Universitat Autònoma de Barcelona

Essays on Labor Economics

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To my family.

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Contents

Preface

In this dissertation, I analyze the determinants and consequences of a mismatch between the skills of workers and the skills required by the occupation they work in. The allocation of talent, which worker performing what type of job, is often considered a key determinant of economic success (Murphy et al. (1991), Banerjee & Newman (1993), Hassler & Rodriguez Mora (2000) and Hsieh et al. (2019)). I study how skills mismatch can be measured and how unemployment insurance policy affects occupational switching, which in turn has implications for the skills mismatch of workers. In the second part of this dissertation I investigate the determinants of in vitro fertilization success, which has important implications for women's career and fertility choices.

In Chapter 1, I compute new measures of skills mismatch for literacy and numeracy based on how well workers sort to jobs. Existing measures of skills mismatch based on the Programme for the International Assessment of Adult Competencies (PIAAC) use information only on the worker's side, and ignore jobs that workers perform or the sorting between workers and jobs. For 13 OECD countries from the PIAAC, I measure workers' skills by their individual test scores and the skill requirements of their jobs by the occupational requirements from the Occupational Information Network (O'NET). I then look at 1) the correlation between the skills and skill requirements in each country and 2) the percentage of workers for whom the absolute difference between the percentile rank of their skills and the skill requirements of their jobs is larger than 50. I show that across countries the new measures of mismatch correlate negatively with measures of aggregate labor productivity, and the correlation is stronger than the existing measures. I also show that there is a negative correlation between the generosity of unemployment benefits provided and skills mismatch.

In Chapter 2, joint with Andrii Parkhomenko, we study the relationship between unemployment benefits and occupational switching. Do unemployment benefits only provide income support for workers during their unemployment spells, or do they also affect post-unemployment outcomes? Using two US data sets, the SIPP and the NLSY79, we document three new facts on the relationship between unemployment benefits and occupational switching. First, unemployed individuals who are eligible for higher unemployment benefits are less likely to switch occupations. Second, conditional on switching, having higher unemployment benefits correlates positively with the cognitive skills requirements of the new occupation. Finally, while the first fact is stronger for workers with longer occupational tenure, the second fact is stronger for workers with shorter occupational tenure. We then build a search model with heterogeneous individuals and jobs to study how unemployment benefits affect skill requirements and wages for workers who experience employment-unemployment-employment transitions. The model features on-the-job search, skill accumulation and depreciation, and skills mismatch (the gap between a worker's skill and the skill requirements of his occupation). The model is able to produce the relationships observed in the data. We then use the model economy to study the effects of linking unemployment benefits to labor market experience. We find that providing larger benefits to workers with shorter labor market experience results in higher average wages.

In Chapter 3, joint with Fane Groes, Daniela Iorio, Mallory Leung and Raul Santaeulàlia-Llopis, we study the determinants of in vitro fertilization (IVF) success using administrative data from Denmark (1995-2009). We find that maternal education significantly determines IVF success (live birth). Compared with high school dropouts, patients with a college (high school) degree have a 21% (13%) higher chance of attaining a live birth through IVF. Our explorations of the mechanisms underlying the education gradient rule out financial constraints, clinic characteristics, and medical conditions. Instead, we argue that the education gradient in IVF reflects educational disparities in IVF productivity (how well women follow the IVF procedure) and psychological factors (how they are affected by undertaking the treatments). We develop a dynamic model of women using IVF technology in which women differ in IVF productivity and the psychological stress associated with undergoing the treatment. In the model, women face a trade-off between a positive probability of succeeding in getting a child through IVF and the psychological cost associated to undergoing the treatment. The estimated model sheds light on the importance of each of the factors in explaining the IVF educational gradient. In particular, we find that differences in average IVF productivity across education groups account for more than 95% of the observed gradient.

Chapter 1

Measures of Skills Mismatch

1.1 Introduction

The skill base of a country is an important factor that determines its economic performance. As a result, the allocation of talent, which workers are performing what types of jobs, is a key determinant of economic success (Murphy et al. (1991), Banerjee & Newman (1993), Hassler & Rodriguez Mora (2000) and Hsieh et al. (2019)). When skills are misallocated, it has consequences for individuals, whose job satisfaction and wages may be negatively affected by this mismatch. Moreover, it has consequence for the economy as a whole, since misallocation of talent prevents countries from reaching their economic potential. The skills mismatch has recently received renewed attention due to the availability of new data on individual skills and on how these skills are put to work (Adalet McGowan & Nicoletti (2015)).

The Programme for the International Assessment of Adult Competencies (PIAAC) carried out by the OECD provides both self-reported information on worker's skills and an objective measure of two particular skills, literacy and numeracy, in the form of a test score. Two empirical measures of mismatch have emerged using the PIAAC data: a measure of skills mismatch by Pellizzari & Fichen (2013), which is used by the OECD [1], and a measure of skill use created by M. Levels & Allen (2013). Both measures rely on only the information for the workers, both self-reported and objective. The first measure looks at workers' answers to questions whether they think they are mismatched, and identifies a group of well-matched workers. Then any worker in the same occupation that has lower or higher PIACC test scores than these well-matched workers are classified as mismatched. The second measure compares the worker's skill from PIACC literacy and numeracy test scores to a measure of skills use. The skill use is constructed from

[1] https://www.oecd.org/employment/skills-and-work/

questions that workers answer on the relative importance of literacy and numeracy skills in their occupation. Hence, both measures exclusively use information in workers, survey questions or test scores.

In this paper, I propose two new measures of mismatch that combine data on test scores from the PIACC with data on skill requirements in different occupations from the Occupational Information Network (O'NET). I compute these measures for 13 OECD countries. The first measure is the correlation between the skills of the workers and the skills requirements of their occupations for each country of the sample. To construct the second measure, I first compute an individual skills mismatch, based on Guvenen et al. (2015), as the absolute difference between a worker's skill percentile rank and skill requirement of her occupation. Then I compute the percentage of workers whose individual mismatch is greater than 50. In contrast to existing measures, the new measures focus on sorting between workers and occupations and measures how close a worker's skills are to the skills requirement of her occupation.

The new measures of skills mismatch deliver very similar results as to the extent of mismatch in each of the countries in the sample. Countries with the lowest mismatch in literacy and numeracy are Germany, Belgium, France. The largest mismatch in terms of literacy is observed in Japan, Slovakia and Poland, while the largest mismatch of numeracy in Slovakia, Poland and Denmark. I then split the measure based on percentages of mismatched workers between the percentages of under- and over-skilled workers. I observe that in countries with large mismatch, the shares of under-skilled workers are higher. Otherwise, the shares of under- and over-skilled workers are similar for literacy whereas for numeracy the shares of under-skilled workers are higher. I compare the new measures to the two existing measures of skills mismatch and show that my measures correlate weakly with the OECD measure. While they correlate positively with the skill use measure for literacy but show a different picture for numeracy.

A natural way to compare different measures of skill mismatch is to study their correlation with a measure of productivity across countries. When a country suffers from large skills mismatch, i.e. many workers' skills do not correspond to the skill requirements of their occupation; overall labor market productivity should be lower. I find that the new measures of mismatch based on sorting are negatively correlated with the aggregate labor productivity. The correlation is 0.675 for the first measure, and 0.69 for the second. In contrast, the existing measures have much weaker correlations with aggregate productivity. The correlations are 0.25 for the OECD measure and 0.32 for the skill use measure.

I next ask which institutional features of the labor markets and education systems may be potential sources of the skill mismatches observed. To this end, I correlate the new measures of mismatch to characteristics of unemployment benefit, education and training systems across the countries I study. I find that more generous unemployment insurance systems in terms of both duration and amount spent per unemployed worker have lower mismatch. The same negative correlation is found between mismatch and public expenditure in training. Last, the share of vocational programmes in all education programs correlates positively with skills mismatch.

The rest of the paper is organized as follows. Section 1.2 describes the data used in the analysis. Section 1.3 introduces the existing measures of mismatch while Section 1.4 introduces the new measures of mismatch proposed in this paper. Section 1.5 shows the correlations between the mismatch measures and institutional aspects of the OECD countries. Section 1.6 concludes.

1.2 Data

The individual level data I use comes from the The Survey of Adult Skills, an international survey conducted as part of the Programme for the International Assessment of Adult Competencies (PIAAC). It collects information about adults between 16 and 65 years old in 24 countries. The data was collected between August 2011 and March 2012, and therefore for each country I have only one cross of individuals.

This data is suitable for analysis of skills mismatch for several reasons. First, as part of The Survey of Adult Skills, individuals performed tests for two skills, literacy and numeracy. These two measures summarize a number of different tasks that are needed to answer correctly the test items provided in the survey. The literacy part asks individuals to recognize words or name objects in pictures, assessing the knowledge of the language directly, identifying information in a text and interpreting and evaluating texts on different levels. As for the numeracy part, the exercises also rely on logic, adaptive reasoning, problem-solving skills and identifying the necessary information. The two measures overlap to a great extent as shown by correlation of 0.87 for all countries in the sample.

In addition, for employed workers, the PIAAC contains information on the skills they use at their current job and the occupation of their current job based on the International

Standard Classification of Occupations (ISCO) 2010 at four digits. Due to confidentiality reasons some countries do not report the 4-digit ISCO 2010 occupation codes and therefore a final sample consisting of 13 countries is used in the analysis. These countries are Belgium, Czech Republic, Denmark, France, Germany, Italy, Japan, Korea, the Netherlands, Poland, Slovak Republic, Spain and the United Kingdom. Further details on the creation of the sample are shown in the appendix.

To obtain the requirements of literacy and numeracy, I use the Occupational Information Network (O'NET). The O'NET is a database of worker and job characteristics in the United States. The database is constantly updated in terms of the number of occupations covered. The 19.0 Database used in this analysis includes information for up to 1100 occupations based on the Standard Occupation Classification of 2010 (SOC 2010).

The information is gathered in a two-stage design; first, a random sample of businesses expected to employ workers in the occupations of interest is drawn and subsequently a random sample of workers in these occupations is drawn; then the individuals in this sample are surveyed by the use of standardized questionnaires. These questionnaires include questions about the importance of different skills in their job, to which respondents answer by choosing a number between 1 and 5 (1 - Not important at all, 2 - Somewhat important, 3 - Important, 4 - Very important, 5 - Extremely important). This information is gathered for a large number of detailed skills in the areas of cognitive abilities, psychomotor abilities, physical abilities and sensory abilities. The detailed skills related to literacy and numeracy are e.g. written comprehension an expression, fluency of ideas or mathematical reasoning.

1.3 Existing measures of skills mismatch

1.3.1 OECD measure

Pellizzari & Fichen (2013) construct a measure of skills mismatch based on the following two questions asked in the PIAAC: 1) *Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?* and 2) *Do you feel that you need further training in order to cope well with your present duties?*. Well-matched workers are identified as those that answer 'No' to both of these questions. For these workers, the authors identify the 95th and 5th percentiles of their test scores for numeracy and literacy in each broad occupation (at 1-digit ISCO level).

Anyone in the same occupation with proficiency scores higher that the 95th percentile is classified as over-skilled and anyone with a proficiency score lower than the 5th percentile is classified as under-skilled.

By including the test scores in the construction of the measure, the authors try to circumvent the problems coming from purely self-reported measures. However, in the appendix I provide evidence that the final OECD measure is still highly reliant on the self-reported questions. In particular, I show that the ranking of countries in terms of the severity of skills mismatch according to the OECD measure is very similar when the test scores are not used.

1.3.2 Skill use measure

M. Levels & Allen (2013) aim to improve upon the OECD measure by looking at the individuals' skills on the one hand and their skills use at work on the other. The mismatch measure they construct represents the extent of skill use relative to one's own skill level.

The PIAAC provides data on how often workers use specific skills related to literacy and numeracy in their job. Each worker reports e.g. how often he reads documents or carries out calculations. Such detailed items are available for three main groups: reading, writing and numeracy. The authors construct a measure of literacy use as a mean of seven reading and four writing items, and they construct numeracy use as a mean of the six numeracy items. As for worker skills, they consider the test scores in numeracy and literacy. Their final measure of mismatch in each skill consists in computing the difference between the standardized test score and skill use (x) and identifying anyone with a value $x \leq |1.5|$ as well-matched. They construct they measure on the pooled set of data for all countries.

This measure improves upon the OECD measure in the sense that individual skills data come purely from the obtained test scores and they also measure how much each individual uses these skills. However, skill use data can suffer from similar issues as other self-reported data. In particular, workers who report not using their skill might either be in an occupation where the skill is not required, or might lack this skill. Thus, this measure is not an objective measure of mismatch.

1.4 New Measures of Mismatch

An individual is mismatched when his skills do not match the skills needed in the occupation or job he performs. In the aggregate, skills mismatch can be summarized in different ways. A macro mismatch occurs when the distributions of the skills in the economy and the skills demanded do not overlap. This can result in individual mismatch as workers with skills that are not demanded take up jobs for which their skills are not fit. The main challenge one faces when computing measures of individual or macro mismatch is that the skills and skill requirements are not measured on the same scale and thus the distributions of supply and demand of skills cannot be easily compared.

Another aggregate way of measuring mismatch is to look at sorting of workers to jobs. Regardless of the distributions of skills demand and supply, to minimize mismatch the workers with the highest level of skills should work in occupations which require the highest amount of these skills and vice versa (positive assortative matching (PAM)). The stronger the PAM, the lower the mismatch in the country given what skills are needed. This is precisely what the measures of mismatch I present in this paper aim at highlighting.

In this paper I compute a measure of skills mismatch which is based on the level to which better workers sort to better occupations, i.e. it is a measure of sorting. The measure of sorting for skills mismatch combines the test scores from PIAAC on the worker's side and the skill requirements data from O'NET on the occupation's side. Therefore, it doesn't rely on any self-reported data on skills. In addition, since the measure is computed with correlations and percentile ranks, the lack of comparability between the scales of measurement of skills and skill requirements is not an issue as only the ranking matters for this measure.

1.4.1 Skill requirements

The O'NET data provides me with detailed descriptors of skills needed to perform occupations, measured at the Standard Occupation Classification from 2010 (SOC 2010) 6-digit level. Thus, to construct the literacy and numeracy measures of requirements, I first identify descriptors belonging to each of these two categories. In order to summarize the different skill requirements in these groups in one measure and retain as much as possible of the variation, I use Principle Component Analysis, commonly done in the literature on skills (Sanders (2012), Postel-Vinay & Lise (2015) and Guvenen et al. (2015)). The results of the first components are summarised in Table 1.1.

Table 1.1 shows how the first component loads on the different worker abilities for each of the groups. The higher the loading of a particular ability, the more important this ability is in the first component. What we observe here is that most of the abilities are loading approximately equally to the first component with the exception of Spatial Orientation. For the literacy, the first principal component explains 52% of the variation and for numeracy 80% of the variation. Finally, the value of the principal component score will be used as the literacy and numeracy requirements measure in the following analysis.

1.4.2 Individual Skills

As mentioned above, the PIAAC provides information about adults' proficiency in information-processing skills; namely literacy and numeracy, which are constructed from the direct assessment part of the survey. These are on a scale from 0 to 500. When checking for the correlation between the two proficiency scores, the mean correlation across all countries in the sample is 0.87.

1.4.3 Measures of Mismatch

In order to assess how well workers sort to jobs with respect to literacy and numeracy, I merge the requirements created with the O'NET data to the PIAAC individuals. A first measure of sorting I consider is the correlation between the skills and requirements in each skill. A high and positive correlation speaks of positive assortative matching and thus a better allocation of workers to jobs. I show in Table 1.2 the correlations of skills and requirements across countries, sorted from highest to lowest. I show these graphically for each of the countries in Appendix 1.

Another way of identifying sorting is to compute an individual measure of skills mismatch based on Guvenen et al. (2015) and summarize the distribution of individual mismatch. The individual measure is based on comparing the percentile rank of an individual's particular skill to the percentile rank of his occupation's skill requirement. The measure of individual mismatch of individual i in occupation o in skill j is then

$$m_{i,j,o} = |q(a_{i,j}) - q(r_{o,j})| \tag{1.1}$$

where $q()$ denotes a percentile rank.

I compute this measure for each individual in my sample for both literacy and numeracy. Then, to summarize this individual measure at the country level, I first compute the percent of individuals who have mismatch higher than values 50, 75 and 90. Results by country are shown in Table 1.3.

Table 1.3 reveals several features of the distribution of mismatch in each country. First, there is a positive correlation between the literacy and numeracy measures of mismatch (0.82 , 0.78 and 0.73 for mismatch of 50, 75 and 90, respectively). Second, the ranking of countries according to the percentage of individuals with literacy mismatch larger than 50 is highly correlated to the more extreme mismatch of 75 and 90. This points to the fact that countries which fare badly in terms large mismatch do so consistently across the right tail of the mismatch distribution.

To further decompose mismatch between over- and under-skilled workers, I compute two additional measures which reflect the extent to which an individual is over-skilled and under-skilled, denoted $m^{OS}_{i,j,o}$ and $m^{US}_{i,j,o}$, respectively. These are constructed as follows

$$m^{US}_{i,j,o} = max\{q(a_{i,j}) - q(r_{o,j}), 0\} \tag{1.2}$$

and

$$m^{OS}_{i,j,o} = min\{q(a_{i,j}) - q(r_{o,j}), 0\} \tag{1.3}$$

Concentrating on the percentage of workers in each country whose mismatch is larger than 50, I decompose this percentage into those that are over- and under-skilled workers and report these in Table 1.4. The decomposition of mismatch into under and over-skilled seems to be quite symmetric, apart from Poland where under-skilling is a significantly larger problem.

Last, in Figure 1.1 I compare the measure of mismatch based on the correlation and the one based on the percentage of individuals. These figures tell a clear picture; the large positive correlation between the two measures results in a similar ranking of the severity of mismatch across countries based on either of these measures.

1.4.4 Comparison of measures

In order to illustrate the difference across the existing measures and the new measures proposed, I compare these in terms of the number of mismatched individuals in each skill in Figure 1.2. I only show results for the new mismatch measure based on the percentage of individuals with mismatch larger than 50 and leave the corresponding graphs with the correlation to the appendix. The new measure of mismatch is not highly correlated with the OECD measure in neither Literacy nor Numeracy. There is a positive and relatively high correlation for Literacy between the new measure and the skill use measure.

1.5 Measures of mismatch and institutional setting

Next, I aim to understand how measures of skills mismatch relate to the institutional setting of the countries. To this end, I collect macroeconomic variables from the OECD related to the labor markets and the education system for the year 2011 of the countries and correlate these to the measures of skills mismatch. While the education system affects the types of skills that workers entry the labor market with, labor market institutions affect how workers sort to jobs. In table 1.5 I report these correlations for both existing measures and for the two measures of sorting presented in this paper and I discuss the potential mechanisms through which mismatch may correlate with these policies.

Education systems vary with respect to how general the skills and knowledge obtained are. Those systems more focused on skills that are very specific to an occupation can create larger mismatches when workers are forced to switch occupation. One way of assessing this is looking at the share of vocational programs in the country. I show in table 1.5 that countries with higher share of vocational programs have larger mismatch as measured by the new skills mismatch measures.

Individuals sort into occupations either while on the job or through spells of unemployment. When switching occupations while on-the-job, workers are likely to accept offers that are better than their current one and thus are less likely to switch to jobs in which they are highly mismatched. However, losing a job involuntarily and entering unemployment can lead to higher mismatches as workers sort into the first available job in order to start earning an income again. Policy regarding unemployment benefits can allow individuals to search for better matches, as suggested by Marimon & Zilibotti (1999). If workers receive unemployment benefits for long enough, they can spend more time looking for the right job. Thus, we expect that countries with more generous unemployment benefit systems will have lower mismatch. In table 1.5 this is reflected in the high and negative correlation of the maximum duration of unemployment benefits with the measures of skills mismatch for both skills (positive for the correlation measure, as a higher correlation implies lower mismatch). These results are in line with Houštecká & Parkhomenko (2019) where we show that unemployment benefits reduce mismatch of workers who transition through unemployment. Moreover, when individuals can undergo training thanks to public training programs, they have the chance to adapt their skills to the occupation where they work. Thus, higher public investment in training should lead to reduced mismatch, which is the case for both sorting measures and the skill use measure, and strongest for the correlation measure of sorting.

1.6 Conclusion

In this paper, I present new measures of aggregate mismatch based on individual data on skills from the PIAAC and data on skill requirements in occupation from the O'NET. I provide two measures of sorting. First, I compute the correlation between skills and skill requirements in each country. Second, I find the percentage of individuals in each country that have a large individual mismatch, measured as the difference between the percentile rank of their skills and the requirement of skills in their occupation.

I compare the new measures to the two existing measures of skills mismatch and show that my measures correlate weakly with the OECD measure. While they correlate positively with the skill use measure for literacy but show a different picture for numeracy. I also find that the new measures of mismatch based on sorting are negatively correlated with the aggregate labor productivity. In contrast, the existing measures have much weaker correlations with aggregate productivity. I next ask which institutional features of the labor markets and education systems may be potential sources of the skill mismatches observed. I find that more generous unemployment insurance systems in terms of both duration and amount spent per unemployed worker have lower mismatch. The same negative correlation is found between mismatch and public expenditure in training. Last, the share of vocational programmes in all education programs correlates positively with skills mismatch.

Chapter 2

Unemployment Insurance and Occupational Switching

2.1 Introduction

In the US, around 60% of individuals who are unemployed end up in a different occupation than the one they had before they became unemployed.[1] At the same time, those who pass through unemployment and switch occupation have significant wage losses compared to those who do not change their occupation or those who change jobs without an unemployment spell. Is the generosity of unemployment benefits related to the probability of an occupational switch? If so, in which way? Do more generous benefits alleviate the losses suffered by unemployed workers who switch occupation by allowing them to search for a good match? Since unemployment insurance is one of the main tools for supporting the unemployed while they search for new jobs, it is critical to understand its effects on how workers sort themselves across occupations.

A large empirical literature has looked at the effects of unemployment benefits on unemployment duration (Lawrence F. Katz (1990), Card & Levine (2000), Bover et al. (2002), Card, D.E. Chetty & Weber (2007)), and post-unemployment outcomes with a focus on re-employment wages (Hagedorn et al. (2013), Johnston & Mas (2016), Schmieder & von Wachter (2016), Nekoei & Weber (2017)). More generous unemployment benefits increase unemployment duration. On the other hand, there is much less agreement on the effects of unemployment benefits on re-employment wages. The existing literature do not investigate, however, the impact of benefits on the fit between the worker's skill and the skills required by his occupation.

[1] Figure obtained from the Survey of Income and Program Participation 1996-2012. Occupational switching is based on 3-digit occupational codes.

In this paper, we study how generosity of unemployment benefits is related to the occurrence and outcomes of occupational switching. Using the Survey of Income and Program Participation (SIPP) and the National Longitudinal Survey of Youth from 1979 (NLSY79) from the US, we first analyze whether individuals who are eligible to higher unemployment benefits are more or less likely to switch occupations. We follow Chetty (2008) and use variation across US states and time in the potential weekly benefit amount of individuals. We document that individuals who are eligible for higher unemployment benefits are less likely to switch occupation. A 100 dollars increase in the weekly benefit amount is associated to a 0.13 lower probability of switching in the SIPP and 0.18 in the NLSY79.[2] This suggests that unemployment benefits enable individuals to search and find a job in their occupation, and avoid costly adjustments to a new occupation.

We then focus on switchers and study whether individuals with higher benefits switch to better or worse occupations relative to individuals with lower benefits. To this end, we first construct a skill requirement of literacy and numeracy for each occupation using the Occupational Information Network (O'NET). We show that these skill requirements are positively correlated with average occupational hourly wages. As a result, they carry information not only about the vertical ranking of occupations but also about the distance between two occupations in terms of the skills needed to perform them. We show that conditional on switching occupation, individuals with higher unemployment benefits exit unemployment to occupations with higher requirements of literacy and numeracy relative to other workers who were in the same occupation before their job loss but enjoy lower benefits. When we rank the occupations according to the literacy requirements, we find that an increase of 100 dollars in the weekly benefit amount enables workers to obtain an occupation that is the next highest on the requirements ladder.

Next, we ask whether these facts differ by occupational tenure of unemployed. Individuals who spend a long time in an occupation accumulate skills in that occupation, and, as a result, are expected to look for jobs in that occupation. In contrast, individuals who are not attached to a particular occupation might simply want to do as good as possible in terms of skill requirements of the new occupation. Our results suggest this is indeed the case. The negative relationship between unemployment benefit generosity and the probability of occupational switching is stronger for long-tenured workers, and the positive relationship between unemployment benefit generosity and re-employment

[2] The average weekly benefit amount that individuals in the sample are eligible for is 156 and 146 in 1996 dollars in the SIPP and the NLSY79, respectively.

requirements is stronger for the low-tenured workers. Finally, we find that for both types of workers higher benefits are associated with higher re-employment wages. In particular, a 100 dollar increase in the weekly benefit amount is associated to a 3% higher re-employment wage.

We next build a search model of heterogeneous individuals and jobs with on-the-job search to study how different unemployment benefits affect the requirements and wages for employment-unemployment-employment (EUE) transitions. In the model, workers are born with an initial level of skills, which they draw from a given skill distribution. Each occupation is characterized by a skill requirement and there is a fixed distribution for occupational requirements. Individuals who are unemployed receive unemployment benefits and sample jobs (occupations) from the distribution of requirements and accept jobs when the surplus from the match is positive. Employed workers also sample offers from the distribution of skill requirements, and can experience an employment-to-unemployment transition. During unemployment, workers' skill depreciates. When employed, individuals lose jobs at an exogenous rate. Besides skills, workers also accumulate general labor market experience that grows while they are employed. Output in a match between a worker and a job depends on skills and labor market experience of the worker and the skill requirements of the job. Output is increasing in the skill requirements of the job and labor market experience of the worker. There is complementarity between skills of a worker and skill requirements of a job. There is, however, also a penalty for skills mismatch between workers and the jobs. The skills mismatch is the difference between each employed worker's skills and the skill requirements of his occupations and the production function includes an explicit cost of being underskilled. As a result, individuals whose skills are lower than what is required produce less. The skills of a worker grows or declines depending on his match. If a worker is underskilled in a job, i.e. his skill is below the requirements of the job, his skills improve. If they are over-skilled, their skill depreciate.

The fact that skills adapt to the skill requirements of occupations implies that longer tenured workers in the model are on average better matched. Thus, when they become unemployed, their skill level at the start of an unemployment spell is close to their previous occupation's requirement. In the model economy higher unemployment benefits make individuals more selective in terms of the requirements of the jobs they receive as their outside option is higher. This results in longer unemployment spells. It also enables workers to accept jobs that are closer to their skills. For longer-tenured individuals an increase in unemployment benefits increases their probability to stay in the same occupation. For short-tenured workers, whose skills are less likely to be close to their pre-unemployment jobs' requirements, higher unemployment benefits mainly lead to an increase in the requirements accepted. For both types of workers, the re-employment wages rise. Furthermore, overall skills mismatch decreases as unemployment benefits increase.

The model is calibrated to match key features of the US labor market, such as average unemployment to employment and employment to employment transition rates, the relationship between wages, skills, skill requirements and labor market experience and the distribution of skill requirements. The model economy provides an ideal environment to study whether unemployment benefits should be linked to labor market experience. What are the benefits of providing more generous benefits to less-experienced workers? Higher benefits will allow these workers to search for better jobs and avoid a large fall in the job ladder. This in turn will affect their skill accumulation and life-time wages. What about more-experienced workers? These workers are more likely to have accumulated skills in an occupation and with lower benefits are less able to stay in the same occupation after an unemployment spell. Our results show that the benefit outweighs the cost. As a result, making benefits depend negatively on labor market experience results in higher average wages.

This paper is related to two strands of the literature. First, it relates to the literature on occupational switching. As in Wiczer (2013) and Visschers & Carrillo-Tudela (2014), we focus on the outcomes of occupational switching for individuals who pass through unemployment, as they suffer on average larger wage losses than individuals switching jobs while employed. We contribute to the literature by highlighting a relationship between unemployment benefits and occupational switching, which has not yet been explored in this strand of the literature.

The way we approach occupations in this paper is by looking at their requirements of cognitive skills. In this sense, the focus of our paper is similar to the contributions of Postel-Vinay & Lise (2015) and Guvenen et al. (2015). We characterize occupations by a one-dimensional skill which is a composite of literacy and numeracy skills while these authors consider multi-dimensional skill requirements. Our approach is closer to Busch (2017) who, following Gathmann & Schönberg (2010), characterizes the distance between occupations as function of the shares of tasks performed in each occupation. Groes et al. (2015) also rank occupations using a one-dimensional index based on average wages. Our skill requirements correlate positively with average occupational wages. However, by focusing on the skill content rather than average wages, we are able to infer how close or far two occupations are, which is critical to measure cost of occupational switching.

Second, this paper relates to a large theoretical and empirical literature that studies the effects of unemployment insurance on post-unemployment outcomes. The focus of the empirical literature has been on the effects of unemployment benefits on re-employment wages and tenure. For Austria, Nekoei & Weber (2017) use an sharp discontinuity in the duration of benefit receipt at the age of 40 and find a positive effect on the wage. They do not find, however, any positive effects on other measures of job quality such as the tenure in the new job or subsequent wage growth. On the other hand, Schmieder & von Wachter (2016) find a negative effect on wages using an age discontinuity in eligibility using German data. For the US, there is a large literature studying the effects of unemployment benefit extensions (Hagedorn et al. (2013), Farber et al. (2015), Hagedorn et al. (2015), Johnston & Mas (2016), Chodorow-Reich et al. (2018)). In particular, Hagedorn et al. (2013) and Johnston & Mas (2016) have shown no significant effect of on post-unemployment wages.

