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Sena Coskun

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Abstract

Understanding the role of heterogeneity across agents is crucial in predicting how the macroeconomic outcomes are affected by these differences. This dissertation presents three papers in which I study labor market outcomes of different segments of the population according to their choice of education and how labor market characteristics affect people's life time choices such as fertility. I argue that productivity differences between education groups are crucial to understand unemployment rate differences between educated and less educated. In countries where college educated workers do not have particularly better skills than high school graduates, they face higher unemployment rates even though they can perform the same jobs as high school graduates. Fertility, on the other hand, is a life time choice affected by not only business cycles but also characteristics of the labor market. I show that fertility presents procyclical features and the fertility decline in recessions is amplified because of cyclical properties of industries as well as gender asymmetry in industry employment. [1]

[1] In this paper, I use data from Eurostat: European Union Survey on Income and Living Conditions (EU-SILC) (2004-2015) and European Union Labor Force Survey (EU-LFS) (1983-2015). The responsibility for all conclusions drawn from the data lies entirely with me.

Acknowledgment

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the most incredible mother ever that I have fear of not being such a great mother like her. Her patience, her never ending energy, her availability like a wild card in our lives made everything possible.

To my mother, Dehen

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Chapter I

A Model for Young Educated Unemployment

1 Introduction

College education promises high life-time earnings, low unemployment, better health, and better outcomes across a whole range of other issues. This is true for most countries along most measures. However, there is an exception to this rule: In some European countries, college educated young people have a higher risk of being unemployed than young high school graduates. This seems contradictory to the thought that education always decreases risk of unemployment. The usual negative relationship between education and unemployment breaks down for young people only in some countries such as Italy, Denmark, and Greece. In these countries, college educated workers experience higher unemployment rates than high school graduates until they are age 30 (Figure I.1). This pattern is very persistent for the above countries (Figure I.3). Then the common relationship is established again for older workers. The US labor market, on the other hand, seems standard in the sense that unemployment rate differences across skill groups always have the same sign. Not only do college educated people always have lower unemployment rates in all states, but also the gap is large (Figure I.2).

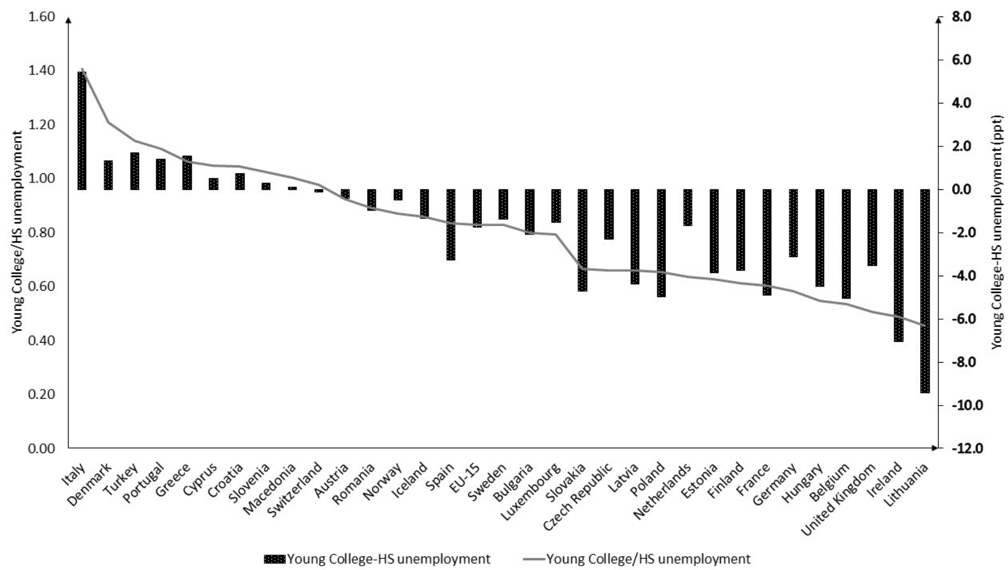


Figure I.1: Europe Average Unemployment Rate Differences

Note: The unemployment rates for the 25-29 age group have been averaged from 2004-2015 for college and high school graduates separately, by using Eurostat statistics. The left axis represents the ratio of the college unemployment rate to the high school unemployment rate. The right axis represents the difference between college educated and high school unemployment rates.

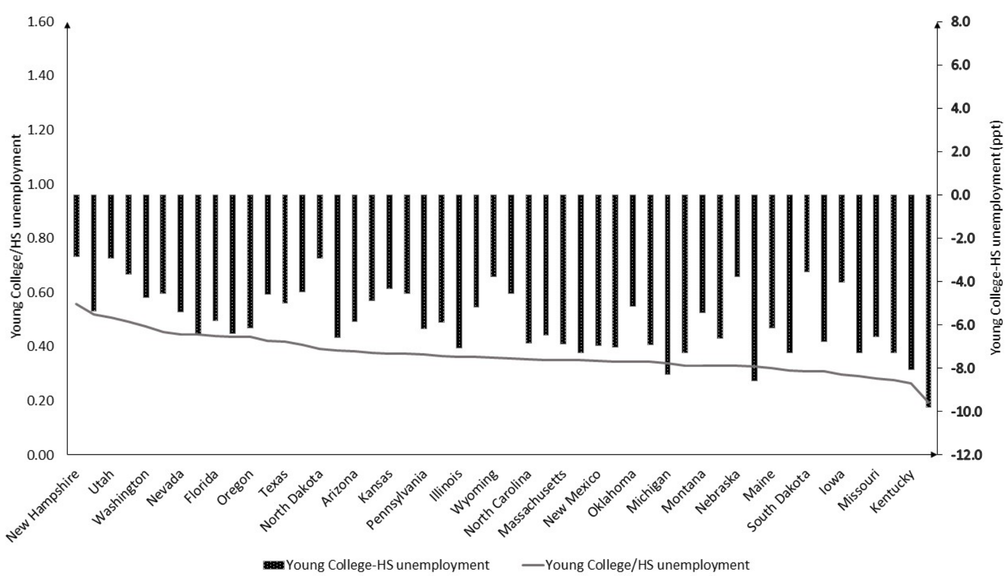


Figure I.2: US Average Unemployment Rate Differences

Note: The unemployment rates for the 25-29 age group have been averaged from 2000-2015 for college and high school graduates separately, by using American Community Survey (ACS). The left axis represents the ratio of the college unemployment rate to the high school unemployment rate. The right axis represents the difference between college educated and high school unemployment rates.

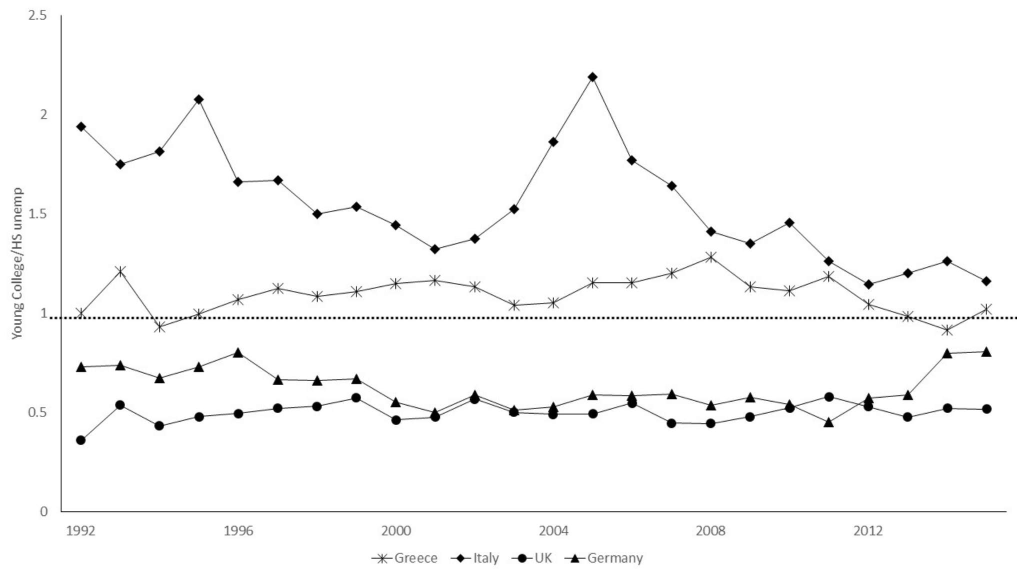


Figure I.3: Time Series of Unemployment Rates

Note: The unemployment rates for the 25-29 age group have been shown for college and high school graduates separately, by using Eurostat statistics. The left axis represents the ratio of college unemployment rate to high school unemployment rate.

We often think of college educated people as having more skills than high school graduates so that they should be able to do the same jobs and more. The phenomenon in which college educated people perform jobs that do not actually require high education is called "over-education" and/or "mismatch" (Duncan & Hoffman (1981); Leuven & Oosterbeek (2011)). This happens when college educated people cannot find suitable jobs and accept the jobs for which they are over-qualified instead of staying unemployed. This type of mismatch related to over-qualification results in "crowding out" of lower educated people in their traditional jobs by higher educated people (Dolado et al. (2000)). Likewise, recent literature focuses on deterioration of labor market outcomes of lower educated people in favor of higher educated people. It has also been shown that the increasing trend in college wage premium contributes to increasing income inequality, and deterioration of labor market outcomes for those who are less educated (Acemoglu & Autor (2011); Acemoglu (2003); Card (2002); Katz & Murphy (1992)). Hence, it has been always thought that labor market outcomes of lower educated people are worsening both in terms of unemployment risk and earnings. Surprisingly, this is not true for young educated workers in some European countries.

