	7242	19	151	0,126
7142	8271	4	151	0,026
7211	7136	11	190	0,058
7211	7212	15	190	0,079
7211	7213	6	190	0,032
7211	7214	7	190	0,037
7211	7221	6	190	0,032
7211	7222	35	190	0,184
7211	7223	28	190	0,147
7211	7231	7	190	0,037
7211	7233	16	190	0,084
7211	8123	16	190	0,084
7211	8211	4	190	0,021
7212	7136	91	1878	0,048
7212	7213	130	1878	0,069
7212	7214	122	1878	0,065
7212	7221	141	1878	0,075
7212	7222	639	1878	0,340
7212	7223	187	1878	0,100
7212	7231	114	1878	0,061
7212	7233	119	1878	0,063
7212	8211	40	1878	0,021
7213	7136	38	1143	0,033
7213	7212	138	1143	0,121
7213	7214	75	1143	0,066
7213	7221	84	1143	0,073
7213	7222	219	1143	0,192
7213	7223	86	1143	0,075
7213	7231	150	1143	0,131
7213	7233	69	1143	0,060
7213	8211	24	1143	0,021
7214	7136	44	1384	0,032
7214	7212	152	1384	0,110
7214	7213	79	1384	0,057
7214	7221	106	1384	0,077
7214	7222	442	1384	0,319
7214	7223	145	1384	0,105
7214	7231	51	1384	0,037
7214	7233	78	1384	0,056
7221	6130	38	1671	0,023
7221	7136	133	1671	0,080
7221	7212	152	1671	0,091
7221	7213	106	1671	0,063
7221	7214	141	1671	0,084
7221	7222	348	1671	0,208
7221	7223	137	1671	0,082
7221	7231	69	1671	0,041
7221	7233	174	1671	0,104
7222	7212	712	3892	0,183
7222	7213	312	3892	0,080
7222	7214	485	3892	0,125
7222	7221	382	3892	0,098
7222	7223	466	3892	0,120
7222	7233	404	3892	0,104
7222	8211	103	3892	0,026
7223	3115	74	3488	0,021
7223	7212	196	3488	0,056
7223	7213	97	3488	0,028
7223	7214	144	3488	0,041
7223	7221	142	3488	0,041
7223	7222	370	3488	0,106
7223	7231	101	3488	0,029
7223	7233	676	3488	0,194
7223	8211	363	3488	0,104
7223	8232	72	3488	0,021
7231	3415	74	3180	0,023
7231	5220	64	3180	0,020
7231	6130	66	3180	0,021
7231	7212	113	3180	0,036
7231	7213	160	3180	0,050
7231	7221	74	3180	0,023
7231	7223	84	3180	0,026
7231	7233	840	3180	0,264
7231	8211	94	3180	0,030
7231	8284	84	3180	0,026
7231	8324	151	3180	0,047
7231	9330	76	3180	0,024
7233	7136	102	2950	0,035
7233	7137	82	2950	0,028
7233	7212	74	2950	0,025
7233	7221	109	2950	0,037
7233	7222	343	2950	0,116
7233	7223	600	2950	0,203
7233	7231	604	2950	0,205
7233	7241	179	2950	0,061
7241	3113	76	1174	0,065
7241	3114	44	1174	0,037
7241	3415	35	1174	0,030
7241	7137	301	1174	0,256
7241	7231	43	1174	0,037
7241	7233	197	1174	0,168
7241	7242	57	1174	0,049
7241	7243	65	1174	0,055
7242	3114	117	701	0,167
7242	3119	20	701	0,029
7242	3121	18	701	0,026
7242	7137	24	701	0,034
7242	7233	20	701	0,029
7242	7241	51	701	0,073
7242	7243	279	701	0,398
7243	2139	26	1164	0,022
7243	2144	30	1164	0,026
7243	3113	42	1164	0,036
7243	3114	186	1164	0,160
7243	3119	28	1164	0,024
7243	3121	52	1164	0,045
7243	3122	28	1164	0,024
7243	3415	35	1164	0,030
7243	7137	38	1164	0,033
7243	7233	32	1164	0,027
7243	7241	81	1164	0,070
7243	7242	261	1164	0,224
7311	3115	6	157	0,038
7311	7222	10	157	0,064
7311	7223	50	157	0,318
7311	7233	18	157	0,115
7311	7242	4	157	0,025
7311	7243	6	157	0,038
7311	8211	11	157	0,070
7311	8232	6	157	0,038
7341	1222	9	246	0,037
7341	2452	9	246	0,037
7341	3415	6	246	0,024
7341	3471	7	246	0,028
7341	4190	9	246	0,037
7341	7343	35	246	0,142
7341	7346	5	246	0,020
7341	8251	102	246	0,415
7411	1314	24	802	0,030
7411	3415	18	802	0,022
7411	5220	43	802	0,054
7411	8271	498	802	0,621
7411	9330	18	802	0,022
7412	1314	12	348	0,034
7412	3415	7	348	0,020
7412	5220	10	348	0,029
7412	8211	7	348	0,020
7412	8271	102	348	0,293
7412	8274	32	348	0,092
7412	9313	7	348	0,020
7412	9320	13	348	0,037
7412	9330	8	348	0,023
7413	1222	6	209	0,029
7413	1239	23	209	0,110
7413	3119	6	209	0,029
7413	8159	7	209	0,033
7413	8271	7	209	0,033
7413	8272	96	209	0,459
7422	1222	9	272	0,033
7422	7124	133	272	0,489
7422	7423	27	272	0,099
7422	8240	19	272	0,070
7422	8285	7	272	0,026
7422	9320	7	272	0,026
7423	1222	24	656	0,037
7423	7124	260	656	0,396
7423	7422	40	656	0,061
7423	8240	134	656	0,204
7423	9320	16	656	0,024
8123	5220	3	117	0,026
8123	7124	5	117	0,043
8123	7211	16	117	0,137
8123	7222	16	117	0,137
8123	7223	8	117	0,068
8123	7231	4	117	0,034
8123	7233	4	117	0,034
8123	8212	3	117	0,026
8123	8271	4	117	0,034
8123	8284	3	117	0,026
8123	9312	4	117	0,034
8123	9320	3	117	0,026
8159	3119	23	187	0,123
8159	3211	5	187	0,027
8159	4131	4	187	0,021
8159	6130	4	187	0,021
8159	7124	6	187	0,032
8159	7137	5	187	0,027
8159	7221	4	187	0,021
8159	7223	16	187	0,086
8159	7231	9	187	0,048
8159	7412	4	187	0,021
8159	8290	6	187	0,032
8159	9313	5	187	0,027
8159	9320	5	187	0,027
8159	9330	6	187	0,032
8211	7212	36	1248	0,029
8211	7213	29	1248	0,023
8211	7222	115	1248	0,092
8211	7223	409	1248	0,328
8211	7231	74	1248	0,059
8211	7233	51	1248	0,041
8211	8284	25	1248	0,020
8211	9320	26	1248	0,021
8212	3115	2	73	0,027
8212	6130	5	73	0,068
8212	7124	6	73	0,082
8212	7136	2	73	0,027
8212	7214	2	73	0,027
8212	7221	3	73	0,041
8212	7222	5	73	0,068
8212	7223	2	73	0,027
8212	7231	4	73	0,055
8212	8159	2	73	0,027
8212	8240	2	73	0,027
8212	8271	2	73	0,027
8212	8285	3	73	0,041
8212	9312	4	73	0,055
8212	9313	4	73	0,055
8212	9320	3	73	0,041
8231	1239	1	43	0,023
8231	4132	1	43	0,023
8231	5220	1	43	0,023
8231	7136	1	43	0,023
8231	7143	1	43	0,023
8231	7212	1	43	0,023
8231	7213	1	43	0,023
8231	7221	2	43	0,047
8231	7223	3	43	0,070
8231	7224	1	43	0,023
8231	7231	2	43	0,047
8231	7233	3	43	0,070
8231	7243	1	43	0,023
8231	7245	1	43	0,023
8231	7341	1	43	0,023
8231	7437	1	43	0,023
8231	8211	1	43	0,023
8231	8221	1	43	0,023
8231	8232	4	43	0,093
8231	8240	1	43	0,023
8231	8251	2	43	0,047
8231	8252	1	43	0,023
8231	8271	4	43	0,093
8231	9142	1	43	0,023
8231	9312	2	43	0,047

8231	9320	3	43	0,070
8231	9330	1	43	0,023
8232	5220	12	445	0,027
8232	7124	19	445	0,043
8232	7213	9	445	0,020
8232	7221	9	445	0,020
8232	7222	23	445	0,052
8232	7223	79	445	0,178
8232	7231	29	445	0,065
8232	7233	19	445	0,043
8232	7241	19	445	0,043
8232	8211	10	445	0,022
8232	8271	9	445	0,020
8232	8284	11	445	0,025
8232	8290	13	445	0,029
8232	9320	13	445	0,029
8232	9330	9	445	0,020
8240	7124	668	1402	0,476
8240	7422	50	1402	0,036
8240	7423	238	1402	0,170
8240	9320	95	1402	0,068
8251	3119	4	146	0,027
8251	3122	3	146	0,021
8251	3439	3	146	0,021
8251	3471	3	146	0,021
8251	7223	3	146	0,021
8251	7341	75	146	0,514
8251	7343	15	146	0,103
8251	8252	5	146	0,034
8253	1222	2	93	0,022
8253	1314	3	93	0,032
8253	4131	2	93	0,022
8253	5220	2	93	0,022
8253	7124	3	93	0,032
8253	7137	2	93	0,022
8253	7223	7	93	0,075
8253	7231	8	93	0,086
8253	7233	6	93	0,065
8253	7341	2	93	0,022
8253	8123	2	93	0,022
8253	8211	5	93	0,054
8253	8232	3	93	0,032
8253	8251	2	93	0,022
8253	8271	3	93	0,032
8253	8287	2	93	0,022
8253	8290	2	93	0,022
8253	8334	4	93	0,043
8253	9330	5	93	0,054
8271	5220	37	1650	0,022
8271	6130	43	1650	0,026
8271	7411	449	1650	0,272
8271	7412	218	1650	0,132
8271	8272	102	1650	0,062
8271	8324	49	1650	0,030
8271	9320	86	1650	0,052
8271	9330	45	1650	0,027
8272	1239	17	233	0,073
8272	3119	5	233	0,021
8272	6130	10	233	0,043
8272	7231	6	233	0,026
8272	7233	6	233	0,026
8272	7413	36	233	0,155
8272	8159	7	233	0,030
8272	8271	23	233	0,099
8272	8278	6	233	0,026
8272	8290	5	233	0,021
8272	9320	22	233	0,094
8274	1222	3	82	0,037
8274	4190	2	82	0,024
8274	5220	4	82	0,049
8274	7124	3	82	0,037
8274	7223	2	82	0,024
8274	7233	4	82	0,049
8274	7412	6	82	0,073
8274	8211	2	82	0,024
8274	8232	3	82	0,037
8274	8253	2	82	0,024
8274	8271	14	82	0,171
8274	8272	4	82	0,049
8274	8334	2	82	0,024
8274	9312	2	82	0,024
8274	9320	7	82	0,085
8278	3121	2	57	0,035
8278	3439	2	57	0,035
8278	5122	7	57	0,123
8278	7223	7	57	0,123
8278	7231	2	57	0,035
8278	8159	3	57	0,053
8278	8271	3	57	0,053
8278	8290	2	57	0,035
8278	8322	2	57	0,035
8278	8324	7	57	0,123
8278	8334	2	57	0,035
8281	7222	13	152	0,086
8281	7223	31	152	0,204
8281	7231	8	152	0,053
8281	7233	17	152	0,112
8281	8211	11	152	0,072
8281	8283	7	152	0,046
8281	8290	4	152	0,026
8281	9320	8	152	0,053
8283	3114	7	143	0,049
8283	4190	3	143	0,021
8283	7124	3	143	0,021
8283	7137	3	143	0,021
8283	7222	3	143	0,021
8283	7223	4	143	0,028
8283	7231	3	143	0,021
8283	7233	3	143	0,021
8283	7241	8	143	0,056
8283	7242	5	143	0,035
8283	7243	31	143	0,217
8283	7311	3	143	0,021
8283	8232	8	143	0,056
8283	8281	9	143	0,063
8283	8284	3	143	0,021
8283	8290	3	143	0,021
8283	9320	7	143	0,049
8283	9330	5	143	0,035
8284	6130	14	432	0,032
8284	7124	15	432	0,035
8284	7222	18	432	0,042
8284	7223	36	432	0,083
8284	7231	67	432	0,155
8284	7233	19	432	0,044
8284	8211	16	432	0,037
8284	8232	12	432	0,028
8284	8271	17	432	0,039
8284	8290	10	432	0,023
8284	9320	22	432	0,051
8284	9330	15	432	0,035
8285	6130	5	206	0,024
8285	7124	72	206	0,350
8285	7231	5	206	0,024
8285	7422	7	206	0,034
8285	7423	18	206	0,087
8285	8240	17	206	0,083
8285	8271	7	206	0,034
8285	9320	10	206	0,049
8287	6130	4	153	0,026
8287	7124	7	153	0,046
8287	7221	5	153	0,033
8287	7222	13	153	0,085
8287	7223	10	153	0,065
8287	7231	16	153	0,105
8287	7233	5	153	0,033
8287	7241	6	153	0,039
8287	7243	5	153	0,033
8287	8211	5	153	0,033
8287	8271	4	153	0,026
8287	9330	6	153	0,039
8290	3114	9	428	0,021
8290	4190	11	428	0,026
8290	5220	11	428	0,026
8290	7124	27	428	0,063
8290	7222	15	428	0,035
8290	7223	36	428	0,084
8290	7231	16	428	0,037
8290	7233	11	428	0,026
8290	7243	10	428	0,023
8290	8211	15	428	0,035
8290	8232	12	428	0,028
8290	8271	30	428	0,070
8290	8284	15	428	0,035
8290	9320	20	428	0,047
8290	9330	14	428	0,033
8322	3415	18	209	0,086
8322	4190	21	209	0,100
8322	5220	20	209	0,096
8322	7124	7	209	0,033
8322	7136	5	209	0,024
8322	7223	5	209	0,024
8322	7231	18	209	0,086
8322	8324	25	209	0,120
8322	9330	14	209	0,067
8324	3415	52	445	0,117
8324	5122	27	445	0,061
8324	5220	13	445	0,029
8324	6130	15	445	0,034
8324	7124	16	445	0,036
8324	7221	9	445	0,020
8324	7231	77	445	0,173
8324	8271	11	445	0,025
8324	8322	18	445	0,040
8324	8334	9	445	0,020
8324	9320	16	445	0,036
8324	9330	30	445	0,067
8332	1313	2	86	0,023
8332	3416	2	86	0,023
8332	6130	5	86	0,058
8332	7124	2	86	0,023
8332	7213	2	86	0,023
8332	7221	2	86	0,023
8332	7222	4	86	0,047
8332	7223	3	86	0,035
8332	7231	7	86	0,081
8332	7233	3	86	0,035
8332	8251	3	86	0,035
8332	8271	2	86	0,023
8332	8272	3	86	0,035
8332	8324	4	86	0,047
8332	9211	2	86	0,023
8332	9312	16	86	0,186
8332	9313	4	86	0,047
8332	9320	2	86	0,023
8334	3415	12	347	0,035
8334	4115	7	347	0,020
8334	4131	11	347	0,032
8334	4190	17	347	0,049
8334	5220	15	347	0,043
8334	6130	13	347	0,037
8334	7124	16	347	0,046
8334	7223	9	347	0,026
8334	7231	17	347	0,049
8334	7233	8	347	0,023
8334	8271	9	347	0,026
8334	8290	10	347	0,029
8334	8324	18	347	0,052
8334	9320	12	347	0,035
8334	9330	54	347	0,156
9113	3119	4	158	0,025
9113	3415	54	158	0,342
9113	3419	12	158	0,076
9113	4131	4	158	0,025
9113	4132	4	158	0,025
9113	4190	33	158	0,209
9113	5220	11	158	0,070
9113	9330	6	158	0,038
9132	3415	10	395	0,025
9132	3439	23	395	0,058
9132	4190	22	395	0,056
9132	5122	11	395	0,028
9132	5220	25	395	0,063
9132	7124	19	395	0,048
9132	7136	17	395	0,043
9132	7137	14	395	0,035
9132	7222	8	395	0,020
9132	7223	9	395	0,023
9132	7231	22	395	0,056
9132	8232	8	395	0,020
9132	8271	22	395	0,056
9132	9320	12	395	0,030
9132	9330	14	395	0,035
9211	6112	20	108	0,185
9211	6130	7	108	0,065
9211	6141	3	108	0,028
9211	8271	6	108	0,056
9211	8284	3	108	0,028
9211	8324	5	108	0,046
9211	8332	4	108	0,037
9211	9312	8	108	0,074
9211	9313	4	108	0,037
9211	9320	3	108	0,028
9211	9330	3	108	0,028
9312	6130	12	409	0,029
9312	7122	10	409	0,024
9312	7124	20	409	0,049
9312	7136	14	409	0,034
9312	7222	16	409	0,039
9312	7223	13	409	0,032
9312	7231	31	409	0,076
9312	7233	11	409	0,027
9312	8324	9	409	0,022
9312	8332	29	409	0,071
9312	9211	10	409	0,024
9312	9313	84	409	0,205
9312	9330	9	409	0,022
9313	6130	11	437	0,025
9313	7122	18	437	0,041
9313	7124	53	437	0,121
9313	7136	23	437	0,053
9313	7212	11	437	0,025
9313	7221	11	437	0,025

9313	7222	17	437	0,039
9313	7223	13	437	0,030
9313	7231	24	437	0,055
9313	7233	13	437	0,030
9313	9312	56	437	0,128
9313	9320	16	437	0,037
9320	4190	26	967	0,027
9320	5220	35	967	0,036
9320	7124	117	967	0,121
9320	7222	31	967	0,032
9320	7223	42	967	0,043
9320	7231	29	967	0,030
9320	7233	27	967	0,028
9320	8211	21	967	0,022
9320	8240	27	967	0,028
9320	8271	46	967	0,048
9320	8284	26	967	0,027
9320	8290	20	967	0,021
9320	8334	24	967	0,025
9320	9330	55	967	0,057
9330	3415	69	1273	0,054
9330	4131	70	1273	0,055
9330	4190	165	1273	0,130
9330	5220	152	1273	0,119
9330	7124	47	1273	0,037
9330	7231	49	1273	0,038
9330	8271	29	1273	0,023
9330	8324	29	1273	0,023
9330	8334	53	1273	0,042
9330	9320	64	1273	0,050

A4 Linked Occupations by More than 5 Percent of Switchers from both Occupations, For Private Sector Employees

Occ. 1 (1)	Pct from occ1 to occ2 (2)	Occ. 2 (3)	Pct from occ2 to occ1 (4)
1210	0,067	1231	0,086
1223	0,145	2142	0,052
1224	0,234	1314	0,057
1224	0,186	5220	0,062
1231	0,086	1210	0,067
1231	0,154	2411	0,157
1231	0,129	3433	0,107
1235	0,079	3416	0,073
1314	0,057	1224	0,234
2113	0,152	2146	0,070
2131	0,095	2132	0,158
2131	0,226	2139	0,159
2131	0,158	3121	0,149
2132	0,158	2131	0,095
2132	0,152	2139	0,085
2132	0,242	3121	0,081
2139	0,159	2131	0,226
2139	0,085	2132	0,152
2139	0,172	3121	0,188
2141	0,144	2142	0,077
2141	0,158	3112	0,073
2142	0,052	1223	0,145
2142	0,077	2141	0,144
2142	0,209	2149	0,107
2142	0,135	3112	0,112
2143	0,052	3113	0,052
2144	0,095	2149	0,087
2144	0,131	3114	0,086
2145	0,212	2149	0,122
2145	0,109	3115	0,090
2146	0,070	2113	0,152
2149	0,107	2142	0,209
2149	0,087	2144	0,095
2149	0,122	2145	0,212
2411	0,157	1231	0,154
2411	0,127	3419	0,070
2411	0,226	3433	0,275
2411	0,077	4121	0,170
3111	0,217	3211	0,204
3112	0,073	2141	0,158
3112	0,112	2142	0,135
3112	0,066	3118	0,115
3113	0,052	2143	0,052
3113	0,125	3114	0,053
3113	0,147	7137	0,100
3113	0,112	7241	0,065
3114	0,086	2144	0,131
3114	0,053	3113	0,125
3114	0,071	3121	0,057
3114	0,064	7242	0,167
3114	0,108	7243	0,160
3115	0,090	2145	0,109
3115	0,071	3118	0,228
3115	0,100	3119	0,123
3116	0,068	3211	0,056
3118	0,115	3112	0,066
3118	0,228	3115	0,071
3119	0,123	3115	0,100
3121	0,149	2131	0,158
3121	0,081	2132	0,242
3121	0,188	2139	0,172
3121	0,057	3114	0,071
3121	0,060	3122	0,232
3122	0,232	3121	0,060
3211	0,204	3111	0,217
3211	0,056	3116	0,068
3415	0,112	3419	0,235
3415	0,101	4190	0,158
3415	0,119	5220	0,217
3416	0,073	1235	0,079
3416	0,078	4132	0,068
3419	0,070	2411	0,127
3419	0,235	3415	0,112
3422	0,101	4133	0,336
3433	0,107	1231	0,129
3433	0,275	2411	0,226
3433	0,053	4121	0,158
4121	0,170	2411	0,077
4121	0,158	3433	0,053
4131	0,104	9330	0,055
4132	0,068	3416	0,078
4133	0,336	3422	0,101
4190	0,158	3415	0,101
4190	0,279	5220	0,244
4190	0,053	9330	0,130
5122	0,136	5123	0,253
5122	0,084	8278	0,123
5122	0,157	8324	0,061
5123	0,253	5122	0,136
5220	0,062	1224	0,186
5220	0,217	3415	0,119
5220	0,244	4190	0,279
7124	0,079	7422	0,489
7124	0,153	7423	0,396
7124	0,130	8240	0,476
7136	0,073	7221	0,080
7137	0,100	3113	0,147
7137	0,240	7241	0,256
7141	0,288	7142	0,523
7142	0,523	7141	0,288
7211	0,084	8123	0,137
7212	0,069	7213	0,121
7212	0,065	7214	0,110
7212	0,075	7221	0,091
7212	0,340	7222	0,183
7212	0,100	7223	0,056
7213	0,121	7212	0,069
7213	0,066	7214	0,057
7213	0,073	7221	0,063
7213	0,192	7222	0,080
7213	0,131	7231	0,050
7214	0,110	7212	0,065
7214	0,057	7213	0,066
7214	0,077	7221	0,084
7214	0,319	7222	0,125
7221	0,080	7136	0,073
7221	0,091	7212	0,075
7221	0,063	7213	0,073
7221	0,084	7214	0,077
7221	0,208	7222	0,098
7222	0,183	7212	0,340
7222	0,080	7213	0,192
7222	0,125	7214	0,319
7222	0,098	7221	0,208
7222	0,120	7223	0,106
7222	0,104	7233	0,116
7223	0,056	7212	0,100
7223	0,106	7222	0,120
7223	0,194	7233	0,203
7223	0,104	8211	0,328
7231	0,050	7213	0,131
7231	0,264	7233	0,205
7233	0,116	7222	0,104
7233	0,203	7223	0,194
7233	0,205	7231	0,264
7233	0,061	7241	0,168
7241	0,065	3113	0,112
7241	0,256	7137	0,240
7241	0,168	7233	0,061
7241	0,055	7243	0,070
7242	0,167	3114	0,064
7242	0,398	7243	0,224
7243	0,160	3114	0,108
7243	0,070	7241	0,055
7243	0,224	7242	0,398
7341	0,415	8251	0,514
7411	0,621	8271	0,272
7412	0,293	8271	0,132
7412	0,092	8274	0,073
7413	0,459	8272	0,155
7422	0,489	7124	0,079
7422	0,099	7423	0,061
7423	0,396	7124	0,153
7423	0,061	7422	0,099
7423	0,204	8240	0,170
8123	0,137	7211	0,084
8211	0,328	7223	0,104
8240	0,476	7124	0,130
8240	0,170	7423	0,204
8251	0,514	7341	0,415
8271	0,272	7411	0,621
8271	0,132	7412	0,293
8271	0,062	8272	0,099
8272	0,155	7413	0,459
8272	0,099	8271	0,062
8274	0,073	7412	0,092
8278	0,123	5122	0,084
8324	0,061	5122	0,157
8332	0,186	9312	0,071
9312	0,071	8332	0,186
9312	0,205	9313	0,128
9313	0,128	9312	0,205
9320	0,057	9330	0,050
9330	0,055	4131	0,104
9330	0,130	4190	0,053
9330	0,050	9320	0,057

A5 Linked Occupations with 2 Links by More than 5 Percent of Switchers from both Occupations, For Private Sector Employees

Occ. 1 (1)	Pct from occ1 to occ2 (2)	Occ. 2 (3)	Pct from occ2 to occ3 (4)	Occ. 3 (5)	Pct from occ3 to occ1 (6)
1223	0,066	2149	0,107	2142	0,052
1223	0,079	3112	0,112	2142	0,052
1224	0,234	1314	0,111	5220	0,062
1224	0,129	3415	0,119	5220	0,062
1224	0,056	4190	0,279	5220	0,062
1231	0,154	2411	0,226	3433	0,107
1231	0,108	3419	0,070	2411	0,157
1231	0,129	3433	0,275	2411	0,157
1314	0,111	5220	0,062	1224	0,234
2113	0,064	2224	0,151	2146	0,070
2131	0,095	2132	0,152	2139	0,159
2131	0,095	2132	0,062	2144	0,075
2131	0,095	2132	0,242	3121	0,149
2131	0,226	2139	0,085	2132	0,158
2131	0,226	2139	0,172	3121	0,149
2131	0,158	3121	0,081	2132	0,158
2131	0,158	3121	0,188	2139	0,159
2131	0,158	3121	0,060	3122	0,149
2132	0,158	2131	0,226	2139	0,085
2132	0,158	2131	0,158	3121	0,081
2132	0,152	2139	0,159	2131	0,095
2132	0,152	2139	0,172	3121	0,081
2132	0,062	2144	0,075	2131	0,095
2132	0,062	2144	0,131	2139	0,085
2132	0,062	2144	0,060	3121	0,081
2132	0,242	3121	0,149	2131	0,095
2132	0,242	3121	0,188	2139	0,085
2139	0,159	2131	0,095	2132	0,152
2139	0,159	2131	0,158	3121	0,188
2139	0,085	2132	0,158	2131	0,226
2139	0,085	2132	0,062	2144	0,131
2139	0,085	2132	0,242	3121	0,188
2139	0,172	3121	0,149	2131	0,226
2139	0,172	3121	0,081	2132	0,152
2139	0,172	3121	0,060	3122	0,088
2141	0,144	2142	0,135	3112	0,073
2141	0,075	2149	0,107	2142	0,077
2141	0,158	3112	0,112	2142	0,077
2142	0,052	1223	0,066	2149	0,107
2142	0,052	1223	0,079	3112	0,112
2142	0,077	2141	0,075	2149	0,107
2142	0,077	2141	0,158	3112	0,112
2142	0,060	2145	0,212	2149	0,107
2142	0,135	3112	0,073	2141	0,144
2143	0,060	3114	0,053	3113	0,052
2143	0,073	7137	0,100	3113	0,052
2144	0,075	2131	0,095	2132	0,062
2144	0,131	2139	0,085	2132	0,062
2144	0,052	2145	0,212	2149	0,087
2144	0,060	3121	0,081	2132	0,062
2144	0,060	3121	0,057	3114	0,086
2145	0,212	2149	0,107	2142	0,060
2145	0,212	2149	0,087	2144	0,052
2146	0,070	2113	0,064	2224	0,151
2149	0,107	2142	0,052	1223	0,066
2149	0,107	2142	0,077	2141	0,075
2149	0,107	2142	0,060	2145	0,212
2149	0,087	2144	0,052	2145	0,212
2224	0,151	2146	0,070	2113	0,064
2411	0,157	1231	0,108	3419	0,070
2411	0,157	1231	0,129	3433	0,275
2411	0,226	3433	0,107	1231	0,154
2411	0,226	3433	0,117	3419	0,070
2411	0,226	3433	0,053	4121	0,170
2411	0,077	4121	0,057	3419	0,070
2411	0,077	4121	0,158	3433	0,275
3111	0,217	3211	0,056	3116	0,057
3112	0,073	2141	0,144	2142	0,135
3112	0,112	2142	0,052	1223	0,079
3112	0,112	2142	0,077	2141	0,158
3112	0,083	3115	0,071	3118	0,115
3113	0,052	2143	0,060	3114	0,053
3113	0,052	2143	0,073	7137	0,100
3113	0,147	7137	0,051	3114	0,053
3113	0,147	7137	0,240	7241	0,065
3113	0,112	7241	0,256	7137	0,100
3114	0,086	2144	0,060	3121	0,057
3114	0,053	3113	0,052	2143	0,060
3114	0,053	3113	0,147	7137	0,051
3114	0,071	3121	0,060	3122	0,071
3114	0,064	7242	0,398	7243	0,160
3114	0,108	7243	0,224	7242	0,167
3115	0,071	3118	0,115	3112	0,083
3115	0,071	3118	0,124	3119	0,123
3116	0,057	3111	0,217	3211	0,056
3118	0,115	3112	0,083	3115	0,071
3118	0,124	3119	0,123	3115	0,071
3119	0,123	3115	0,071	3118	0,124
3121	0,149	2131	0,095	2132	0,242
3121	0,149	2131	0,226	2139	0,172
3121	0,081	2132	0,158	2131	0,158
3121	0,081	2132	0,152	2139	0,172
3121	0,081	2132	0,062	2144	0,060
3121	0,188	2139	0,159	2131	0,158
3121	0,188	2139	0,085	2132	0,242
3121	0,057	3114	0,086	2144	0,060
3121	0,060	3122	0,149	2131	0,158
3121	0,060	3122	0,088	2139	0,172
3121	0,060	3122	0,071	3114	0,071
3122	0,149	2131	0,158	3121	0,060
3122	0,088	2139	0,172	3121	0,060
3122	0,071	3114	0,071	3121	0,060
3211	0,056	3116	0,057	3111	0,217
3415	0,101	4190	0,279	5220	0,217
3415	0,101	4190	0,053	9330	0,054
3415	0,119	5220	0,062	1224	0,129
3415	0,119	5220	0,244	4190	0,158
3419	0,070	2411	0,157	1231	0,108
3419	0,070	2411	0,226	3433	0,117
3419	0,070	2411	0,077	4121	0,057
3433	0,107	1231	0,154	2411	0,226
3433	0,275	2411	0,157	1231	0,129
3433	0,275	2411	0,077	4121	0,158
3433	0,117	3419	0,070	2411	0,226
3433	0,053	4121	0,170	2411	0,226
4121	0,170	2411	0,226	3433	0,053
4121	0,057	3419	0,070	2411	0,077
4121	0,158	3433	0,275	2411	0,077
4131	0,116	4190	0,053	9330	0,055
4190	0,158	3415	0,119	5220	0,244
4190	0,279	5220	0,062	1224	0,056
4190	0,279	5220	0,217	3415	0,101
4190	0,053	9330	0,054	3415	0,101
4190	0,053	9330	0,055	4131	0,116
4190	0,053	9330	0,119	5220	0,244
5122	0,084	8278	0,123	8324	0,061
5220	0,062	1224	0,234	1314	0,111
5220	0,062	1224	0,129	3415	0,119
5220	0,062	1224	0,056	4190	0,279
5220	0,217	3415	0,101	4190	0,279
5220	0,244	4190	0,158	3415	0,119
5220	0,244	4190	0,053	9330	0,119
7124	0,079	7422	0,099	7423	0,396
7124	0,079	7422	0,070	8240	0,476
7124	0,153	7423	0,061	7422	0,489
7124	0,153	7423	0,204	8240	0,476
7124	0,130	8240	0,170	7423	0,396
7124	0,130	8240	0,068	9320	0,121
7136	0,073	7212	0,075	7221	0,080
7137	0,100	3113	0,052	2143	0,073
7137	0,100	3113	0,112	7241	0,256
7137	0,051	3114	0,053	3113	0,147
7137	0,082	7233	0,061	7241	0,256
7137	0,240	7241	0,065	3113	0,147
7212	0,069	7213	0,066	7214	0,110
7212	0,069	7213	0,073	7221	0,091
7212	0,069	7213	0,192	7222	0,183
7212	0,069	7213	0,075	7223	0,056
7212	0,065	7214	0,057	7213	0,121
7212	0,065	7214	0,077	7221	0,091
7212	0,065	7214	0,319	7222	0,183
7212	0,065	7214	0,105	7223	0,056
7212	0,075	7221	0,080	7136	0,073
7212	0,075	7221	0,063	7213	0,121
7212	0,075	7221	0,084	7214	0,110

7212	0,075	7221	0,208	7222	0,183
7212	0,075	7221	0,082	7223	0,056
7212	0,340	7222	0,080	7213	0,121
7212	0,340	7222	0,125	7214	0,110
7212	0,340	7222	0,098	7221	0,091
7212	0,340	7222	0,120	7223	0,056
7212	0,100	7223	0,106	7222	0,183
7212	0,061	7231	0,050	7213	0,121
7212	0,063	7233	0,116	7222	0,183
7212	0,063	7233	0,203	7223	0,056
7213	0,121	7212	0,065	7214	0,057
7213	0,121	7212	0,075	7221	0,063
7213	0,121	7212	0,340	7222	0,080
7213	0,121	7212	0,061	7231	0,050
7213	0,066	7214	0,110	7212	0,069
7213	0,066	7214	0,077	7221	0,063
7213	0,066	7214	0,319	7222	0,080
7213	0,073	7221	0,091	7212	0,069
7213	0,073	7221	0,084	7214	0,057
7213	0,073	7221	0,208	7222	0,080
7213	0,192	7222	0,183	7212	0,069
7213	0,192	7222	0,125	7214	0,057
7213	0,192	7222	0,098	7221	0,063
7213	0,075	7223	0,056	7212	0,069
7213	0,075	7223	0,106	7222	0,080
7213	0,060	7233	0,116	7222	0,080
7213	0,060	7233	0,205	7231	0,050
7214	0,110	7212	0,069	7213	0,066
7214	0,110	7212	0,075	7221	0,084
7214	0,110	7212	0,340	7222	0,125
7214	0,057	7213	0,121	7212	0,065
7214	0,057	7213	0,073	7221	0,084
7214	0,057	7213	0,192	7222	0,125
7214	0,077	7221	0,091	7212	0,065
7214	0,077	7221	0,063	7213	0,066
7214	0,077	7221	0,208	7222	0,125
7214	0,319	7222	0,183	7212	0,065
7214	0,319	7222	0,080	7213	0,066
7214	0,319	7222	0,098	7221	0,084
7214	0,105	7223	0,056	7212	0,065
7214	0,105	7223	0,106	7222	0,125
7214	0,056	7233	0,116	7222	0,125
7221	0,080	7136	0,073	7212	0,075
7221	0,091	7212	0,069	7213	0,073
7221	0,091	7212	0,065	7214	0,077
7221	0,091	7212	0,340	7222	0,098
7221	0,063	7213	0,121	7212	0,075
7221	0,063	7213	0,066	7214	0,077
7221	0,063	7213	0,192	7222	0,098
7221	0,084	7214	0,110	7212	0,075
7221	0,084	7214	0,057	7213	0,073
7221	0,084	7214	0,319	7222	0,098
7221	0,208	7222	0,183	7212	0,075
7221	0,208	7222	0,080	7213	0,073
7221	0,208	7222	0,125	7214	0,077
7221	0,082	7223	0,056	7212	0,075
7221	0,082	7223	0,106	7222	0,098
7221	0,104	7233	0,116	7222	0,098
7222	0,183	7212	0,069	7213	0,192
7222	0,183	7212	0,065	7214	0,319
7222	0,183	7212	0,075	7221	0,208
7222	0,183	7212	0,100	7223	0,106
7222	0,183	7212	0,063	7233	0,116
7222	0,080	7213	0,121	7212	0,340
7222	0,080	7213	0,066	7214	0,319
7222	0,080	7213	0,073	7221	0,208
7222	0,080	7213	0,075	7223	0,106
7222	0,080	7213	0,060	7233	0,116
7222	0,125	7214	0,110	7212	0,340
7222	0,125	7214	0,057	7213	0,192
7222	0,125	7214	0,077	7221	0,208
7222	0,125	7214	0,105	7223	0,106
7222	0,125	7214	0,056	7233	0,116
7222	0,098	7221	0,091	7212	0,340
7222	0,098	7221	0,063	7213	0,192
7222	0,098	7221	0,084	7214	0,319
7222	0,098	7221	0,082	7223	0,106
7222	0,098	7221	0,104	7233	0,116
7222	0,120	7223	0,056	7212	0,340
7222	0,120	7223	0,194	7233	0,116
7222	0,120	7223	0,104	8211	0,092
7222	0,104	7233	0,203	7223	0,106
7223	0,056	7212	0,069	7213	0,075
7223	0,056	7212	0,065	7214	0,105
7223	0,056	7212	0,075	7221	0,082
7223	0,056	7212	0,340	7222	0,120
7223	0,056	7212	0,063	7233	0,203
7223	0,106	7222	0,183	7212	0,100
7223	0,106	7222	0,080	7213	0,075
7223	0,106	7222	0,125	7214	0,105
7223	0,106	7222	0,098	7221	0,082
7223	0,106	7222	0,104	7233	0,203
7223	0,194	7233	0,116	7222	0,120
7223	0,104	8211	0,092	7222	0,120
7231	0,050	7213	0,121	7212	0,061
7231	0,050	7213	0,060	7233	0,205
7233	0,116	7222	0,183	7212	0,063
7233	0,116	7222	0,080	7213	0,060
7233	0,116	7222	0,125	7214	0,056
7233	0,116	7222	0,098	7221	0,104
7233	0,116	7222	0,120	7223	0,194
7233	0,203	7223	0,056	7212	0,063
7233	0,203	7223	0,106	7222	0,104
7233	0,205	7231	0,050	7213	0,060
7233	0,061	7241	0,256	7137	0,082
7241	0,065	3113	0,147	7137	0,240
7241	0,256	7137	0,100	3113	0,112
7241	0,256	7137	0,082	7233	0,061
7241	0,055	7243	0,224	7242	0,073
7242	0,167	3114	0,108	7243	0,224
7242	0,073	7241	0,055	7243	0,224
7242	0,398	7243	0,160	3114	0,064
7243	0,160	3114	0,064	7242	0,398
7243	0,224	7242	0,167	3114	0,108
7243	0,224	7242	0,073	7241	0,055
7412	0,092	8274	0,171	8271	0,132
7422	0,489	7124	0,153	7423	0,061
7422	0,099	7423	0,396	7124	0,079
7422	0,070	8240	0,476	7124	0,079
7422	0,070	8240	0,170	7423	0,061
7423	0,396	7124	0,079	7422	0,099
7423	0,396	7124	0,130	8240	0,170
7423	0,061	7422	0,489	7124	0,153
7423	0,061	7422	0,070	8240	0,170
7423	0,204	8240	0,476	7124	0,153
8211	0,092	7222	0,120	7223	0,104
8240	0,476	7124	0,079	7422	0,070
8240	0,476	7124	0,153	7423	0,204
8240	0,170	7423	0,396	7124	0,130
8240	0,170	7423	0,061	7422	0,070
8240	0,068	9320	0,121	7124	0,130
8271	0,132	7412	0,092	8274	0,171
8274	0,171	8271	0,132	7412	0,092
8278	0,123	8324	0,061	5122	0,084
8324	0,061	5122	0,084	8278	0,123
9320	0,121	7124	0,130	8240	0,068
9330	0,054	3415	0,101	4190	0,053
9330	0,055	4131	0,116	4190	0,053
9330	0,119	5220	0,244	4190	0,053

A6 Linked Occupations with 3 Links by More than 5 Percent of Switchers from both Occupations, For Private Sector Employees

Occ. 1 (1)	Pct from occ1 to occ2 (2)	Occ. 2 (3)	Pct from occ2 to occ3 (4)	Occ. 3 (5)	Pct from occ3 to occ4 (6)	Occ. 4 (7)	Pct from occ4 to occ1 (8)
1210	0,050	1239	0,079	5220	0,062	1224	0,077
1210	0,096	3415	0,119	5220	0,062	1224	0,077
1223	0,079	3112	0,073	2141	0,144	2142	0,052
1224	0,077	1210	0,050	1239	0,079	5220	0,062
1224	0,077	1210	0,096	3415	0,119	5220	0,062
1224	0,234	1314	0,096	3415	0,119	5220	0,062
1224	0,129	3415	0,101	4190	0,279	5220	0,062
1224	0,056	4190	0,158	3415	0,119	5220	0,062
1224	0,056	4190	0,053	9330	0,119	5220	0,062
1231	0,154	2411	0,077	4121	0,158	3433	0,107
1231	0,072	3415	0,112	3419	0,070	2411	0,157
1231	0,108	3419	0,070	2411	0,226	3433	0,107
1231	0,129	3433	0,117	3419	0,070	2411	0,157
1231	0,129	3433	0,053	4121	0,170	2411	0,157
1239	0,079	5220	0,062	1224	0,077	1210	0,050
1314	0,096	3415	0,119	5220	0,062	1224	0,234
2131	0,095	2132	0,152	2139	0,172	3121	0,149
2131	0,095	2132	0,062	2144	0,131	2139	0,159
2131	0,095	2132	0,062	2144	0,060	3121	0,149
2131	0,095	2132	0,242	3121	0,188	2139	0,159
2131	0,095	2132	0,242	3121	0,060	3122	0,149
2131	0,226	2139	0,085	2132	0,062	2144	0,075
2131	0,226	2139	0,085	2132	0,242	3121	0,149
2131	0,226	2139	0,172	3121	0,081	2132	0,158
2131	0,226	2139	0,172	3121	0,060	3122	0,149
2131	0,158	3121	0,081	2132	0,152	2139	0,159
2131	0,158	3121	0,081	2132	0,062	2144	0,075
2131	0,158	3121	0,188	2139	0,085	2132	0,158
2131	0,158	3121	0,057	3114	0,086	2144	0,075
2131	0,158	3121	0,060	3122	0,088	2139	0,159
2132	0,158	2131	0,226	2139	0,172	3121	0,081
2132	0,158	2131	0,158	3121	0,188	2139	0,085
2132	0,152	2139	0,159	2131	0,158	3121	0,081
2132	0,152	2139	0,172	3121	0,149	2131	0,095
2132	0,062	2144	0,075	2131	0,226	2139	0,085
2132	0,062	2144	0,075	2131	0,158	3121	0,081
2132	0,062	2144	0,131	2139	0,159	2131	0,095
2132	0,062	2144	0,131	2139	0,172	3121	0,081
2132	0,062	2144	0,131	3114	0,071	3121	0,081
2132	0,062	2144	0,060	3121	0,149	2131	0,095
2132	0,062	2144	0,060	3121	0,188	2139	0,085
2132	0,242	3121	0,149	2131	0,226	2139	0,085
2132	0,242	3121	0,188	2139	0,159	2131	0,095
2132	0,242	3121	0,060	3122	0,149	2131	0,095
2132	0,242	3121	0,060	3122	0,088	2139	0,085
2139	0,159	2131	0,095	2132	0,062	2144	0,131
2139	0,159	2131	0,095	2132	0,242	3121	0,188
2139	0,159	2131	0,158	3121	0,081	2132	0,152
2139	0,159	2131	0,158	3121	0,060	3122	0,088
2139	0,085	2132	0,158	2131	0,158	3121	0,188
2139	0,085	2132	0,062	2144	0,075	2131	0,226
2139	0,085	2132	0,062	2144	0,060	3121	0,188
2139	0,085	2132	0,242	3121	0,149	2131	0,226
2139	0,085	2132	0,242	3121	0,060	3122	0,088
2139	0,172	3121	0,149	2131	0,095	2132	0,152
2139	0,172	3121	0,081	2132	0,158	2131	0,226
2139	0,172	3121	0,081	2132	0,062	2144	0,131
2139	0,172	3121	0,057	3114	0,086	2144	0,131
2139	0,172	3121	0,060	3122	0,149	2131	0,226
2141	0,144	2142	0,052	1223	0,079	3112	0,073
2141	0,075	2149	0,107	2142	0,135	3112	0,073
2142	0,052	1223	0,079	3112	0,073	2141	0,144
2142	0,135	3112	0,073	2141	0,075	2149	0,107
2143	0,060	2144	0,131	3114	0,053	3113	0,052
2143	0,073	7137	0,051	3114	0,053	3113	0,052
2143	0,073	7137	0,240	7241	0,065	3113	0,052
2144	0,075	2131	0,226	2139	0,085	2132	0,062
2144	0,075	2131	0,158	3121	0,081	2132	0,062
2144	0,075	2131	0,158	3121	0,057	3114	0,086
2144	0,131	2139	0,159	2131	0,095	2132	0,062
2144	0,131	2139	0,172	3121	0,081	2132	0,062
2144	0,131	2139	0,172	3121	0,057	3114	0,086
2144	0,131	3114	0,053	3113	0,052	2143	0,060
2144	0,131	3114	0,071	3121	0,081	2132	0,062
2144	0,060	3121	0,149	2131	0,095	2132	0,062
2144	0,060	3121	0,188	2139	0,085	2132	0,062
2144	0,060	3121	0,060	3122	0,071	3114	0,086
2149	0,107	2142	0,135	3112	0,073	2141	0,075

2411	0,157	1231	0,072	3415	0,112	3419	0,070
2411	0,157	1231	0,129	3433	0,117	3419	0,070
2411	0,157	1231	0,129	3433	0,053	4121	0,170
2411	0,226	3433	0,107	1231	0,108	3419	0,070
2411	0,226	3433	0,053	4121	0,057	3419	0,070
2411	0,077	4121	0,158	3433	0,107	1231	0,154
2411	0,077	4121	0,158	3433	0,117	3419	0,070
2411	0,078	4190	0,158	3415	0,112	3419	0,070
3112	0,073	2141	0,144	2142	0,052	1223	0,079
3112	0,073	2141	0,075	2149	0,107	2142	0,135
3112	0,059	3119	0,123	3115	0,071	3118	0,115
3113	0,052	2143	0,060	2144	0,131	3114	0,053
3113	0,052	2143	0,073	7137	0,051	3114	0,053
3113	0,052	2143	0,073	7137	0,240	7241	0,065
3113	0,125	3114	0,064	7242	0,073	7241	0,065
3113	0,125	3114	0,108	7243	0,070	7241	0,065
3113	0,071	3115	0,100	3119	0,051	3114	0,053
3113	0,147	7137	0,082	7233	0,061	7241	0,065
3113	0,112	7241	0,256	7137	0,051	3114	0,053
3113	0,112	7241	0,055	7243	0,160	3114	0,053
3114	0,086	2144	0,075	2131	0,158	3121	0,057
3114	0,086	2144	0,131	2139	0,172	3121	0,057
3114	0,086	2144	0,060	3121	0,060	3122	0,071
3114	0,053	3113	0,052	2143	0,060	2144	0,131
3114	0,053	3113	0,052	2143	0,073	7137	0,051
3114	0,053	3113	0,071	3115	0,100	3119	0,051
3114	0,053	3113	0,112	7241	0,256	7137	0,051
3114	0,053	3113	0,112	7241	0,055	7243	0,160
3114	0,071	3121	0,081	2132	0,062	2144	0,131
3114	0,064	7242	0,073	7241	0,065	3113	0,125
3114	0,064	7242	0,073	7241	0,256	7137	0,051
3114	0,064	7242	0,073	7241	0,055	7243	0,160
3114	0,108	7243	0,070	7241	0,065	3113	0,125
3114	0,108	7243	0,070	7241	0,256	7137	0,051
3115	0,071	3118	0,115	3112	0,059	3119	0,123
3115	0,100	3119	0,051	3114	0,053	3113	0,071
3118	0,115	3112	0,059	3119	0,123	3115	0,071
3119	0,051	3114	0,053	3113	0,071	3115	0,100
3119	0,123	3115	0,071	3118	0,115	3112	0,059
3121	0,149	2131	0,095	2132	0,152	2139	0,172
3121	0,149	2131	0,095	2132	0,062	2144	0,060
3121	0,149	2131	0,226	2139	0,085	2132	0,242
3121	0,081	2132	0,158	2131	0,226	2139	0,172
3121	0,081	2132	0,152	2139	0,159	2131	0,158
3121	0,081	2132	0,062	2144	0,075	2131	0,158
3121	0,081	2132	0,062	2144	0,131	2139	0,172
3121	0,081	2132	0,062	2144	0,131	3114	0,071
3121	0,188	2139	0,159	2131	0,095	2132	0,242
3121	0,188	2139	0,085	2132	0,158	2131	0,158
3121	0,188	2139	0,085	2132	0,062	2144	0,060
3121	0,057	3114	0,086	2144	0,075	2131	0,158
3121	0,057	3114	0,086	2144	0,131	2139	0,172
3121	0,060	3122	0,149	2131	0,095	2132	0,242
3121	0,060	3122	0,149	2131	0,226	2139	0,172
3121	0,060	3122	0,088	2139	0,159	2131	0,158
3121	0,060	3122	0,088	2139	0,085	2132	0,242
3121	0,060	3122	0,071	3114	0,086	2144	0,060
3122	0,149	2131	0,095	2132	0,242	3121	0,060
3122	0,149	2131	0,226	2139	0,172	3121	0,060
3122	0,088	2139	0,159	2131	0,158	3121	0,060
3122	0,088	2139	0,085	2132	0,242	3121	0,060
3122	0,071	3114	0,086	2144	0,060	3121	0,060
3415	0,112	3419	0,070	2411	0,157	1231	0,072
3415	0,112	3419	0,070	2411	0,078	4190	0,158
3415	0,101	4190	0,279	5220	0,062	1224	0,129
3415	0,101	4190	0,053	9330	0,055	4131	0,166
3415	0,101	4190	0,053	9330	0,119	5220	0,217
3415	0,119	5220	0,062	1224	0,077	1210	0,096
3415	0,119	5220	0,062	1224	0,234	1314	0,096
3415	0,119	5220	0,062	1224	0,056	4190	0,158
3415	0,119	5220	0,244	4190	0,053	9330	0,054
3419	0,070	2411	0,157	1231	0,072	3415	0,112
3419	0,070	2411	0,157	1231	0,129	3433	0,117
3419	0,070	2411	0,226	3433	0,107	1231	0,108
3419	0,070	2411	0,226	3433	0,053	4121	0,057
3419	0,070	2411	0,077	4121	0,158	3433	0,117
3419	0,070	2411	0,078	4190	0,158	3415	0,112
3433	0,107	1231	0,154	2411	0,077	4121	0,158
3433	0,107	1231	0,108	3419	0,070	2411	0,226
3433	0,117	3419	0,070	2411	0,157	1231	0,129
3433	0,117	3419	0,070	2411	0,077	4121	0,158
3433	0,053	4121	0,170	2411	0,157	1231	0,129
3433	0,053	4121	0,057	3419	0,070	2411	0,226
4121	0,170	2411	0,157	1231	0,129	3433	0,053
4121	0,057	3419	0,070	2411	0,226	3433	0,053
4121	0,158	3433	0,107	1231	0,154	2411	0,077
4121	0,158	3433	0,117	3419	0,070	2411	0,077
4131	0,166	3415	0,101	4190	0,053	9330	0,055
4131	0,169	5220	0,244	4190	0,053	9330	0,055
4190	0,158	3415	0,112	3419	0,070	2411	0,078
4190	0,158	3415	0,119	5220	0,062	1224	0,056
4190	0,279	5220	0,062	1224	0,129	3415	0,101