While most of this research looks at the effects of programs that extend the usual maximum duration of benefits[3], the focus of our paper is on changes in the level of unemployment benefits rather than the duration of unemployment. We use variation across US states and time in the weekly benefit amount individuals are eligible for as Chetty (2008) and Kuka (2018). McCall & Chi (2008) also follow a similar approach and find a positive effect on re-employment wages. However, none of the existing papers study the effects of unemployment benefits on occupational switching and skill requirements.

Burdett (1979) and Marimon & Zilibotti (1999) also focus on unemployment insurance and mismatch in models with labor frictions. In contrast to these papers, the current model allows for skill accumulation, and on-the-job search. Including these features has important implications for the effects of unemployment insurance. In particular, the effect of unemployment benefits on re-employment requirements has longer-term implications due to skill accumulation. Moreover, workers can obtain better matches through on-the-job and thus the effects of unemployment benefits on mismatch are dampened. Another paper that relates unemployment benefit generosity to skills mismatch is Houštecká (2019). In this paper, cross-country measures of skills mismatch are shown to be negatively correlated with the generosity of the unemployment benefit system, supporting the

[3]The maximum duration of unemployment benefits in each state is 26 weeks; however, there are some differences as to the minimum of weeks that individuals are eligible. In this paper, we do not take these differences into consideration

evidence found in our paper.

The model builds on Postel-Vinay & Lise (2015) and Lise et al. (2016). As in Postel-Vinay & Lise (2015), there is an explicit cost of mismatch, and skill accumulation and depreciation. Our focus is, however, on the effects and design of unemployment benefits. Lise et al. (2016) also analyze the effects of unemployment policy on resulting matches. However, the policy experiments studied in this paper can shed light on long-term positive effects of unemployment benefits due to skill accumulation over the life-cycle.

We suggest that unemployment benefits should be negatively related to overall labor market experience through the skill accumulation skill accumulation channel. In this way, the paper provides a similar policy recommendation as Michelacci & Ruffo (2015) who suggest that unemployment benefit generosity should depend negatively on age. However, these authors argue that this is the case as liquidity constraints are sizeable for younger workers whereas moral hazard is more severe in older workers.

The rest of the paper is organized as follows. Section 2.2 describes the data used and Section 2.3 describes the sample selection, while Section 2.4 describes the construction of the measures of skill requirements of occupations. Section 2.5 shows the sample statistics, while Section 2.6 presents empirical evidence on the relationship between unemployment benefits and occupational switching, skill content, and wages in the new occupations. Section 2.7 lays out the model, Section 2.8 describes the simulation of the benchmark economy and presents its results. Section 2.9 presents results of an alternative unemployment benefit scheme and Section 2.10 concludes.

2.2 Data

The data used in this paper come from four sources: the Survey of Income and Program Participation (SIPP), the National Longitudinal Survey of the Youth 1979 (NLSY79), the Occupational Information Network (O'NET) and the Employment and Training Administration's *Significant Provisions of State Unemployment Insurance Laws*. The SIPP and the NLSY79 are used as the two main sources to determine the employment-unemployment-employment spells of individuals. The O'NET is needed for computing cognitive skill requirements of occupations and the Significant Provisions of State Unemployment are used to construct a Benefit Calculator of individual unemployment benefits.

2.2.1 SIPP

The SIPP is a longitudinal survey that collects information on income, participation in government programs and employment.[4] The survey is organised in panels, and each panel contains a new sample of individuals who are interviewed in *waves* every four months. The panels have 9 to 12 waves, thus an individual is followed for between three to four years. The structure of the SIPP allows one to track workers over time and has been used extensively in the recent literature for studying labour market dynamics in the US such as e.g. Chetty (2008), Wiczer (2013), Visschers & Carrillo-Tudela (2014) and Choi & Fernández-Blanco (2017).

The SIPP is well-suited for the analysis of this paper as we observe individuals for a period long enough to be able to determine labour market flows into unemployment and back to employment. It contains monthly information for earnings and occupation at 4 digit level based on the Standard Occupation Classification. This combined with weekly information on labour market status allows us to identify occupational switching of EUE spells and pre-unemployment wages. The latter are key for the determination of the eligibility of unemployment benefits.

2.2.2 NLSY79

The NLSY79 is a longitudinal survey that follows individuals born between 1957 and 1964. Initially, 12,686 individuals were interviewed in 1979. From this, we use only the cross-sectional sample of 6,111 individuals which is representative of the non-institutionalized civilian segment of people living in the United States in 1979 and born between January 1, 1957, and December 31, 1964 (ages 14-21 as of December 31, 1978). The NLSY79 surveys were conducted annually until 1994 and bi-annually since.

The NLSY79 includes a Work History file which contains weekly labor market status and weekly hours worked for up to 5 jobs since the last interview. For each of the jobs in a particular interview (which correspond to employers), individuals report occupation, industry and rate of pay. In addition, employers can be linked across interviews using unique employer IDs. Thus, one can observe individuals changing labor market status at weekly frequency since 1978.

[4] The SIPP data can be found at https://www.census.gov/sipp/.

An advantage of the NLSY79 is that all participants took The Armed Services Vocational Aptitude Battery (ASVAB) in 1980. This test had been previously used to determine enlistment eligibility for potential recruits in the army. The test was conducted according to standard ASVAB procedural guidelines and tested for major competencies including 10 different components, e.g. general science, arithmetic reasoning or word knowledge. The test scores are available separately for each component and as overall ASVAB score, known as the Armed Forces Qualification Test (AFQT) score. The AFQT score has been used widely as a proxy for ability, e.g. Keane & Wolpin (1997) and Neal & Johnson (1996), and the separate component test scores have been used to compute measures of skills mismatch (Guvenen et al. (2015), Postel-Vinay & Lise (2015)).

2.2.3 O'NET

The Occupational Information Network (O'NET) is a database of worker and job characteristics in the United States.[5] The database is constantly updated in terms of the number of occupations covered. The 20.0 Database used in this analysis includes information for up to 1100 occupations based on the Standard Occupation Classification of 2010 (SOC 2010).

The information is gathered in a two-stage design; first, a random sample of businesses expected to employ workers in the occupations of interest is drawn and subsequently a random sample of workers in these occupations is drawn; then the individuals in this sample are surveyed by the use of standardized questionnaires. These questionnaires include questions about the importance of different abilities in their job, to which respondents answer by choosing a number between 1 and 5 (1 - Not important at all, 2 - Somewhat important, 3 - Important, 4 - Very important, 5 - Extremely important). This data is used to determine the skill requirements of jobs. The O'NET data has been widely used by economists to study topics related to the importance occupation specific skills and for constructing the measures of skills mismatch by Guvenen et al. (2015), Postel-Vinay & Lise (2015) as these requirements are the complements of the ASVAB skills for the other side of the market.

2.2.4 Benefit calculator

The last source of data is a calculator of unemployment benefits based on US state laws regarding unemployment insurance. The calculator is based on three sources: 1) the

[5] The O'NET data can be found at https://www.onetcenter.org/.

Heller-Hurwicz Data Initiative [6] 2)Chetty (2008) and 3) from the Significant Law Provisions which we have used to update earlier laws (1979-1984).

In order to identify the eligibility and weekly benefit amount (WBA) that an individual can receive, the calculator uses as inputs a summary statistic of the earnings in the twelve months prior to unemployment.[7] The summary statistics can be the base period wage (BPW), the high quarter wage (HQW) or two highest quarters average (H2Q). The BPW is the sum of all wages, the HQW is the wage of the quarter with the highest wages and the H2Q is a the average of the two highest quarters. The legislation on unemployment insurance in each state then specifies the following aspects of the calculation the WBA: 1) the summary statistic for pre-unemployment earnings used 2) the replacement rate (i.e. the fraction of either BPW, HQW or H2Q that is replaced) and 3) a maximum and minimum amount of WBA that an individual can receive. Some states also provide additional benefits based on the number of dependents. Once WBA is determined, the States also specify an eligibility criterion in the form of a minimum threshold for the base period wage and for earnings to be spread out throughout the period, e.g. the BPW should be at least 1.5 of the HQW.

In this paper, we use the individual weekly benefit amount resulting from the calculator as our main measure of unemployment benefit generosity. Any variation in WBA at the state and year level comes from variation in the replacement rate (which is usually around 50%), the minimum and maximum WBA, the policy regarding dependents and the eligibility criteria in each state.

2.3 Sample selection

2.3.1 SIPP

Using data between 1996-2012 from the Survey of Income and Program Participation, we construct the sample of individuals who are observed passing through an EUE spell. An individual is employed when he reports to have a job and has observed earnings. A job

[6] The Heller-Hurwicz Data Initiative is a longitudinal data gathering project in the Heller-Hurwicz Economics Institute. This Initiative constructed and aims at maintaining a publicly available unemployment insurance database which can be used together with individual panel data to construct estimates of UI benefit available to workers. I thank Zachary Mahone for providing me with an earlier stage of this calculator.

[7] For any individual that has information on earnings only for the last quarter, the benefit calculator assumes that their base period wage was 4 times the earnings in that quarter.

is defined by an employer and thus an individual can switch jobs (employers) but stay in the same occupation.

To construct the sample of EUE transitions, we first identify all individuals who lose a job. We keep job losses that can be identified as involuntary, i.e. the individual reports that they are "On layoff, Discharged/fired, Job was temporary and ended, Employer bankrupt or Slack work or business", leaving us with 29,902 job losses. We drop individuals who don't report to be searching for a job. We also drop spells in small states which cannot be separately identified in the 1996 and 2001 SIPP panels as state-specific laws regarding unemployment insurance cannot be determined for these.[8] We only keep the first two spells of each individual and drop anyone whose occupation before unemployment was the armed forced.[9] Next, we drop spells for which we don't observe more than 3 months before the job loss which is necessary for the benefit calculator. Finally, we drop the top and bottom 0.1% of reported earnings. This leaves us with 10,675 spells that end in re-employment within the sample.

2.3.2 NLSY79

We follow the sample selection of Guvenen et al. (2015). For the 1979-2014 period, we construct weekly labor histories using the Work History Data File that includes weekly information on the labor market status of the individual. In addition, for each job reported we also have information on the employer ID, pay rate, occupation and industry. Thus, we can link employers through survey years to obtain a consistent panel.[10]

We drop individuals who spent at least 2 years in the army, individuals who spent more than 10 years out of the labor force, and those who had entered the labor market before the survey has started. We also drop individuals who have missing information on their ASVAB scores and we drop observations with missing information on wages, occupation and demographic characteristics. Earnings in each job in the NLSY79 are reported as a pay rate and it includes tips, overtime and bonuses. We drop the top and bottom 0.1% of reported wages in each survey year.

[8] These states are Maine, North Dakota, South Dakota, Vermont and Wyoming

[9] Given that in the SIPP individuals are observed for maximum 4 years, individuals with a large number of unemployment spells are likely to be different from the rest. We thus keep only few of their spells in estimation and in a robustness check eliminate all these individuals completely.

[10] Even though there is information for up to 5 jobs we only focus on the main job which we define as the job with the largest earnings.

An advantage of the NLSY79 over the SIPP is that having full information on the labor market history of each individual allows us to compute occupational tenure in each occupation. Before computing occupational tenure, we correct mis-coded occupational switches in the NLSY79 following Kambourov & Manovskii (2009) and Guvenen et al. (2015). We can observe a substantial amount of occupational switches for the same employer that revert in the next survey year. We assign to each employer the occupation which is reported most often across different survey years. [11]

We identify spells of unemployment with the following procedure. A separation occurs when an individual changes his labor status from employed to unemployed and re-employment occurs when an individual reports having a job with positive earnings. We identify 26,089 EUE spells. Of these, we only keep those during which the individual was unemployed in the first period of losing the job and those that resulted in re-employment at a different employer. We are thus left with 16,548 spells.

2.4 Skill requirements

To construct numeracy and literacy requirements, we use two different strategies. To construct the skill requirements used in the measure of skill mismatch of Guvenen et al. (2015) we follow their strategy and construct requirements that are comparable to the ASVAB skills provided in the NLSY. In order to make the requirements comparable to the ASVAB skills measured, we convert 26 O'NET descriptors [12] into 4 ASVAB measures using a crosswalk from the Defense Manpower Data Center.[13] This crosswalk contains a relatedness scale between each of the O'NET descriptors and each of the ASVAB skills.

The O'NET dataset provides an importance scale from 1 to 5 for detailed skills. We identify skills that fall into the categories of literacy and numeracy (e.g. oral and written comprehension or mathematical reasoning). The detailed skills are presented in Table 2.1.

[11] Since the occupational codes were based on the Census 1970 codes up to 1994 and on the Census 2000 codes thereafter, we then convert all occupational codes to Dorn's occ1990dd occupational codes (Dorn (2009)).This crosswalk is available at https://www.ddorn.net/data.htm.

[12] These descriptors are oral comprehension, written comprehension, deductive reasoning, inductive reasoning, information ordering, mathematical reasoning, number facility, reading comprehension, mathematics skill, science, technology design, equipment selection installation, operation and control, equipment maintenance, troubleshooting, repairing, computers and electronics, engineering and technology, building and construction, mechanical, mathematics knowledge, physics, chemistry, biology, english language, social perceptiveness, coordination persuasion, negotiation instructing, service orientation.

[13] http://www.asvabprogram.com/downloads/Technical_Chapter_2010.pdf, Accessed June 2017

We then summarise these using principal component analysis. The first principal component explains 70% and 80% in literacy and numeracy components, respectively. The scores obtained for the first principal component are rescaled to lie between 0 and 1 for each skill separately. As a result, we assign each occupation at a 4-digit level a requirement of each skill between 0 and 1. We then merge these requirements to the two main datasets, the SIPP and the NLSY, using occupational codes. In Table 2.2 we show occupations with the lowest and highest requirements of each skill.

Figures 2.1 and 2.2 show the relationship between the literacy requirements obtained from the O'NET data and mean hourly wages per occupation from the SIPP between 1996 and 2012. Both literacy and numeracy requirements of an occupation (measured by the 3-digit SOC 2000 classification) are positively correlated with hourly wages. Another way of assessing whether the requirements are a sign of quality of the occupation is to see how these correlate with the share of college-educated workers in an occupation. This is confirmed in figures 2.3 and 2.4, which show a positive correlation between the share of college educated workers and both literacy and numeracy requirements.

2.5 EUE Spells

Table 2.3 reports the number of EUE transitions observed in each sample together with the numbers of occupational switchers and individuals. We can see that occupational switching is large, 70% in the SIPP and 80% in the NLSY79 at three-digit level. In the SIPP only few individuals have more than one spell. In contrast, in the NLSY79 the number of observations is much smaller than the number of spells as individuals are observed over a longer span. On average, we observe 4.3 EUE spells for an individual in the NLSY79.

Table 2.4 reports summary statistics of both EUE samples. We can observe that the SIPP sample is on average older. Both samples have close to equal numbers of each gender. As for education, in the NLSY79 more than 60% have low education (High School Diploma or below) whereas in the SIPP this proportion is lower, around 48%. The average duration of an unemployment spell is around 7 months in both data sets. The individuals in the SIPP were eligible on average to a higher weekly benefit amount; however, take-up is low in both datasets.

Figures 2.5 and 2.6 show the distributions of the weekly benefit amount in the SIPP and the NLSY samples of EUE spells. We can observe that the distribution is left-skewed in both data sets and most individuals have a weekly benefit amount lower than 300 in 1996 dollars. In both datasets there are also individuals who reach the maximum benefit amount which in some states is as high as 500 in 1996 dollars.

2.6 Empirical evidence

A central focus of this paper is the extent to which unemployment benefits help in attenuating the drop from the job ladder of individuals who pass through an unemployment spell and switch occupation. Thus, it is of interest to understand the relationship between unemployment benefits, occupational switching and the wage and requirement changes that individuals with different unemployment benefits experience.

2.6.1 Probability of switching occupation

In order to understand better the effect of unemployment benefits on post-unemployment outcomes, we run a linear probability model on the probability of finding a job in an occupation different from the one of the job before unemployment. As the main explanatory variable of interest we include the weekly benefit amount the individual is eligible for, obtained from the Benefit Calculator. We control for gender, age, state unemployment rate, unemployment duration, a piecewise spline for earnings and tenure in the job before unemployment, occupation, state, year of spell and education fixed effects (FE). For the NLSY79, we use in addition tenure in the occupation before unemployment and the AFQT score as a proxy for individual skill. For the SIPP, we use a 3-digit occupational classification, comprising 91 different occupations. For the NLSY79 we use Dorn's occupational classification comprising over four hundred different occupations. For each data set we run two specifications; one without and one with state FEs and year FEs. Results are shown in Table 2.5.

The effect of the unemployment duration on occupational switching is positive and significant for both specifications and both data sets. This is consistent with the literature on occupational switching. The novel evidence we show is the effect of unemployment benefits. The coefficient on the weekly benefit amount that an individual is eligible for is negative and significant in all specifications. Given that we control for a spline of pre-unemployment earnings and state and year fixed effects, any differences in unemployment benefits come from within-state changes in one of the aspects of the legislation regarding unemployment benefits. These results thus speak to the fact that if two individuals had the same earnings before unemployment and were in the same occupation, the one with the higher weekly benefit amount was less likely to switch occupation. This also occurs keeping unemployment duration fixed. In particular, 100 dollars increase in the weekly benefit amount lowers the probability of switching occupation by 0.18 in the SIPP and by 0.13 in the NLSY79.

2.6.2 Skill requirements

Having established that higher unemployment benefits decrease the likelihood of switching occupations, we now study its effect on the requirements of literacy and numeracy in post-unemployment jobs. We restrict the analysis to individuals who switched occupations and we regress the requirements of literacy in the new job on duration of the unemployment spell and the weekly benefit amount. We again control for gender, age, state unemployment rate, a piecewise spline for earnings and tenure in the job before unemployment, occupation, state, year of spell and education fixed effects (FE). We perform the analysis for literacy and numeracy separately and we report results in Table 2.6.

The first two columns of Table 2.6 show results for the requirements of literacy and numeracy of the occupation to which individuals have switched in the SIPP; the second two show the same for the NLSY79. The coefficient for the weekly benefit amount is positive and statistically significant for both literacy and numeracy. This means that controlling for earnings in the previous job and the occupation before unemployment, individuals with higher unemployment benefits obtained jobs with higher requirements in both literacy and numeracy relative to low-benefit individuals. In particular, an increase of 100 dollars in the weekly benefit amount results on average in obtaining an occupation which is the next highest on the ladder of requirements. The effect is larger in magnitude for numeracy in the NLSY and for literacy in the SIPP.

2.6.3 Occupational Tenure

The first two facts provide evidence of a negative relationship between unemployment benefit generosity and occupational switching and a positive relationship between unemployment benefits and re-employment skill requirements. Next, we investigate whether these two effects differ by occupational tenure. We are able to do this since the NLSY includes the complete history of the labor market experience of workers. We split the sample between individuals with occupational tenure of the occupation they held before job loss above and below the median, which is 2 years in the sample.

Results from the regressions for occupational switching and re-employment skill requirements by occupational tenure are shown in Table 2.7. The significant negative coefficient of the weekly benefit amount for occupational switching comes mostly from the individuals with long occupational tenure. On the other hand, the positive relationship between the weekly benefit amount and the re-employment, while present for both groups, is stronger for those with short occupational tenure.

2.6.4 Wages

Most of the literature that relates unemployment benefits to post-unemployment outcomes looks at the effect on re-employment wages. We find a positive relationship between unemployment benefits and the quality of the occupation at re-employment (both in terms of staying or switching to highly-ranked occupations relative to low benefit generosity). Is this accompanied by a positive re-employment wage effect?

As a first step, we inspect the difference in the densities of the percentage wage changes of individuals with unemployment benefits above or below the average. To this end, we regress the percentage changes in wage on previous wages and keep the residuals. This way, we compare individuals who had the same wage but different wage growth. Thus, all variation in the benefit level comes from state and time variation in laws regarding unemployment insurance.

We plot the density of this residual wage growth for individuals with above average and below average unemployment benefits in Figure 2.7. Individuals with above average unemployment benefits experienced a higher wage growth when obtaining a job after unemployment. This is confirmed by the results from a regression of the log wages in the new job on log wages in the previous job and the weekly benefit amount, shown in Table 2.8. Controlling for earnings in the previous job, individuals with higher unemployment benefits had higher re-employment waged. In particular, a 100 dollar increase in the weekly benefit amount results in a 3 percent higher re-employment wage.

2.6.5 Robustness Checks

The results presented in the previous section show a negative relationship between unemployment benefit generosity and occupational switching while a positive relationship between unemployment benefit generosity and re-employment skill requirements and wages. In this section, we show that these relationships are robust to several specifications which can rule out some of the potential endogeneities of unemployment benefit policy.

Unemployment Duration

In the main regressions we control for unemployment duration. Thus, we are comparing two individuals whose spells had the same length. By doing that, we find the magnitude for the selectivity effect of unemployment benefits: how much more selective in terms of the quality of the new job were individuals with the same duration? However, unemployment benefits also can have an affect on duration itself. If the effect on duration is positive, then this can imply negative consequences for the workers as well through duration dependence. To find out the net effect of unemployment benefits, we run the main regressions without controlling for unemployment duration as well. All main results hold also when not controlling for duration which is evidence that the selectivity effect of unemployment benefits dominates the duration dependence effect.

Unobserved Individual Characteristics

In the NLSY79 sample, individuals are followed for up to 33 years and thus each individual goes through several spells (on average 4.3 per individual). To control for time-invariant individual characteristics that are correlated both with the benefit level and the outcomes I run all main regressions with individual fixed effects, shown in Appendix B.3. The signs of the main results are the same even though the significance is not preserved due to the still small number of spells per individual.

In the SIPP, given that within a maximum of 4 years the individuals with many unemployment spells are likely to be fundamentally different from those with few; I only keep individuals with at most 3 of the spells in the analysis. However, most individuals only observe one such spell which rules out the possibility of using an individual fixed effects regression. However, we can distinguish between individuals who were fired/discharged versus lost their job for more exogenous reasons such as Business closure. We show in Appendix B.4 that results hold and are stronger for those spells in which individuals lost their jobs for more exogenous reasons.

2.7 Model

We next set up a dynamic model of job search with heterogeneous individuals and firms to study how unemployment benefits affect re-employment wages and occupational switching. The model is calibrated to match some key features of the US economy and produces the observed relationships between unemployment benefit generosity and occupational switching, re-employment requirements and wages. In addition, the model allows us to analyze the effects of unemployment benefits on skills mismatch and evaluate alternative unemployment benefits policies. In particular, we use the model to study whether linking unemployment benefit generosity to labor market experience can generate gains in life-time wages.

2.7.1 Environment

The environment builds on Postel-Vinay & Lise (2015). There are individuals who are heterogeneous in their level of skill $x \in (0, 1)$ which takes on K values and is drawn from an exogenous distribution $\Omega(x)$ at entry to the labor market. There are heterogeneous jobs with skill requirements $y \in (0, 1)$ taking values on the same K with sampling distribution $F(y)$. In a given match, a job's skill requirement remains fixed while a worker's skill accumulates or depreciates depending on the skill requirement of the job. During unemployment a worker's skill depreciates. Workers are also characterized by labor market experience E.

The output in a worker-job match is given by $f(x, E, y)$. There is a penalty when a worker's skills are lower than the requirement of skill of the job ($x < y$). For a particular worker with skill x, $f_y(x, E, y) > f_y(x, E, y') \; \forall y, y'$ such that $y < x$ and $y' > x$. Hence, the marginal product of the skill requirement y is lower when the individual is under-skilled than when he is over-skilled or well-matched. In addition, when the penalty of mismatch is high, it is possible that $f(x, E, y) > f(x, E, y')$ even if $y' > y$ so a worker produces less output in a job with higher requirements.

Employed workers have an arrival rate of skill accumulation which depends on x and y and is denoted by $\eta^e_{x,y}$. When $x_k < y_k$, skills accumulate by jumping to the next level of skill x_{k+1} and when $x > y$ skills depreciate by jumping to a lower level of skill x_{k-1}. When the worker is well matched, his skill stays constant. Employed workers also accumulate one year more of labor market experience at a rate φ. Unemployed workers have an arrival rate of skill depreciation $\eta^u_{x,y}$ and their skill depreciates by jumping to a lower level of skill x_{k-1}.

Both unemployed and employed workers sample jobs from $F(y)$ at the rates λ_0 and λ_1, respectively. Employed workers lose jobs at an exogenous rate δ. When unemployed, they receive unemployment benefits $b(w_p)$ which depends on last period wage w_p. A firm is defined as one job of requirement y. Workers exit the market at the rate ξ.

2.7.2 Rent sharing and value functions

Let the value of being an unemployed worker be given by $U(x_k, E, w_p)$ and the value of an employed worker by $W(x_k, E, y, w)$. Let the value of a match between worker and a job be $P(x_k, E, y, w_p)$.

Unemployed workers

The value of an unemployed worker is given by

$$\begin{aligned} rU(x_k, E, w_p) &= b(w_p) - \xi U(x_k, E, w_p) + \eta^u_{x,y}\left(U(x_{k-1}, E, w_p) - U(x_k, E, w_p)\right) \\ &\quad + \lambda_0 \int \max\{W(x_k, E, y, w) - U(x_k, E, w_p), 0\} dF(y), \end{aligned}$$

where r is the rate of time preference.

When unemployed workers are matched with a job, they receive a wage $w = \phi_0(\mathbf{x}, y)$ such as the workers gets a share β of the match surplus, $P(x, E, y, w_p) - U(x, E, w_p)$,

$$W(x, E, y, \phi_0(\mathbf{x}, y)) - U(x, E, w_p) = \beta\left[P(x, E, y, w_p) - U(x, E, w_p)\right]. \tag{2.1}$$

When faced with an offer, unemployed workers will have 2 thresholds to determine their optimal decisions, described in Figure 2.8.

Employed workers

The value of being an employed worker is given by

$$\begin{aligned}
rW(x_k, E, y, w) &= w + \delta(U(x_k, E, w_p) - W(x_k, E, y, w)) \\
&\quad -\xi W(x_k, E, y, w) + \eta^e_{x<y}\left(W(x_{k+1}, E, y, w) - W(x_k, E, y, w)\right) \\
&\quad +\eta^e_{x>y}\left(W(x_{k-1}, E, y, w) - W(x_k, E, y, w)\right) \\
&\quad +\lambda_1 \int \max\left\{W(x, E, z, \phi_1(\mathbf{x}, z)) - W(x_k, E, y, w), 0\right\} dF(y') \\
&\quad +\varphi\left(W(x_k, E+1, y, w) - W(x_k, E, y, w)\right),
\end{aligned}$$

where $\phi_1(\mathbf{x}, y)$ denotes the wage the individual obtains and is obtained in the following way. When sampling alternative job offers, individuals are faced with three options

1. When the match value of the sampled job with requirements y' is such that $P(x, E, y', w_p) > P(x, E, y, w_p)$, the individual accepts the new job and gets a wage $\phi_2(\mathbf{x}, y, y')$ such that

$$W(x, E, y', \phi_1(x, y, y')) = \beta P(x, E, y', w_p) + (1-\beta) P(x, E, y, w_p). \tag{2.2}$$

2. If $W(x, E, y, w) < P(x, E, y', w_p) < P(x, E, y, w_p)$, then the individual stays in his current job and he extracts a wage such that

$$W(x, E, y, \phi_1(, y', y)) = \beta P(x, E, y, w_p) + (1-\beta) P(x, E, y', w_p). \tag{2.3}$$

3. If $P(x, E, y', w_p) < W(x, E, y, w)$, the worker stays in the current job with the same wage

When faced with an offer, employed workers will have 4 thresholds to determine their optimal decisions, described in Figure 2.9.

The thresholds y^E_1 and y^E_2 determine an interval of y in which the match surplus is high enough such that $W(x, E, y, w_p) < P(x, E, y', w_p) < P(x, E, y, w_p)$ and the worker stays in his current job but extracts a higher wage. Between y^E_2 and y^E_3 the match surplus of the newly sampled job, $P(x, E, y')$ becomes larger than the current surplus $P(x, E, y)$ and the worker moves to job y'. As requirements of the offer increase further and the mismatch penalty starts to have an effect, between y^E_3 and y^E_4 the surplus of offers $P(x, E, y')$ is such that the worker stays with his current firm and re-negotiates his wage and beyond y^E_4 the penalty is so high that he rejects the offers as $P(x, E, y') < W(x, E, y)$.

The match value $P(x_k, E, y, w_p)$ is given by

$$
\begin{aligned}
rP(x_k, E, y, w_p) \quad = \quad & f(x_k, E, y) - \xi P(x_k, E, y, w_p) + \delta(U(x_k, E, w_p) - P(x_k, E, y, w_p)) \\
& + \eta^e_{x<y}\beta\left(P(x_{k+1}, E, y', w_p) - P(x_k, E, y, w_p)\right) \\
& + \eta^e_{x>y}\beta\left(P(x_{k-1}, E, y', w_p) - P(x_k, E, y, w_p)\right) \\
& + \lambda_1\beta \int \max\{P(x_k, E, y', w_p) - P(x_k, E, y, w_p), 0\} dF(y') \\
& + \varphi(P(x_k, E+1, y, w_p) - P(x_k, E, y, w_p)).
\end{aligned}
$$

2.8 Benchmark Economy

In order to evaluate the effects of unemployment benefit changes in the model, we first calibrate the model economy. To this end, we need to specify a skills distribution, parametrize the production function, the unemployment benefit rule and the skill requirements distribution $F(y)$. Next, we fix some parameters of the model to their data counterparts or values commonly used in the literature, and calibrate the remaining parameters using the simulated method of moments.

2.8.1 Parametric specification

We specify a production function based on Postel-Vinay & Lise (2015), which is given by

$$
f(x, E, y) = E \times \left(\alpha_0 + \alpha_1 y - \kappa \min\{x - y, 0\}^2 + \alpha_2 yx\right) \tag{2.4}
$$

together with the assumption that $\alpha_0, \alpha_1 > 0$. This implies that in a higher requirement job, more is produced. The parameter α_2 controls the complementarity between the worker's skill and the skill requirements of his occupation. The parameter κ represents the cost of being under-skilled and implies that when an individual's skill is below the required skill in the job, there is a loss in production.