In this paper, I propose and quantify two potential explanations for the "young, educated, unemployed" phenomenon. First, is the "*Labor market frictions*" hypothesis and the second is the "*Productivity hypothesis*". Many of these countries that have this pattern also suffer from high unemployment and high youth unemployment, which are often thought to be due to frictions in the labor market such as the rules like high minimum wages, hiring and firing restrictions, and unemployment benefits (Blanchard & Jimeno (1995); Blanchard & Wolfers (2000); Ljungqvist & Sargent (1998)). The *"Labor market frictions hypothesis"* claims that frictions also cause young educated people to be more unemployed. However, there is a second possibility that the cause not be only frictions but it might also be related to productivities. The *"Productivity hypothesis"* offers a complementing explanation where productivity of educated people is not very high relative to less educated people and that's why they are unemployed. I am able to disentangle the two hypotheses because they have different implications for wages. Under the *"Productivity hypothesis"*, we should expect not only high unemployment, but also low wages (Acemoglu (1999)). In contrast, under the *"Labor market frictions hypothesis",* conditional on being unemployed, wages would not be necessarily be depressed as much. Raw data provides suggestive evidence for this negative correlation between the unemployment differential pattern and relative wages (Figure I.4); we should expect a positive correlation if the *"Labor market frictions hypothesis"* is the only relevant explanation. One should also note that in the countries with high prevalence of mismatch, college wage premium may seem depressed due to the fact that high educated people are working in low-skill jobs and earning lower wages. A similar picture with a stronger correlation that is a better representation of actual productivity differences after

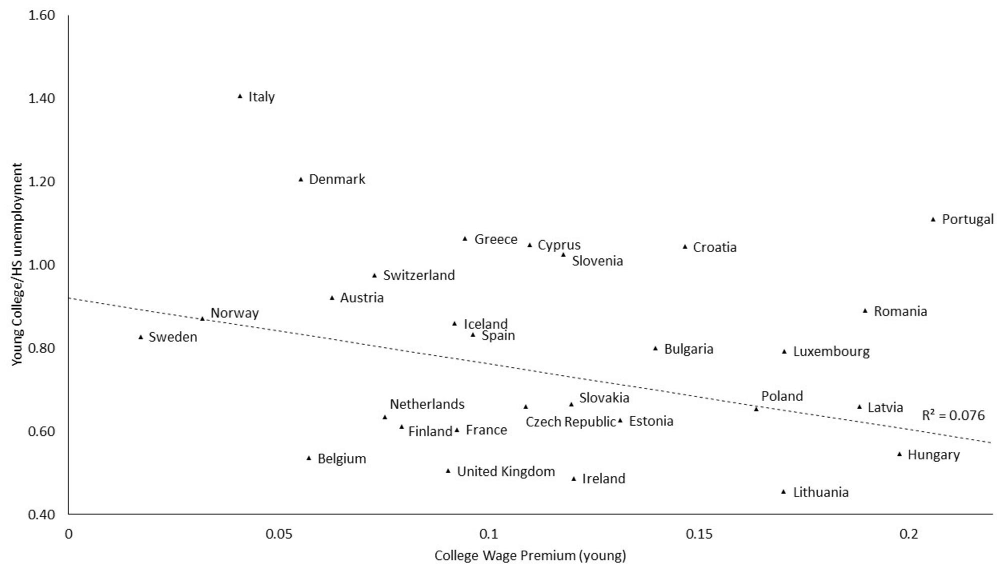


Figure I.4: Relative Unemployment vs. Relative Wage

Note: The college wage premium is the log ratio of average earnings of college graduates to average earnings of high school graduates. It has been calculated for only the 25-29 age bracket and averaged across years 2004-2015 by using EU-SILC. The left axis represents the ratio of college unemployment rates to high school unemployment rate for the age group 25-29 averaged for 2004-2015. Regression results are based on weighted averages according to labor force sizes composed of the 25-29 age group who have at least a high school degree.

taking into account confounding factors will be shown later in the paper.

To incorporate these two potential hypotheses, I am going to estimate a structural model with the following ingredients: The model is going to allow for labor market frictions and also for productivity to vary for different types of workers. It has all the flexibility I need, such as education-age specific labor groups aggregated in unique production function where perfectly competitive production firms are using bargaining firms to hire the type of labor they need. Bargaining firms function in a canonical Mortensen-Pissarides framework with heterogeneous jobs and heterogeneous labor in which job mismatch (highly educated working in low skilled) and on-the-job search (if highly educated are mismatched) are possible. Firms post different types of vacancies, and there is a free-entry condition. I also propose a structural estimation method, which allows me to estimate key parameters of the model such as relative efficiencies. I use confidential European micro-data (EU-SILC) to estimate relative efficiencies between types of workers that are then used in calculation of relative productivity of workers. My model allows me to observe the wage-marginal productivity gap, by which I also update the wage data using the structure of the model to back out marginal product of labor. Moreover, I estimate friction parameters, such as vacancy costs and mismatch, search intensities to match unemployment rates and mismatch rates of different types in the data. I repeat this procedure for all the countries. Hence, I am able to estimate country-specific parameters to make a cross-country comparison in age-education specific unemployment rates.

In order to disentangle the effects of the *"Labor market frictions hypothesis"* and the *"Productivity hypothesis"* in explaining the "*young, educated, unemployed*" phenomenon, I perform a counterfactual analysis. I am able to determine the degree to which productivity and/or labor market frictions play a role in creating those differences. Productivity differences between types of workers will be estimated from the wage data at country level and labor market frictions will be estimated within the model to match the observed rates in the data. First, I aim at targeting age-education specific unemployment rates as well as mismatch rates[2]. To disentangle the effects of two explanations, I am going to perform a counterfactual analysis by asking the question, "What would have happened to Italy if Italy had the same frictions as in the UK?" and vice versa. I repeat this analysis with several two-country pairs: UK vs. Italy, UK vs. Denmark, and Italy vs. Spain.

I also make extensive use of publicly available data to enrich the model and to give additional evidence, such as university completion age, pension replacement rates, job vacancy and migration statistics. I use confidential European micro-data (EU-LFS and EU-SILC) to estimate specific information, such as on-the-job search intensity and mismatch rates for several demographic subgroups and countries. These datasets allow me to address

[2]Mismatch rate in a country is the ratio of college educated people who are working in unskilled occupations relative to the labor force. More details about data description exists in Appendix E.

some questions that may be related such as job search methods, field of study, type of job contracts, college completion rates, migration and family connections. I compare search methods of different age groups in different countries and find that job search methods are more informal (mostly through family connections) in Southern Europe, especially for younger people. I analyze field of study differences across countries for different age groups, focusing on youth and do not find any significant common trend that promises to explain the pattern about unemployment rates. I also show that in the countries with the "*young, educated, unemployed*" phenomenon, we do also observe temporary job contracts more often. Furthermore, those countries do not have a particularly high college completion age, which may give less time to young educated people to find their first job. Finally, through my model, I address the effect of strong family connections in terms of providing income security to youth. I show that this can affect high and low educated people symmetrically with counterfactual implications to what has been observed.

To my best knowledge, this paper is the first to study higher unemployment rates among educated young people by bringing up the pieces referring to both the supply and demand side of the labor market concerning education, mismatch, frictions, and productivity. We can draw several important conclusions from my analysis. In countries with the "*young, educated, unemployed*" phenomenon, the productivity difference between high and low skilled workers is narrower. The productivity difference between young and old within the highly educated group is wider; mismatch rates are also lower. These three facts play a role in determining vacancy creation in favor of unskilled jobs, which worsens the situation of educated workers. In other words, high-skill relative to low-skill vacancy creation is positively correlated with high skilled relative to low skilled efficiency. The available vacancy data also favors of this result. Furthermore, my counterfactual analysis shows that productivity differences between labor groups explain a substantial part of the unemployment rate differences across countries. They even become more important in countries with higher labor market frictions that have high vacancy posting costs and/or low mismatch rates. Several two-country comparisons show that productivity differences can explain 20% to 60% of differences in relative youth unemployment rates of and 25% to 100% of differences in relative unemployment rates of older age groups. My findings are in line with previous literature (Albrecht & Vroman (2002); Acemoglu (1999)) in the sense that having low high-skill productivity pushes the economy towards a low-skill equilibrium with fewer skill jobs and increases overall unemployment rates. However, it differs by first showing that even with skilled productivity being low, cross-skill matching equilibrium[3] can exist; secondly, it affects unemployment rates of subgroups asymmetrically. Finally, endogenizing productivity through a relative supply channel makes general equilibrium effects less pronounced. In this paper, I not only address the "*young, educated, unemployed*" phenomenon but also highlight deeper issues affecting the labor market in these countries. The results suggest that improving education policy and fostering firms' demand for skills may have important roles to play in ameliorating labor market outcomes of the "*young, educated, unemployed*".

2 Related Literature

Unemployment has become a chronic problem in Europe since the '80s. Blanchard & Summers (1987) suggest that hysteresis theories explain this feature as being path-dependent and foreseen to last longer. Ljungqvist & Sargent (1998) argue that high unemployment is due to "welfare states' diminished ability to cope with more turbulent economic times, such as the ongoing restructuring from manufacturing to the service industry, adoption of new information technologies, and a rapidly changing international economy". On the other

[3]Cross-skill matching equilibrium is an equilibrium wherein educated people are performing both skilled and unskilled jobs at the same time, as opposed to ex-post segmentation in which everyone only performs one type of job (Albrecht & Vroman (2002)).

hand, institutional factors in the labor market, such as unemployment benefits, employment protection, and minimum wages have been thought to cause frictions by preventing the labor market's ability to respond economic conditions, which in turn creates even higher unemployment rates. Blanchard & Wolfers (2000) find that shocks seem to be a greater determinant of rising unemployment rates when considering the fact that institutions have existed since a very long time without necessarily causing such an increase. However, the countries that are more successful in achieving lower unemployment rates are the ones that implemented several labor market reforms (Saint-Paul (2004)).

It is not only the overall unemployment but also the youth unemployment problem (especially in Southern Europe) that attracts the most attention in policy debates. In Spain, youth unemployment was chronically high (above 20%) since 2000s, but skyrocketed after 2010 and has never fallen below 40% since. In Italy and Greece, numbers are similar; the youth unemployment rate was 35% by 2016. The focus on the youth labor market starts with Freeman (1976), where the deterioration of the US youth labor market has been attributed to the increasing share of the youth population. This view is later called the "cohort crowding hypothesis", which assumes the baby-boomer generation crowded out the younger generations in labor market, hence we should expect an improvement in youth conditions with the retirement of the baby boomer generation. However, this hypothesis has been tested and has not been found as strong as thought by Korenman & Neumark (2000); Shimer (2001). Labor market dualism, in other words temporary versus permanent job contracts that mostly favor older people, has been thought to increase youth unemployment rates in Spain (Dolado et al. (2015)).

Another pillar of the problem discussed is related to the supply and demand structure of different skills. As university enrollment rates increase in many countries, even at a faster rate in previously less educated countries such as Spain and Portugal, an increase in supply of skilled workers occurs. The term "over-education" is first used by Freeman in the '70s by coining the term, "The Overeducated American" (Freeman & Wise (1982)), mentioning that the college attainment in the US increased at a fast rate, which decreased the college wage premium with the influx of a higher educated supply into the labor market. However, "skill biased technological change" (SBTC) states that the shock to the demand side of the labor market shifted the college wage premium again in favor of educated people in the US during '80s (Katz & Murphy (1992)). The skill biased technological hypothesis assumes that new technologies are complementary to skilled labor; by favoring skill labor, unskilled labor suffered from low wages. In other words wage inequality and/or unemployment increased (Katz & Murphy (1992); Saint-Paul (1994)). However, the slowdown of wage premium during 90's despite the advances in computer technology, operates less in favor of SBTC where Autor et al. (1998) states that skill upgrading and organizational changes contributed to the change in growth in demand for skill labor. Acemoglu (1999) explains changes in wage inequality and unemployment rates mostly harms the less skilled through the increase in the proportion of skilled workers and/or skill-biased technical change, which results in change in the composition of jobs, increasing the demand for skills. Card (2002) also views that SBTC fails to explain not only slowdown in wage premium in the '90s but also other dimensions of wage differences such as gender and racial gaps and age gradient, for which he also introduces age dimension in calculating returns to education (Card & Lemieux (2001)). The patterns of skill premia are summarized by the changes in technology and supply of skills. Acemoglu (2003), on the other hand, introduces the effect of international trade, where he mentions that on top of the classical theory about supply and demand factors, trade also contributes to the effects of SBTC with increases in wage inequality. Some cross-sectional facts are listed by Krueger et al. (2010) and college premium has been found to be highest in the US, Canada, and Mexico and lowest in Germany, Spain, and

Italy. A recent cross-country study to understand patterns of returns to skill by Hanushek et al. (2015) finds that returns to numeracy skills is highest in the US and Germany and lowest in Cyprus, Italy, Denmark, and Norway. Finally, more recent research on skills and employment focuses on the theory of "job polarization" (Acemoglu & Autor (2011);Autor et al. (2006);Goos et al. (2009)).