4190	0,053	9330	0,054	3415	0,119	5220	0,244
4190	0,053	9330	0,055	4131	0,166	3415	0,101
4190	0,053	9330	0,055	4131	0,169	5220	0,244
4190	0,053	9330	0,119	5220	0,062	1224	0,056
4190	0,053	9330	0,119	5220	0,217	3415	0,101
5220	0,062	1224	0,077	1210	0,050	1239	0,079
5220	0,062	1224	0,077	1210	0,096	3415	0,119
5220	0,062	1224	0,234	1314	0,096	3415	0,119
5220	0,062	1224	0,129	3415	0,101	4190	0,279
5220	0,062	1224	0,056	4190	0,158	3415	0,119
5220	0,062	1224	0,056	4190	0,053	9330	0,119
5220	0,217	3415	0,101	4190	0,053	9330	0,119
5220	0,244	4190	0,053	9330	0,054	3415	0,119
5220	0,244	4190	0,053	9330	0,055	4131	0,169
7124	0,079	7422	0,099	7423	0,204	8240	0,476
7124	0,079	7422	0,070	8240	0,170	7423	0,396
7124	0,079	7422	0,070	8240	0,068	9320	0,121
7124	0,153	7423	0,061	7422	0,070	8240	0,476
7124	0,153	7423	0,204	8240	0,068	9320	0,121
7124	0,130	8240	0,170	7423	0,061	7422	0,489
7136	0,073	7212	0,069	7213	0,073	7221	0,080
7136	0,073	7212	0,065	7214	0,077	7221	0,080
7136	0,073	7212	0,340	7222	0,098	7221	0,080
7136	0,115	7233	0,116	7222	0,098	7221	0,080
7137	0,051	3114	0,053	3113	0,052	2143	0,073
7137	0,051	3114	0,053	3113	0,112	7241	0,256
7137	0,051	3114	0,064	7242	0,073	7241	0,256
7137	0,051	3114	0,108	7243	0,070	7241	0,256
7137	0,082	7233	0,061	7241	0,065	3113	0,147
7137	0,240	7241	0,065	3113	0,052	2143	0,073
7212	0,069	7213	0,066	7214	0,077	7221	0,091
7212	0,069	7213	0,066	7214	0,319	7222	0,183
7212	0,069	7213	0,066	7214	0,105	7223	0,056
7212	0,069	7213	0,073	7221	0,080	7136	0,073
7212	0,069	7213	0,073	7221	0,084	7214	0,110
7212	0,069	7213	0,073	7221	0,208	7222	0,183
7212	0,069	7213	0,073	7221	0,082	7223	0,056
7212	0,069	7213	0,192	7222	0,125	7214	0,110
7212	0,069	7213	0,192	7222	0,098	7221	0,091
7212	0,069	7213	0,192	7222	0,120	7223	0,056
7212	0,069	7213	0,075	7223	0,106	7222	0,183
7212	0,069	7213	0,060	7233	0,116	7222	0,183
7212	0,069	7213	0,060	7233	0,203	7223	0,056
7212	0,065	7214	0,057	7213	0,073	7221	0,091
7212	0,065	7214	0,057	7213	0,192	7222	0,183
7212	0,065	7214	0,057	7213	0,075	7223	0,056
7212	0,065	7214	0,077	7221	0,080	7136	0,073
7212	0,065	7214	0,077	7221	0,063	7213	0,121
7212	0,065	7214	0,077	7221	0,208	7222	0,183
7212	0,065	7214	0,077	7221	0,082	7223	0,056
7212	0,065	7214	0,319	7222	0,080	7213	0,121
7212	0,065	7214	0,319	7222	0,098	7221	0,091
7212	0,065	7214	0,319	7222	0,120	7223	0,056
7212	0,065	7214	0,105	7223	0,106	7222	0,183
7212	0,065	7214	0,056	7233	0,116	7222	0,183
7212	0,065	7214	0,056	7233	0,203	7223	0,056
7212	0,075	7221	0,063	7213	0,066	7214	0,110
7212	0,075	7221	0,063	7213	0,192	7222	0,183
7212	0,075	7221	0,063	7213	0,075	7223	0,056
7212	0,075	7221	0,084	7214	0,057	7213	0,121
7212	0,075	7221	0,084	7214	0,319	7222	0,183
7212	0,075	7221	0,084	7214	0,105	7223	0,056
7212	0,075	7221	0,208	7222	0,080	7213	0,121
7212	0,075	7221	0,208	7222	0,125	7214	0,110
7212	0,075	7221	0,208	7222	0,120	7223	0,056
7212	0,075	7221	0,082	7223	0,106	7222	0,183
7212	0,075	7221	0,104	7233	0,116	7222	0,183
7212	0,075	7221	0,104	7233	0,203	7223	0,056
7212	0,340	7222	0,080	7213	0,066	7214	0,110
7212	0,340	7222	0,080	7213	0,073	7221	0,091
7212	0,340	7222	0,080	7213	0,075	7223	0,056
7212	0,340	7222	0,125	7214	0,057	7213	0,121
7212	0,340	7222	0,125	7214	0,077	7221	0,091
7212	0,340	7222	0,125	7214	0,105	7223	0,056
7212	0,340	7222	0,098	7221	0,080	7136	0,073
7212	0,340	7222	0,098	7221	0,063	7213	0,121
7212	0,340	7222	0,098	7221	0,084	7214	0,110
7212	0,340	7222	0,098	7221	0,082	7223	0,056
7212	0,340	7222	0,104	7233	0,203	7223	0,056
7212	0,100	7223	0,106	7222	0,080	7213	0,121
7212	0,100	7223	0,106	7222	0,125	7214	0,110
7212	0,100	7223	0,106	7222	0,098	7221	0,091
7212	0,100	7223	0,194	7233	0,116	7222	0,183
7212	0,100	7223	0,104	8211	0,092	7222	0,183
7212	0,061	7231	0,050	7213	0,066	7214	0,110
7212	0,061	7231	0,050	7213	0,073	7221	0,091
7212	0,061	7231	0,050	7213	0,192	7222	0,183
7212	0,061	7231	0,050	7213	0,075	7223	0,056
7212	0,061	7231	0,264	7233	0,116	7222	0,183
7212	0,061	7231	0,264	7233	0,203	7223	0,056
7212	0,063	7233	0,116	7222	0,080	7213	0,121
7212	0,063	7233	0,116	7222	0,125	7214	0,110

7212	0,063	7233	0,116	7222	0,098	7221	0,091
7212	0,063	7233	0,116	7222	0,120	7223	0,056
7212	0,063	7233	0,203	7223	0,106	7222	0,183
7212	0,063	7233	0,205	7231	0,050	7213	0,121
7213	0,121	7212	0,065	7214	0,077	7221	0,063
7213	0,121	7212	0,065	7214	0,319	7222	0,080
7213	0,121	7212	0,075	7221	0,084	7214	0,057
7213	0,121	7212	0,075	7221	0,208	7222	0,080
7213	0,121	7212	0,340	7222	0,125	7214	0,057
7213	0,121	7212	0,340	7222	0,098	7221	0,063
7213	0,121	7212	0,100	7223	0,106	7222	0,080
7213	0,121	7212	0,063	7233	0,116	7222	0,080
7213	0,121	7212	0,063	7233	0,205	7231	0,050
7213	0,066	7214	0,110	7212	0,075	7221	0,063
7213	0,066	7214	0,110	7212	0,340	7222	0,080
7213	0,066	7214	0,110	7212	0,061	7231	0,050
7213	0,066	7214	0,077	7221	0,091	7212	0,069
7213	0,066	7214	0,077	7221	0,208	7222	0,080
7213	0,066	7214	0,319	7222	0,183	7212	0,069
7213	0,066	7214	0,319	7222	0,098	7221	0,063
7213	0,066	7214	0,105	7223	0,056	7212	0,069
7213	0,066	7214	0,105	7223	0,106	7222	0,080
7213	0,066	7214	0,056	7233	0,116	7222	0,080
7213	0,066	7214	0,056	7233	0,205	7231	0,050
7213	0,073	7221	0,080	7136	0,073	7212	0,069
7213	0,073	7221	0,091	7212	0,065	7214	0,057
7213	0,073	7221	0,091	7212	0,340	7222	0,080
7213	0,073	7221	0,091	7212	0,061	7231	0,050
7213	0,073	7221	0,084	7214	0,110	7212	0,069
7213	0,073	7221	0,084	7214	0,319	7222	0,080
7213	0,073	7221	0,208	7222	0,183	7212	0,069
7213	0,073	7221	0,208	7222	0,125	7214	0,057
7213	0,073	7221	0,082	7223	0,056	7212	0,069
7213	0,073	7221	0,082	7223	0,106	7222	0,080
7213	0,073	7221	0,104	7233	0,116	7222	0,080
7213	0,073	7221	0,104	7233	0,205	7231	0,050
7213	0,192	7222	0,183	7212	0,065	7214	0,057
7213	0,192	7222	0,183	7212	0,075	7221	0,063
7213	0,192	7222	0,183	7212	0,061	7231	0,050
7213	0,192	7222	0,125	7214	0,110	7212	0,069
7213	0,192	7222	0,125	7214	0,077	7221	0,063
7213	0,192	7222	0,098	7221	0,091	7212	0,069
7213	0,192	7222	0,098	7221	0,084	7214	0,057
7213	0,192	7222	0,120	7223	0,056	7212	0,069
7213	0,192	7222	0,104	7233	0,205	7231	0,050
7213	0,075	7223	0,056	7212	0,065	7214	0,057
7213	0,075	7223	0,056	7212	0,075	7221	0,063
7213	0,075	7223	0,056	7212	0,340	7222	0,080
7213	0,075	7223	0,056	7212	0,061	7231	0,050
7213	0,075	7223	0,106	7222	0,183	7212	0,069
7213	0,075	7223	0,106	7222	0,125	7214	0,057
7213	0,075	7223	0,106	7222	0,098	7221	0,063
7213	0,075	7223	0,194	7233	0,116	7222	0,080
7213	0,075	7223	0,194	7233	0,205	7231	0,050
7213	0,075	7223	0,104	8211	0,092	7222	0,080
7213	0,075	7223	0,104	8211	0,059	7231	0,050
7213	0,131	7231	0,264	7233	0,116	7222	0,080
7213	0,060	7233	0,116	7222	0,183	7212	0,069
7213	0,060	7233	0,116	7222	0,125	7214	0,057
7213	0,060	7233	0,116	7222	0,098	7221	0,063
7213	0,060	7233	0,203	7223	0,056	7212	0,069
7213	0,060	7233	0,203	7223	0,106	7222	0,080
7214	0,110	7212	0,069	7213	0,073	7221	0,084
7214	0,110	7212	0,069	7213	0,192	7222	0,125
7214	0,110	7212	0,075	7221	0,063	7213	0,066
7214	0,110	7212	0,075	7221	0,208	7222	0,125
7214	0,110	7212	0,340	7222	0,080	7213	0,066
7214	0,110	7212	0,340	7222	0,098	7221	0,084
7214	0,110	7212	0,100	7223	0,106	7222	0,125
7214	0,110	7212	0,061	7231	0,050	7213	0,066
7214	0,110	7212	0,063	7233	0,116	7222	0,125
7214	0,057	7213	0,121	7212	0,075	7221	0,084
7214	0,057	7213	0,121	7212	0,340	7222	0,125
7214	0,057	7213	0,073	7221	0,091	7212	0,065
7214	0,057	7213	0,073	7221	0,208	7222	0,125
7214	0,057	7213	0,192	7222	0,183	7212	0,065
7214	0,057	7213	0,192	7222	0,098	7221	0,084
7214	0,057	7213	0,075	7223	0,056	7212	0,065
7214	0,057	7213	0,075	7223	0,106	7222	0,125
7214	0,057	7213	0,060	7233	0,116	7222	0,125
7214	0,077	7221	0,080	7136	0,073	7212	0,065
7214	0,077	7221	0,091	7212	0,069	7213	0,066
7214	0,077	7221	0,091	7212	0,340	7222	0,125
7214	0,077	7221	0,063	7213	0,121	7212	0,065
7214	0,077	7221	0,063	7213	0,192	7222	0,125
7214	0,077	7221	0,208	7222	0,183	7212	0,065
7214	0,077	7221	0,208	7222	0,080	7213	0,066
7214	0,077	7221	0,082	7223	0,056	7212	0,065
7214	0,077	7221	0,082	7223	0,106	7222	0,125
7214	0,077	7221	0,104	7233	0,116	7222	0,125
7214	0,319	7222	0,183	7212	0,069	7213	0,066
7214	0,319	7222	0,183	7212	0,075	7221	0,084

7214	0,319	7222	0,080	7213	0,121	7212	0,065
7214	0,319	7222	0,080	7213	0,073	7221	0,084
7214	0,319	7222	0,098	7221	0,091	7212	0,065
7214	0,319	7222	0,098	7221	0,063	7213	0,066
7214	0,319	7222	0,120	7223	0,056	7212	0,065
7214	0,105	7223	0,056	7212	0,069	7213	0,066
7214	0,105	7223	0,056	7212	0,075	7221	0,084
7214	0,105	7223	0,056	7212	0,340	7222	0,125
7214	0,105	7223	0,106	7222	0,183	7212	0,065
7214	0,105	7223	0,106	7222	0,080	7213	0,066
7214	0,105	7223	0,106	7222	0,098	7221	0,084
7214	0,105	7223	0,194	7233	0,116	7222	0,125
7214	0,105	7223	0,104	8211	0,092	7222	0,125
7214	0,056	7233	0,116	7222	0,183	7212	0,065
7214	0,056	7233	0,116	7222	0,080	7213	0,066
7214	0,056	7233	0,116	7222	0,098	7221	0,084
7214	0,056	7233	0,203	7223	0,056	7212	0,065
7214	0,056	7233	0,203	7223	0,106	7222	0,125
7214	0,056	7233	0,205	7231	0,050	7213	0,066
7221	0,080	7136	0,073	7212	0,069	7213	0,073
7221	0,080	7136	0,073	7212	0,065	7214	0,077
7221	0,080	7136	0,073	7212	0,340	7222	0,098
7221	0,080	7136	0,115	7233	0,116	7222	0,098
7221	0,091	7212	0,069	7213	0,066	7214	0,077
7221	0,091	7212	0,069	7213	0,192	7222	0,098
7221	0,091	7212	0,065	7214	0,057	7213	0,073
7221	0,091	7212	0,065	7214	0,319	7222	0,098
7221	0,091	7212	0,340	7222	0,080	7213	0,073
7221	0,091	7212	0,340	7222	0,125	7214	0,077
7221	0,091	7212	0,100	7223	0,106	7222	0,098
7221	0,091	7212	0,061	7231	0,050	7213	0,073
7221	0,091	7212	0,063	7233	0,116	7222	0,098
7221	0,063	7213	0,121	7212	0,065	7214	0,077
7221	0,063	7213	0,121	7212	0,340	7222	0,098
7221	0,063	7213	0,066	7214	0,110	7212	0,075
7221	0,063	7213	0,066	7214	0,319	7222	0,098
7221	0,063	7213	0,192	7222	0,183	7212	0,075
7221	0,063	7213	0,192	7222	0,125	7214	0,077
7221	0,063	7213	0,075	7223	0,056	7212	0,075
7221	0,063	7213	0,075	7223	0,106	7222	0,098
7221	0,063	7213	0,060	7233	0,116	7222	0,098
7221	0,084	7214	0,110	7212	0,069	7213	0,073
7221	0,084	7214	0,110	7212	0,340	7222	0,098
7221	0,084	7214	0,057	7213	0,121	7212	0,075
7221	0,084	7214	0,057	7213	0,192	7222	0,098
7221	0,084	7214	0,319	7222	0,183	7212	0,075
7221	0,084	7214	0,319	7222	0,080	7213	0,073
7221	0,084	7214	0,105	7223	0,056	7212	0,075
7221	0,084	7214	0,105	7223	0,106	7222	0,098
7221	0,084	7214	0,056	7233	0,116	7222	0,098
7221	0,208	7222	0,183	7212	0,069	7213	0,073
7221	0,208	7222	0,183	7212	0,065	7214	0,077
7221	0,208	7222	0,080	7213	0,121	7212	0,075
7221	0,208	7222	0,080	7213	0,066	7214	0,077
7221	0,208	7222	0,125	7214	0,110	7212	0,075
7221	0,208	7222	0,125	7214	0,057	7213	0,073
7221	0,208	7222	0,120	7223	0,056	7212	0,075
7221	0,082	7223	0,056	7212	0,069	7213	0,073
7221	0,082	7223	0,056	7212	0,065	7214	0,077
7221	0,082	7223	0,056	7212	0,340	7222	0,098
7221	0,082	7223	0,106	7222	0,183	7212	0,075
7221	0,082	7223	0,106	7222	0,080	7213	0,073
7221	0,082	7223	0,106	7222	0,125	7214	0,077
7221	0,082	7223	0,194	7233	0,116	7222	0,098
7221	0,082	7223	0,104	8211	0,092	7222	0,098
7221	0,104	7233	0,116	7222	0,183	7212	0,075
7221	0,104	7233	0,116	7222	0,080	7213	0,073
7221	0,104	7233	0,116	7222	0,125	7214	0,077
7221	0,104	7233	0,203	7223	0,056	7212	0,075
7221	0,104	7233	0,203	7223	0,106	7222	0,098
7221	0,104	7233	0,205	7231	0,050	7213	0,073
7222	0,183	7212	0,069	7213	0,066	7214	0,319
7222	0,183	7212	0,069	7213	0,073	7221	0,208
7222	0,183	7212	0,069	7213	0,075	7223	0,106
7222	0,183	7212	0,069	7213	0,060	7233	0,116
7222	0,183	7212	0,065	7214	0,057	7213	0,192
7222	0,183	7212	0,065	7214	0,077	7221	0,208
7222	0,183	7212	0,065	7214	0,105	7223	0,106
7222	0,183	7212	0,065	7214	0,056	7233	0,116
7222	0,183	7212	0,075	7221	0,063	7213	0,192
7222	0,183	7212	0,075	7221	0,084	7214	0,319
7222	0,183	7212	0,075	7221	0,082	7223	0,106
7222	0,183	7212	0,075	7221	0,104	7233	0,116
7222	0,183	7212	0,100	7223	0,194	7233	0,116
7222	0,183	7212	0,100	7223	0,104	8211	0,092
7222	0,183	7212	0,061	7231	0,050	7213	0,192
7222	0,183	7212	0,061	7231	0,264	7233	0,116
7222	0,183	7212	0,063	7233	0,203	7223	0,106
7222	0,080	7213	0,121	7212	0,065	7214	0,319
7222	0,080	7213	0,121	7212	0,075	7221	0,208
7222	0,080	7213	0,121	7212	0,100	7223	0,106
7222	0,080	7213	0,121	7212	0,063	7233	0,116

7222	0,080	7213	0,066	7214	0,110	7212	0,340
7222	0,080	7213	0,066	7214	0,077	7221	0,208
7222	0,080	7213	0,066	7214	0,105	7223	0,106
7222	0,080	7213	0,066	7214	0,056	7233	0,116
7222	0,080	7213	0,073	7221	0,091	7212	0,340
7222	0,080	7213	0,073	7221	0,084	7214	0,319
7222	0,080	7213	0,073	7221	0,082	7223	0,106
7222	0,080	7213	0,073	7221	0,104	7233	0,116
7222	0,080	7213	0,075	7223	0,056	7212	0,340
7222	0,080	7213	0,075	7223	0,194	7233	0,116
7222	0,080	7213	0,075	7223	0,104	8211	0,092
7222	0,080	7213	0,131	7231	0,264	7233	0,116
7222	0,080	7213	0,060	7233	0,203	7223	0,106
7222	0,125	7214	0,110	7212	0,069	7213	0,192
7222	0,125	7214	0,110	7212	0,075	7221	0,208
7222	0,125	7214	0,110	7212	0,100	7223	0,106
7222	0,125	7214	0,110	7212	0,063	7233	0,116
7222	0,125	7214	0,057	7213	0,121	7212	0,340
7222	0,125	7214	0,057	7213	0,073	7221	0,208
7222	0,125	7214	0,057	7213	0,075	7223	0,106
7222	0,125	7214	0,057	7213	0,060	7233	0,116
7222	0,125	7214	0,077	7221	0,091	7212	0,340
7222	0,125	7214	0,077	7221	0,063	7213	0,192
7222	0,125	7214	0,077	7221	0,082	7223	0,106
7222	0,125	7214	0,077	7221	0,104	7233	0,116
7222	0,125	7214	0,105	7223	0,056	7212	0,340
7222	0,125	7214	0,105	7223	0,194	7233	0,116
7222	0,125	7214	0,105	7223	0,104	8211	0,092
7222	0,125	7214	0,056	7233	0,203	7223	0,106
7222	0,098	7221	0,080	7136	0,073	7212	0,340
7222	0,098	7221	0,080	7136	0,115	7233	0,116
7222	0,098	7221	0,091	7212	0,069	7213	0,192
7222	0,098	7221	0,091	7212	0,065	7214	0,319
7222	0,098	7221	0,091	7212	0,100	7223	0,106
7222	0,098	7221	0,091	7212	0,063	7233	0,116
7222	0,098	7221	0,063	7213	0,121	7212	0,340
7222	0,098	7221	0,063	7213	0,066	7214	0,319
7222	0,098	7221	0,063	7213	0,075	7223	0,106
7222	0,098	7221	0,063	7213	0,060	7233	0,116
7222	0,098	7221	0,084	7214	0,110	7212	0,340
7222	0,098	7221	0,084	7214	0,057	7213	0,192
7222	0,098	7221	0,084	7214	0,105	7223	0,106
7222	0,098	7221	0,084	7214	0,056	7233	0,116
7222	0,098	7221	0,082	7223	0,056	7212	0,340
7222	0,098	7221	0,082	7223	0,194	7233	0,116
7222	0,098	7221	0,082	7223	0,104	8211	0,092
7222	0,098	7221	0,104	7233	0,203	7223	0,106
7222	0,120	7223	0,056	7212	0,069	7213	0,192
7222	0,120	7223	0,056	7212	0,065	7214	0,319
7222	0,120	7223	0,056	7212	0,075	7221	0,208
7222	0,120	7223	0,056	7212	0,063	7233	0,116
7222	0,104	7233	0,203	7223	0,056	7212	0,340
7222	0,104	7233	0,203	7223	0,104	8211	0,092
7222	0,104	7233	0,205	7231	0,050	7213	0,192
7223	0,056	7212	0,069	7213	0,066	7214	0,105
7223	0,056	7212	0,069	7213	0,073	7221	0,082
7223	0,056	7212	0,069	7213	0,192	7222	0,120
7223	0,056	7212	0,069	7213	0,060	7233	0,203
7223	0,056	7212	0,065	7214	0,057	7213	0,075
7223	0,056	7212	0,065	7214	0,077	7221	0,082
7223	0,056	7212	0,065	7214	0,319	7222	0,120
7223	0,056	7212	0,065	7214	0,056	7233	0,203
7223	0,056	7212	0,075	7221	0,063	7213	0,075
7223	0,056	7212	0,075	7221	0,084	7214	0,105
7223	0,056	7212	0,075	7221	0,208	7222	0,120
7223	0,056	7212	0,075	7221	0,104	7233	0,203
7223	0,056	7212	0,340	7222	0,080	7213	0,075
7223	0,056	7212	0,340	7222	0,125	7214	0,105
7223	0,056	7212	0,340	7222	0,098	7221	0,082
7223	0,056	7212	0,340	7222	0,104	7233	0,203
7223	0,056	7212	0,061	7231	0,050	7213	0,075
7223	0,056	7212	0,061	7231	0,264	7233	0,203
7223	0,056	7212	0,063	7233	0,116	7222	0,120
7223	0,106	7222	0,183	7212	0,069	7213	0,075
7223	0,106	7222	0,183	7212	0,065	7214	0,105
7223	0,106	7222	0,183	7212	0,075	7221	0,082
7223	0,106	7222	0,183	7212	0,063	7233	0,203
7223	0,106	7222	0,080	7213	0,121	7212	0,100
7223	0,106	7222	0,080	7213	0,066	7214	0,105
7223	0,106	7222	0,080	7213	0,073	7221	0,082
7223	0,106	7222	0,080	7213	0,060	7233	0,203
7223	0,106	7222	0,125	7214	0,110	7212	0,100
7223	0,106	7222	0,125	7214	0,057	7213	0,075
7223	0,106	7222	0,125	7214	0,077	7221	0,082
7223	0,106	7222	0,125	7214	0,056	7233	0,203
7223	0,106	7222	0,098	7221	0,091	7212	0,100
7223	0,106	7222	0,098	7221	0,063	7213	0,075
7223	0,106	7222	0,098	7221	0,084	7214	0,105
7223	0,106	7222	0,098	7221	0,104	7233	0,203
7223	0,194	7233	0,116	7222	0,183	7212	0,100
7223	0,194	7233	0,116	7222	0,080	7213	0,075
7223	0,194	7233	0,116	7222	0,125	7214	0,105

7223	0,194	7233	0,116	7222	0,098	7221	0,082
7223	0,194	7233	0,205	7231	0,050	7213	0,075
7223	0,104	8211	0,092	7222	0,183	7212	0,100
7223	0,104	8211	0,092	7222	0,080	7213	0,075
7223	0,104	8211	0,092	7222	0,125	7214	0,105
7223	0,104	8211	0,092	7222	0,098	7221	0,082
7223	0,104	8211	0,092	7222	0,104	7233	0,203
7223	0,104	8211	0,059	7231	0,050	7213	0,075
7223	0,104	8211	0,059	7231	0,264	7233	0,203
7231	0,050	7213	0,121	7212	0,063	7233	0,205
7231	0,050	7213	0,066	7214	0,110	7212	0,061
7231	0,050	7213	0,066	7214	0,056	7233	0,205
7231	0,050	7213	0,073	7221	0,091	7212	0,061
7231	0,050	7213	0,073	7221	0,104	7233	0,205
7231	0,050	7213	0,192	7222	0,183	7212	0,061
7231	0,050	7213	0,192	7222	0,104	7233	0,205
7231	0,050	7213	0,075	7223	0,056	7212	0,061
7231	0,050	7213	0,075	7223	0,194	7233	0,205
7231	0,050	7213	0,075	7223	0,104	8211	0,059
7231	0,264	7233	0,116	7222	0,183	7212	0,061
7231	0,264	7233	0,116	7222	0,080	7213	0,131
7231	0,264	7233	0,203	7223	0,056	7212	0,061
7231	0,264	7233	0,203	7223	0,104	8211	0,059
7233	0,116	7222	0,183	7212	0,069	7213	0,060
7233	0,116	7222	0,183	7212	0,065	7214	0,056
7233	0,116	7222	0,183	7212	0,075	7221	0,104
7233	0,116	7222	0,183	7212	0,100	7223	0,194
7233	0,116	7222	0,183	7212	0,061	7231	0,264
7233	0,116	7222	0,080	7213	0,121	7212	0,063
7233	0,116	7222	0,080	7213	0,066	7214	0,056
7233	0,116	7222	0,080	7213	0,073	7221	0,104
7233	0,116	7222	0,080	7213	0,075	7223	0,194
7233	0,116	7222	0,080	7213	0,131	7231	0,264
7233	0,116	7222	0,125	7214	0,110	7212	0,063
7233	0,116	7222	0,125	7214	0,057	7213	0,060
7233	0,116	7222	0,125	7214	0,077	7221	0,104
7233	0,116	7222	0,125	7214	0,105	7223	0,194
7233	0,116	7222	0,098	7221	0,080	7136	0,115
7233	0,116	7222	0,098	7221	0,091	7212	0,063
7233	0,116	7222	0,098	7221	0,063	7213	0,060
7233	0,116	7222	0,098	7221	0,084	7214	0,056
7233	0,116	7222	0,098	7221	0,082	7223	0,194
7233	0,116	7222	0,120	7223	0,056	7212	0,063
7233	0,203	7223	0,056	7212	0,069	7213	0,060
7233	0,203	7223	0,056	7212	0,065	7214	0,056
7233	0,203	7223	0,056	7212	0,075	7221	0,104
7233	0,203	7223	0,056	7212	0,340	7222	0,104
7233	0,203	7223	0,056	7212	0,061	7231	0,264
7233	0,203	7223	0,106	7222	0,183	7212	0,063
7233	0,203	7223	0,106	7222	0,080	7213	0,060
7233	0,203	7223	0,106	7222	0,125	7214	0,056
7233	0,203	7223	0,106	7222	0,098	7221	0,104
7233	0,203	7223	0,104	8211	0,092	7222	0,104
7233	0,203	7223	0,104	8211	0,059	7231	0,264
7233	0,205	7231	0,050	7213	0,121	7212	0,063
7233	0,205	7231	0,050	7213	0,066	7214	0,056
7233	0,205	7231	0,050	7213	0,073	7221	0,104
7233	0,205	7231	0,050	7213	0,192	7222	0,104
7233	0,205	7231	0,050	7213	0,075	7223	0,194
7233	0,061	7241	0,065	3113	0,147	7137	0,082
7241	0,065	3113	0,052	2143	0,073	7137	0,240
7241	0,065	3113	0,125	3114	0,064	7242	0,073
7241	0,065	3113	0,125	3114	0,108	7243	0,070
7241	0,065	3113	0,147	7137	0,082	7233	0,061
7241	0,256	7137	0,051	3114	0,053	3113	0,112
7241	0,256	7137	0,051	3114	0,064	7242	0,073
7241	0,256	7137	0,051	3114	0,108	7243	0,070
7241	0,055	7243	0,160	3114	0,053	3113	0,112
7241	0,055	7243	0,160	3114	0,064	7242	0,073
7242	0,073	7241	0,065	3113	0,125	3114	0,064
7242	0,073	7241	0,256	7137	0,051	3114	0,064
7242	0,073	7241	0,055	7243	0,160	3114	0,064
7243	0,160	3114	0,053	3113	0,112	7241	0,055
7243	0,160	3114	0,064	7242	0,073	7241	0,055
7243	0,070	7241	0,065	3113	0,125	3114	0,108
7243	0,070	7241	0,256	7137	0,051	3114	0,108
7422	0,489	7124	0,130	8240	0,170	7423	0,061
7422	0,099	7423	0,204	8240	0,476	7124	0,079
7422	0,070	8240	0,476	7124	0,153	7423	0,061
7422	0,070	8240	0,170	7423	0,396	7124	0,079
7422	0,070	8240	0,068	9320	0,121	7124	0,079
7423	0,396	7124	0,079	7422	0,070	8240	0,170
7423	0,061	7422	0,489	7124	0,130	8240	0,170
7423	0,061	7422	0,070	8240	0,476	7124	0,153
7423	0,204	8240	0,476	7124	0,079	7422	0,099
7423	0,204	8240	0,068	9320	0,121	7124	0,153
8211	0,092	7222	0,183	7212	0,100	7223	0,104
8211	0,092	7222	0,080	7213	0,075	7223	0,104
8211	0,092	7222	0,125	7214	0,105	7223	0,104
8211	0,092	7222	0,098	7221	0,082	7223	0,104
8211	0,092	7222	0,104	7233	0,203	7223	0,104
8211	0,059	7231	0,050	7213	0,075	7223	0,104

8211	0,059	7231	0,264	7233	0,203	7223	0,104
8240	0,476	7124	0,079	7422	0,099	7423	0,204
8240	0,476	7124	0,153	7423	0,061	7422	0,070
8240	0,170	7423	0,396	7124	0,079	7422	0,070
8240	0,170	7423	0,061	7422	0,489	7124	0,130
8240	0,068	9320	0,121	7124	0,079	7422	0,070
8240	0,068	9320	0,121	7124	0,153	7423	0,204
9320	0,121	7124	0,079	7422	0,070	8240	0,068
9320	0,121	7124	0,153	7423	0,204	8240	0,068
9330	0,054	3415	0,119	5220	0,244	4190	0,053
9330	0,055	4131	0,166	3415	0,101	4190	0,053
9330	0,055	4131	0,169	5220	0,244	4190	0,053
9330	0,119	5220	0,062	1224	0,056	4190	0,053
9330	0,119	5220	0,217	3415	0,101	4190	0,053

A7 One-way Linked Occupations by More than 5 Percent of Switchers from Original Occupations, For Private Sector Employees

Occ 1 (1)	Occ 2 (3)	Pct from occ1 to occ2 (2)
1222	1312	0,065
1222	3115	0,056
1222	7223	0,067
1223	1222	0,079
1223	1313	0,132
1223	7124	0,066
1229	1210	0,068
1229	1233	0,068
1229	1237	0,060
1229	1319	0,068
1233	1210	0,089
1233	3415	0,345
1233	3419	0,104
1234	1210	0,054
1234	1233	0,054
1234	2419	0,054
1234	3121	0,054
1234	3415	0,163
1234	3419	0,185
1234	3429	0,054
1235	1239	0,065
1235	3415	0,129
1235	3419	0,058
1235	7411	0,050
1237	1222	0,073
1237	1239	0,073
1237	2144	0,073
1237	2149	0,098
1237	2419	0,061
1237	3152	0,073
1239	3415	0,057
1314	7231	0,055
2113	2145	0,064
2113	2149	0,104
2113	2211	0,072
2131	3415	0,051
2132	4190	0,062
2141	1210	0,103
2141	1317	0,055
2142	3415	0,052
2143	2142	0,056
2143	2145	0,094
2143	2149	0,172
2143	3415	0,077
2145	3415	0,056
2146	1239	0,056
2146	2145	0,077
2146	2149	0,197
2224	1210	0,055
2224	1237	0,096
2224	2149	0,055
2224	2211	0,055
2224	2229	0,082
2224	2419	0,082
2224	3415	0,096
2331	4190	0,061
2331	7231	0,147
2419	2139	0,079
2419	3415	0,105
2419	3419	0,102
2421	1210	0,091
2421	2411	0,136
2421	2429	0,318
2451	2443	0,086
2451	3131	0,152
2451	3429	0,057
3111	3119	0,072
3111	4190	0,167
3112	3415	0,057
3112	7124	0,078
3115	3415	0,085
3116	3115	0,080
3116	3119	0,080
3116	7136	0,102
3119	3415	0,051
3121	4190	0,105
3122	4190	0,065
3141	3115	0,324
3141	3415	0,074
3141	7233	0,118
3142	3121	0,054
3142	3141	0,135
3142	3439	0,216
3142	4133	0,054
3142	6152	0,054
3142	8113	0,054
3152	2149	0,059
3152	3115	0,098
3152	3119	0,063
3152	7223	0,054
3211	1239	0,056
3211	3119	0,120
3211	4190	0,139
3211	8159	0,065
3224	1224	0,130
3224	1239	0,696
3224	3415	0,087
3416	3115	0,051
3416	3415	0,144
3416	3419	0,062
3416	4190	0,118
3416	5220	0,058
3422	3415	0,153
3422	4190	0,289
3429	3415	0,178
3429	3419	0,188
3429	3422	0,061
3431	3415	0,122
3431	3419	0,106
3431	4115	0,059
3431	4190	0,085
3433	4190	0,074
3439	3415	0,097
3439	3419	0,070
3439	4190	0,061
3471	1317	0,065
3471	2141	0,065
3471	2451	0,052
3471	2452	0,091
3471	3415	0,078
3471	4190	0,052
3471	5220	0,065
3471	7341	0,065
4115	3415	0,094
4115	3419	0,075
4115	4190	0,183
4121	4190	0,192
4132	3415	0,183
4132	4190	0,136
4132	5220	0,061
4133	3415	0,075
4133	4190	0,123
5122	3415	0,070
5123	5220	0,076
5123	7124	0,051
6130	7124	0,080
6130	7231	0,067
6130	7233	0,093
6130	8271	0,056
7122	2149	0,065
7122	3112	0,092
7122	7124	0,082
7122	9313	0,065
7129	7124	0,200
7129	7221	0,067
7129	7222	0,170
7135	7124	0,589
7136	3115	0,054
7139	7124	0,289
7139	7136	0,086
7139	7223	0,059
7139	7231	0,066
7141	7242	0,230
7142	7242	0,126
7211	7136	0,058
7211	7212	0,079
7211	7222	0,184
7211	7223	0,147
7211	7233	0,084
7311	7222	0,064
7311	7223	0,318
7311	7233	0,115
7311	8211	0,070
7341	7343	0,142
7411	5220	0,054
7413	1239	0,110
8123	7222	0,137
8123	7223	0,068
8159	3119	0,123
8159	7223	0,086
8212	6130	0,068
8212	7124	0,082
8212	7222	0,068
8212	7231	0,055
8212	9312	0,055
8212	9313	0,055
8231	7223	0,070
8231	7233	0,070
8231	8232	0,093
8231	8271	0,093
8231	9320	0,070
8232	7222	0,052
8232	7223	0,178
8232	7231	0,065
8251	7343	0,103
8253	7223	0,075
8253	7231	0,086
8253	7233	0,065
8253	8211	0,054
8253	9330	0,054
8271	9320	0,052
8272	1239	0,073
8272	9320	0,094
8274	9320	0,085
8278	7223	0,123
8278	8159	0,053
8278	8271	0,053
8281	7222	0,086
8281	7223	0,204
8281	7231	0,053
8281	7233	0,112
8281	8211	0,072
8281	9320	0,053
8283	7241	0,056
8283	7243	0,217
8283	8232	0,056
8283	8281	0,063
8284	7223	0,083
8284	7231	0,155
8284	9320	0,051
8285	7124	0,350
8285	7423	0,087
8285	8240	0,083
8287	7222	0,085
8287	7223	0,065
8287	7231	0,105
8290	7124	0,063
8290	7223	0,084
8290	8271	0,070
8322	3415	0,086
8322	4190	0,100
8322	5220	0,096
8322	7231	0,086
8322	8324	0,120
8322	9330	0,067
8324	3415	0,117
8324	7231	0,173
8324	9330	0,067
8332	6130	0,058
8332	7231	0,081
8334	8324	0,052
8334	9330	0,156
9113	3415	0,342
9113	3419	0,076
9113	4190	0,209
9113	5220	0,070
9132	3439	0,058

9132	4190	0,056	9211	6112	0,185	9312	7231	0,076
9132	5220	0,063	9211	6130	0,065	9313	7124	0,121
9132	7231	0,056	9211	8271	0,056	9313	7136	0,053
9132	8271	0,056	9211	9312	0,074	9313	7231	0,055

A8 Appendix on Wage Regressions

Table A-12: Wage regressions for fulltime privately employed workers

	OLS (1)	GLS/RE (2)	IV-OLS (3)	IV-GLS/RE (4)
occ. ten.	0.0309***	0.0154***	-0.0016	0.0246***
	(29.22)	(20.30)	(-0.622)	(20.24)
occ. ten. sq	-0.0036***	-0.0014***	0.0037***	-0.0017***
	(-20.78)	(-11.62)	-7.410	(-10.39)
occ. ten. cub	0.0001***	0.0000***	-0.0002***	0.0000***
	(13.63)	-5.595	(-9.151)	-5.105
ind. ten.	0.0078***	0.0066***	-0.0130***	0.0012
	-6.133	-7.665	(-4.714)	-1.152
ind. ten. sq	-0.0017***	-0.0013***	0.0024***	-0.0002
	(-7.325)	(-8.553)	-4.792	(-0.901)
ind. ten. cub	0.0001***	0.0000***	-0.0001***	-0.0000
	-5.413	-6.304	(-5.335)	(-0.148)
firm ten.	0.0100***	0.0062***	-0.0315***	-0.0124***
	-4.966	-5.022	(-5.548)	(-6.385)
firm ten. sq	-0.0015***	-0.0013***	0.0026***	0.0005**
	(-6.032)	(-9.032)	-3.927	-2.155
gen. exp.	0.0276***	0.0357***	0.0430***	0.0231***
	(22.90)	(39.47)	(13.99)	(16.01)
gen. exp. sq	-0.0013***	-0.0020***	-0.0057***	-0.0015***
	(-7.735)	(-16.35)	(-11.43)	(-9.592)
gen. exp. cub	0.0000***	0.0001***	0.0002***	0.0000***
	-5.014	(10.54)	(11.01)	-7.477
Constant	5.3416***	5.2180***	5.6013***	5.3875***
	(741.8)	(701.3)	(505.6)	(600.2)
Occ. Spell dummies	yes	yes	yes	yes
5 education dummies	yes	yes	yes	yes
OJ	yes	yes	yes	yes
Number of children	yes	yes	yes	yes
Marriage and Union dummies	yes	yes	yes	yes
County unemployment rate	yes	yes	yes	yes
Time and regional dummies	yes	yes	yes	yes
1 digit ind. and occ. dummies	yes	yes	yes	yes
Observations	426164	426164	426164	426164
R-squared	0.439	.	0.427	.

*** p<0.01, ** p<0.05, * p<0.1, and t statistics in parentheses

Table A-13: Wage regressions for fulltime privately employed workers, who graduated from 1994-1999 and had at most 3 years of general experience at time of graduation

	OLS	GLS/RE	IV-OLS	IV-GLS/RE
	(1)	(2)	(3)	(4)
occ. ten.	0.0644***	0.0505***	0.0635***	0.0542***
	-7.477	-7.671	-4.775	-6.547
occ. ten. sq	-0.0109***	-0.0097***	-0.0159***	-0.0124***
	(-4.012)	(-4.737)	(-4.196)	(-5.408)
occ. ten. cub	0.0008***	0.0007***	0.0013***	0.0009***
	-3.275	-3.833	-4.041	-4.645
ind. ten.	-0.0153	-0.0024	0.0032	-0.0250**
	(-1.501)	(-0.308)	(0.166)	(-2.403)
ind. ten. sq	0.0030	0.0003	-0.0012	0.0071**
	(0.966)	(0.111)	(-0.201)	-2.288
ind. ten. cub	-0.0001	0.0001	0.0001	-0.0005*
	(-0.351)	(0.412)	(0.291)	(-1.900)
firm ten.	0.0345***	0.0275***	0.0096	0.0055
	-5.137	-5.321	(0.571)	(0.666)
firm ten. sq	-0.0045***	-0.0038***	-0.0015	-0.0013
	(-5.265)	(-5.689)	(-0.763)	(-1.352)
gen. exp.	0.0402***	0.0379***	0.0188***	0.0422***
	-9.953	(11.45)	-3.498	(11.95)
gen. exp. sq	-0.0028***	-0.0005	0.0083***	0.0006
	(-2.818)	(-0.639)	-4.999	(0.753)
gen. exp. cub	0.0001	-0.0001**	-0.0008***	-0.0002***
	(0.835)	(-2.161)	(-6.496)	(-4.083)
Constant	4.9924***	4.9504***	5.0002***	0.0000
	(333.5)	(349.8)	(195.2)	()
Occ. Spell dummies	yes	yes	yes	yes
5 education dummies	yes	yes	yes	yes
OJ	yes	yes	yes	yes
Number of children	yes	yes	yes	yes
Union dummy	yes	yes	yes	yes
Marriage dummy	yes	yes	yes	yes
County unemployment rate	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
1 digit industry dummies	yes	yes	yes	yes
1 digit occupation dummies	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes
Observations	57584	57584	57584	57584
R-squared	0.562	.	0.558	.
Number of pnr		15172		15172
R-squared overall		0.558		0.552

*** p<0.01, ** p<0.05, * p<0.1, and t statistics in parentheses

Table A-14: Wage regressions for fulltime public and private employees allowing for spells of non-employment and part-time work

	OLS	GLS	IV-OLS	IV-GLS
	(1)	(2)	(3)	(4)
occ. ten.	0.0180***	0.0056***	-0.0078***	0.0056***
	(42.33)	(18.58)	(-7.595)	(13.72)
occ. ten. sq	-0.0019***	-0.0005***	0.0028***	-0.0003***
	(-33.32)	(-12.20)	(15.74)	(-6.161)
occ. ten. cub	0.0000***	0.0000***	-0.0001***	0.0000**
	(22.11)	-6.776	(-16.62)	-2.472
ind. ten.	0.0049***	0.0032***	0.0069***	-0.0014***
	-8.150	-7.993	-7.654	(-3.016)
ind. ten. sq	-0.0005***	-0.0006***	-0.0008***	0.0000
	(-5.929)	(-9.214)	(-6.309)	(0.613)
ind. ten. cub	0.0000***	0.0000***	0.0000***	0.0000
	-9.194	-9.687	-7.348	(0.446)
firm ten.	-0.0023**	0.0045***	-0.0583***	-0.0184***
	(-2.025)	-6.673	(-17.87)	(-18.22)
firm ten. sq	-0.0009***	-0.0010***	0.0046***	0.0014***
	(-6.894)	(-13.00)	(13.28)	(12.30)
gen. exp.	0.0332***	0.0356***	0.0293***	0.0359***
	(69.10)	(92.53)	(38.49)	(69.28)
gen. exp. sq	-0.0016***	-0.0015***	-0.0024***	-0.0017***
	(-30.11)	(-39.21)	(-32.98)	(-37.49)
gen. exp. cub	0.0000***	0.0000***	0.0001***	0.0000***
	(18.58)	(20.75)	(26.85)	(22.42)
Constant	5.3325***	5.0052***	5.1812***	5.0364***
	(978.8)	(935.5)	(696.5)	(897.9)
Occ. Spell dummies	yes	yes	yes	yes
5 education dummies	yes	yes	yes	yes
OJ	yes	yes	yes	yes
Number of children	yes	yes	yes	yes
Union dummy	yes	yes	yes	yes
Marriage dummy	yes	yes	yes	yes
County unemployment rate	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
1 digit industry dummies	yes	yes	yes	yes
1 digit occupation dummies	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes
Observations	1266782	1266782	1266782	1266782
R-squared	0.419	.	0.402	.
Number of pnr		310127		310127

*** p<0.01, ** p<0.05, * p<0.1, and t statistics in parentheses

Table A-15: Returns to 2, 5, and 8 years of tenure, public and private worker sample

	2 years	5 years	8 years
OLS			
Occupation	0.029	0.048	0.045
	(0.001)	(0.001)	(0.001)
Industry	0.008	0.015	0.022
	(0.001)	(0.001)	(0.001)
Employer	-0.008	-0.035	-0.078
	(0.002)	(0.003)	(0.002)
IV_GLS			
Occupation	0.010	0.021	0.027
	(0.001)	(0.001)	(0.002)
Industry	-0.003	-0.005	-0.008
	(0.001)	(0.001)	(0.001)
Employer	-0.031	-0.058	-0.060
	(0.002)	(0.002)	(0.002)

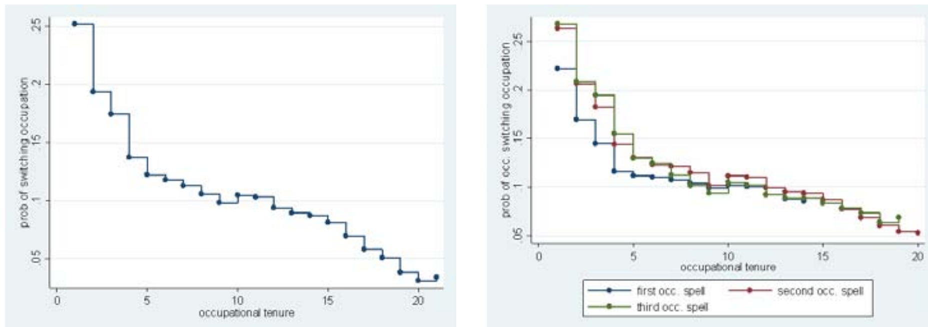
Note: Standard errors in parentheses

A9 Appendix on Hazard rates

Table A-16: Returns to 2, 5, and 8 years of tenure, public and private worker sample

	Private	public and private
	Column 1	Column 2
occ.ten.1	-2,520	-
	(-1.60)	-
occ.ten.2	-2,820	-
	(-1.79)	-
occ.ten.3	-3,019	1,623
	(-1.92)	(17,140)
occ.ten.4	-3,215	1,444
	(-2.04)	(15,250)
occ.ten.5	-3,294	1,323
	(-2.09)	(13,970)
occ.ten.6	-3,395	1,079
	(-2.16)	(11,380)
occ.ten.7	-3,416	1,000
	(-2.17)	(10,530)
ind.ten.	-0,478	-0,341
	(-25.94)	(-44,030)
ind.ten.sq	0,076	0,041
	(19.90)	(30,440)
ind.ten.cub	-0,004	-0,002
	(-17.35)	(-24,750)
firm.ten.	-0,490	-0,336
	(-30.15)	(-39,750)
firm.ten.sq	0,056	0,037
	(23.58)	(31,880)
gen.exp.	0,625	0,283
	(43.14)	(57,280)
gen.exp.sq	-0,078	-0,025
	(-33.69)	(-42,650)
gen.exp.cub	0,003	0,001
	(27.72)	(33,940)
occ. ten. 8-21 dummies other	yes	yes
other explanatory variables	yes	yes
total obs.	404800	1266756
log likelihood	-178720,66	-559774,41

z statistics in parentheses



(a) Probability of switching occupation by occupational tenure

(b) Probability of switching occupation by occupational spell number and occupational tenure

Figure A-1: Hazard rate out of occupations by occupational tenure, over all and by occupational spell number for large sample including public sector workers and allowing for spells of non-employment and part-time work.

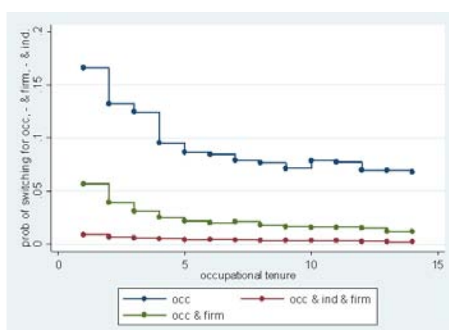


Figure A-2: Hazard rate out of occupations by occupational tenure, over all and by occupational spell number for large sample including public sector workers and allowing for spells of non-employment and part-time work.