Unemployment benefits are a function of the previous period wage w_p

$$
b(w_p) = \rho \times w_p \tag{2.5}
$$

where ρ is the replacement rate. This mimics the way that unemployment insurance is calculated in the US.

2.8.2 Calibration

We first fix some parameters outside of the model. These parameters are shown in Table 2.9. The monthly interest rate r is fixed to correspond to a 5% annual interest rate and the attrition rate ξ implies an average 47 years of working life corresponding between ages 18 to 65. The surplus sharing rule is fixed at 0.5 following Pissarides (2009). The unemployment benefits are set at the 50% of the last period wages as in Chetty (2008) and Michelacci & Ruffo (2015). For the distribution of skills we construct a combination of literacy and numeracy skills in the NLSY79 and fit a beta distribution to it, with parameters a_x and b_x. Last, the parameter δ is calibrated directly from the data the employment to unemployment transition rate in the NLSY79.

This leaves us with the following vector of parameters to be calibrated, $\theta = (\lambda_0, \lambda_1, a_y, b_y, \alpha_0, \alpha_1, \alpha_2, \kappa, \eta^e_{x>y}, \eta^e_{x<y}, \eta^u, \varphi)$. These parameters correspond to the job arrival rates when unemployed and employed, the parameters of the beta distribution for the requirements of skills, the parameters of the production function and the skill accumulation/depreciation rates. These are calibrated to match the following moments in the data: (1) the average unemployment to employment transition rate, (2) the average employment to employment transition rate, (3) the mean and variance of the skill requirements of jobs held by individuals, (4) the coefficients of a regression of log wages on i) skill at entry to the labor market ii) current requirements iii) interaction between the two and iv) experience and (5) the correlation between x^s and y at 5, 10 and 15 years of labor market experience.

We then simulate $N = 10,000$ workers over $T = 1,500$ periods where a period is a month. Individuals start unemployed and draw a skill from the skill distribution. When unemployed, an individual receives the unemployment benefit $b(w_p) = \rho \times w_p$ and samples jobs from the sampling distribution $F(y)$ at rate λ_0. His skill depreciates at the rate η^u. When employed, the individual is hit by a job destruction shock with probability δ or receives an outside offer with probability λ_1. If hit by a job destruction shock, the individual becomes unemployed. If he receives an outside offer, he samples jobs with skill requirements y from the beta distribution $\beta(a_y, b_y)$ and according to the surplus of the offer, he decides whether to switch jobs, re-negotiate wage but stay in the current job or if to stay in the current job with the same wage. Individuals exit the market at rate ξ.

We compute the moments using the simulated data and find a θ that makes the model moments close to the data moments. The values of parameters resulting from the calibration are shown in Table 2.10.

The relative value of the job arrival rates while employed and unemployed, λ_0/λ_1 is equal to 0.34 which is similar to the literature (Postel-Vinay & Lise (2015)). The positive α_1 confirms that more is produced in a higher-requirement occupation and the large and positive κ points to the fact that the cost of mismatch is high. In addition, the values of the parameters $\eta^e_{x<y}$ and $\eta^e_{x>y}$ imply that cognitive skills are accumulated faster than they are lost.

2.8.3 Model Fit

The fit of the moments is shown in table 2.11. The model does well in matching the average transition rates from unemployment and employment and two moments of the distribution of accepted requirements. Moreover, the model captures well the fact that workers sort to occupations with requirements closer to their skills as they spend time in the labor market. In particular, the correlation between skills x and the occupational requirements y increases from 0.43 to 0.51 from workers with 5 years of tenure to ones with 15. In the model, this occurs both due to the cost of mismatch and through on-the-job search.

The results of the regression of log wages on skills at entry to the labor market, x^{se}, the skill requirements of the occupation, their interaction and years of labor market experience (equation (2.6)) are shown in table 2.12. The model captures the positive relationship between wages and the skills at entry to the labor market as well as the occupational skill requirements. Moreover, it features the complementarity between skills and skill requirements given by β_3.

$$\log(w_{it}) = \beta_0 + \beta_1 x_i^{se} + \beta_2 y_{it} + \beta_3 x_i^{se} y_{it} + \beta_4 E \tag{2.6}$$

The calibrated model matches well key relationships between skills, skill requirements and wages. Next, we validate the model in light of the facts relating unemployment benefit generosity, occupational switching and re-employment requirements and wages. In order to do this, we use the calibrated model to study the effects of varying the replacement rate of unemployment benefits, ρ.

2.8.4 Response of Wages and Requirements to Changing Benefits

In the model, changes in unemployment benefit generosity correspond to changes in the replacement rate ρ of the last period wage. Figures 2.10 and 2.11 show the matching matrix for unemployed workers in economies with a replacement rate of 60% and 70% of last period wages, respectively. For each level of skills, the yellow area represents the skill requirements acceptable to the individuals of that skill level. The effects of increasing unemployment benefit generosity in the model are twofold. First, individuals stop accepting very low-requirement jobs as these are not profitable enough. Second, individuals with the lowest skills stop accepting high-requirement jobs as the cost of mismatch make these jobs less desirable. Together, both effects make individuals more likely to select occupations with requirements closer to their skills, thus lowering skills mismatch.

The effect that increasing unemployment benefit has on acceptable jobs has different implications for workers with different lengths of occupational tenure. The fact that over time workers' skills adapt to the requirements of their occupation results in longer tenured workers in the model being on average better matched. Thus, when they become unemployed, their skill level at the beginning of the spell is close to their previous occupation's requirement. When job offers arrive, these workers are therefore more likely to accept jobs in the same occupation as they had before unemployment. This is consistent with the documented negative relationship between unemployment benefits and occupational switching for long tenured workers. On the other hand, workers with short tenure will accept jobs that are not necessarily close to their previous occupation. Instead, these workers look for jobs closer their skill and on average this results in an increase of requirements.

Table 2.13 shows the effects of increasing the replacement rate for unemployment, aggregate output, skills mismatch and characteristics of the EUE spells. First, a higher replacement rate increases the unemployment rate as workers stay unemployed longer while searching for jobs. As workers are more selective, employed workers are on average in better matches and average output per worker increases. Overall, the negative effect of higher unemployment is offset by the positive sorting effect and aggregate output rises.

In terms of the EUE spells, re-employment wages and requirements increase with the replacement rate. Relative to the occupational switching in the benchmark economy, occupational switching falls by 10 percentage points when the replacement rates increases from 50% to 70%. Next, we separate workers by occupational tenure at job loss (more and less than 2 years). Relative to occupational switching in the benchmark economy, the occupational tenure falls by 12 (8) percentage points for long-tenured (short-tenured) workers.

In the model, increasing unemployment benefits has no monetary cost. Thus, the positive effects that we show do not take into account the costs of financing these increases in unemployment benefits. As a next step, we investigate whether keeping the overall benefits paid out in the benchmark economy, there are any gains to redistribute the existing benefits between workers with different tenure.

2.9 Should Unemployment Benefits Depend on Labor Market Experience?

The current system of unemployment benefits replaces a fraction of the previous wage and the replacement rate is the same for all individuals. We ask whether individuals with less labor market experience should have higher replacement rates than those with more labor market experience. On the one hand, less experienced workers are less likely to have accumulated skills in a particular occupation and thus, when unemployed would like to do as good for themselves as possible. Higher benefits can help them to wait for jobs with higher skill requirements. This in turn affects their skill accumulation and their life-time wages. On the other hand, if more experience workers get lower benefits, they are less able to stay in the same occupation after an unemployment spell. This can generate efficiency losses.

To evaluate these effects, we now propose to make the replacement rate of the previous wage ρ dependent on labor market experience E in the following way

$$\rho = \alpha + \beta E \tag{2.7}$$

We first set a value of α and simulate the economy with different values of β to find the β such that the total benefits paid out is the same as in the benchmark economy. In the benchmark economy, $\rho = 0.5$ which translates to $\alpha = 0.5$ and $\beta = 0$. The scenario in which less experiences workers have a higher replacement rate than more experienced workers corresponds to cases when $\alpha > 0.5$ and $\beta < 0$ (where the replacement rate is subject to a non-negativity constraint). The opposite scenario occurs when $\alpha < 0.5$ and $\beta > 0$. We look for the combination of α and β that maximize average life-time wages.

Results for 10 values of α and β are shown in table A1. As we increase (decrease) α from the benchmark economy value of 0.5, average life-time wages increase (decrease) relative to the benchmark. However, beyond $\alpha = 0.8$, the increasing trend in average life-time wages reverts. The optimal α and β are equal to 0.8 and -0.024, respectively. Consider two workers with same w_p, one has 1 year of tenure and other 5. The less experienced worker would have a replacement rate of 0.776 whereas the more experienced worker would have a replacement rate of 0.68. The average wages in this case are 12% higher than in the benchmark economy.

The results of this exercise speak to the gains of making unemployment benefits negatively related to overall labor market experience. In this scenario, individuals accumulate more skills as when passing through EUE spells, they are able to get higher-requirement jobs early in their career. This relates our paper to Michelacci & Ruffo (2015) who argue that unemployment benefits should be negatively related to age. They argue that younger workers have larger liquidity constraints while for older workers moral hazard is more severe. While the policy recommendation we present is similar to these authors, we highlight a different channel, skill accumulation.

2.10 Conclusions

In this paper, we study the relationship between unemployment benefits and occupational switching. We first provide evidence on how unemployment benefits affect occupational switching by studying EUE transitions in two US data sets, the SIPP and the NLSY79. We document that unemployed individuals who are eligible to higher unemployment benefits are less likely to switch occupation. This effect is present in both data sets, controlling for a number of individual, spell and macroeconomic characteristics. The second fact that we document pertains to the requirements of two cognitive skills (literacy and numeracy) of the occupations that individuals move after unemployment. Conditional on switching, individuals with higher unemployment benefits move to occupations with higher requirements of both literacy and numeracy relative to low-benefit individuals. Finally, while the first fact is stronger for workers with longer occupational tenure, the second fact is stronger for workers with shorter occupational tenure. For all workers, these effects are accompanied by obtaining higher re-employment wages. These results point to the function of unemployment benefits as a search subsidy such that individuals are either able to stay in their occupation or not fall off the ladder.

In order to understand how benefits affect skill accumulation and mismatch, we build a search model of heterogeneous individuals and jobs with on-the-job search to study how unemployment benefits affect skill requirements and wages for workers who experience employment-unemployment-employment transitions. We calibrate the model using the SIPP and the NLSY data. We find that mismatch between the worker's skill and requirements decreases as unemployment benefits increase. We also study how unemployment benefits that explicitly depend on labor market experience affect skill accumulation over the life-cycle.

Chapter 3

Educational Disparities in the Battle Against Infertility: Theory and Evidence from IVF Success

3.1 Introduction

Assisted reproductive techniques (ARTs) are increasingly becoming standard inputs of the fertility decision-making processes as they circumvent the infertility constraints generated by delayed childbearing or biological characteristics of the couple. In Denmark alone, about 5% of all children were born after in vitro fertilization (IVF) in 2009. These numbers continue to increase over time with no sign of deceleration. The proportion of IVF children has been growing steadily since the 1990s from less than 2% in 1995 to slightly more than 5% in 2009 (Figure 3.1).[1] At the same time, the increase in IVF use goes hand in hand with the decision of many women to delay childbearing. On the one hand, there is wage premium to delay childbearing (Caucutt et al., 2002; Gayle & Miller, 2012; Adda et al., 2016; Leung et al., 2016). On the other hand, fecundity decreases with age. The introduction of the IVF technology in the '80s relaxed this biological constraint, but by how much depends on the IVF success (i.e., live births) rate.

While IVF technology is a well-established treatment for infertility initiated almost 35 years ago, the determinants of IVF success are not fully understood. For example, prognostic factors identified by medical studies are uterine receptivity, ovarian sensitivity, morphological grading of embryos, and their chromosomal competence, which translate into "luck" in the popular view. In this direction, recent literature has considered the

[1] This pattern echoes the annual growth in ART services in other developed countries, from 5% to 10% in the past decade (de Mouzon et al., 2010; Connolly et al., 2010).

outcome of IVF treatment as a natural experiment, and used it to estimate the effect of a first child on female labor outcomes (Lundborg et al., 2016).[2] But is it really the case that "nature" provides almost perfect randomness of IVF success? In this paper, we reconsider this view. In particular, we focus on socio-economic status, and specifically on education, as a determinant of IVF success.[3]

In order to estimate the education gradient in IVF, we use the Danish administrative registers (DAR). The DAR provides us with a rich and large scale dataset on all IVF treatments. In particular, the DAR offers both longitudinal and detailed information about individual and family characteristics and the entire history of infertility treatments used by *all* Danish women since 1995 including their demographics and socioeconomic statuses, and the clinic characteristics.

Our main result is the presence of large and significant education disparities in IVF success, when controlling for individual and partner's characteristics (such as age, income, marital status, and employment status), clinic fixed effects, health status and infertility causes. Among childless women, patients who have at least a college degree are about 21% more likely to attain a live birth at the first trial (cycle) than women who do not have a high school degree. This figure is 13% for childless women with a high school degree or some college. This gradient in IVF success is observed in similar magnitudes also in subsequent trials, pointing to a persistent difference in the success of achieving a child through IVF for higher educated women.

We next explore whether differences in other observable factors across education groups can explain the observed IVF gradient. To this end, we control for indicators of (un)healthy behaviors such as body size, smoking and alcohol consumption. However, our results stand robust to the inclusion of these additional confounding factors. Another potential concern are financial constraints. While infertility treatments are quite expensive, Danish couples are allowed to receive free fertility treatments at any public hospital in the first three trials with an embryo transfer. Hence, by focusing only on the

[2]Relatedly, Cristia (2008) uses the outcome of insemination treatments as natural experiments.

[3]For example, the Jones Institute at the Easter Virginal Medical School (has the first and therefore the oldest program in the United States, with the first IVF baby born in this country. Her birth date was December 28, 1981) states that the main factors affecting IVF outcome are: 1) age of the woman (and consequently, her ovarian reserve) 2) normalcy of the uterus 3) semen quality 4) success or failure of fertilization and cleavage in vitro and 5) number of embryos transferred and cryopreserved (therefore augmenting the total reproductive potential of a given IVF cycle). https://www.evms.edu/patient_care/specialties/jones_institute_for_reproductive_medicine/services/in_vitro_fertilization_ivf/_in_vitro_fertilization_-_ivf_-_success_rates/. We control for all of them and still get an education gradient.

free trials, the potential selection problem in the utilization of these treatments based on financial constraints are mitigated. The IVF gradient is present even when considering only free trials and controlling for household wealth.[4] Last, our results are robust to finer specifications of education. We find that the probability of IVF success increases in education even when we divide the population into finer educational groups.

We also estimate the gradient separately for each of the stages of the IVF procedure: aspiration (egg retrieval), embryo transfer, and live birth conditional on embryo transfer. We find a significantly positive education gradient in success in all stages. Importantly, our main results on the education gradient in IVF success in the first trial persist even when we condition on at least one embryo being implanted into the woman's womb: college graduates are about 20% more likely to attain a live birth than women who do not have a high school degree. This figure is 13% similar for childless women with a high school degree or some college. A possible explanation is that only the best-quality embryo(s) are selected, and the quality itself might have been influenced by education.[5] This finding indicates that, once an embryo has been implanted in the uterus, the "assignment" of children to women who seek their first pregnancy is *not* purely idiosyncratic. This piece of evidence casts some doubts on the validity of using IVF success as a shock to fertility to identify the effect of a first child on female labor supply.

The fact that the more-educated people are faster at succeeding in achieving a favorable health outcome has received alternative explanations in health economics. Grossman (2006) distinguishes between "allocative efficiency" and "productive efficiency" mechanisms. "Allocative efficiency" refers to the notion that the more-educated individuals choose different health inputs because they face different prices and have access to different resources. For example, individuals with higher levels of education are more likely to adopt newer medical techniques and drugs recently approved by the FDA, as they have lower costs of searching for higher-quality treatment (Lleras-Muney & Lichtenberg, 2005). In the case of the utilization of IVF treatments, however, we find an education gradient even when we exploit variation *within* a clinic (where patients face the same IVF inputs), which seems to rule out this argument. Instead, our results point in the direction of "productive efficiency", i.e., that highly-educated individuals have better health outcomes than lower-educated ones, even when they all face the same prices and constraints. A better knowledge on how to use the newly acquired information about the IVF technol-

[4]Note that 80% of the treatments in our sample are free.

[5]Evidence from the medical literature indicates that there are ways to help improve the health of the ovaries and the egg quality. Factors that are relevant for egg quality (and in turn for the embryo) include age, diet, BMI, hormonal issues, stress, and smoking.

ogy, i.e., higher ability to manage similar IVF inputs, can determine the organizational capital that yields higher "IVF productive efficiency" by the more educated individuals.

On the other hand, there is evidence in the medical literature that the IVF procedure takes an emotional toll due to the different sources of psychological stress that women face before and during the procedure (Ardenti et al., 1999; Yong et al., 2000; An et al., 2013). If the levels of stress and how women cope with stress affect the outcomes of IVF and are correlated to education, this could partly explain the IVF gradient we observe.

Therefore, we study whether and how relevant these two mechanisms (i.e. productive efficiency and psychological stress) are for the presence of the observed IVF gradient. To do so, we first check whether there is evidence of the presence of both mechanisms based on observable characteristics. We document that there is selection both into and out of IVF based on education. In particular, we find that dropouts rates, which we conjecture can reflect differences in how women cope with a failed treatment, differ significantly across education groups. Women with a College degree are less likely to drop out after the first cycle by 4.05 percentage points than high-school dropouts. This number grows to 9.6 percentage points after the fifth cycle. One way in which productive efficiency can be increased is if organizational behavior is backed up by a partner. We thus study whether a partner's education contributes to the IVF gradient. We find that in the first cycle, there exists a positive and significant partner's education gradient.

While these results speak to the presence of both mechanisms, the gradient persists as there likely remain unobservable characteristics that correlate to both psychological factors and productive efficiency. We next develop a dynamic model of women using IVF technology in which women differ in IVF productivity (how well women follow the IVF procedure) and the psychological stress associated with undergoing the treatment. In the model, women face a trade-off between a positive probability of succeeding in getting a child through IVF and the cost of psychological stress associated with undergoing the treatment.

Our model focuses on women who are undergoing IVF treatments to get a first child. Each women is endowed with an IVF productivity parameter and a level of psychological stress associated with IVF treatments. In each period, corresponding to a treatment, women decide whether to continue with an additional IVF treatment or to drop out from IVF. If an individual decides to continue with an IVF treatment, then she faces the trade-off between a positive probability of succeeding in getting an IVF child that delivers an additional stream of future utility starting next period and the psychological stress associated with going through IVF that reduces current utility. If an individual decides to drop out from IVF, then her entire life is childless. The success probability depends both on the individual IVF productivity and the psychological stress.

We estimate the distributions the distributions of IVF productivity and psychological stress by education group by matching conditional success and dropout rates. The estimated model sheds light on the importance of each of the factors in explaining the IVF educational gradient. In particular, counterfactual exercises reveal that more than 95% of the of the IVF gradient can be attributed to differences in productive efficiency, whereas dropout over treatments is determined mostly from differences in the distributions of psychological cost.

Our paper contributes to several strands of the literature. First, it relates to a vast literature studying the link between education and fertility ((Currie & Moretti, 2003; McCrary & Royer, 2011)). In general, highly educated women tend to have fewer children because they are more likely to participate in the labor force (Buckles, 2008; Goldin & Olivetti, 2013; Olivetti, 2014; Goldin & Mitchell, 2016) and face a wage premium in delaying childbirth (Caucutt et al., 2002; Gayle & Miller, 2012; Adda et al., 2016; Leung et al., 2016). We document a positive education gradient in IVF which could mitigate the well-known negative relationship between education and fertility (Jones et al., 2010).

We also contribute to the literature studying the determinants and outcomes of IVF. The determinants of utilization of IVF have been studied in the US context. For example, Schmidt (2007) uses variation across time and space to document that insurance mandates increase first birth rates for women over 35. Bitler & Schmidt (2012) show that insurance mandates have a positive effect on the utilization of infertility treatments (including IVF) for older and more educated women. Our paper relates closely to the empirical literature which links outcomes of ART or IVF outcomes to female labor supply (Cristia, 2008; Lundborg et al., 2016). In particular, contrary to Lundborg et al. (2016), we find a significantly positive education gradient in IVF success in the first trial even when we condition on at least one embryo being implanted into the woman's womb. This result suggests caution when using the outcome of ART or IVF as an exogenous source of variation in fertility to identify the effect of a first child on female labor supply.

Last, our paper speaks to the literature on the importance of education on health outcomes and behavior (D. Goldman & Lakdawalla, 2001; Cutler & Lleras-Muney, 2006, 2012). In particular, we give evidence on the educational disparities in IVF success. Other examples of education disparities in productive efficiency arise from the efficient adoption of health technologies such as complex contraceptive methods (Rosenzweig & Schultz, 1989), self-management of disease including compliance with AIDS and diabetes treatment which are fairly demanding (D. P. Goldman & Smith, 2002), success in quitting smoking (Lillard et al., 2007), and understanding of the risks involved in not wearing a seatbelt (Cutler & Lleras-Muney, 2012).

The rest of the paper is organized as follows. In Section 3.2, we describe the institutional setting in Denmark, and the administrative Danish register panel data used in our analysis. We also provide descriptive statistics of women seeking a pregnancy through IVF treatments. In Section 3.3 we pose our benchmark econometric specification and describe the main results. We conduct robustness exercises and explore the mechanisms behind the gradient in Section 3.4. We introduce the model and describe the estimation and counterfactual exercises in Section 3.5. Section 3.6 concludes the study.

3.2 Institutional Background and Data

In this section, we first describe the Danish institutional setting related to the Law of Artificial Insemination, paying particular attention to couples' eligibility for subsidized treatment and their rights. Second, we discuss the Danish register panel data and provide details on the construction of our variable for live births from infertility treatments. Third, we discuss descriptive statistics of IVF in Denmark.

3.2.1 Institutional Background

During the entire time-span of our sample (1994-2009), Danish women had the right to artificial insemination by an in vitro method if they fulfilled the following three criteria (Ministry of Health, 1997, 2006): (i) the woman must be younger than 45 years of age at the beginning of a treatment period; (ii) the doctor needs the consent of both, the woman and the man in the couple, being treated; (iii) the couple must, in the doctor's opinion, be suitable to take care of a child, and the woman must be able (both mentally and physically) to undergo pregnancy. Further, the eligibility requirements for couples to receive *free* fertility treatments at a public hospital were the following: First, the couple was not allowed to have any joint children. Second, the couple should have attempted pregnancy naturally for at least 12 months; however, depending on the woman's age and the couple's medical history, the treatment could start earlier. Third, the woman must not be older than 40 years old at the beginning at the treatment.[6] Fourth, only the first three successful treatments were free. A treatment was considered successful if it transferred at least one healthy embryo into the woman's womb. See Ministry of Health (2006, 2012, 2013) for details. In our sample, 83% of the couples who succeeded in having the first child did so within the allotted free treatments, and 76% were treated in the public sector.

After the initial first three treatments, the couple must go to a private fertility clinic for further treatments, and pay their cost. However, the law does allow leftover frozen eggs from the couple's past treatments to be used at public hospitals when seeking a new pregnancy even after the allotted number of free trials, and, in some regions, free treatment may occur when the couple seeks help to have a second child (Danish Health Insurance, 2013).

Treatments can terminate at any time during the IVF process for a number of reasons, including over-stimulation, cysts in the ovaries, no healthy eggs to retrieve, no fertilization of the eggs, or unsuccessful pregnancy after the embryo transfer. Sucessful IVF treatments involve not only medical interventions but an intensive amount of patient self-management, as its procedure is strict and complex. Clinics follow a standard protocol that is described in detail in Appendix C.1.

3.2.2 The Administrative Danish Register Panel Data

We use unique administrative Danish register panel data from the entire Danish population from 1994 to 2009. We are interested in two specific sources of information. The first is the Danish National Board of Health, which contains detailed information about all women using in vitro techniques to achieve a pregnancy (e.g., date of cycle/treatment, reasons for undergoing treatment, if the treatment includes aspiration and/or transference, if the treatment results in a live birth). This is referred to as the IVF register, and includes the medical aspects of the individual fertility treatment histories.
The second source is Statistics Denmark, which includes register data of annual information on socioeconomic variables (e.g., age, gender, education), income information (yearly income, earnings, and wealth), characteristics of employment (e.g., employed, self-employed, unemployed, out of the labor market), and general health information of the population. The IVF and the Statistics Denmark registers can be merged through a personal identifier. The data also includes a family-ID to link the individual to her

[6] While 40 years is the limit age to receive free IVF treatment in Denmark, paid IVF treatment is allowed for all women younger than 45 years old. That is, it is illegal to provide IVF treatment to women older than 45 years old in Denmark.

spouse/cohabiting partner, children, parents, and other household members. Labor income and wealth measures are deflated to the year 2000 level using Consumer Price Index data from Denmark. Patients are classified into three mutually exclusive educational categories: less than high school education, high school and trade and some college education, and college and higher education. We also consider specifications where the population is divided into six groups: less than high school, high school, vocational school, two years of college, college, and Master or Ph.D..

The medical records of patients at visits to any general practitioner (GP) contain information about the number of yearly services performed by the GP (e.g. consultation, blood test, vaccination, etc.), and the reimbursement (in Danish Kroner, DKK) that the GP receives from the state for the provided services. The medical records from visits to hospitals are grouped into diagnosis code by the main diagnosis of the ICD10 (the 10th revision of the International Statistical Classification of Diseases).

For every treatment, the IVF register records when the treatment started, when the eggs were retrieved (aspiration), whether and when the embryo(s) were selected and then transferred to the woman's womb, and whether this resulted in a live birth, which is our measure of IVF success.[7] Before the start of the cycle height in centimeters and weight in kilos were recorded and women completed a questionnaire eliciting lifestyle information (e.g., number of cigarettes smoked per day and number of alcoholic beverages consumed per week). This information is available from 2006 onward.

In sum, a notable aspect of the dataset is that it contains rich information about the socio-economic status of the couple, the entire history of fertility treatments, infertility causes, medical conditions and health behaviors (smoking, drinking, BMI, etc) prior to treatments, and an identifier of the hospital that provided each treatment. This aspect of the data is important because it enables us to verify if an education gradient in IVF success is partially driven by systematic differences among less and more educated women.

[7]While the number of live births is only available until 2005, we can still impute it for 2006 -2009 by examining the birth records in the Statistics Denmark family register for all women in the IVF register. For all fertility treatments, we compute the expected birth date as the start date plus 280 days, which is the expected pregnancy duration. We then check whether the woman has a birth at most 90 days before the expected birth date or at most 21 days after the expected birth date. If a woman had a child during this period, we classify the treatment as a success. However, for women with multiple treatments less than 3 months apart, the above approach gives multiple potential births less than 3 months apart. If this is the case, we classify the last treatment in a sequence as the success and the other treatments in the sequence as failures.

3.2.3 IVF in Denmark: Stylized Facts

Our sample includes all Danish women 25 to 45 years of age with recorded education in our registers, who were married or cohabiting with a man, and did not have prior children before seeking the first treatment in 1994-2009. We consider this age group in order to ensure that they completed their education.[8] By doing so, we exclude about 2.5% of treatments of young patients who were 20-24 years old. Since we want to follow women from their first IVF treatment, we exclude all women with treatments in 1994. With this restriction, we drop additionally 1.7% of the treatments. This way, we can start counting initial treatments in 1995, and we classify a treatment as first if the woman did not receive any treatments in 1994.[9]

Our final sample consists of a total of 21,130 women and 67,981 initiated treatments (i.e., cycles) to conceive the first child in vitro in Denmark for the 1996-2009 period. The median number of cycles per couple is 2, and the maximum is 20. Regarding the cycles to conceive the first child, about 80% were performed in the public sector. In some specifications we focus on the first 5 treatments to conceive the first child which represent 86% of all the initiated treatments (58,303).

Following the law, we consider a treatment to be still eligible for the free quota if in the past the patient received less than three treatments reaching the stage of embryo implantation in a public hospital since the couple entered the sample, conditional on having no previous children. The free treatments can occur only at public hospitals, there is no reimbursement of the expenses if the couple undergoes an IVF treatment in the private sector. Note that the number of free treatments may exceed three, because this upper bound is conditional on a successful embryo transfer. After the initial free treatments, treatments should, according to the law, take place in private clinics. Almost 10% of all treatments in public hospitals should not be free according to our classification. In most cases, these are patients who want to conceive a second child in vitro using the embryos frozen in previous cycles, as mentioned in Section 3.2.1. We now turn to describe who enters into treatment.

[8]For the same reason, we also exclude individuals above 25 still in school (approximately 1% of the sample).

[9]Since our data show the stock of women in treatment during a year, we do not know whether they had treatments before the sample period started. In order to identify the first treatment, we assume that if she enters a fertility treatment that does not result in a child, she either stops the treatment or continues receiving treatments with no break longer than a year.