"Mismatch" and "crowding-out hypothesis", on the other hand, adds another layer to SBTC and its consequences by stating that the situation of lower educated people worsened even more not only due to SBTC but also due to the possibility of mismatch. In other words, higher educated people can work in low skilled jobs for which they are over-qualified if they cannot find suitable jobs. Hence, they become mismatched and perform on-the-job search to find a suitable job for their qualifications. This phenomenon has been thought of as one of the explanations for high unemployment rates among lower educated people because with mismatch possibility, they have been crowded-out from their traditional jobs (Dolado et al. (2000)). A review of OECD countries about the effects of tertiary expansion did not find any evidence for over supply and crowding-out Hansson (2007). Finally, unemployment insurance has been found to help get a suitable job rather than going to mismatch, although it reduces employment (Marimon & Zilibotti (1999)).

Over-education and its consequences in terms of wages was first studied by Duncan & Hoffman (1981) and later summarized by Leuven & Oosterbeek (2011), pointing to the difficulties in estimating the wage effects of over-schooling and under-schooling, hence it has been thought that mismatch literature still requires much attention. Mismatch has also been analyzed in a multi-dimensional way where the definition of mismatch is not only based on the education level, but also some cognitive and non-cognitive skills for each occupation level (Guvenen et al. (2015)). Macro-consequences of mismatch have been studied by Patterson et al. (2016) for the UK market. They do find that sectoral labor misallocation accounts for a "productivity puzzle" in the UK. Similarly, mismatch can also account for the rise in unemployment by lowering aggregate job finding rates (Sahin et al. (2014)). They argue that mismatch in the US explains one-third of the total observed increase in the unemployment rate, which can be more severe for college graduates.

The youth unemployment problem has another facet related to the transition from school to work. The question of interest might also be related to the type of orientation throughout the education system both in terms of the difference between vocational vs. general and field of study. There are subtle differences among European countries, where enrollment rates are low in Italy and high in the UK. Humanities and art majors are highest in Norway and lowest in Finland (Teichler (2000)). Schmitt (2011) points to differences in broad knowledge based systems versus systems providing direct preparation to the labor market and claims that the transition is fast in the UK and slow in Italy. Leuven et al. (2016) argue that the quality of the educational institution has little effect in determining labor market outcomes where there are big differences in payoffs for different fields of studies in Norway.

Finally, skilled migration, which results in brain drain from the sending country and brain gain to the destination country, has been thought of affecting unemployment. Boeri et al. (2012) provide an extensive study on differences in attracting skilled workers worldwide and its effects on employment. They do mention that immigration does not necessarily lower native employment, larger skill share in the population has more of a positive employment effect through complementarity, efficiency and specialization argument. However, the question arises with the ability of not only attracting students but also keeping them in the country to benefit from "brain gain". In that sense, Italy is not able to keep foreign PhD students; 88% of them leave the country. The link between migration and educated unemployment in developing countries has been studied by Fan & Stark (2007) in a search theoretical framework. They suggest that "educated unemployment" is caused by the prospect of international migration (possibility of a brain drain) where the developing country may end up with even more educated workers but still may suffer from brain drain and educated unemployment.

3 Model

I provide a model with rich heterogeneity based on the canonical Mortensen-Pissarides model. The model has heterogeneous labor (young vs. old, educated vs. uneducated) because my question of interest is to explain the differences in unemployment rates across those groups. It also allows for highly educated workers to get mismatched in the low-skill sector[4], hence allowing them to perform on-the-job search because observed mismatch rates across countries also differ and will be targeted in calibration. Mismatch search intensity is endogenous in the model. Furthermore, stochastic aging has also been introduced to link young and old people in order to reflect the idea of life-cycle decision making. Finally, I allow types of workers to be imperfect substitutes to reflect the interdependency of different groups in an economy.

There are four types of workers; young educated, young uneducated, old educated, and old uneducated. They are imperfect substitutes to each other in the production process (Card & Lemieux (2001)). There are heterogeneous jobs: skilled jobs available to young, skilled jobs available to old, unskilled jobs available to young, unskilled jobs available to old (Dolado et al. (2000);Dolado et al. (2009);Albrecht & Vroman (2002)). This allows workers to be matched in different types of jobs where educated workers can work in unskilled jobs,

[4]This paper assumes vertical mismatch which goes only in one direction, i.e. high educated can work in low skilled job but not vice versa. There are other types of mismatches based on more detailed field-occupation categories as well as mismatches according to multidimensional skills such as cognitive, social etc...For my purpose of focusing on unemployment rates and cross-country analysis, vertical mismatch in one direction is a plausible one.

in which case they will called mismatched young and mismatched old. There is stochastic aging to allow young workers to consider their position when they become old. Workers' productivities are functions of their relative efficiencies and relative supply, hence any change in relative supply of one group has potential to affect marginal products of other by creating general equilibrium effects contrary to previous literature (Albrecht & Vroman (2002); Acemoglu (1999)). I use a standard constant returns to scale matching function.

The economy in this model consists of households, production firms, and the bargaining firms[5]. Production firms produce a unique final output by using different types of labor, but they cannot hire workers directly; they need intermediary bargaining firms [6]. Bargaining firms post vacancies to hire each type of labor in the matching process. They provide labor to production firms, and they receive marginal product of labor for each labor they provide.

3.1 Distribution of Labor Force

Summary of the distribution of the labor force in the model is as follows:

$$
\begin{aligned}
1 &= \underbrace{\alpha}_{\text{young}} + \underbrace{(1-\alpha)}_{\text{old}} \\
&= \underbrace{\alpha\mu}_{\text{young uneducated}} + \underbrace{\alpha(1-\mu)}_{\text{young educated}} + \underbrace{(1-\alpha)\hat{\mu}}_{\text{old uneducated}} + \underbrace{(1-\alpha)(1-\hat{\mu})}_{\text{old educated}}
\end{aligned}
$$

$$
\alpha\mu = \underbrace{u(l,y)}_{\text{unemployed}} + \underbrace{L_y}_{\text{employed}}
$$

[5]Distinction between bargaining and production firms is similar to Christiano et al. (2016)

[6]This assumption is not crucial; it is made to have a more clear picture. There is no conflict between production and bargaining firms. One can always think of bargaining firms as human resource departments of production firms. Autor (2008) discusses the functioning of labor market intermediation.

$$\alpha(1-\mu) = \underbrace{u(h,y)}_{\text{unemployed}} + \underbrace{H_y}_{\text{employed in skilled}} + \underbrace{M_y}_{\text{employed in unskilled}}$$

$$(1-\alpha)\hat{\mu} = \underbrace{u(l,o)}_{\text{unemployed}} + \underbrace{L_o}_{\text{employed}}$$

$$(1-\alpha)(1-\hat{\mu}) = \underbrace{u(h,o)}_{\text{unemployed}} + \underbrace{H_o}_{\text{employed in skilled}} + \underbrace{M_o}_{\text{employed in unskilled}}$$

3.2 Households

Households consist of four types of people: young educated, young uneducated, old educated, and old uneducated [7]. Fractions of young people (α), uneducated people within young (μ) and uneducated people within old ($\hat{\mu}$), are exogeneous. They are aging stochastically (de la Croix et al. (2013)): young people become old with probability σ and old people become retired with probability ω[8]. Corresponding labor market tightness functions, job finding and job filling probabilities are given in section 3.5.

Young high educated: Young educated refers to people between 25-29 years old that have at least a college degree. A young high educated unemployed person receives an unemployment benefit of b_y. She can look for jobs in both the skilled and unskilled market, where her search intensity may be different for unskilled jobs ($\tilde{\lambda}_y$[9]). She finds a skilled job with probability of $f(\theta_{2y})$[10] and accepts, thus switches from being unemployed to employed in the skilled market. She may also find an unskilled job with probability of $\tilde{\lambda}_y f(\theta_{1y})$ and may accept it if the job value exceeds the unemployment value. If a young high educated

[7]Young refers to age 25-29, old refers to age 30-64 when matching the model to the data.

[8]Distribution of labor force can be seen in Appendix A.1

[9]$\tilde{\lambda}_y$will be estimated in calibrating the model to target unemployment and mismatch rates observed in data.

[10]θ_{2y} is the tightness of the young skilled market; $f(\theta_{2y})$ is the job finding probability in the corresponding market, in which the function is derived from constant returns to scale matching function.

person is employed in a skilled job, the job can be destroyed exogeneously with probability δ, and she switches to being unemployed. If she is employed in an unskilled job, hence "mismatched", she is performing on-the-job search with some λ_y intensity and finds a job in a skilled market with probability $f(\theta_{2y})$. In this case, she switches from a "mismatched" state to an "employed in skilled sector" state. Finally, stochastic aging implies that she may become "old" with probability σ. The decision problem can be described by the following Bellman equations:

- Value of being unemployed:

$$
\begin{aligned}
rU(h,y) = \; & \underbrace{b_y}_{\substack{\text{unemp. benefit} \\ \text{or outside option}}} + \underbrace{(f(\theta_{2y})}_{\substack{\text{job find. probability} \\ \text{in skilled market}}} \underbrace{[W(s,h,y) - U(h,y)]}_{\substack{\text{switch from unemployment} \\ \text{to employment}}} \\
& + \underbrace{\tilde{\lambda}_y}_{\substack{\text{mismatch search} \\ \text{intensity}}} \underbrace{f(\theta_{1y})}_{\substack{\text{job finding probability} \\ \text{in unskilled market}}} \underbrace{\max[0, W(n,h,y) - U(h,y)]}_{\substack{\text{switch from unemp.} \\ \text{to employment} \\ \text{if worthwhile}}} \\
& + \underbrace{\sigma[U(h,o) - U(h,y)]}_{\text{switch to "old" state}}
\end{aligned}
\tag{I.1}
$$

- Value of working in a skilled market:

$$
\begin{aligned}
rW(s,h,y) = \underbrace{w(s,h,y)}_{\text{wage}} + &\underbrace{\delta}_{\substack{\text{job}\\ \text{destruction}}} \underbrace{[U(h,y) - W(s,h,y)]}_{\substack{\text{switch from unemp.}\\ \text{to employment}}} \\
+ &\underbrace{\sigma[W(s,h,o) - W(s,h,y)]}_{\text{switch to "old" state}}
\end{aligned}
\tag{I.2}
$$

- Value of working in an unskilled market:

$$
\begin{aligned}
rW(n,h,y) = \underbrace{w(n,h,y)}_{\text{wage}} + &\underbrace{\delta}_{\substack{\text{job}\\ \text{destruction}}} \underbrace{[U(h,y) - W(n,h,y)]}_{\substack{\text{switch from employment}\\ \text{to unemployment}}} \\
+ &\underbrace{\lambda_y}_{\substack{\text{on-the-job search}\\ \text{intensity}}} \underbrace{f(\theta_{2y})}_{\substack{\text{job finding probability}\\ \text{in skilled market}}} \underbrace{[W(s,h,y) - W(n,h,y)]}_{\text{switch to skilled job}} \\
+ &\underbrace{\sigma[W(n,h,o) - W(n,h,y)]}_{\text{switch to "old" state}}
\end{aligned}
\tag{I.3}
$$

Young low educated: Young educated refers to people between 25-29 years old and have a high school degree. A young low educated unemployed person receives an unemployment benefit of b_y. She can only look for jobs in unskilled market. She finds an unskilled job with a probability of $f(\theta_{1y})$ and accepts, thus switching from being unemployed to employed in an unskilled market. When a young low educated person is employed, the job can be destroyed exogeneously with probability δ, and she switches to being unemployed. Finally, stochastic aging implies that she may become "old" with probability σ.