Table A-17: Multinomial Logit for fulltime private sample

	Occ. Column 1	occ. and firm Column 2	Occ. and ind. Column 3	Occ., firm, and ind. Column 4
occ.ten.1	-2,183	-4,111	-4,411	-1,675
	(-20,080)	(-13,850)	(-10,230)	(-13,420)
occ.ten.2	-2,531	-4,329	-4,569	-1,897
	(-22,960)	(-14,400)	(-10,400)	(-14,810)
occ.ten.3	-2,770	-4,484	-4,647	-2,026
	(-25,010)	(-14,850)	(-10,540)	(-15,660)
occ.ten.4	-2,981	-4,651	-4,943	-2,175
	(-26,670)	(-15,280)	(-11,090)	(-16,590)
occ.ten.5	-3,057	-4,819	-4,931	-2,230
	(-27,160)	(-15,720)	(-10,970)	(-16,840)
occ.ten.6	-3,165	-4,789	-5,091	-2,358
	(-28,010)	(-15,590)	(-11,230)	(-17,600)
occ.ten.7	-3,179	-5,009	-5,164	-2,313
	(-28,150)	(-16,210)	(-11,430)	(-17,290)
occ.ten.8	-3,176	-5,016	-5,042	-2,394
	(-27,990)	(-16,090)	(-11,150)	(-17,580)
occ.ten.9	-3,170	-4,975	-4,904	-2,395
	(-27,850)	(-15,880)	(-10,830)	(-17,360)
occ.ten.10	-3,091	-4,984	-4,999	-2,379
	(-27,120)	(-15,760)	(-10,970)	(-17,000)
occ.ten.11	-3,034	-4,776	-5,061	-2,211
	(-26,530)	(-15,120)	(-11,030)	(-15,790)
occ.ten.12	-3,071	-4,798	-5,146	-2,204
	(-26,630)	(-15,010)	(-11,060)	(-15,460)
occ.ten.13	-3,139	-5,068	-5,068	-2,501
	(-26,810)	(-15,320)	(-10,800)	(-16,490)
occ.ten.14	-3,194	-5,117	-5,307	-2,386
	(-26,450)	(-14,910)	(-10,750)	(-15,040)
occ.ten.15	-35,506	-35,419	-32,576	2,913
	(-0,000)	(-0,000)	(-0,000)	(1,860)
ind.ten.	-0,430	0,110	-1,047	-0,682
	(-19,460)	(1,950)	(-9,560)	(-19,270)
ind.ten.sq	0,073	0,001	0,123	0,091
	(16,020)	(0,110)	(4,470)	(11,660)
ind.ten.cub	-0,004	-0,001	-0,005	-0,004
	(-14,470)	(-1,280)	(-2,840)	(-8,710)
firm.ten.	-0,463	-1,054	-0,091	-0,369
	(-23,600)	(-21,270)	(-1,010)	(-12,090)
firm.ten.sq	0,055	0,105	0,030	0,041
	(19,440)	(13,670)	(2,240)	(8,950)
gen.exp.	0,680	0,524	0,693	0,541
	(38,660)	(11,930)	(9,240)	(21,560)
gen.exp.sq	-0,082	-0,072	-0,080	-0,074
	(-29,380)	(-10,010)	(-6,680)	(-17,570)
gen.exp.cub	0,003	0,003	0,003	0,003
	(24,070)	(8,410)	(5,330)	(14,170)
other explanatory variables	yes	yes	yes	yes
total obs.		404800		
log likelihood		-245066,19		

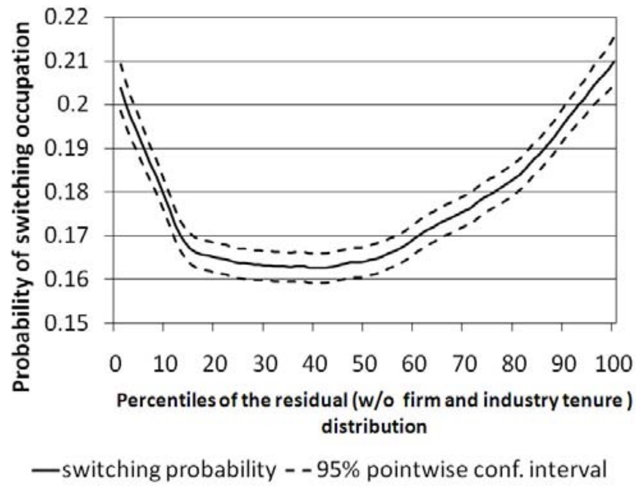
z statistics in parentheses

Table A-18: Multinomial Logit for fulltime private and public sample

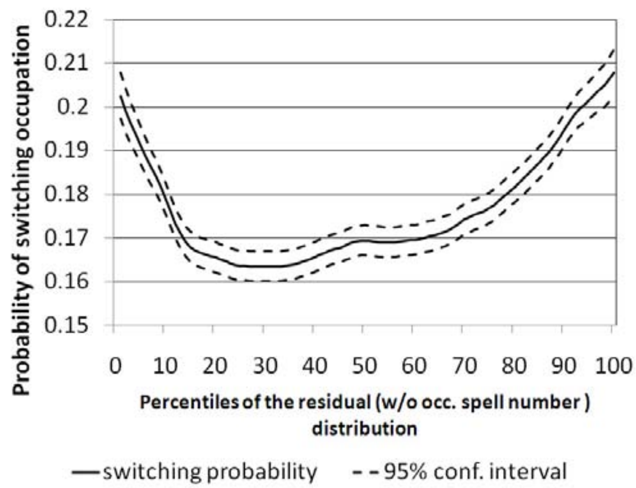
	Occ. Column 1	occ. and firm Column 2	Occ. and ind. Column 3	Occ, firm, and ind Column 4
occ.ten.3	1,456	1,291	14,788	0,699
	(13,500)	(3,090)	(46,920)	(3,170)
occ.ten.4	1,279	1,183	14,720	0,585
	(11,870)	(2,830)	(45,930)	(2,650)
occ.ten.5	1,169	1,061	14,520	0,501
	(10,850)	(2,540)	(44,800)	(2,270)
occ.ten.6	0,898	0,942	14,353	0,386
	(8,330)	(2,250)	(43,690)	(1,750)
occ.ten.7	0,844	0,751	14,347	0,350
	(7,820)	(1,790)	(43,150)	(1,580)
occ.ten.8	0,749	0,733	14,050	0,266
	(6,930)	(1,750)	(41,260)	(1,200)
occ.ten.9	0,649	0,551	14,230	0,265
	(5,990)	(1,310)	(41,920)	(1,190)
occ.ten.10	0,628	0,531	14,137	0,169
	(5,780)	(1,260)	(40,950)	(0,760)
ind.ten.	-0,318	0,193	-0,695	-0,520
	(-36,040)	(6,820)	(-9,790)	(-31,080)
ind.ten.sq	0,039	-0,015	0,076	0,056
	(25,920)	(-2,980)	(4,600)	(17,440)
ind.ten.cub	-0,002	0,000	-0,003	-0,002
	(-21,480)	(0,310)	(-3,240)	(-12,380)
firm.ten.	-0,207	-1,041	-0,165	-0,381
	(-20,980)	(-34,760)	(-2,690)	(-22,280)
firm.ten.sq	0,026	0,095	0,026	0,033
	(19,590)	(21,200)	(2,970)	(13,180)
gen.exp.	0,226	0,208	0,323	0,205
	(34,960)	(10,880)	(8,710)	(20,100)
gen.exp.sq	-0,019	-0,023	-0,027	-0,024
	(-26,820)	(-10,890)	(-6,440)	(-20,070)
gen.exp.cub	0,001	0,001	0,001	0,001
	(21,360)	(10,220)	(5,070)	(17,130)
education	yes	yes	yes	yes
number of children	yes	yes	yes	yes
union,marriage	yes	yes	yes	yes
county unempl.rate	yes	yes	yes	yes
time dummies	yes	yes	yes	yes
1 digit industry dummies	yes	yes	yes	yes
1 digit occupation dummies	yes	yes	yes	yes
regional dummies	yes	yes	yes	yes
total obs.			1266783	
log likelihood			-733982,97	

z statistics in parentheses

A10 Appendix on U-shapes in Occupational Mobility



(a) residual distribution from wage regression not including firm and industry tenure



(b) residual distribution from wage regression not including occupational spell number

Figure A-3: Non-parametric plot of probability of switching occupation by worker's percentile in residual distributions from different wage regressions.

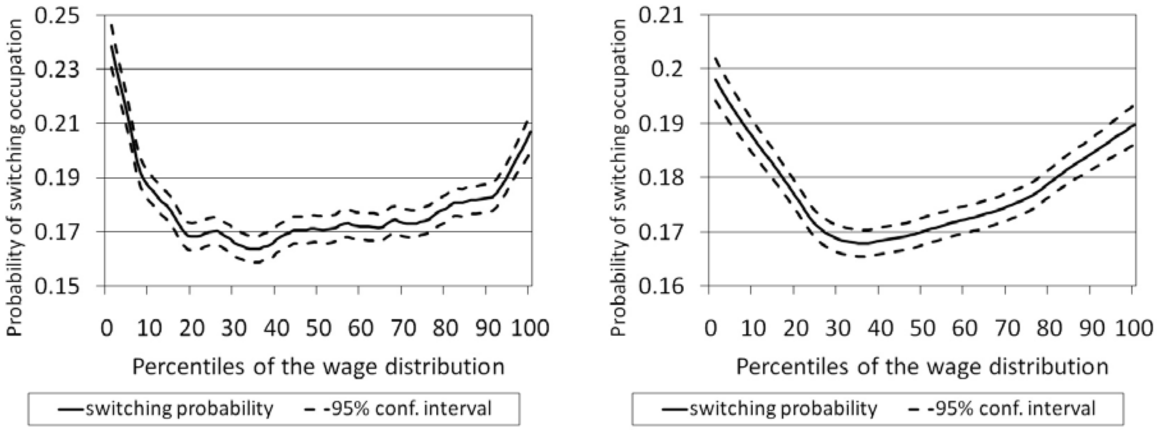


Figure A-4: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation and year for half and double bandwidth.

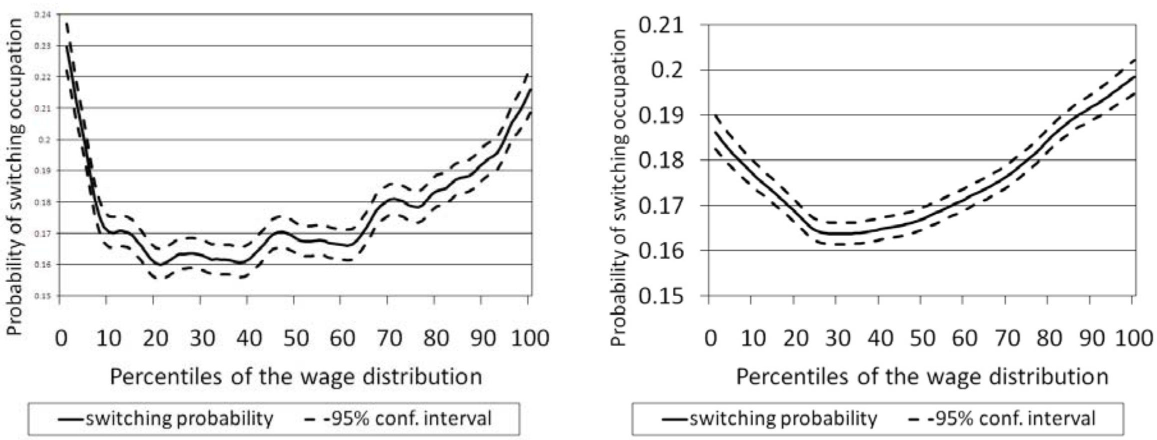


Figure A-5: Non-parametric plot of probability of switching occupation by worker's percentile in the wage residuals for half and double bandwidth.

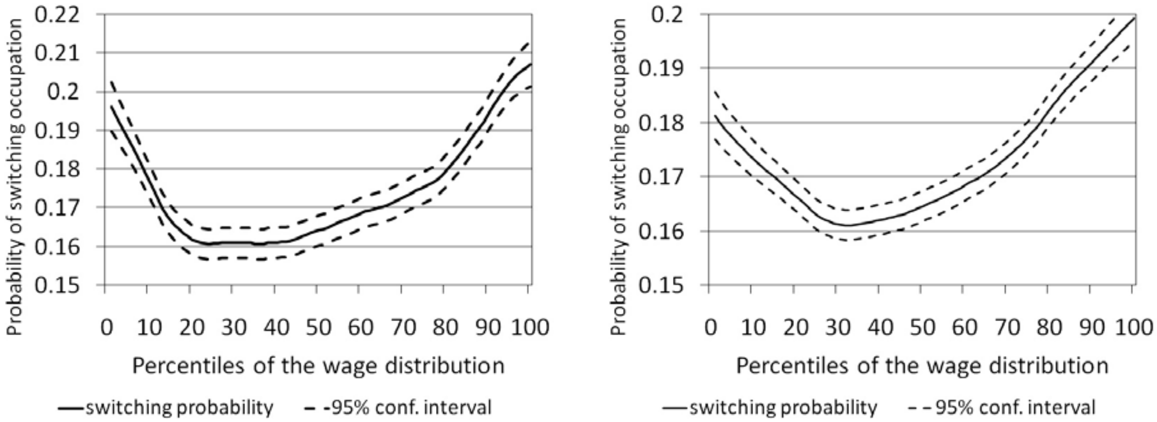


Figure A-6: Non-parametric plot of probability of switching occupation by worker's percentile in the wage within occupation, year, and years after graduation for half and double bandwidth.

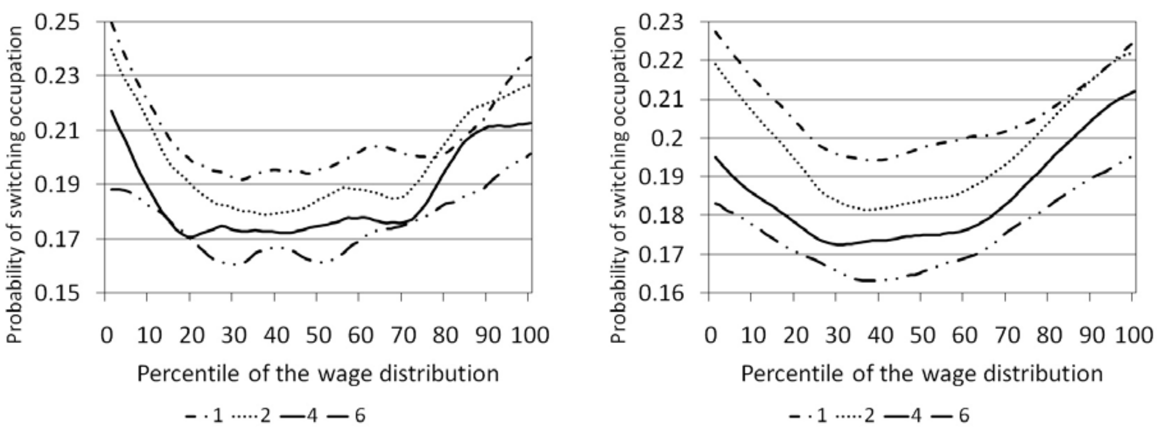
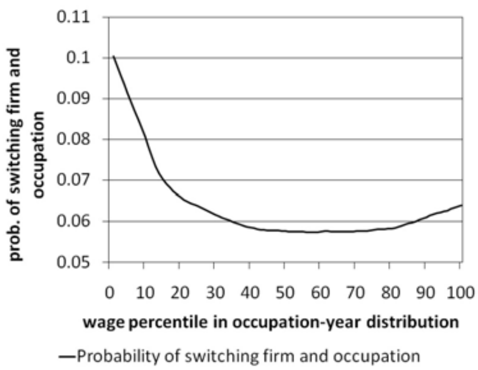
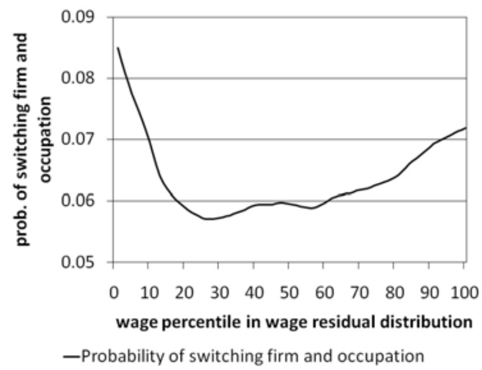


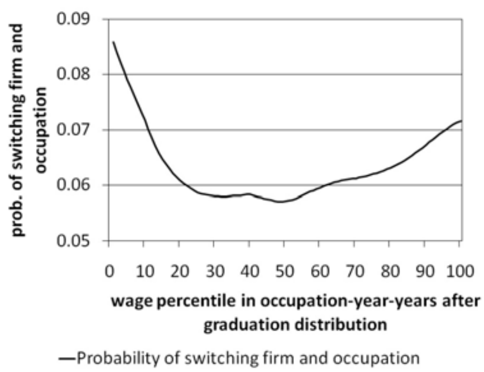
Figure A-7: Non-parametric plot of probability of switching occupation by worker's percentile in the wage within occupation, year, and 1, 2, 4, and 6 years after graduation for half and double bandwidth.



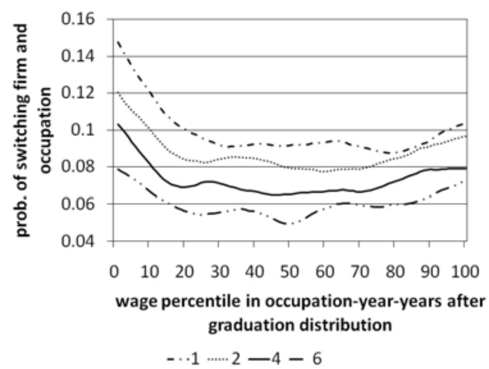
(a) wage distribution of raw wages within occupation and year



(b) wage distribution of wages residual



(c) wage distribution of raw wages within occupation, year, and year after graduation



(d) wage distribution of raw wages within occupation, year, and year after graduation for 1, 2, 4, and 6 years after graduation

Figure A-8: Non-parametric plot of probability of switching occupation AND firm by worker's percentile in the wage distribution.

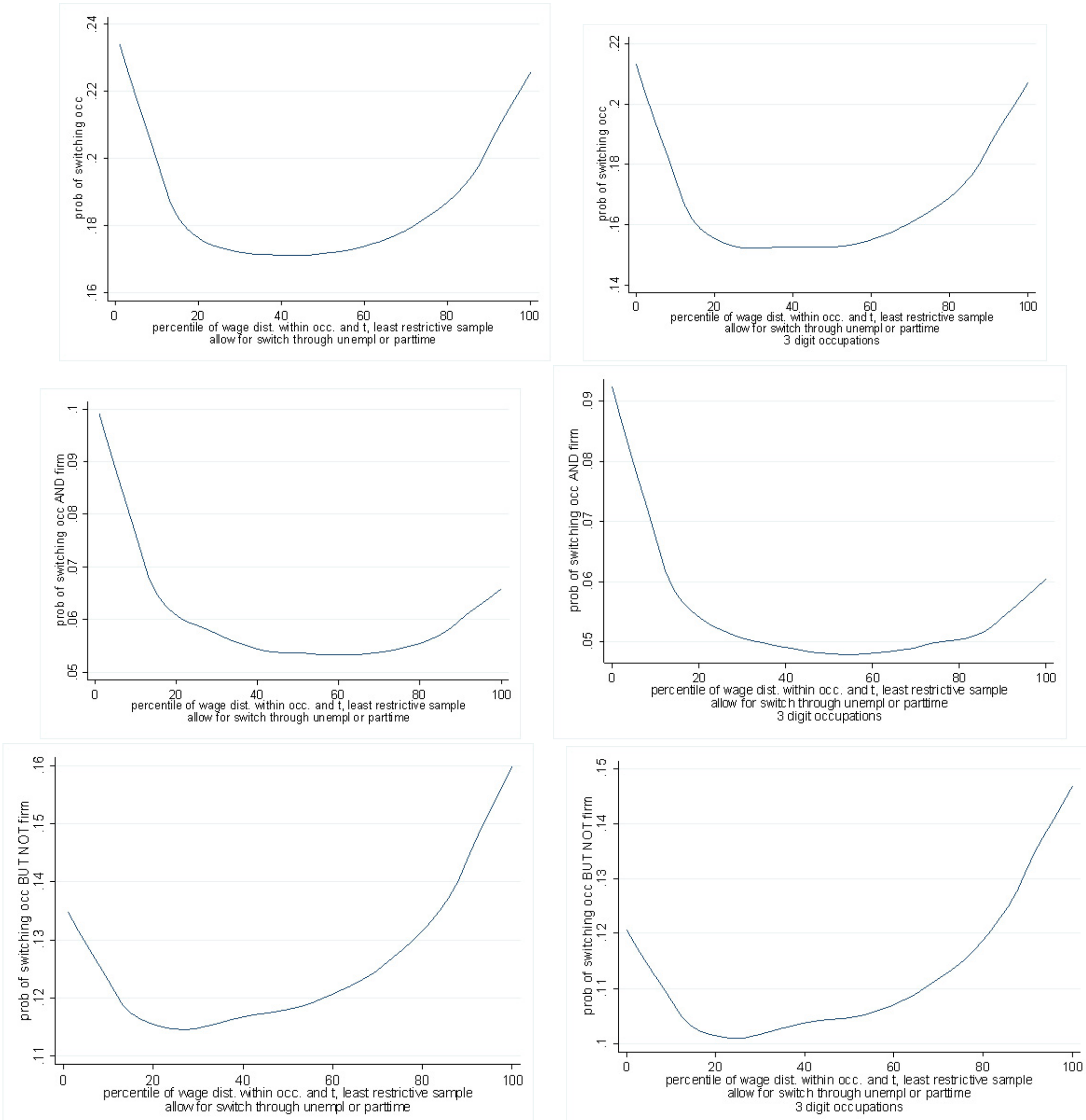


Figure A-9: Probability of switching occupation, occupation and firm, and occupation but not firm. Percentiles of wage distribution within occupation and year.

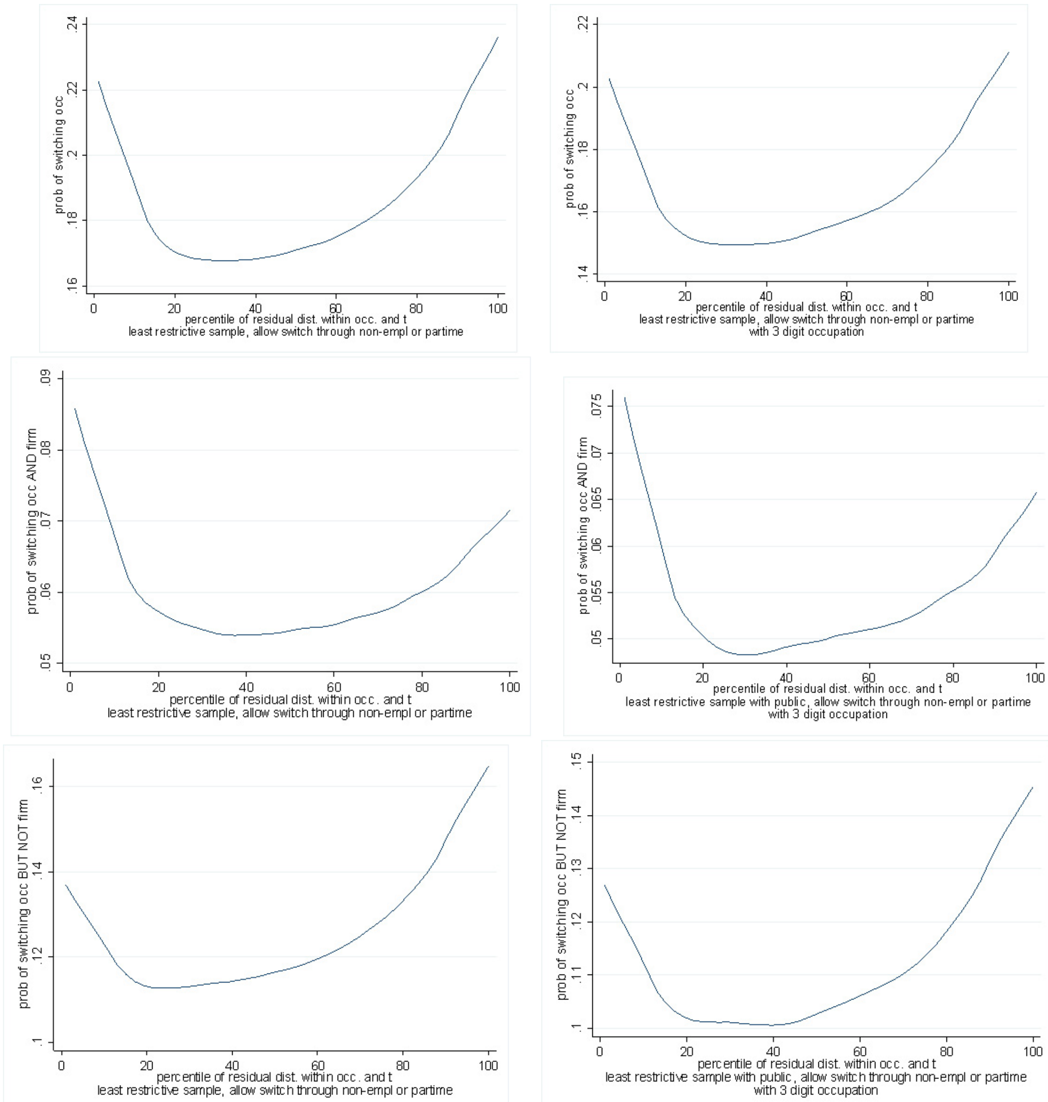


Figure A-10: Probability of switching occupation, occupation and firm, and occupation but not firm. Percentiles of residual wage distribution.

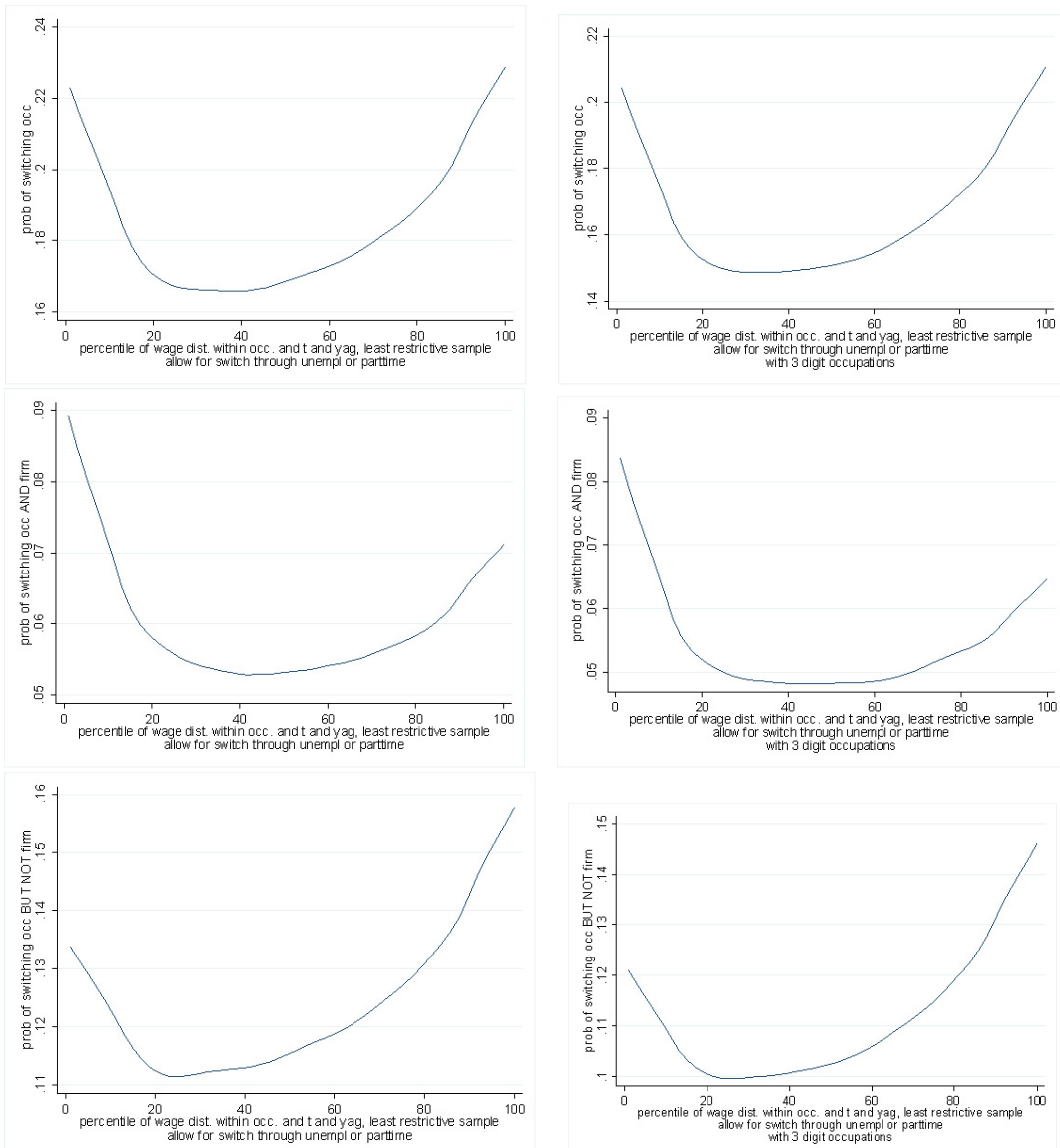


Figure A-11: Probability of switching occupation, occupation and firm, and occupation but not firm. Percentiles of wage distribution within occupation, year and year after graduation.

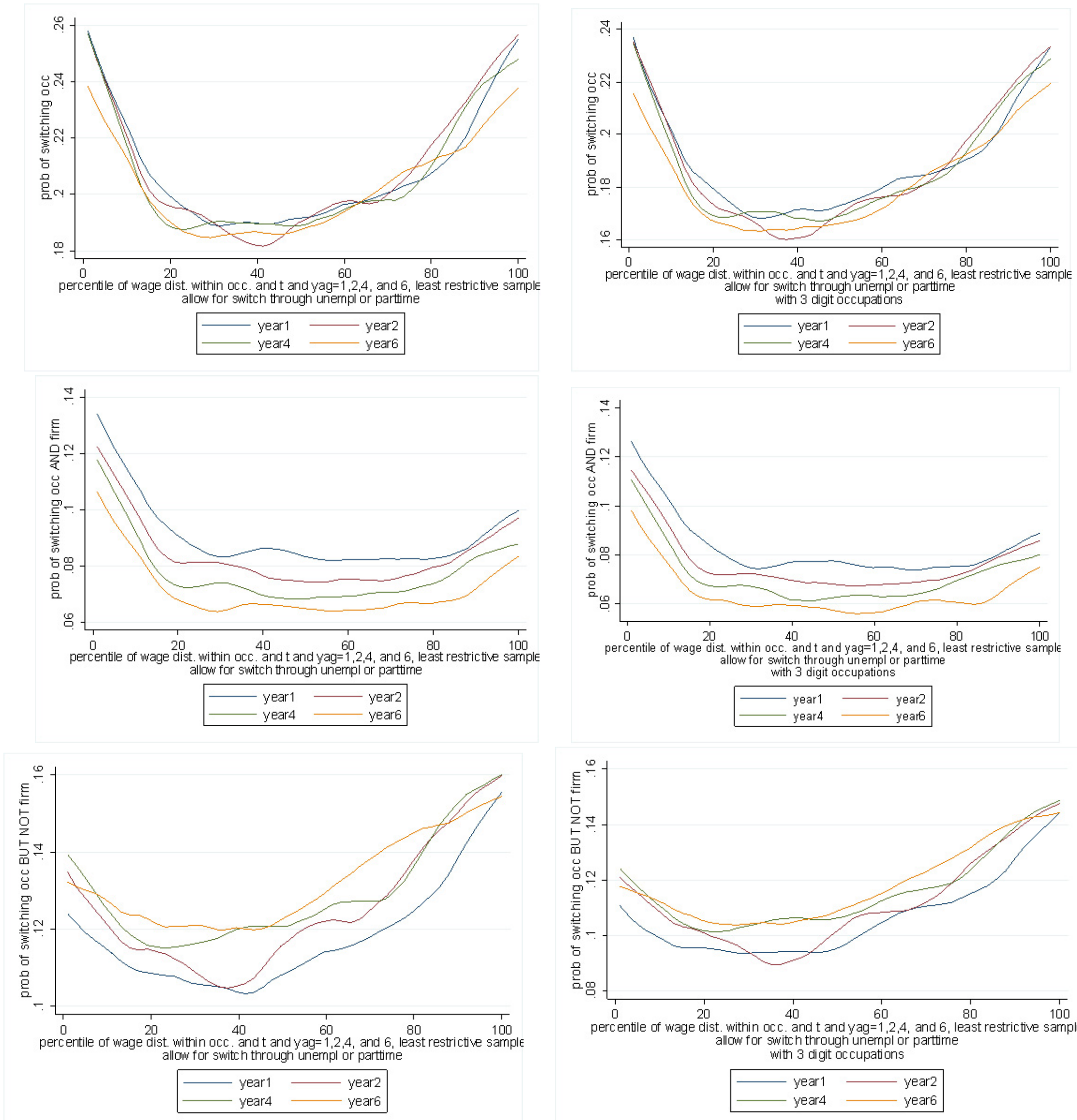


Figure A-12: Probability of switching occupation, occupation and firm, and occupation but not firm. Percentiles of wage distribution within occupation, year and 1, 2, 4 and 6 years after graduation.

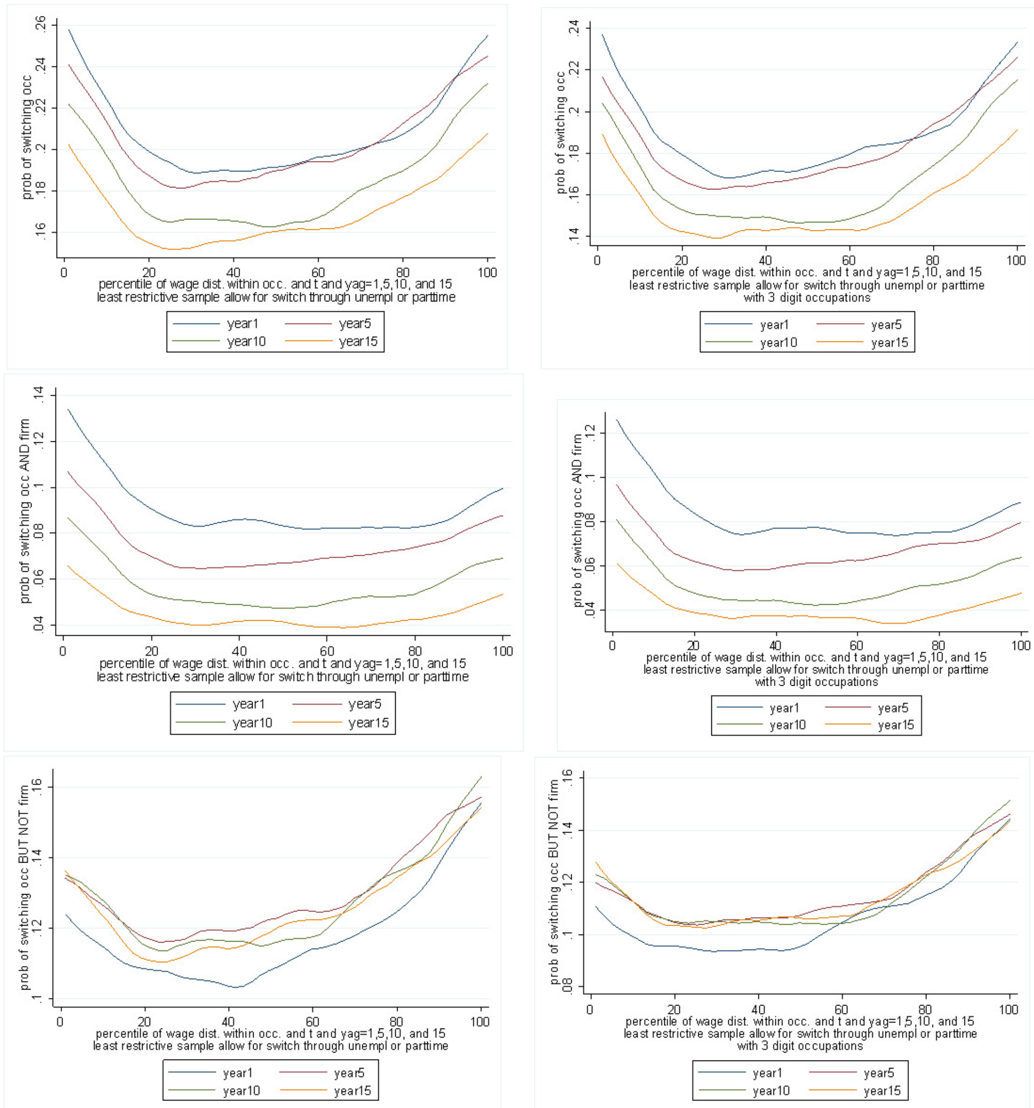
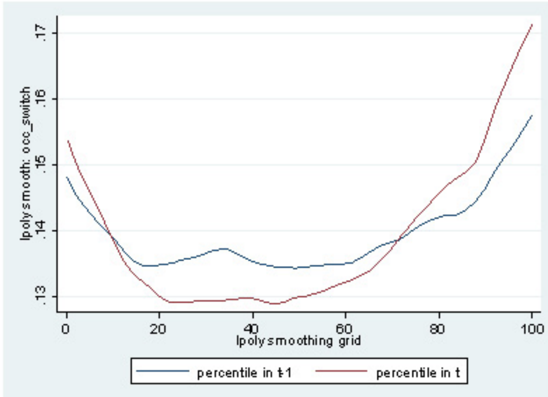
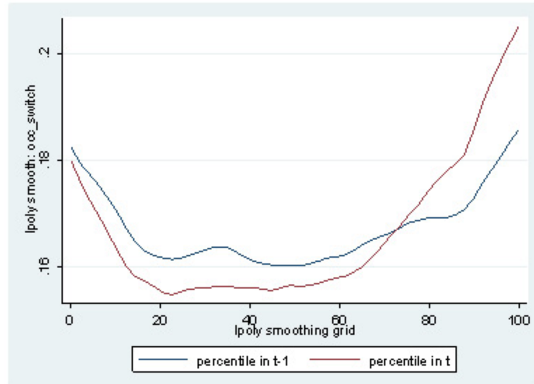


Figure A-13: Probability of switching occupation, occupation and firm, and occupation but not firm. Percentiles of wage distribution within occupation, year and 1, 5, 10, and 15 years after graduation.



(a) Probability of switching occupation between year t and t+1 for workers in the same occupation in year t-1 and t depending on wage percentile in their occupation t and t-1



(b) Probability of switching occupation between year t and t+1 for workers in the any occupation in year t-1 and t depending on wage percentile in their occupation t and t-1

Figure A-14: Non-parametric plot of probability of switching occupation between year t and t+1 by worker's percentile in the wage within occupation and year in period t-1 and t.

A11 Appendix: Direction of Occupational Mobility, Condition on Changing Occupation

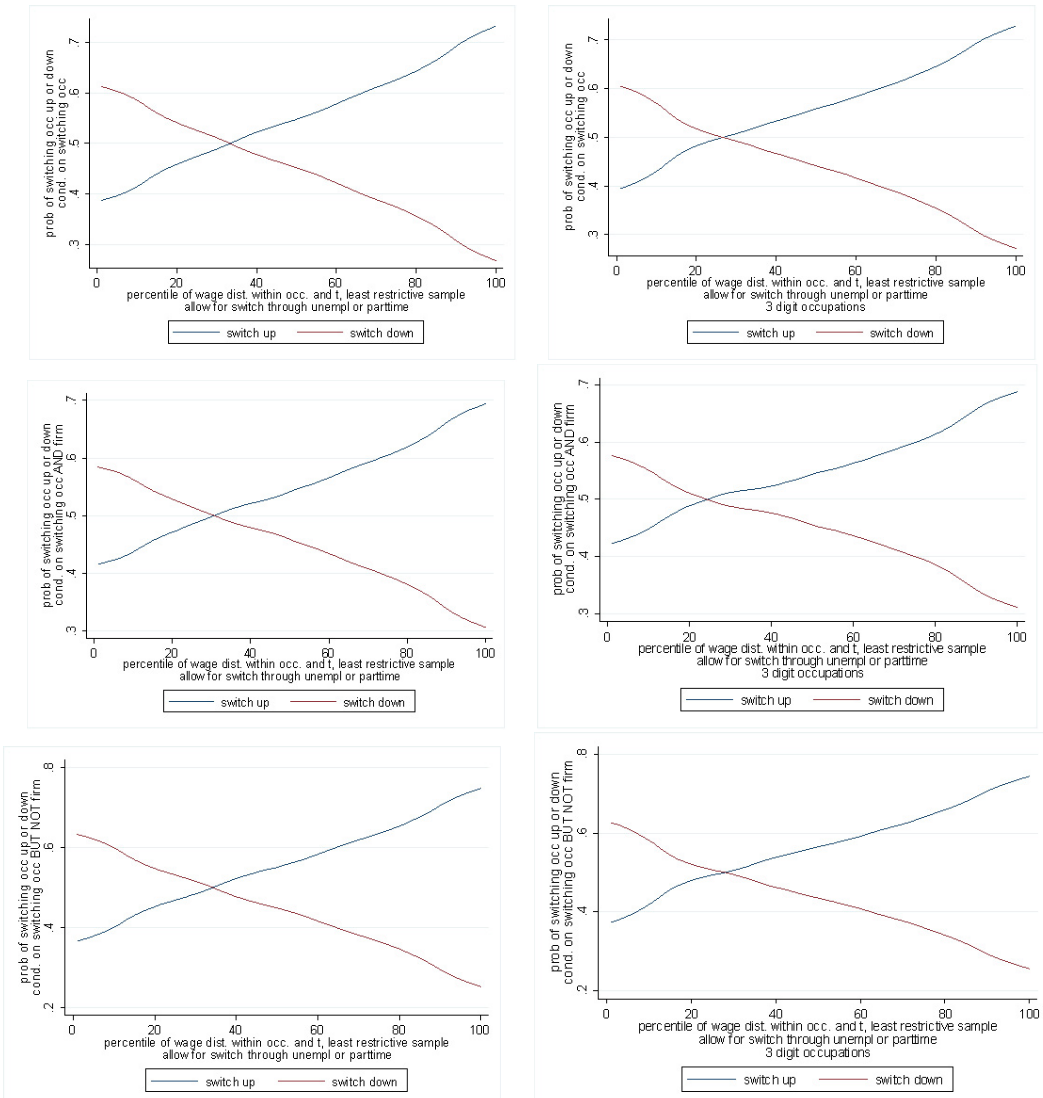


Figure A-15: Probability of switching to occupations with higher or lower average wage conditional on switching occupation. Percentiles of wage distribution within occupation and year.

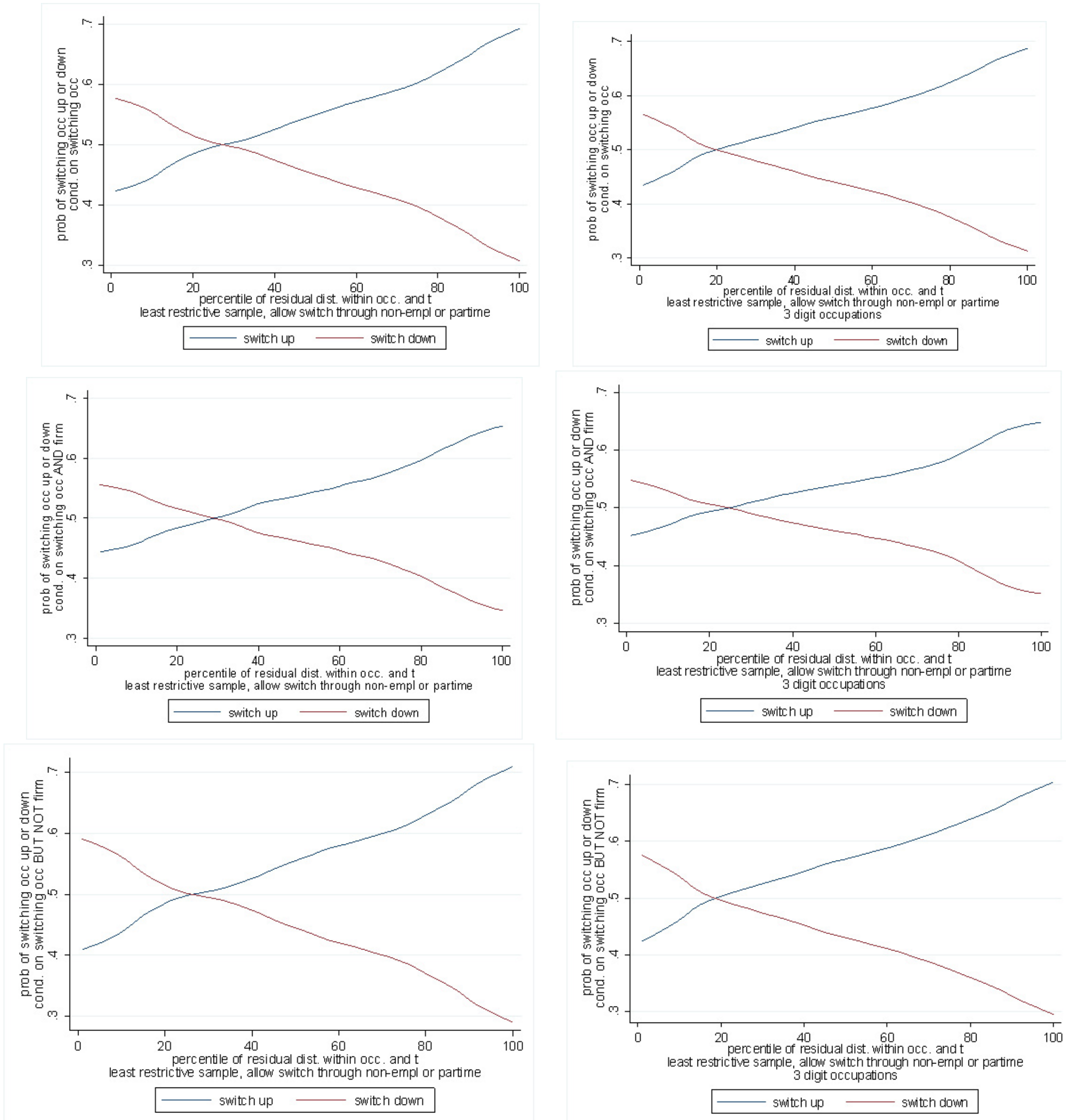


Figure A-16: Probability of switching to occupations with higher or lower average wage conditional on switching occupation. Percentiles of residual wage distribution.

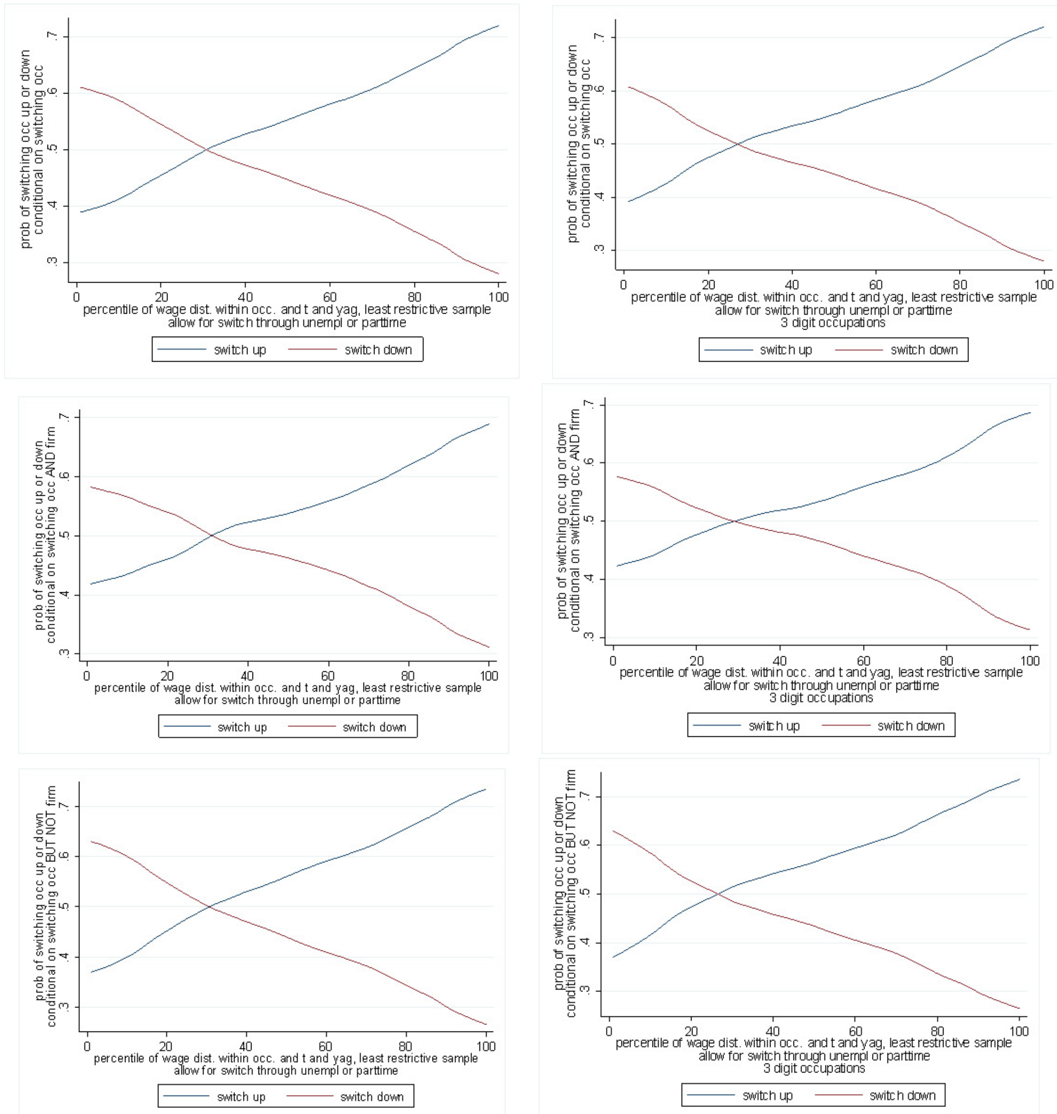


Figure A-17: Probability of switching to occupations with higher or lower average wage conditional on switching occupation. Percentiles of wage distribution within occupation, year and year after graduation.