3.2.4 Characteristics of IVF Patients

In our sample, the majority of IVF patients have a high school degree or some college (51%), followed by college graduates or higher (36%).[10]

Table 3.1 compares the socioeconomic and demographic characteristics of IVF patient subsamples by education groups, namely high school dropouts (henceforth "$<$ *HS*"), high school graduates or some college (henceforth "*HS*"), and college graduates or higher (henceforth "*College*") seeking the first IVF treatment. Individuals in the *College* group were slightly older when they were first treated.[11] The less educated ones were slightly more likely to be married (59%) than those with a *HS* degree or *College*. Both individual and spousal income increased with education. The vast majority of the sample was employed, with approximately 94% among highly educated women; that proportion drops to 89% in the *HS* group and then falls to 72% for high school dropouts. There are minor differences in the share of women who were on leave or self-employed between the groups. Paralleling the increase in the propensity to work as education increases, the proportion of women who were out of the labor force or unemployed was 22.6% in the $<$ *HS* group, 7% in the *HS* group, and 4% in the *College* group. Regarding the distribution of treatments provided in the public sector, about 84% of patients were treated in the public sector the first time, and we did not observe remarkable differences across education groups. That proportion varies from 88% among high school dropouts to 80% among college graduates.[12]

We observed similar differences across education groups when we considered the last treatment seeking the first pregnancy (Table C2). Note that a couple might have discontinued IVF treatment either because they had a live birth or faced a failed implantation or natural miscarriage. Within each group, the proportion of cycles in the public sector slightly decreased because of couples undergoing more than three cycles. Further, the proportion of married couples and (individual and spousal) income increased to some

[10] In 1996 the majority of IVF patients have a high school degree or some college (51%), but this figure goes down in 2009 (43%). In 2009 the majority of IVF patients are college graduates (50%), a group that represented 28% of the IVF sample in 1996. In turn, there is a drop in the number of patients with less than a high school degree who accounted for 21% of the total IVF patients in 1996 but only 7% in 2009. We include time dummies in our analysis to control for this time variation in education across years.

[11] This is mainly driven by women holding at least a master's degree who are on average 33 years old. College graduates are instead on average 31.8 years old.

[12] A similar figure for the public sector is obtained if we consider all treatments that are eligible to be free: 84% of patients are treated in a public hospital; 88% of the $<$ *HS* group, 84% of *HS* group, and 79% of the *College* group. If instead we count all treatments for the first child: 79% overall; 86% in the $<$ *HS* group, 81% in *HS* group, and 75% in the *College* group.

extent, which indicates that married and rich couples were more likely to persist in being treated after a failure.

As a first step to understanding the relationship between education and IVF success rate, Table 3.1 displays the success rate (measured by the fraction of IVF live births) among less and more educated women. The IVF success rate with the first treatment was 21% for the $< HS$ group, 25% for the *HS* group, and 26% for the *College* group. The difference is sharper if we consider success in the last treatment seeking the first pregnancy (Table C2): 47%, 54%, and 57% for the $< HS$, *HS*, and *College* groups, respectively. Instead, the average number of treatments is similar across education groups: 2.59 for the $< HS$ group, 2.62 for the *HS* group, and 2.64 for college graduates or higher.

Since highly educated women were slightly older when they underwent the first IVF cycle to conceive a child, Table 3.2 shows the relationship between patient's age, access to IVF in public and private sectors, and success rate. The fraction of first treatments provided by the public sector moderately decreased with age: 87% for women 25-29 years old, 85% for women 30-34 years old, and 77% for women 35-40 years old. The same pattern is displayed if we consider all treatments that were eligible to be free. When we enlarge the sample to all treatments seeking the first successful pregnancy, a large majority of treatments was still provided by the public sector: about 80% (panel (a), Table 3.2). The data allows us to examine the IVF success rate at the treatment and hospital level. In the latter case, we give equal weight to all hospitals (panel (c), Table 3.2), whereas in the former case, we place more weight on the high-volume hospitals (panel (b), Table 3.2).

The overall success rate in the public sector was higher than in the private sector (25.6% versus 21.2% at the treatment level and 25.9% versus 18.3% at the hospital level). Since older women were somewhat more likely to be treated in the private sector, we also examined whether this difference remained when we looked at the distribution of live births in the public and private sectors across age groups. At the treatment level, the success rate was fairly identical across sectors for the mid-range age groups. However, while younger women had higher success rates in the public sector (i.e., 29.0% versus 26.3%), the reverse was true for older women (0.0% versus 6.0%). At the hospital level, we observe similar patterns.

Finally, there are also educational disparities in infertility causes, medical conditions, alcohol habits, smoking, BMI etc. Table 3.3 displays some interesting differences across education groups in terms of the diagnoses of infertility causes across education groups (note that doctors may report a woman to have more than one infertility cause). In particular, less educated women were more likely to report a fallopian tube defect, with an incidence of 36% against 21% in the *College* group. On the contrary, male causes, as well as other medical causes and unspecified causes, were more likely to be diagnosed among highly educated women, which may reflect the somewhat higher age at entry.

The number of services from GPs per year tended to decrease with education, 9.2 for the < *HS* group, 8.1 for the *HS* group, and 7.5 for the *College* group. This differential is also present in the average cost of the GP service (DKK 691 for the least educated group and DKK 563 for the most educated group). In addition, as one might expect, less educated women were more likely to be diagnosed with a number of other diseases prior to fertility treatment.[13] Finally, our data-set contains information about smoking, alcohol consumption, and BMI from 2006 to 2009. We find that IVF patients with higher education reported smoking fewer cigarettes in the year before the treatment. The proportion of individuals that reported not smoking any cigarettes at all is 59.8% for the < *HS* group, 72.6% for the *HS* group, and 79.8% for the *College* group. In contrast, individuals with college or higher degree tended to consume more alcohol prior treatment. For example, the proportion of individuals that reported not drinking alcohol is 48.4% for individuals with less than a high school degree, 40.3% for high school (and some college) and 35.8% for college or higher. More educated individuals also tended to have smaller body sizes according to BMI indicators.

3.3 The IVF-Education Gradient

3.3.1 Empirical Strategy

As documented above, lower and more educated women are different in a number of dimensions (age, income, employment status, medical conditions, BMI, smoking, etc) and, to some extent, sort into different sectors. Thus, an immediate concern is that educational disparities in IVF outcomes may partially reflect these differences. To account for the influence of these systematic differences in individual and clinic characteristics, we estimate the following equation:

$$b_{ijht}^{IVF} = cons + \sum_{s>0} \alpha_s \mathbf{1}_{s_i} + \beta_t + \gamma_h + \eta x_{ij} + \varepsilon_{ij}, \tag{3.1}$$

[13]Disease incidence is below 3% in most cases. Two of the diagnoses with the highest incidence were "genitourinary system" and "pregnancy or childbirth", which is understandable since this is a sample who experienced fertility problems and was actively trying to become pregnant.

where b_{ij}^{IVF} is a dummy variable equal to 1 if a live birth is attained with the IVF treatment j for woman i in the hospital h at year t. s_i is a measure of the individual i's educational attainment, namely (i) less than high school, (ii) high school or some college, or (iii) college or higher. β_t is a year fixed effect, and γ_h is a clinic fixed effect.[14]

The vector x_{it} denotes a full set of individual demographic and socioeconomic characteristics, health status and infertility causes. In particular, it includes dummy variables for age; marital status; logged female's labor income; logged spousal labor income; a categorical variable for labor market status taking values for "on leave" status, self-employed, employed, out of labor force, and unemployed. Patients' and spouses' incomes are expressed at year 2000 price levels deflated using the Danish Consumer Price Index. ε_{it} is a contemporaneous term reflecting heteroscedastic robust standard errors $N(0, \sigma^2_{\varepsilon,i})$.

Note that, while the coverage of infertility treatments for childless couples at a fertile age largely mitigates the potential selection problem in the utilization of these treatments based on education, a positive education gradient in IVF could still be the result of patients sorting into different clinics, as patients across clinics might be affected by unobserved clinic characteristics that are correlated with both individual education and IVF success.[15] In order to account for this confounding factor in the estimation of the education gradient we exploit only the variation of education across patients within a clinic, who essentially faced the same practitioners, description of protocol, equipment, facilities, etc. Before presenting our estimation results, we examine the extent of variation in patients' educational attainment that is left after removing hospital and year fixed effects. The overall mean and standard deviation are 13.7 and 2.3, respectively. After removing these fixed effects, we retain more than 90% of the variation (from 2.30 to 2.21), which is reassuring in terms of the precision of our estimates.

Our parameter of interest is α_s, which captures the relative effect of college (or higher education) and high school attainment (or some college) with respect to the reference educational attainment group (i.e., less than high school). Hence, if there is a positive education gradient in IVF, the estimated term α_s will be positive and significant. We next report our results for the benchmark model and interpret our results.

[14]Unfortunately, we cannot control for doctor fixed effects. However, to the extent that the quality of doctors differs by clinic, the clinic fixed effects will control for doctor heterogeneity, in particular, if patients can (and do) move across clinics.

[15]One concern is the presence of disparities in the amount of available resources across education groups, which in turn generates differences in accessibility to expensive medical technologies. If the higher-educated mothers have access to better IVF technology, they will have better success in attaining a live birth simply due to higher productive efficiency. This argument can be stated in general for a wide set of medical technologies; see Grossman (1972); Kenkel (1991); Thompson et al. (2008); and Cutler & Lleras-Muney (2012).

3.3.2 Results

First, we estimate a linear probability model (LPM) using information on all women 25 to 45 years of age who underwent an IVF process, as specified in equation (3.3). We start by reporting in Table 3.4 the results for the first cycle women underwent, which might be viewed as the cleanest because of possible attrition in repeated cycles.

The outcome is clear: There is a large and highly significant education gradient in IVF success rates in all specifications. Compared to the reference group, patients with high school degrees or some college education have a 3.19 percentage-point higher probability of attaining a live birth through IVF, holding age constant, including health status measures, socioeconomic characteristics, infertility causes, year fixed effects and clinic fixed effects (column 5, Table 3.4). The estimated coefficient for patients with a college degree is even higher: 5.13.[16] To see this, consider that the average chances of attaining a live birth through IVF in the first cycle are 23.82%, so the education gradient results in a 5.13x100/23.82 = 21.53% higher chance of successful IVF treatment (out of the total chances) for college graduates, and (3.19x100/23.82=)13.39% for women with high school degrees or some college, when compared to individuals without high school degrees.

We first explore how the coefficient of the gradient with no controls (column 1, Table 3.4) changes as we introduce year fixed effects and health status in our baseline regression (column 3, of Table 3.4). We find that adding these controls increases the education gradient in the first cycle for the *College* group. Specifically, *College* patients are associated with a 5.34 (instead of 5.18) percentage-point higher probability of attaining a live birth compared to $<$ *HS* patients. On the contrary, for *HS* patients, the estimate decreases from 4.08 to 3.38-percentage points.[17] The gradient slightly decreases when we include socioeconomic characteristics in infertility causes in our regressions. Our main specification includes in addition fertility causes and clinic fixed effects (column 5, Table 3.4).

Consistent with the medical literature, we find that age is an important determinant of IVF success in all specifications in Table 3.4. As patients age, the probability of suc-

[16]Not controlling for health status, individual characteristics and infertility causes changes the estimates slightly but the IVF-education gradient is still large (column 2, Table 3.4). Patients with high school degrees or some college education have a 3.75 percentage-point higher probability of attaining a live birth through IVF, and patients with a college degree or higher have a 5.8 percentage-point higher probability of attaining a live birth through IVF.

[17]Whether we used a dummy for each diagnosis given at hospitals during the year prior to treatment, or an indicator equal to 1 if the patient has been diagnosed with any disease did not alter the robustness of the results.

cessful IVF births decreases. The estimated coefficients of the average number of GP services are negative and significant whereas the coefficients of their monetary cost are close to zero. As for socioeconomic characteristics, a 10% increase in individual income is associated with a 4.62 percentage points increase in the IVF success whereas spousal income has a smaller and insignificant effect. Further, patients who were employed, self-employed, outside the labor force and on leave were less likely to succeed than patients who were in school (i.e., the reference group).

Regarding infertility causes, there is no significant association between IVF success rate and cervical defects, ovulation defects, male causes and unspecified causes. In contrast, we observe that for those women who undergo infertility treatment because of a defect of the fallopian tube the probability of IVF success drops by 2.36 percentage points; and for those patients with "other causes" of infertility this probability drops by 3.54 percentage points. Note that while the former cause of infertility is more prevalent in the $<$ *HS* group, the latter one is more prevalent in the *College* group, and might be related to the quality of the eggs because these patients are slightly older when they enter into treatment. The fact that the absolute value of the coefficient of "other causes" is the highest among all infertility causes may partially explain why we observe that the education gradient in the *College* group increases.

Our main results are based on the first treatment (i.e. cycle) of IVF that women undergo. We next explore whether the gradient is also present in subsequent cycles. To this end, we run our baseline regression for the first five treatments which amount to 86% of all cycles. Results in Table 3.5 show a positive IVF gradient for first five treatments separately and together under 'all'. While we don't observe any particular pattern of the gradient across treatments numbers, the gradient becomes insignificant for the HS group in several treatments beyond the first one. On the other hand, College graduates are significantly more successful than high school dropouts in all first five treatments. In addition, when pooling the first five treatments together, the gradient is comparable to the one of the first cycle in magnitude (last column, Table 3.5).

Throughout our analysis, we have focused on a LPM specification. Our results with a logit model imply an almost identical IVF-education gradient (Table C1).[18]

[18]For example, at the margin, the estimate of the gradient is 5.13 percentage-points for the *College* group and 3.18 for the *HS* group (column 5, Table C1), against an estimate of 5.13 and 3.19 that we find for the *College* group and the *HS*, respectively, in the baseline specification (column 5, Table 3.4). Similarly, the gradient remains robust in the other columns of Table C1.

3.4 Robustness

3.4.1 (Un)Healthy Behavior

Table 3.3 shows that more and less educated women display some differences in infertility causes, health problems experienced before IVF, smoking, drinking, and BMI, which the medical literature considers "risk factors" to achieving a successful pregnancy. Hence, we examine whether the educational disparities simply reflect these differences.

Information on behavioral factors such as smoking, alcohol consumption, and BMI is available only for 2006-2009. Hence, we first replicate our results for this time span (column 2, Table 3.6). Note that the education gradient in column (2) is higher than in column (1), which indicates that the educational disparities may become larger over time. Then we compare these results with the ones obtained when we also include BMI, the number of cigarettes smoked and the number of units of alcohol consumption per week. We find that when including BMI and cigarettes smoked per day the size of education gradient has a small decrease from 6.64 percentage points to 6.39 percentage points for *HS* patients, and a slightly larger decrease from 9.27 percentage points to 8.79 percentage points for *College* patients (column 4, Table 3.6). When including also alcohol consumption, the gradient is somewhat higher perhaps because highly educated women reported to drink more (column 5, Table 3.6).[19].

3.4.2 Financial Constraints

We next restrict our attention to those treatments that were eligible to be free which helps rule out issues associated with potential financial constraints. When we restrict the sample to the treatments eligible to be free (i.e. for women who were below 40 and treated in the public sector), the sample size shrinks from 21,130 to 17,422 IVF cycles, but the IVF-education gradient remains significantly positive and slightly larger in magnitude (column 3, Table 3.7), most likely caused by the exclusion of ineligible women above 40 who are predominantly highly educated and have low fertility. We also include specifications in which we directly control for household wealth (columns 4-6, Table 3.7). The IVF education gradient decreases slightly when wealth is included. However, it remains large and positive. Not surprisingly, wealth is positively related to IVF success.

[19] All specifications include an indicator for missing information on BMI, smoking and alcohol consumption

3.4.3 Technological improvements

The increasing pattern of IVF children (Figure 1) opens the question on the potential stationarity of the education gradient in IVF. The reason is that improvements in the use of available technologies (e.g., frozen eggs) together with potential changes in the selection of IVF patients across education groups can affect the education gradient in IVF. We now entertain the possibility of a nonstationary education gradient with the following specification:

$$b_{ijht}^{IVF} = cons + \sum_{s>0} \alpha_{st} \mathbf{1}_{s_i} \mathbf{1}_t + \beta_t + \gamma_h + \eta x_{ij} + \varepsilon_{ij}, \tag{3.2}$$

Table 3.8 shows an increasing pattern, especially for the College group where the probability of a live birth is 3.68 percentage points higher than for high-school dropouts for the 1995-1999 period, 3.68 pp for the 2000-2004 period and increases to 6.64 pp in the 2005-2009 period.

The evolution of the IVF-Education gradient over time partly, though not fully, explains the different results in Lundborg et al. (2016). In contrast to our findings, these authors find no gradient and then use IVF outcome as an instrument to assess the effects of fertility on labor market outcomes. To make a closer comparison between their work and ours we also reproduce to the extent that we can their sample and empirical strategy. We report results for different time periods in Table C3 where we condition on at least one embryo being implanted into the woman's womb. We also include a specification where we control for average years of schooling. Perhaps, the main difference is that we find a significantly positive education gradient in IVF success in the first trial. Running the same empirical model for the later sample 2006-2009, we find an increase in the gradient even when we condition on an implanted embryo. This piece of evidence calls into question the validity of using the outcome of IVF as an exogenous source of variation in fertility to identify the effect of a first child on female labor supply (Lundborg et al., 2016), in particular, for the latter period.[20]

[20] In fact, this putative natural experiment must satisfy the randomness criterion. However, while the IVF outcome is drawn by biological mechanisms, the assumption of randomness is not fully credible in light of our results. Identification of the effect of first child on labor market outcome rests on the assumption that IVF success is not correlated with the error term. Therefore, the description of what is in the error term is critical to assess the reliability of their estimates. Even if Lundborg et al. (2016) control for education, the application of this instrument is likely to provide biased estimates if IVF success is not orthogonal to unobservable factors that could affect labor market outcomes. Consider for example personality traits that are correlated with education: some medical evidence indicates that personality traits and ability to cope with stressful situations may affect the outcome of IVF and, at the same time, an emerging literature in labor economics documents that personality traits are associated with employment status and wages, and this relationship is not fully mediated by education. See, e.g.,

3.4.4 A Finer Specification for Education

It is noteworthy that our main findings are not an artifact of our measure of education. One might think that the gradient is mainly driven by patients with a Master or Ph.D. degree. They are the ones who are more likely to delay childbearing for career concerns and enter into treatment at an older age, which might be the cause of infertility rather than medical factors. If that were the case, we might estimate a positive education gradient conditioning on age. However, we find that the probability of IVF success increases in education even when we divide the population into finer educational groups, see column 1 of Table 3.9. Relative to high-school dropouts, high school graduates have 3.68 percentage point higher chance to succeed , compared to 4.07 for women with two years of college, 4.76 for college graduates, and 6.16 for women with a master or Ph.D. degree (column 1, Table 3.9). This implies a 0.0616*100/23.85 = 25.8% higher success for a PhD woman, relative to a dropout woman. Finally, we show that one more year of education is associated with a 0.7 percentage points higher probability of a IVF success (column 2, Table 3.9).

3.4.5 IVF Stages within cycles

Whether a pregnancy results in a live birth relies on the successful completion of three different stages of the IVF procedure,[21] namely 1) aspiration, the process of egg retrieval, 2) embryo transfer, which is conditional on having at least one healthy embryo resulting from insemination of the retrieved eggs and 3) the pregnancy phase.

Several factors influence the success of each of the stages. These include factors that relate directly to the behavior of women previous to and during the IVF procedure, such as healthy behaviors and the precision with which women follow the IVF protocol. Another important factor is the grading of the embryo(s). Only the best quality embryo(s) are selected, and their quality might be associated with education.[22] Evidence from the medical literature indicates that there are ways to help improve the health of the ovaries

Heckman et al. (2006); Almlund et al. (2011); Fletcher (2013), and references therein.

[21] We describe the stages of the IVF procedure in detail in Appendix C.1

[22] For instance, using data from three (academic or private) clinics in the greater Boston area, Mahalingaiah et al. (2011) document that patients with a graduate school education have statistically significantly higher peak estradiol levels than patients without a college degree, which in turn affect the odds of cycle cancellation before egg retrieval.

and the egg quality. Factors that are relevant for egg quality, and in turn for the embryo, are age, diet, BMI, hormonal issues, stress, alcohol consumption and smoking.[23]

To asses the determinants of a failure due to a lack of eggs to be retrieved, healthy embryos to implant or a natural miscarriage after implantation, we next estimate our baseline regression separately for each of the stages of the IVF procedure, conditional on arrive to that stage. For live birth we also include indicators of the number of embryos implanted. The results are given in Table 3.10.

We find an educational gradient in all stages of the IVF process, although it increases in magnitude with each stage. Women with a High school degree are 1.5 percentage points more likely to get the eggs extracted than high-school dropouts. This number is 2.4 for women with a College degree. Conditional on successful aspiration, women with a High school degree are 2.7 percentage points more likely to achieve at least one healthy embryo after insemination than high-school dropouts, compared to 3.5 for College graduates. Strikingly, the estimated coefficients of the gradient in live birth conditional on an embryo being transferred into the womb are virtually identical to the ones in our baseline specification (Table 3.4), even when we control for the number of embryos implanted (columns 3 and 4, Table 3.10).

Given that the probability of success, conditional on an embryo transfer, is 28.92 in our sample, these estimates implies that on average college graduates are about 20% more likely to attain a live birth than women who do not have a high school degree. This figure is similar for childless women with a high school degree or two years of college: 13%. This finding seems to suggest that whether a pregnancy will end in miscarriage is not purely idiosyncratic.

3.4.6 Selection into (and out of) IVF

Not all infertile women who seek to have a child decide to undertake IVF treatment. This IVF participation decision is likely to reflect monetary costs of IVF treatment, psychological costs, preferences, and so on. Since not all municipalities in Denmark have an IVF clinic, *ceteris paribus*, differences in the decision to participate in IVF treatment can be generated by differential access to IVF clinics; these transit costs can be of the monetary

[23]For example, Shah et al. (2011) show that obesity is associated with fewer normally fertilized oocytes, lower estradiol levels, and lower pregnancy and live birth rates. Rossi et al. (2011) find that consumption of as few as four alcoholic drinks per week is associated with a decrease in IVF live birth rate, after controlling for cycle number, cigarette use, body mass index, and age.

or psychological type.

For these reasons, we next study the education gradient and the determinants of IVF success with a standard two-stage Heckman selection model that incorporates an IVF participation equation. The IVF participation equation includes a dummy for the existence of a municipal IVF clinic as an exclusion restriction.[24]

Table 3.11 shows the results for this selection. The sample size is now 921,644— that is, the total number of women between ages 25 and 45 who are married or cohabitating with a man. The main finding is that the IVF-education gradient remains remarkably similar to when we do not take the IVF participation decision into account. IVF patients with a high school degree have a 4.37-percentage-point higher probability of a live birth than high school dropouts, and IVF patients with a college degree have a 7.31-percentage-point higher probability than high school dropouts. Recall that in the benchmark case these figures were 3.19 percentage points for high school graduates and 5.13 percentage points for college graduates (note that we are referring to the benchmark results with health status and diagnosed infertility causes controls; see column (5) in Table 3.4).

Finally, the participation decision summarized by the selection equation in column (2) of Table 3.11 is interesting in itself. We find an education gradient in terms of IVF participation. IVF patients with a high school degree participate about percentage points more often than high school dropouts, and for patients with a college degree, participation is percentage points higher than high school dropouts.[25] Perhaps not surprisingly, women who have visited the GP more often are more likely to participate in IVF.

Overall, the fact that our results regarding the determinants of IVF success are largely robust to selection issues suggests that the decision to adopt IVF technology is arguably rather unconstrained in Denmark; that is, it is very likely that the vast majority of infertile women seeking to have a child are able to undergo the IVF process.[26]

Next, we investigate whether in addition to a gradient in success in IVF and selection

[24]Our exercise is analogous to that standard in the labor literature that estimates wage equations controlling for selection of labor market participation.

[25]These marginal effects are computed using the estimates in column (2) of Table 3.11 evaluated at the average values for age and years.

[26]Following our previous analogy with the labor market, and for comparison purposes, we know this is typically not the case for the decision of labor market participation, which might indeed be constrained by aggregate labor market conditions that increase involuntary unemployment.

into IVF, there exists selection out it IVF. To this end, we estimate the following equation

$$d_{ijht}^{IVF} = cons + \sum_{s>0} \alpha_s \mathbf{1}_{s_i} + \beta_t + \gamma_h + \eta x_{ij} + \varepsilon_{ij}, \tag{3.3}$$

where d_{ijht}^{IVF} is the probability that a woman drops out after treatment j. Only women who do not achieve a live birth and discontinue treatment are counted as dropouts at each treatment. We report results for drop-out after the first 5 treatments and in all treatments together in Table 3.12. We observe a negative gradient in selection out. In particular, high school dropouts are 3.01 percentage points less likely to drop out than high school dropouts after the first cycle. The corresponding figure for college graduates is 4.05. This negative dropout gradient can be noticed in all subsequent cycles. While for college graduates the probability to drop out relative to high school dropouts increases in absolute value monotonically with each treatment, for high school graduates the pattern is less clear.[27]

3.4.7 Partner's education gradient

One way in which the efficiency in terms of IVF outcomes can be increased is if organizational behavior is backed up by a partner. To study this hypothesis, we replicate the results in Table 3.5 conditioning on male education and report results in Table 3.13. Strikingly, in the first treatment both female and male educations are significantly and positively associated with IVF success. Further, the estimated coefficients of the female gradient in the first treatment are only slightly smaller than those in the baseline specifications (2.85 versus 3.15 for high-school graduates and 4.32 versus 5.34 for college graduates), and their size is about a third larger than those of the male gradient in Table 3.13.

3.5 A Model of IVF Treatments and Success Rates

Our empirical evidence shows a large and significant educational gradient in IVF success rates. College-graduate women have a 21.53% higher probability of succeeding in IVF than high-school dropouts and high school graduates have a 13.39% higher probability of succeeding in IVF than high-school dropouts. In this section, we explore whether heterogeneity in the efficiency of producing a live birth through IVF and (or) heterogeneity

[27]Note that results in the first five columns are run separately for each treatment. In the next section, we also estimate a duration model where dropout at each treatment is estimated using all the observations, with women exiting due to a live birth considered as censored observations.

in psychological stress associated with the IVF procedure can explain our results.

The rigors of completing a cycle of IVF entail strict adherence to an intense schedule of appointments, blood tests, ultrasound tests, and procedures, and patients compliance with medications (see Section A in the appendix). Therefore, a better knowledge of how to use the newly acquired information about the IVF technology, i.e., higher ability to manage similar IVF inputs, can determine the organizational capital that yields higher "IVF productive efficiency" by the more educated individuals. On the other hand, undertaking a cycle can take an emotional toll on the individuals, resulting both from stress related to the treatment itself as well as from the risk of a spontaneous abortion (An et al. (2013)). These psychological costs can affect negatively the willingness of individuals to continue in treatment after a failed cycle.

To assess whether productive efficiency (z) and psychological stress (b) are plausible mechanisms behind our education gradient in IVF success, we propose a model for women using IVF technology in order to get a first child. In our model both the number of IVF treatments (i.e., the IVF drop-out rates) and the IVF success rates are endogenous and depend on the individual types (z, b). Since the productive efficiency and the psychological costs are unobservable, we use our model to infer their distributional properties. In particular, we use the actual behavior of success rates and drop out rates across education groups and across the number treatments as targeting moments. We then conduct a series of counterfactuals on our model to assess the role of z and b in explaining our empirical results.

3.5.1 The household problem

Our model focuses on individuals who are undergoing IVF treatments to get a first child. This sample choice is consistent with our empirical analysis. We follow individuals from their first IVF treatment ($t = 1$) to their last IVF treatment (we set a maximum of $T = 6$). A period in the model corresponds to an IVF treatment. After the first IVF treatment, i.e., for each and all periods $t \in \{1, T\}$ where T is the maximum number of treatments, women decide whether to continue with an additional IVF treatment or to drop out from IVF. We denote this discrete choice with $d = \{0, 1\}$, where $d = 1$ implies the continuation of IVF treatment and $d = 0$ implies otherwise. If an individual decides to continue with an IVF treatment, then she faces the trade-off between a positive probability of succeeding in getting an IVF child that delivers an additional stream of future utility starting next period and the psychological stress associated with going through IVF that reduces current utility. If an individual decides to drop out from IVF, then her entire life is childless. That is, when individuals stop IVF treatment they cannot choose to re-enter the IVF treatment in future periods and, also, there are not other means of enjoying a child. In this context, women exit IVF treatment either because they succeed in getting an IVF child or because they decide to opt to live childless from that period onward. Each individual is endowed with a productivity parameter (z) that determines the degree of productive efficiency in IVF success and a psychological stress (b) associated with IVF treatments.

For treatments (i.e, periods) $t > 1$, childless individuals must choose between going through an additional IVF treatment or dropping out from IVF. That is, individuals solve:

$$V(n=0,t;z,b) = \max\left\{V^{d=0}\left(n=0,t;z,b\right), V^{d=1}\left(n=0,t;z,b\right)\right\}, \tag{3.4}$$

where $d \in \{0,1\}$ is a discrete choice variable that equals one (zero) if individuals choose (not) to undergo IVF treatment number t and $n \in \{0,1\}$ is a discrete variable denoting number of children. The individual's type is permanent and defined by her ability to follow IVF procedure (z) and her psychological stress (b).

The value of dropping out from IVF treatments implies a childless existence for the remaining lifetime of the individual. Precisely, dropping from IVF in period t delivers the following present-value utility,

$$V^{d=0}(n=0,t;z,b) = \sum_{\tau=t}^{T} \beta^{\tau-t} \ln y,$$

which is the discounted utility in logarithmic form of the future stream of income given by a deterministic and constant $\{y\}_{t=\tau}^{T}$.

The value of undergoing IVF treatment t is,

$$\begin{aligned} V^{d=1}(n=0,t;z,b) &= \ln y - |b|t^2 \\ &+ \beta\left[\pi(z,b)V(n=1,t+1;z,b) + (1-\pi(z,b)))V(n=0,t+1;z,b)\right] \end{aligned} \tag{3.5}$$

subject to the IVF success probability,

$$\pi(z,b) = \frac{exp(b)}{exp(b) + exp(-lnz)}, \tag{3.6}$$

where note that the success probability depends on the individual permanent productivity in IVF success, $z > 0$, the psychological stress associated with IVF treatment, $b \in [-1, 1]$. Two remarks are in order. First, note that the probability of IVF success increases with individual permanent productivity z, *ceteris paribus*. In particular, with $\Delta > 0$,

$$\pi(z + \Delta, b) > \pi(z, b) \quad \forall b.$$

Second, the fact that b can take on positive and negative values captures the notion that for some individuals ($b > 0$) a higher psychological stress increases the probability of IVF success, while for some other individuals ($b < 0$) a higher psychological stress decreases the probability of IVF success. Specifically,

$$\lim_{b \to \infty} \pi(z, b) = 1 \text{ and } \lim_{b \to -\infty} \pi(z, b) = 0, \ \forall z.$$

The idea is that b captures a wide range of types of psychological stress. For example, some individuals work better under pressure (reference) and this effect might offset negative impacts of stress on performance for some individuals.