- Value of being unemployed:

$$rU(l,y) = b_y + \underbrace{f(\theta_{1y})}_{\substack{\text{job finding probability} \\ \text{in unskilled market}}} [W(n,l,y) - U(l,y)] + \sigma[U(l,o) - U(l,y)] \quad \text{(I.4)}$$

- Value of working in unskilled market:

$$rW(n,l,y) = w(n,l,y) + \delta[U(l,y) - W(n,l,y)] + \sigma[W(n,l,o) - W(n,l,y)] \quad \text{(I.5)}$$

Old high educated: Old educated refers to people between ages 30-64 years old and have at least a college degree. An old high educated unemployed person receives an unemployment benefit of b_o. She can look for jobs in both the skilled and unskilled market, where her search intensity is less for unskilled jobs ($\tilde{\lambda}_o$). She finds a skilled job with a probability of $f(\theta_{2o})$ and accepts, thus switching from being unemployed to employed in a skilled market. She may also find an unskilled job with a probability of $\tilde{\lambda}_o f(\theta_{1o})$ and may accept it if the job value exceeds the unemployment value. If an old high educated person is employed in a skilled job, the job can be destroyed exogeneously with probability δ and she switches and becomes unemployed. If she is employed in an unskilled job, hence "mismatched", she is performing on-the-job search with some λ_o intensity and finds a job in skilled market with probability $f(\theta_{2o})$. In this case, she switches from a "mismatched" state to an "employed in skilled sector" state. Finally, stochastic aging implies that she may become "retired" with probability ω and continue to receive pension benefits, which is a function of her last wage. [11]

- Value of being unemployed:

$$\begin{aligned} rU(h,o) = b_o + & \underbrace{(f(\theta_{2o})}_{\substack{\text{job finding probability}\\ \text{in skilled market}}} [W(s,h,o) - U(h,o)] \\ & + \underbrace{\tilde{\lambda}_o}_{\substack{\text{mismatch search}\\ \text{intensity}}} \underbrace{f(\theta_{1o})}_{\substack{\text{job finding probability}\\ \text{in unskilled market}}} \underbrace{\max[0, W(n,h,o) - U(h,o)]}_{\substack{\text{switch from unemp}\\ \text{to employment}\\ \text{if worthwhile}}} \\ & + \underbrace{\omega[\underbrace{R(h,u)}_{\substack{\text{value of retirement}\\ \text{for high educated unemployed}}} - U(h,o)]}_{\text{switch to "retirement" state}} \end{aligned} \tag{I.6}$$

[11]Details of retirement value can be found in section 3.5

- Value of working in skilled market:

$$rW(s,h,o) = w(s,h,o) + \delta[U(h,o) - W(s,h,o)] + \omega[\underbrace{R(s,h)}_{\substack{\text{value of retirement}\\ \text{for high skilled}}} - W(s,h,o)] \tag{I.7}$$

- Value of working in unskilled market:

$$\begin{aligned} rW(n,h,o) &= w(n,h,o) + \delta[U(h,o) - W(n,h,o)] \\ &+ \underbrace{\lambda_o}_{\substack{\text{on-the-job search}\\ \text{intensity}}} \underbrace{f(\theta_{2o})}_{\substack{\text{job finding probability}\\ \text{in skilled market}}} [W(s,h,o) - W(n,h,o)] \\ &+ \omega[\underbrace{R(n,h)}_{\substack{\text{value of retirement}\\ \text{for mismatched}}} - W(n,h,o)] \end{aligned} \tag{I.8}$$

Old low educated: Old low educated refers to people between 30-64 years old and have a high school degree. An unemployed old low educated person receives an unemployment benefit of b_o. She can only look for jobs in unskilled market. She finds an unskilled job with a probability of $f(\theta_{1o})$ and accepts, thus switching from being unemployed to employed in unskilled market. When an old low educated person is employed, the job can be destroyed exogeneously with probability δ and she switches to become unemployed. Finally, stochastic aging implies that she may become "retired" with probability ω and continue to receive pension benefits, which is a function of her last wage[12].

- Value of being unemployed:

$$rU(l,o) = b_o + f(\theta_{1o})[W(n,l,o) - U(l,o)] + \omega[\underbrace{R(l,u)}_{\substack{\text{value of retirement} \\ \text{for low educated unemployed}}} - U(h,o)] \tag{I.9}$$

- Value of working in unskilled market:

$$rW(n,l,o) = w(n,l,o) + \delta[U(l,o) - W(n,l,o)] + \omega[\underbrace{R(n,l)}_{\substack{\text{value of retirement} \\ \text{for low skilled}}} - W(n,l,o)] \tag{I.10}$$

3.3 Bargaining Firms

The role of the bargaining firms in this model is similar to a classical firm in search matching model à la Mortensen-Pissarides. They observe the productivity level of each type of worker, job switching probabilities, and post vacancies available for each type of labor: skilled young, skilled old, unskilled young, and unskilled old. Skilled jobs can only be filled by educated workers; low skilled jobs can be filled by uneducated workers or educated

[12]Details of retirement value can be found in section 3.5

workers, in which case they will be called mismatched workers. Nash Bargaining occurs between workers and bargaining firms and wage is determined[13]. Bargaining firms create one unit of labor from each match and provide that to production firms and get marginal product of that type of labor as revenue. They pay wage as labor cost and initial vacancy costs for each vacancy that they post. They are paying vacancy costs for skilled jobs posted for young and old (c_{2y}, c_{2o}), as well as low skilled jobs posted for young and old (c_{1y}, c_{1o}). The problem from the firm side is simple, as firms are posting different vacancies available for every type of labor and face only one tightness for their corresponding job filling probabilities[14]. Skilled jobs can only be filled by educated workers, but unskilled jobs can be filled by both types, so it depends on the probability of who comes first. When a vacancy is filled, a firm switches from vacancy state to job state. Hence, the value of a vacancy $V(i,j)$[15], where $i \in \{s,n\}$ for skilled and low skilled and $j \in \{y,o\}$ for a job posted for young becomes:

- Value of skilled vacancy available for young:

$$rV(s,y) = \underbrace{-c_{2y}}_{\substack{\text{skilled vacancy cost}\\ \text{available to young}}} + \underbrace{p(\theta_{2y})}_{\substack{\text{skilled job filling}\\ \text{probability by young}}} \underbrace{[J(s,h,y) - V(s,y)]}_{\substack{\text{switch from vacancy}\\ \text{to job state}}} \tag{I.11}$$

[13]See Section 3.5 for surplus sharing equations
[14]Details of job filling probabilities can be found in Section 3.5
[15]Free-entry condition implies $V(i.j) = 0$ for all i,j.

- Value of unskilled vacancy available for young:

$$rV(n,y) = -c_{1y} + \underbrace{\kappa_{ny}}_{\substack{\text{prob. of facing}\\ \text{low educated}}} \underbrace{p(\theta_{1y})}_{\substack{\text{unskilled job}\\ \text{filling probability}}} \underbrace{[J(n,l,y) - V(n,y)]}_{\substack{\text{switch from vacancy}\\ \text{to job state}}} \tag{I.12}$$

$$+ \underbrace{(1-\kappa_{ny})}_{\substack{\text{probability of facing}\\ \text{high educated}}} \underbrace{p(\theta_{1y})}_{\substack{\text{unskilled job}\\ \text{filling probability}}} \underbrace{[J(n,h,y) - V(n,y)]}_{\substack{\text{switch from vacancy to}\\ \text{mismatched job state}}}$$

where κ_{ny} is the probability of facing an uneducated young worker and κ_{no} is the probability of facing a low educated old worker. ($\kappa_{ny} = \frac{u(l,y)}{u(l,y)+\tilde{\lambda}_y u(h,y)}$,$\kappa_{no} = \frac{u(l,o)}{u(l,o)+\tilde{\lambda}_o u(h,o)}$)

- Value of skilled vacancy available for old:

$$rV(s,o) = \underbrace{-c_{2o}}_{\substack{\text{skilled vacancy cost}\\ \text{available to old}}} + \underbrace{p(\theta_{2o})}_{\substack{\text{skilled job filling}\\ \text{probability by old}}} \underbrace{[J(s,h,o) - V(s,o)]}_{\substack{\text{switch from vacancy}\\ \text{to job state}}} \tag{I.13}$$

- Value of unskilled vacancy available for old:

$$rV(n,o) = -c_{1o} + \underbrace{\kappa_{no}}_{\substack{\text{prob of facing}\\ \text{low educated}}} \underbrace{p(\theta_{1o})}_{\substack{\text{unkilled job}\\ \text{filling prob}}} \underbrace{[J(n,l,o) - V(n,o)]}_{\substack{\text{switch from vacancy}\\ \text{to job state}}} \tag{I.14}$$
$$+ \underbrace{(1-\kappa_{no})}_{\substack{\text{probability of facing}\\ \text{high educated}}} \underbrace{p(\theta_{1o})}_{\substack{\text{unskilled job}\\ \text{filling probability}}} \underbrace{[J(n,h,o) - V(n,o)]}_{\substack{\text{switch from vacancy to}\\ \text{mismatched job state}}}$$

When a job is created, a worker will produce her marginal product of labor, which will depend on her type, her relative efficiency, and relative supply. The firm pays the corresponding wage, which is determined in equilibrium. The job can be destroyed with exogenous probability δ, and the firm switches from job state to vacancy state. Note that for a mismatched worker, the job destruction rate becomes $\delta + \lambda f(\theta_2)$. With δ probability, the job is destroyed exogenously; with $\lambda f(\theta_2)$ probability, the worker will find a job in the skilled sector and quit the job.