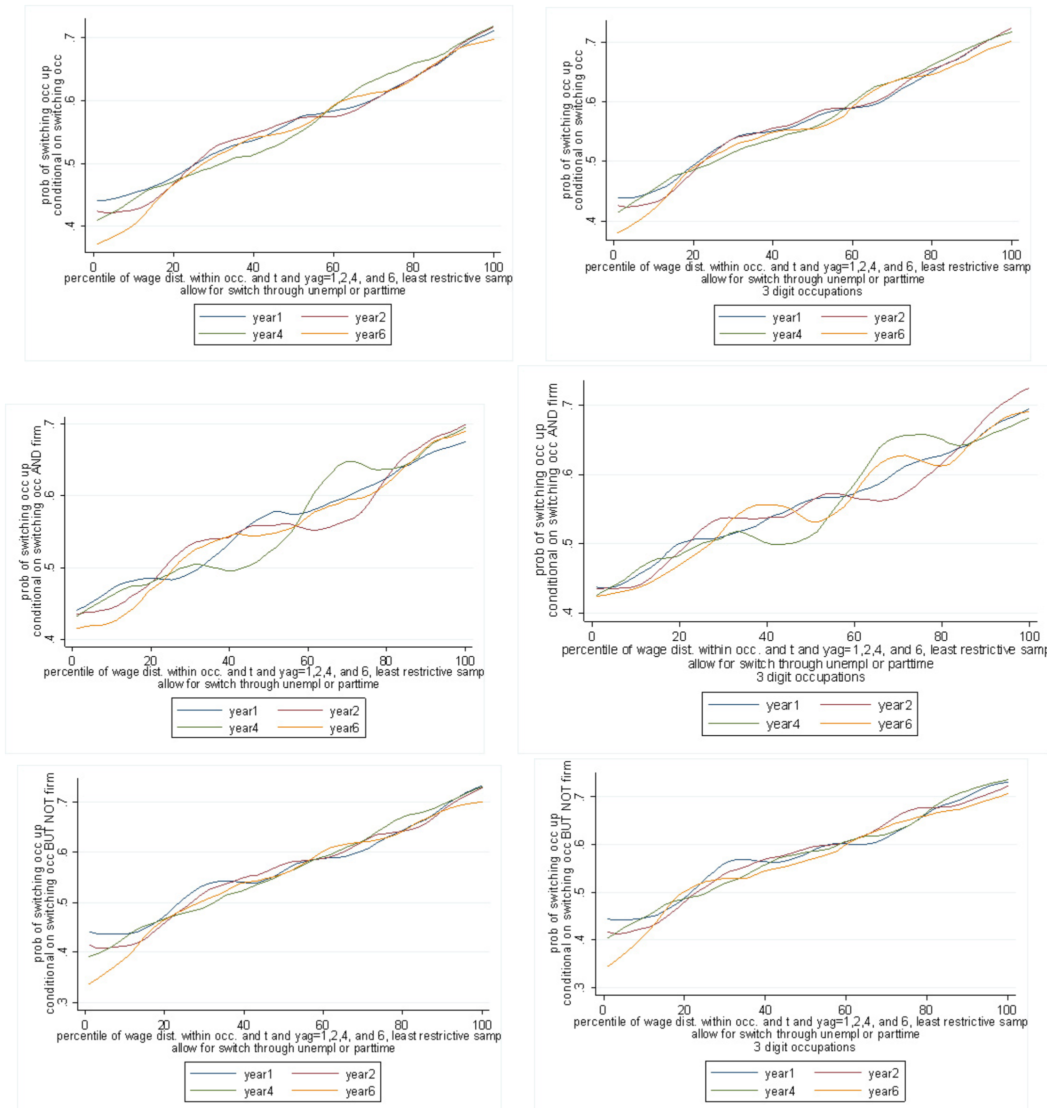


Figure A-18: Probability of switching to occupations with higher average wage conditional on switching occupation. Percentiles of wage distribution within occupation, year and 1, 2, 4 and 6 years after graduation.

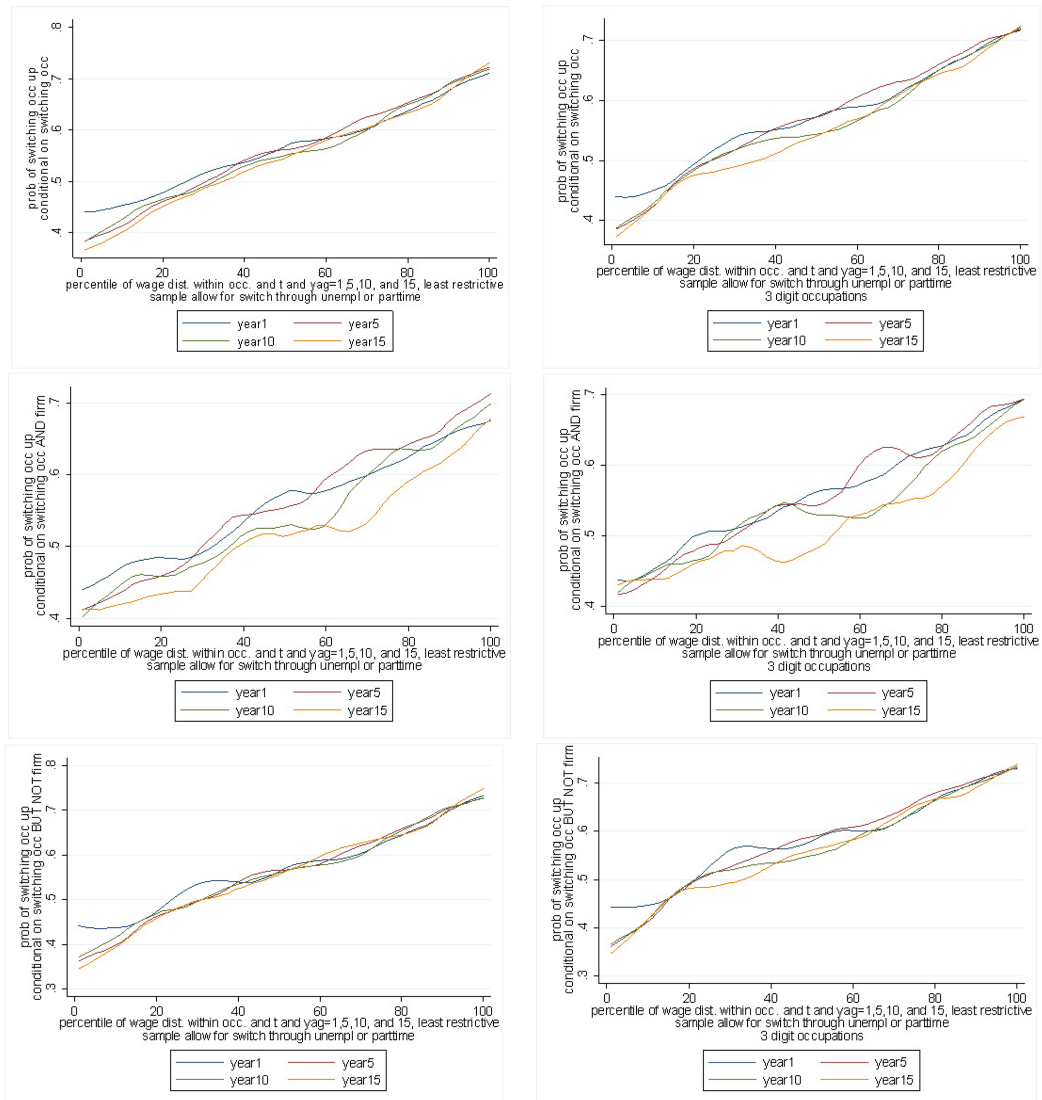


Figure A-19: Probability of switching to occupations with higher average wage conditional on switching occupation. Percentiles of wage distribution within occupation, year and 1, 5, 10, and 15 years after graduation.

A12 Appendix of mobility in response to occupations changing rank

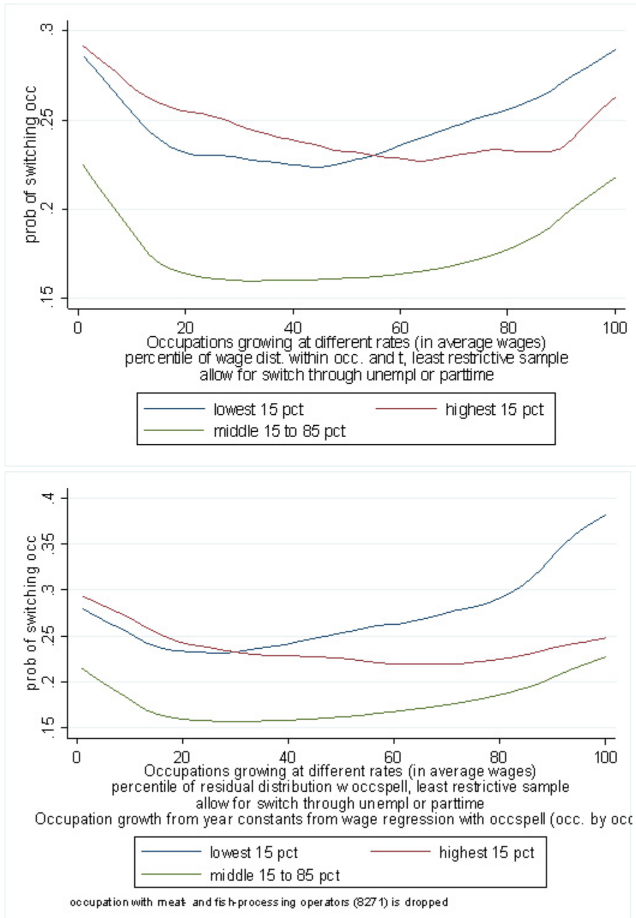


Figure A-20: Non-parametric plot of direction of occupational mobility of the public and private worker sample for occupations growing at different rates.

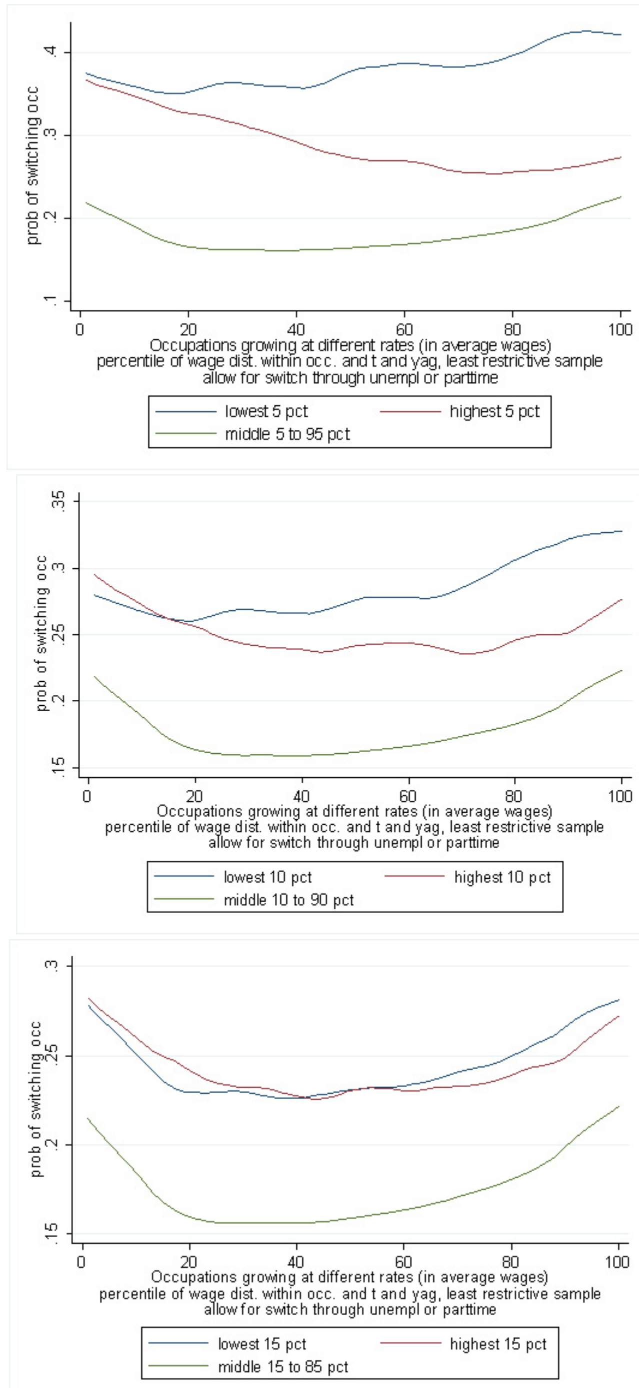


Figure A-21: Non-parametric plot of direction of occupational mobility of the public and private worker sample for occupations growing at different rates. Percentiles in wage distribution are calculation within occupation, year, and years after graduation.

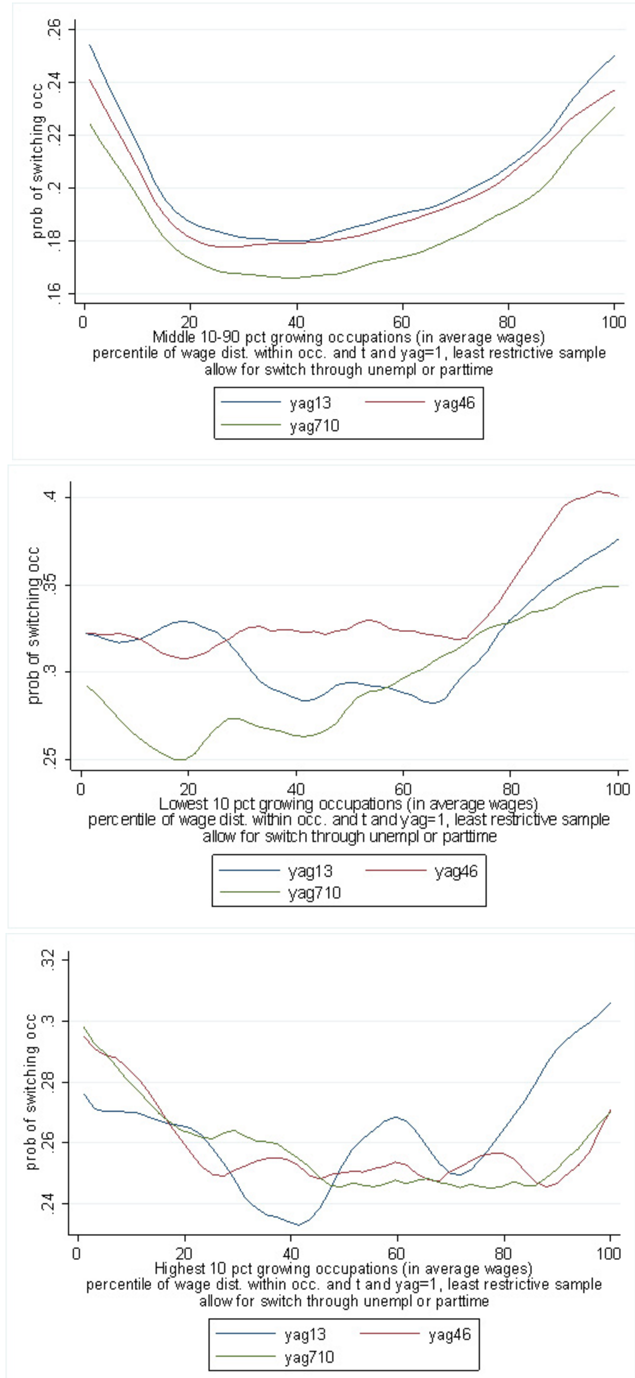


Figure A-22: Non-parametric plot of direction of occupational mobility of the public and private worker sample for occupations growing at different rates. Percentiles in wage distribution are calculation within occupation, year, and years after graduation. Plots of different groups of years after graduation.

The U-Shapes of Occupational Mobility*

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Abstract

Using administrative panel data on 100% of the Danish population we document a new set of facts characterizing the patterns of occupational mobility. We find that a worker's probability of switching occupation is U-shaped in his position in the wage distribution in his occupation. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. Workers with higher (lower) relative wage within their occupation tend to switch to occupations with higher (lower) average wages. Higher (lower) paid workers within their occupation tend to leave it when relative productivity of that occupation declines (rises).

These facts are not implied by existing theories of occupational mobility that mostly treat occupations as horizontally differentiated sets of tasks. We suggest that it might be productive to think of occupations as forming vertical hierarchies. Workers who are unsure of their abilities learn about them by observing their output realizations. Employment opportunities in each occupation are scarce, inducing competition among workers for them. Complementarities in the production function between worker's ability and productivity of an occupation induce sorting of workers into occupations according to their expected ability. We present an equilibrium model of occupational choice with these features and show analytically that it is consistent with patterns of mobility described above.

Chapter 3 of PhD thesis

*First version: June 2008. This version: July 2009. We would like to thank Martin Browning, Mette Ejrnæs and seminar participants at the University of Maryland, the 2008 Copenhagen Microeconometrics Summer Workshop and the Search & Matching workshop at the University of Pennsylvania for their comments. This research has been supported by the National Science Foundation Grants No. SES-0617876 and No. SES-0752076.

1 Introduction

When a worker switches detailed occupational categories (technician, engineer, manager) he or she moves to an observationally different technology often requiring a different set of tasks to be performed. The fraction of workers switching occupations is remarkably large. Kambourov and Manovskii (2008) document that close to 20% of workers in the U.S. switch occupations in a given year. Moreover, these gross flows are much larger than the net flows that are needed to account for the changing sizes of occupations. What is it that induces workers to undertake all these occupational changes? We provide new evidence on the patterns of occupational mobility and suggest that the standard theories of occupational mobility are not consistent with these facts. We then proceed to develop a new theory of occupational mobility.

There are two commonly used classes of models of occupational mobility. The first one, described in, e.g., McCall (1990) and Neal (1999), is based on match-specific occupational sorting. Occupations are perceived as identical (e.g., not different with respect to skill requirements), but workers find out the quality of their specific match to an occupation over time. Match-specific sorting occurs when workers realize that their match-specific shock is bad and abandon the match in favor of (the search for) a better one. The predictions from this theory are based on selection: Since those workers that are content with their match stay in their occupation, this theory predicts that the probability of switching occupation declines with tenure in that occupation, which is consistent with the data. Moreover, since good matches survive longer, wages and tenure are positively correlated in the cross-section of workers - an observation that is also consistent with the data.

A closer look at the data that we take in this paper, however, reveals that the fundamental selection mechanism in these match-specific sorting models is not consistent with the data. Virtually any model in which productivities are drawn independently for each worker-occupation-match rather than representing a permanent trait of either the occupation or the worker would predict that the probability of switching occupation is negatively related to wages which indicate match quality. Instead, we find a strong evidence that the probability of switching occupation is U-shaped in wages: not only is it people with wages lower than the occupational average, but also those with wages above the average that are more likely to switch.

The second class of existing models focuses on net mobility, which is explained by fluctuating demands for services of different occupations. They generally also imply that it is either only the people on the lower part of the wage distribution within an occupation or only in the upper part of the distribution that tend to switch in response to a change in demand conditions, rather than workers on both ends of the spectrum. This is the property of the classic Roy

(1951) model (and its extensions in, e.g., Moscarini (2001)). The models in Kambourov and Manovskii (2005, 2009a) generically have a similar prediction. They represent a version of the island economy model of Lucas and Prescott (1974) where islands are interpreted as occupations and workers accumulate occupation-specific human capital. Human capital is destroyed upon switching occupations which implies that, if workers with different levels of human capital are perfectly substitutable in the occupational production function, it is the low human capital, and hence, low wage, workers that switch first if occupational demand declines. If occupational demand rises, no one leaves the occupation.

We will show below that in the data most occupations exhibit U-shapes in mobility. On top of this, however, when an occupation experience an *increase* in demand, workers in the lower part of the wage distribution of that occupation tend to *leave* it. None of the existing theories are consistent with this pattern. The data further implies that occupational switching is non-random. A worker who is in the upper tail of the wage distribution in some occupation and decides to switch to another occupation, on average moves to an occupation with higher mean earnings. A worker who is in the lower tail of the wage distribution in some occupation and decides to switch to another occupation, on average moves to an occupation with lower mean earnings.[1] Once again, existing models do not generate such patterns. The reason is that the literature has treated occupations as horizontally differentiated sets of tasks. We think, however, that it might be productive to think of occupations as also forming vertical hierarchies.

In our theory, workers have different innate abilities. Workers and employers learn about these abilities by observing the output realizations. In difference to, e.g., Johnson (1978), Miller (1984), Papageorgiou (2007), and Eeckhout and Weng (2009) the speed of learning is independent of the occupation the individual is working in, which allows us to consider more than two occupations without loosing tractability.[2] This turns out to be important to understand the U-shapes in the switching pattern. Employment opportunities in each occupation are scarce - for example because other factor inputs to production are fixed or exhibit increasing costs when more employment is created.

With scarce employment opportunities workers compete for jobs. With complementarities

[1] Nevertheless, a worker who leaves an occupation from the top of its wage distribution on average experiences a decline of his wage growth upon a switch, while a switcher from the bottom of the occupational distribution experience an increase in wage growth.

[2] Closest in spirit are Papageorgiou (2007) and Eeckhout and Weng (2009) who have a sorting model. Both consider two occupations. In Papageorgiou (2007) news is asymmetric in the sense that a higher probability of being good in one sector implies a higher probability of being bad in the the other sector. In Eeckhout and Weng (2009), similar to our paper, news is symmetric in the sense that positive news about the ability in one sector also means a higher productivity in the other sector.

in the production function between workers' ability and productivity of an occupation, the more able workers will in equilibrium occupy the jobs in more productive occupations. As agents learn that they are either too good or too bad for a given profession they switch to a more appropriate one, which induces the U-shapes. Those workers that are talented move to more productive occupations, while those that are less talented switch to less productive occupations. Even those workers that switch to lower productivities benefit relative to staying. If they would attempt to stay they would block a better suited worker from the job. In a competitive labor market this opportunity cost translates directly into low wages for the inappropriate worker. In fact that wage is below the wage in a less productive profession for which the opportunity costs are not that high.[3] A similar logic applies with free entry when jobs in more productive occupations have higher capital costs: With complementarities in production only workers with high ability will be willing to pay the cost of creating a job in a highly productive occupation.

Extensions of this idea that allow for changing occupational productivities reveal that occupations with rising productivity indeed expand their high-ability workforce while shedding lower-ability workers in order to match the skill of their workforce to the productivity of the jobs. Similarly, occupations with declining productivity increase their low-ability workforce and loose the high-ability workers to better occupations. These insights obtain with fixed production factors as well as when entry is not fully elastic. In another extension we take into account that even in our vertically differentiated view of occupations a switch requires a new set of skills which induces costs to occupational switching (see e.g. Shaw (1984, 1987); Kambourov and Manovskii (2009b)). For example, engineers that move up to manage small groups need to adjust their human resource skills, while those that move down to become technicians need to adjust their applied skills. We extend our analysis to allow for occupation-specific human capital accumulation and retraining costs and show that U-shapes still arise. Since our findings challenge the importance of selection for wage growth because both bad *and good* workers leave occupations, human capital is the obvious remainder that can account for the positive relation between wages and occupational tenure.[4]

This theory of occupational mobility is related to the setup in Gibbons, Katz, Lemieux, and Parent (2005), which also features learning that is independent of occupational choice. Their main focus is not the switching patterns directly, but on an econometric instrumental variable approach that allows for a consistent determination of the parameters of a wage equation in the presence of such learning. Despite differences in focus and functional form, our analysis can be applied to their model, as we do in the discussion section. Conversely, adaptation of their

[3]The wage offer might in fact become negative, which we might interpret as firing.

[4]Our theory does generate returns to general experience as workers are able to sort better after learning.

econometric technique will allow consistent estimation of the parameters also in our model.

As a word of caution, we do not think that the simple vertical sorting mechanism that we propose accounts for the full extent of occupational mobility. Both vertical and horizontal moves arise in the labor market, i.e. some occupations are considered better than others while some are just different. And among those that can be ranked the ranking might change over time. Therefore it is likely that match-specific components and the volatility of productivities of occupations or of the demands for their services are responsible for a nontrivial share of mobility. We do think, however, that the mechanism we emphasize should be an important part of any comprehensive theory of occupational mobility.

The remainder of the paper is organized as follows. In Section 2 we describe the set of new facts that characterize occupational mobility. In Section 3 we present the model that is consistent with the facts we document. Section 4 presents relevant extensions to our theory and Section 5 discusses it's contributions vis a vis the existing literature. Section 6 concludes.

2 The U-shapes of occupational mobility: Evidence

2.1 Data

We use the administrative Danish register data covering 100% of the population in the years 1980 to 2002. The first part of the data is from the Integrated Database for Labor Market Research (IDA), which contains annual information on socioeconomic variables (e.g., age, gender, education, etc.) and characteristics of employment (e.g., private sector or government, occupations, industries, etc.) of the population. Information on wages is extracted from the Income Registers and consists of the hourly wage in the job held in the last week in November of each year. Wage information is not available for workers who are not employed in the last week of November. The wages are deflated to the 1995 wage level using Statistics Denmark's consumer price index and trimmed from above and below at the 0.995 and 0.005 percentile for each year of the selected sample described below.

We use the Danish rather that the U.S. data for two reasons. First, the sample size is much larger. One of our objectives is to document the patterns of occupational mobility depending on the position of the individual in the wage distribution within her occupation. A sample sufficiently large to be representative *in each occupation* is essential for this purpose. Second, the administrative data minimizes the amount of measurement error in occupational coding that plagues the available US data (see Kambourov and Manovskii (2009b)). Nevertheless, we find that the features of occupational mobility that can be compared between the U.S. and

Denmark are quite similar (see Groes (2009)). This leads us to expect that the patterns of occupational mobility that we describe using Danish data generalizes to, e.g., the U.S.

2.1.1 Sample selection

While the Danish register data dates back to 1980, because information on firm tenure is available only after 1995 and because of a change in the occupational classification in 1995, we study the data spanning the 1995-2002 period (the latter cut-off was dictated by the data availability at the time we performed the analysis). We use the pre-1995 data in constructing some of the variables. For example, in 1995 the two occupational classifications used in the Danish register data are linked to the worker's job which allows us to construct measures of occupational tenure. For example, a worker will be considered to have 5 years of occupational experience in 1996 if he is observed in the same occupation in 1995 and 1996 according to the new occupational classification and at the same time has the same occupational classification from 1992 to 1995 according to the old occupational classification.

We only select male workers in order to minimize the impact of the fertility decision on labor market transitions. Due to data limitations the sample is restricted to full time workers in the private sector. In the period 1995 to 1998 we do not observe the workplace of public employees and, to be able to use tenure information, we choose to include only the privately employed (rather than further restricting the time dimension of the data). The part-time workers are excluded because they do not have as dependable wage information. The sample is restricted to employees because we do not observe earnings for the self employed.

To construct experience and tenure variables we need to observe each individual's entire labor market history. Thus, our sample includes all individuals completing their education in or after 1980 if they remain in the sample at least until 1995. The sample includes graduates from all types of education from 7th grade to a graduate degree conditional on observing the individual not going back to school for at least three years after graduation. Thus, a worker who completed high school, worked for three years, then obtained a college degree and went back to full time work will have two spells in our sample: first, the three years between high school and college, and second, after graduating from college. If he worked for less than three years between high school and college, he joins our sample only after graduating from college. We truncate the workers' labor market histories the first time we observe them in part-time employment, public employment, self employment, or at the first observation with missing wage data.

Finally, since we study occupational mobility between consecutive years, the sample only includes workers with valid occupation data in the year after we use them in the analysis[5] (e.g., we use information from 2002 for this purpose).

Descriptive statistics of our sample are provided in the Table 1. Column 1 is the sample described above. Column 2 is for the sample where there is at least 10 workers in each occupation in each year. Column 3 is for the sample with at least 10 workers in each occupation, year, and years after graduation category and column 4 is for the sample with at least 100 workers in each occupation and year. These samples will be used in the analyses below.

Table 1: Summary statistics for the overall sample and subsamples

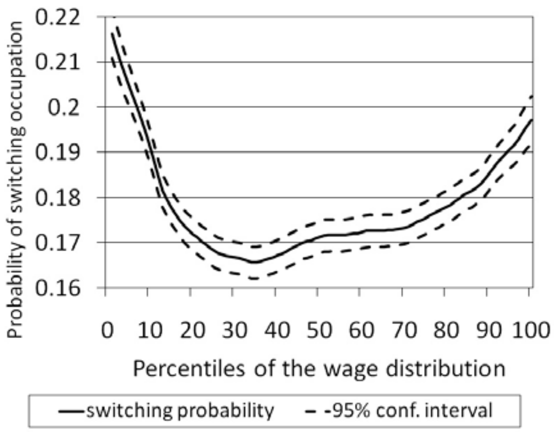
	Full sample	Over 10 per occupation and year	Over 10 per occupation, year, and experience	Over 100 per occupation and year
Number of observations	404800	402136	368520	375367
Number of occupations	353	229	143	105
Age	29.67	29.66	29.49	29.57
Occupational tenure	4.41	4.41	4.41	4.44
Occupational spell number	1.69	1.69	1.67	1.68
Occupational switchers	0.18	0.18	0.17	0.17
Employer tenure	2.36	2.36	2.33	2.35
Industry tenure	3.38	3.38	3.35	3.38
Years after graduation	6.49	6.49	6.40	6.48
Less than 12 years of school	0.04	0.04	0.04	0.04
Apprenticeship education	0.69	0.69	0.70	0.70
2 year university	0.10	0.10	0.10	0.10
Bachelor	0.10	0.10	0.09	0.08
Masters degree or above	0.07	0.07	0.06	0.06
Hourly wage in DKK in 1995	170.16	170.13	168.75	169.49
Married	0.30	0.30	0.30	0.30
Union	0.94	0.94	0.94	0.94
Number of children	0.71	0.71	0.70	0.71

2.2 U-shapes in the probability of occupational switching

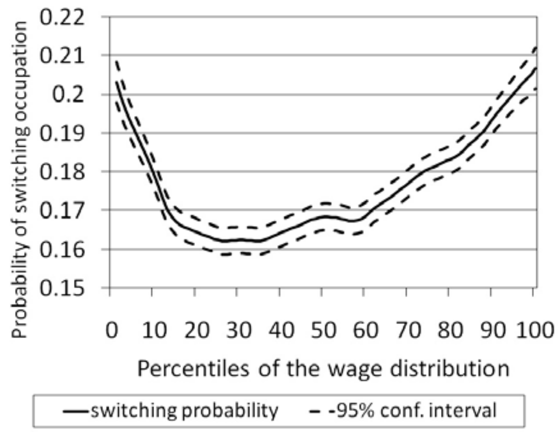
In this section we present evidence of U-shapes in the probability of occupational switching. Figure 1(a) is a non-parametric plot (from a kernel smoothed local linear regression with band-

[5]In Groes (2009) we show that all results hold for a larger sample including both private and public sector workers who are allowed spells of non-employment and part time work. Furthermore, we allow workers to switch occupation through non-employment and part time work.

width 5) of the probability of switching out of an occupation as a function of a worker's position in the wage distribution *in that occupation* in a given year. The probability of switching occupation is clearly U-shaped in wages. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. The workers in the middle wage deciles have the lowest probability of switching occupations.



(a) wage distribution of raw wages within occupation and year



(b) wage distribution of wage residuals

Figure 1: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution.

Figure 1(a) is based on raw wage data. Figure 1(b) indicates that we also observe a U-shaped pattern of occupational mobility in the position of the worker in the distribution of residual wages in his occupation in a given year. We generate residual wages by estimating a standard wage regression

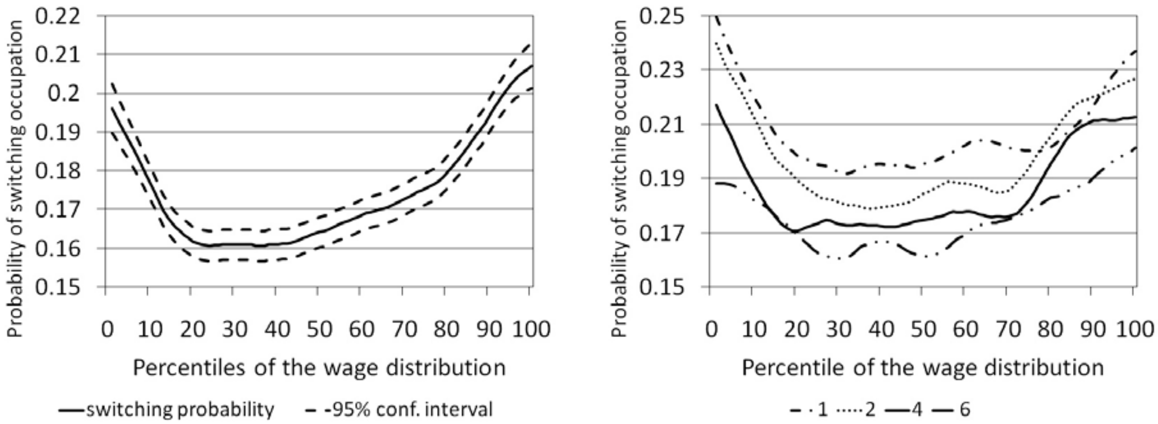
$$lnw_{ijt} = X_{ijt}\beta + \epsilon_{ijt}, \tag{1}$$

where w_{ijt} is real hourly wage of an individual i working in occupation j in period t. The explanatory variables in X include dummies for calendar years, third degree polynomials in general experience, occupational tenure, industry tenure, a second degree polynomial in firm tenure, number of occupational spells, education, marital status, union membership, and regional dummies. These wage regressions are estimated separately for each occupation.[6]

The U-shapes further hold if we look at wage percentiles within occupation, year, and years after graduation. Figure 2(a) plots the probability of switching occupation as a function

[6]Figure A-1 in Appendix A2 shows that excluding the regressors firm and industry tenure or excluding dummies for the occupational spell number in the wage regression does not change the qualitative result of the U-shape in occupational mobility. In the Appendix Figures A-2 to A-5 we show that the U-shapes hold for bandwidths which are half and double of what we use in Figures 1 and 2.

of worker's position in the wage distribution of workers in the same occupation, calendar year, and years after graduation. Figure 2(b) separately graphs occupational mobility for 1, 2, 4, and 6 years after graduation. The figure shows U-shapes in occupational mobility for all years after graduation and shows that the level of mobility decreases with years after graduation for almost all percentiles of the within occupation, calendar year, and years since graduation wage distribution.



(a) wage distribution of raw wages within occupation, year, and years after graduation

(b) wage distribution of raw wages within occupation, year, and years after graduation for different years after graduation

Figure 2: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation, year, and years after graduation.

An additional informative statistic is the percentage of occupation-year pairs that exhibit U-shapes. Computing this statistics requires enough workers in each occupation in each year to accurately predict a probability of changing occupation in different parts of the wage distribution of that occupation. Thus, we restrict the sample to occupations that include at least 100 workers in a given year and we divide the wage distribution of each occupation into quintiles. We define U-shapes in each occupation-year pair in two ways. First, we count an occupation in a given year as having a U-shape if the quintile with the highest probability of changing occupation is either quintile 1 or quintile 5. Second, we count an occupation in a given year as having a U-shape if, in addition, the quintile with the lowest probability of changing occupation is in the interior, i.e., quintile 2, 3, or 4. There are 598 occupation-year observations with at least 100 workers. 95 Percent of these have maximum probability of switching occupation in one of the extreme quintiles when the quintiles are based on raw wages. When the quintiles are defined on the wage residuals, 98% of occupations exhibit U-shapes according to this definition. In addition, 66% of the these occupations have a global minimum in the interior of the distribution of raw wages and 77% of the these occupations have a global minimum in the interior of the distribution of wage residuals[7].

2.3 U-shapes in the direction of occupational switching

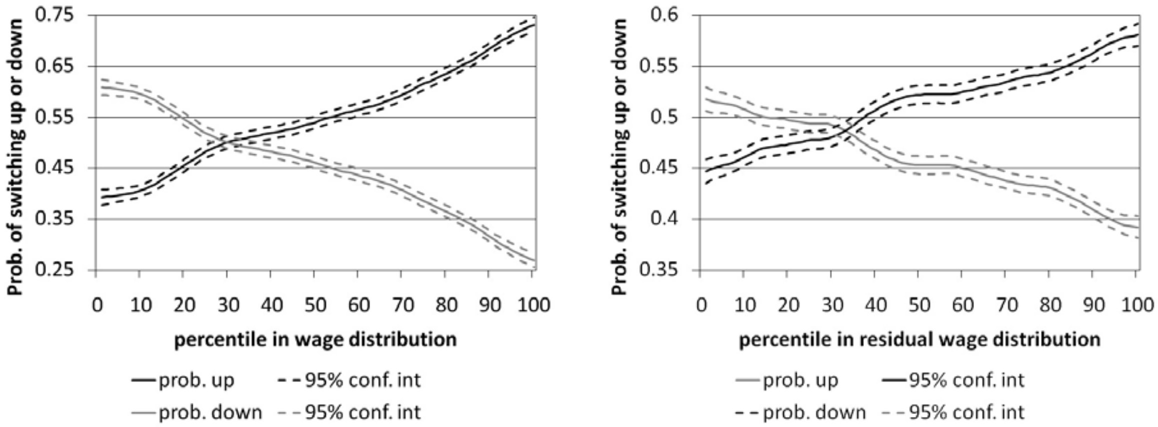
In this section we document another prominent feature of the data: conditional on changing occupation, workers with higher (lower) relative wage *within* their occupation tend to switch to occupations with higher (lower) *average* wages. We first find the average wage of the occupations in a given year in order to determine the ranking between occupations. Similarly to our analysis of probability of occupational switching, we rank occupations based on their raw wages or residual wages adjusted for worker characteristics. To obtain the ranking based on raw wages, we find the average real wage of all full time private sector workers in a given occupation in a given year.[8] To obtain the ranking based on residual wages, we use our selected sample to run a similar wage regression as in Equation 1 for each occupation where we include time dummies in the regression (without the intercept). We interpret the coefficients on these time dummies as the average occupational wage in a given year, adjusted for human capital accumulation of workers in the occupation as well as other worker characteristics such as education, regional dummies, and marital status. For this wage regression we include only occupations which have more than 100 observations in total over the 8 year period 1995-2002.

Figure 3(a) plots the probability of switching to an occupation with a higher or lower average wage as a function of the worker's position in the wage distribution of the occupation he or she is leaving. The sample on which the figure is based consists of all workers who switched occupation in a given year and occupations are ranked based on the raw average wages. Figure 3(b) presents corresponding evidence when occupations are ranked based on residual wages and the direction of occupational mobility is plotted against the percentile in the distribution of residual wages within an occupation the worker is switching from. The evidence contained in these figures suggest that, conditional on switching occupation, the higher wage a person had in his occupation before the switch the higher is the probability that the worker will switch to an occupation with a higher average wage. Similarly, the lower wage a worker has in his occupation the higher is the probability that he will switch to an occupation with a lower average wage than in the occupation he switches from.

Figure 4(a) illustrates that similar results hold if we further condition on workers position

[7]In Groes (2009) we show that this way of measuring U-shapes is robust to letting the wage percentiles be a 2^{nd} order polynomial in each occupation and testing for the significance of the polynomials.

[8]Note that this is a bigger sample than our selected sample, which only consists of workers who graduated after 1980 and who never worked in the public sector, worked part time, etc. The results are, however, robust to only looking at the average wages in our selected sample.



(a) wage distribution of raw wages within occupation and year. Average wage in occupation from population.

(b) wage distribution of wage residuals. Average wage in occupation from time constants in wage regression

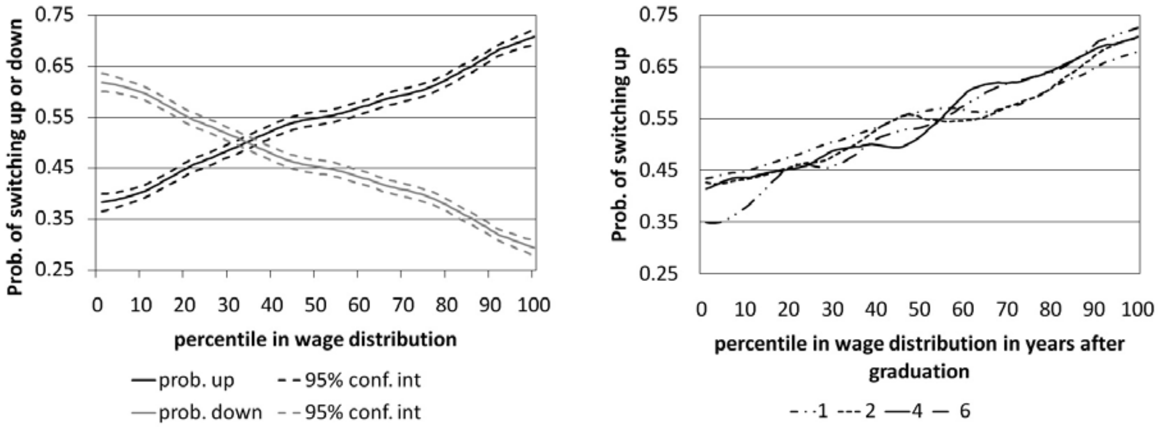
Figure 3: Non-parametric plot of direction of occupational mobility, conditional on switching occupation.

in the distribution of wages in his occupation in a given year *and* among people with the same number of years since graduation. This figure is comparable to figure 3(a) in that occupational average wages are calculated from raw wages of the population in the occupation in a given year. Finally, Figure 4(b) shows that the direction of occupational mobility is similar for individuals who graduated 1, 2, 4, or 6 years prior.

2.4 Summary

To summarize the evidence presented so far, the probability of switching out of most occupations is U-shaped in the position of the worker in the wage distribution of that occupation. Workers with high wages relative to their occupational average switch to occupations with higher average wages. Workers with low wages relative to their occupational average switch to occupations with lower average wages.

As mentioned in the Introduction, these patterns are not implied by the existing theories of occupational mobility. Hence, in what follows we develop an alternative theory that is consistent with these features of the data. We confront additional implications of our theory with the data as we derive them.



(a) wage distribution of raw wages within occupation, year, and year after graduation. Average wage in occupation from population.

(b) wage distribution of raw wages within occupation, year, and year after graduation for individual years after graduation. Average wage in occupation from population.

Figure 4: Non-parametric plot of direction of occupational mobility, conditional on switching occupation.

3 The U-shapes of occupational mobility: Theory

The economy is set in a discrete-time infinite horizon setting, where workers choose employment in different occupations over time.

Workers: Each period a measure α of workers enters the labor market. The index for an individual worker will be i throughout. Each worker is in the labor force for T periods. Workers are risk-neutral and discount the future by factor β. Each worker has an ability level a_i that is drawn from a normal distribution with mean μ_a and variance σ_a. The amount of output that a worker can produce depends on his ability. In particular, he produces

$$X_i = a_i + \varepsilon_i \tag{2}$$

in a given period, where ε_i is a normally distributed noise term with mean zero and variance σ_ε. Workers don't know their precise ability, but observe the output they produce, even if they choose home production. We assume that the worker observes a first draw after finishing school, i.e. before the first time in the labor market, so that not all workers are identical when entering the labor force.[9]

While we think that not only ability but also occupation-specific human capital accumulation is an essential feature that leads to wage growth and that limits occupational switching,

[9]The signal after school could have a different variance than the output realization - this would only complicate the notation slightly without altering the qualitative results.

we first abstract from this to highlight the main insights of vertical occupational sorting in the simplest setting possible. We briefly return to this point in Section 4.

Occupations: There are a finite number of occupations, indexed by $k \in \{0, 1, ..., K\}$, in which workers can be employed. In each occupation the number of job opportunities is fixed to some measure γ_k that is constant over time. One can think of a limited measure γ_k of entrepreneurs who know how to implement the specific technology k, and each needs exactly one workers to operate the technology. The limited number of jobs in an occupation allows entrepreneurs to earn rents. We discuss entry of entrepreneurs in Section 4.

Each unit of the good (or service) that is produced sells in the market at some exogenously given price P_k. We refer to the price of output also as the productivity of the occupation, and rank occupations in order of increasing productivity such that $P_K > ... > P_k > ... > P_0 = 0$. We interpret the lowest occupation as home production, which means that it is available to everybody.[10] An entrepreneur of type k who employs worker i thus obtains revenues

$$R_{ki} = P_k X_i.$$

This revenue function is supermodular, i.e. entrepreneurs in more productive occupations gain more from employing a more able worker than entrepreneurs in less productive occupations.[11]

Wages: We consider a competitive economy without matching frictions. The only frictions are information frictions in the sense that workers' abilities are not known. We assume that firms compete by posting output-contingent wages $w(X)$. An entrepreneur in occupation k who employs worker i has then an expected profit

$$\Pi_k = E(P_k X_i - w_k(X_i))$$

If an entrepreneur in occupation k can ensure himself some expected profit Π_k in any period by employing some specific worker i, he can simply offer wage contract

$$w_k(X) = P_k X - \Pi_k \tag{3}$$

[10] Availability to everybody means that $\gamma_0 > \alpha T$. The home production option guarantees that workers who have negative ability can still obtain a non-negative payoff. Our assumption that output is also observed in home production implies that there is no differential in the speed of learning.

[11] We note here that it is trivial to account not only for price differences but also for differences in the productivity of output generation across occupations because we can reinterpret P_k as the combination of selling price and the firms contribution to output. For example, an equivalent interpretation of our setup is that prices in all occupations are identical, but workers in occupation k product $P_k a_i$ units of output. In this interpretation jobs in more productive occupations can be viewed as higher up in a hierarchy that produces a homogeneous good (i.e. one manager may be equally important to production as several of his subordinates).

to any arbitrary worker. Worker i is still willing to work at this firm because his expected wage is unchanged, and any other worker who accepts the job does not make the firm worse off. Therefore, such a "selling-the-shop" wage schedule has the effect that the firm does not need to know the type of the worker, but just needs to know how much profit it wants to secure to itself. It then adjusts the worker's wages according to (3) through performance-dependent boni/penalties in order to achieve this profit. We can therefore reinterpret the model as the workers offering a payoff Π_k to the entrepreneurs in occupation k for the right to work there and retain the surplus that is created.

For workers only the expected wage that they can earn in a given occupation matters. If firms obtain expected profits Π_k with the wage schedule in (3) and a worker holds a belief about his own ability with a *mean* of A_i in this period, then his expected wage when working in occupation k is

$$\overline{w}_k(A_i) = P_k A_i - \Pi_k. \tag{4}$$

Without any costs to switching occupations it is clear that workers will choose the occupation that offers the highest expected wage. (We discuss switching costs together with specific human capital in the extensions.) Therefore, if workers switch occupations this happens because the expected wage in the alternative occupation is higher than the expected wage that they can obtain in their old occupation given the new information about their ability. While this sounds like voluntary quits by the worker, one may easily think of this as layoffs: If a worker realizes that he is worse than expected, the expected wage that he obtains after leaving profit Π_k to the entrepreneur might be very low in the current occupation. Such a wage offer might be interpreted as firing.

We have taken the stance that firms offer output contingent contracts so that workers self-select in the appropriate occupations even if the firm has no information about the prior work history (and the revealed signals). If the firm does observe the prior work history and has symmetric information relative to the worker, it can equally well offer a fixed wage based on the expected ability. This would correspond to the expected wage in (4). While we take a stance favoring the former, the prediction of U-shapes is robust to this assumption. We show U-shapes both in realized wages as well as in the expected wages that arise if the firm bears the risk of employment.

To formalize the optimal choice by the workers, let $I_k(A, \Pi)$ be the following indicator function: $I_k(A, \Pi) = 1$ if the expected wage according to (4) in occupation k is higher than in any other occupation, and $I_k(A, \Pi) = 0$ otherwise. Clearly this indicator depends on the vector $\Pi = (\Pi_1, \Pi_2, ..., \Pi_K)$ of profits that have to be left to the firms.

Updating: Neither workers nor entrepreneurs are sure about a worker's true ability. Each worker observes his output X_i and updates his beliefs according to Bayes' law. We are agnostic about whether firms learn as well, i.e. whether they observe the output history of a worker or not. The driving force in this model is the workers belief about his *mean* ability A_i in a given period. Of interest in solving the model is

1. how a worker updates his belief about his individual *mean* ability. This determines how individuals change occupations.

2. how beliefs about the *mean* ability are distributed across the population. This determines the equilibrium profits Π_k and the associated wage offers according to (4).

For the first point, it is convenient to use the concept of precision, which is the inverse of the variance. Let $\phi_a = 1/\sigma_a$ and $\phi_\varepsilon = 1/\sigma_\varepsilon$, and define $\phi_t = \phi_a + t\phi_\varepsilon$ as the cumulative precision. A worker's initial belief about his mean ability before any output realization is $A_i^0 = \mu_a$. Consider a worker who has prior A_i^t in any period $t \in \{0, 1, .., T\}$ of his life and observes output realization X_i. Standard results on updating of normal distributions establish that his posterior mean A_i^{t+1} is the precision-weighted average of his prior mean and the observation

$$A_i^{t+1} = \frac{\phi_t}{\phi_{t+1}} A_i^t + \frac{\phi_\varepsilon}{\phi_{t+1}} X_i. \tag{5}$$

The weight on the prior increases the more observations have already been observed in the past, i.e. the higher is t. Correspondingly, the weight on the most recent observation decreases with years in the labor market. Workers become more convinced over time of their ability. Since workers draw once before entering the labor market, A_i^1 is the prior at the beginning of the first period of work. So the worker's posterior belief about his *exact ability* a_i is a normal with mean A_i^{t+1} and a variance of $1/\phi_{t+1}$.

For agents with prior A^t the realization of output and the resulting posterior mean A^{t+1} is still random. We denote the distribution of this posterior by $G_t(A^{t+1}|A^t)$ and its density by $g_t(.|.)$. One can show that this posterior is normally distributed with mean A^t and precision $\phi_t\phi_{t+1}/\phi_\epsilon$.[12] It is not important that the update is normally distributed. The following qualitative properties suffice for the results we want to show: $g_t(.|A)$ is single-peaked and symmetric

[12] Conditional on knowing the true ability a of a worker, the output X is distributed normally with mean a and precision ϕ_ϵ, i.e. $X \sim N(a, \phi_\epsilon)$. Yet the ability is not known. Rather, the individual only knows his expected ability A while his true ability is a draw $a \sim N(A, \phi_t)$. Integrating out the uncertainty over his ability implies that output is distributed $X \sim N(A, \phi_\epsilon\phi_t/\phi_{t+1})$. We are not interested in the output per se, but in the update $A' = (\phi_\varepsilon X + \phi_t A)/\phi_{t+1}$ that is a function of output. This linear combination implies that that the posterior distribution $G_t(A'|A)$ is a normal with mean A and precision $\phi_t\phi_{t+1}/\phi_\varepsilon$, i.e. $A' \sim N(A, \phi_t\phi_{t+1}/\phi_\varepsilon)$

around its peak at A, and shifting the mean A simply shifts the entire distribution about the posterior horizontally in the sense that $g_t(A'|A) = g_t(A' + \delta|A + \delta)$ for any δ. We call this last property lateral adjustment.