Therefore, the value of undergoing IVF treatment t defined in equation (3.5) is given by the current felicity of consuming the individual's endowment ($\ln y$) minus the psychological cost of undergoing IVF treatment which we assume is increasing in the number of treatments ($|b|t^2$),[28] plus the expected utility of the IVF outcome. If the IVF outcome is success (i.e., an IVF child is born alive), which occurs with probability $\pi(z, b)$, then agents discontinue further IVF treatments and enjoy utility

$$V(n = 1, t + 1) = \sum_{\tau = t+1}^{T} \beta^{\tau - (t+1)} \left[\ln y + \ln(1 + n)\right]$$

for the rest of their lifetime where $n \in \{0, 1\}$ is a discrete variable that denotes the number of children and $\ln(1+n)$ captures the joy of having children. Note that the shape of the felicity function from enjoying a child ensures that not all individuals will want to have a child at all costs, i.e., $\frac{\partial \ln(1+n)}{\partial n} < \infty$. Indeed, if $n = 0$, then we are back to the present-value utility of leaving IVF treatment without a child.

[28]This assumption captures the idea that the psychological costs increases with each failure. This follows from Missmer et al. (2011) who document that the proportion of couples discontinuing treatment after a failure increased with cycle number.

3.5.2 Model solution

We solve this model backwards for each value of $z \in [0, 10]$ and $b \in [-1, 1]$. In each period, individuals choose whether to stay in treatment by comparing the values of treating and dropping out. The decisions on treatment are plotted for each treatment number.

Figure 3.2 shows the policy function for the maximum number of treatments depending on psychological cost $|b|$ for three different levels of productivity z. The dashed lines show the policy function for the absolute value of the negative value of b. The policy function is close to symmetric at lower levels of the psychological cost; at higher psychological cost some women with the same value of $|b|$ whose $b < 0$ have lower maximum number of treatments. In addition, the value of z has little impact on the choice to drop out. In other words, differences in IVF productivity have no impact on the maximum number of treatments that women are willing to undertake. This can also be seen from Figure 3.3 where for each treatment we plot the combination of values of IVF productivity (z) and psychological cost (b) for which individuals undertake that treatment. The fact that differences in z will allow us to attribute differences in drop-out rates solely to differences in psychological stress b.

3.5.3 Estimation Targets

In Sections 3.3 and 3.4 we present evidence on the IVF gradient in success and drop-out rates in the first 5 treatments. We observe that there is not only a significant and positive IVF gradient across treatments, but also a negative gradient in dropout rates across treatments.

Since our model abstracts from features which we show to be related to IVF success such as age and health behavior, we use as targets of our estimation success and drop-out rates conditional on all the observables included in our baseline regression, i.e. age, health status measures, socioeconomic characteristics, infertility causes, year fixed effects and clinic fixed effects. To estimate all success and dropout rates together, we estimate a duration model for 1) IVF success where dropout is considered as censored and for 2) dropout where IVF success is considered to be censored.

We show in Table 3.14 the resulting conditional success and dropout rates. The decreasing pattern of success rates across treatments is similar for each education group. On the contrary, we can observe that conditional dropout rates increase with treatment number and are highest for the lowest educational group. This can be interpreted through the lens of our model as evidence that women with lower education face higher psychological stress related to IVF than women with higher education. While the HS dropouts show the highest conditional dropout rates for all treatments, differences between the HS and some college and the College and higher groups become apparent especially in later treatments. In fact, dropout after the first treatment are almost identical in the HS and College groups.

3.5.4 Model Estimation and Fit

There are two parameters that are fixed before estimation. We normalize consumption path to an exogenously given value $\{y_t\}_{t=0}^{T} = y = 1$ for all individuals and fix the discount rate to 0.99. We are left with the distributions of the unobserved variables z and b separately by education group (less than high school, high school, and college). In particular, the distribution of b is estimated non-parametrically while we estimate the mean of a log-normal distribution for z and fix its variance to the same value in each education group $\{\sigma_z^2\}_{e=\{C,HS,<HS\}} = 0.04$.[29] The log-normality of z is to ensure that productivity always takes nonnegative values.

The moments that we use to estimate non-parametrically the distribution of b are the five conditional IVF drop-out rates per education group (one per treatment apart from the last one where dropout is deterministic),

$$DR(e,t) = \frac{\int_{Z\times B} \mathbf{1}_{d(z,b,t)=0} d\Phi_e(z,b,t)}{\int_{Z\times B} d\Phi_e(z,b,t)} \tag{3.7}$$

where $\Phi_e(z,b,t)$ is the joint distribution of z, b for a given education group e and period t, $\mathbf{1}_{d(z,b,t)=0}$ is an indicator function for each type (z,b) that is equal to one if the type chooses not to continue treatment t. Then, the numerator in equation (3.7) is the endogenous population of education group e that at period t chooses to discontinue IVF treatment (this is endogenous for each and all t) and the denominator in equation (3.7) is the endogenous population of education group e that at period t must decide whether to undergo IVF treatment t or not (this is endogenous for $t \geq 2$).

[29] This is due to the fact that variance of z cannot be identified from the observed success probabilities.

We also target five success rates per education group (one per treatment),

$$SR(e,t) = \int_{Z\times B} \pi(z,b) \frac{\mathbf{1}_{d(z,b,t)=1}}{\int_{Z\times B} \mathbf{1}_{d(z,b,t)=1} d\Phi_e(z,b,t)} d\Phi_e(z,b,t),$$

where $\pi(z,b)$ is the individual IVF probability of success defined in equation (3.6).

The fact that IVF productivity affects the decision to drop out in a negligible way ensures that the identification of the distribution of $|b|$ comes from the drop-out rates. Then, z and the way the mass of each $|b|$ is distributed in the negative and positive sides can be identified from the success rates in all treatments.

Thus, our estimation strategy is the following. In order to obtain the correct distributions for the psychological cost $|b|$ for each education group, we first use the empirical conditional drop-out rates in each education group to obtain the number of individuals that drop out at each treatment. We then identify the segments of the support of $|b|$ for each maximum dropout from the policy function. We then populate the interval the interval between -1 and 1 by drawing from a uniform distribution between the number of individuals who drop out at each. To understand how the mass of each $|b|$ is distributed in the negative and positive sides, we simulate the model by varying the mean of z and adding mass to different segments to match the dropout and success rates. The estimated mean of z for each education group is shown in Table 3.15. Not surprisingly, average productivity in IVF increases with education, reflecting the higher success in IVF live births.

We show in Figure 3.4 the fit of the model. In panel a) the fit for dropout rates per education group and panels b) and c) show the fit in terms of the success rates per treatment for each education group and the fit of the gradient, respectively. We can observe that the model slightly underestimates the dropout rates at higher treatments for the two lower education groups. In terms of success rates, the model fits well the decreasing pattern of success rates. As for the fit of the gradient, the model fits well the average gradient across education groups.

3.5.5 Evolution of z and b over treatments

The decreasing pattern in IVF success over treatment is due to the combination of 1) women with higher z achieving live birth earlier on and thus exiting and 2) at each treatment the proportion of dropouts with $b < 0$ is higher than 0.5 (i.e. there are more women for whom the effect of psychological stress on the outcome is positive who drop out). We next examine the evolution of the average z and b of women at each treatment to shed light on the importance of each of the effects in explaining the evolution of the success rates over time.

Figure 3.5 panel a) shows the evolution of the average z over the treatments for all three education groups together with the population and panels b) c) and d) show the average z for each education group separately so that the negative slope can be appreciated. As higher IVF productivity women are more likely to obtain a child through IVF, they leave the sample and on average lower IVF productivity women stay in the sample, contributing to the decrease in success rates. However, this decrease is extremely small, since the difference from the first to the fifth treatment is 0.00025 for the $< HS$ group and around 0.0005 for the HS and $College$ groups.

Figure 3.6 we show the evolution of the average and variance of b across treatments for each education group. As expected, the average b decreases with each treatment as women with higher psychological cost exit earlier. The changes in average b are large enough to bring about the decrease in success rates across treatments. Similarly, the variance decreases as women with extreme values of b drop out in earlier treatments.

3.5.6 What Drives the Education Gradient in IVF Success? Counterfactual Experiments

Our model produces the observed success rates in the data and the average gradient per education group. We attribute the differences in success rates by education groups to differences in productive efficiency (z) and psychological stress (b). The estimated model thus allows us to understand how much of the gap in success between the education groups can be closed if the two lower education groups have the same distributions of IVF productivity and psychological stress as the College group.

IVF productivity

To understand how much the gap between the three education groups would close if all had the IVF productivity of the highest education group, we simulate our model for the less than high school and high school groups with the average IVF productivity of the college group, $\mu_{e=H,z}$. In Figure 3.7 we can see the implied success rate for each education group in the left panel and the gradient in success in the right panel.

The success rates of all three education groups are virtually identical in the first three treatments, the gradient is still present in the later treatments, where college graduates show higher success rates than other groups. This speaks to the fact that IVF productivity largely accounts for the gradient observed.

Psychological cost

We next simulate our model for the less than high school and high school groups with their respective estimated average productivity z but with the psychological stress distribution of the college group and show the success rates in Figure 3.8. Psychological stress accounts for the drop-out rates across treatments.

3.6 Conclusion

In this paper, we investigate the education gradient associated with a well-established medical technology, IVF. The unique structure of the administrative Danish register allowed us to estimate this gradient using comparisons across patients within clinics, and to control for a wide range of individual characteristics, pre-treatment medical conditions, infertility causes, number of embryos implanted, body size, and unhealthy behaviors such as past smoking and drinking. It is noteworthy that the potential selection into treatment is mitigated by the fact that, in Denmark, IVF patients are treated for free in the first three cycles reaching the stage of embryo implantation.

We found that highly educated women do better in these treatments. Specifically, women with a college degree are about 21% more likely to attain a live birth than high school dropouts in the first cycle, and women with high school degree achieve similar results (i.e., they are 13% more likely to have a successful pregnancy than high school dropouts). That is, there is a large and highly significant education gradient in IVF success. Finally, educational disparities are present even when we control for embryo(s) being implanted. This result suggests caution when using the outcome of ART or IVF as an exogenous source of variation in fertility to identify the effect of a first child on female labor supply (Cristia, 2008; Lundborg et al., 2016). In fact, while this putative natural experiment arises from biological mechanisms, the assumption of randomness is not fully credible in light of our results.

We then study whether and how relevant two mechanisms (productive efficiency and psychological stress) are for the presence of the observed IVF gradient. We develop a dynamic model of women using IVF technology in which women differ in IVF productivity (how well women follow the IVF procedure) and the psychological stress associated with undergoing the treatment. In the model, women face a trade-off between a positive probability of succeeding in getting a child through IVF and the cost of psychological stress associated with undergoing the treatment. Our results suggest that differences in IVF productivity drive the educational gradient. This finding is important as it suggests that there is room for policy aiming at increasing the IVF productivity of the lower educated groups.

Our findings open a new set of research questions. As long as access to IVF technology may delay motherhood, women career and fertility choices are likely to be influenced by the determinants of IVF success, which are the object of our study. The fact that we find striking educational disparities in IVF success may contribute to explain changes in selection into motherhood and disparities in labor-force participation and occupational upgrading. We are currently pursuing this line of research.

Quantifying educational disparities in IVF success is important. These disparities potentially shape the opportunity cost of delaying childbearing differently among more and less educated women, which in turn may factor into different fertility choices and labor market outcomes across education groups.
In general, highly educated women tend to have fewer children because they are more likely to participate in the labor force (Buckles, 2008; Goldin & Olivetti, 2013; Olivetti, 2014; Goldin & Mitchell, 2016). However, with the adoption of IVF technology, highly educated women can choose to delay child-bearing because of IVF rather than not have a child at all. This could potentially increase fertility in the older ages (Schmidt, 2007)[30] and affect the birth-spacing and aggregate fertility. Further, a positive education gradient in IVF could mitigate the well-known negative relationship between fertility and education (Jones et al., 2010).[31]

[30]In line with this argument, in our sample, a 1% increase in years of schooling is associated with a 3% increase in the age of women seeking the first IVF treatment. A woman with at least a master's degree is, on average, 1.5 years older than a high-school drop out when she seeks an IVf treatment for the first time.

[31]This is consistent with the estimated fertility patterns in our sample, where a 10% increase in years of education is associated with an 11% decrease in the likelihood of having at least one child in the female population and 4.3% decrease for women who undergo IVF treatment to achieve a pregnancy.

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Tables and Figures: Chapter 1

Table 1.1: First Principal Components Loading

Skill	Loading	Skill	Loading
Literacy		*Numeracy*	
Oral comprehension	0.2781	Deductive reasoning	0.4613
Written comprehension	0.2968	Inductive reasoning	0.4462
Oral expression	0.2713	Mathematical Reasoning	0.4442
Written expression	0.2903	Number facility	0.4508
Fluency of ideas	0.2988		
Originality	0.2833		
Problem sensitivity	0.2931		
Information Ordering	0.2726		
Category Flexibility	0.2810		
Memorization	0.2630		
Flexibility of Closure	0.2452		
Perceptual Speed	0.1494		
Spatial Orientation	-0.0601		
Visualization	0.1144		
Selective Attention	0.2096		
Time sharing	0.2360		

Notes: This table shows the loadings of the first component of the ability requirements from O'NET.

Table 1.2: Sorting Measure 1: Correlations

Country	Literacy	Numeracy
France	.38	.46
Belgium	.37	.39
Spain	.37	.4
Germany	.35	.38
Korea	.34	.36
Denmark	.31	.33
Netherlands	.3	.33
UK	.3	.36
Italy	.28	.35
Czech Republic	.28	.32
Poland	.24	.27
Japan	.23	.33
Slovakia	.2	.26

Notes: This table shows the correlation between the test scores and the skill requirements of literacy and numeracy across the samples.

Table 1.3: Sorting measure 2: Summary measures

Country	Literacy			Numeracy		
	MM > 50	MM > 75	MM > 90	MM > 50	MM > 75	MM > 90
Germany	13.25	1.59	.08	12.64	1.81	.19
Belgium	13.25	1.85	.12	12.16	2.18	.12
France	13.56	1.79	.13	10.69	1.43	.18
Spain	13.97	1.47	.09	12.83	1.74	.06
Korea	14.38	2.07	.09	13.83	2.39	.18
UK	14.56	2.06	.25	12.75	2.03	.17
Italy	15.08	2.77	.33	14.49	2.14	.37
Netherlands	15.12	2.64	.2	14.1	2.35	.15
Denmark	15.82	2.69	.18	15.35	2.71	.36
Poland	16.27	2.93	.34	15.44	3.11	.4
Czech Republic	16.91	3.67	.33	14.97	2.72	.31
Japan	17.38	3.7	.34	13.78	2.46	.24
Slovakia	18.2	3.65	.34	16.48	3.15	.34

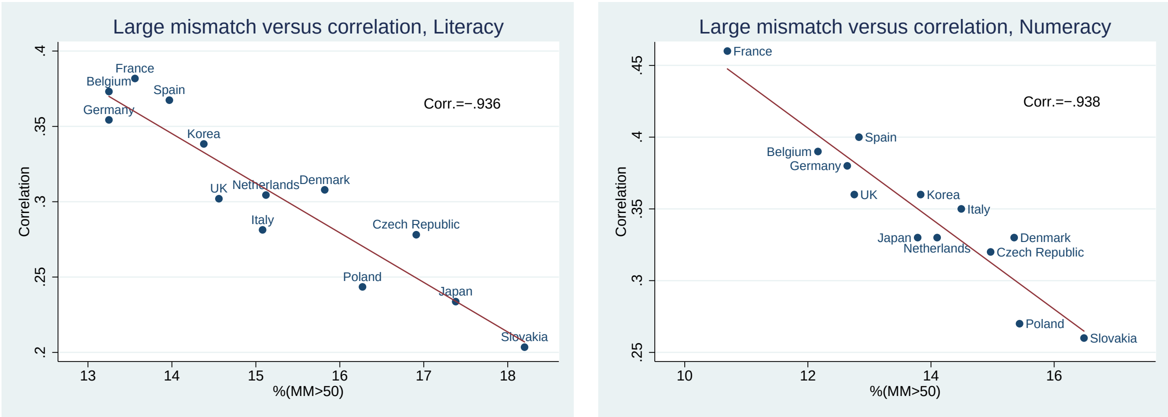
Notes: This table shows summary statistics of the individual mismatch distributions in Literacy and Numeracy, computed using the PIAAC and O'NET data. Individual mismatch is measured as the absolute value of the difference between the percentiles of skill and skill requirement. The table contains the number of individuals with mismatch higher than 50, 75 and 90. Countries are sorted according to the percentage of individuals with literacy mismatch higher than 50.

Table 1.4: Measure of sorting: Under and over-skilling

Country	Literacy MM > 50	Literacy Overskilled	Literacy Underskilled	Numeracy MM > 50	Numeracy Overskilled	Numeracy Underskilled
Germany	13.25	6.72	7.04	12.64	5.68	6.88
Belgium	13.25	6.54	6.9	12.16	5.96	6.23
France	13.56	6.9	6.25	10.69	5.31	5.69
Spain	13.97	6.65	7.34	12.83	5.82	6.62
Korea	14.38	6.95	7.48	13.83	6.4	7.27
UK	14.56	7.48	7.36	12.75	6.04	7.16
Italy	15.08	7.76	7.58	14.49	6.88	6.88
Netherlands	15.12	8.11	7.24	14.1	6.4	7.75
Denmark	15.82	9.19	6.66	15.35	8.79	6.56
Poland	16.27	5.17	11.2	15.44	5.61	9.91
Czech Republic	16.91	8.61	8.58	14.97	7.36	7.14
Japan	17.38	7.99	9.76	13.78	5.87	7.72
Slovakia	18.2	8.65	9.74	16.48	6.9	9.49

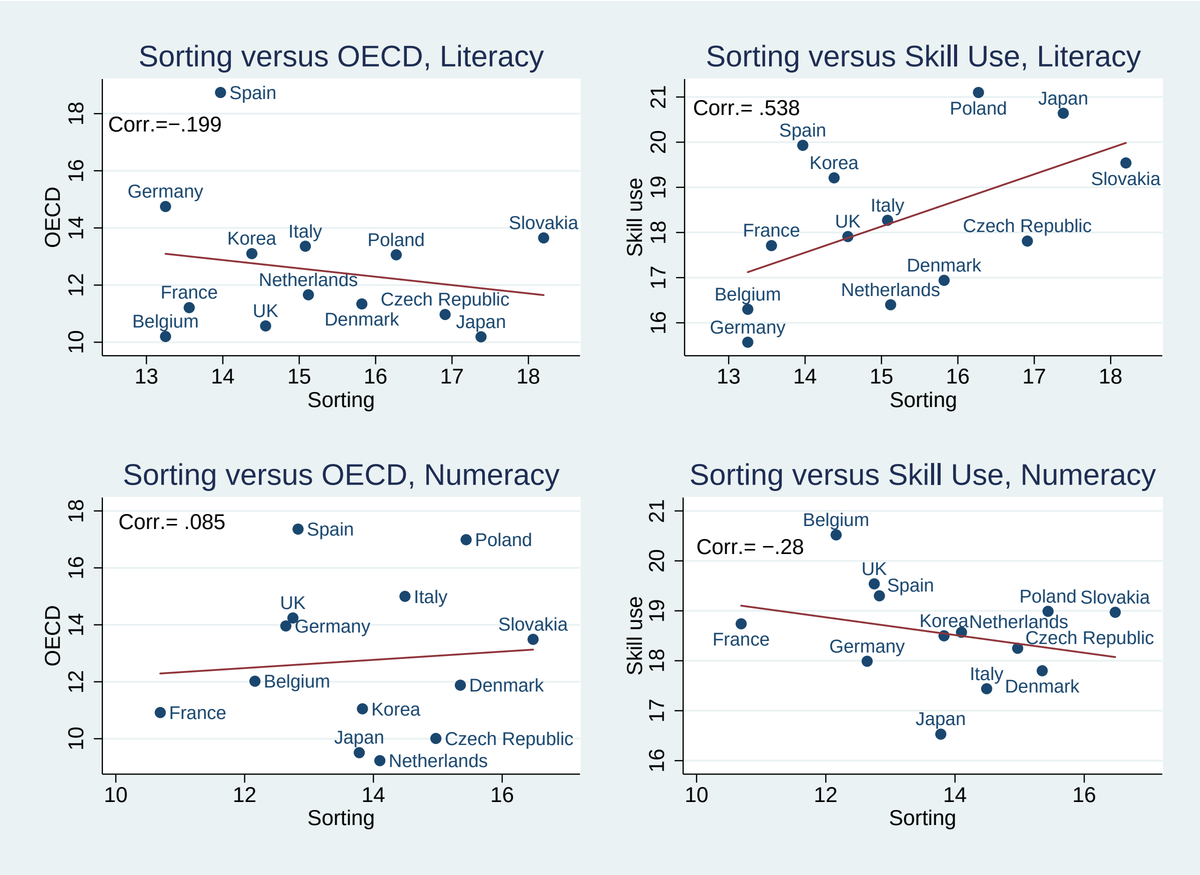
Notes: This table shows the percentage of individuals in each country that have individual mismatch larger than 50. Individual mismatch is measured as the absolute value of the difference between the percentile ranks of skill and skill requirement. It also decomposes the number between those whose percentile rank in the skills distribution is higher than in the requirements distribution and are thus over-skilled and those for who the reverse occurs and are thus under-skilled.

Figure 1.1: New measures of mismatch



Notes: These figures show the relationship between two alternative measures of mismatch: the correlation between the test scores and skill requirements and the percentage of individuals in each country with individual mismatch higher than 50. Individual mismatch is computed as the difference between the percentile rank in the skills distribution and the percentile rank in the skill requirements distribution.

Figure 1.2: Measures of mismatch: comparison



Note: This figure shows the comparison of the sorting measures to the two existing measures of mismatch, one created by the OECD and the one of skill use.

Table 1.5: Correlations of mismatch measures with macroeconomic variables

Variable	OECD		Skill use		Correlation		%($MM > 50$)	
	Lit.	Num.	Lit.	Num.	Lit.	Num.	Lit.	Num.
Labour productivity								
GDP/employment	-.24	-.25	-.49	.15	.63	.72	-.67	-.71
GDP/hours worked	-.24	-.29	-.68	.14	.61	.69	-.64	-.7
Unemployment benefit policy								
Maximum duration of benefits	-.1	-.06	-.42	.54	.6	.46	-.53	-.46
Spending on benefits per unemployed	-.35	-.51	-.7	.13	.5	.39	-.47	-.41
Other								
Unemployment Rate	.73	.69	.37	.36	.06	.05	.01	.04
Wage dispersion	.27	-.02	.35	-.29	-.18	-.23	.1	.18
Public expenditure in training	.03	-.08	-.46	-.16	.5	.44	-.36	-.24
Share of vocational programmes	.1	-.01	-.26	.1	-.2	-.34	.27	.43

Notes: This table shows the correlations between each of the measures (two existing measures and two new measures) of mismatch and macroeconomic variables from the OECD for the year 2011.

Tables and Figures: Chapter 2

Table 2.1: Literacy, Numeracy skills

Literacy	Numeracy
Oral Comprehension	Mathematical Reasoning
Written Comprehension	Number Facility
Oral Expression	Mathematics
Written Expression	
Deductive Reasoning	
Inductive Reasoning	
Information Ordering	
Reading Comprehension	
Active Listening	
Writing	
Speaking	

Notes: This table shows the descriptors included in the O'NET assigned to the broader categories of literacy and numeracy skills.

Table 2.2: Skill requirements

	Literacy	Numeracy
Lowest	Dining Room Helpers	Barbers, Hairdressers, Cosmetologists
Highest	Lawyers	Actuaries, Mathematicians, Statisticians

Notes: This table shows the occupations with the maximum and minimum requirements for literacy and numeracy.

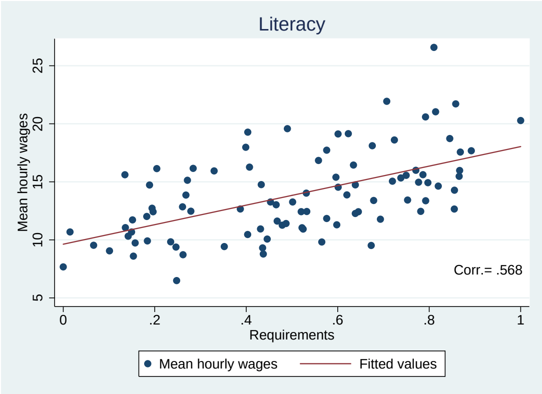


Figure 2.1: Mean wages and literacy

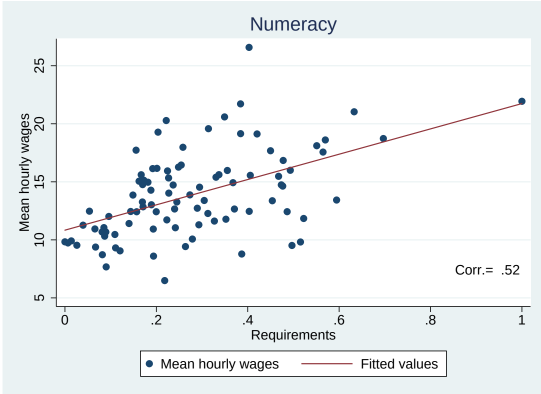


Figure 2.2: Mean wages and numeracy

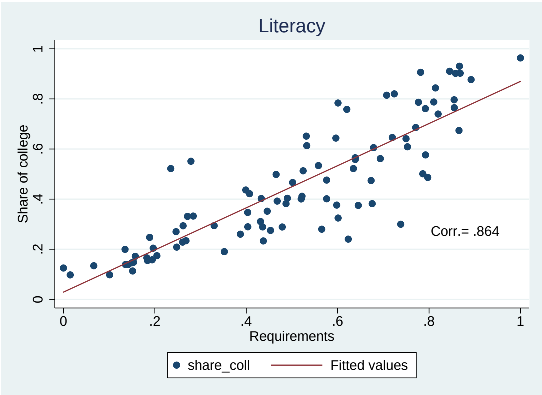


Figure 2.3: Share of college and literacy

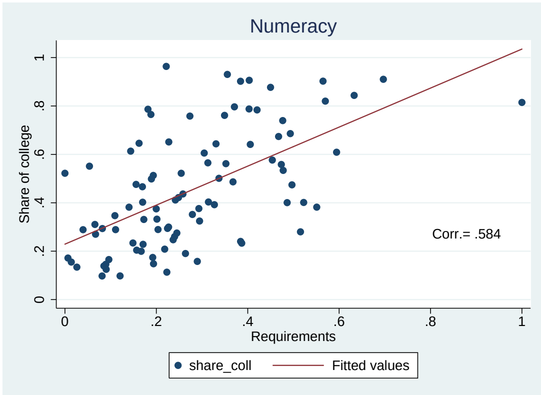


Figure 2.4: Share of college and numeracy

Notes: These figures are constructed using the wages in the SIPP data for years 1996-2013. All wages are expressed in January 1996 dollars, adjusted using the CPI.

Table 2.3: EUE Transtions

SIPP 1996-2012	
Total	10,675
Switch occupation (3 digits)	7,302
Switch occupation (2 digits)	6,431
Individuals	9,868
NLSY79	
Total	16,548
Switch occupation (Dorn detailed)	13,718
Switch occupation (Dorn broad)	10,752
Individuals	3,763

Notes: This table shows the final samples of EUE spells obtained from the SIPP data 1996-2013 and the NLSY79 data 1979-2014.

Table 2.4: Sample Statistics, EUE Sample

	SIPP		*NLSY79*	
	Mean	St. Dev.	Mean	St. Dev.
Demographics				
Age	36.4	12	27.7	8.9
Female	.45	0.5	0.47	0.5
Married	.45	0.5	0.357	0.479
Tenure in old job	23.1	21.8	-	-
Tenure in occupation	-	-	96.964	160.139
HS or below	0.48	0.5	0.62	.5
Duration of spell	7.9	6	7	11
Unemployment benefits				
Wba	156	103	146	83
Take-up	.485	0.5	0.13	0.34

Notes: This table shows summary statistics of the samples of EUE spells obtained from the SIPP data 1996-2013 and the NLSY79 data 1979-2014.