- Value of skilled job filled by young:

$$rJ(s,h,y) = \underbrace{MPL(H_y)}_{\substack{\text{marginal product of}\\ \text{young high skilled}}} - \underbrace{w(s,h,y)}_{\substack{\text{young high}\\ \text{skilled wage}}}$$
$$+\,\delta \underbrace{[V(s) - J(s,h,y)]}_{\substack{\text{switch from job}\\ \text{to vacancy state}}} + \underbrace{\sigma[J(s,h,o) - J(s,h,y)]}_{\text{switch to old state}}$$

- Value of skilled job filled by old:

$$rJ(s,h,o) = \underbrace{MPL(H_o)}_{\substack{\text{marginal product of}\\ \text{old high skilled}}} - \underbrace{w(s,h,o)}_{\substack{\text{old high}\\ \text{skilled wage}}} \tag{I.15}$$
$$+\,(\underbrace{\delta}_{\substack{\text{exogeneous}\\ \text{job destruction}}} + \underbrace{\omega}_{\substack{\text{retirement}\\ \text{probability}}})\underbrace{[V(s) - J(s,h,o)]}_{\substack{\text{switch from job}\\ \text{to vacancy state}}}$$

- Value of unskilled job filled by young low educated:

$$
\begin{aligned}
rJ(n,l,y) = & \underbrace{MPL(L_y)}_{\substack{\text{marginal product of} \\ \text{young low skilled}}} - \underbrace{w(n,l,y)}_{\substack{\text{young low} \\ \text{skilled wage}}} \\
& + \delta \underbrace{[V(n) - J(n,l,y)]}_{\substack{\text{switch from job} \\ \text{to vacancy state}}} + \underbrace{\sigma[J(n,l,o) - J(n,l,y)]}_{\text{switch to old state}}
\end{aligned}
$$

- Value of unskilled job filled by old low educated:

$$
\begin{aligned}
rJ(n,l,o) = & \underbrace{MPL(L_o)}_{\substack{\text{marginal product of} \\ \text{old low skilled}}} - \underbrace{w(n,l,o)}_{\substack{\text{old low} \\ \text{skilled wage}}} \\
& + (\underbrace{\delta}_{\substack{\text{exogeneous} \\ \text{job destruction}}} + \underbrace{\omega}_{\substack{\text{retirement} \\ \text{probability}}}) \underbrace{[V(n) - J(n,l,o)]}_{\substack{\text{switch from job} \\ \text{to vacancy state}}}
\end{aligned}
\tag{I.16}
$$

- Value of unskilled job filled by young high educated:

$$rJ(n,h,y) = \underbrace{MPL(M_y)}_{\substack{\text{marginal product of}\\ \text{young mismatched}}} - \underbrace{w(n,h,y)}_{\substack{\text{young}\\ \text{mismatched wage}}}$$
$$+ [\delta + \underbrace{\lambda_y f(\theta_{2y})}_{\text{on the job search}}][V(n) - J(n,h,y)] + \sigma[J(n,h,o) - J(n,h,y)]$$

- Value of unskilled job filled by old high educated:

$$rJ(n,h,o) = \underbrace{MPL(M_o)}_{\substack{\text{marginal product of}\\ \text{old mismatched}}} - \underbrace{w(n,h,o)}_{\substack{\text{old}\\ \text{mismatched wage}}} \tag{I.17}$$
$$+ [\delta + \underbrace{\lambda_o f(\theta_{2o})}_{\text{on the job search}} + \underbrace{\omega}_{\text{retirement probability}}][V(n) - J(n,h,o)]$$

3.4 Production Firms

Production firms are perfectly competitive and need two types of workers (low skilled and high skilled) to produce the final output (Card & Lemieux (2001)). Aggregate production function is given by:

$$Y = [\theta_h H^\rho + \theta_l \tilde{L}^\rho]^{1/\rho}$$

H is skilled (high educated) labor, $\tilde{L}$ is effective low skilled labor (high or low educated), θ_h and θ_l are technological efficiency parameters, and $\rho = 1 - \frac{1}{\sigma_E}$ is a function of elasticity of substitution (σ_E) between education levels in the production function. Effective low skilled labor can be either high or low educated because high educated workers can perform low skilled jobs, and in such a case, we call them "mismatched workers". They are perfect substitutes of each other but may have different efficiencies.

$$\tilde{L} = \alpha_p M + L$$

L is low educated, low skilled labor, M is high educated, low skilled labor (mismatched), and α_p is relative efficiency of mismatched labor compared to low educated labor.

Each type of labor is formed by young and old workers who are imperfect substitutes of each other, where ψ_p, β_p, γ_p are relative efficiencies of young workers with respect to old for high educated, mismatched and low educated, respectively, and $\eta = 1 - \frac{1}{\sigma_A}$ is a function of elasticity of substitution between age levels .

$$H = [\psi_p H_y^\eta + H_o^\eta]^{1/\eta}$$

$$M = [\beta_p M_y^\eta + M_o^\eta]^{1/\eta}$$

$$L = [\gamma_p L_y^\eta + L_o^\eta]^{1/\eta}$$

Production firms observe labor supply determined in the bargaining process, and production occurs. Marginal product of each type of labor, which is a function of relative efficiencies and relative supply, is determined and given to bargaining firms for each labor they provide to production firms.

3.5 Equilibrium Conditions

There is standard constant returns to scale matching function $m(v,u) = v^{1/2}u^{1/2}$. Since we have 4 different markets, corresponding matching functions are as follows:

- $m(v(n,y), u(l,y) + \tilde{\lambda}_y u(h,y))$
- $m(v(n,o), u(l,o) + \tilde{\lambda}_o u(h,o))$
- $m(v(s,y), u(h,y) + \lambda_y M_y)$
- $m(v(s,o), u(h,o) + \lambda_o M_o)$

Without loss of generality, probability of finding a job is $f(\theta) = \theta p(\theta)$ and $p(\theta) = m(1, 1/\theta)$ is probability of filling a vacancy where θ is labor market tightness.$v(i,j)$ stands for number of vacancies where $i \in \{n, s\}$ for low skilled, skilled jobs and mismatch jobs and $j \in \{y, o\}$ for young and old. $u(i,j)$ stands for number of unemployed people where $i \in \{l, h\}$ for low educated and high educated and $j \in \{y, o\}$ for young and old. Finally, M_y and M_o stands for educated workers working in low skilled market. Note that since educated workers search in mismatched market less intensely, the actual number of job seekers in mismatched market becomes $\tilde{\lambda}_y u(h,y)$ for young where $\tilde{\lambda}_y$ is search intensity in low skilled market. Also, the actual number of job seekers in skilled market is $u(h,y) + \lambda_y M_y$ where both unemployed educated people are seeking for a job and mismatched workers are performing on-the-job search with intensity λ. There are 4 labor market tightness parameters determined endogenously. θ_{1y} is for young low skilled market, θ_{1o} is for old low skilled market, θ_{2y} is for young skilled market, θ_{2o} is for old skilled market:

- $\theta_{1y} = \frac{v(n,y)}{u(l,y)+\tilde{\lambda}_y u(h,y)}$
- $\theta_{1o} = \frac{v(n,o)}{u(l,o)+\tilde{\lambda}_o u(h,o)}$
- $\theta_{2y} = \frac{v(s,y)}{u(h,y)+\lambda_y M_y}$
- $\theta_{2o} = \frac{v(s,o)}{u(h,o)+\lambda_o M_o}$

Value of being retired is fixed and depends on worker's last job where people receive ν fraction[16] of their last income (except the case of switching from being unemployed to employed where they receive the same benefit) where:

$R(h,u) = b_o/r$, $R(l,u) = b_o/r$, $R(n,l) = \upsilon w(n,l,o)/r$, $R(s,h) = \upsilon w(s,h,o)/r$, $R(n,h) = \upsilon w(n,h,o)/r$

Bargaining firms determine wages with Nash Bargaining where the surplus sharing rule is:

$$\underbrace{(1-\beta)}_{\text{firm's bargaining share}} [W(i,j,k) - U(j,k)] = \underbrace{\beta}_{\text{worker's bargaining share}} [J(i,j,k) - V(i,k)]$$

$$(1-\beta)[W(s,h,y) - U(h,y)] = \beta[J(s,h,y) - V(s,y)] \tag{I.18}$$

$$(1-\beta)[W(s,h,o) - U(h,o)] = \beta[J(s,h,o) - V(s,o)] \tag{I.19}$$

$$(1-\beta)[W(n,h,y) - U(h,y)] = \beta[J(n,h,y) - V(s,y)] \tag{I.20}$$

[16]Country specific pension replacement rates are used in calibration. See Appendix A for details.

$$(1-\beta)[W(n,h,o)-U(h,o)] = \beta[J(n,h,o)-V(s,o)] \tag{I.21}$$

$$(1-\beta)[W(n,l,y)-U(l,y)] = \beta[J(n,l,y)-V(n,y)] \tag{I.22}$$

$$(1-\beta)[W(n,l,o)-U(l,o)] = \beta[J(n,l,o)-V(n,o)] \tag{I.23}$$

Steady state conditions:

For each market; the left-hand sides are for people entering the market and right-hand sides are people leaving the market

- **Skilled Market:**

$$\underbrace{f(\theta_{2y})(u(h,y)+\lambda_y M_y)}_{\text{inflow to emp by unemp and mismatched high educated young}} = \underbrace{(\delta+\sigma)[\alpha(1-\mu)-u(h,y)-M_y]}_{\text{outflow from employment}} \tag{I.24}$$

$$\underbrace{f(\theta_{2o})\overbrace{(u(h,o)+\lambda_o M_o)}^{\text{due to job finding}}+\overbrace{\sigma[\alpha(1-\mu)-u(h,y)-M_o]}^{\text{due to switch to old state}}}_{\text{inflow to emp by unemp and mismatched high educated old}} = \underbrace{(\delta+\omega)[(1-\alpha)(1-\hat{\mu})-u(h,o)-M_o]}_{\text{outflow from employment}} \tag{I.25}$$

- **Unskilled Market:**

$$\underbrace{f(\theta_{1y})u(l,y)}_{\text{inflow to emp by unemployed low educated}} = \underbrace{(\delta+\sigma)(\alpha\mu-u(l,y))}_{\text{outflow from employment}} \tag{I.26}$$

$$\underbrace{\overbrace{f(\theta_{1o})u(l,o)}^{\text{due to job finding}} + \overbrace{\sigma[(\alpha\mu-u(l,y))]}^{\text{due to switch to old state}}}_{\text{inflow to emp by low educated old}} = \underbrace{(\delta+\omega)((1-\alpha)\hat{\mu}-u(l,o))}_{\text{outflow from employment}} \tag{I.27}$$

- **Mismatch Market:**

$$\underbrace{f(\theta_{1y})u(h,y)\tilde{\lambda}_y}_{\text{inflow to mismatch by high educated young}} = \underbrace{[\delta + f(\theta_{2y})\lambda_y + \sigma]M_y}_{\text{outflow from mismatch}} \tag{I.28}$$

$$\underbrace{\overbrace{f(\theta_{1o})u(h,o)\tilde{\lambda}_o}^{\text{due to job finding}} + \overbrace{\sigma M_y}^{\text{due to switch to old state}}}_{\text{inflow to mismatch by high educated old}} = \underbrace{[\delta + f(\theta_{2o})\lambda_o + \omega]M_o}_{\text{outflow from mismatch}} \tag{I.29}$$

We assume free entry condition which implies $V(i,j) = 0$ for all i and j.