For the second point, note that at any point in time there is a measure α of workers that have been in the labor force for $t \in \{1, ..., T\}$ periods. Call the measure of workers in cohort t that have a belief regarding their mean ability weakly below A by $F^t(A)$, which is a non-normalized normal distribution.[13] We call the sum of this measure over the cohorts $F(A) = \sum_{t=1}^{T} F^t(A)$. Note that this distribution is independent of the choices of the agents because workers learn about their type in any eventuality. This simplifies the specification of an equilibrium substantially.[14] For simplicity we will assume that there are enough workers with positive levels of ability to fill all the jobs.[15]

Equilibrium: We are considering a standard stationary competitive equilibrium in this matching market between occupations and workers. Stationary means that the entrepreneurs' profits $(\Pi_1, \Pi_2, ..., \Pi_K)$ and the associated wage offers according to (3) are constant over time. Equilibrium implies that the workers' decisions equate demand and supply, where Π_k can be interpreted as the price workers have to pay to take over a job in occupation k.

Definition 1 *An equilibrium is a vector of profits* $\Pi = (\Pi_0, ..., \Pi_K)$ *with* $\Pi_0 = 0$ *such that markets clear, i.e. for all* $k > 0$

$$\int I_k(A, \Pi) dF = \gamma_k.$$

As is standard in competitive equilibrium theory, one can interpret the market profits Π as optimal decisions by the entrepreneurs. Decreasing the demanded profit (i.e. increasing the wage) is not optimal because already all entrepreneurs employ a worker. Increasing the demanded profit (i.e. decreasing the wage) does not attract any worker, because workers expect

[13] Non-normalized means that the mass under the density does not necessarily add up to one. In our case id adds up to $F^t(\infty) = \alpha$ since the size of cohort t is α. Let $\tilde{F}_t$ be the probability that any given worker has a belief about his mean ability below A in period t. Then $F^t = \alpha\tilde{F}_t$. At the beginning of period t the workers have observed t output observations. The only relevant information for the worker is the average $\bar{X}$ of these output realizations. Conditional on a this is distributed normally with mean a and precision $t\phi_\varepsilon$. Since a is not known, an agent with prior μ_a faces realizations of $\bar{X}$ that are normal with mean μ_a and precision $t\phi_\varepsilon\phi_a/\phi_t$. Since the update is $A^t = (t\phi_\varepsilon\bar{X} + \phi_a\mu_a)/\phi_t$, $\tilde{F}^t$ is normal mean μ_a and precision $\phi_t\phi_a/(t\phi_\varepsilon)$.

[14] Other work such as Jovanovic and Nyarko (1997) and Papageorgiou (2007) focuses on differential speed of learning, which substantially complicates the analysis and limits the analysis in these papers to two occupations only. Moreover, these papers do not consider the implications for the U-shapes of switching behavior on which our analysis is centered.

[15] The precise condition for this is $\alpha T - F(0) > \sum_{k=1}^{K} \gamma_k$. Otherwise entrepreneurs in the less productive occupations do not fill their positions and thus these low occupations will not be observed.

to be able to work at the market wages. The indicator function $I_k(A, \Pi)$ ensures that workers indeed take optimal decisions when determining market clearing.

3.1 Analysis of Sorting

The tractability of the model arises from the fact that every period workers can reoptimize and therefore their life-time optimal decision is also the decision that maximizes the payoffs in each period. Since the distribution of mean abilities remains constant, we can solve most aspects with the standard tools for the analysis of static matching models. We provide these results first. Then we turn to problem that workers face over time as their individual uncertainty induces agents to switch occupations as they transit to the stationary economy. These individual uncertainty yields high gross mobility of workers between occupations, even though the net mobility is by assumption zero in steady-state. Since gross mobility dwarfs net mobility in magnitude, this seems to be an important starting point. We will introduce reasons for net mobility in the extension section.

3.1.1 Preliminaries

The model can be easily be solved. In a given period, a worker's decision only depends on his prior A about his mean ability. The revenue function $R = PA$ is super-modular, i.e. $\partial^2 R/(\partial P \partial A) > 0$. A result from the matching literature going back to Becker (1973) is that under supermodularity entrepreneurs in more productive occupations match with workers with higher mean ability in equilibrium. This is easy to see in our setup. Firms with higher productivity clearly make higher profits. A worker will choose occupation $k \geq 1$ over occupation $k-1$ only if the expected wage according to (4) is higher in the former, i.e.

$$P_k A - \Pi_k \geq P_{k-1} A - \Pi_{k-1}.$$

This is equivalent to

$$A \geq \frac{\Pi_k - \Pi_{k-1}}{P_k - P_{k-1}} := B_k, \tag{6}$$

where B_k is the mean ability at which a worker is exactly indifferent between the two occupations. This shows that workers with a higher belief about their mean ability choose higher occupations. since these workers can always mimic the choices of workers with lower beliefs, they have to earn higher wages than those. And since they choose better occupations, better occupations can be identified by the fact that they pay on average higher wages.

Since we assumed that there are enough workers with positive mean ability, all but the home production occupation will obtain strictly positive profits in equilibrium. To fulfill market clearing, it has to hold for all $k > 0$ that

$$F(B_{k+1}) - F(B_k) = \gamma_k, \tag{7}$$

where $B_{K+1} = \infty$. Moreover, (6) implies $B_1 = \Pi_1/P_1$ and the measure of employed workers has to equal the overall demand for workers, which determines Π_1.[16] Then (6) and (7) can be used successively for higher k to determine the profits for all higher occupations. This constructively gives existence and exact levels for the profits in all occupations.

3.1.2 Occupational mobility conditional on expected ability

An important part of the previous analysis is that it gives the levels B_k that determine at which belief a worker switches to a different occupation.

Consider a worker who has worked for $t > 1$ years and had a prior of $A \in [B_k, B_{k+1})$ in his t'th year of work. That is, he chose occupation k in the last period he worked. He will switch to a higher occupation between t and $t+1$ if his posterior $A^{t+1} > B_{k+1}$. We denote the probability of such an upward switch out of occupation k by $s_k^+(t, A^t)$. Conditioning on A^t is identical to *conditioning on the expected wage* $\bar{w}$ in (4) because of the one-to-one mapping between the two. The switching probability is given by

$$s_k^+(t, A^t) = 1 - G_t(B_{k+1}|A^t).$$

Similarly, if $A^{t+1} < B_k$ then the worker will switch to a lower occupation with a lower mean wage. We denote the probability of such a downward switch out of occupation k by $s_k^-(t, A^t)$ and have

$$s_k^-(t, A^t) = G_t(B_k|A^t).$$

The total switching probability is then $s_k(t, A) = s_k^-(t, A) + s_k^+(t, A)$. The domain of these functions is $[B_k, B_{k+1})$ because only with these priors would a worker choose occupation k.

In the following we will adopt the following convention, where our properties always refer to the second argument and not to the cohort indicator. Fix the cohort indicator t, then

Definition 2 (U-shapes) *A function $f(t, .)$ is U-shaped if it has local maxima at the boundaries of its domain and one of these is a global maximum.*

[16]The condition is $\alpha T - F(B_0) = \sum_{k=1}^{K} \gamma_k$.

Definition 3 (Strict U-shapes) *A function $f(t,.)$ is strictly U-shaped if it is U-shaped and its negative $-f(t,.)$ is strictly quasi-concave.*

U-shapes capture the qualitative feature that switching probabilities increase toward each of the ends of the domain, i.e. in the context of $s(t,.)$ switching becomes more likely for workers with low and high expected wages (abilities). Strict U-shapes additionally ensure that the switching probability increases monotonically from its interior minimum toward the extremes of the domain.

We will first consider the overall switching probability of a worker with prior $A \in [B_k, B_{k+1})$ in his t'th year of his work life

$$s_k(t,A) = G_t(B_k|A) + 1 - G_t(B_{k+1}|A).$$

We consider interior occupations $k \in \{1,...,K-1\}$ that are not at the extreme end of the spectrum. Since the distribution $g_t(A'|A)$ is symmetric and quasi-concave, the switching probability is lowest when the prior A is at the midpoint between B_k and B_{k+1} and increases the more the prior moves toward either side of the interval. Figure 5 illustrates this. The solid curve is the distribution of the posterior mean of an agent with prior $\overline{B}_k := \frac{B_k+B_{k+1}}{2}$. For this worker it is least likely that his posterior lies outside the boundaries B_k and B_{k+1}. The dotted curve to the right is the distribution of the posterior mean for a worker starting with a prior above $\overline{B}_k$. It is more likely that his posterior lies above B_{k+1} compared to the solid curve, and this increase in the upper tail outweighs the decrease in the lower tail below B_k.

Proposition 4 *In each interior occupation k and for each cohort t, the switching probability $s_k(t,A)$ is strictly U-shaped in A.*

Proof. Let $\delta_k = (B_{k+1} - B_k)/2$ be half of the distance of interval $[B_k, B_{k+1})$, and recall that $\overline{B}_k = B_k + \delta_k$. Any other belief A can be written in terms of the distance δ from $\overline{B}_k$. Then

$$\begin{aligned} s_k(t,\overline{B}_k) - s_k(t,\overline{B}_k+\delta) &= G_t(B_k|\overline{B}_k) - G(B_k|\overline{B}_k+\delta) + G_t(B_{k+1}|\overline{B}_k+\delta) - G_t(B_{k+1}|\overline{B}_k) \\ &= G_t(-\delta_k|0) - G(-\delta_k-\delta|0) + G_t(\delta_k-\delta|0) - G_t(\delta_k|0) \\ &= \int_0^\delta \left[g_t(-\delta_k-\varepsilon|0) - g_t(\delta_k-\varepsilon|0)\right] d\varepsilon, \end{aligned} \quad (8)$$

where the second equality follows from lateral adjustment. Clearly this distance is zero when $\delta = 0$. Symmetry around zero and single-peakedness imply that the integrand in (8) is strictly negative for any $\varepsilon > 0$. Therefore, this interval is strictly negative for $\delta > 0$. When $\delta < 0$

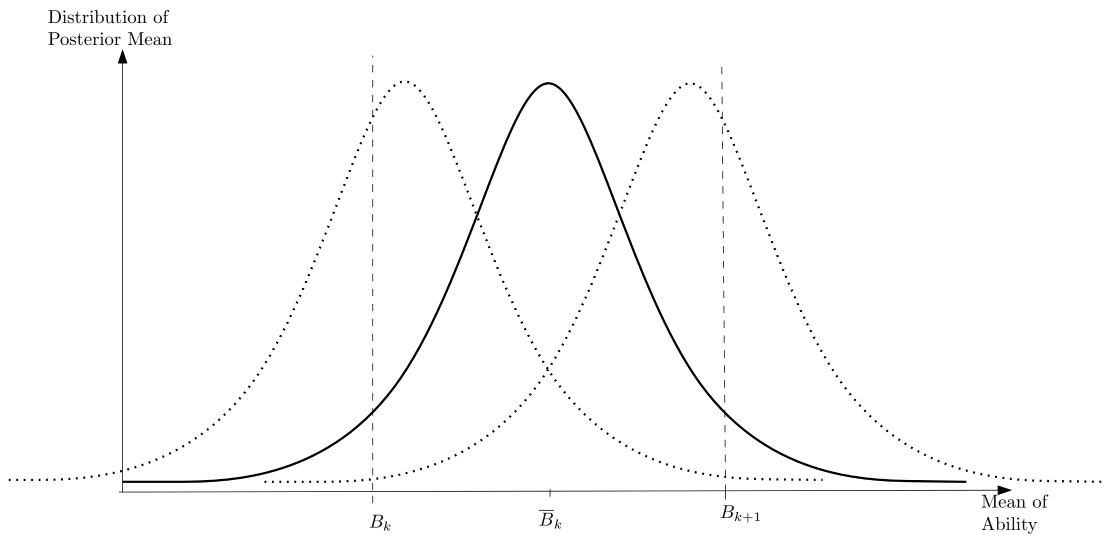


Figure 5: Illustration of the proof of Propositions 4 and 5.

the integrand of (8) is positive for all relevant ε but the range is negative, and so the integral becomes negative. The proposition obtains because integral (8) decreases in the absolute value $|\delta|$. ■

For the extreme occupations of home production $k = 0$ and of $k = K$ the negative $-s(t, .)$ is also quasi-concave, but the minimum is at the extreme of the domain, in the case of home production workers at the top are most likely to switch while in the case of the highest occupation workers at the bottom are most likely to switch.[17] The U-shapes are likely to persist when we condition on belief A but not on cohort t, yet theoretically there are cases where this does not hold. The reason is that at the same expected ability older workers have more precision and switch less. If young workers are mainly in the middle of the interval of mean abilities associated with a given occupation, while old workers are more at one side, this composition effect between cohorts can lead workers with interior abilities to switch more than those with abilities that are a bit more to the side. It is possible to construct examples where this happens in some occupation.

Next, we describe the direction of switching. Consider some occupation $k \in \{1, ..., K\}$. Intuitively, workers with high ability within this occupation and associated high average wages are the ones that are most likely to have output realization that tell them that they are appropriate for better occupations. In Figure 5 this is visible because the tail of the distribution that exceeds the upper bound increases as the distribution is shifted to the right. Workers with low belief about their mean ability are more likely to find out that they are not good

[17]Proposition 5 provides a more general formal proof for this.

enough and should move to a less productive occupation. As we mentioned before, such a switch might manifest itself through firing if the employer learns the same as the worker, or as a quit due to the fact that the wage in absence of high performance is not good enough in the current occupation. The following proposition captures this intuition about switching behavior. It characterizes the probability for upward and downward switches *conditional* on switching. If the switching probability $s_k(t, A) > 0$, then the conditional probability of switching up is $s_k^+(t, A)/s_k(t, A)$, and similar for downward switches.

Proposition 5 *Consider workers of experience t in interior occupation k that switch. The higher ability workers are more likely to switch up and the lower ability workers are more likely to switch down: $s_k^+(t, A)/s_k(t, A)$ is increasing and $s_k^-(t, A)/s_k(t, A)$ is decreasing in A.*

Proof. We can write $s_k^+(t, A) = 1 - G_t(B_{k+1}|A) = 1 - G_t(B_{k+1} - A|0)$, where the second equality follows from lateral adjustment. This is clearly increasing in A. A similar argument establishes that $s_k^-(t, A)$ is decreasing in A. This immediately implies that $s_k^-(t, A)/(s_k^-(t, A) + s_k^+(t, A))$ is increasing, while 1 minus this term is decreasing. ■

The analysis so far considered occupational switching conditional on the prior A^t, which is equivalent to condition on the expected wage $\overline{w}_k(A^t)$ in (4). This is the easiest benchmark to establish in this environment.

3.1.3 Occupational mobility conditional on the realized wage

If the firm is not completely symmetrically informed about the worker's ability, it is optimal to induce self-selection by the worker by offering the output-contingent wages $w_k(X_i)$ in (3) via boni or penalties for good and bad performance. Performance pay serves therefore a selection mechanism to attract people with the desired skills rather than an incentive device. An econometrician might not be able to elicit the belief A^t or the associated expected wage. Rather, he only observes the *realized wage* $w_k(X_i)$ that already includes performance boni or penalties. In analogy to our earlier definition about switching probabilities, we will denote the switching probabilities of a worker of cohort t who earned a wage w in the period t of his work life as $S_k(t, w)$. Similarly, $S_k^+(t, w)$ denotes the probability of upward switches and $S_k^-(t, w)$ the probability of downward switches. The domain of these functions is the entire real line since realized wages can take any value. We will establish the following two results.

Proposition 6 *In each interior occupation k and for each cohort t, the switching probability $S_k(t, w)$ is U-shaped in w.*

Proof. See Appendix A1.1. ■

Figure 6 illustrates the logic behind the result. Given the wage w, we can back out from (3) the output realization $X(w)$ which is positively related with the wage. A worker with prior A will switch if his posterior mean exceeds the upper bound B_{k+1}. For given output $X(w)$ those workers with $A > A_w = (B_{k+1} - (1-\alpha)X(w))/\alpha$ switch upward, where $\alpha = \phi_t/\phi_{t+1}$ is the weight in updating according to (5). Since the prior A is below B_{k+1} for workers who chose occupation k, no worker switches up if $X(w)$ below B_{k+1}. By a similar logic, for $X(w)$ above B_k no worker switches down, so that the switching probability is minimal in the interior. The range of prior means A for which the workers switch upward becomes larger as the wage increases, and for high enough wages even the lowest type with prior B_k would switch upward and the switching probability becomes one. Similarly, when wages are low enough all workers will switch down and again the switching probability has a local (and global) maximum of one.[18]

Weak U-shapes arise even if we do not condition on cohort identifier t, i.e. we only condition on the wage a person received in a given period in an occupation. Clearly for some intermediate wages the switching probability is less than one, while for very low and for very high wages any worker that chose occupation k is induced to switch.

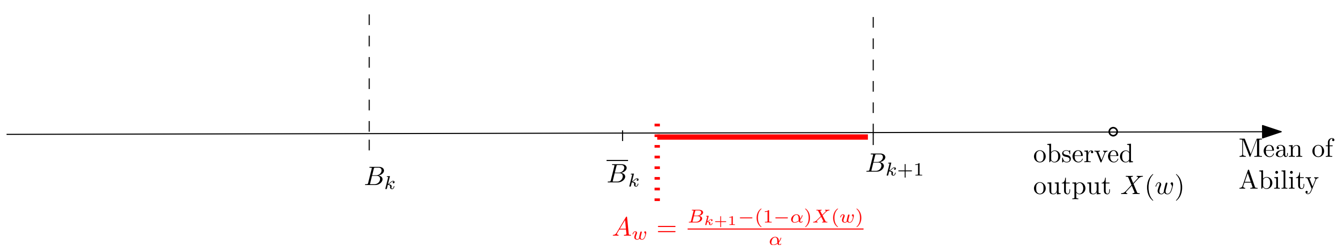


Figure 6: Illustration of the proof of Propositions 6 and 7.

As in Section 3.1.2 we again obtain the following directions for switching similar to those in the data.

Proposition 7 *In interior occupation k, among workers of experience t that switch the higher wage workers are more likely to switch up and lower wage workers are more likely to switch down. That is, $S_k^+(t,w)/S_k(t,w)$ is increasing in w and $S_k^-(t,w)/S_k(t,w)$ is decreasing in w.*

[18]The reason why the switching probability might not be strictly U-shaped has to do with an inference effect. Consider a wage w at which all workers with prior mean above A_w switch upward. At a higher wage w' the range of priors at which workers will switch extends, i.e. $A_{w'}$ is lower than A_w. While this extends the region $[A_w, B_{k+1})$ in which workers switch and decreases the region $[B_k, A_{w'})$ where workers stay, it also changes the likelihood that a given worker at this wage is from the first interval relative to the second. It is possible that higher wages mean that the lower interval is more likely, which can lead to non-monotonicities.

Proof. Conditional on switching means that output $X(w) = (w - \Pi_k)/P_k$ is either below B_k, in which the case the worker switches downward for sure. Or $X(w)$ is above B_{k+1}, in which case the move is upward because the belief about mean ability has improved. ■

3.1.4 Wage changes associated with occupational switching: Theory

The model has the immediate feature that cohorts with more years in the labor market receive on average higher wages. This is an immediate effect of learning, which allows workers to sort themselves into more appropriate occupations.

As a secondary result of our analysis we also obtain predictions about the behavior of wages of workers of the same cohort who switch occupations relative to those who stay in an occupation.

Corollary 8 *Consider workers who work in occupation k after t years of labor market experience, and consider the wage in year $t+1$. The average wage for those workers who stay in occupation k is strictly higher than for those who switch down to an occupation lower than k, and is strictly lower than for those who switch up to an occupation higher than k.*

The result follows immediately because wages are linear in expected ability and these expected abilities are strictly ranked: workers who switch up do so because their expectation about their ability went up above B_{k+1} while workers who stayed have an expectation about mean ability in $[B_k, B_{k+1}]$ and workers who switched down have expectations about their mean ability below B_k.

When workers switch from occupation k to occupation k', we can compare the wage relative to stayers in k as in the preceding corollary. Alternatively, we can compare the wages of the switchers to those who stayed in occupation k', i.e. the stayers in the occupation into which the switchers moved. The model has a tendency towards lower wages for workers who switch up relative to the incumbents of the occupation they move to, while switchers to lower occupations tend to do better than the incumbents. This is easy to show for adjacent occupations that are not too large.[19]

Proposition 9 *Consider workers with the same labor market experience and occupations that are not too large. Workers that switch from occupation k up into occupation $k' = k+1$ earn on average less than those that were already in k' and stayed there. Worker that witch from*

[19] An important part of the proof is the concavity in the relative range, which leads to differentials in the slope of the distribution of updates in the relevant range. Concavity is only a sufficient condition and not necessary, but significantly simplifies the argument.

occupation k down into occupation $k' = k-1$ earn on average more than those that were already in k' and stayed there.

Proof. Consider workers with t years of labor market experience that chose occupation k and those that chose occupation k'. In year $t+1$ we compare their wages, conditional on choosing k'. All workers that we compare have some belief A^t in B_{k-1}, B_k in year t. We are only interested in workers that have a belief in the same range in $t+1$. The distribution of the update is concave in the relevant region if $B_{k+1} - B_{k-1}$ is not too large since normal distributions are concave around their mean.[20] The range $B_{k+1} - B_{k-1}$ is small when the occupations are not too large.

The workers update A^{t+1} is distributed symmetrically around A^t. If $k' > k$, the density of the update at each point in $[B_k, B_{k+1}]$ is higher (because of symmetry and single-peakedness) and has a larger derivative (because of concavity) for any stayer than for any switcher. It then follows directly that the conditional distribution of the update, conditional on $A^t \in [B_k, B_{k+1}]$, for stayers first order stochastically dominates the distribution for switchers. The implication for expected wages follows immediately. For $k' < k$ the density is still higher but the derivative is lower, which directly implies that the distribution for switchers first order stochastically dominates the distribution for stayers. ■

Finally, we should note that for stayers there is no particular channel for wage gains from one period to the next in this simple environment (we discuss human capital later). Nevertheless overall wages grow due to better assignment of workers over time. There is scope for wage gains for both types of switchers in this model: Workers who switch down do so because they had a particularly bad wage this period and are likely to do better next period, and additionally switch to a more suitable occupation. It can be shown that these workers always exhibit wage gains.[21] Workers who switch to higher occupations did so because they had a particularly productive

[20] In particular we require $B_{k+1} - B_{k-1} < \sqrt{\phi_{t+1}/(\phi_\epsilon + \phi_t)}$.

[21] Consider a worker with wage w in occupation k and associate output $X(w) = (w + \Pi_k)/P_k$. He switches downward only if $A \geq B_k$ but $X(w) < B_k$, and thus $X(w) < A$. If he stayed in occupation k, then his expected wage according to (4) after switching is $P_k A' - \Pi_k$ where $A' = \alpha A + (1-\alpha)X(w)$ and $\alpha = \phi_t/\phi_{t+1}$. We have

$$\begin{aligned} P_k A' - \Pi_k &> w \\ \Leftrightarrow P_k \alpha A + P_k(1-\alpha)X(w) - \Pi_k &> w \\ \Leftrightarrow \alpha A &> \alpha X(w), \end{aligned} \tag{9}$$

which we showed to be true. Moreover, a worker only switches if this improves his expected wage relative to staying in the previous occupation, and therefore $E^-(w'|w) > P_k A' - \Pi_k > w$. This proves that a downward move is on average associated with an improvement of the wage. The logic does not apply to upward shifts, because in this case $X(w) > A$. Therefore inequality (9) is no longer true and the wage would on average go down relative to the previous period if the worker remained in k. Whether the reallocation improves the wage enough relative to this wage decrease depends on the exact difference $P_{k+1} - P_k$.

year. While their productivity is likely to be not as high next period (mean reversion towards the prior), the gain due to a better suited occupation can outweigh this effect and lead to gains in expected wages.

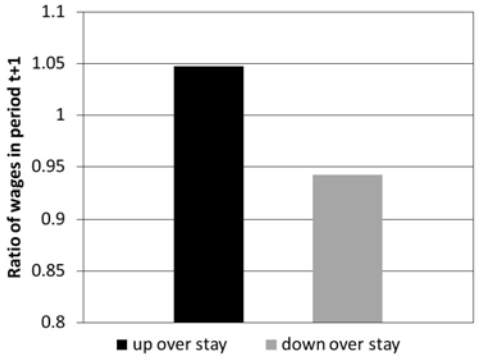
3.1.5 Wage changes associated with occupational switching: Evidence

Closer investigation of the data supports these conclusions about wage dynamics. Workers who switched to higher ranking occupations from period t to $t+1$ have higher wages, in their new occupation in period $t+1$, than workers who stayed in the same original occupation from period t to $t+1$. The opposite is true for workers who switched to lower ranking occupation from period t to $t+1$ who have lower wages in their new occupation in period $t+1$ than the wage in period $t+1$ of workers who stayed in the same original occupation from period t to $t+1$. This is the ordering of corollary 8.

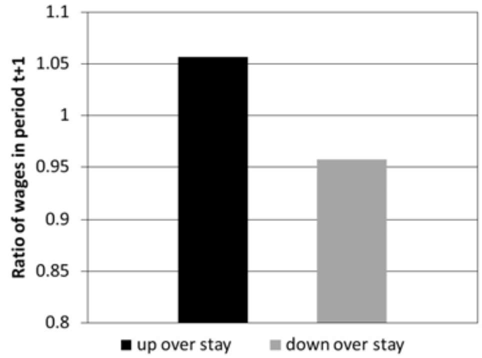
In order to see the patterns from corollary 8 in the data we compare wage in period $t+1$ of workers who stay in the same occupation from period t to $t+1$ to workers who switch occupation up or down from period t to $t+1$. For workers who were in the same occupation, k, in period t we find the ratio of wages in period $t+1$ of workers who switched to higher ranking occupations over workers who stayed in occupation k and the ratio of wages in period $t+1$ of workers who switched to lower ranking occupations over workers who stayed in occupation k. This gives K ratios of wages from period $t+1$ for up-switchers over stayers and K ratios of wages from period $t+1$ for down-switchers over stayers. We take the weighted average of these ratios according to the number of workers in each occupation who switched either up or down. Figure 7(a) shows the weighted average of these ratios.

The ratio of up-switchers over stayers are above 1, which indicates that the wages in period $t+1$ of workers who switch up from t to $t+1$ is higher than the wage of workers who stayed in the switchers original occupation from period t to $t+1$. In a similar way the ratio of down-switchers over stayers is below 1 indicating that workers who switched to lower ranking occupations have lower wages after the switch than workers who stayed in the same original occupation.

Figure 7(b) shows that the ranking in corollary 8 also is valid when we condition on general labor market experience. The ratios in figure 7(b) is found for each group of workers from the same original occupation and with same number of years after graduation. This gives $K{*}\mathit{maximum\ years\ in\ sample}$ number of ratios of up-switchers over stayers and down-switchers over stayers. We again take the weighted average of the ratios according the number of switchers in each group. The weighted average is presented in figure 7(b) and shows that corollary 8 also holds in the data when we conditional on general labor market experience.



(a) Ratio of real wages in year $t+1$ for workers who switch occupation over workers stay conditional on originating from the same occupation in period t.



(b) Ratio of real wages in year $t+1$ for workers who switch occupation over workers stay conditional on originating from the same occupation in period t and conditional on the same years of general experience.

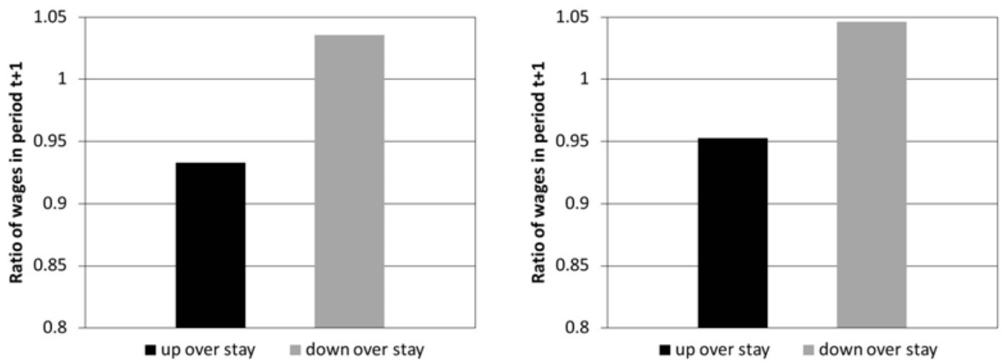
Figure 7: Weighted average of ratios of real wages in year $t+1$ for workers who switch occupation over workers stay in the same original occupation from year t and $t+1$.

Figure 7 shows what happens to workers who switch from occupation k to occupation k' relative to stayers in occupation k. Alternatively, figure Figure 8 shows what happens to the wages of switchers relative to those who stayed in occupation k'. This is the evidence from the data of proposition 9. In figure 8(a) we construct the weighted average of ratios of wages in period $t+1$ from switchers over stayers conditional on being in the same occupation, k', in year $t+1$. From figure 8(a) it is clear that workers who switched to higher ranking occupations have lower wages after the switch than the stayers in the occupation into which the up-switchers moved and that the opposite is true for workers who switched to lower ranking occupations.

The ranking from proposition 9 is also true in the data when we condition on years of general labor market experience. Figure 8(b) shows the weighted average of ratios when we further condition on the same years of labor market experience. The ratio of workers who switched to higher ranking occupations over the stayers from their new occupation is less than 1, meaning the up-switchers on average have lower wages than the workers who stayed in the occupation they switch into. For workers who switched to lower ranking occupations the opposite is true.

4 Extensions

In this section we discuss three extensions. First, we introduce changes to the productivity of occupations. Second, we allow for entry of firms. Third, we allow for human capital and



(a) Ratio of real wages in year $t+1$ for workers who switch occupation over workers stay conditional on being in the same occupation in period $t+1$.

(b) Ratio of real wages in year $t+1$ for workers who switch occupation over workers stay conditional on being in the same occupation in period $t+1$ and conditional on the same years of general experience.

Figure 8: Weighted average of ratios of real wages in year $t+1$ for workers who switch occupation over workers stay in the same original occupation from year t and $t+1$.

switching costs (but leave productivities constant).

4.1 Changing Occupational Productivities

We denote calendar time by τ and index occupations by a name $r \in \{0, 1, ..., K\}$ rather than their rank in terms of productivity, with $r = 0$ still being home production. We continue to assume that prices $P_r^\tau > 0$ are a (realization of a possibly stochastic) function of calendar time for all occupations $r > 0$. We assume still that the measure of entrepreneurs in an occupation remains constant. Let $r_\tau(k)$ be the name of the occupation that has a productivity that is higher than that in k other occupations. Since workers optimal occupational choice still coincides with the choices that maximizes their utility in the current period and since the distribution F of beliefs remains stationary, we can solve the model period by period as outlined in the previous section. In each period we can assign prices $P_k = P^\tau_{r_\tau(k)}$ and solve for the period equilibrium profits and cutoffs via the same equations (6) and (7) from the previous section. This delivers the boundaries B_k for this period. The lower and upper boundaries for the beliefs of workers in occupation $r_\tau(k)$ in this period are then $\underline{B}^\tau_{r_\tau(k)} = B_k$ and $\overline{B}^\tau_{r_\tau(k)} = B_{k+1}$. We assume strict ranks of occupations in all periods and denote by Γ_r^τ the measure of all jobs that have weakly lower output prices (i.e. do not belong to more productive occupations) than the jobs in occupation r in period τ. We call Γ_r^τ the *position* of occupation r in the distribution of productivities.

When the positions for all occupations remain constant between two consecutive periods, the switching behavior of workers $s_r(t, A)$ is exactly as outlined in the previous section.[22] When the position of a specific occupation r stays constant for two periods, i.e. $\Gamma_r^\tau = \Gamma_r^{\tau+1}$, it is easy to show that still the cutoffs that determine who stays in the occupation remain constant, i.e. $\underline{B}_r^\tau = \underline{B}_r^{\tau+1}$ and $\overline{B}_r^\tau = \overline{B}_r^{\tau+1}$, and so the switching behavior of workers in occupation r remains unchanged. Moreover, in this case it follows directly from lateral adjustment in updating and symmetry that workers with the highest and lowest belief have equal switching probabilities. This changes when the relative rankings change.

Proposition 10 *When an occupation improves its position, $\Gamma_r^{\tau+1} > \Gamma_r^\tau$, the workers with the lowest prior mean in occupation r are more likely to switch then than their counterparts with the highest priors, and the ability of the workforce improves in the sense of first order stochastic dominance relative to the previous period. For a declining occupations with $\Gamma_r^{\tau+1} < \Gamma_r^\tau$ the opposite is the case.*

Proof. We will consider the case $\Gamma_r^{\tau+1} > \Gamma_r^\tau$; the other case follows by analogous arguments. In period τ the workers with the highest belief in occupation r have belief $\overline{B}_r^\tau$ and those with the lowest belief have $\underline{B}_r^\tau$. The shift in the position implies that $\underline{B}_r^{\tau+1} > \underline{B}_r^\tau$ and $\overline{B}_r^{\tau+1} > \overline{B}_r^\tau$. Workers stay in occupation r if their posterior belief is in $[\underline{B}_r^{\tau+1}, \overline{B}_r^{\tau+1})$. Since this interval is closer to $\overline{B}_r^\tau$ than to $\underline{B}_r^\tau$ the likelihood that the update falls in this interval is higher for the high worker types. The fact that the mean abilities of the workers that choose occupation r get higher in the sense that $\underline{B}_r^{\tau+1} > \underline{B}_r^\tau$ and $\overline{B}_r^{\tau+1} > \overline{B}_r^\tau$ implies first order stochastic dominance of the ability distribution. ■

Changes in the position of an occupation have direct consequences for the wages that are paid. Clearly, since the workforce becomes better the improvement is associated with rising wages. Also we obtain predictions for the wages of stayers, i.e. of those workers that do not change occupations. The conditions in the following propositions are fulfilled for example when two occupations of equal size switch productivities while the productivities of all other occupations stay the same, but also hold under other reasons for changes in position induced by shifts of multiple occupations.

Proposition 11 *If the position of an occupation increases sufficiently in the sense that $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$, then workers that stay in this rising occupation all earned wages above the occupation average in period τ. For a sufficient decline $\Gamma_r^{\tau+1} \leq \Gamma_r^\tau - \gamma_r$ workers that stay in this declining occupation earned wages below the occupation average.*

[22] The function $S_r(t, w)$ is constant only if also the prices remain constant for both periods.

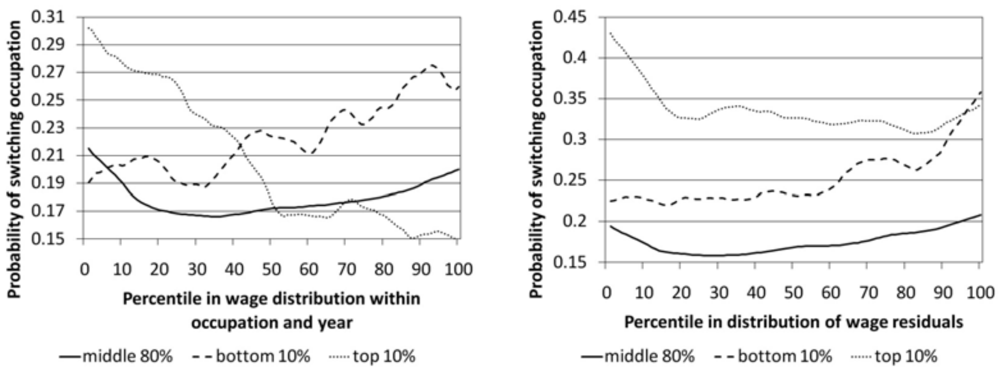
Proof. The rising occupation attracts workers with mean ability in $[\underline{B}_r^\tau, \overline{B}_r^\tau)$ in τ. The condition $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ implies that the lower bound in the next period is higher than the upper bound in τ, i.e. $\underline{B}_r^{\tau+1} \geq \overline{B}_r^\tau$. Since the average wage $\bar{w}_r^\tau(\overline{B}_r^\tau)$ according to (3) of the worker with the highest belief $A = \overline{B}_r^\tau$ is above the occupation average in period τ, workers that earn below average wages earn a wage below $\bar{w}_r^\tau(\overline{B}_r^\tau)$. They therefore have output observations X that are below $\overline{B}_r^\tau$. Therefore no worker with below average wages improves his posterior above $\overline{B}_r^\tau$, and therefore none of them improves his posterior into the range $[\underline{B}_r^{\tau+1}, \overline{B}_r^{\tau+1})$. In contrast, some of the workers with above average wages improve their posteriors into $[\underline{B}_r^{\tau+1}, \overline{B}_r^{\tau+1})$ and are suited for the rising occupation. A similar argument applies to the declining occupation. ■

The result is driven by the fact that only those workers stay whose posterior improves in line with the increase in occupational importance and who, thus, remain suitable for this occupation. Only workers with above average wages fulfill this criterion. Even if we relax $\Gamma_r^{\tau+1} \geq \Gamma_r^\tau + \gamma_r$ a bit such that high ability workers remain even after an output realization below their expected average, the statement still remains true because these retained workers still earn more than the occupational average. If we relax this condition further some workers with high prior will stay even when they earn wages below the occupational average because their posterior is still sufficiently above initial period's lower bound $\underline{B}_r^\tau$. In general, the more $\Gamma_r^{\tau+1}$ improves over Γ_r^τ, the higher the lower bound of wages of the workers who still remain in the occupation. Similarly for a declining occupation: The more the position $\Gamma_r^{\tau+1}$ drops below Γ_r^τ, the lower the higher bound on wages of the workers who still remain in the occupation.

4.1.1 Mobility in response to shocks: Evidence

Consistent with the theory, in the data we find that lower paid workers in a given occupation tend to leave it when occupational productivity rises, while higher paid workers in a given occupation are more likely to leave it when productivity of the occupation declines. We examine this in the data by studying occupations with different growth rates of the average wage. The average wage of an occupation is found in the same two ways as in section 2.3. First, we find the average wage of the full time private sector workers in a given occupation in a given year. Alternatively, we find the average wage of an occupation in a given year by using our selected sample to run a wage regression for each occupation where we include time dummies in the regression. We use use the coefficients on the time dummies in the regression as the average residual occupational wage in a given year.

Next, for each of these two notions of the average wage, we calculate the percent increase between each two consecutive years between 1995 and 2002. Figure 9(a) plots three groups of



(a) wage distribution of raw wages within occupation and year. Growth rates of average wage in occupation from population.

(b) wage distribution of wages residuals. Growth rates of average wage in occupation from time constants in wage regression.

Figure 9: Non-parametric plot of direction of occupational mobility, conditional on switching occupation.

occupations, separated by the growth rates in raw average wages between years t and $t+1$. The first group consists of the 10 percent of occupations with the lowest growth rates, the second group is the 10 percent of occupations with the highest growth rates, and the third group is the occupations with growth rates in average occupational wages in the middle 80 percent. For the three different occupational groups we plot the probabilities of switching occupation as function of the workers' position in wage distribution in their occupation in year t. Figures 9(a) and 9(b) show that workers in the lowest growing occupations between t and $t+1$ have higher probability of leaving their occupation between t and $t+1$ if the are from the upper end of the occupational wage distribution in year t. Workers in the fast growing occupations have higher probability of changing occupation if they are in the low end of the wage distribution in their occupation. Workers in occupation, which grows faster than the slowest 10 percent but slower than the fastest 10 percent, have a probability of changing occupation that is U-shaped in their in their wage percentile.[23]

4.2 Free Entry into Occupations

In the previous section we have taken the number of jobs per occupation as fixed. Here we briefly outline that the model extends to an economy in which jobs can be created at some opportunity cost. Clearly entry costs have to differ between occupations to sustain several occupations with different productivities (since otherwise only the most productive occupations will operate).

[23]The results is robust to calculating average wage change of the occupation only from workers who stay in the occupation between t and $t+1$.

Assume that the per-period cost to create and maintain a job in occupation k (or r if we adopt the notation from the previous subsection) is given by $C_k(\gamma_k) = \bar{c}_k + c(\gamma_k)$, except for home production sector $k = 0$ where entry costs $C_0(\gamma_0) = 0$. That is, there is a fixed cost $\bar{c}_k$ independent of the number of other entrepreneurs who create jobs, and a component $c(\gamma_k)$ that depends on the overall number of entrants into the occupation.

If we assume that $c(\gamma_k) = 0$, then we have perfectly elastic supply of jobs. This corresponds to a model in which workers can simply rent jobs at cost $\bar{c}_k$. Occupations with lower productivity have to have lower costs as otherwise no worker would rent the machine. In such a world the gross per-period profits Π_k have to equal the per-period cost $\bar{c}_k$. The model is particularly simple to solve because firms profits are exogenously tied to the entry costs.

The drawback of having only fixed costs $\bar{c}_k$ is the response of the market when productivities change over time. Among the occupations that hire workers, those with lower productivity have to have lower fixed costs because otherwise they would not be competitive and would not hire any workers. As long as the rank of occupations does not change the analysis is straightforward. Yet if an occupation changes rank with the next higher occupation, then it has higher productivity and lower costs and the other occupation completely disappears. There are various reasons why we don't expect this to occur: Prices might change in response to output changes or costs might change in response to the number of jobs in the occupation. The second might reflect the fact that resources into production become scarce when more entrepreneurs produce. Alternatively, it can be interpreted as cost heterogeneity among entrepreneurs and $c(\gamma_k)$ reflects the costs of the marginal entrant: The more entrepreneurs enter the less able the marginal one is.[24] We integrate this idea into the model by assuming that $c(.)$ is increasing and convex. If prices are always high enough to cover the fixed cost, then Inada conditions on the second component ensure that even with changing productivities no occupation completely vanishes, but the level of operation might substantially vary.[25][26]

An equilibrium is now a tuple $\Pi = (\Pi_0, ..., \Pi_K)$ of profits and a tuple $\gamma = (\gamma_0, ...\gamma_K)$ of

[24]In the interpretation all infra-marginal entrants will generate profits larger than their costs. Only the marginal entrant will be exactly indifferent to entering.

[25]In particular, it is easy to verify that the following conditions ensure employment in all occupations $k > 0$ in all periods. Assume that $c'(0) = 0$ and there is some constant $\psi > 0$ and employment level $e = [\alpha T - F(\psi)]/K$ such that $\lim_{\gamma \to \varepsilon} c'(\gamma) = \infty$. This ensures that no occupation employs more than e workers. Moreover, let $P > 0$ be the lowest price that can ever arise in any occupation (apart from home production). Then $\psi P > \max_k \bar{c}_k$ ensures that it is optimal to have at least some employment in each occupation at each point in time because the worker with ability ψ never gets employed and therefore could be hired for free.

[26]Another alternative formulation that ensures the operation of all occupations is that prices are changing while entry costs remain constant, i.e. $P_k(\gamma_k)$ is dependent on the level of employment and C_k is fixed. Together with some Inada conditions still all occupation remain active, but the requirement that $\Pi_k = C_k$ implies that the equilibrium ordering of the productivities $P_k(\gamma_k)$ of occupations cannot change.

entry levels such that all conditions in Equilibrium Definition 1 are satisfied and additionally it holds that $\Pi_k = C(\gamma_k)$ for all $k > 0$. All results regarding switching behavior from Section 3 apply, only that now the cutoffs B_k are determined in a way that incorporates optimal entry. It is easy to solve for these cutoffs by considering the following set of equations in analogy to (6) and (7)

$$\begin{aligned} \frac{C(\gamma_k) - C(\gamma_{k-1})}{P_k - P_{k-1}} &= B_k, & (10) \\ F(B_k) - F(B_{k-1}) &= \gamma_k, & (11) \end{aligned}$$

for all $k > 0$.

Equation system (10) and (11) allows us to determine the size of each occupation in each period even in the case when productivities are changing as in the previous Subsection 4.1. We can now define an improving occupation in the sense of Proposition 10 as one that improves its position at both the high and the low end, i.e. $\Gamma_r^{\tau+1} > \Gamma_r^{\tau}$ and $\Gamma_r^{\tau+1} - \gamma_r^{\tau+1} > \Gamma_r^{\tau} - \gamma_r^{\tau}$.[27] A sufficient increase in the sense of Proposition 11 still means $\Gamma_r^{\tau+1} \geq \Gamma_r^{\tau} + \gamma_r^{\tau}$. With these extended definitions the propositions remain valid. If on the other hand an occupation with increasing productivity expands so much in size that the measure of jobs with strictly lower productivities $\Gamma_r - \gamma_r$ actually decreases, it starts to employ not only more high ability but also more low ability workers. When we consider a smooth increase in the productivity of occupation m and hold the other productivities fixed, it is easy to see that the expansion of the workforce is continuous but the position switches upward when it overtakes another profession, at which point indeed both upper and lower position Γ_r and $\Gamma_r - \gamma_r$ increase jointly and the ability of the work force improves substantially in the sense of first order stochastic dominance.

4.3 Human Capital and Switching Costs

Here we briefly introduce human capital and switching costs in the basic environment of Section 4.1. Whenever a worker wants to switch into occupation k he has to pay cost κ_k. This captures application effort, retraining costs and time the worker is not on the job. A worker who is t years of experience in the labor market has human capital $H(t)$. Moreover, a worker who has already worked ι consecutive years in occupation k has human capital $h_k(\iota)$ in the next period. We normalize both forms of human capital to be zero in the first year, and assume that the human capital functions are weakly increasing. If a worker switches occupation, he looses his human capital and $\iota = 0$. The output of a worker with t years of general labor market

[27]Again superscripts indicate the period.

experience and ι years of occupational experience in occupation k is in analogy to (2)

$$X_k = a_i + H(t) + h_k(\iota) + \varepsilon_i. \tag{12}$$

Wages are still determined by (3) given the profit Π_k that firms want to obtain. The main difference to the previous sections is that workers solve a dynamic programming problem when deciding on the optimal occupation decision. Since human capital is a deterministic function, a worker who observes his output can back out $\tilde{X}_i = a_i + \varepsilon_i$, and therefore learning is not affected by human capital accumulation and the distribution of mean abilities F remains unchanged. We again consider a stationary equilibrium where firms' equilibrium profits Π_k remain constant over time. We define the precise notion of an equilibrium for this setup in Appendix A1.2.

Consider first the implication of general human capital ($H(t)$ strictly increasing) for occupational switching, abstracting from switching costs ($h_k(\iota) = 0$, $\kappa = 0$). Compared to a world without human capital the distribution of worker productivity now shifts by $H(t)$ for workers with t years of experience, since the relevant measure of a worker's ability in producing output is $a_i + H(t)$. Even though new workers have the same relevant ability in either case, with general human capital older workers become more productive and induce tougher competition for jobs in productive occupations. Therefore, young workers start lower and in expectation move up to better occupations over the lifetime. *Human capital induces a drift towards more productive occupations.* This leads naturally to somewhat higher aggregate probability of switching to higher than to lower occupations, as is visible in Figure 3.[28]

Even in the presence of switching costs ($h_k(\iota)$ increasing, $\kappa > 0$) it is straightforward to show that our insights on U-shapes in Propositions 6 and 7 carry over to this setting. For any interior occupation $k \in \{1, ..., K-1\}$ there is an upper and lower bound on the prior mean A among the agents that choose these occupations. Given that the expected wage per period is

$$P_k(A + H(t) + h_k(\iota)) - \Pi_k$$

workers with very low priors will not have enough periods of employment left to recover the losses if they don't choose home production. For agents with very high priors it clearly dominates to choose the highest occupation. Therefore the priors of workers who choose intermediate occupations are bounded. After very high wage observations any worker that chose an intermediate occupation will update his prior above the upper bound and choose occupation K, so

[28]Hall and Kasten (1976) and a number of later papers (e.g., Miller (1984), Sichernam and Galor (1990)) have also found that there is a systematic tendency for workers to move up to higher paying occupations with age. Wilk and Sackett (1996) have noted the tendency of workers to move to occupations requiring higher cognitive skills with age.

that for very high occupations the probability to switch upward is one. Similarly, for very low wage observations the probability to switch downward is one. For some intermediate wages some agents do not change occupations, introducing an interior minimum.

5 Connection to existing models

5.1 Basic Search Models

As outlined in the Introduction, work on occupation-specific mobility is based on the assumption that workers sort themselves according to the fit of the worker to the occupation. The standard assumption is that all occupations are essentially the same, only that a worker might fit better to some occupation than to another. This is usually modeled as a shock which the worker learns over time (McCall (1990), Neal (1999)). In such models low wages are an indication of a bad match, and low wage workers are the ones who leave in order to find a better match. In contrast to such "horizontal" heterogeneity of occupations we pursue the idea of "vertical" heterogeneity in which some occupations are more productive than others. Also workers are heterogeneous, and there is complementarity between workers and occupations. In such a world a bad fit can be characterized by underqualification *or overqualification* of a worker for a particular job. This means that not only low wage workers leave an occupation, but also very qualified workers with high wages.

5.2 Roy model

The idea that occupations might be vertically ordered goes back at least to Roy (1951). In the basic version of the Roy model according to the formalization in Heckman and Honore (1990) there are two occupations 1 and 2. Each worker is endowed with a two-dimensional skill set (s_1, s_2) that describes his skill in each occupation. A worker observes his skills perfectly but they are unobserved by the econometrician. The skill-endowment in the population is governed by some two-dimensional type distribution. The output in occupation i can be sold for price P_i to which we refer as the occupation's productivity. The wage of a worker with skills (s_1, s_2) is $P_1 s_1$ in occupation 1 and $P_2 s_2$ in occupation 2. Each worker chooses the occupation where he earns the highest wage.

Figure 10 illustrates the implications of the Roy model. The dotted curve illustrates the skill distribution. In general this can be some arbitrary cloud. The specific version drawn is one of absolute advantage in which a person with a high skill in one occupation also has a high skill in the other occupation. The solid curve is the indifference curve between the two sectors:

All workers whose type lies below that line prefer occupation 1 while all workers whose types lie above prefer occupation 2. Since wages are linear in skills, the line goes through the origin. The distinguishing feature is that there are enough jobs in each occupation, and each worker who wants to work in an occupation can do so and earn the prevailing wages. Occupational switching arises only if prices change and the solid curve shifts, i.e. the model focuses on gross mobility.

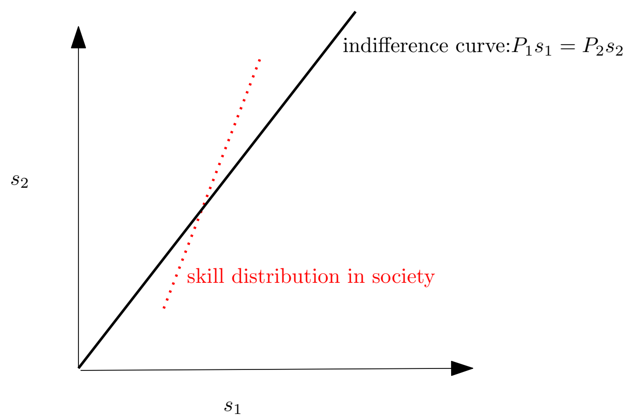


Figure 10: Illustration of the Roy model. s_i and P_i: skill level and price of output in occupation $i \in \{1, 2\}$.