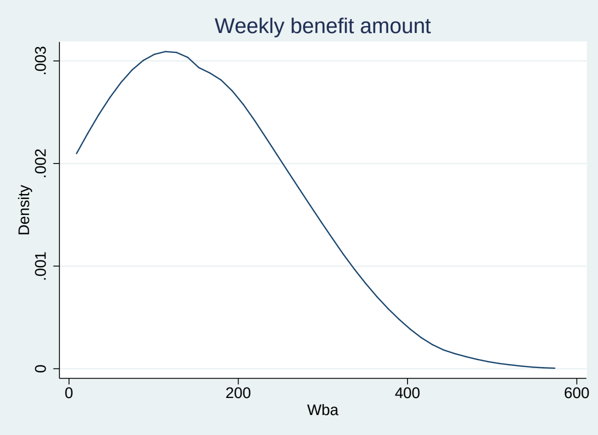


Figure 2.5: Weekly benefit amount, SIPP

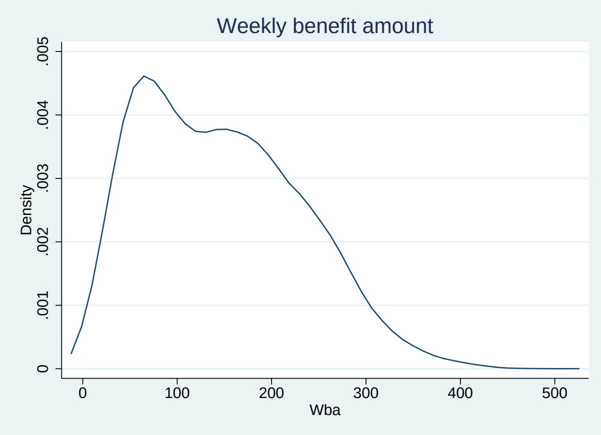


Figure 2.6: Weekly benefit amount, NLSY

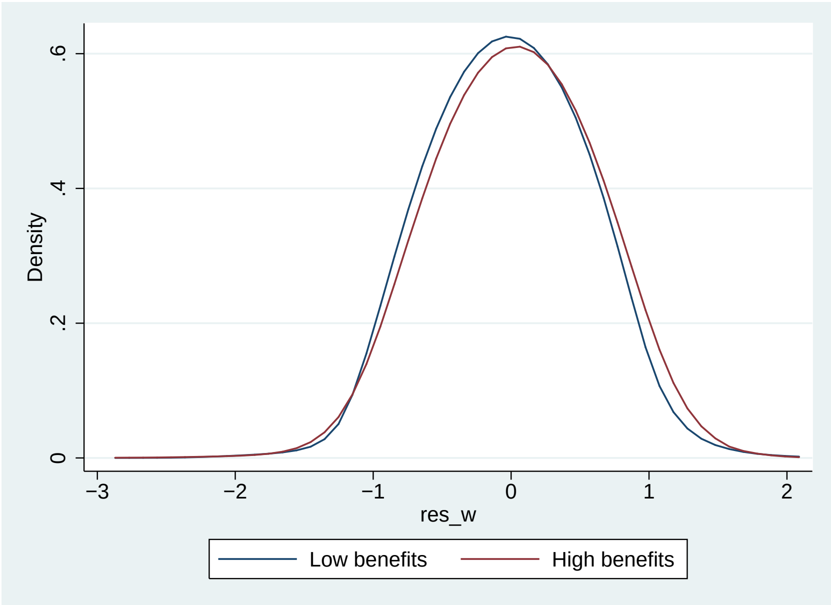
Notes:These figures show the kernel density of the weekly benefit amount in the sample of the SIPP and the NLSY79. The weekly benefit amount is expressed in January 1996 dollars, adjusted using the CPI.

Table 2.5: Effect of unemployment benefits of occupational switching

	NLSY		SIPP	
VARIABLES	Switch	Switch	Switch	Switch
U. Dur.	0.00518***	0.00525***	0.0499***	0.0486***
	(0.000737)	(0.000759)	(0.00488)	(0.00500)
Female	0.0817	0.0737	-0.0563	-0.0479
	(0.0608)	(0.0600)	(0.0556)	(0.0563)
Married	-0.0532	-0.0522	-0.183***	-0.185***
	(0.0463)	(0.0476)	(0.0467)	(0.0459)
Unemp. Rate	-0.00386	-0.00692	-0.0394***	-0.0952***
	(0.0101)	(0.0213)	(0.0112)	(0.0238)
Age	-0.0747***	-0.0835*	-0.0415***	-0.0435***
	(0.0177)	(0.0448)	(0.00989)	(0.0103)
Age^2	0.00108***	0.00121*	0.000423***	0.000450***
	(0.000276)	(0.000698)	(0.000127)	(0.000133)
Tenure	0.00339***	0.00345***	-0.000379	-0.000474
	(0.000269)	(0.000275)	(0.000475)	(0.000473)
Occ. Ten.	-0.00267***	-0.00270***		
	(0.000211)	(0.000203)		
Skill (AFQT)	2.33e-06**	2.34e-06**		
	(1.06e-06)	(1.16e-06)		
Wba/100	**-0.163*** **	**-0.183*** **	**-0.131*** **	**-0.126*** **
	(0.0494)	(0.0538)	(0.0246)	(0.0287)
Constant	3.353***	3.991***	2.948***	3.239***
	(0.787)	(1.078)	(0.284)	(0.357)
Observations	15,805	15,796	10,617	10,609
Pseudo R2	0.121	0.130	0.0829	0.0911
State FE		x		x
Year FE		x		x

Notes: This table shows the linear probability model results for the probability of switching occupation in the SIPP and the NLSY79 samples of EUE spells. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is equal to one when the individual has switched occupation. The occupation is defined as the 3-digit SOC 2000 occupational codes in columns (1) and (2) and the 4-digit Dorn's classification occupational codes (occ1990dd) in columns (3) and (4). Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

Figure 2.7: Wage changes by differences in UI



Notes: This figures show the kernel densities of 'clean' percentage changes in hourly wages between the new and old job for individuals with unemployment benefits above and below the mean. The 'clean' percentage changes are obtained as residuals from a regression of the true percentage changes on the levels of the wage in the old job. These are constructed using a bandwidth of 0.5 using the wages in the SIPP data for years 1996-2013. All wages are expressed in January 1996 dollars, adjusted using the CPI.

Table 2.6: Effect of unemployment benefits on requirements

	NLSY		SIPP	
VARIABLES	Lit.R. New	Num.R. New	Lit.R. New	Num.R. New
U. Dur.	-0.00301	-0.00371	-0.000668**	-0.000620**
	(0.00458)	(0.00520)	(0.000305)	(0.000232)
Female	-1.917***	-6.296***	0.0800***	0.0302***
	(0.625)	(0.711)	(0.00586)	(0.00384)
Married	1.647***	2.055***	0.0232***	0.00990**
	(0.470)	(0.514)	(0.00547)	(0.00416)
Unemp. Rate	-0.130	-0.0368	-0.00267	0.000229
	(0.149)	(0.157)	(0.00283)	(0.00216)
Age	0.631	0.532	-0.00468***	-0.00339***
	(0.464)	(0.443)	(0.00159)	(0.000930)
Age^2	-0.00927	-0.00742	5.46e-05**	3.37e-05***
	(0.00747)	(0.00703)	(2.11e-05)	(1.22e-05)
Tenure	0.00403	0.00103	7.27e-06	8.51e-07
	(0.00248)	(0.00227)	(4.96e-05)	(3.00e-05)
Wba/100	**1.791*** **	**2.017*** **	**0.0114*** **	**0.00868*** **
	(0.475)	(0.553)	(0.00403)	(0.00209)
Constant	45.49***	47.59***	0.435***	0.290***
	(6.956)	(7.460)	(0.0510)	(0.0302)
Observations	13,697	13,697	7,286	7,286
R-squared	0.172	0.140	0.302	0.213
State FE	x	x	x	x
Year FE	x	x	x	x
Pseudo R2	0.172	0.140	0.302	0.213

Notes: This table shows the regression results for all occupational switchers. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the requirement of literacy in the new occupation. Regressors include year, state, industry and highest education fixed effects and the log of the wage in the job previous to unemployment. Errors are clustered at state level.

Table 2.7: Results by occupational tenure

VARIABLES	Short Occ. T. Switch	Long Occ. T. Switch	Short Occ. T. L.Req	Long Occ. T. L.Req
Dur.	0.000236**	0.000655***	0.0146**	-0.00812
	(8.95e-05)	(6.65e-05)	(0.00700)	(0.00497)
Married	-0.0115	-0.00246	1.292*	1.388**
	(0.00714)	(0.00922)	(0.667)	(0.556)
UR	0.000366	-0.00244	-0.324	-0.172
	(0.00226)	(0.00326)	(0.211)	(0.224)
Age	-0.00401	-0.00945	1.627**	-0.0683
	(0.00727)	(0.00903)	(0.613)	(0.557)
Age^2	0.000102	0.000113	-0.0231**	0.00136
	(0.000130)	(0.000128)	(0.0111)	(0.00861)
Tenure	0.00359***	0.000550***	0.0140	0.00569**
	(0.000630)	(3.74e-05)	(0.0430)	(0.00254)
Skill (AFQT)	1.07e-07	5.14e-07**	8.87e-05***	8.04e-05***
	(1.39e-07)	(2.00e-07)	(1.52e-05)	(8.84e-06)
Wba/100	**-0.009**	**-0.023****	**0.019*****	**0.009***
	(0.0101)	(0.00883)	(0.550)	(0.498)
Constant	1.142***	1.096***	0.2966**	0.6324***
	(0.107)	(0.211)	(0.1353)	(0.0099)
Observations	8,238	8,222	8,238	8,222
R-squared	0.095	0.177	0.192	0.314
Pseudo R2	0.0949	0.177	0.192	0.314

Notes: This table shows the regression results for all occupational switchers. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the requirement of literacy in the new occupation. Regressors include year, state, industry and highest education fixed effects and the log of the wage in the job previous to unemployment. Errors are clustered at state level.

Table 2.8: Effect of unemployment benefits on wages

	NLSY		SIPP	
VARIABLES	Log Wage Post.	Log Wage Post.	Log Wage Post.	Log Wage Post.
U. Dur.	-0.000675***	-0.000626***	-0.00172**	-0.00171**
	(0.000107)	(0.000110)	(0.000715)	(0.000652)
Female	-0.124***	-0.122***	-0.0704***	-0.0701***
	(0.0117)	(0.0118)	(0.00886)	(0.00848)
Married	0.0355***	0.0405***	0.0158*	0.0179**
	(0.0113)	(0.0106)	(0.00801)	(0.00850)
Unemp. Rate	-0.00617**	-0.00252	0.00159	-0.00244
	(0.00237)	(0.00543)	(0.00236)	(0.00444)
Tenure	-0.000186***	-0.000151**	-0.000351***	-0.000340***
	(6.32e-05)	(6.43e-05)	(9.75e-05)	(0.000102)
Occ. Ten.	0.000217***	0.000197***		
	(6.36e-05)	(6.36e-05)		
Age	0.0127**	0.0101	0.00875***	0.00952***
	(0.00490)	(0.00915)	(0.00178)	(0.00181)
Age^2	-0.000221***	-9.90e-05	-8.37e-05***	-9.21e-05***
	(7.68e-05)	(0.000170)	(2.33e-05)	(2.36e-05)
Wba/100	**0.130*** **	**0.126*** **	**0.0325*** **	**0.0317*** **
	(0.0112)	(0.00994)	(0.00642)	(0.00672)
Constant	2.487***	2.531***	1.492***	1.369***
	(0.107)	(0.146)	(0.109)	(0.107)
Observations	13,864	13,864	7,086	7,086
R-squared	0.244	0.266	0.489	0.498
Pseudo R2	0.244	0.266	0.489	0.498
State FE		x		x
Year FE		x		x

Notes: This table shows the regression results for all EUE spells in the SIPP and the NLSY79. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log wage in the job obtained after unemployment. Regressors include year, state, industry and highest education fixed effects and the log of the wage in the job previous to unemployment. Errors are clustered at state level.

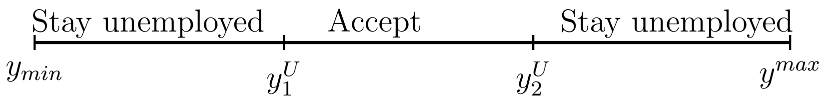


Figure 2.8: Thresholds for unemployed workers

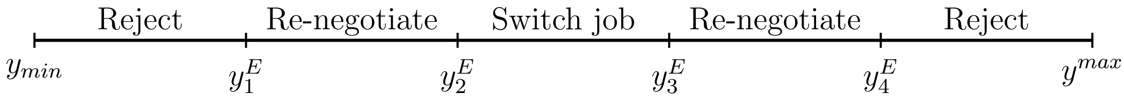


Figure 2.9: Thresholds for employed workers

Table 2.9: Parameters

Parameter	Description	Value	Source
r	Interest rate	0.004	5% annual
ξ	Death rate	0.0018	47 years
β	Surplus sharing rule	0.5	fixed
ρ	U. benefits	0.5	Chetty(2008)
a_x	x distribution	1.03	NLSY79
b_x	x distribution	1.2	NLSY79
δ	Job dest. rate	0.02	NLSY79 E2U

Notes: This table shows the parameters of the model that are fixed ex-ante or calibrated outside of the model.

Table 2.10: Parameters calibrated through SMM

Parameter	Description	Value
λ_0	Job arrival rate	0.23
λ_1	Job arrival rate while employed	0.08
α_0	Production	150
α_1	Production	143
α_2	Production	200
κ	Cost of mismatch	3500
a_y	y distribution	1.5
b_y	y distribution	1.9
$\eta^e_{x>y}$	Skill change when over-skilled	0.002
$\eta^e_{x<y}$	Skill change when under-skilled	0.006
η^u	Skill change when unemployed	0.0023
φ	Labor market experience change	0.08

Notes: This table shows the parameters of the model that are calibrated through SMM. The first part of the table shows the fixed parameters and the second part shows the calibrated parameters.

Table 2.11: Model Fit

Moment	Target	Data	Source
U2E transitions	0.23	0.24	NLSY79
E2E transitions	0.024	0.030	NLSY79
Requirements			
Mean	0.40	0.42	O'NET and NLSY79
Std	0.25	0.24	O'NET and NLSY79
Correlations (x^s *and* y)			
5 years	0.43	0.43	O'NET and NLSY79
10 years	0.49	0.49	O'NET and NLSY79
15 years	0.51	0.52	O'NET and NLSY79

Notes: This table shows the model and data moments used to calibrate the parameters. The correlations are measured at 5, 10 and 15 years of labor market experience.

Table 2.12: Regression results

Coefficient	Model	Data
β_0	5	5.2
β_1	.002	.0024
β_2	.0047	.0050
β_3	0.0001	.0002
β_4	0.056	0.05

Notes: This table shows the coefficients of the regression of log wages on skills at entry to the labor market, the skill requirements of the occupation, their interaction and years of labor market experience obtained from the data and the model.

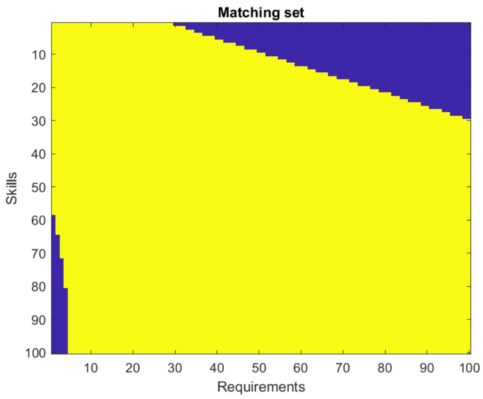


Figure 2.10: $\rho = 60\% w_p$

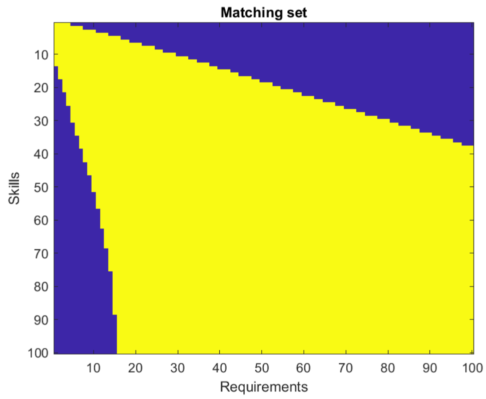


Figure 2.11: $\rho = 70\% w_p$

Notes: These figures show the matching matrix of the economies with a varying replacement rate.

Table 2.13: Effects of varying the replacement rate

Replacement rate	50%	60%	70%
Unemployment rate	8.9	9.5	12.8
Aggregate Output	11,958	12,333	12,355
Average Output per worker	13.60	13.65	13.74
Average mismatch	0.0144	0.0128	0.0107
EUE			
Occupational switching	100	97	90
Req. dif.(Old-New)	0.0340	0.0153	-0.0055
Log wage dif.	-0.2007	-0.1564	-0.1161
Switching by tenure			
Short tenure	100	98	92
Long tenure	100	96	88

Note: This table shows the results of varying the replacement rate on aggregate outcomes and on EUE spells. Short occupational tenure corresponds to less than 2 years.

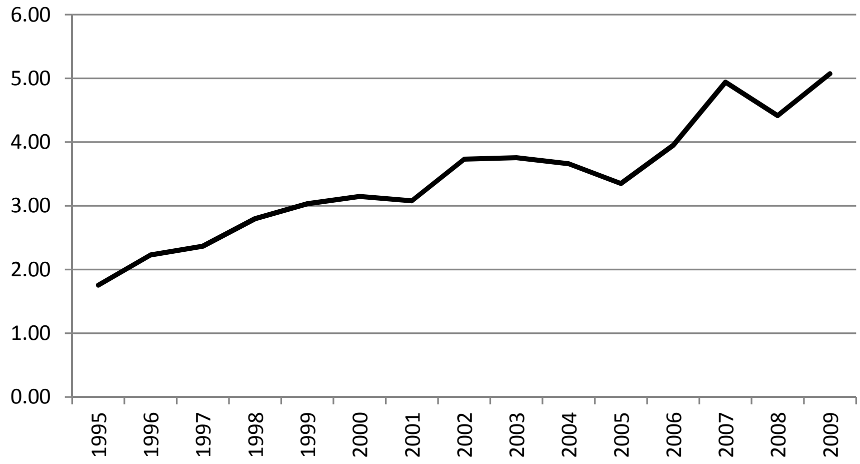
Table 2.14: Effect of α and β on wages

α	β	Life-time Wages
0.9	-0.032	108
0.8	-0.024	112
0.7	-0.012	109
0.6	-0.006	105
0.5	0	100
0.4	0.013	98
0.3	0.021	95
0.2	0.036	92
0.1	0.040	87

Note: This table shows how different combinations of α and β which imply the same of benefits spent as in the benchmark economy affects average life-time wages.

Tables and Figures: Chapter 3

Figure 3.1: IVF Children (%), Fraction of All Births: Denmark (1995-2009)



Notes: The fraction of IVF children (%) is computed as the number of births from the IVF register over number total births in the population in a given year.

Table 3.1: Demographic Characteristics of IVF Patients: First Treatment

Education	< *HS*	*HS*	*College*
Age	31.5	31.3	32.1
Married (%)	59.2	58.0	56.8
Patient's income	185,255	233,303	280,186
Spousal income	262,038	312,799	352,513
Employment status (%):			
On leave	1.7	0.7	0.4
Self-employment	3.2	3.0	1.4
Employed	72.6	88.9	94.1
Out of labor force	11.1	3.4	2.0
Unemployed	11.5	4.0	2.1
Treated in public hospital (%)	87.0	83.8	79.7
Live births (%)	20.9	24.9	26.0
Sample (%)	12.8	51.0	36.2
Observations	2,714	10,775	7,641

Notes: In terms of education groups, we denote IVF patients with less than high school as < *HS*, high school or some college as *HS*, and college or higher degree as *College*. Income is in DKK, deflated by CPI to year 2000. Employment status is measured the year prior to treatment.

Table 3.2: IVF Treatments by Age in Public and Private Sectors

	All	Age 25-29	30-34	35-40	41+
(a) Treatments in the public sector:					
Only first treatment (%)	82.7	87.3	84.8	76.8	2.6
Only free-eligible treatments (%)	83.2	87.5	85.8	79.4	3.8
All (%)	80.8	86.5	83.8	76.2	4.1
(b) IVF success rate: Treatment level					
Public Sector	25.6	29.0	25.8	19.2	0.0
Private Sector	21.2	26.3	26.0	14.6	6.0
(c) IVF success rate: Hospital level					
Public Sector	25.9	29.6	27.3	18.1	0.0
Private Sector	18.3	26.5	23.5	10.9	6.9

Notes: The unit of observation is a treatment in panel (b), and the hospital in panel (c).

Table 3.3: Medical Conditions of IVF Patients by Education Groups

Variable	*< HS*	*HS*	*College*
(a) Infertility causes (%):			
Cervical defect	0.77	1.38	1.82
Ovulation defect	12.16	11.14	12.30
Fallopian tube defect	36.07	24.97	21.20
Male causes	36.00	40.40	42.52
Other causes	15.03	21.62	27.23
Unspecified causes	18.42	23.47	22.24
(b) Health Status:			
General practitioner (GP) services:			
Average number of GP services	9.20	8.07	7.47
Average cost of GP services	691.14	594.48	563.66
Disease Diagnosis (%):			
Infectious diseases	0.59	0.42	0.31
Neoplasms	0.22	0.18	0.22
Blood diseases	0.15	0.06	0.08
Endocrine diseases	1.47	0.86	0.90
Mental Illness	0.18	0.14	0.12
Nervous system	0.70	0.47	0.41
Eye diseases	0.44	0.43	0.48
Ear diseases	0.59	0.29	0.26
Circulatory system	0.37	0.45	0.64
Respiratory system	1.14	0.58	0.56
Digestive system	2.06	1.63	1.36
Skin diseases	1.18	0.70	0.79
Musculoskeletal system	3.76	2.36	1.95
Genitourinary system	33.42	30.89	27.64
Pregnancy or childbirth	6.19	6.26	6.82
Prenatal diseases	0.04	0.02	0.03
Malformations chromosomal	0.18	0.33	0.34
Abnormal laboratory findings	3.35	2.51	2.43
Injuries	9.99	7.97	7.38
Factors for health contact	12.90	12.16	11.44
(c) Health Behavior:			
BMI (%):			
BMI<20	8.5	10.2	12.9
20≤BMI<25	36.8	42.6	49.4
25≤BMI<30	22.8	21.9	17.7
BMI≥30	15.3	10.7	6.3
Missing	16.7	14.6	13.7
Cigarettes smoked per week (%):			
# of cigarette = 0	59.8	72.6	79.8
1≤ # of cigarette ≤5	4.5	3.5	2.8
6≤ # of cigarette ≤10	8.2	3.6	1.5
# of cigarette ≥ 11	8.5	3.6	1.1
Missing	19.0	16.7	14.8
Alcohol consumption per week (%):			
# of units = 0	48.4	40.3	35.8
1≤ # of units ≤3	17.2	23.5	28.3
4≤ # of units ≤5	2.1	5.8	7.7
# of units ≥ 6	3.4	3.9	5.5
Missing	28.8	26.4	22.6

Notes: We denote IVF patients with less than high school as *< HS*, high school or some college as *HS*, and college or higher degree as *College*. Average cost is in DKK, deflated by CPI to year 2000.

Table 3.4: Education Gradient in IVF Success (Live Births)

IVF Live Births	(1)	(2)	(3)	(4)	(5)
High School	0.0408***	0.0375***	0.0338***	0.0313***	0.0319***
	(0.00884)	(0.00880)	(0.00892)	(0.00908)	(0.00909)
College	0.0518***	0.0580***	0.0534***	0.0499***	0.0513***
	(0.00928)	(0.00925)	(0.00951)	(0.00976)	(0.00983)
Age Dummies		✓	✓	✓	✓
Time Dummies			✓	✓	✓
Health Status:					
Average number of GP services			-0.00197*	-0.00218*	-0.00234**
			(0.00117)	(0.00118)	(0.00118)
Average cost of GP services			4.14e-08	6.96e-08	6.06e-08
			(1.49e-07)	(1.49e-07)	(1.49e-07)
Disease(s) Diagnoses			✓	✓	✓
Socioeconomic Characteristics:					
Married				-0.0146**	-0.0118*
				(0.00609)	(0.00609)
Log total income				0.00452*	0.00462*
				(0.00258)	(0.00261)
Log spousal income				0.00322	0.00393
				(0.00265)	(0.00263)
Employment status:					
On leave				-0.0269	-0.0289
				(0.0354)	(0.0354)
Self-employment				-0.00552	-0.00735
				(0.235)	(0.234)
Employed				-0.0186	-0.0215
				(0.151)	(0.151)
Out of labor force				-0.0424**	-0.0415**
				(0.0206)	(0.0206)
Infertility causes:					
Cervical defect					-0.0049
					(0.0254)
Ovulation defect					-0.0073
					(0.0111)
Fallopian Tube defect					-0.0236**
					(0.0103)
Male causes					-0.0117
					(0.00847)
Other causes					-0.0354***
					(0.0104)
Unspecified causes					-0.0141
					(0.0114)
Clinic Fixed Effects					✓
Constant	0.209***	0.265***	0.252***	0.187***	0.207***
	(0.00780)	(0.0138)	(0.0181)	(0.0474)	(0.0495)
Observations	21,130	21,130	21,130	21,130	21,130
R-squared	0.001	0.015	0.018	0.019	0.027

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. HS denotes high school. Age is measured as starting from 1 to better capture the nonlinearities occurring from age 25 to 45. Employment status reference category is "in school". All specifications are run on the first treatment.

Table 3.5: Education Gradient in IVF Success (Live Birth) by Treatments

	Treatment Number					
IVF Live Births:	1	2	3	4	5	All
High School	0.0319***	0.0198*	0.0368***	0.0307**	0.0266	0.0304***
	(0.00909)	(0.0102)	(0.0117)	(0.0144)	(0.0183)	(0.00523)
College	0.0513***	0.0425***	0.0605***	0.0404***	0.0521***	0.0516***
	(0.00983)	(0.0110)	(0.0127)	(0.0156)	(0.0199)	(0.00567)
Full controls	✓	✓	✓	✓	✓	✓
Constant	0.207***	0.134***	0.244***	0.224**	0.102	0.224***
	(0.0495)	(0.0488)	(0.0622)	(0.102)	(0.102)	(0.0248)
Observations	21,130	15,345	10,701	6,920	4,207	58,303
R-squared	0.027	0.026	0.031	0.025	0.045	0.022

Notes: Robust standard errors are in parentheses. They are clustered at the individual level in the last column. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. All specifications include controls for labor market outcomes, marital status, clinic fixed effect, year fixed effects, health status and infertility causes.

Table 3.6: (Un)Healthy Behavior: Education Gradient in IVF Success (Live Birth) Conditional on Health Behavior

IVF Live Births:	Benchmark (1)	2006-2009 (2)	2006-2009 (3)	2006-2009 (4)	2006-2009 (5)
High School	0.0319***	0.0664***	0.0651***	0.0639***	0.0643***
	(0.00909)	(0.0214)	(0.0214)	(0.0216)	(0.0216)
College	0.0513***	0.0927***	0.0896***	0.0879***	0.0884***
	(0.00983)	(0.0217)	(0.0217)	(0.0221)	(0.0222)
Full controls	✓	✓	✓	✓	✓
Health Behavior:					
BMI:					
BMI<20			✓	✓	✓
$20 \leq$ BMI≤ 25			✓	✓	✓
$25 \leq$ BMI≤ 30			✓	✓	✓
Cigarettes smoked per day:					
# of cigarettes = 0				✓	✓
$1 \leq$ # of cigarettes ≤ 5				✓	✓
$6 \leq$ # of cigarettes ≤ 10				✓	✓
Alcohol consumption per week:					
# of unit = 0					✓
$1 \leq$ # of unit ≤ 3					✓
$4 \leq$ # of unit ≤ 5					✓
Constant	0.207***	0.217**	0.197**	0.190*	0.207*
	(0.0495)	(0.0970)	(0.0997)	(0.1020)	(0.1060)
R-squared	0.027	0.031	0.031	0.032	0.032

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. All specifications include the controls, clinic fixed effect, clinic trends and year fixed effects of the baseline specification. General practitioner (GP) services (e.g., consultation, blood test, vaccination, etc.) and diseases (see Table 3 for a classification of diagnosis) are recorded the year prior to treatment. Reference group for cigarettes is more than 10, reference group for alcohol consumption is more than 5, reference group for BMI is above 30. Estimates for missing values of cigarettes, alcohol and BMI are suppressed. Our sample consists of the first treatments of first child.

Table 3.7: Financial Constraints: Education Gradient in IVF Success (Live Birth) Conditional on Free Quota Eligibility

IVF Live Births:	Benchmark (1)	Under 40 (2)	Under 40 Public Sector (3)	Benchmark w/ wealth (4)	Under 40 w/ wealth (5)	Under 40 Public Sector w/ wealth (6)
High School	0.0319***	0.0339***	0.0332***	0.0314***	0.0332***	0.0327***
	(0.00909)	(0.00924)	(0.00993)	(0.00909)	(0.00925)	(0.00993)
College	0.0513***	0.0527***	0.0559***	0.0505***	0.0517***	0.0550***
	(0.00983)	(0.0100)	(0.0109)	(0.00983)	(0.0100)	(0.0109)
Full controls	✓	✓	✓	✓	✓	✓
Wealth (2000)				1.57e-08**	2.43e-08***	2.01e-08**
				(7.82e-09)	(8.22e-09)	(9.56e-09)
Constant	0.207***	0.203***	0.194***	0.215***	0.215***	0.201***
	(0.0495)	(0.0516)	(0.0567)	(0.0496)	(0.0517)	(0.0568)
Observations	21,130	20,605	17,422	21,130	20,605	17,422
R-squared	0.027	0.024	0.022	0.028	0.024	0.022

Notes: Robust standard error are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. HS denotes high school. The specification uses socio-econ characteristics and health controls as in Table 3.6, column 1, including the clinic fixed effect and year fixed effects.

Table 3.8: Technological Improvements: The IVF-Education Gradient Success (Live Births) Across Time

IVF Live Births:	1995-1999 (1)	2000-2004 (2)	2005-2009 (3)	Full Sample (4)
High School	0.0408***	0.0161	0.0405**	0.0319***
	(0.0137)	(0.0160)	(0.0196)	(0.00909)
College	0.0368**	0.0459***	0.0664***	0.0513***
	(0.0158)	(0.0172)	(0.0200)	(0.00983)
Full Controls:	✓	✓	✓	✓
Observations	6,844	7,461	6,825	21,130
R-squared	0.028	0.047	0.027	0.027

Notes: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust t-statistics in parentheses. We control for age dummies, time dummies, health status, socioeconomic characteristics, infertility causes, and clinic fixed effects.