Finally, marginal product of labor of each type is as follows:

$$MPL(H_y) = \frac{\partial Y}{\partial H_y} = \theta_h \psi_p Y^{1-\rho} H^{\rho-\eta} H_y^{\eta-1} \tag{I.30}$$

$$MPL(H_o) = \frac{\partial Y}{\partial H_o} = \theta_h Y^{1-\rho} H^{\rho-\eta} H_o^{\eta-1} \tag{I.31}$$

$$MPL(M_y) = \frac{\partial Y}{\partial M_y} = \theta_l \alpha_p \beta_p Y^{1-\rho} \tilde{L}^{\rho-1} M^{1-\eta} M_y^{\eta-1} \tag{I.32}$$

$$MPL(M_o) = \frac{\partial Y}{\partial M_o} = \theta_l \alpha_p Y^{1-\rho} \tilde{L}^{\rho-1} M^{1-\eta} M_o^{\eta-1} \tag{I.33}$$

$$MPL(L_y) = \frac{\partial Y}{\partial L_y} = \theta_l \gamma_p Y^{1-\rho} \tilde{L}^{\rho-1} L^{1-\eta} L_y^{\eta-1} \tag{I.34}$$

$$MPL(L_o) = \frac{\partial Y}{\partial L_o} = \theta_l Y^{1-\rho} \tilde{L}^{\rho-1} L^{1-\eta} L_o^{\eta-1} \tag{I.35}$$

Equilibrium is determined by production and bargaining firms simultaneously. Bargaining firms take the productivity of each type of labor determined by production firms as given and post vacancies and determine wages accordingly. Production firms observe the labor supply determined in the bargaining process and produce output accordingly. Labor market equilibrium consists of a set of values which are the number of unemployed $(u(h,y), u(h,o), u(l,y), u(l,o))$, mismatched workers $(M_y,\ M_o)$, number of vacancies $(v(s,y),\ v(s,o),\ v(n,y),\ v(n,o))$ and wages $(w(s,h,y),\ w(s,h,o),\ w(n,l,y),\ w(n,l,o),\ w(n,h,y),\ w(n,h,o))$ which solve 20 asset value equations, 6 steady state conditions, 6 surplus sharing equations with 4 free entry conditions. For an interior solution, necessary restrictions are as follows: 1-Wages should be greater than zero. 2-Value of a job to firm is greater than zero. 3-Value of being employed is greater than value of being unemployed.

In equilibrium, marginal product of labor is determined by the number of workers employed in each type of market. In turn, bargaining firms receive this as revenue and hire workers for the production firm. Equilibrium is characterized by:

- Given marginal productivity, labor market solution (between workers and bargaining firms) gives number of employed people in each category.
- Given number of people in each category production side gives marginal productivity in each category.

3.6 Model Properties

In this section, I would like to show how equilibrium outcomes change with different features of the model. My model consists of some additional features compared to a standard version of the Mortensen-Pissarides model. First of all, markets are not independent from each other; imperfect substitution between age groups and education groups make them interdependent on each other, producing general equilibrium effects. Moreover, stochastic aging brings the idea of considering to enter into different markets for young people, where market tightness and job switching probabilities are different. Finally, allowing for mis-

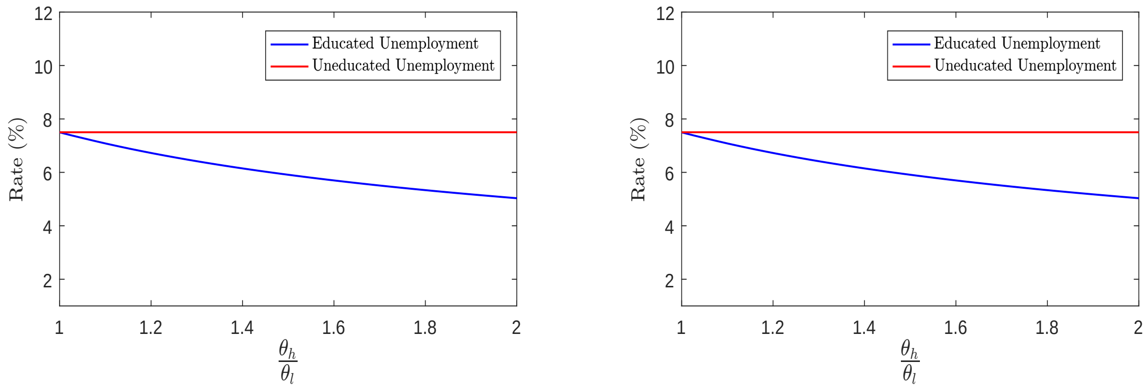


Figure I.5: Relative Technological Efficiency vs. Unemployment Rates: Symmetric Case

match, hence on-the-job search, certainly affects the unemployed pool among the educated, as well as market tightness for the uneducated. (See Table IV.4 for parameter values for each case)

The question of interest in this paper is relative unemployment rates between the educated and uneducated for young and old separately. Throughout the analysis, I am going to focus on these two measures: (u_{hy}/u_{ly} for referring to the ratio of young college unemployment rate to young high school unemployment rate, and u_{ho}/u_{lo} for the old group). First, consider a baseline economy that is completely segregated (no possibility of mismatch) where everything is symmetric between groups (i.e.they are perfect substitutes to each other and there is no stochastic aging, there are equal number of people in each category, they all have the same productivity, vacancy posting costs for different jobs are the same). In this scenario, unemployment rates across groups should be the same. Now, I examine the effect of increasing relative technological efficiency (θ_h/θ_l) on unemployment rates. Figure I.5 shows that as educated workers become relatively more and more productive, they have lower unemployment rates because firms create more vacancies as a response. But there is no impact on lower educated unemployment rates, as markets are completely segregated.

As a second step, I introduce imperfect substitution between age and education groups

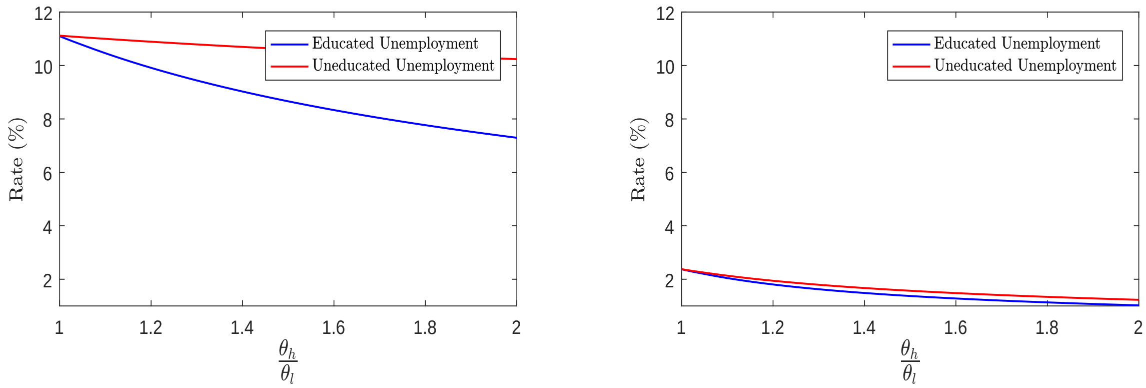
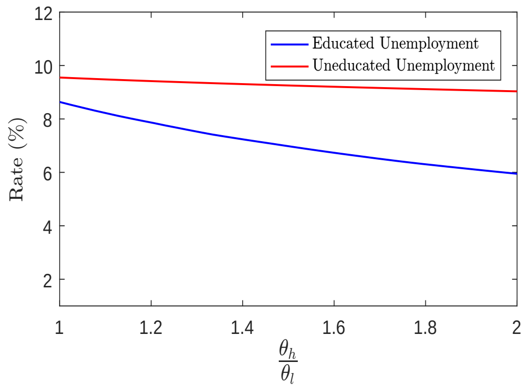


Figure I.6: Relative Technological Efficiency vs. Unemployment Rates: Imperfect Substitution, Stochastic Aging

as well as stochastic aging. Imperfect substitution makes types of workers interdependent on each other. Hence, productivity increase on one side also affects the outcomes of the other side. In other words, not only do educated workers have lower unemployment rates as their productivity increases, but also lower educated workers' unemployment decreases slightly because overall productivity in the economy is higher, which fosters job creation. Stochastic aging, on the other hand, works in determining relative unemployment rates of young vs. old due to the prospect of the future. Since retirement value depends on the last wage received, old people do not prefer entering into retirement from unemployment. That's why stochastic aging decreases the unemployment level of old people (Figure I.6). Moreover, knowing that old workers earn higher wages, young people are less willing to accept jobs, which increases youth unemployment rates. This feature also matches the unemployment rates observed in the data, as youth unemployment rate is always much higher than overall unemployment rate.

Third, I introduce simple macro-evidences into the model: i.e., young ratio in the labor force (fewer than old) and educated ratio (fewer than uneducated) among young and old to see the composition effects at unemployment levels and the effects of increasing the relative



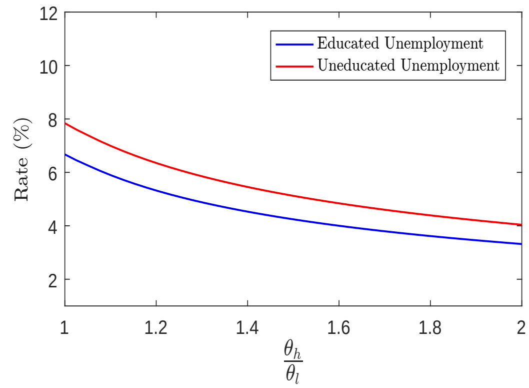


Figure I.7: Relative Technological Efficiency vs. Unemployment Rates: Relative Supply

technological efficiency (θ_h/θ_l) on unemployment rates together with composition effects. There are fewer young people (age 25-29) in the work force than older people. Hence, introducing the characteristics of population structure instead of having equal numbers of young and old produces a relative supply effect, decreases the unemployment rate of young, and increases unemployment rate of old. Moreover, there are more uneducated workers than educated workers in the work force. Hence, decreasing the education ratio again produces a relative supply effect and decreases the unemployment rate of educated relative to uneducated; even with an equal productivity level $(\theta_h/\theta_l = 1)$, educated people have lower unemployment rates (Figure I.7).