In our model workers are characterized by their ability a that is common across all sectors. Of main concern is the learning about this ability. Yet with only two sectors and known abilities our model can be compared to the Roy model. The main difference to the Roy model is that the skill distribution is (a, a) and thus goes through the origin, while the indifference curve does no longer go through the origin since the profits that entrepreneurs earn in each of the occupations introduces an intercept. These profits are due to the scarcity of the production opportunities, which introduces competition among workers for jobs and sets our approach apart from the Roy model. We illustrate the features of our model in Figure 11.

For given prices P_1 and P_2 the models are similar since that Figures (10) and (11) are rotations of one another. In this sense one can interpret our model as an extension of the Roy model to multiple occupations and learning about one's type which induces net mobility even when productivities are not changing. When prices P_1 and P_2 are changing, our model still resembles the Roy model when there are fixed costs of entry of entrepreneurs into occupations because each worker can simply "rent" at job at the entry cost.

When the number of entrepreneurs is fixed due to a limited stock of knowledgeable entrepreneurs (or if the production costs of the marginal entrepreneur is increasing in the mass of

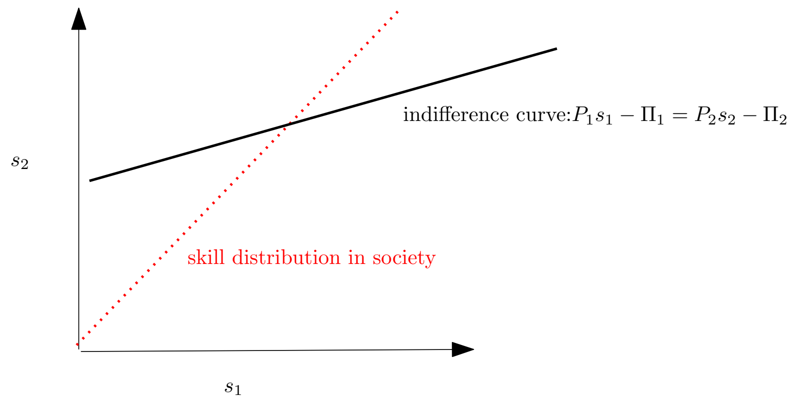


Figure 11: Illustration of our model. $s_i = a$: skill level in occupation $i \in \{1, 2\}$. P_i and Π_i: Price of output and profit in occupation $i \in \{1, 2\}$.

entrants) then our model differs with respect to the standard Roy model when prices change. For example if price P_1 goes up, in the Roy model the black indifference curve becomes flatter and therefore more workers choose jobs in occupation 1 - i.e. the low productivity workers from sector one change to sector two. In contrast, in our model in Figure 11 both the slope and the intercept of the indifference curve change: Jobs in occupation 1 become more attractive, but since their supply is limited their price will rise and the intercept between the dotted and solid curve remains. Workers behavior will change substantially once P_1 becomes so large that the ranking between occupations change, i.e. when occupation 1 becomes more productive than occupation 1. Then good workers sort themselves into the now better occupation 2 while worse workers select themselves into occupation 1. Occupations that move up in the productive hierarchy increase their high-skilled workforce but reduce their low-skilled workforce, while in the Roy model all workers stay in an occupation that becomes more productive.

The difference in predictions is driven by differing assumptions about the scarcity of production factors. In the Roy model, there is abundance of production opportunities in each occupation. This turns the economy into an individual worker's decision problem that is independent of the other workers. If an occupation becomes more productive while the others stay unchanged, than each worker will view the more productive occupation as more attractive than before. No worker will quit this occupation, and some will enter because it now dominates their previous occupation. In contrast, in our model scarcity production factors implies that the opportunity cost of employing some type of worker is endogenous and depends on which other worker types are available in the economy. When productivity of an occupation increases then it is not only the productivity of its existing workforce that increases, but also the productivity of alternative workers that are not currently employed there. Exactly at the point when one occupation exceeds another in terms of productivity, the opportunity cost of forgoing alternative workers exceeds the increase in productivity of the existing workforce because of the complementarities between workers and firms. While human capital and match-specific factors will prevent an extreme exchange of the workforce between the occupations in reality, the efficiency effect of better sorting is still likely to lead to shedding of bad workers and expansion of good workers in particularly fast-growing occupations.

5.3 Learning about Ability

In our model agent i sorts himself into the occupation that has the highest expected wage given his past output realizations, i.e.,sorting is based on: $E[P_k(a_i + \varepsilon_{it}) - \Pi_k | X_0, X_1, ..., X_{t-1}] = P_k A_{it} - \Pi_k$. Now assume alternatively that wages are raised to an exponential: $E[e^{\{P_k(a_i+\varepsilon_{it})-\Pi_k\}} | X_0, X_1, ..., X_{t-1}]$. This specification resembles the setup in Gibbons, Katz, Lemieux, and Parent (2005), who additionally have a term in the exponent that captures observable characteristics. Exponentiation has two main effects. First, the costs Π_k are now a fraction and are thus harder to interpret. Second, the error terms on no longer zero on average. Rather, positive errors are more important than negative ones. Since the same key features are at work as in our model, similar results can be derived for the switching decisions. The expectation can be rewritten as $e^{\{P_k A_{it}+(1/2)P_k^2 \phi_t^{-2} - \Pi_k\}}$. Since workers preferences are invariant to monotone transformations, we can take the logarithm of this expression, and a worker now sorts himself into the occupation with the highest

$$P_k A_{it} + (1/2) P_k^2 \phi_t^{-2} - \Pi_k.$$

In this specification, mean ability alone is no longer a sufficient statistic to determine current period decisions. Rather, of two agents with similar mean ability A, the one with the higher variance will sort himself into the higher occupation. Since ϕ_t goes up with general labor market experience, the middle term deterministically decreases for older workers, and it decreases more in high occupations than in low ones. Therefore, this model induces a drift to lower occupations as workers age, but otherwise the decisions are similar to our slightly simpler setting.

5.4 Island Economies

The scarcity of production factors in our approach is similar to the setup in Lucas and Prescott (1974). In their language each occupation is called an island. The prices on each island are determined competitively given the scarcity of the production factors. This leads to an efficient allocation of resources in our model as well as in theirs. In contrast to their model we have heterogeneous workers and a supermodular production function, which leads to sorting of specific workers to specific islands. The learning in our environment leads to the specific correlations of wages and switching behavior that seems consistent with the data that we document.

5.5 Career Progressions

Jovanovic and Nyarko (1997), Sichernam and Galor (1990) suggest that some occupations form rungs of a career ladder. Workers spend time on the lower rungs accumulating skills that allow them to perform effectively at higher rungs. Our setup and these theories share the idea that occupations maybe vertically ranked. However, while their models describe only the upward mobility or theory generates mobility in both directions.

6 Conclusion

Using administrative panel data on 100% of Danish population we document a new set of facts characterizing the patterns of occupational mobility. We find that a worker's probability of switching occupation is U-shaped in her position in the wage distribution in her occupation. It is the workers with the highest or lowest wages in their occupations who have the highest probability of leaving the occupation. Workers with higher (lower) relative wage within their occupation tend to switch to occupations with higher (lower) average wages. Higher (lower) paid workers within their occupation tend to leave it when relative productivity of that occupation declines (rises).

These facts are not implied by existing theories of occupational mobility that mostly treat occupations as horizontally differentiated sets of tasks. We suggest that it might be productive to think of occupations as forming vertical hierarchies. Workers who are unsure of their abilities learn about them by observing their output realizations. Employment opportunities in each occupation are scarce, inducing competition among workers for them. Complementarities in the production function between worker's ability and productivity of an occupation induce sorting of workers into occupations according to their expected ability. We present an equilibrium model of occupational choice with these features and show analytically that it is consistent with patterns of mobility described above.

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APPENDICES

A1 Omitted Proofs and Derivations

A1.1 Proof of Proposition 6

Consider an agent at the beginning of his t'th year in the labor market who has prior A about his mean ability and who chose occupation k this period. After observing wage w he can infer by (3) his output $X(w) = (w + \Pi_k)/P_k$ in the current period. Given that the worker chose occupation k, his prior is in $[B_k, B_{k+1})$. His posterior is according to (5) $A' = \alpha A + (1-\alpha)X(w)$, where the weight $\alpha = \phi_t/\phi_{t+1}$ depends on his labor market experience t. He will switch only if his posterior either exceeds B_{k+1} or is below B_k. Therefore, for any $X(w) \in [B_k, B_{k+1})$ or respectively for wages $w \in [P_k B_k - \Pi_k, P_k B_{k+1} - \Pi_k)$ the switching probability for workers is zero, and therefore the minimum of $S_k(t, w)$ is in the interior of the domain. For wages above $P_k B_{k+1} - \Pi_k$ workers will switch upward if $\alpha A + (1-\alpha)X(w) > B_{k+1}$. Even the worker with the lowest belief $A = B_k$ will switch if $\alpha B_k + (1-\alpha)X(w) > B_{k+1}$ or equivalently if $w > P_k(B_{k+1} - \alpha B_k)/(1-\alpha) - \Pi_k$. Therefore, toward the upper end of the domain the switching probability becomes one and therefore we have a local (and global) maximum. Similarly, for all low wages below $w < P_k(B_k - \alpha B_{k+1})/(1-\alpha) - \Pi_k$ the switching probability is also one, only that in this case workers switch to lower occupations.

A1.2 Equilibrium definition with human capital and switching costs

The output-contingent wages of workers are still given by (3), where output is now determined by (12). The expected wage for a worker in occupation k with prior mean A and experience ι in this occupation is therefore in analogy to (4)

$$\bar{w}_k(A, t, \iota) = P_k[A + H(t) + h_k(\iota)] - \Pi_k.$$

For any given profit vector $\Pi = (\Pi_0, ..., \Pi_K)$ workers can forecast their expected wages in all occupations for given prior and given experience. A worker can then evaluate his optimal choice of occupation by simple backward induction. A worker's state vector at the beginning of each period is (t, k, ι, A) : his year in the labor market t, the occupation k he was last employed in, the consecutive years of experience in this occupation ι and his belief about his mean ability A. Newborns start with home production as their previous occupation. In the last year of his life the worker optimizes

$$V(T, k, \iota, A) = \max\left\{\bar{w}_k(A, T, \iota), \max_{m \neq k}\{\bar{w}_m(A, T, 0) - \kappa_m\}\right\},$$

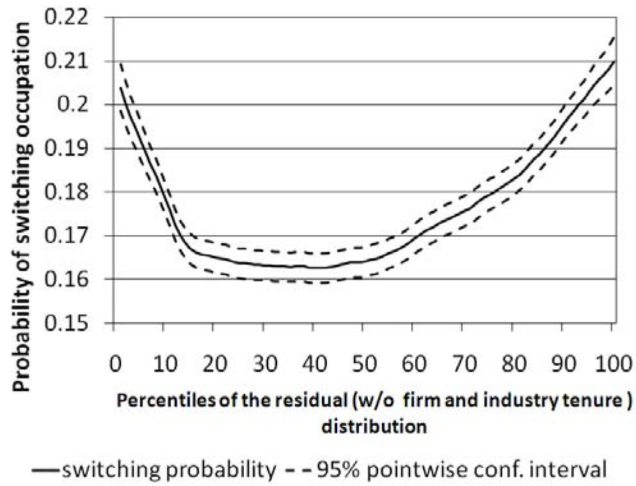
i.e. he chooses whether to stay in his previous occupation or to switch to a new occupation with zero experience and pay the switching costs. This gives a decision rule $d(T, k, \iota, A|\Pi) \in \{0, ..., K\}$ regarding the occupation that the worker chooses given the profits that firms make. Similarly, a worker with $t < T$ years of experience maximizes his expected payoff including the continuation value

$$V(t, k, \iota, A) = \max \left\{ \begin{array}{c} \bar{w}_k(A, t, \iota) + \beta E_{A'} V(t+1, k, \iota+1, A'), \\ \max_{m \neq k} \{\bar{w}_m(A, t, 0) - \kappa_m + \beta E_{A'} V(t+1, m, 1, A')\} \end{array} \right\},$$

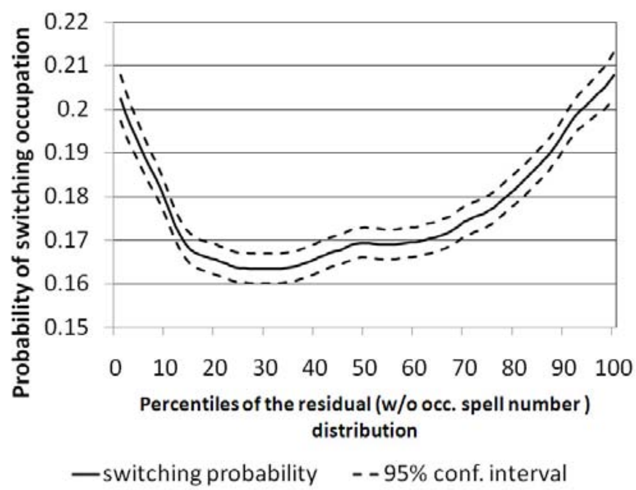
where $\beta \in (0, 1]$ is the discount factor and A' is the update about the worker's mean ability. The solution to this problem gives again a decision rule $d(t, k, \iota, A|\Pi) \in \{0, ..., K\}$. It is straightforward to show that for given profit vector Π these decision rules are unique for almost all ability levels A. Given the distribution $F^t(A)$ of priors of each cohort and these decision rules, one can derive for given Π the steady-state number of agents that choose occupation k, call it $v_k(\Pi)$. Similar to Equilibrium Definition 1 we can now define:

Definition 12 *An equilibrium is a vector of profits* $(\Pi_0, ...\Pi_K)$ *such that* Π_0 *and* $v_k(\Pi) = \gamma_k$ *for all* $k > 0$.

A2 Appendix Figures



(a) residual distribution from wage regression not including firm and industry tenure



(b) residual distribution from wage regression not including occupational spell number

Figure A-1: Non-parametric plot of probability of switching occupation by worker's percentile in residual distributions from different wage regressions.

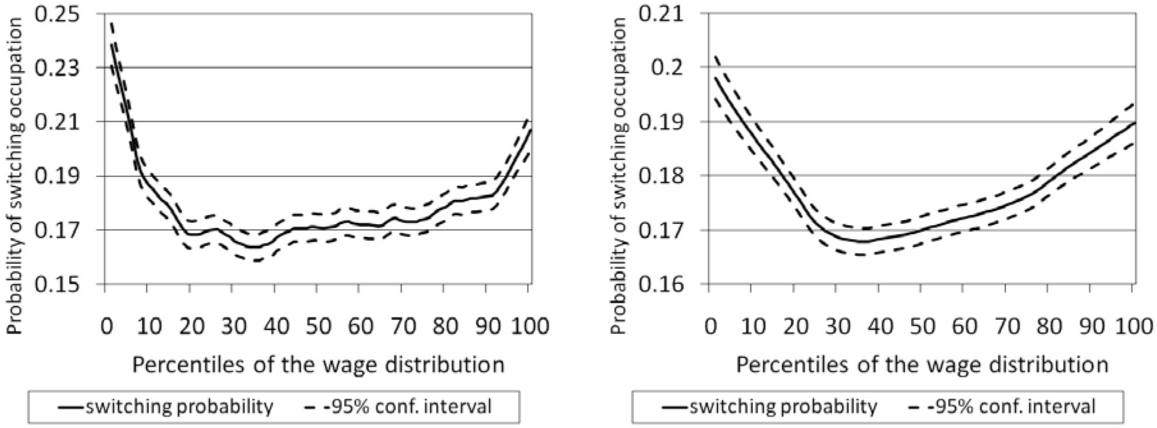


Figure A-2: Non-parametric plot of probability of switching occupation by worker's percentile in the wage distribution within occupation and year for half and double bandwidth.

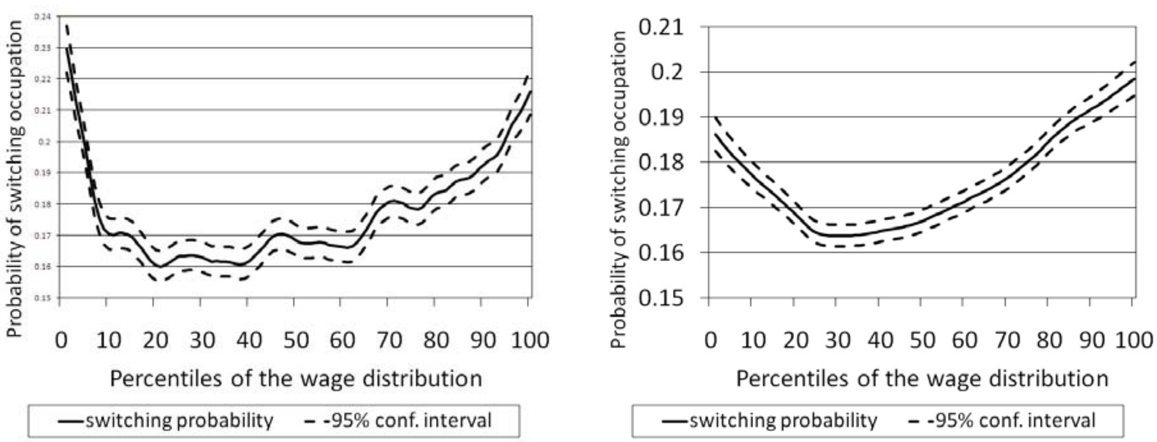


Figure A-3: Non-parametric plot of probability of switching occupation by worker's percentile in the wage residuals for half and double bandwidth.

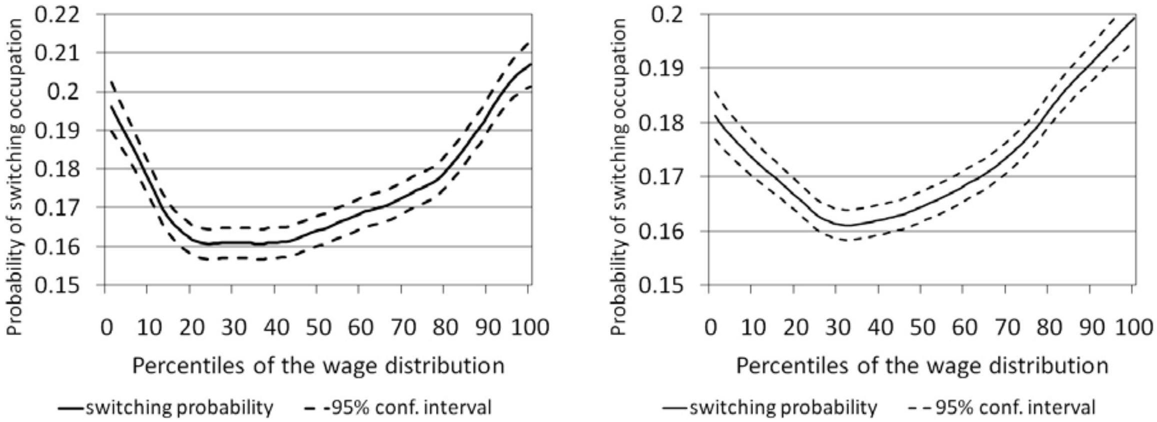


Figure A-4: Non-parametric plot of probability of switching occupation by worker's percentile in the wage within occupation, year, and years after graduation for half and double bandwidth.

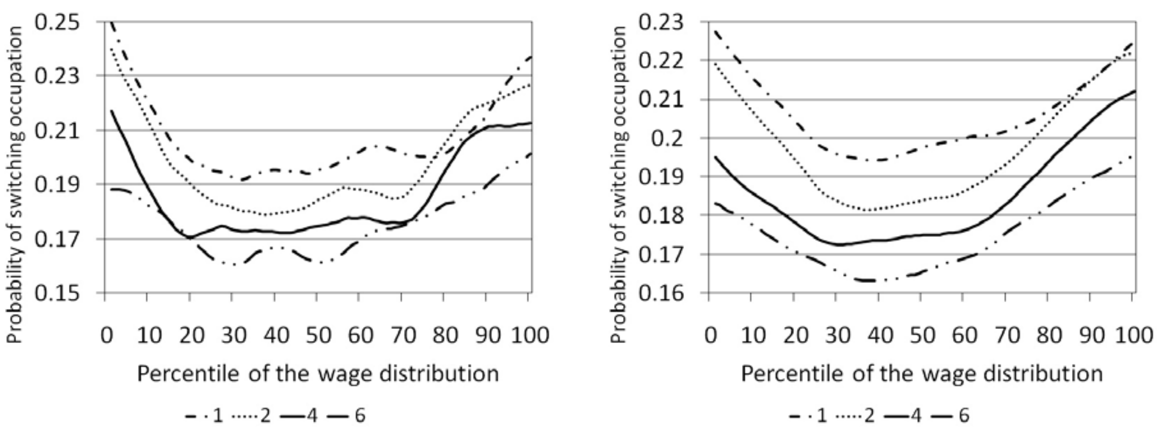


Figure A-5: Non-parametric plot of probability of switching occupation by worker's percentile in the wage within occupation, year, and 1, 2, 4, and 6 years after graduation for half and double bandwidth.

Occupational Mobility and Aggregate Unemployment
-exploiting the link between education and occupation*

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Abstract

This paper analyzes the effects of graduation time on occupational choice for a sample of young men who all graduate from an apprenticeship in wall painting. The graduates during low unemployment initially have high probability of working as a painter, low unemployment probability, and higher incomes than painters if they work in a different occupation than painting. The young men who graduate during high unemployment initially have low probability of working as painters, high unemployment, and if they work in a different occupation than painting, they have lower incomes than their painting occupation counterparts. Exploiting the link between education and occupation we use a dynamic discrete choice model to model the occupational choice of young men trained as painters. The model has two occupations where one of them is the painting occupation and it has endogenous human capital accumulation in both occupations. Job offer probabilities for the two occupations depend on aggregate unemployment. Using the model we find that over the workers' 40 years in the labor market, the group who graduated during low unemployment has an 81 % average participation rate in painting and the group who graduated during high unemployment has an average participation rate of 70 % over their 40 years in the labor market. By increasing the job offer probability in the painting occupation in the first year after graduation to 100 % the participation percentages over the workers' 40 year work life change to 78 % for the high unemployment graduation group and to 84 % for the group who graduated during low unemployment.

Chapter 4 of PhD thesis

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1 Introduction

The occupation a workers choose is highly related to the education the workers have. In this paper we use 11 cohorts of males graduating with a wall-painting apprenticeship to analyze how occupational choice relates to education. On average close to 70 % of this group of educated painters are working as painters, 10 % work in other occupations and 20 % are not working. The percent of educated painters working as painters vary with their time after graduation and it varies with with the business cycle. For people graduating with an apprenticeship in the expansion in 1984-1986 there were 90 % working as painters one year after graduation and for people graduating with a painting apprenticeship in the recession from 1987-1993 there were on average 63 % of the them who worked as painters the first year after graduation. Ten years after graduation there are on average 70 % from both the graduation groups who work as painters.

The research question of this paper is to analyze how workers' occupational choices are related to their education and how these occupational choices are affected by the aggregate unemployment rate in their field of training and by the aggregate unemployment rate in the overall economy. Using a discrete dynamic choice model, which takes account of most workers preferring to work in their field of education, we want to analyze if there are any long term consequences of graduating in a recession or an expansion in terms of occupational choices in a given year after graduation and over the workers' lifecycles.

One strand of literature on occupational mobility models is e.g. McCall (1990) and Neal (1999) where occupations are perceived as identical (e.g., not different with respect to skill requirements), but workers find out the quality of their specific match to an occupation over time. This paper extends the literature on occupational mobility from McCall (1990) and Neal (1999) by allowing occupations to be different and letting workers direct their search to the occupation in which they have trained for. Furthermore, this paper contributes to the literature on occupational mobility by analyzing who switches between which occupations when. This is related to the second strand of literature on occupational mobility models which explains how occupational mobility is related to fluctuating demands for services of different occupations. The Roy (1951) model (and its extensions in, e.g., Moscarini (2001)) predict that it is the low productivity workers who leave the occupation in response to a negative change in demand conditions. The models in Kambourov and Manovskii (2005, 2009a) generically have a similar prediction. They present a version of the island economy model of Lucas and Prescott (1974) where islands are interpreted as occupations and workers accumulate occupation-specific human capital. Human capital is destroyed upon switching occupations which implies that, if workers with different levels of human capital are perfectly substitutable in the occupational production function, it is the low human capital, and hence, low wage, workers that switch first if occupational demand declines. If occupational demand rises, no one leaves the occupation.

Our model has two occupations, one is the occupation the workers trained for and one is the alternative occupation, which in our case is an aggregation of all other occupations. Workers receive job offers from each occupation with some probability each period and when demand declines it is the workers with the least experience who will be affected more in terms of job offer probabilities. However, experience in the occupation that the worker trained for has a higher payoff in the other occupation than experience from the other occupation has in the occupation for which the trained was trained. For this reason, there is a general drift of workers from the occupation they trained for to the other occupation when experience increases in the training-specific occupation. When demand increases all workers will have higher job offer probabilities in both occupations. Furthermore, since we only have two occupations it is possible to keep track of experience in both occupations, such that workers who switch back to an occupation they have worked in before can use their human capital accumulate in the occupation from before they switched out of it.

We show that most workers choose to work in the occupation they trained for and workers choice of occupation fluctuates with the aggregate unemployment rate. Workers who graduate when unemployment rate is high are less likely to work in an occupation related to their field of education but the majority of workers return to the occupations they trained for when unemployment rate falls. None of the existing theories on occupational mobility have a link between education and occupation. Some models on occupational mobility (e.g. Groes, Kircher, and Manovskii (2009)) have that workers have one occupation in which their wages on average always will be highest however, only by observing the workers choices will this specific occupation be revealed. It is therefore not possible to determine whether workers are in their preferred occupation right after graduation since we need many consecutive observations in the same occupation to infer that this is the optimal occupation for the worker. One advantage of our theory is that we know when the worker is not in the occupation he is trained for and we can therefore do counterfactual experiments on how workers who graduate during a recession will react if e.g. the government helps them to a job in their preferred occupation after they graduate.

We choose to model the occupational choices of painters because it is clear what occupation they trained for. Having a clear link between education and occupation allows us to differentiate further than the choice of blue collar or white collar from e.g. Keane and Wolpin (1997). In the case of painters this is important because 85 % of the educated painters who work in another occupation than painting work in a blue collar occupation. Furthermore, our setup allows for occupational choices that are directed to a specific occupation, which differs from Neal (1999), Pavan (2007), and McCall (1990) where initial choice of occupation is random.

The model presented in this paper builds on Keane and Wolpin (1997) and Eckstein and Wolpin (1999). The setup is a finite-horizon dynamic discrete choice model of occupational choice where one of the occupations is the one the workers trained for. In each period individuals choose from a set of mutually exclusive alternatives over a finite horizon in order to maximize discounted expected utility. Initially all individuals in the model are homogenous in the sense that they are all in their first year after graduation from a painting apprenticeship. However, the painting apprentices graduate in different years with different aggregate unemployment rates in painting and different aggregate unemployment rates from the overall population, which influences the job offer probabilities, both to receive a job offer as a painter and to receive a job offer in another occupation than painting.

For Denmark, Holm, Groes, and Olsen (2001) has analyzed the effect on graduation year on further unemployment rates and employment in industries related to the education. They use a reduced form logit estimation with spline functions for age to analyze a sample of engineers, school teachers, and unskilled workers. They find that workers who graduate in a recession converges to the average worker in terms of unemployment rates by their third year after graduation. Furthermore they find that workers who graduate in a recession initially have lower participation in an industry related to their occupation but the workers return to the given industry when the unemployment rate changes. The return to the industry related to their education happens fast, such that by 2 years after graduation there are no significant differences in overall- and specific industry related employment probabilities of people who graduate during a recession or an expansion.

In this paper we find that workers also do return to the occupation they trained for however, people who graduate in a recession never catch up with people who graduate in an expansion in terms of participation rates in the painting occupation. The advantage of our paper is that we model the workers choices and we will therefore be able to perform counterfactual analyses that can give suggestions to how government sponsored programs can help people who graduate during a recession.

The main results from our model are that our model is able to fit most of the patterns in occupational mobility and transition rates for people graduating with an apprenticeship in painting. Using the model to perform a counterfactual experiment we find that increasing the job offer probability in the painting occupation to 100 % for all workers in the first year after they graduate increases the average employment rate in the painting occupation more for the group who graduated during high unemployment than for the group who graduated during low unemployment. The results from the model show that the group who graduated during high unemployment has on average 70 % participation in the painting occupation in all 40 years they are in the labor market and for the group who graduated during low unemployment this participation rate is 81 %. By increasing the job offer probability in the painting occupation in the first year after graduation to 100 % the participation percentages over the workers' 40 year work life change to 78 % for the high unemployment graduation group and to 84 % for the group who graduated during low unemployment.

The remainder of the paper is organized as follows. In Section 2 we describe the sample of workers graduating with a painters apprenticeship we use in this paper and in 3 we describe the occupational mobility patterns and wages over their life cycle and business cycle. In Section 4 we present the model and in section 5 we show the results from the model using different parameter choice. In section 6 we present our counterfactual analysis with the preferred parameters from the model and in section 7 we conclude.

2 Data

We use the administrative Danish register data covering 100% of the population in the years 1980 to 2002. The first part of the data is from the Integrated Database for Labor Market Research (IDA), which contains annual information on socioeconomic variables (e.g., age, gender, education, etc.) and characteristics of employment (e.g., wage worker, self employed, unemployed, out of the labor force, occupations, industries, etc.) of the population. Information on wages and income is extracted from the Income Registers and consists of either the hourly wage in the job held in the last week in November of each year or the after tax income of the year. Wage and occupational information is not available for workers who are not employed in the last week of November. The wages and income are deflated to 1980 Danish Kroner using Statistics Denmark's consumer price index.

We use the Danish rather than the U.S. data for two reasons. First, the sample size is much larger. We select males who all graduated from the same education. It is possible to be this restrictive with the Danish data and at the same time end up with a sufficiently large sample size. Second, the administrative data minimizes the amount of measurement error in occupational coding that plagues the available US data (see Kambourov and Manovskii (2009b)).

2.0.1 Sample selection

We select all males who at the ages between 17 and 23 who graduated from a wall-painting apprenticeship in the period 1983 to 1993. While the Danish register data dates back to 1980 we choose the first year of graduation of our sample to be 1983. During the period 1980-1993 the painting apprenticeships lasted 3 years in Denmark, and we choose 1983 as the first graduation year because then we can observe graduates from this period both when they started and when they graduated from their apprenticeship. We let 1993 be the last year an individual can graduate from their apprenticeship because there was a law change in the painting education in 1990. People entering a painting degree after 1990 would be both in school half time and work as an apprentice half time, which is different from our chosen sample where all training occurs at the chosen firm of the apprenticeship. We restrict the sample to include people between the ages of 17 and 23 at the time of their graduation in order to minimize experience before the apprenticeship and this way to get as homogenous a sample as possible. We only select male workers in order to minimize the impact of the fertility decision on labor market transitions and we delete all people's entire history if we observe them returning back to school. We select graduation years in the early part of the data period in order to be able to follow the individuals for as long time as possible in the labor market.

There are four reasons why we chose to analyze painters rather than people from another education/occupation. First, it is clear what occupation an apprenticeship as a painter trains people for and it is clear what working as a painter entails. Second, there are relatively large cohorts of painters graduating such that restricting the sample to only one type of education still leaves a sizable sample. Third, we would like a sample who are likely to be influenced by business cycles, which also means choosing a sample of workers who work mostly in the private sector. Forth, the Danish data experiences a break in the occupational classification in 1995 and the painting occupation is one of the few occupations, which have their own occupational category before and after 1995.

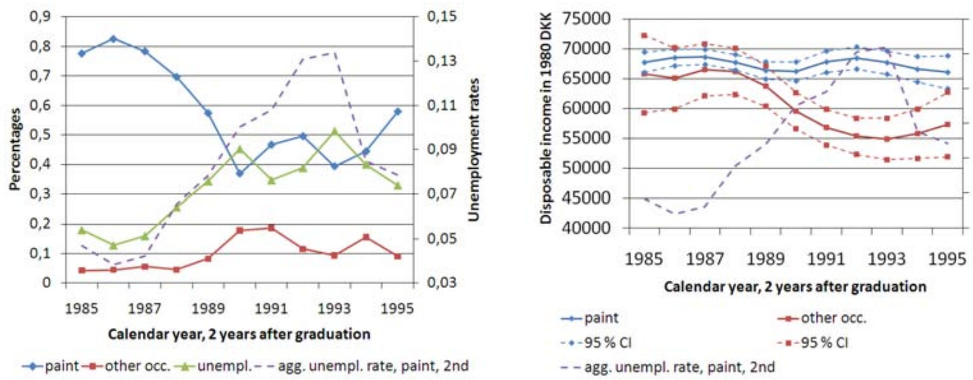
There are 2,522 people graduating during the period 1983-1993 where 1,830 of these were males. Of these 1,830 there are 1,644 who do not return to school during the period we observe them. We use occupational codes to classify the majority of workers in painting or in some other occupation. Occupations included as a painter-occupation are: painting, leadership of companies with more or less than 10 employees, leadership in craftsmanship companies, leadership in detail companies, and leadership of companies in the building sector. After classifying workers with occupational codes there is 29 % of people who are listed as workers during the year but who do not have an occupational code. We drop one person who has missing occupational information all years he is in the sample. We further classify people with missing occupational codes as painter if they are registered as full time workers in an industry related to painting, classified as painting businesses. This reduces the number of missing occupations to 18 %. We proceed to drop people's entire history in the sample if they have more than 2 years of missing observations in the sample, which is seven percent of all observations and reduces the sample to 1,523 people. For people with one year of a missing occupational code we impute their occupational category if possible. If a worker has the same occupation before and after the missing observation and if he works in the same industry during all three observations, we classify him with the occupation he had before and after the missing occupation. Furthermore, if a workers has the same industry in any of the years around his missing observation as he has in the missing year, we attach the occupation from the matching industry year. Finally we drop all people who after these procedures still have a missing occupational observation. This leaves a sample of 20,302 observations, which is 1,427 people graduating with an apprenticeship from 1983 to 1993.

Table A-1 in the appendix shows what employment the painters have after graduation. In table A-1 some people are registered both as working in an occupation and being not employed. There are seven different employment states, which are painting employee, self employed painter, blue collar work in construction, other blue collar work, white collar work, and not working. For our further analysis we will simplify these labor markets into three categories. The first category is painting, which includes employed and self employed painters, the second is working in another occupation than painting, which consist of both types of blue collar and white collar workers, and the last category is not working. We classify an individual as not working if he is unemployed more than 20 % in a given year, otherwise we classify him as working in either painting or another occupation.

We use disposable income as our income measure following le Maire and Schjerning (2007). The gross income is calculated from wage income, capital income, labor market contributions (since 1994), taxable and non-taxable benefits. To obtain disposable income we subtract tax payments. It is not possible to use hourly wages as income measure since the self employed do not receive wages but we will use the notation of wages and income interchangeably.

3 Pattern of Painters

In this section we present a set of descriptive statistics from the data, which motivates the focus of our model. We want to analyze the occupational patterns of people graduating with a painting apprenticeship. Figure A-1 in the appendix shows the percentage of our sample working in painting, working in another occupation than painting and not working in the years after they graduate from their apprenticeship. It is clear from figure A-1 that for all years after graduation, the majority of people with a painting apprenticeship work as painters. The unemployment rate is highest two years after graduation and the probability of working in another occupation than painting increases with years after graduation.



(a) Percentages of people two years after graduation in 3 states.

(b) Yearly disposable income of people two years after graduation in 2 states.

Figure 1: Percentages in painting, other occupations, and not working and disposable income in 1890 Danish Kroner in painting and other occupations of people with a painting apprenticeship two years after graduation.

Figure A-1 is the average for all 11 cohorts graduating from 1983 to 1993. Throughout the period 1983 to 1993 both the overall average unemployment rate and the unemployment rate for all people, in the population, trained as painters has changed. Figure 1(a) shows the employment states of people two years after graduation in the period 1985 to 1995 and what the unemployment rate was for everyone in the population trained as painters during the same period. Figure 1(a) shows there are up to 20 percentage points difference in the probability of working as a painter for people who graduated when unemployment rate was low, in the middle of the 1980's, as opposed to people graduating when unemployment rate is high, in the beginning of the 1990's. At the same time, the percentages of people, two years after graduation, working in another occupation than painting or not working are higher when the unemployment rate is high. Furthermore, the average income of people working in another occupation than painting is lower when unemployment rate is high than the the average income of people working in another occupation than painting when unemployment rate is low. Figure 1(b) shows this for the same people two years after graduation as in figure 1(a). Figure 1(b) also shows that the average income of people, two years after graduation, working in painting does not vary much with the unemployment rate. Motivated by figure 1(a) and 1(b) we divide the sample into two groups. The first group are those who graduated during the low unemployment from 1983 to 1986 and the second group are those who graduated during the high unemployment from 1987 to 1993. It is the descriptive statistics of these two groups which will be the focus of our model.

Figure 2 shows the percentage of people working as painters by years after graduation for the two groups. As figure 1(a) showed the percentage of the sample working as painters is smaller for the group who graduated during the recession for the initial years after graduation. Figure A-2 in the appendix shows that these differences are significant up to 5 years after graduation but after this there are no significant differences in the percentages who work as painters from the two groups.

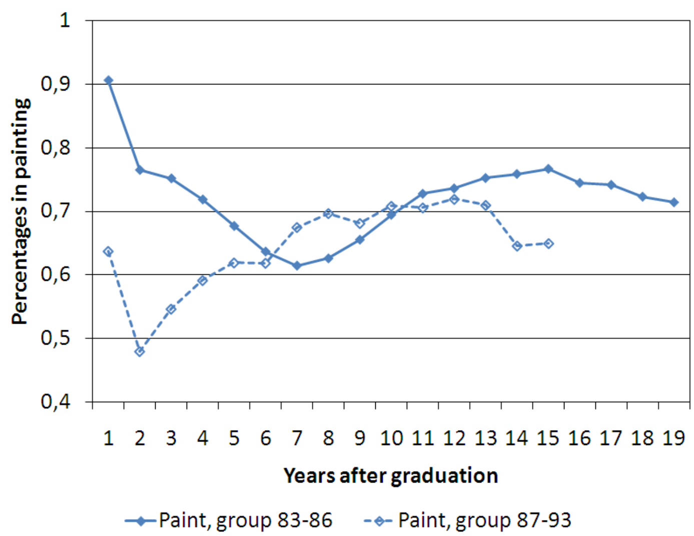
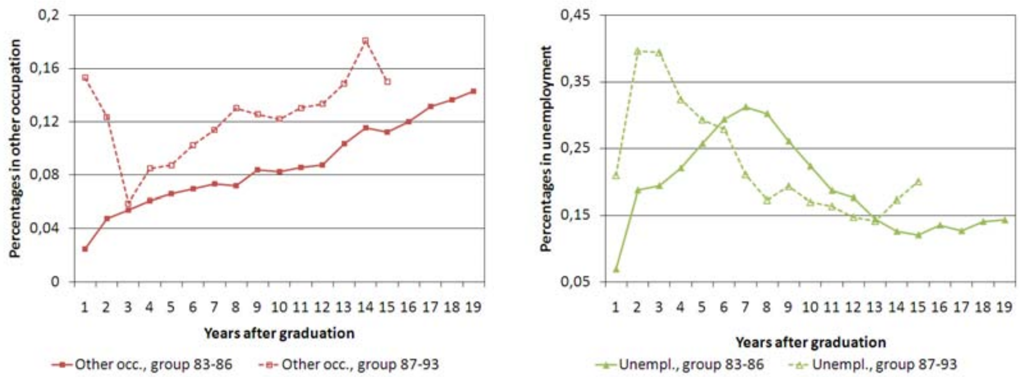


Figure 2: Percentages of people with a painting apprenticeship working in another occupation than painting for 1983-1986 graduates and 1987-1993 graduates by years after graduation.

Figure 3(a) shows the percentage of the sample working in another occupation than painting by years after graduation for the two groups. The graduates from 1987 to 1993 have a higher percentage working in other occupations than painting, relative to the group who graduated from 1983 to 1986, for all years after graduation. However, figure A-3 shows that with the number of observations in the sample the difference in the percentages working in other occupations than painting between the two groups are only significant for the first two years.

The model presented in section 4 includes differences in employment probabilities in the two occupations shown above, which depend on the year of graduation. In the model, the arrival rate of job offers in the two occupations also determine part of the unemployment for the two groups. Figure 3(b) shows that the unemployment rate of the two groups have different



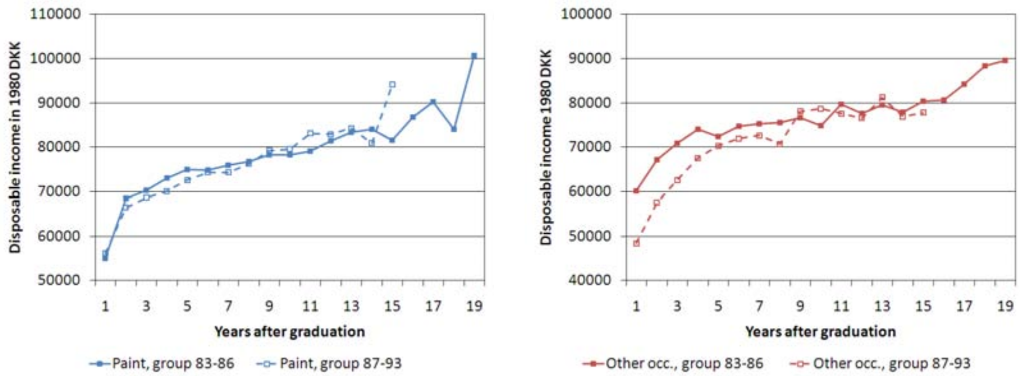
(a) Percentages of two graduation groups working in other occupations than painting.

(b) Percentages of two graduation groups not working.

Figure 3: Percentage of people with a painting apprenticeship working in other occupations than painting or not working for 1983-1986 graduates and 1987-1993 graduates by years after graduation.

patterns over their first 15 years after graduation and figure A-4 in the appendix shows that these differences are significantly different for most of the years. The main aim of our model is to replicate the percentages in each of the three states for the two groups graduating when either the unemployment rate was low from 1983 to 1986 or when the unemployment rate was high from 1987 to 1993. Table A-2 in the appendix show the same percentages as figures 2, 3(a), and 3(b) as well as the number of people from the sample in each of the three states.

A second feature of the data we would like the model to replicate is the average income of the sample in the two occupations by the two different graduation groups. Figure 4(a) shows that the average disposable income in 1980 Danish Kroner for the sample working as painters does not differ much by the year of graduation and figure A-2 in the appendix shows that income of graduates from 1983-1986 are not significantly different from graduates from 1987-1993. Both groups have a large income increase between the first and second year after graduation, which is likely to be related to the transition from working as an apprentice to being employed as a (educated) painter. From figure 2 we can further see that the percentage of the sample working as painters drops after the first year for both graduation groups, which is also likely to be related to the transition from being an apprentice to being an employed painter. In the model we model the first year of graduation separately to capture this fact. Figure 4(b) shows that the average income of the 1987-1993 graduation groups working in other occupations than painting is lower than the 1983-1986 graduation group up to nine years after graduation and figure A-6 in the appendix shows that these differences are significant for the first 3 years after graduation and it is these differences in average income between the two graduation groups that we also want our model to capture.



(a) Income of two graduation groups working in painting.

(b) Income of two graduation groups working other occupations than in painting.

Figure 4: Yearly disposable income in 1980 Danish Kroner of two graduation groups, 1983-1986 and 1987-1993. By years after graduation for painters and the sample working in other occupations than painting.

The last descriptive statistics of the sample of graduates, from a painting apprenticeship, are the transition probabilities between the three states. Table A-3 and A-4 in the appendix show the transition probabilities for the two different graduation groups their first eight years in the sample. We choose to only show the first eight years because this is the longest a graduate from 1993 can be in the sample. Table A-3 and A-4 show that there are higher persistence in each state for the graduates from 1983 to 1986 relative to the graduates from 1987 to 1993. The largest difference in the persistence is in other occupations than painting where conditional on working in another occupation than painting the period before, the graduates from 1983 to 1986 has 72.8 % probability of working in another occupation than painting in a given period and for the 1987-1993 graduates this percentage is only 57.8 %. Table 1 and 2 below shows that the transition rates have larger differences when we look at the transitions between two and three years after graduation.

For the graduates from 1983 to 1986 the persistence in other occupations than painting is the same for 2 to 3 years after graduation as it is the first eight years in the sample but for the graduates from 1987 to 1993 the persistence in other occupations, between 2 and 3 years after graduation, is significantly lower at 17.8 %. Furthermore, the percentage of the sample graduating from 1987 to 1993 who chooses painting after working in another occupation than painting two years after graduation is 46.6 %. From the transition probabilities in table A-3, A-4, 1, and 2 and the percentage of the sample in each state from figure 2, 3(a), and 3(b) we find that people with a painting apprenticeship graduating during high unemployment are

Table 1: Transition matrix between 2 to 3 years after graduation for graduates from 1983 to 1986.

	Status in t		
Status in $t-1$	Paint	Other Occ.	Unempl.
Paint			
Number	399	7	60
Row %	85.6	1.5	12.9
Other Occ.			
Number	6	21	2
Row %	20.7	72.4	6.9
Unempl.			
Number	53	5	56
Row %	46.5	4.4	49.1

more likely to choose to work in another occupation than painting than those who graduate during low unemployment but the high unemployment graduates are also more likely to switch from the other occupation to working as a painter. In the model we would like to capture this fact that high unemployment graduates initially choose another occupation than painting but switches into painting after a while. In the model different arrival rates of job offers dependent of the aggregate unemployment rate of all painters in the population and the overall aggregate unemployment rate of all occupations in the population. Graduates who do not receive a job offer as a painter after graduation can be employed in another occupation than painting (if they receive a job offer in that occupation) and once they receive a job offer as a painter they can switch into painting. Lastly, table A-5 in the appendix shows the persistence probabilities in the three states for the two different graduation groups by years after graduation. The persistence of working as a painter is close to the same for the two groups 8 years after graduation and the difference between the groups varies between 1 to 6 percentage points from 4 to 7 years after graduation. The patterns are similar for the persistence of working in other occupations than painting and not working. The longer time after graduation the closer the two graduation cohorts get to each other in terms of persistence.

4 Model

In this section we present a finite-horizon dynamic discrete choice model of occupational choice where one of the occupations is the one the workers trained for. This model follows the dynamic programming approach to labor supply of e.g. Wolpin (1992), Keane and Wolpin (1997), Eck-

Table 2: Transition matrix between 2 to 3 years after graduation for graduates from 1987 to 1993.

	Status in t		
Status in $t-1$	Paint	Other Occ.	Unempl.
Paint			
Number	297	9	84
Row %	76.2	2.3	21.5
Other Occ.			
Number	47	18	36
Row %	46.5	17.8	35.6
Unempl.			
Number	101	21	201
Row %	31.3	6.5	62.2

stein and Wolpin (1999), and Cohen-Goldner and Eckstein (2008). In each period individuals choose from a set of mutually exclusive alternatives over a finite horizon in order to maximize discounted expected utility. Initially all individuals in the model are homogenous in the sense that they are all in their first year after graduation from a painting apprenticeship. However, the painting apprentices graduate in different years with different aggregate unemployment rates in painting and different aggregate unemployment rates for over all in the population, which influences the job offer probabilities, both to receive a job offer as a painter and to receive a job offer in another occupation than painting. So far, the model is not estimated but we present parameters for the model, which match most of the data moments described in section 3. See section 5 for a discussion of the chosen parameters.

Each individual in the sample graduates from their painting apprenticeship between the age of 17 and 23 and starts in the labor market at 1 year after graduation ($a = 1$), and retires after 40 years ($a = A = 40$). The individuals graduate in 11 different years, from 1983 to 1993, where each year, t, has an associated aggregate unemployment rate of all painters from population and an associated aggregate unemployment rate for all occupations in the populations. The aggregate unemployment rates are known with perfect foresight by the individuals. From the first year of the model (1984) to 2002 we use actual aggregated unemployment rates from the population. After 2002 we use the average unemployment rate during the previous period, which is 7.5 % for the painting occupation and % 6.5 for the overall population. Each period after graduation the individual can choose between working as a painter ($d^1_{a,t} = 1$), working in another occupation than painting ($d^2_{a,t} = 1$) or not working ($d^3_{a,t} = 1$). The three choices are mutually exclusive such that $\sum_{j=1}^{3} d^j_{a,t} = 1$ for every year after graduation, a, and every calendar year, t, [1]. The periodic utility is,

$$U_{a,t} = C_{a,t} \tag{1}$$

where $C_{a,t}$ is consumption of a man educated from a painting apprenticeship a years after graduation in the calendar t. The budget constraint is given by,

$$C_{a,t} = w^1_{a,t} d^1_{a,t} + w^2_{a,t} d^2_{a,t} + b_{a,t} d^3_{a,t} \tag{2}$$

where $w^1_{a,t}$ is the wage in the painting occupation, $w^2_{a,t}$ is the wage in the occupations, which is not painting, and $b_{a,t}$ is the benefits received if unemployed. The wages (disposable income) are stochastically offered in each period and follows a log linear function of the $\sqrt{K^j_{t,a}}$ with cross experience terms, $\sqrt{K^{-j}_{t,a}}$, where $\sqrt{K^j_{t,a}}$ is the occupation-specific experience in occupation j, $j = 1, 2$ and $\sqrt{K^{-j}_{t,a}}$ is the experience from the other occupation. We choose the square root of experience in order to let disposable in be an increasing and concave function of experience. The wage function for painters is,

$$ln(w^1_{a,t}) = \gamma^1_0 + \gamma^1_1 * \sqrt{K^1_{t,a-1}} + \gamma^1_2 * \sqrt{K^2_{t,a-1}} + \xi^1_{a,t} \tag{3}$$

and the wage offer function for working in another occupation than painting is,

$$ln(w^2_{a,t}) = \gamma^2_0 + \gamma^2_1 * \sqrt{K^1_{t,a-1}} + \gamma^2_2 * \sqrt{K^2_{t,a-1}} + \xi^2_{a,t} \tag{4}$$

The accumulation of human capital in the painting occupation, $j = 1$, is determined by the following equation:

$$K^1_{t,a} = K^1_{t,a-1} + d^1_{a,t} \tag{5}$$

and the accumulation of human capital in the other occupation, $j = 2$, is determined by the following equation:

$$K^2_{t,a} = K^2_{t,a-1} + d^2_{a,t} \tag{6}$$

The shocks to income, $\xi^j_{a,t}$ for $j = 1, 2$, are joint normally distributed $N(0, \Omega)$ and serially uncorrelated, such that $E(\xi^j_{a,t} \xi^j_{a-1,t}) = 0$. We first show results from the model where the

[1] For notational simplicity we omit the individual index in this section

correlation parameters and standard deviation of the income shocks are zero and show that in order to match the income in the other occupation than painting of both the graduate groups we need some stochastic element in the offered wages. The benefit during non-employment are given by a linear function of years after graduation, for all t:

$$b_{a,t} = \alpha_0 + \alpha_1 * a \tag{7}$$

The level and linear coefficient of the function of benefits are chosen to match the painters' average received benefit level by years after graduation from the data.[2].