Table 3.9: A Finer Specification for Education

	6 Categories	Schooling Years
High School	0.0368***	
	(0.0135)	
Vocational School	0.0296***	
	(0.00944)	
2 years College	0.0407***	
	(0.0140)	
Bachelor	0.0476***	
	(0.0103)	
Master or PhD	0.0616***	
	(0.0126)	
Schooling Years		0.00678***
		(0.00136)
Age Dummies	✓	✓
Time Dummies	✓	✓
Health Status	✓	✓
Socioeconomic Characteristics	✓	✓
Infertility Causes	✓	✓
Clinic Fixed Effects	✓	✓
Constant	0.212***	0.145***
	(0.0496)	(0.0134)
Observations	21,130	21,130
R-squared	0.028	0.03

Notes: *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. Robust standard errors are in parenthesis. The omitted category is HS dropouts.

Table 3.10: The IVF-Education Gradient (Live Births): Different Stages of the IVF treatment

Outcome:	Aspiration (1)	Embryo Transfer (2)	Live Birth (3)	Live Birth (4)
High School	0.0151***	0.0274***	0.0312***	0.0307***
	(0.00532)	(0.00846)	(0.0111)	(0.0110)
College	0.0239***	0.0354***	0.0521***	0.0531***
	(0.00549)	(0.00894)	(0.0119)	(0.0118)
Full Controls	✓	✓	✓	✓
2 Eggs Trans.				0.122***
				(0.00799)
$\geq$3 Eggs Trans.				0.107***
				(0.0191)
Constant	0.826***	0.783***	0.357***	0.253***
	(0.0233)	(0.0369)	(0.0489)	(0.0494)
Observations	21,130	20,132	17,151	17,151
R-squared	0.062	0.033	0.032	0.044

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust t-statistics in parentheses. Observations in Columns (3) and (4) are treatments that reached the embryo implantation stage. Our sample is restricted to 1st child and 1st treatment.

Table 3.11: The IVF-Education Gradient (Live Births): Selection Equation

	IVF Live Births (1)	IVF Participation (2)	Mills (3)
HS and some college	0.0437*	0.0724***	
	(0.0224)	(0.00966)	
College and higher degree	0.0731*	0.135***	
	(0.0390)	(0.0103)	
Age Dummies	✓	✓	
Time Dummies	✓	✓	
Health Status:			
Average number of GP services	-0.000221	0.0115***	
	(0.00340)	(0.000997)	
Average cost of GP services	-5.77e-08	-7.51e-07***	
	(2.59e-07)	(1.30e-07)	
Disease(s) Diagnoses	✓	✓	
Socioeconomic Characterisitcs:			
Married	0.0253	0.234***	
	(0.0649)	(0.00635)	
Log total income	0.00648	0.0113***	
	(0.00436)	(0.00311)	
Log spousal income	0.00742	0.0242***	
	(0.00738)	(0.00318)	
Employment status:			
On leave	-0.0261	0.00470	
	(0.0378)	(0.0383)	
Self-employment	-0.00802	-0.0135	
	(0.0245)	(0.0242)	
Employed	-0.00606	0.0742***	
	(0.0253)	(0.0152)	
Out of labor force	-0.0627	-0.118***	
	(0.0396)	(0.0218)	
λ			0.1973
			(0.3190)
IVF Clinics per Women (by Municipality)		108.3**	
		(45.82)	
Constant	-0.438	-2.914***	
	(1.012)	(0.0556)	
Observations	921,644	921,644	

Notes: Robust t-statistics in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Results come from a two-stage Heckman selection model.

Table 3.12: Selection out of IVF

	Treatment Number					
IVF Dropout:	1	2	3	4	5	All
High School	-0.0301***	-0.0237**	-0.0285**	-0.0402**	-0.0311	-0.0320***
	(0.00699)	(0.00928)	(0.0128)	(0.0174)	(0.0232)	(0.00507)
College	-0.0405***	-0.0417***	-0.0575***	-0.0777***	-0.0960***	-0.0563***
	(0.00745)	(0.00985)	(0.0135)	(0.0183)	(0.0241)	(0.00536)
Full controls	✓	✓	✓	✓	✓	✓
Constant	0.220***	0.223***	0.221***	0.468***	0.849***	0.210***
	(0.0327)	(0.0456)	(0.0664)	(0.120)	(0.118)	(0.0241)
Observations	21,130	15,345	10,701	6,920	4,207	58,303
R-squared	0.077	0.059	0.060	0.057	0.063	0.049

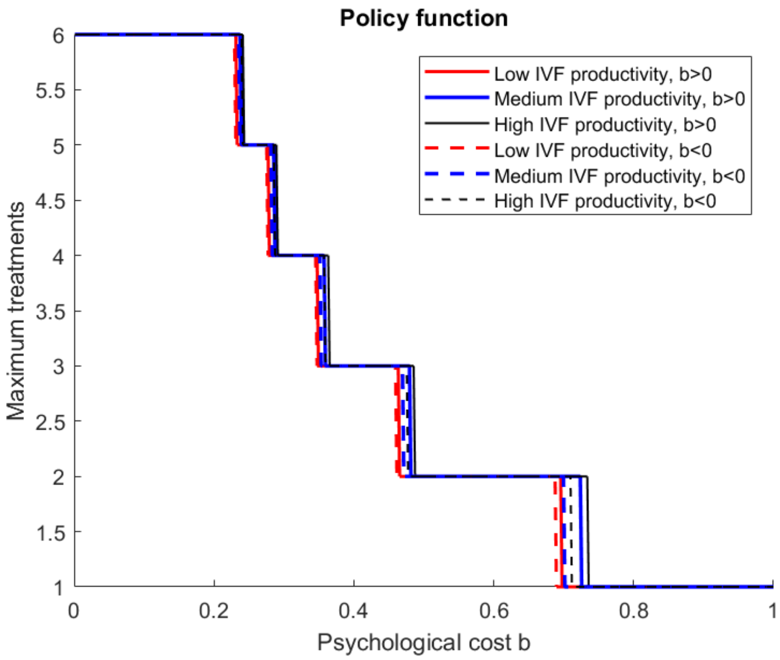
Notes: Robust standard errors are in parentheses. They are clustered at the individual level in the last column. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. All specifications include controls for labor market outcomes, marital status, clinic fixed effect, year fixed effects, health status and infertility causes.

Table 3.13: Education Gradient in IVF (Live Birth) with Spousal Education Control

	Treatment Number					
IVF Live Births:	1	2	3	4	5	All
High School	0.0285***	0.0129	0.0361***	0.0271*	0.0216	0.0263***
	(0.00932)	(0.0104)	(0.0120)	(0.0149)	(0.0189)	(0.00538)
College	0.0432***	0.0283**	0.0609***	0.0301*	0.0467**	0.0431***
	(0.0104)	(0.0117)	(0.0135)	(0.0167)	(0.0214)	(0.00602)
High School, Partner	0.0186**	0.0241**	0.00884	0.0110	0.0343*	0.0181***
	(0.00845)	(0.00941)	(0.0113)	(0.0140)	(0.0176)	(0.00493)
College, Partner	0.0269***	0.0436***	0.00432	0.0332**	0.0259	0.0275***
	(0.0102)	(0.0115)	(0.0136)	(0.0169)	(0.0212)	(0.00595)
Full Controls	✓	✓	✓	✓	✓	✓
Observations	20,847	15,143	10,567	6,835	4,154	57,546
R-squared	0.028	0.028	0.031	0.025	0.045	0.022

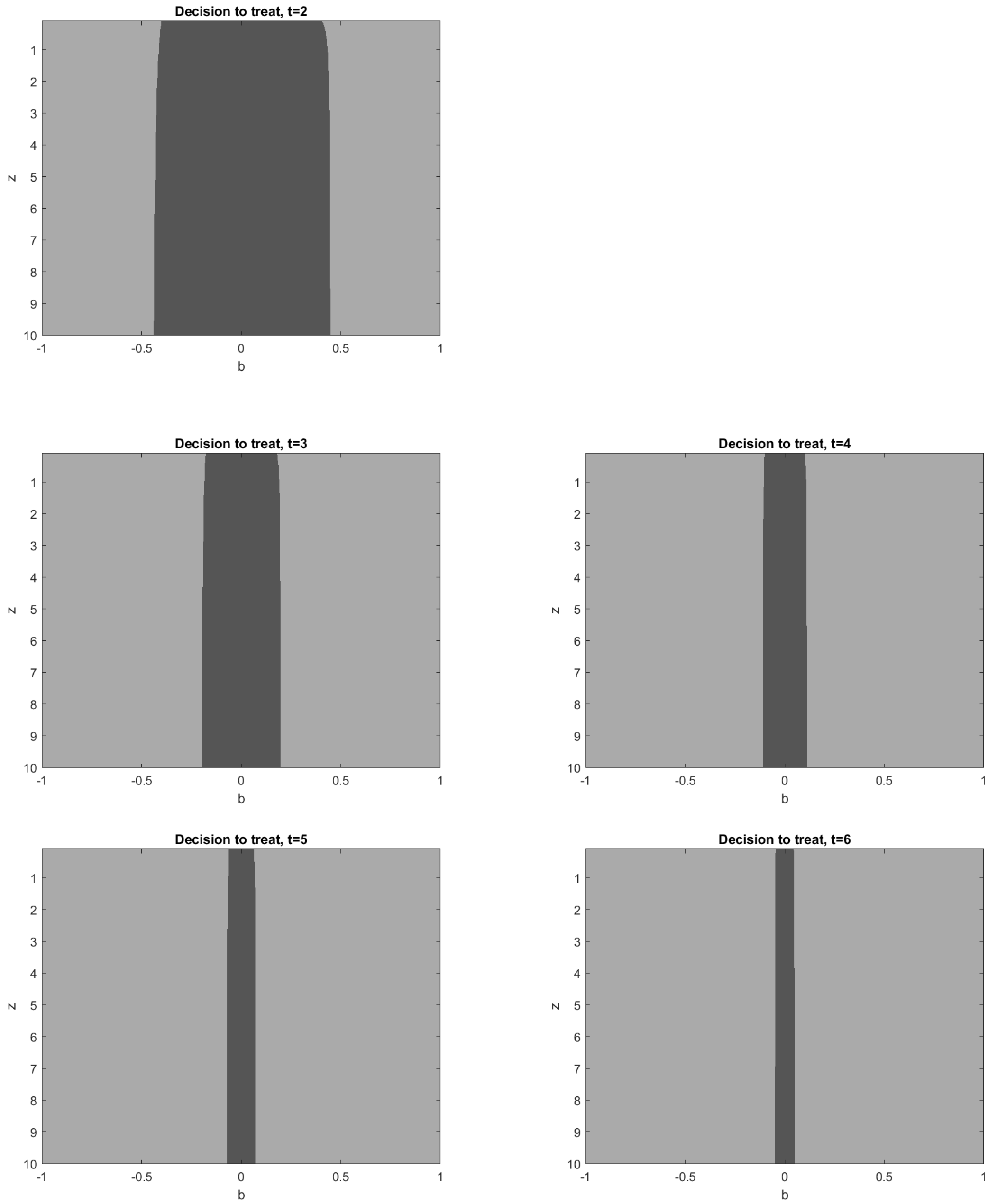
Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. All specifications include controls for labor market outcomes, marital status, clinic fixed effect and year fixed effects. There are 283 observations for which spousal education is missing.

Figure 3.2: Drop-out policy function



Notes: The figure shows the policy function on the maximum number of treatments depending on $|b|$ for three different levels of productivity z. The dashed lines show the policy function for the absolute value of the negative value of b.

Figure 3.3: Effects of b and z on t



Notes: The first figure shows the policy function for the maximum number of treatments. The next 5 figures show for each treatment $t = 2$ up to $t = 5$ the combinations of b and z (in dark gray) for which individuals decide to treat in the corresponding treatment.

Table 3.14: Estimation Targets: Conditional Success and Dropout Rates

Treatment	1	2	3	4	5
Success rates:					
Less than HS	0.201***	0.182***	0.172***	0.170***	0.159***
	(0.00732)	(0.00829)	(0.00976)	(0.0123)	(0.0159)
HS and some college	0.233***	0.213***	0.212***	0.205***	0.198***
	(0.00388)	(0.00431)	(0.00514)	(0.00638)	(0.00819)
College and higher	0.250***	0.240***	0.236***	0.218***	0.229***
	(0.00463)	(0.00522)	(0.00612)	(0.00733)	(0.00936)
Dropout rates:					
Less than HS	0.156***	0.189***	0.256***	0.321***	0.315***
	(0.00750)	(0.00907)	(0.0119)	(0.0158)	(0.0204)
HS and some college	0.136***	0.182***	0.239***	0.278***	0.292***
	(0.00364)	(0.00450)	(0.00587)	(0.00756)	(0.00974)
College and higher	0.138***	0.174***	0.214***	0.242***	0.245***
	(0.00422)	(0.00505)	(0.00635)	(0.00790)	(0.00989)

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. HS denotes high school. All specifications include controls for labor market outcomes, marital status, clinic fixed effect, year fixed effects, health status and infertility causes.

Table 3.15: Estimated average IVF productivity

Education	$< HS$	HS	College and above
μ_z	0.2231	0.2765	0.3104

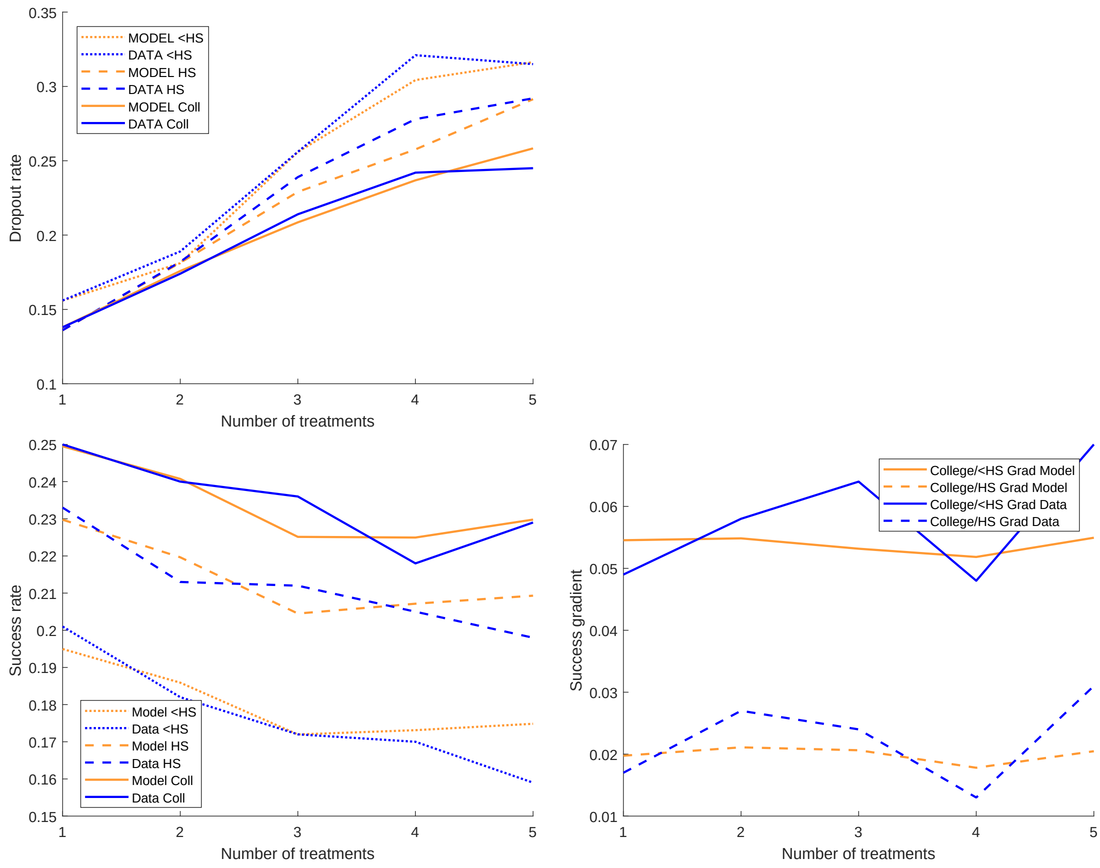


Figure 3.4: Model Fit

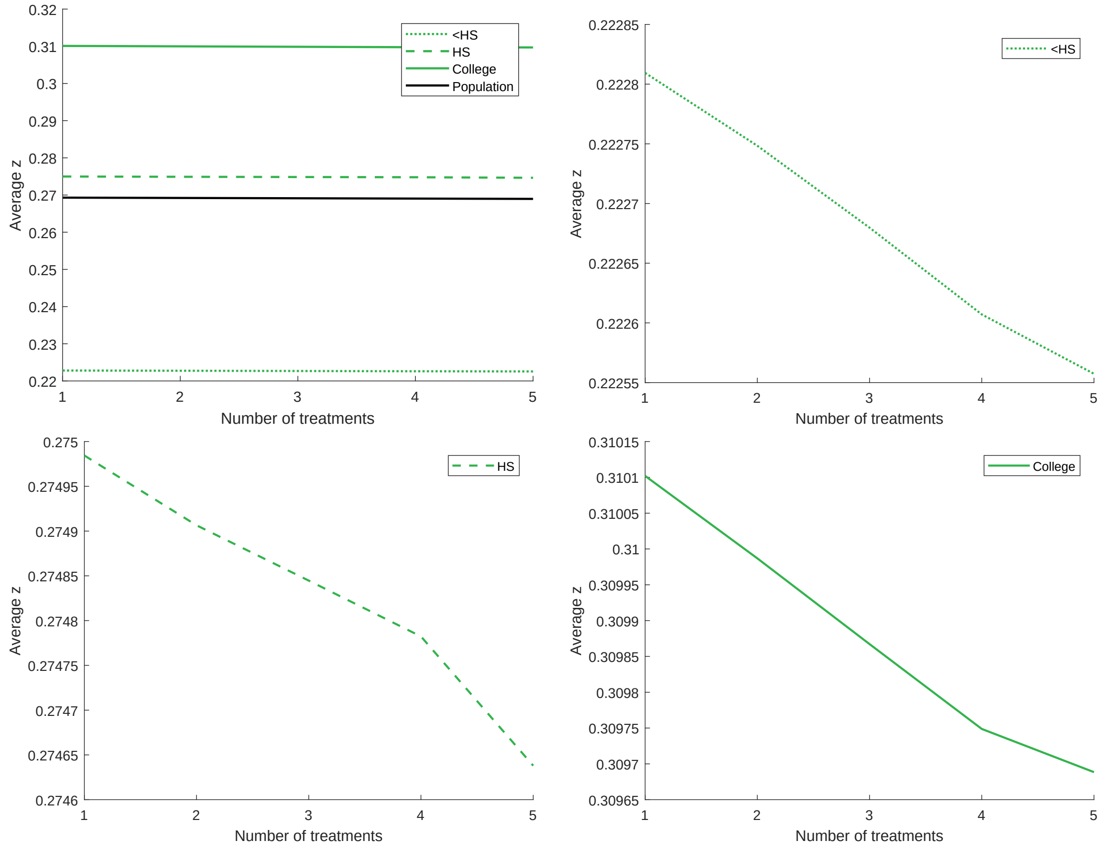


Figure 3.5: Evolution of average z

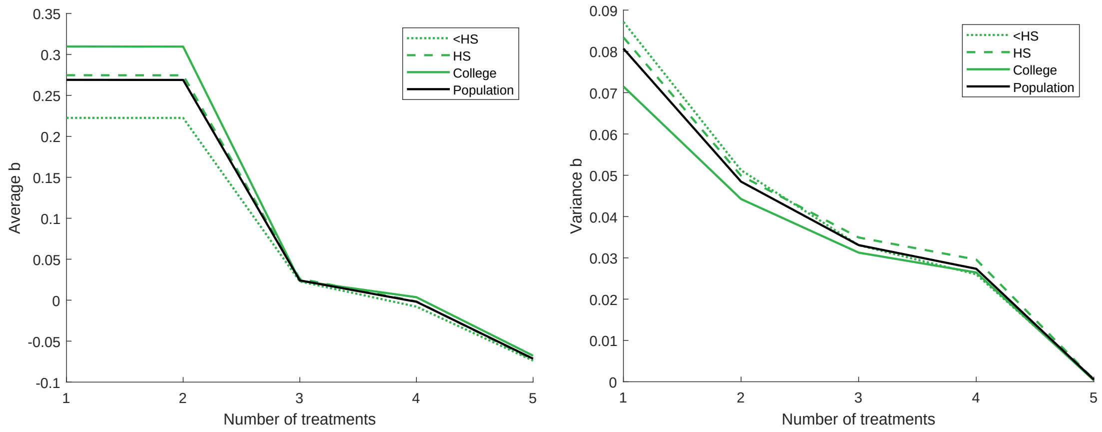


Figure 3.6: Evolution of mean and variance of b

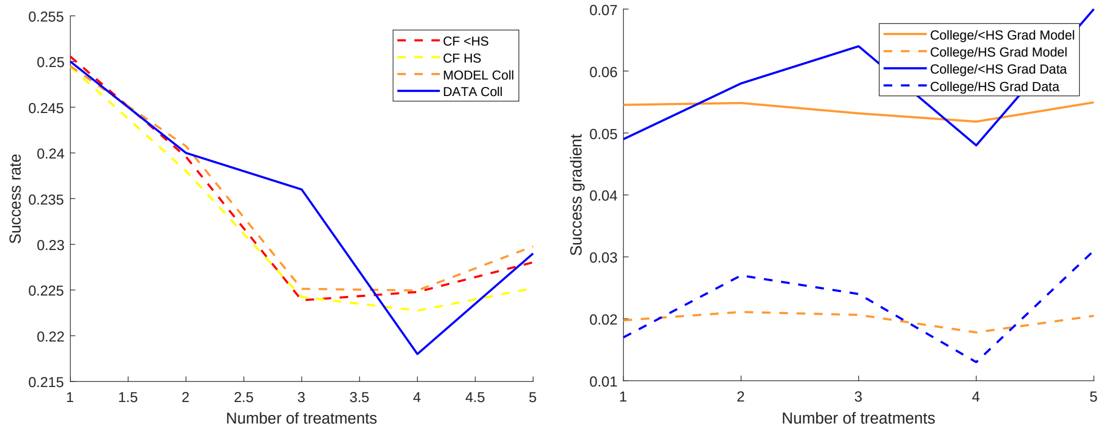


Figure 3.7: Counterfactual exercise 1

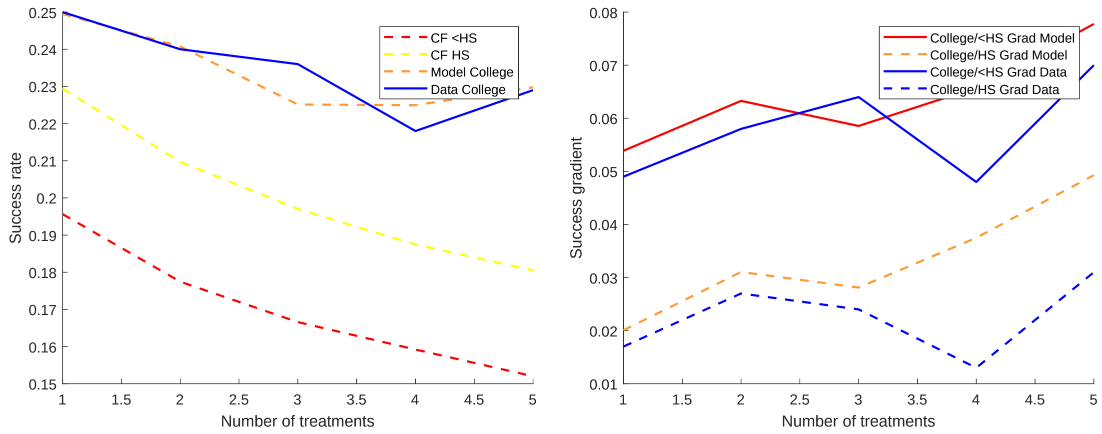


Figure 3.8: Counterfactual exercise 2

Appendix: Chapter 1

A.1 Samples

For the measure of sorting, I use only employed individuals with a valid 4-digit ISCO code and information on the their skills. For the skill use measure, I follow M. Levels & Allen (2013) in including only individuals who do not report to be "Apprentice" and "Student". As for the OECD measure, the sample used is those who have information on the self-reported mismatch. Table A1 shows the sample sizes by country for each of the measures.

Table A1: Sample Selection

Country	Cze	Bel	Gbr	Dnk	Nld	Fra	Esp	Jpn	Kor	Pol	Svk	Ita	Ger
Total	6102	5412	8890	7288	5170	6975	6055	5278	6632	9336	5723	4620	5379
Sorting													
Employed	3673	3335	5909	5342	3943	4505	3386	3881	4393	5122	3319	2868	4070
ISCO	3601	3305	4038	4938	3909	4461	3336	3780	4345	5046	3203	2705	3766
Skill use													
Not Apprentice	3587	3296	4019	4907	3894	4394	3323	3771	4337	5024	3172	2698	3766
OECD													
Self-rep.	3484	3231	3923	4743	3797	4045	3177	3670	4149	4717	3106	2630	3689

Notes: This table shows the sample selection and sample sizes for each country analyzed. The sample selection criteria include only employed individuals with a valid occupational code, who are not in an apprenticeship and have self-reported information on under- and over-skilling.

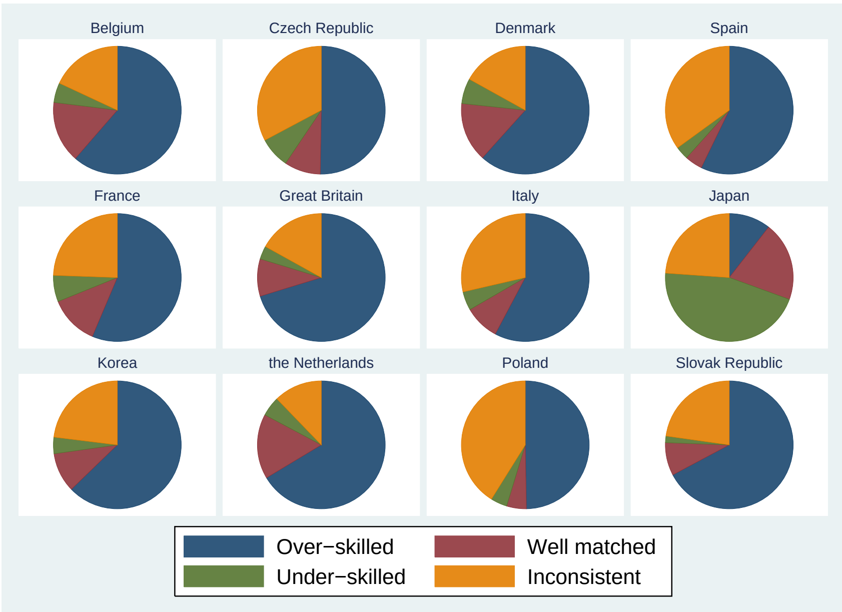
A.2 OECD measure

The OECD (Pellizzari & Fichen (2013)) constructs a measure of mismatch based on the following two questions asked in the PIAAC interview regarding the appropriateness of the respondent's skills for her current job :

- Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?
- Do you feel that you need further training in order to cope well with your present duties?

In the studies that base mismatch on these questions, the respondents that answer 'No' to both questions would be identified as well matched; when the answer to the first one was 'Yes' ('No') but the answer to the second one was 'No' ('Yes'), then this person can be categorised as over-skilled (under-skilled).

Figure A1: Self-reported mismatch



Note: This figure shows the proportions of people in each country where the answer to both questions was such that they could be identified as over-skilled, well matched and under-skilled. Obtained from PIAAC

To illustrate the problem with self-reported mismatch based on these questions, the data from the PIAAC is used to construct Figure A1. This figure shows the proportions of people in each country where the answer to both questions was such that they could be identified as over-skilled, well matched and under-skilled. However, we also observe quite large proportions of people who answer 'Yes' to both questions and would therefore be both under- and over-skilled.

Figure A1 shows that in most countries there is a large part of self-reported over-skilled workers. As for self-reported under-skilled workers, the proportion is very small with the exception of Japan, which could be due to cultural reasons. This points to the fact that those reporting to be well-matched in some countries can in reality be either under- or over-skilled and therefore measures based on the answers to the above stated questions could be biased.

The OECD measure aims to improve upon these simple self-reported measures by also taking advantage of other information provided in the PIAAC, namely the test scores for the literacy and numeracy tests that are part of the survey. The measure is constructed as follows. Workers that self-report to be well matched by answering 'No' to both of the questions above are identified. Then for these workers the 95th and 5th percentiles of the scores (for numeracy and literacy, separately) in each occupation (at 1-digit ISCO level) are identified. Anyone in the same occupation with proficiency scores higher that the 95th percentile is classified as over-skilled and anyone with a proficiency score lower than the 5th percentile is classified as under-skilled. In order to illustrate the shortcomings of this measure, I show in detail how this measure is computed through its two stages.

The OECD measure drops ISCO codes 0 (armed forces) and 6 (skilled agricultural and fishery workers) and ISCO codes 1 (managers) and 2 (professionals) have been grouped together. Moreover, occupations with fewer than 10 self-reported well matched workers have also been dropped. The ISCO occupations considered were therefore the following:

For each 1-digit ISCO level

- **Stage 1**: Identify those 'well-matched'
- **Stage 2**: Identify 5th and 95th percentile score (literacy or numeracy) of those 'well-matched' and well matched fall between these values

Table A2 shows the percentage of the respondents who are employed and have declared themselves to be well matched, by occupation and country. These are the results of 'Stage 1'.