As a fourth step, I introduce the mismatch channel with an average intensity by allowing educated people to search in the unskilled market and perform on-the-job search if they are mismatched. The first direct effect is on the educated unemployment rate; the ability to work in other markets decreases the educated unemployment rate. More importantly, the mismatch channel dampens the effect of technological efficiency on unemployment rates. In other words, changes in unemployment rates become less responsive to the change in relative technological efficiency (See Figure I.8; the slope decreases relative to Figure I.7). The mechanism behind that is when educated workers become more and more productive, they

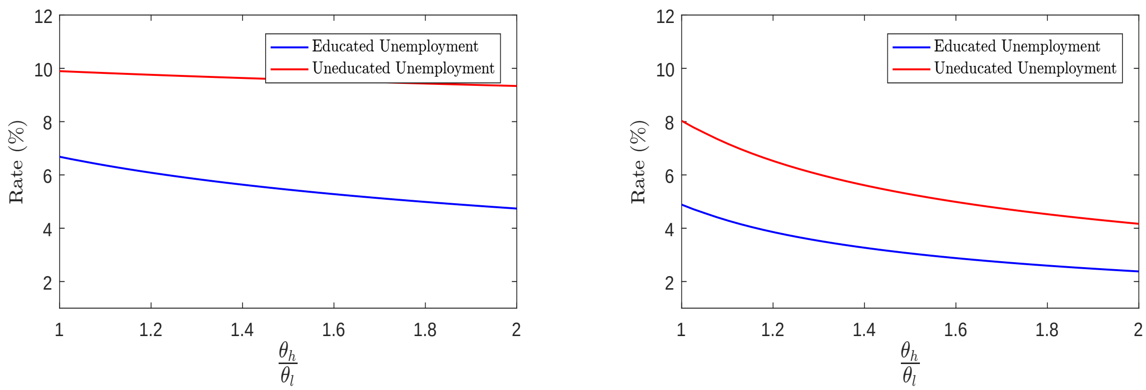
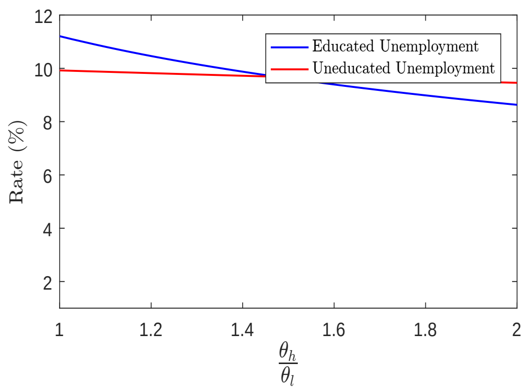


Figure I.8: Relative Technological Efficiency vs. Unemployment Rates: Mismatch Channel

have lower unemployment rates, as skilled vacancy creation is fostered as before. But when they become more productive, mismatched workers also start to switch to skilled jobs, which inflates the skilled job seekers' pool further and dampens the decrease in unemployment rate in response to technological efficiency.

Finally, I exogenously increase the vacancy posting cost of skilled jobs available to young. Figure I.9 shows that the young educated unemployment rate jumps because firms create much less skilled vacancies available to them. For low levels of relative technological efficiency, educated young have a higher unemployment rate than uneducated young, but that reverses as they get more and more productive. In other words, if educated workers have very high productivity relative to the uneducated, they will still perform better in terms of unemployment, despite the fact that labor market frictions (e.g. high vacancy costs) are destroying their jobs. However, if they are not particularly different than low educated workers and skilled job creation is too costly, then they have higher unemployment rates.

All in all, examining different channels of the model by building up each part step by step allows me to see how unemployment rates change and how the response of unemploy-



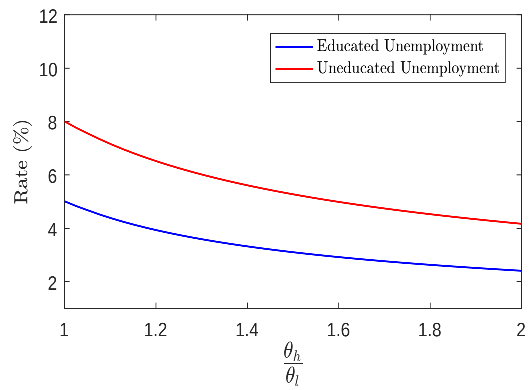


Figure I.9: Relative Technological Efficiency vs. Unemployment Rates: Vacancy Cost

ment rates changes. The three main lessons in this exercise are as follows: The relative technological efficiency is an important determinant for relative unemployment rates; mismatch channel makes labor market flows more fluid, hence less responsive to other shocks; vacancy posting cost, as well as mismatch intensity, determines the level of unemployment.

4 Structural Estimation

I take weighted mean of the left hand sides[17] of the second equations to get estimates of right hand sides. The regressions are weighted according to the aggregated employment level of every country. Hence H, M, L which are the aggregate number of high educated working in high skilled jobs, low educated working in low skilled jobs and mismatched workers (high educated working in low skilled jobs) in the economy can be calculated.

$$\frac{MPL(H_y)}{MPL(H_o)} = \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial H_o}} = \psi_p(\frac{H_y}{H_o})^{\eta-1} \Longrightarrow log(\frac{MPL(H_y)}{MPL(H_o)})_{it} - (\eta-1)log(\frac{H_y}{H_o})_{it} = log(\psi_p)$$

[17]Subscript i refers to the country and t refers to year.

$$\frac{MPL(M_y)}{MPL(M_o)} = \frac{\frac{\partial Y}{\partial My}}{\frac{\partial Y}{\partial M_o}} = \beta_p(\frac{M_y}{M_o})^{\eta-1} \Longrightarrow log(\frac{MPL(M_y)}{MPL(M_o)})_{it} - (\eta-1)log(\frac{M_y}{M_o})_{it} = log(\beta_p)$$

$$\frac{MPL(L_y)}{MPL(L_o)} = \frac{\frac{\partial Y}{\partial L_y}}{\frac{\partial Y}{\partial L_o}} = \gamma_p(\frac{L_y}{L_o})^{\eta-1} \Longrightarrow log(\frac{MPL(L_y))}{MPL(L_o)})_{it} - (\eta-1)log(\frac{L_y}{L_o})_{it} = log(\gamma_p)$$

The ratio of marginal product of labor of mismatched workers to low skilled workers helps to identify relative efficiency between mismatched and low educated workers (α_p). Below 2 equations identify α_p together. Hence, $\tilde{L}$ which is the effective number of low skilled workers in the economy can be calculated.

$$\frac{MPL(M_y)}{MPL(L_y)} = \frac{\frac{\partial Y}{\partial M_y}}{\frac{\partial Y}{\partial L_y}} = \frac{\alpha_p\beta_p}{\gamma_p}(\frac{M}{L})^{1-\eta}(\frac{M_y}{L_y})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(M_y)}{MPL(L_y)})_{it} - (\eta-1)log(\frac{M_y}{L_y})_{it} - (1-\eta)log(\frac{M}{L})_{it} - log(\frac{\hat{\beta}_p}{\hat{\gamma}_p}) = log(\alpha_p)$$

$$\frac{MPL(M_o)}{MPL(L_o)} = \frac{\frac{\partial Y}{\partial M_o}}{\frac{\partial Y}{\partial L_o}} = \alpha_p(\frac{M}{L})^{1-\eta}(\frac{M_o}{L_o})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(M_o)}{MPL(L_o)})_{it} - (\eta-1)log(\frac{M_o}{L_o})_{it} - (1-\eta)log(\frac{M}{L})_{it} = log(\alpha_p)$$

The ratio of marginal product of labor of high educated workers to low skilled and mismatched workers helps to identify technological efficiency between low skilled and high skilled jobs by taking elasticity of substitution between education levels (ρ) as fixed[18] .

[18] ρ is taken as 0.75 which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy

These 4 equations identify θ_h/θ_l together.

$$\frac{MPL(H_y)}{MPL(M_y)} = \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial M_y}} = \frac{\theta_h}{\theta_l}\frac{\psi_p}{\alpha_p\beta_p}\frac{H^{\rho-1}}{\tilde{L}^{\rho-1}}(\frac{H}{M})^{1-\eta}(\frac{H_y}{M_y})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(H_y)}{MPL(M_y)})_{it} - (\eta-1)log(\frac{H_y}{M_y})_{it} - (1-\eta)log(\frac{H}{M})_{it} - (\rho-1)log(\frac{H}{\tilde{L}})_{it}$$
$$- log(\frac{\hat{\psi}_p}{\hat{\alpha}_p\hat{\beta}_p}) = log(\frac{\theta_h}{\theta_l})$$

$$\frac{MPL(H_o)}{MPL(M_o)} = \frac{\frac{\partial Y}{\partial H_o}}{\frac{\partial Y}{\partial M_o}} = \frac{\theta_h}{\theta_l}\frac{1}{\alpha_p}\frac{H^{\rho-1}}{\tilde{L}^{\rho-1}}(\frac{H}{M})^{1-\eta}(\frac{H_o}{M_o})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(H_o)}{MPL(M_o)})_{it} - (\eta-1)log(\frac{H_o}{M_o})_{it} - (1-\eta)log(\frac{H}{M})_{it} - (\rho-1)log(\frac{H}{\tilde{L}})_{it}$$
$$- log(\frac{1}{\hat{\alpha}_p}) = log(\frac{\theta_h}{\theta_l})$$

$$\frac{MPL(H_y)}{MPL(L_y)} = \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial L_y}} = \frac{\theta_h}{\theta_l}\frac{\psi_p}{\gamma_p}\frac{H^{\rho-1}}{\tilde{L}^{\rho-1}}(\frac{H}{L})^{1-\eta}(\frac{H_y}{L_y})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(H_y)}{MPL(L_y)})_{it} - (\eta-1)log(\frac{H_y}{L_y})_{it} - (1-\eta)log(\frac{H}{M})_{it} - (\rho-1)log(\frac{H}{\tilde{L}})_{it}$$
$$- log(\frac{\hat{\psi}_p}{\hat{\gamma}_p}) = log(\frac{\theta_h}{\theta_l})$$

(1992)