Each period after graduation the workers get offered a job in each occupation with probability $Q^j_{a,t}$, which follows a logistic form:

$$Q^j_{a,t} = \frac{Z^j_{a,t}}{1 + Z^j_{a,t}}, (j = 1, 2) \tag{8}$$

where the specification of $Z^j_{a,t}$ depends on the aggregate unemployment rate in the period, t, and what the worker was doing during the previous period, $a - 1$, such that for the painting occupation in all periods after the first year after graduation, $a > 1$, $Z^1_{a,t}$ is given by:

$$Z^1_{a,t} = \lambda^1_0 + \lambda^1_1 * K^1_{t,a-1} + \lambda^1_2 * d^1_{a-1,t} + \lambda^1_3 R^P_t + \lambda^1_4 (R^P_t - R^A_t) \tag{9}$$

and in the first period after graduation, $a = 1$, the $Z^1_{1,t}$ component of the job offer probability for the painting occupation is given by:

$$Z^1_{1,t} = \delta^1_0 + \delta_1 R^P_t + \delta_2 (R^P_t - R^A_t) \tag{10}$$

For all period after graduation, $a > 0$, the $Z^2_{a,t}$ component of the job offer probability in the other occupation than painting is given by:

$$Z^2_{a,t} = \lambda^2_0 + \lambda^2_1 * K^2_{t,a-1} + \lambda^2_2 * d^2_{a-1,t} + \lambda^2_3 R^P_t + \lambda^2_4 (R^P_t - R^A_t) \tag{11}$$

[2]An extension of this function is a more thorough breakdown of the benefit laws over the period. This is the plan for a future extension of the model. We do not allow for any stochastic elements in the benefit level nor do we allow the benefit level to depend on past income or experience. If this was the case, individuals would need to take the expectation over their benefit levels when making their optimal choices. In the current version this is not the case since people know their benefit levels with perfect foresight because the benefit levels only vary with years after graduation. Another possible extension is to include insurance status as a state variable. Workers who are insured have the possibility to receive unemployment benefits, which are higher than the welfare benefits that workers without insurance have the possibility to receive. It is also possible to include other types of benefits such as early retirement benefits, sickness benefits, and invalid benefits to get an indicator of whether the individuals are out of the labor market.

In the specification of $Z^j_{a,t}$ in equation 9 to 11, $K^j_{t,a-1}$ is past experience in the occupation, $d^j_{a-1,t}$ is an indicator whether or not the person worked in the occupation during the previous period, R^P_t is the aggregate unemployment rate for people educated as painters in the population in calendar year t, and $R^P_t - R^A_t$ is the difference in the aggregate unemployment rate of painters and the overall aggregate unemployment rate in calendar year t. Each period after graduation the individuals draw two shocks $\theta^j_a \sim U[0,1]$ for $j = 1, 2$ and if $\theta^j_a \leq Q^j_{a,t}$ the workers receives a job offer in the occupation. In the model θ and ξ are independent.

The setup of the model described above gives a state $S_{a,t} = \{a, K^j_{t,a-1}, d^j_{a-1,t}, R^P_t, R^A_t, \xi^j_{a,t}, \theta^j_{a,t}\}$ for $j = 1, 2$. The individuals maximize the expected present value of utility over their lifetime:

$$V_{a,t}(S_{a,t}) = \max_{d_{a,t}} E[\sum_{a=1}^{A} \beta^{a-1} \sum_{j=1}^{3} U^j_{a,t} d^j_{a,t} | S_{a,t}] \tag{12}$$

The maximization problem in 12 is achieved by an optimal sequence of choices of the control variable $d^j_{a,t}$ given realization of the shocks and utility in the period. The optimization problem in 12 can be written as a set of alternative specific value functions, each obeying the Bellman (1957) equation:

$$V_{a,t}(S_{a,t}) = \max_{j \in \{1,2,3\}} \{V^1_{a,t}(S_{a,t}), V^2_{a,t}(S_{a,t}), V^3_{a,t}(S_{a,t})\} \tag{13}$$

where the alternative specific value functions, for $a \in [1, A-1]$, are given by:

$$V^j_{a,t}(S_{a,t}) = U^j_{a,t} + \beta E \max\{V_{a+1,t+1}(S_{a+1,t+1} | S_{a,t}, a, d^j_{a,t} = 1)\} \tag{14}$$

and the value function the last period before retirement, at $a = A$ or $a = 40$ is:

$$V^j_{a,t}(S_{a,t}) = U^j_{a,t} \tag{15}$$

In equation 14, E is the expectation operator taken over the joint distribution of ξ_a and the probability of a job offer, which depends on $Z^j_{a,t}(K^j_{t,a-1}, d^j_{a-1,t}, R^P_t, R^A_t)$. The decision process for the sample of individuals just finishing their painting apprenticeship is to decide in each period whether to work as a painter, work in another occupation than painting, or not work in order to maximize their lifetime utility. They do so, taking into account their endogenous human capital accumulation in the two occupations and the changes in the job offer probabilities their choices create. Each period after graduation individuals are offered a job in either, both, or none of the two occupations, and dependent on the job offer, they decide if they want to work, and if so in what occupation. We solve the model by backwards recursion.

5 Results and Parameter Choices

The parameters of the model presented above in section 4 are so far taken partly from reduced form regression and partly by testing the model to match the data as close as possible. It is the plan for future research to estimate the parameters of the model. There are 25 parameters we need to decide on and in order to structure the choice of parameters the model is first presented without stochastic wages. This leaves 22 parameters, where we set the discount parameter, $\beta = 0.95$. The rest of the parameters are:

5.1 Parameter Choices

From the wage function: $\gamma_0^j, \gamma_1^j, \gamma_2^j$ for $j = \{1, 2\}$
From the job offer probabilities when $a > 1$ for and $a > 0$ for the other occupation: $\lambda_0^j, \lambda_1^j, \lambda_2^j, \lambda_3^j, \lambda_4^j$ for $j = \{1, 2\}$ and when $a = 1$, the job offer probability parameters for painters are: $\delta_0, \delta_1, \delta_2$
From the benefit function: α_0, α_1

The first two parameters are from the benefit function estimated from the data, where $\alpha_0 = 54,800$ and $\alpha 1 = 560$ [3]. In choosing the parameters for the wage function and the function for job offer probabilities we run reduced form estimations to guide our choices. The results of the two OLS wage regressions from equation 3 and 4 and the three logit regressions for the job probabilities from equation 9, 10, and 11 are shown in the appendix table A-6 to A-7. From the OLS regression of disposable income in table A-6 the coefficient of painting experience is 0.1073 conditional on working as a painter, such that five years of experience as a painter gives an extra income of 24 % if working as a painter. Five years of experience as a painter gives 21 % higher wages if working in another occupation than painting. Experience in another occupation than painting gives an extra 22 % disposable income if working in another occupation than painting whereas five years of other experience than painting only gives 6 % higher income in the painting occupation. These results from the OLS regressions suggest that painting experience can be transferred to other occupations whereas experience in another occupation than painting is less valued for working as a painter. We will use these coefficients in our benchmark analysis, which we name the reduced form benchmark.

Table A-7 shows the coefficient of 5 logit estimation for the probability of working as a painter and the probability working in another occupation than painting as function of ex-

[3] The α_0 and α_1 parameters are estimated from a linear OLS with deflated disposable income as the dependent variable and a constant term and years after graduation as regressors.

perience, past participation, the unemployment rate for painters in the population and the difference in unemployment rates of painter from the population minus the aggregate unemployment rate of the population. Column 1 and 2 in table A-7 show probability of working as a painter from 2 to 13 years after graduation and the probability of working in another occupation than painting 1 to 13 years after graduation as function of the unemployment rate of painters and the difference of the painter and the aggregate unemployment rate. Only including the unemployment rates in the probability of working a 1 percentage point increase in the aggregate painters unemployment rate decreases the probability of working as a painter by 2.6 % and a one percentage point higher unemployment rate in painting over the aggregate unemployment rate (ie. when unemployment of painters is 0.13 and aggregate unemployment is 0.12) decreases the probability of working as a painter by 0.2 %. The probability of working in another occupation than painting also decreases with the unemployment rate of painters but increases with the difference in the unemployment rates. When the unemployment rate of painters increases by 1 percentage point the probability of working in another occupation than painting decreases by 0.9 % and when the unemployment rate of painters is 1 percentage point higher than the unemployment rate of the overall population the probability of working in another occupation than painting increases by 2 %. Figure A-7 in the appendix shows the two unemployment rates over the period 1984 to 2002. From figure A-7 it is clear that the two unemployment rates follow the same cycle and the unemployment rate of painters is more volatile than the overall unemployment rate. Column 3 in table A-7 shows the correlation of the unemployment rates and the probability of working in painting the first year after graduation. The coefficients of unemployment for working in painting the first year after graduation follow the patterns from 2 to 13 years after graduation and we will use the coefficients from column 3 for the reduced form benchmark in our model. Column 4 and 5 from table A-7 include the parameter values we will use for the benchmark values in the probability of receiving a job offer in painting after the first year after graduation and in the probability of receiving a job offer in another occupation than painting for all years after graduation. The logit regressions in column 4 and 5 also includes experience and past period's participation in the given occupation, which are both positively related to the probability of receiving work in the occupation.

Besides using the coefficients from the reduced form estimations we also pick parameters to match the data as close as possible. We choose new parameters for the two wage functions and the two job offer functions. The chosen parameters are given from the four following equations:

$$ln(w^1_{a,t}) = 10.96 + 0.115 * \sqrt{K^1_{t,a-1}} + 0.0364 * \sqrt{K^2_{t,a-1}} + \xi^1_{a,t} \tag{16}$$

$$ln(w^2_{a,t}) = 10.92 + 0.091 * \sqrt{K^1_{t,a-1}} + 0.095 * \sqrt{K^2_{t,a-1}} + \xi^2_{a,t} \tag{17}$$

$$Z^1_{a,t} = -2.27 + 0.16 * K^1_{t,a-1} + 2.2 * d^1_{a-1,t} + 16.0 * R^P_t - 65.0(R^P_t - R^A_t) \tag{18}$$

$$Z^2_{a,t} = -2.0 + 0.60 * K^2_{t,a-1} + 2.0 * d^2_{a-1,t} + 0.0 * R^P_t + 0.0(R^P_t - R^A_t) \tag{19}$$

5.2 Results

In this section we present results from the model using different parameter choices. We show results without income shocks from the reduced form parameters and the chosen parameters from equation 16 to 19. Next we show the results from the chosen parameters when we also include stochastic incomes. We first show evidence on the participation rates in the painting occupation and the other occupation, next we show the results on income, and last we show evidence on the transition probabilities. Finally we show how sensitive the simulated participation rates are to different choices of parameter values.

We simulate 40 years of data for 10,000 individuals for each of the 11 years of graduation. Individuals have the same uniform draws of θ^j_a and the same income shocks, ξ^j_a, for $j = 1, 2$ for the different years of graduation, but the 10,000 individuals have different shocks across individuals and across years after graduation.

Figure A-8 in the appendix shows the simulated data by using parameters from the reduced form estimations. In the first year after graduation the percentages working in painting match the data because the parameters are estimated separately for year 1. Figure 8(a) and figure 9(b) show the painters' job offer probabilities and their acceptance percentages each year after graduation. It is clear from the figures that the workers always initially choose to work as a painter if they receive a job offer and around 8 years after graduation some people start to reject their painting job offers. Using the reduced form parameters does no match the data well for the painters and in figure 9(c) and 9(d) it is clear that they do not match the participation rate in the other occupation either. For the other occupation the job offer probabilities from the reduced form estimates are always lower than the data.

The results from the chosen parameters are shown in figure A-9. The simulated data does not match the real data perfectly however, the model does capture most of the patterns from the data. In figure 9(a) the simulated data has the lowest participation rates in painting 6 years after graduation and the data has the lowest participation rate 7 years after graduation and the simulated data has too high participation rates in the later period after graduation. For graduates from the period 1987-1993 working as painters, figure 9(b) shows that the the simulated data also captures most of the patterns from the data but has too high participation rates in painting in year 2 after graduation and too low participation rates in the later years after graduation. The major exception from matching the patterns from the data is the first two years after graduation for the 1987-1993 graduation group who works in the other occupation. Figure 9(d) shows that the 1987-1993 graduation group has a high percentage of people from the data working in the other sector for the first two years after graduation and the model does not match this. In the sensitivity analysis of the parameter choices we show, in section 5.3, that this initial decline is not something the model is able to capture. We will discuss a possible reason why the model is unable to match the early years for people working in the other occupation than painting in section 5.4. From figure 9(c) and 9(d) it is furthermore worth noticing that the job offer probabilities in the other occupation are much higher that the participation rates while for the people who works as painters this difference is much smaller.

Figure A-9 shows the results using the chosen parameters and figure A-10 shows the same parameter choices but also including a joint normally distributed shock for the incomes in painting and the other occupation. The standard deviation of the two shocks are 0.15 and their correlation is 0.2. The overall result, when including the stochastic incomes, is that the percentages of the simulated people who work as painters decrease while the percentages of people who work in the other occupations increase. Furthermore, it is no longer all the people who have been offered a job as a painter who works as a painter. The reason for these patterns can be found in figure A-11, which shows the incomes in the two occupations with and without shocks.

The top two graphs in figure A-11 are the incomes for painters. These graphs show that the simulated data from the reduced form estimates slightly underestimate income profile for people who work as painters and the chosen parameters creates a steeper income profile, which matches the data after around 6 years after graduation for the 1983-1986 graduation group in figure 11(a) and almost always lies below the data for the 1987-1993 graduation group in figure 11(b). Including the stochastic income in the model increases the average income levels for painters all years after graduation and matches the data closer for both graduation groups. The incomes of individuals who work in the other occupation than painting are given in figure 11(c) for the 1983-1986 graduation group and in figure 11(d) for the later 1987-1993 graduation group. The simulated data from the reduced form estimates and the chosen parameters have a hard time matching the income profiles for individuals who work in the other occupation than painting. For the early graduation group from 1983-1986, the simulated average income data is initially below the actual average income of people who work in the other occupation and for the later graduation group the simulated average income is initially above the actual average income. Including stochastic income in the model increases the income for individuals working in the other occupation more than the painters' income for both graduation groups for all years after graduation. This is because the difference between the percent of people who are offered a job in the other occupation and the percentage of people participating in the other occupation decreases when stochastic income is introduced. At the same time not all individuals who are offered a job as a painter works as painters with stochastic incomes. For the workers who are offered a job in both occupations, the ones with a high shock to income in the other occupation and a low income shock in painting choose to work in the other occupation than painting. When there are no stochastic incomes these individuals would work as painters. The reason why the model is unable to match the income profile for individuals working in the other occupation than painting is most likely the same reason why the the model cannot match the first few years after graduation for the 1987-1993 graduation group. We will discuss possible extensions to the model to match this part of the data better in section 5.4.

The last part of moments from the model are the transition rates. The parameters in the model have not been chosen to match the transition rates and especially the transition rates in the early periods after graduation need improvement. Table A-8 and table A-9 show the transition rates between 2 and 3 years after graduation when data are simulated using the reduced form estimates. The two tables show that too few people switch into painting and too many people stay in unemployment and switch into unemployment. The transition rates for the first 8 years after graduation are presented in tables A-10 and A-11. These transition rates look closer to the transition rates from the actual data but there are again too many individuals switching into unemployment and staying unemployed. Table A-12 show the persistence in each state still using the reduced form estimates as parameters in the model. As was the case for the transition matrices the persistence in unemployment is again too high and the persistence in the other occupation than painting is too low.

The transition rates from the model look closer to the data when we use our chosen parameters. Table A-13 to A-16 show transition rates from 2-3 years after graduation and 2-8 years after graduation when we use our chosen parameters in the model. The transition rates are all closer to the real data than when we used the reduces form parameters but between year 2 and

3 after graduation the model again has hard time matching the transition rates for individuals who are working in the other occupation 2 years after graduation. This is the problem from earlier that arises again that the model cannot replicate participation in the other occupation in the first 3 years after graduation. For the first 8 years after graduation the persistence in unemployment for the 1983-1986 graduation group is a little too low and the persistence of working in the other occupation than painting is a little too high for the 1987-1993 graduation group. In table A-17 we show the persistence over time in the three states using our chosen parameters in the model. The persistence in painting and unemployment are close to the data, but the persistence in the other occupation than painting is too low for both graduation groups. Tables A-18 to A-22 show the same five transition tables when we include stochastic income in the model. The transition rates from the model with stochastic income do worse in terms of matching the transition rates from the data compared to not including stochastic incomes. Especially, the persistence in each of the three states becomes worse. The persistence in painting and the other occupation is too low and the persistence in unemployment is too high.

Above we show how the model matches moments in the data using different sets of parameters. The set of parameters, which match the data best are the chosen parameters without stochastic income. We will use the chosen parameters in our sensitivity analysis in section 5.3 below as well as in the the counterfactual experiment in section 6.

5.3 Sensitivity Analysis of Parameter Choices

In this section we show how the participation rates in painting and the other occupation changes, when we change the values of the chosen parameters without stochastic income. We show the results for changing the parameters from the two job offer functions. All figures from this section are presented in the appendix. Figures A-12 and A-13 show what happens when we change λ_1^1 and λ_1^2, which are the coefficients on experience in the job offer function. Increasing the coefficient on painting experience in job offer function for painting, λ_1^1, increases the percentage of people working in painting and decreases the percentage of people working in the other occupation. The changes in percentage participation in each occupation is highest for the later years after graduation when experience is higher. Figure A-13 shows similar qualitative results when we change λ_1^2, which is the coefficient on experience in the other occupation in the job offer function for the other occupation. The difference is that the participation in both occupations is not as sensitive to changes in λ_1^2 as they are to changes in λ_1^1.

Figures A-14 and A-15 show the response to changes in λ_2^1 and λ_2^2, which are the coefficients on past participation in each occupation. Increasing the coefficient on past participation in the job offer function for painters increases the percentages of people working as painters and decreases the percentages of people who work in the other occupation as presented in figure A-14. The response in participation from changing the coefficient on past participation in the other occupation is again less sensitive than changing the coefficient in the job offer function for the painting occupation, as can be seen from figure A-15.

Next we show how sensitive the simulated data from the model is to changes in the unemployment rates. Figures A-16 and A-17 show the results from changing the parameters, λ_3^1 and λ_3^2 on the unemployment rate for painters in the two job offer functions. An increase in the parameter λ_3^1 increases the job offer probability for painters overall and especially when unemployment rate is high. From figure A-16 we see that increasing λ_3^1 increases the percentage working as painters and decreases the percentage working in the other occupation. Figure A-17 shows that increasing the coefficient on the painting unemployment rate, λ_3^2, in the job offer function for the other occupation has very little effect on the participation rates in painting but increases the probability of working in the other occupation in all years after graduation.

Finally, we show in figures A-18 and A-19 the model's response to changing the parameter on the difference in aggregate unemployment rates, $(R_t^P - R_t^A)$. An increase λ_4^1 in figure A-18 raises the participation in painting for almost all years after graduation with the exception of the first 4 years after graduation from the 1983-1986 graduation group who graduated when the aggregate painting unemployment rate was lower than the overall unemployment rate. Figure A-19 shows that the same size increase in λ_4^2 has very little effect on the participation rate in painting but increases the participation in the other occupation for almost all years after graduation.

By changing the parameters of the model we are able to capture different parts of the moments in data. As noted earlier, the major obstacle in terms of matching moments from the data is the early years in the other occupation. The model makes both the graduation groups have low participation in the other occupation early on and increase in participation over the lifecycle. We will discuss possible solutions to this problem in the next section.

5.4 Possible Extensions of the Model

In this section we discuss two possible extensions of the model, which both can increase the participation rate in the other occupation in the years right after graduation. The first extension is alterations of the two wage functions. Currently, the experience in painting has high payoffs in the other occupation, but experience in the other occupation has little payoff in the painting occupation. The parameters on experience together with the concavity of the wage functions induces people to work early in the painting occupation and transfer their experience from painting into the other occupation later on. This increases the participation in the other occupation over time but causes the participation in the other occupation to be low right after graduation. A possible alteration of the wage functions is to let the experience parameters enter in the following way:

$$ln(w_a^j) = \gamma_0^j + \gamma_1^j * \sqrt{K_{a-1}^j + \phi^j * K_{a-1}^{-j}} \tag{20}$$

where $\phi^j \in [0, 1]$ and can be interpreted as how much a unit of experience from the other occupation is worth relative to a unit of experience from the chosen occupation.

The second extension of the model is to include serving in military as a forth choice in the first two or three years after graduation. As seen from table A-1, there are 8 % of the sample who works in the military the first year after graduation. The choice to work in the military should be modeled to depend on the unemployment rate for painters because 80 % of the people who work in the occupation for the 1987-1993 graduation group are in the military and it is therefore mostly these people who represents the initially high participation in the other occupation for the given group. Including the military as a choice in the first 2 years after graduation would likely also improve the transition rates for the 1987-1993 graduation group. This group has low persistence in the other occupation and high transitions from the other occupation into the painting occupation, both features which could be captured by a choice to serve temporarily in the military.

6 Counterfactual Experiments

In this section we investigate how our sample of painting apprentices behave if we change the job offer probability in the first year after graduation to be 100 % for the painting occupation. We use our chosen parameters without stochastic income for this counterfactual experiment. The average participation rates from the model for the two graduation groups in the three states, painting, other occupation, and unemployment are given in table 3.

Table 3 shows that the early graduation group who graduated during low unemployment have higher participation rates in painting in the first 10 years after graduation and in all 40 years of working than the later graduation group who graduated during high unemployment. The early graduation group also has lower participation in the other occupation than painting and they have lower unemployment rates. Using our chosen parameters the results from the model show that there are long term consequences of graduating when unemployment is high in

Table 3: Average participation rates for first 10 years after graduation and all 40 years from the model using chosen parameters.

	First 10 years		All 40 years	
status	Grad. 83-86	Grad. 87-93	Grad. 83-86	Grad. 87-93
paint	0.72	0.62	0.81	0.70
other	0.07	0.10	0.11	0.18
unempl	0.21	0.27	0.08	0.12

terms of participation rates in the occupation for which the workers trained. The counterfactual experiment gives both graduation groups the same probability of receiving a job offer in the painting occupation the first year after graduation, namely 100 % probability of a job offer. The results on the average participation rates from the experiment can be seen in table 4. Increasing the job offer probability in the painting occupation to 100 % in the first year after graduation increases the participation rates for both graduation groups but it increases the painting participation rates more for the later graduation group who graduated during high unemployment.

Table 4: Counterfactual average participation rates for first 10 years after graduation and all 40 years from the model using chosen parameters with 100 % job offer probability in painting first year after graduation.

	First 10 years		All 40 years	
status	Grad. 83-86	Grad. 87-93	Grad. 83-86	Grad. 87-93
paint	0.75	0.73	0.84	0.78
other	0.06	0.07	0.09	0.13
unempl	0.19	0.20	0.07	0.09

By comparing table 3 and table 4 we can see that the average participation rate in the painting occupation over the first ten years after graduation increases by 3 percentage point for the early graduation group while the participation rate increases by 11 percentage points for the later graduation group. The average participation rates in painting also increases more for the later graduation group for all 40 years they are in the model when setting the job offer probability to 100 % in painting in the first year after graduation.

In figures A-20 and A-21 we show the result on participation rates in the two occupations for the two graduation groups from the counterfactual experiment. Figure 20(a) shows that the 1983-1986 graduation group only has a small increase in painting participation the first year after graduation from the counterfactual experiment. This is because their participation rate in painting already is very high in the first year after graduation and as a result of this, the experiment does not change the participation rates much over the first 20 years after graduation. The opposite is true for the 1987-1993 graduation group. This group initially had an average participation rate in painting the first year after graduation which was 65 %. By increasing the job offer probability to 100 % in the painting occupation in the first year after graduation, this group finds an average participation rate in painting, which is around 7 percentage points higher than the participation rate was before the experiment. The participation rates in the other occupation than painting are shown in figure A-21. The participation rate in the other occupation than painting is the opposite of what happens for the participation in the painting; the 1983-1986 graduation group has a small reaction to the experiments whereas the 1987-1993 graduation group decreases their participation in the other occupation than painting by around 5 percentage points.

7 Conclusion

In this paper we use 11 cohorts of males graduating with a wall-painting apprenticeship to analyze how occupational choice relates to education. We use a model which builds on the dynamic discrete choice models in Keane and Wolpin (1997) and Eckstein and Wolpin (1999) but we allow workers' occupational choice to be directed to the occupation that they trained for. We use the model to analyze how workers' occupational choices are related to their education and how these occupational choices are affected by the aggregate unemployment rate in their field of training and by the aggregate unemployment rate in the overall economy.

We show how the participation rate is in the painting occupation, in other occupations than painting, and the unemployment rate for two different graduation groups, one that graduated during low unemployment and one that graduated during high unemployment. For people graduating with an apprenticeship during the expansion from 1984-1986 there were 90 % working as painters one year after graduation and for people graduating with a painting apprenticeship during the recession from 1987-1993 there were on average 63 % of the them who worked as painters the first year after graduation. Ten years after graduation there are on average 70 % from both of the graduation groups who work as painters.

We use the model to match these participation rates as well as participation rates in another occupation than painting and in unemployment. Using the parameters from the the best fit of the data we predict that over the workers' 40 years in the labor market, the group who graduated during low unemployment has 81 % average participation rate in painting and the group who graduated during high unemployment has an average participation rate of 70 % over their 40 years in the labor market. With the chosen parameters for the model we perform a counterfactual experiment, which allows for the job offer probability in the painting occupation to be 100 % in the first year after graduation for both graduation groups. By increasing the job offer probability in the painting occupation in the first year after graduation to 100 %, the participation percentages over the workers' 40 year work life change to 78 % for the high unemployment graduation group and to 84 % for the group who graduated during low unemployment.

The model is still preliminary and it has a hard time matching the participation rate in the other occupation than painting in the first few years after graduation. We discuss possible extension of the model where one of them is to include the choice to temporarily enter the military in the first or second year after graduation.

Most of our results are presented without stochastic incomes in the two occupations and matching the data when including stochastic incomes in the model is also future research. Including the stochastic incomes decreases the persistence in each state. At the moment the only source of state dependence in the model is the indicator of past participation in the job offer probability. It could be interesting to include unobserved individual specific heterogeneity in the model such that the wage shocks and the job offer draws become serially correlated. This can allow for more state dependence and is also a plan for a future development of the model.

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A1 Percent in Occupation Before Aggregation

Table A-1: Percent of graduates with painting apprenticeship in different employment categories by year after graduation

years after graduation	paint empl.	paint self empl.	construction blue collar	other blue collar	white collar	military	non-employment
1	0.771	0.003	0.005	0.010	0.006	0.083	0.124
2	0.718	0.020	0.008	0.025	0.010	0.062	0.166
3	0.741	0.033	0.015	0.037	0.013	0.018	0.162
4	0.749	0.042	0.018	0.048	0.015	0.008	0.140
5	0.729	0.048	0.020	0.048	0.016	0.008	0.145
6	0.685	0.069	0.022	0.067	0.018	0.005	0.153
7	0.682	0.087	0.022	0.080	0.015	0.006	0.132
8	0.674	0.104	0.016	0.087	0.020	0.004	0.121
9	0.647	0.111	0.019	0.082	0.024	0.004	0.131
10	0.673	0.120	0.017	0.075	0.021	0.005	0.104
11	0.647	0.137	0.014	0.084	0.021	0.004	0.108
12	0.634	0.158	0.016	0.088	0.014	0.003	0.099
13	0.616	0.171	0.017	0.091	0.024	0.002	0.096
14	0.619	0.172	0.018	0.099	0.025	0.001	0.080
15	0.605	0.172	0.016	0.093	0.025	0.001	0.101
16	0.601	0.201	0.014	0.085	0.024	0.003	0.083
17	0.553	0.226	0.018	0.080	0.035	0.000	0.101
18	0.563	0.208	0.016	0.082	0.041	0.000	0.106
19	0.585	0.202	0.011	0.117	0.032	0.000	0.085
20	0.333	0.667	0.000	0.000	0.000	0.000	0.000
	0.679	0.096	0.016	0.066	0.018	0.015	0.125

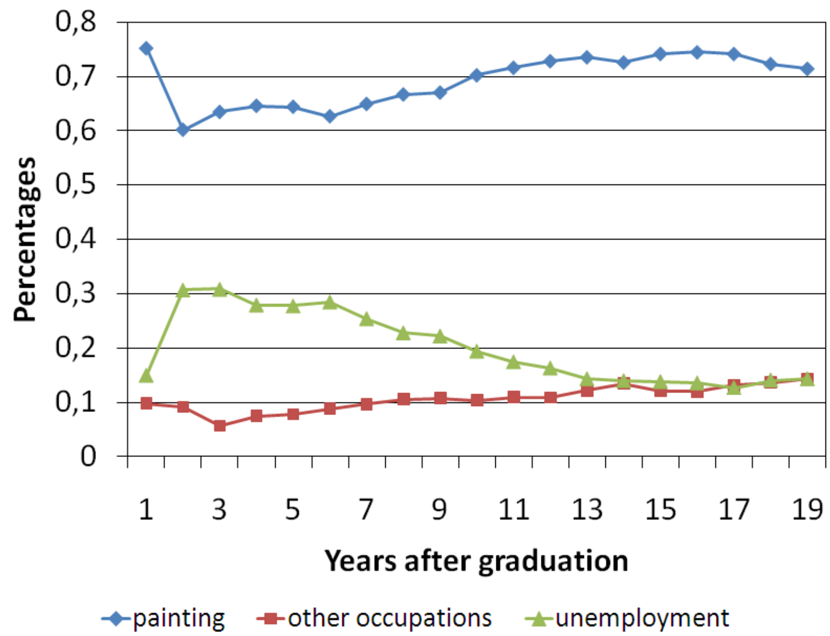


Figure A-1: Percentages people with a painting apprenticeship working as painters, working in another occupation than painting, and not working.

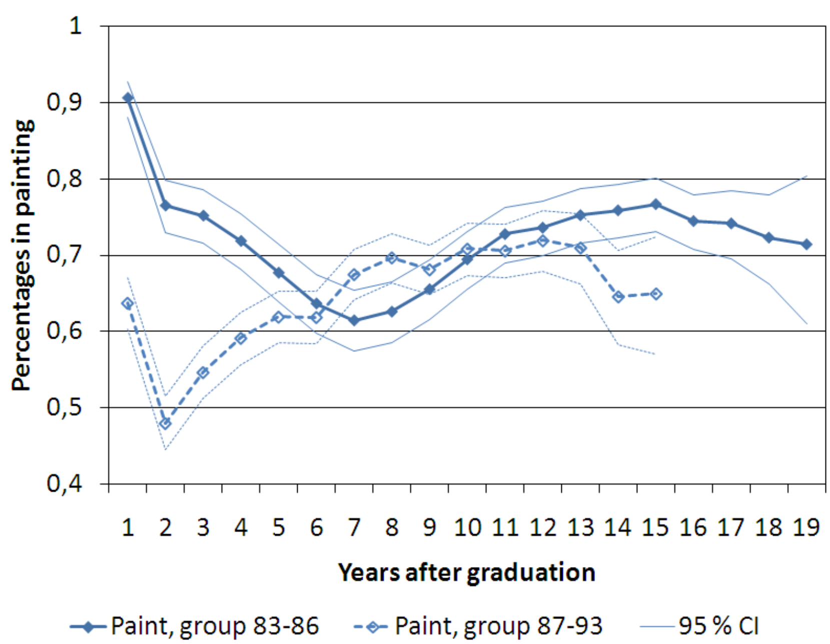


Figure A-2: Percentages people with a painting apprenticeship working as painters for 1983-1986 graduates and 1987-1993 graduates by years after graduation. 95 % confidence intervals included.

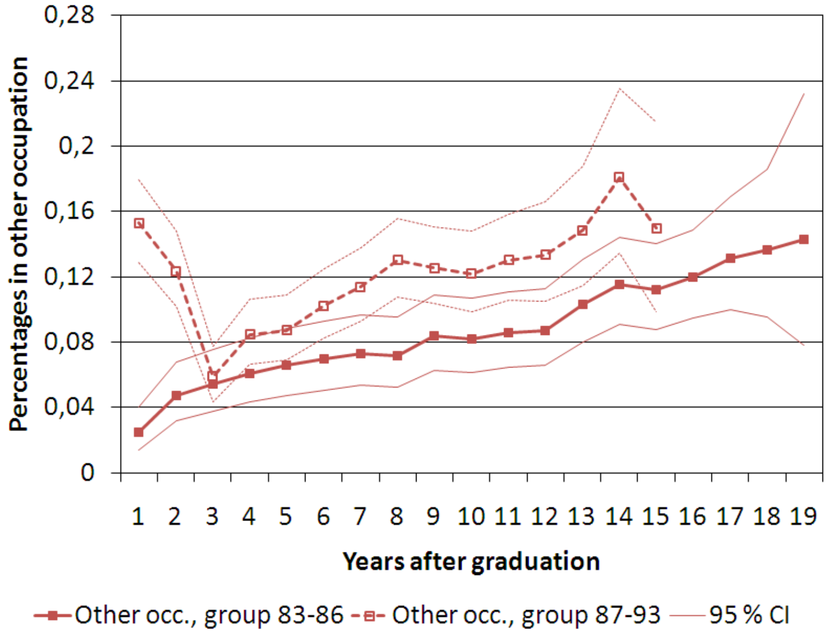


Figure A-3: Percentages people with a painting apprenticeship in another occupation than painting for 1983-1986 graduates and 1987-1993 graduates by years after graduation. 95 % confidence intervals included.

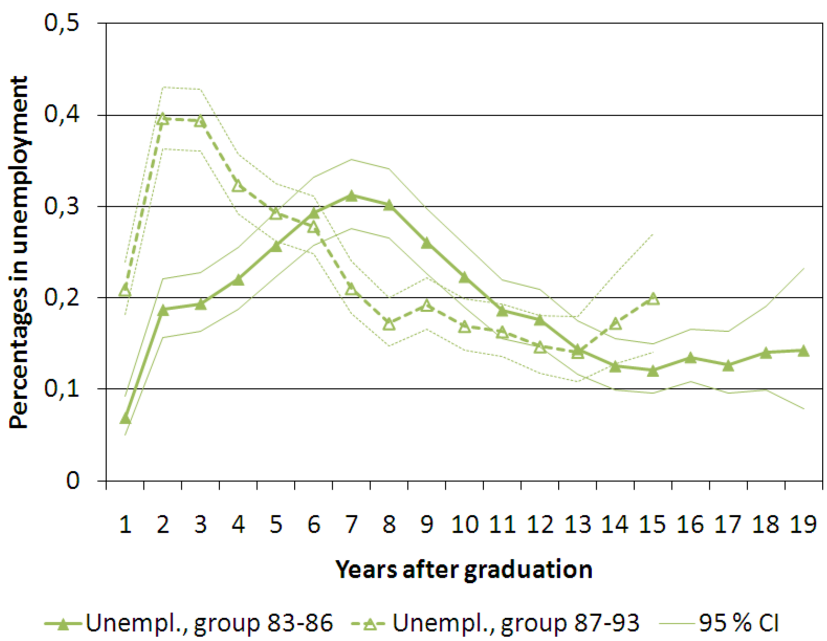


Figure A-4: Percentages people with a painting apprenticeship not working for 1983-1986 graduates and 1987-1993 graduates by years after graduation. 95 % confidence intervals included.

Table A-2: Percent of graduates with painting apprenticeship in different employment categories by year after graduation

	Graduated 1983-1986			Graduated 1983-1986		
Years after grad.	Paint	Other occ.	Unempl.	Paint	Other occ	Unempl.
1	552	15	42	521	125	171
	90.6	2.5	6.9	63.8	15.3	20.9
2	466	29	114	392	101	324
	76.5	4.8	18.7	48.0	12.4	39.7
3	458	33	118	445	48	321
	75.2	5.4	19.4	54.7	5.9	39.4
4	437	37	134	481	69	263
	71.9	6.1	22.0	59.2	8.5	32.3
5	411	40	156	503	71	238
	67.7	6.6	25.7	61.9	8.7	29.3
6	384	42	177	502	83	226
	63.7	7.0	29.4	61.9	10.2	27.9
7	370	44	188	545	92	170
	61.5	7.3	31.2	67.5	11.4	21.1
8	375	43	181	562	105	139
	62.6	7.2	30.2	69.7	13.0	17.2
9	392	50	156	548	101	155
	65.6	8.4	26.1	68.2	12.6	19.3
10	414	49	133	506	87	121
	69.5	8.2	22.3	70.9	12.2	16.9
11	433	51	111	471	87	109
	72.8	8.6	18.7	70.6	13.0	16.3
12	438	52	105	367	68	75
	73.6	8.7	17.6	72.0	13.3	14.7
13	444	61	85	277	58	55
	75.3	10.3	14.4	71.0	14.9	14.1
14	447	68	74	157	44	42
	75.9	11.5	12.6	64.6	18.1	17.3
15	451	66	71	104	24	32
	76.7	11.2	12.1	65.0	15.0	20.0
16	435	70	79			
	74.5	12.0	13.5			
17	293	52	50			
	74.2	13.2	12.7			
18	175	33	34			
	72.3	13.6	14.0			
19	65	13	13			
	71.4	14.3	14.3			

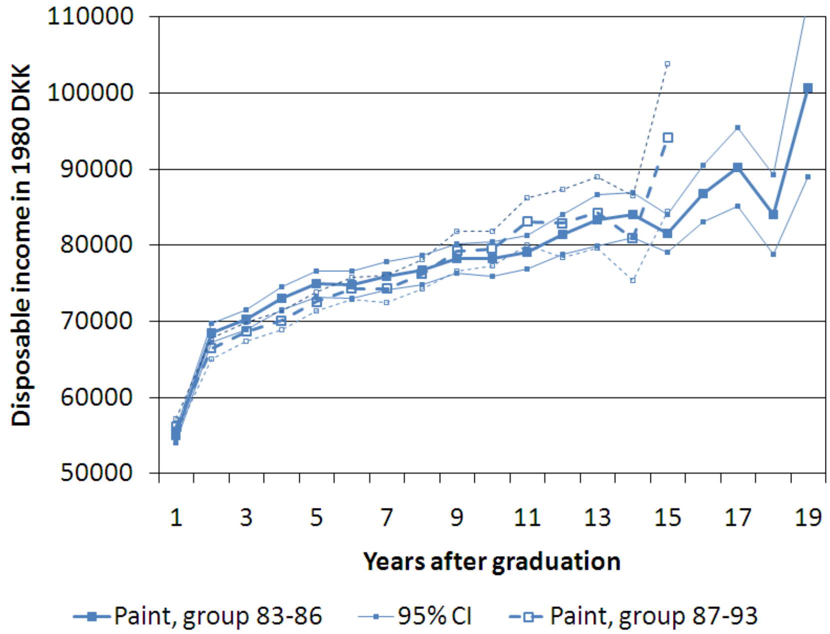


Figure A-5: Yearly disposable income in 1980 Danish Kroner of two graduations groups, 1983-1986 and 1987-1993. By years after graduation for the sample working as painters.

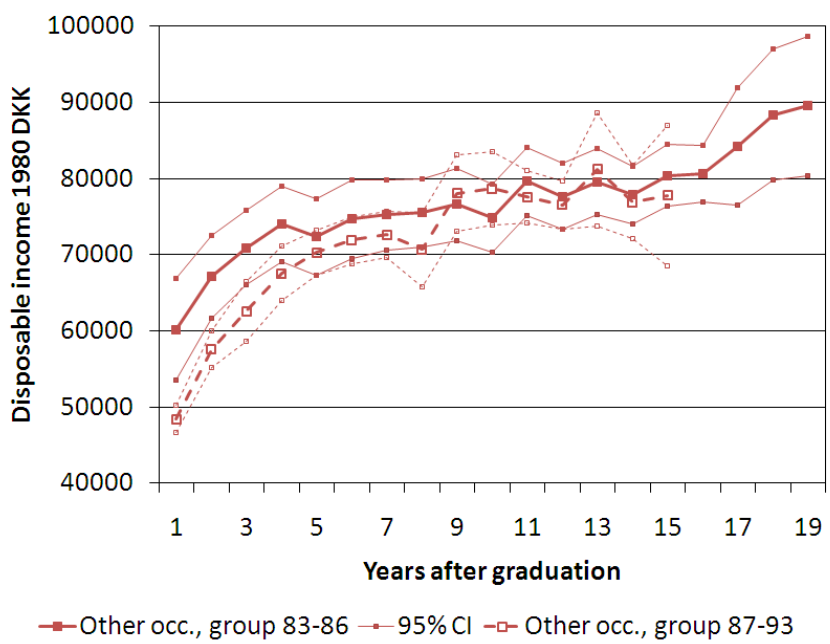


Figure A-6: Yearly disposable income in 1980 Danish Kroner of two graduations groups, 1983-1986 and 1987-1993. By years after graduation for the sample working in other occupations than painting.

Table A-3: Transition matrix up to 8 years after graduation for graduates from 1983 to 1986.

	Status in t		
Status in $t-1$	Paint	Other Occ.	Unemp.
Paint			
Number	2,583	55	434
Row %	84.1	1.8	14.1
Other Occ.			
Number	37	174	28
Row %	15.5	72.8	11.7
Unempl.			
Number	281	39	606
Row %	30.4	4.2	65.4

Table A-4: Transition matrix up to 8 years after graduation for graduates from 1987 to 1993.

	Status in t		
Status in $t-1$	Paint	Other Occ.	Unemp.
Paint			
Number	2,737	123	523
Row %	80.9	3.6	15.5
Other Occ.			
Number	141	340	107
Row %	24.0	57.8	18.2
Unempl.			
Number	552	106	1,051
Row %	32.3	6.2	61.5

Table A-5: Persistence in each state for the two graduation groups. Percent in the in the state in year t conditional on being in the state in year t-1.

	Graduated 1983-1986			Graduated 1983-1986		
Years after graduation	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period
1	.	.	.	.	.	.
2	0.82	0.80	0.67	0.61	0.40	0.75
3	0.86	0.72	0.49	0.76	0.18	0.62
4	0.87	0.70	0.64	0.83	0.67	0.61
5	0.84	0.78	0.66	0.83	0.78	0.61
6	0.81	0.75	0.69	0.84	0.75	0.62
7	0.82	0.69	0.68	0.89	0.77	0.56
8	0.86	0.70	0.69	0.89	0.76	0.55
9	0.86	0.74	0.61	0.87	0.71	0.62
10	0.91	0.70	0.66	0.92	0.76	0.60
11	0.89	0.67	0.55	0.90	0.85	0.61
12	0.90	0.76	0.61	0.93	0.83	0.61
13	0.89	0.83	0.49	0.93	0.89	0.71
14	0.92	0.85	0.55	0.89	0.93	0.63
15	0.92	0.78	0.57	0.87	0.79	0.67
16	0.91	0.77	0.68	.	.	.
17	0.90	0.80	0.56	.	.	.
18	0.91	0.88	0.65	.	.	.
19	0.91	0.63	0.75	.	.	.

Table A-6: Wage regression for painters and other occupation

	Wage regression for painters	Wage regression for other occupation
	(1)	(2)
paint exp.	0.1073***	0.0919***
	(29.19)	(14.60)
other occ. exp.	0.0264***	0.0978***
	(2.756)	(15.07)
Constant	10.9490***	10.9178***
	(1321)	(832.0)
Observations	11667	1640
R-squared	0.068	0.190

*** p<0.01, ** p<0.05, * p<0.1
t statistics in parentheses

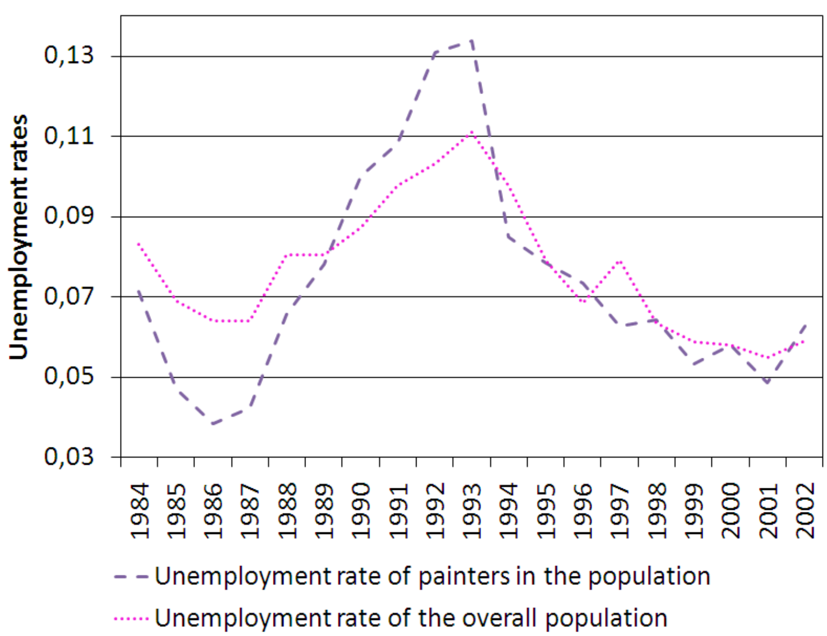


Figure A-7: Yearly unemployment rates of (educated) painters from the population and the overall population.

Table A-7: Logit regressions for participation in painters and other occupation

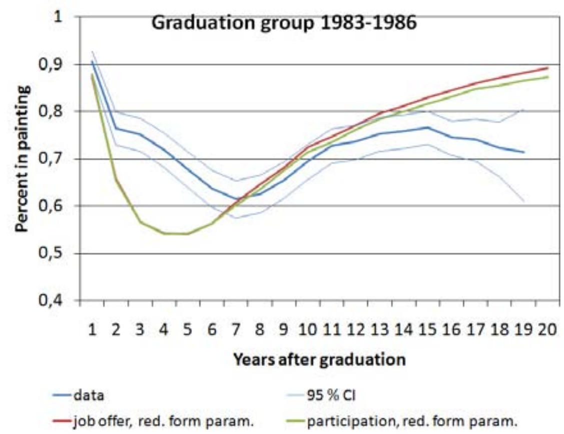
	Painting 2 to 13 years after grad. (1)	Other occ. 1 to 13 years after grad. (2)	Painters first year after grad. (3)	Painting 2 to 13 years after grad. (4)	Other occ. 1 to 13 years after grad. (5)
paint exp.				0.2683***	
				*0.0541****	
				(30.28)	
past partic. in paint				2.2355***	
				*0.4765****	
				(50.54)	
other exp.					0.5495***
					*0.0265****
					(23.19)
past partic. in other					2.6991***
					*0.3474****
					(31.57)
unempl. painters	-11.5306***	-10.9517***	-19.8763**	7.6705***	6.3442**
	*-2.5738****	*-0.9111****	*-3.4188***	*1.5453****	*0.3055***
	(-9.563)	(-5.732)	(-2.266)	(4.770)	(2.531)
unempl diff.	-1.0966	24.5204***	-8.9883	-28.6543***	-4.6380
	-0.2448	*2.0399****	*-1.5460*	*-5.7729****	*-0.2234*
	(-0.462)	(6.474)	(-0.604)	(-9.267)	(-0.953)
Constant	1.6286***	-1.4146***	2.7265***	-2.2726***	-3.8890***
	(16.43)	(-9.244)	(3.576)	(-15.59)	(-18.43)
Observations	14996	16422	1426	14996	16422

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

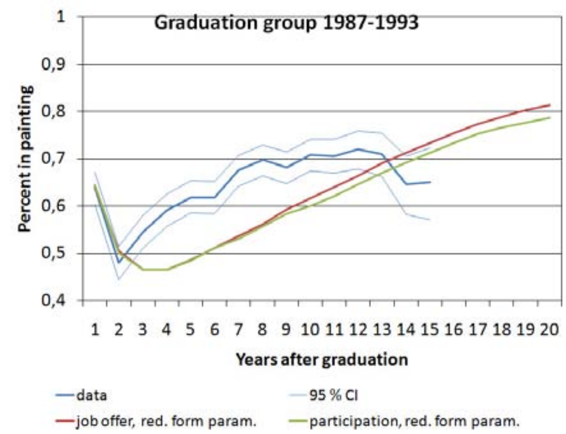
Italic numbers are marginal coefficient calculated at the mean

z statistics in parentheses

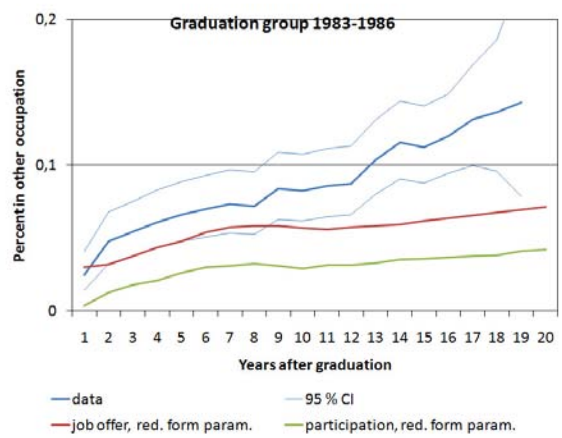
A2 Appendix Results from Different Parameter Choices



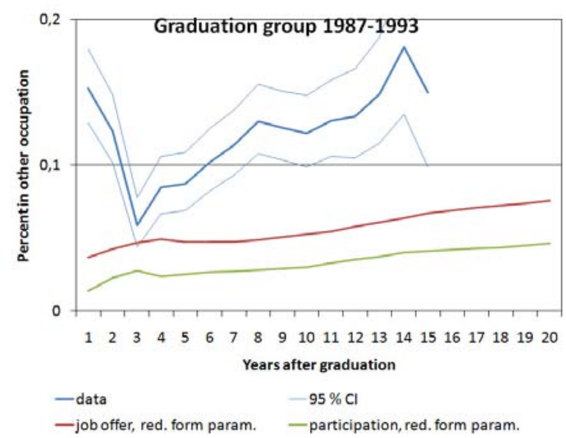
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

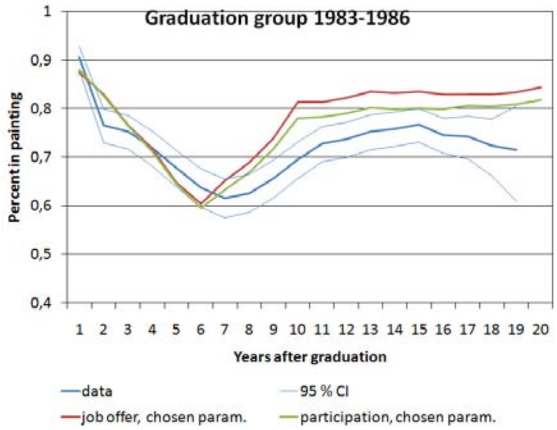


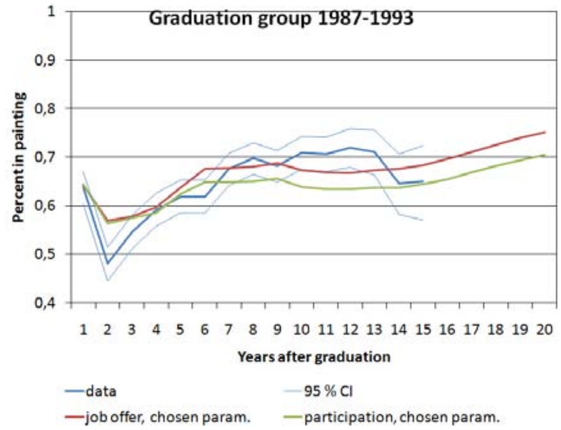
(c) Percentages of people from graduation years 1983-1986 working in other occupations.