Table A2: Self-declared well-matched individuals

ISCO	Bel.	Cze.	Dnk	Sp.	Fr.	UK	It.	Jp.	Ko.	Ndls.	Pol.	Svk
1&2	14.57	9.29	15.23	3.53	10.21	9.57	7.09	12.5	6.12	17.55	2.40	4.93
3	14.37	8.22	17.24	2.80	12.98	7.66	6	13.46	6.69	15.44	3.36	8.42
4	16.49	6.45	17.14	3.70	10.99	9.61	7.50	26.49	5.23	13.99	2.99	6.42
5	13.70	9.45	12.33	4.82	11.85	8.38	9.91	20.82	11.56	13.19	4.90	9.19
7	18.08	10.65	13.94	5.51	11.40	9.52	12.28	19.69	9.60	20.53	5.74	10.19
8	16.16	7.73	15.85	3.01	12.06	9.96	10.42	27.16	9.39	15.96	6.06	9.94
9	16.37	12.60	12.47	4.65	14.02	12.44	12.20	36.59	17.90	19.73	7.97	13.36

Notes: This table shows the percentage of the respondents who are employed and have declared themselves to be well matched, by occupation and country.

What we observe Table A2 is that in all the countries the occupations with the largest percentage of self-defined well-matched workers are "Craft and related trades worker" (ISCO 7) and "Elementary occupations" (ISCO 9). As for the minimum, this varies largely between countries. Overall we can see that Spain and Poland have the lowest proportions of workers that asses themselves to be well matched for all ISCO. Table A3 shows the results of Stage 2 and compares the percentage of well-matched individuals in each of the stages of computing the OECD measure.

What we observe is that in some occupations a 9% of self-reported individuals becomes as high as 94% after the second stage. It is noticeable that Spain reports only 37.8% of well-matched workers in literacy and 52% in numeracy of those in occupations under "Technicians and associate professionals". The overall mismatch in terms of percentage is considerably lower after Stage 2 for each country, but Figure A2 shows the ranking of countries in terms of mismatch after both stages, for numeracy and literacy. The fact that the rankings are very close points to the fact that this measure still relies heavily on the self-reported mismatch.

Table A3: Self-declared well-matched individuals

Isco	1&2		3		4		5		7		8		9	
St.	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Belgium	14.6	89.7	14.4	89.4	16.4	88.1	13.7	88.5	18.0	88.2	16.1	86.3	16.3	78.2
Czech Republic	9.3	93.5	8.2	87.8	6.4	82.6	9.4	90.3	10.6	91.7	7.7	94.5	12.6	84.4
Denmark	15.2	88.2	17.2	91.7	17.1	82.5	12.3	88.8	13.9	88.6	15.8	83.2	12.4	84.1
Spain	3.5	91.91	2.80	52.64	3.7	89.7	4.8	75.40	5.51	69.81	3.0	79.8	4.6	95.1
France	10.2	94.5	13.0	90.6	10.9	91.6	11.8	85.7	11.4	82.1	12.06	85.0	14.0	82.9
UK	9.6	92.1	7.7	80.33	9.6	70.7	8.3	87.8	9.5	83.4	9.9	82.3	12.4	76.8
Italy	7.1	96.2	6	72.7	7.5	85.3	9.9	86.0	12.2	92.2	10.4	77.7	12.2	82.2
Japan	12.5	92.0	13.5	88.3	26.5	92.3	20.8	89.1	19.6	90.0	27.1	93.2	36.5	89.1
Korea	6.1	89.4	6.7	94.7	5.2	88.9	11.6	84.9	9.6	87.6	9.4	94.6	17.9	86.0
Netherlands	17.6	90.0	15.4	91.7	14.0	91.6	13.1	91.4	20.5	93.9	15.9	92.4	19.7	85.2
Poland	2.4	80.8	3.4	89.7	2.9	59.7	4.9	89.2	5.7	82.3	6.0	92.4	7.9	82.8
Slovakia	4.9	87.9	8.4	81.8	6.4	88.1	9.1	83.3	10.1	94.2	9.9	89.2	13.3	78.9

Notes: This table shows the percentage of well matched individuals by country and occupation (based on the one-digit ISCO classification) after stages 1 and 2 of the construction of the OECD measure.

Figure A2: Rankings across stages

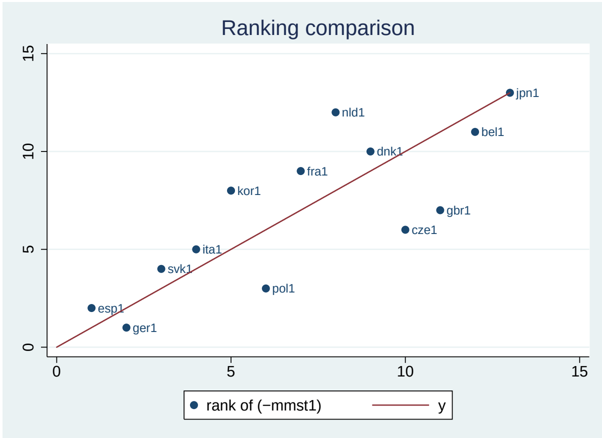


Figure A3: Literacy rankings

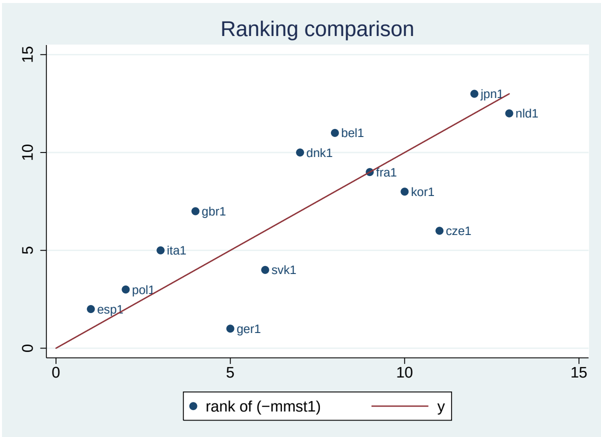


Figure A4: Numeracy rankings

Note: These figures show the ranking of the countries in terms of mismatch based on the first and second stages of the construction of the OECD measure, for literacy and numeracy.

The resulting mismatch according to the OECD measure for literacy and numeracy together with the decomposition into under- and over-skilling is shown in Table A4. Generally, we can see that the OECD measure determines that the country with the highest mismatch in both literacy and numeracy is Spain. On the other hand, Japan has one of the lowest mismatches in both literacy and numeracy. Once the mismatch is decomposed into those who are under- and over-skilled, another pattern emerges, namely that the variation across countries is larger in the over-skilling component of mismatch, which ranges from 6 to 15 for literacy and 5 to 14 for numeracy. In addition, in all countries, the number of overskilled are higher than the number of under-skilled workers, for both skills. When comparing literacy and numeracy, we can observe that these are not exactly

Table A4: OECD Measure Mismatch

Country	Literacy			Numeracy		
	MM	OS	US	MM	OS	US
Japan	10.19	6.61	3.58	9.51	6.01	3.50
Belgium	10.20	6.32	3.88	12.03	7.74	4.29
UK	10.57	6.83	3.74	14.24	10.50	3.74
Czech Republic	10.97	8.63	2.34	10.01	7.56	2.45
France	11.21	7.09	4.12	10.92	7.75	3.17
Denmark	11.34	6.78	4.56	11.88	6.90	4.98
Netherlands	11.66	6.38	5.28	9.23	5.49	3.74
Poland	13.06	8.78	4.28	16.99	14.20	2.79
Korea	13.10	10.23	2.87	11.06	8.67	2.39
Italy	13.36	9.45	3.91	15.00	12.07	2.93
Slovakia	13.65	10.18	3.47	13.49	10.72	2.77
Germany	14.75	12.47	2.28	13.96	12.52	1.44
Spain	18.74	15.71	3.03	17.36	14.12	3.24

Notes: This table shows the percentage of mismatched individuals (MM), and over-skilled (OS) and under-skilled (US) individuals by country, for literacy and numeracy using the OECD measure.

aligned, as countries such as Netherlands and Poland which are in the mid-range for literacy mismatch, for numeracy show very different results, the Netherlands having the lowest mismatch and Poland the second highest one.

Apart from the issues already highlighted, this measure also faces problems since requirements of the jobs are not taken into account. In particular, the questions about mismatch are not specific to any skills and therefore an individual employed in an occupation where only manual skills are required and has a low literacy score, even if he reports to be over-skilled for his job, the fact that the minimum score of self-reported workers are larger than his score, he will be classified as under-skilled. This fact comes mostly because the occupations are too coarse and because requirements are not taken into account.

A.3 Skill use measures

In their paper, M. Levels & Allen (2013) aim to improve upon the OECD measure by looking at the individuals' skills on the one hand and their skills use at work, available in the PIAAC on the other. The mismatch measure they construct represents the extent of skill use relative to one's own skill level. They construct they measure on the pooled set of data for all countries.

- For each of numeracy and literacy, they take the individual's test score
- They construct literacy use as a mean of seven reading use items and four write use items
- They construct numeracy use as a mean of six numeracy use items
- They standardise all 4 of the above and for each skill compute the difference between the standardised test score and use
- All individuals with a value x such that $x \leq |1.5|$ points above or below zero are well-matched

We show the resulting mismatch in Table A5. One can notice that the results across countries are quite different for numeracy and literacy. For literacy, Japan, Poland and Slovakia seem to be countries where there skills are underutilized (more over-skilled workers). In Spain we can notice that in both skills, most of the labour force is under-skilled or the skills most over-utilized.

Table A5: Measure of Skill Use

Country	Literacy			Numeracy		
	MM	OS	US	MM	OS	US
Germany	15.6	4.8	10.8	18.0	9.1	8.9
Belgium	16.3	8.4	7.9	20.6	15.4	5.2
Netherlands	16.5	9.6	6.9	18.6	13.7	4.9
Denmark	17.0	4.5	12.5	17.8	11.3	6.5
France	17.8	7.6	10.12	18.6	6.5	12.1
Czech Republic	17.8	10.5	7.3	18.4	5.9	12.5
UK	18.0	5.8	12.2	19.6	7.8	11.8
Italy	18.2	7.5	10.7	17.5	6.5	11.0
Korea	19.2	7.0	12.2	18.5	4.8	13.7
Slovakia	19.7	14.2	5.5	19.0	11.0	8.0
Spain	20.0	6.7	13.3	19.3	4.4	14.9
Japan	20.7	15.4	5.3	16.5	12.7	3.8
Poland	21.2	13.76	7.5	19.1	7.2	11.9

Notes: This table shows the percentage of mismatched individuals (MM), and over-skilled (OS) and under-skilled (US) individuals by country, for literacy and numeracy using the measure of Skill Use.

Appendix: Chapter 2

B.1 Wage losses

Table A1: Wage changes of job transitions

EE spells	Mean	Median	Std.
By occupational switching			
Stay in occupation	.023	.001	.30
Switch occupation	.023	.004	.48
EUE spells	Mean	Median	Std.
By occupational switching			
Stay in occupation	-.008	-.005	.29
Switch occupation	-.028	-.010	.39

Note: This table shows the changes in log wages of workers switching jobs through unemployment (EUE) or while employed (EE). Data comes from the SIPP 1996-2012.

B.2 Duration results

Table B1: Effect of unemployment benefits on individuals who have taken up benefits

	NLSY		SIPP	
VARIABLES	Dur.	Dur.	Dur.	Dur.
Female	7.110***	7.217***	0.750***	0.760***
	(1.083)	(1.090)	(0.174)	(0.179)
Married	5.774***	6.030***	0.0723	0.0219
	(0.895)	(0.907)	(0.117)	(0.118)
Unemp. Rate	1.163***	1.148***	0.603***	0.130*
	(0.144)	(0.310)	(0.0395)	(0.0678)
Age	1.111**	1.199*	0.0964***	0.0884***
	(0.418)	(0.696)	(0.0222)	(0.0217)
Age^2	-0.00979	-0.00402	-0.00101***	-0.000860***
	(0.00604)	(0.0117)	(0.000301)	(0.000292)
Tenure	0.0223***	0.0214***	0.0104***	0.00894***
	(0.00574)	(0.00559)	(0.00114)	(0.00113)
Occ. Ten.	-0.00960***	-0.00852***		
	(0.00326)	(0.00301)		
Skill (AFQT)	-8.71e-05***	-8.76e-05***		
	(1.98e-05)	(2.08e-05)		
Wba	0.833	0.796	-0.107	-0.0441
	(0.785)	(0.882)	(0.126)	(0.124)
Constant	14.03	7.110	0.979	5.686***
	(9.159)	(12.91)	(0.727)	(0.808)
Observations	16,530	16,530	10,635	10,635
R-squared	0.065	0.077	0.077	0.131
Pseudo R2	0.0650	0.0766	0.0767	0.131
State FE		x		x
Year FE		x		x

Notes: This table shows the regression results for unemployment in the SIPP and the NLSY79 samples of EUE spells. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

B.3 Individual fixed effects in the NLSY79

Table C1: Individual fixed effects regression

VARIABLES	(1) Switch	(2) Switch
U. Dur.	0.00659***	0.00664***
	(0.00102)	(0.00104)
Unemp. Rate	0.0104	-0.00111
	(0.0180)	(0.0299)
Req. Old	0.000681	0.000546
	(0.00135)	(0.00137)
Age	-0.0186***	-0.0807
	(0.00558)	(0.110)
Tenure	0.00354***	0.00362***
	(0.000407)	(0.000410)
Occ. Ten	-0.00195***	-0.00203***
	(0.000271)	(0.000273)
Wba	-0.107	-0.101
	(0.0904)	(0.0949)
Constant	2.237***	3.902**
	(0.276)	(1.725)
Observations	9,480	9,472
Pseudo R2	0.153	0.165
State FE		x
Year FE		x

Notes: This table shows the linear probability model results for the probability to switch occupation in the NLSY79 sample of EUE spells. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

B.4 Reason for job loss in the SIPP

Table D1: Switching Regressions by Reason of Job Loss

	Fired		Business dissolved	
VARIABLES	Switch	Switch	Switch	Switch
U. Dur.	0.0520***	0.0513***	0.0588***	0.0559***
	(0.00706)	(0.00792)	(0.00991)	(0.00978)
Female	0.0748	0.0675	0.00715	0.0292
	(0.0695)	(0.0693)	(0.0844)	(0.0840)
Married	-0.156***	-0.156**	-0.0856	-0.0842
	(0.0589)	(0.0635)	(0.0744)	(0.0787)
Unemp. Rate	-0.0511***	-0.0704**	-0.0151	-0.148***
	(0.0115)	(0.0325)	(0.0182)	(0.0400)
Req. Old	1.372***	1.429***	0.488***	0.464***
	(0.143)	(0.142)	(0.140)	(0.148)
Tenure	0.000155	1.43e-05	0.000804	0.000591
	(0.000454)	(0.000464)	(0.000666)	(0.000661)
Wba	**-0.239*** **	**-0.237*** **	**-0.118** **	**-0.100** **
	(0.0459)	(0.0504)	(0.0493)	(0.0484)
Constant	-0.595	-0.635	0.533	1.487***
	(0.559)	(0.541)	(0.545)	(0.573)
Observations	6,828	6,823	3,830	3,827
Pseudo R2	0.0551	0.0674	0.0364	0.0576
State FE		x		x
Year FE		x		x

Notes: This table shows the linear probability model results for the probability to switch occupation in the SIPP sample of EUE spells. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

Table D2: Requirements Regressions by Reason of Job Loss

	Fired		Business dissolved	
VARIABLES	Req. New	Req. New	Req. New	Req. New
U. Dur.	-0.000306	-0.000439	0.000373	7.84e-05
	(0.000407)	(0.000403)	(0.000709)	(0.000724)
Female	0.0983***	0.102***	0.0947***	0.0951***
	(0.00799)	(0.00803)	(0.00681)	(0.00691)
Married	0.0208**	0.0209**	0.0166	0.0173
	(0.00863)	(0.00850)	(0.0118)	(0.0126)
Unemp. Rate	0.00137	-0.00105	-0.00190	0.000163
	(0.00161)	(0.00444)	(0.00202)	(0.00582)
Req. Old	0.156***	0.150***	0.143***	0.142***
	(0.0229)	(0.0219)	(0.0183)	(0.0194)
Tenure	4.20e-05	4.37e-05	-7.54e-05	-6.16e-05
	(5.92e-05)	(5.79e-05)	(9.46e-05)	(9.57e-05)
Wba	**0.00986***	**0.00719**	**0.0197*****	**0.0166*****
	(0.00515)	(0.00448)	(0.00525)	(0.00554)
Constant	0.315**	0.298*	0.147***	0.137***
	(0.150)	(0.151)	(0.0444)	(0.0499)
Observations	4,684	4,684	2,603	2,603
R-squared	0.294	0.315	0.297	0.318
Pseudo R2	0.294	0.315	0.297	0.318
State FE		x		x
Year FE		x		x

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

Notes: This table shows the regression results for re-employment requirements in the SIPP sample of EUE spells. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

B.5 Other robustness checks

Unemployment benefit take-up

The main analysis is run on all spells of involuntary spells. However, the take-up rate in the US is quite low and thus not all the individuals were necessarily collecting benefits. Take-up of unemployment benefits has been shown to be a function of how generous the unemployment benefit system in place is and is thus endogenous. I show in the appendix that take-up is indeed dependent on the generosity of the unemployment benefits and show in addition all the main results for only individuals who took up benefits.

The SIPP includes a question on the receipt of unemployment benefit; the NLSY79 includes a monthly variable on the amount of unemployment benefits received. I identify a spell in which an individual has taken up benefits as a spell in which the individual reports receiving unemployment benefit any time during the spell (any month within the spell) for the SIPP (NLSY79). The main results of all regressions for individuals who took up benefits are the same in terms of sign and significance and are shown in Table E1.

Table E1: Effect of unemployment benefits on individuals who have taken up benefits

	NLSY				SIPP			
VARIABLES	Switch	Lit.R. New	Num.R. New	Log Wage Post.	Switch	Lit.R. New	Num.R. New	Log Wage Post.
U. Dur.	0.00932***	-0.0269**	-0.0107	-0.00124***	0.00840***	-0.00129***	-0.00151***	-0.00434***
	(0.00227)	(0.0125)	(0.0132)	(0.000253)	(0.000849)	(0.000427)	(0.000314)	(0.000988)
Female	-0.122	-1.729	-5.409**	-0.0582	0.00805	0.0865***	0.0276***	-0.0738***
	(0.205)	(1.799)	(2.100)	(0.0388)	(0.0123)	(0.00862)	(0.00592)	(0.0110)
Married	0.0309	-0.513	0.274	0.0523**	-0.0287**	0.0246***	0.0121**	0.0193
	(0.150)	(1.335)	(1.450)	(0.0260)	(0.0137)	(0.00675)	(0.00525)	(0.0126)
Unemp. Rate	0.0744	-0.493	-0.671*	-0.000588	-0.0217***	-0.00737	-0.00109	-0.00407
	(0.0481)	(0.425)	(0.379)	(0.00871)	(0.00587)	(0.00475)	(0.00379)	(0.00561)
Age	0.0630	0.222	-0.391	0.0385**	-0.00855**	-0.00333	-0.00146	0.0119***
	(0.109)	(1.136)	(1.142)	(0.0189)	(0.00375)	(0.00262)	(0.00174)	(0.00337)
Age^2	-0.000617	-0.00644	0.00194	-0.000394	9.43e-05**	3.38e-05	9.50e-06	-0.000126***
	(0.00160)	(0.0155)	(0.0160)	(0.000321)	(4.56e-05)	(3.35e-05)	(2.13e-05)	(4.17e-05)
Tenure	0.00285***	0.000653	-0.00204	-0.000156	1.98e-05	3.99e-05	2.49e-05	-0.000253**
	(0.000403)	(0.00393)	(0.00359)	(0.000127)	(0.000117)	(5.47e-05)	(3.33e-05)	(0.000117)
Wba	-0.311**	2.580**	3.556***	0.108***	-0.0196**	0.0159***	0.0117***	0.0367***
	(0.129)	(1.211)	(1.212)	(0.0323)	(0.00821)	(0.00462)	(0.00320)	(0.00841)
Constant	1.424	46.04**	65.41***	1.572***	1.077***	0.441***	0.248***	1.223***
	(1.940)	(20.96)	(18.36)	(0.266)	(0.105)	(0.0802)	(0.0592)	(0.167)
Observations	1,806	1,776	1,776	1,980	5,161	3,478	3,478	3,186
R-squared		0.312	0.274	0.376	0.143	0.360	0.269	0.546
State FE	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Pseudo R2	0.193	0.312	0.274	0.376	0.143	0.360	0.269	0.546

Notes: This table shows the regression results for switching, literacy, numeracy and wages in the SIPP and NLSY79 sample of EUE spells for individuals who took up benefits. Robust standard errors are shown in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Regressors include year, state, industry and highest education fixed effects and a spline of pre-unemployment earnings. Errors are clustered at state level.

Earnings

The main regressions show a wage effect in the new job. In Table E2 we show that results do not change when considering earnings in the new jobs instead of hourly wages.

Table E2: Effect of unemployment benefits on earnings

	NLSY		SIPP	
VARIABLES	earn_new_log	earn_new_log	Log Earnings Post.	Log Earnings Post.
U. Dur.	-0.00136***	-0.00126***	-0.00517**	-0.00468**
	(0.000143)	(0.000139)	(0.00194)	(0.00186)
Female	-0.280***	-0.279***	-0.196***	-0.191***
	(0.0211)	(0.0206)	(0.0252)	(0.0248)
Married	0.0219	0.0184	0.0721***	0.0779***
	(0.0180)	(0.0174)	(0.0180)	(0.0177)
Unemp. Rate	-0.00247	-0.0167***	0.0110**	-0.00868
	(0.00325)	(0.00622)	(0.00486)	(0.0117)
Tenure	-0.000340***	-0.000306***	-0.000190	-0.000228
	(7.78e-05)	(8.21e-05)	(0.000195)	(0.000202)
ten_occ	0.000314***	0.000281***		
	(7.97e-05)	(7.71e-05)		
Age	0.0427***	0.0453***	0.0292***	0.0279***
	(0.00661)	(0.0125)	(0.00523)	(0.00520)
Age^2	-0.000624***	-0.000577**	-0.000405***	-0.000397***
	(0.000103)	(0.000251)	(7.15e-05)	(7.07e-05)
Wba	0.220***	0.223***	0.128***	0.138***
	(0.0145)	(0.0135)	(0.0149)	(0.0151)
Constant	5.651***	5.685***	5.757***	5.890***
	(0.169)	(0.240)	(0.159)	(0.171)
Observations	13,873	13,873	8,044	8,044
R-squared	0.239	0.259	0.209	0.224
Pseudo R2	0.239	0.259	0.209	0.224
State FE		x		x
Year FE		x		x

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

Notes: This table shows the regression results for all EUE spells in the SIPP and the NLSY79. Robust standard errors are shown in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of earnings in the job obtained after unemployment. Regressors include year, state, industry and highest education fixed effects and the log of the earnings in the job previous to unemployment. Errors are clustered at state level.

Appendix: Chapter 3

C.1 The IVF Procedure

The IVF procedure that women have to go through generally involves three phases. The first phase is the diagnosis of why the couple is infertile, which involves an analysis of the sperm quality and female fertility. All women who are in our sample of IVF-treated women have undergone the clarification procedure.

The second phase is strict and complex. It consists of the aspiration of oocytes (egg retrieval), the insemination, and the embryo transfer. This involves both medical interventions and patient's strict adherence to treatment. We can break this phase into six consecutive steps (Dansk Fertilitetsklinik, 2016).[1] In a first step, the patient will start a down-regulation of follicle stimulation hormones (FSH) two weeks prior to the ovarian stimulation process. The down-regulation improves the control on the future ovarian stimulation (e.g., prevents premature ovulation) and requires the application of two different nose sprays. One of the sprays needs to be applied twice per day and one four times per day.[2] The second step is the ovarian stimulation process that starts with the menstrual period. This process refers to hormone stimulation with FSH through daily injections that must be taken at the same time every evening. During this process nasal sprays are applied the same number of times (four) per day, though in less quantity. Ovarian stimulation is monitored with regular (three-to-five) blood and ultrasound tests.[3] The third step consists of an injection to release the eggs around ten days after the stimulation begins. This injection releases the eggs precisely forty hours after its application. It is very important that the patient manages to follow procedure and takes the injection at the time determined by the doctor. The fourth step is the egg retrieval, and it is performed by doctors. The fifth step is insemination. This is a purely medical procedure without patient involvement which may lead to at least one healthy embryo to be transferred on the basis of the

[1] The second phase of the IVF procedure can either be "long" or "short". For concreteness, we focus on the description of the "long" procedure with six steps that embeds the "short" one. We follow the description provided by the oldest fertility clinics in Denmark (Dansk Fertilitetsklinik, 2016).

[2] Alternatively, the patient injects herself with one daily Lupron injection in the belly at night.

[3] The last day of stimulation, FSH injections are complemented with a human chorionic gonadotropin (HCG) injection to support the normal development of an egg in a woman's ovary.

morphological grading of the embryos.[4] The sixth step is the embryo transfer, which takes place approximately two-three days after the eggs retrieval, if there were healthy embryos to implant. Doctors assess the quality of the embryos on the basis of some aspects of their microscopic appearance: Cell number, cell regularity, degree of fragmentation, granularity, etc.

The third phase spans from the embryo transfer to the potential birth of the child. In the two weeks following the transfer, patients must place one tablet three times a day, or apply a gel twice daily, in the vagina to ensure the mucosa matures correctly, and then take a pregnancy test. Patient must then follow a standard healthy life style conducive to a successful pregnancy.

C.2 Robustness

[4] Blastocyst culture helps select the best quality embryos for transfer and reduces multiple pregnancy risks.

Table C1: Education Gradient in IVF (Live Births): Logit Specification

IVF Live Births	(1)	(2)	(3)	(4)	(5)
HS and some college	0.0408***	0.0375***	0.0343***	0.0315***	0.0318***
	(0.00884)	(0.00877)	(0.00893)	(0.00917)	(0.00914)
College and higher degree	0.0518***	0.0583***	0.0541***	0.0501***	0.0513***
	(0.00927)	(0.00929)	(0.00959)	(0.00993)	(0.00995)
Age Dummies		✓	✓	✓	✓
Time Dummies			✓	✓	✓
Health Status:					
Average number of GP services			-0.00207	-0.00233*	-0.00253**
			(0.00126)	(0.00127)	(0.00127)
Average cost of GP services			4.53e-08	7.91e-08	7.51e-08
			(1.59e-07)	(1.59e-07)	(1.59e-07)
Disease(s) Diagnoses			✓	✓	✓
Socioeconomic Characterisitcs:					
Married				-0.0148**	-0.0119*
				(0.00604)	(0.00603)
Log total income				0.00597*	0.00635*
				(0.00362)	(0.00376)
Log spousal income				0.00389	0.00483
				(0.00329)	(0.00336)
Employment status:					
On leave				-0.0280	-0.0298
				(0.0389)	(0.0387)
Self-employment				-0.00527	-0.00685
				(0.0241)	(0.0240)
Employed				-0.0194	-0.0225
				(0.0150)	(0.0150)
Out of labor force				-0.0461**	-0.0444*
				(0.0228)	(0.0227)
Infertility causes:					
Cervical defect					-0.00454
					(0.0255)
Ovulation defect					-0.00844
					(0.0109)
Fallopian Tube defect					-0.0245**
					(0.0105)
Male causes					-0.0124
					(0.00860)
Other causes					-0.0363***
					(0.0106)
Unspecified causes					-0.0146
					(0.0115)
Clinic Fixed Effects					✓
Observations	21,130	21,116	21,111	21,111	21,106

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. HS denotes high school. Age is measured as starting from 1 to better capture the nonlinearities occurring from age 25 to 45. Employment status reference category is "in school". All specifications include clinic fixed effect and year fixed effects.

Table C2: Demographic Characteristics of IVF Patients: Last Treatment

Education	< *HS*	*HS*	*College*
Age	32.4	32.1	32.8
Married (%)	62.7	62.5	61.4
Patient's income	186,796	236,828	287,755
Spousal income	268,945	319,680	370,118
Employment status (%):			
On leave	3.0	1.5	1.0
Self-employment	3.5	3.4	1.8
Employed	69.4	85.5	91.8
Unemployed	10.3	4.0	2.1
In school	0.8	1.2	1.1
Out of labor force	13.0	4.3	2.3
Treated in public hospital (%)	84.9	82.3	76.3
Live births (%)	47.0	54.4	56.6
Number of total treatments	2.59	2.62	2.64
Observations	2,689	10,793	7,648

Notes: In terms of education groups, we denote IVF patients with less than high school as < *HS*, high school or some college as *HS*, and college or higher degree as *College*. Entries are means conditional on first treatment in panel (a) and on last treatment in panel (b). Standard deviations in parentheses. Income is in DKK, deflated by CPI to year 2000. Employment status is measured the year prior to treatment.

Table C3: The IVF-Education Gradient (Live Births) Conditional on Embryo Transfer: Different Specifications of Education and Time Periods

	1995-1999 (1)	2000-2004 (2)	2005-2009 (3)	Full Sample (4)
Education Specification:				
(a) Benchmark:				
HS and some college	0.0482***	-0.00334	0.0454*	0.0308***
	(0.0164)	(0.0191)	(0.0232)	(0.0109)
College and higher degree	0.0406**	0.0247	0.0710***	0.0478***
	(0.0187)	(0.0204)	(0.0236)	(0.0116)
(b) Average Schooling Years	0.00283	0.00582**	0.00899***	0.00618***
	(0.00279)	(0.00269)	(0.00278)	(0.00158)
Additional Controls:				
Age Dummies	✓	✓	✓	✓
Time Dummies	✓	✓	✓	✓
Health Status	✓	✓	✓	✓
Socioeconomic Characteristics	✓	✓	✓	✓
Infertility Causes	✓	✓	✓	✓
Clinic Fixed Effects	✓	✓	✓	✓
Constant	✓	✓	✓	✓
Observations	5,649	6,129	5,742	17,520

Notes: Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$. HS denotes high school. Age is measured as starting from 1 to better capture the nonlinearities occurring from age 25 to 45. Employment status reference category is "in school". All specifications include clinic fixed effect and year fixed effects.