(d) Percentages of people from graduation years 1987-1993 working in other occupations.

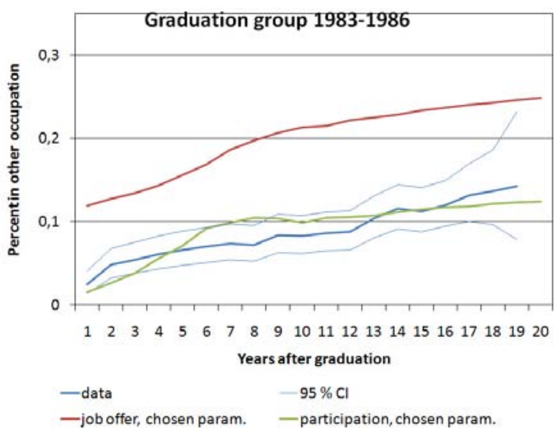
Figure A-8: Percentages in painting and other occupations from data and simulated data with parameters from reduced form estimations.

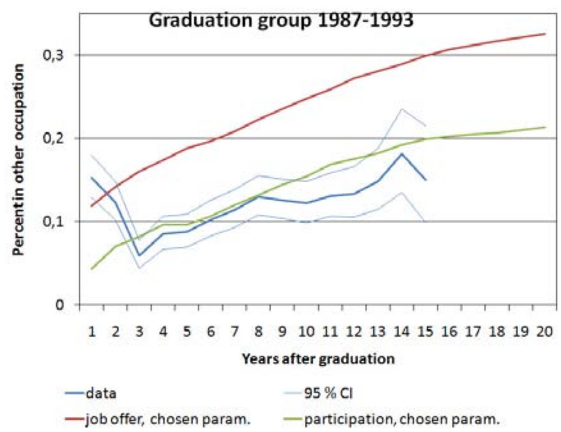




(a) Percentages of people from graduation years 1983-1986 working as painters.

(b) Percentages of people from graduation years 1987-1993 working as painters.

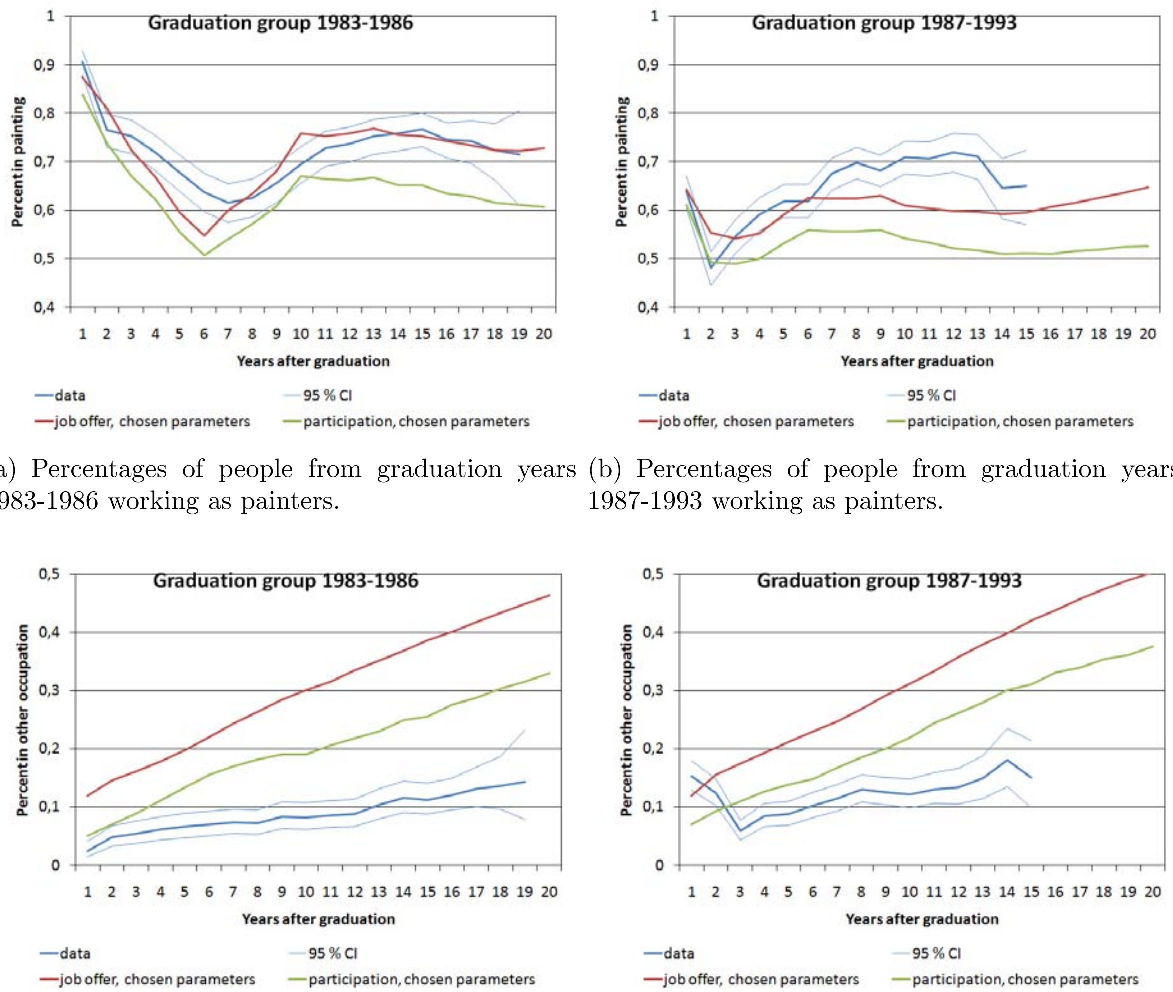




(c) Percentages of people from graduation years 1983-1986 working in other occupations.

(d) Percentages of people from graduation years 1987-1993 working in other occupations.

Figure A-9: Percentages in painting and other occupations from data and simulated data with parameters chosen to "fit" data.



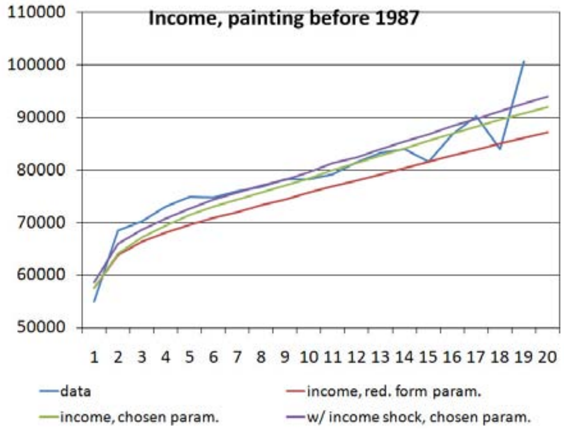
(a) Percentages of people from graduation years 1983-1986 working as painters.

(b) Percentages of people from graduation years 1987-1993 working as painters.

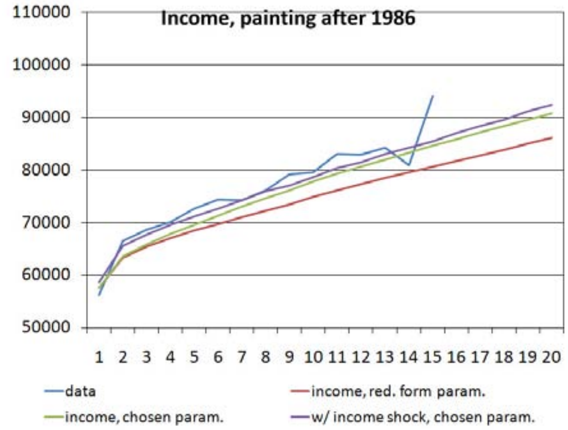
(c) Percentages of people from graduation years 1983-1986 working in other occupations.

(d) Percentages of people from graduation years 1987-1993 working in other occupations.

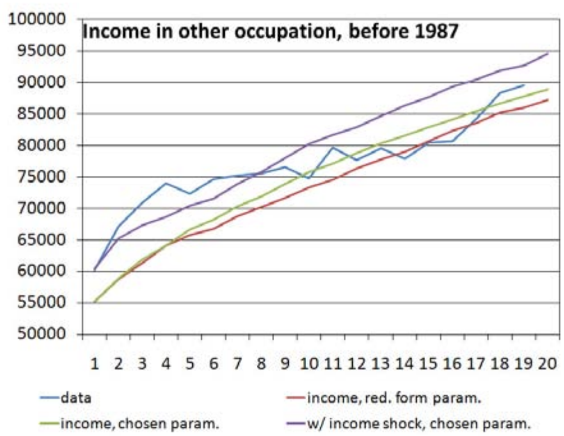
Figure A-10: Percentages in painting and other occupations from data and simulated data with parameters chosen to "fit" data without income shock. Figures are simulated data with income shocks in the model.



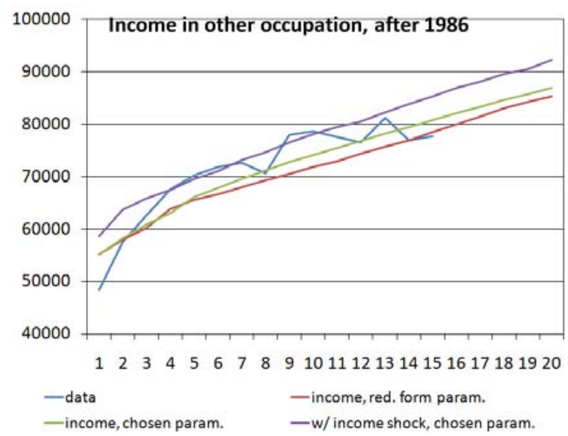
(a) Disposable income of people from graduation years 1983-1986 working as painters.



(b) Disposable income of people from graduation years 1987-1993 working as painters.



(c) Disposable income of people from graduation years 1983-1986 working in other occupations.



(d) Disposable income of people from graduation years 1987-1993 working in other occupations.

Figure A-11: Disposable income in 1980 Danish Kroner in painting and other occupations from data and simulated data with parameters chosen to "fit" data without income shock. Figures are simulated data from reduced form parameters and chosen parameters with and without income shocks in the model.

Table A-8: Transition matrix between 2 to 3 years after graduation for graduates from 1983 to 1986. Data simulated from reduced form estimates.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,76	0,01	0,23
Other Occ.			
Row %	0,14	0,42	0,44
Unempl.			
Row %	0,19	0,03	0,78

Table A-9: Transition matrix between 2 to 3 years after graduation for graduates from 1987 to 1993. Data simulated from reduced form estimates.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,75	0,01	0,24
Other Occ.			
Row %	0,15	0,44	0,40
Unempl.			
Row %	0,18	0,03	0,79

Table A-10: Transition matrix from 2 to 8 years after graduation for graduates from 1983 to 1986. Data simulated from reduced form estimates.

	Status in t		
Status in t-1	Paint	Other Occ.	Unemp.
Paint			
Row %	0,80	0,01	0,19
Other Occ.			
Row %	0,15	0,52	0,33
Unempl.			
Row %	0,24	0,03	0,74

Table A-11: Transition matrix from 2 to 8 years after graduation for graduates from 1987 to 1993. Data simulated from reduced form estimates.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,79	0,01	0,21
Other Occ.			
Row %	0,14	0,50	0,36
Unempl.			
Row %	0,20	0,02	0,78

Table A-12: Persistence in each state for the two graduation groups. Percent in the in the state in year t conditional on being in the state in year t-1. Simulated data from reduced form estimates.

		Graduated 1983-1986			Graduated 1983-1986	
Years after graduation	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period
1	.	.	.	.	.	.
2	0,72	0,32	0,80	0,69	0,37	0,81
3	0,76	0,42	0,78	0,75	0,44	0,79
4	0,79	0,44	0,77	0,78	0,47	0,79
5	0,81	0,52	0,75	0,80	0,54	0,77
6	0,83	0,50	0,73	0,82	0,51	0,76
7	0,86	0,56	0,70	0,83	0,55	0,76
8	0,88	0,59	0,69	0,85	0,58	0,75
9	0,89	0,61	0,66	0,87	0,63	0,74
10	0,91	0,66	0,66	0,88	0,67	0,76
11	0,92	0,73	0,67	0,89	0,70	0,75
12	0,93	0,74	0,64	0,91	0,76	0,74
13	0,94	0,81	0,65	0,92	0,78	0,75
14	0,94	0,83	0,66	0,93	0,81	0,75
15	0,95	0,82	0,65	0,94	0,82	0,76

Table A-13: Transition matrix between 2 to 3 years after graduation for graduates from 1983 to 1986. Data simulated from chosen parameters.

	Status in t		
Status in t-1	Paint	Other Occ.	Unemp.
Paint			
Row %	0,85	0,02	0,13
Other Occ.			
Row %	0,30	0,47	0,23
Unempl.			
Row %	0,34	0,07	0,58

Table A-14: Transition matrix between 2 to 3 years after graduation for graduates from 1987 to 1993. Data simulated from chosen parameters.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,79	0,03	0,18
Other Occ.			
Row %	0,25	0,52	0,22
Unempl.			
Row %	0,30	0,08	0,61

Table A-15: Transition matrix from 2 to 8 years after graduation for graduates from 1983 to 1986. Data simulated from chosen parameters.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,84	0,02	0,14
Other Occ.			
Row %	0,21	0,62	0,17
Unempl.			
Row %	0,33	0,09	0,59

Table A-16: Transition matrix from 2 to 8 years after graduation for graduates from 1987 to 1993. Data simulated from chosen parameters.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,82	0,03	0,16
Other Occ.			
Row %	0,18	0,67	0,15
Unempl.			
Row %	0,32	0,08	0,59

Table A-17: Persistence in each state for the two graduation groups. Percent in the in the state in year t conditional on being in the state in year t-1. Simulated data from chosen parameters.

	Graduated 1983-1986			Graduated 1983-1986		
Years after graduation	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period
1	.	.	.	.	.	.
2	0,88	0,35	0,51	0,74	0,48	0,66
3	0,85	0,47	0,58	0,79	0,52	0,61
4	0,84	0,55	0,61	0,80	0,58	0,60
5	0,81	0,61	0,66	0,84	0,63	0,58
6	0,79	0,65	0,64	0,85	0,71	0,54
7	0,84	0,65	0,55	0,85	0,78	0,57
8	0,86	0,68	0,53	0,86	0,80	0,57
9	0,89	0,72	0,48	0,87	0,83	0,55
10	0,92	0,74	0,39	0,86	0,84	0,60
11	0,91	0,84	0,43	0,87	0,86	0,58
12	0,92	0,83	0,41	0,88	0,86	0,58
13	0,93	0,87	0,41	0,89	0,88	0,58
14	0,93	0,89	0,43	0,88	0,89	0,56
15	0,94	0,89	0,43	0,90	0,90	0,57

Table A-18: Transition matrix between 2 to 3 years after graduation for graduates from 1983 to 1986. Data simulated from chosen parameters and including stochastic income in the model.

	Status in t		
Status in t-1	Paint	Other Occ.	Unemp.
Paint			
Row %	0,81	0,05	0,14
Other Occ.			
Row %	0,23	0,53	0,23
Unempl.			
Row %	0,31	0,08	0,61

Table A-19: Transition matrix between 2 to 3 years after graduation for graduates from 1987 to 1993. Data simulated from chosen parameters and including stochastic income in the model.

	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,74	0,06	0,20
Other Occ.			
Row %	0,18	0,56	0,26
Unempl.			
Row %	0,26	0,07	0,67

Table A-20: Transition matrix from 2 to 8 years after graduation for graduates from 1983 to 1986. Data simulated from chosen parameters and including stochastic income in the model.

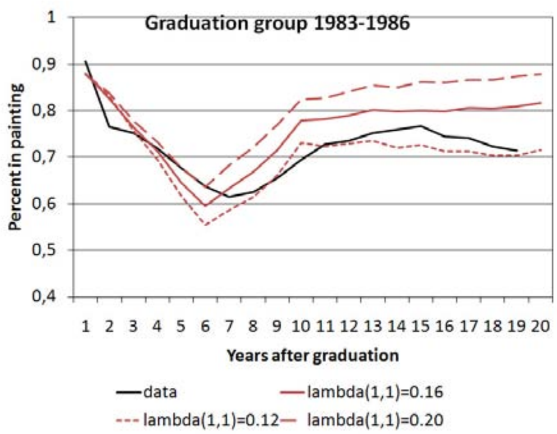
	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,79	0,06	0,15
Other Occ.			
Row %	0,20	0,62	0,18
Unempl.			
Row %	0,29	0,10	0,61

Table A-21: Transition matrix from 2 to 8 years after graduation for graduates from 1987 to 1993. Data simulated from chosen parameters and including stochastic income in the model.

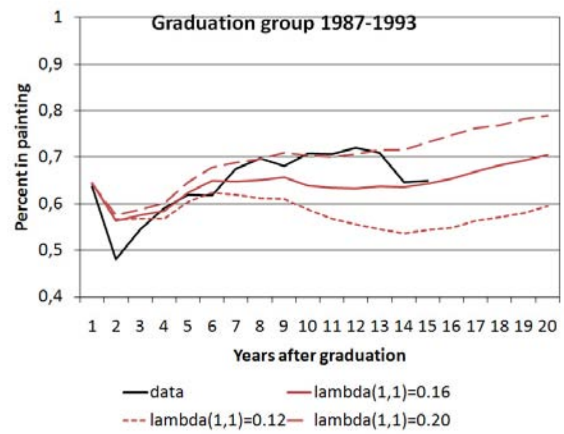
	Status in t		
Status in t-1	Paint	Other Occ.	Unempl.
Paint			
Row %	0,77	0,06	0,17
Other Occ.			
Row %	0,19	0,62	0,19
Unempl.			
Row %	0,27	0,09	0,64

Table A-22: Persistence in each state for the two graduation groups. Percent in the in the state in year t conditional on being in the state in year t-1. Simulated data from chosen parameters and including stochastic income in the model.

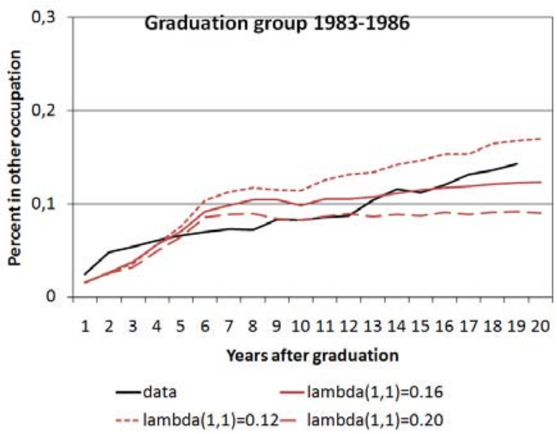
		Graduated 1983-1986			Graduated 1983-1986	
Years after graduation	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period	Percentage in paint if paint previous period	Percentage in other occ. if other occ. previous period	Percentage in unempl. if unempl. previous period
1	.	.	.	.	.	.
2	0,82	0,47	0,59	0,68	0,52	0,73
3	0,81	0,53	0,61	0,74	0,56	0,67
4	0,80	0,58	0,63	0,76	0,58	0,65
5	0,76	0,63	0,67	0,79	0,60	0,61
6	0,75	0,65	0,66	0,80	0,61	0,59
7	0,79	0,66	0,57	0,80	0,67	0,61
8	0,81	0,66	0,54	0,80	0,69	0,60
9	0,83	0,67	0,50	0,81	0,71	0,59
10	0,86	0,66	0,40	0,80	0,74	0,61
11	0,84	0,70	0,45	0,80	0,75	0,59
12	0,84	0,71	0,43	0,80	0,76	0,59
13	0,85	0,72	0,43	0,81	0,78	0,60
14	0,85	0,75	0,44	0,81	0,79	0,58
15	0,85	0,74	0,45	0,82	0,79	0,59



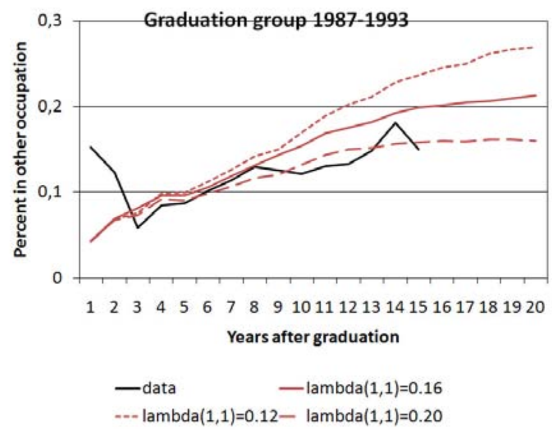
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

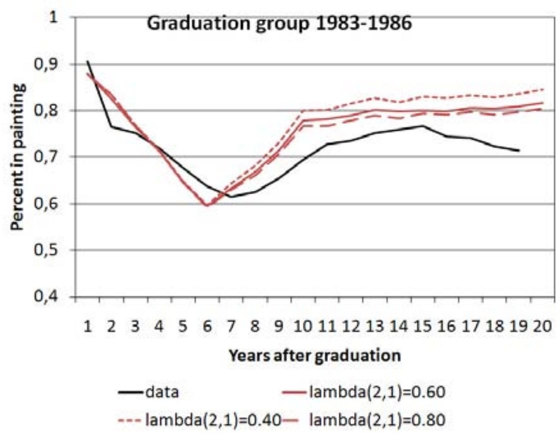


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

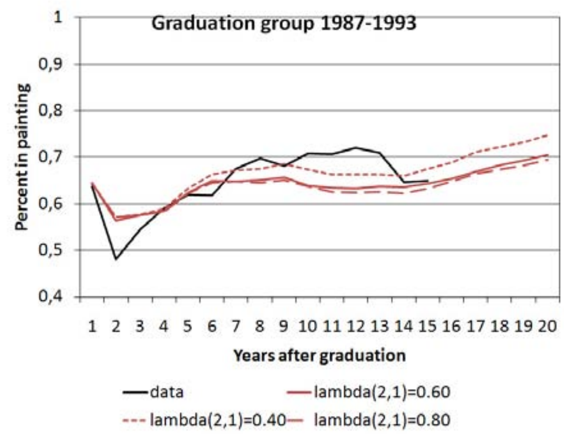


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

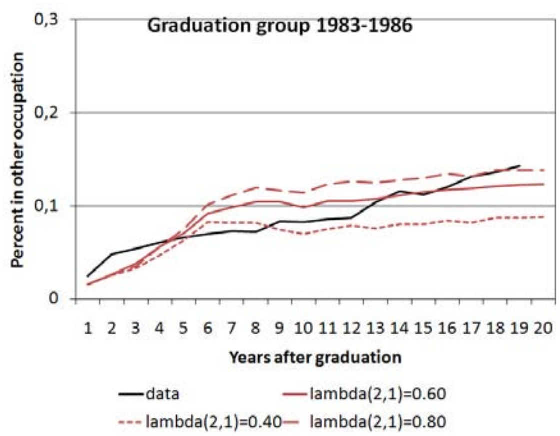
Figure A-12: Percentages in painting and other occupations from data and simulated data varying λ_1^1.



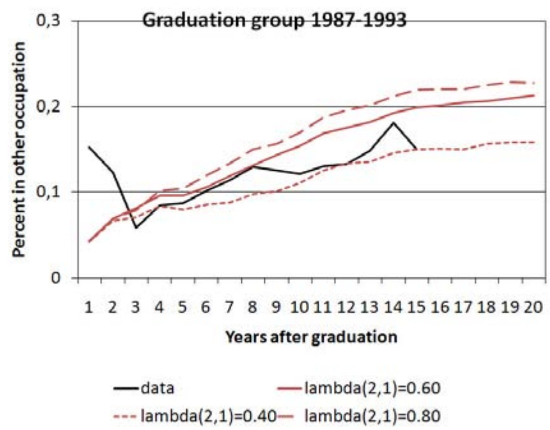
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

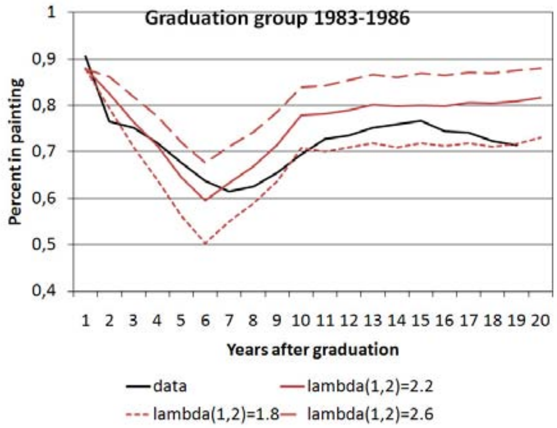


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

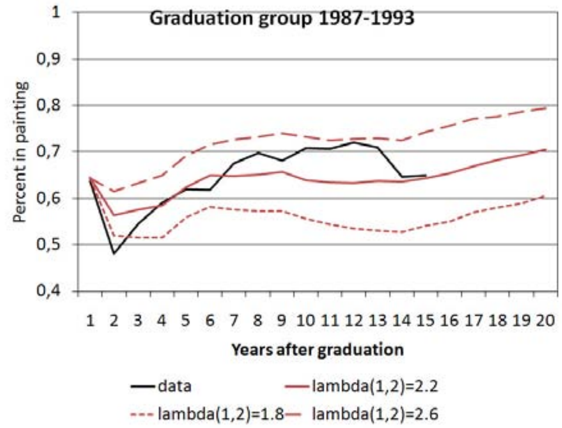


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

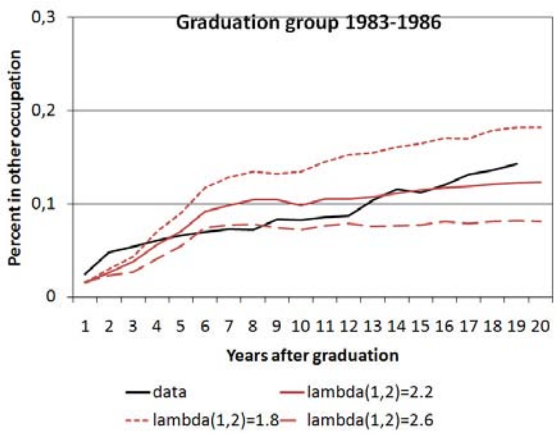
Figure A-13: Percentages in painting and other occupations from data and simulated data varying λ_1^2.



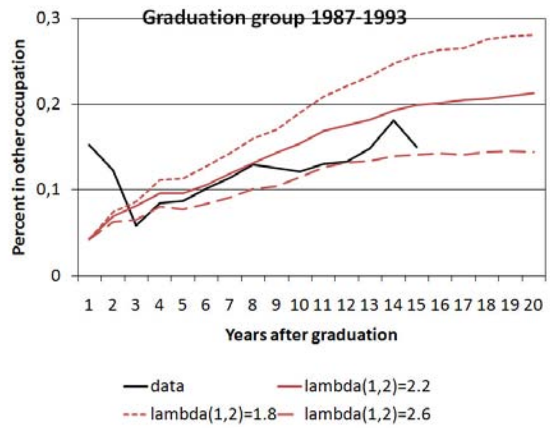
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

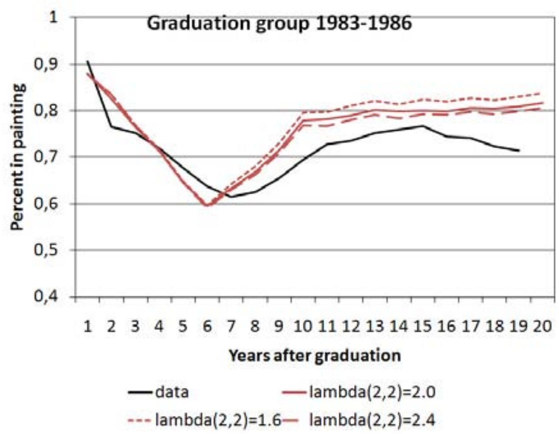


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

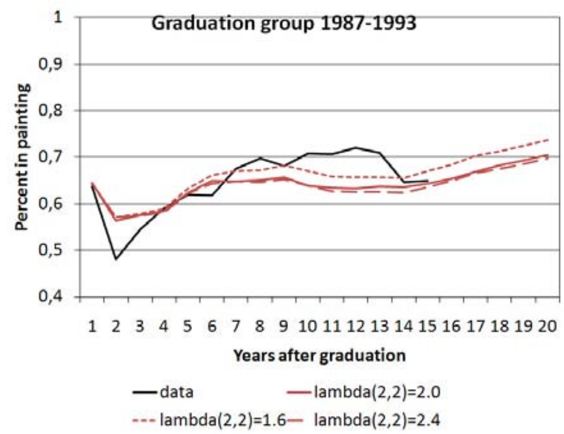


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

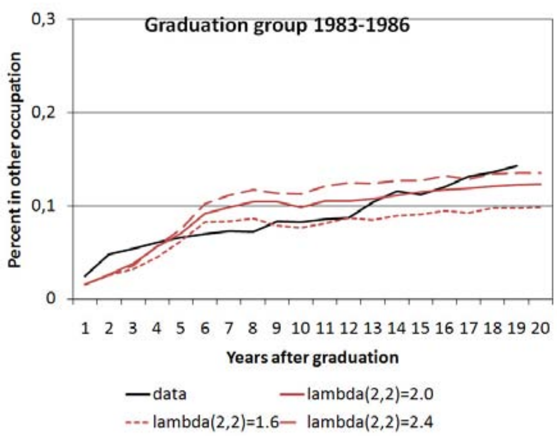
Figure A-14: Percentages in painting and other occupations from data and simulated data varying λ_2^1.



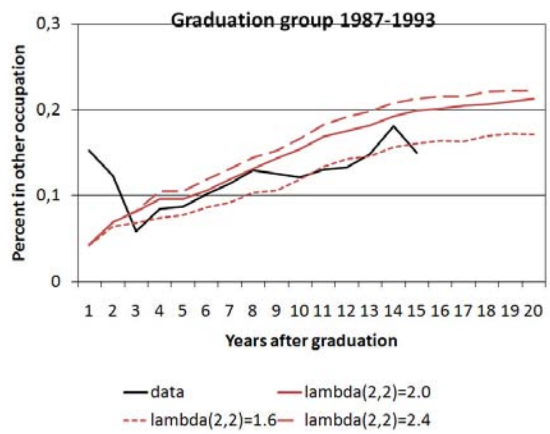
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

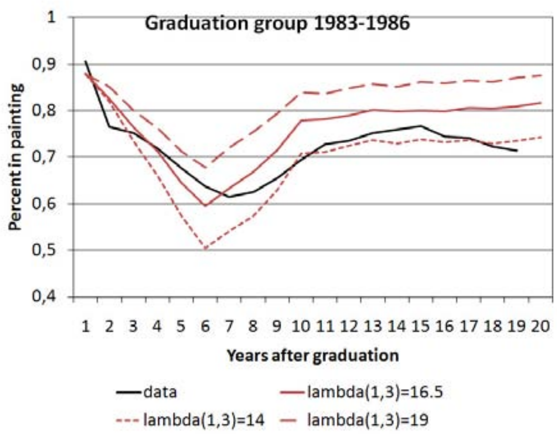


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

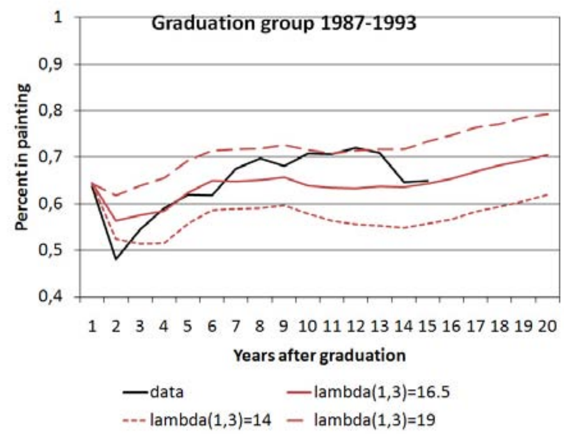


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

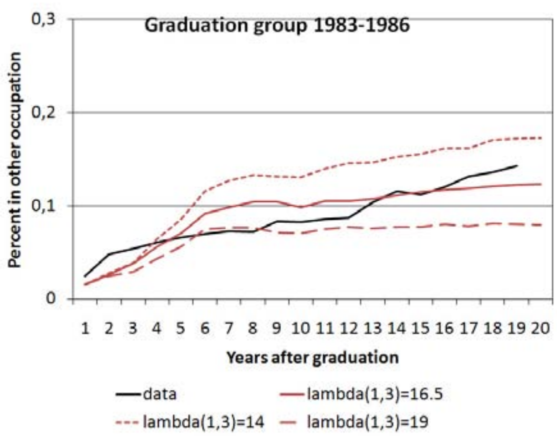
Figure A-15: Percentages in painting and other occupations from data and simulated data varying λ_2^2.



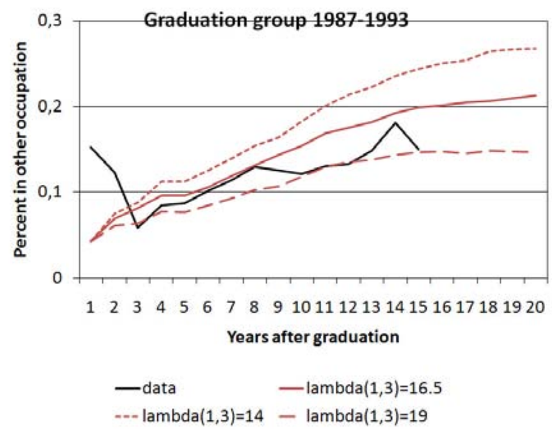
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

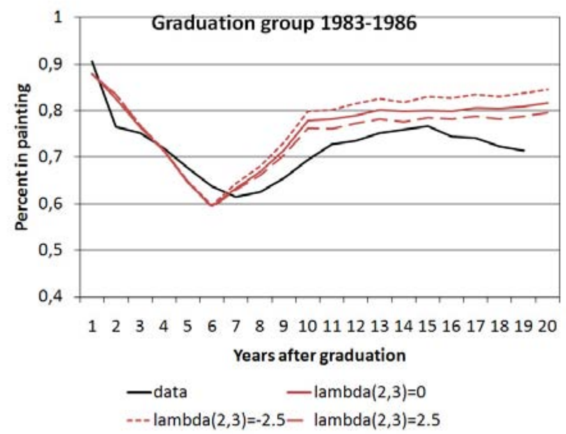


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

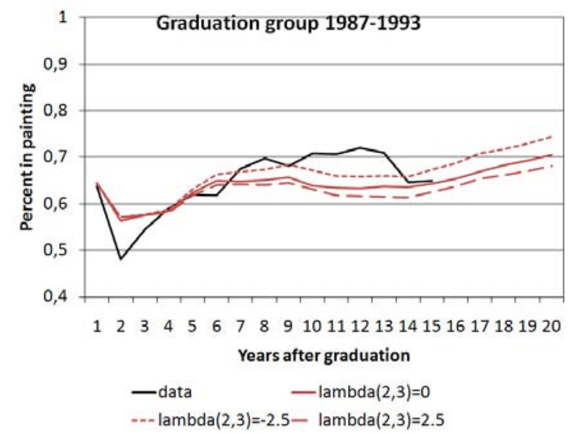


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

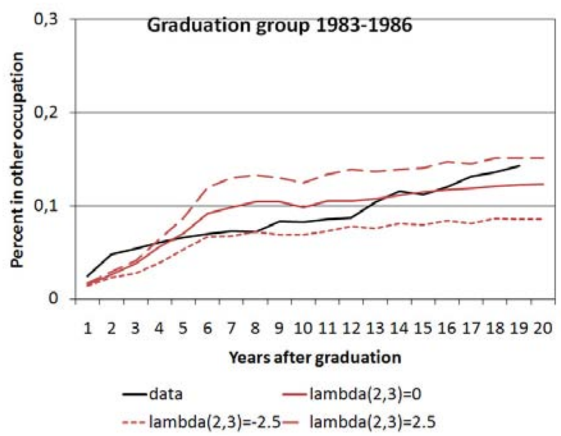
Figure A-16: Percentages in painting and other occupations from data and simulated data varying λ_3^1.



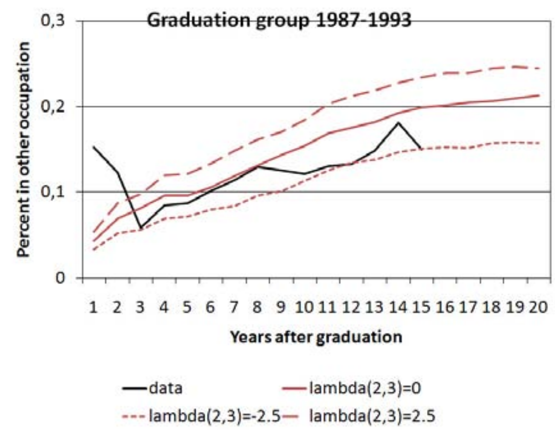
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

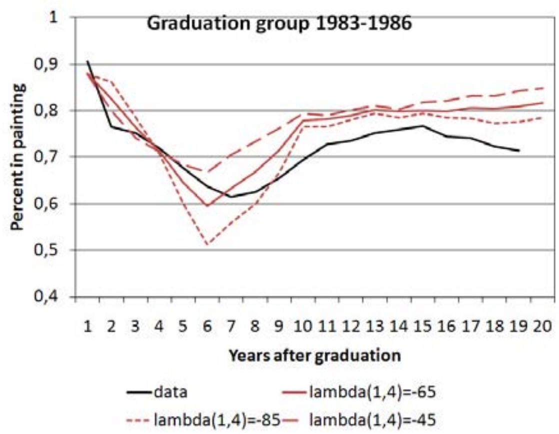


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

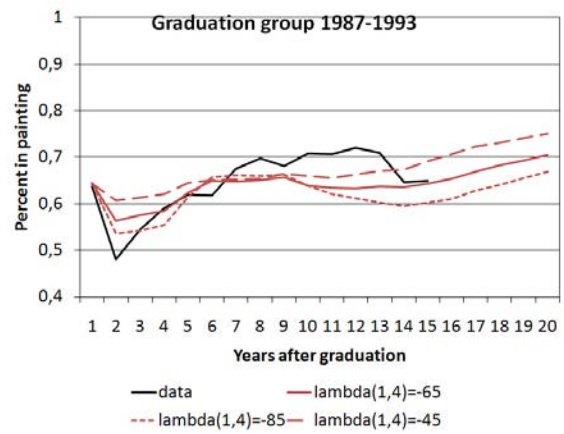


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

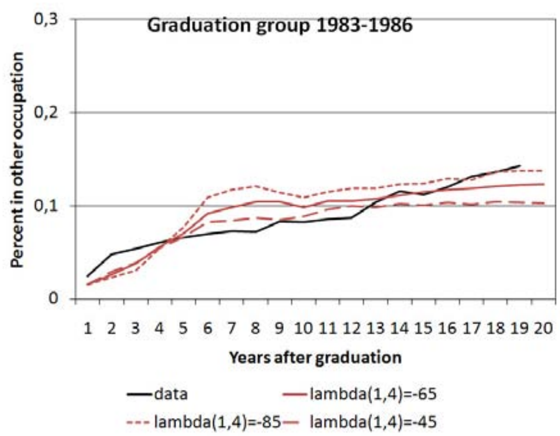
Figure A-17: Percentages in painting and other occupations from data and simulated data varying λ_3^2.



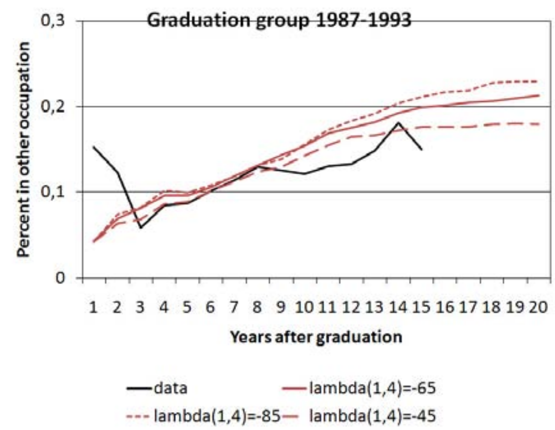
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

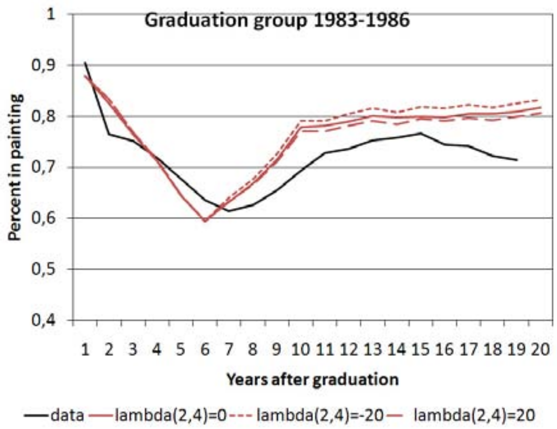


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

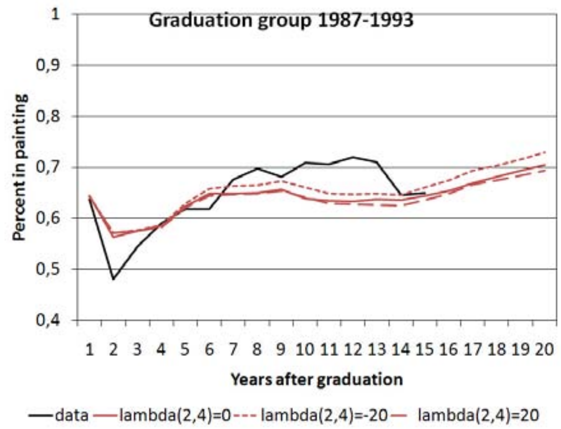


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

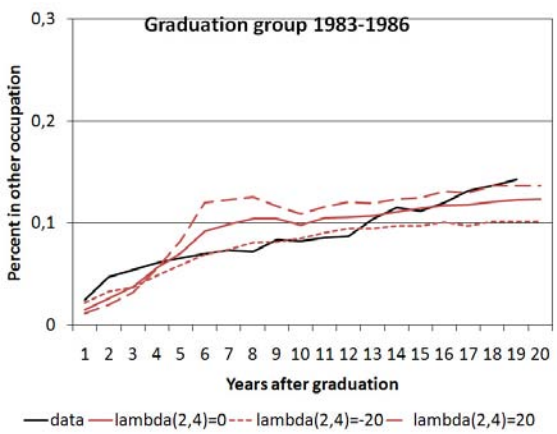
Figure A-18: Percentages in painting and other occupations from data and simulated data varying λ_4^1.



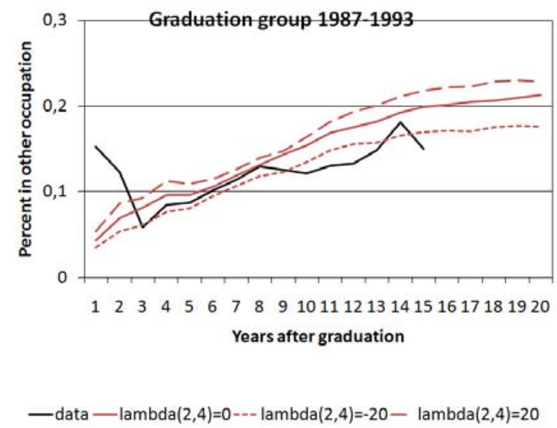
(a) Percentages of people from graduation years 1983-1986 working as painters.



(b) Percentages of people from graduation years 1987-1993 working as painters.

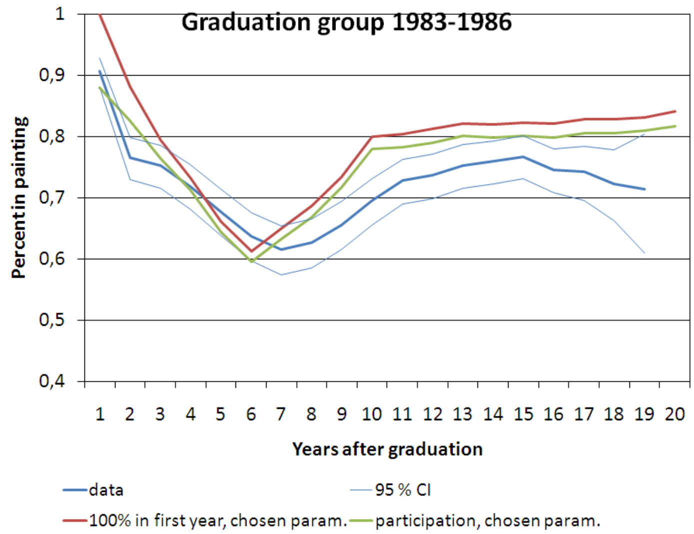


(c) Percentages of people from graduation years 1983-1986 working in other occupations.

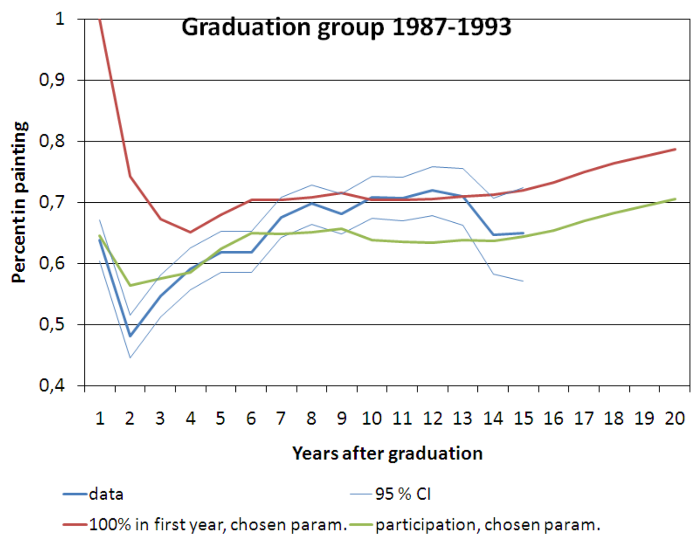


(d) Percentages of people from graduation years 1987-1993 working in other occupations.

Figure A-19: Percentages in painting and other occupations from data and simulated data varying λ_4^2.

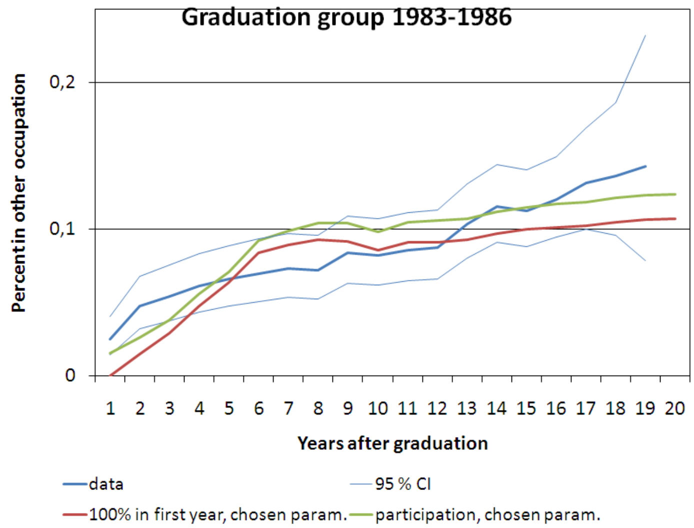


(a) Percentages of people from graduation years 1983-1986 working as painters.

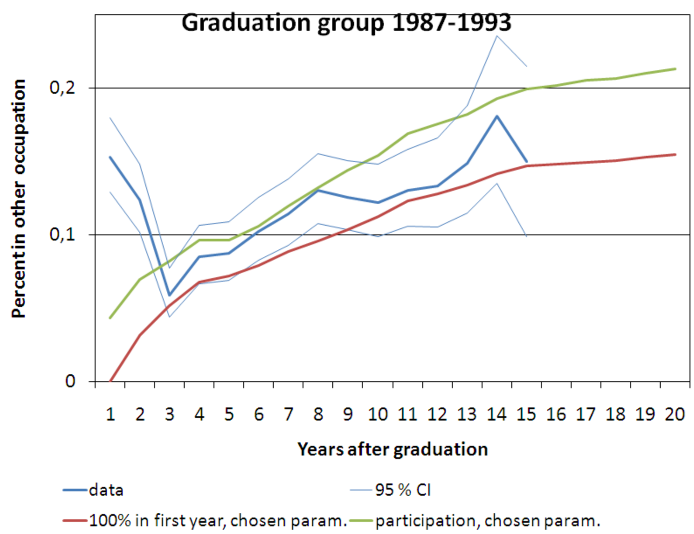


(b) Percentages of people from graduation years 1987-1993 working as painters.

Figure A-20: Percentages in painting from data and simulated data with the chosen parameters. Counterfactual experiment of increasing job offer probability in painting to be 100 % in the first year after graduation.



(a) Percentages of people from graduation years 1983-1986 working in other occupations.



(b) Percentages of people from graduation years 1987-1993 working in other occupations.

Figure A-21: Percentages in other occupation from data and simulated data with the chosen parameters. Counterfactual experiment of increasing job offer probability in painting to be 100 % in the first year after graduation.