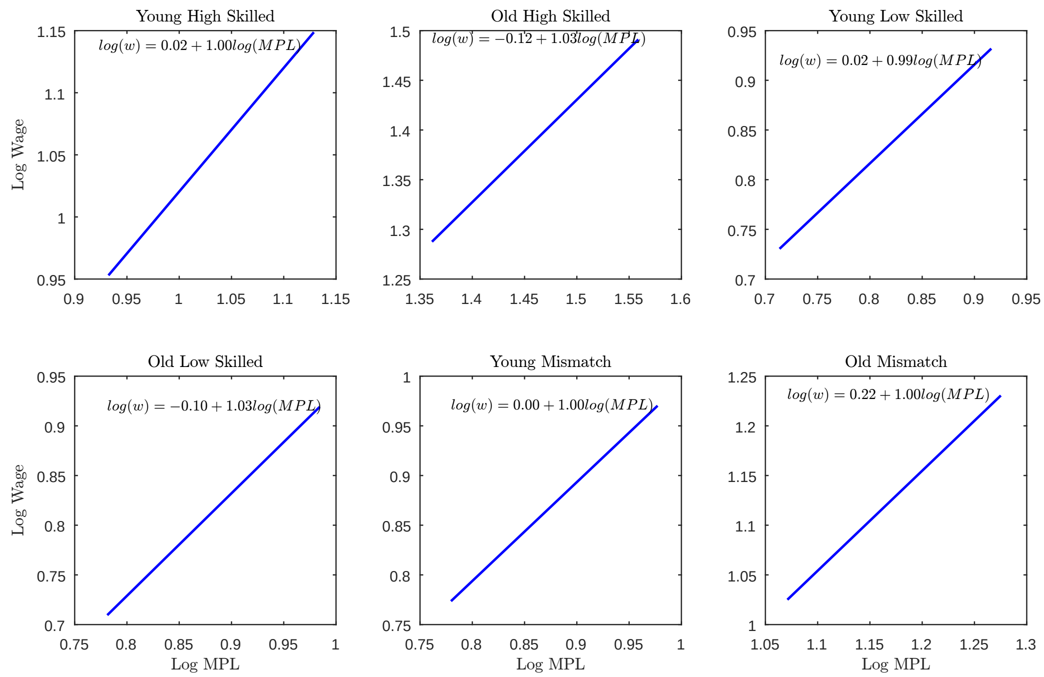


Figure I.10: Wage-MPL Gap

$$\frac{MPL(H_o)}{MPL(L_o)} = \frac{\frac{\partial Y}{\partial H_o}}{\frac{\partial Y}{\partial L_o}} = \frac{\theta_h}{\theta_l}\frac{H^{\rho-1}}{\tilde{L}^{\rho-1}}(\frac{H}{L})^{1-\eta}(\frac{H_o}{L_o})^{\eta-1} \Longrightarrow$$
$$log(\frac{MPL(H_o)}{MPL(L_o)})_{it} - (\eta-1)log(\frac{H_o}{L_o})_{it} - (1-\eta)log(\frac{H}{M})_{it} - (\rho-1)log(\frac{H}{\tilde{L}})_{it}$$
$$= log(\frac{\theta_h}{\theta_l})$$

With the above procedure and with iteration to correct wage-MPL gap, I am able to estimate relative efficiencies of workers (ψ_p, β_p, γ_p, α_p, θ_h/θ_l) to be used in the model to explain unemployment rate differentials.

Chapter II

Analysis of "Young, Educated, Unemployed" Phenomenon

1 Data

I use publicly available data sources such as Eurostat, OECD, and Worldbank to present macroeconomic facts on unemployment rates, education enrollment rates, population structure, and country-specific policy parameters, such as pension replacement rates. For Europe, I also used EU-SILC and EU-LFS confidential micro-data to estimate relative efficiency parameters as well as mismatch rates and on-the-job search intensity. For the US, I used publicly available American Community Survey (ACS) micro-data to do a similar exercise as in Europe for robustness check.

1.1 EU-SILC

European Union Statistics on Income and Living Conditions is a survey that covers all of the European Union, as well as candidate countries. It is the only dataset that provides income information together with demographics and occupation for all European countries. EU-SILC data exists from 2004 onward for most countries. Although the coverage is not as big as EU-LFS, it is very similar to EU-LFS in several regards.

I use EU-SILC to estimate mismatch rates and relative efficiencies. The population of interest is people ages 25-64, who at least have a high school degree and who participate in the labor force. Note that the mismatch concept that I am using is vertical mismatch, which means that people may have a higher education level than is required for a certain occupation. The education levels that I am considering are college degree and up versus a high school degree. The mismatch measure that is suitable to use in a cross-country comparison is “realized matches” based on the average education levels of occupations (Leuven & Oosterbeek (2011); Duncan & Hoffman (1981)). I first measure the average education level for every occupation at a two-digit level. If the ratio of college educated workers in a certain occupation exceeds 50%, I define that occupation as skilled; otherwise, it is defined as unskilled. Although countries differ in their average education level, hence occurrence of mismatch, I use the same skilled versus unskilled definition for every country in order to not cause bias. Secondly, I assign every individual as young (25-29) or old (30-64)[19] and high educated (college degree and up) vs. low educated (high school degree only). Thirdly, I assign every individual as unemployed, high skilled (if high educated and working in a skilled job), low skilled (if low educated and working in an unskilled job), or mismatched (if high educated and working in an unskilled job). Then, I calculate the mismatch ratio among young and old for every country by taking annual averages. Finally, I exclude unemployed people and calculate average hours worked, average yearly income, average hourly income, and number of people employed for six types of workers (young educated, young uneducated, young mismatched, old educated, old uneducated, old mismatched) for every year and every country. Hence, I construct my aggregated dataset, which is a time series of cross section over 12 years and 29 countries,[20] with average hourly income and employment level of six types of labor to be used in estimation of relative efficiencies. One shortcoming of the dataset that it excludes Germany due to some restrictions in Germany’s policy about data sharing.

[19]Since the unemployment rates that I am matching is for these age groups specifically, all the analysis is done based on these age groups.

[20]A list of countries and coverage years can be found in Appendix B

1.2 EU-LFS

European Union Labor Force Survey is the longest time series dataset that has coverage of many European countries, as well as candidate countries. It has detailed demographics and labor market information (except income). I use EU-LFS to calculate average unemployment rates for different groups (young educated, young uneducated, etc.)[21]. Moreover, I do analyze composition of majors as well as major specific unemployment rates to see common trends, if there are any. Furthermore, I estimate on-the-job search probability of workers who have been mismatched. EU-LFS also has ad-hoc modules every year that provide additional detailed questions on a pre-selected topic. By using the 2009 ad-hoc module "Entry of Young People into the Labor Market", I also document differences in the types of first job contracts, the method by which first job is found, to analyze cross-country differences.

2 Model Parameterization and Estimation

2.1 Parameters

There are four sets of parameters used in the model. [22]

1. Standard search-matching parameters such as bargaining power, exogenous job destruction rate, discount rate, and elasticity of substitution are taken from the literature.

2. Country-specific observable characteristics such as young ratio, educated ratio, pension replacement rate, and on-the-job search intensity are parameterized using Eu-

[21] I also used EU-SILC to calculate average unemployment rates and it gives very similar results. I am following with EU-LFS for reliability because the coverage is bigger.

[22] Parameter lists are given in Appendix E and F.

rostat, OECD and EU-LFS. The macro-facts to be used as targets, such as age-education specific unemployment rates, are taken from Eurostat. Mismatch rate is calculated at country level by using EU-SILC confidential micro-data [23].

3. Relative efficiencies of different types of workers (ψ_p, β_p, γ_p, α_p, θ_h/θ_l) are estimated by using EU-SILC for Europe and ACS for the US.

4. Unobserved friction parameters, such as mismatch search intensity and vacancy posting costs, are estimated within the model to match the unemployment rates and mismatch rates to the data.

Estimation of relative efficiencies and showing the implications on relative unemployment rates is an important feature of this paper. I contribute to the literature by proposing an estimation strategy that can be applied to understand any type of unemployment differential within or across countries. My methodology also allows me to quantify the effects of different channels on unemployment rates. More specifically, I am able to measure the relative contributions of observable country characteristics, estimated worker efficiencies, and labor market frictions in determining relative unemployment rates. In other words, except standard parameters taken from the literature, countries differ in many different ways that I am either observing or estimating, which allows me to quantify country effects.

2.2 Estimation of Relative Efficiencies

I propose a way of estimating relative efficiencies by using the whole structure of the model. Then I construct an updated wage data by using the implications of the model. First, I perform the estimation assuming that wage is equal to the marginal product of labor. Then I insert estimated efficiencies in my model and observe produced wages and the wage-MPL

[23] More details about estimation procedure exists in Appendix B

gap, then I update my wage data based on the relationship from my model and perform the estimation again. This iteration can be done many times, but after the first iteration the changes are relatively smaller so I have chosen to do the iteration only once.

The ratio of the wage of young workers to old workers within each category helps to identify relative efficiencies between young and old. In my aggregated dataset, I have wages and employment level for six types of workers for every year and every country. By taking η fixed[24], relative wage as well as relative supply of young vs. old within each category (skill, unskilled, mismatched) identify ψ_p, β_p, γ_p which are relative efficiency of young with respect to old for high skilled, mismatched and low skilled respectively. Hence H, M, L (the aggregate number of high educated working in high skilled jobs, low educated working in low skilled jobs and mismatched workers in the economy) can be calculated. As a second step, the wage ratio of mismatched workers to low skilled workers helps to identify relative efficiency between mismatched and low educated workers (α_p). Therefore, $\tilde{L}$, which is the effective number of low skilled workers in the economy, can be calculated. The ratio of the wage of high educated workers to low skilled and mismatched workers helps to identify the technological efficiency θ_h/θ_l between low skilled and high skilled jobs by taking elasticity of substitution between education levels (ρ) as fixed[25] . (See Appendix G for details of the estimation).

Obtaining MPLs from Wage

In my model, marginal product of labor (MPL) of different types are used as inputs of the model through the estimation of relative efficiencies. However, I observe a clear linear relationship between wages (as output of the model) and MPLs, given set of efficiency

[24] η is taken as 0.8 which is in the range of estimates of Card & Lemieux (2001)

[25] ρ is taken as 0.75, which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy (1992)

parameters. By using the structure of the model and this relationship for every type of worker, I can use the wage data to back out MPLs. It can be thought of eliminating wages from the effect of labor market frictions. The updated wage data will be constructed by using the actual wage data and the relationship between wage and productivity in the model. By changing economy-wide productivity Z in aggregate output $Y = Z[\theta_h H^\rho + \theta_l \tilde{L}^\rho]^{1/\rho}$, I reproduce equilibrium wages and productivity. In Figure II.1, I document the relationship between wage and productivity for every category from the simulated data for an example economy. As we see, the coefficient is almost 1, which means that workers who are working in the jobs for which they are qualified, they receive almost their productivities despite the labor market frictions. However, the intercept is much negative for mismatched workers, which means that they are receiving less than their productivities. This is expected because they are working in jobs in which they cannot fully exploit their productivities. This in turn rises the question of "efficiency loss due to mismatch" (Sahin et al. (2014)). In an economy where the number of mismatches is high, the actual productivity is not fully exploited and aggregate output realization can be less than it potentially could be. This exercise is performed for every country separately, because having a different labor market setting is affecting the relationship.

2.3 Testing the Mechanism

Skilled vacancy creation relative to low skilled vacancy creation positively correlates with skilled relative to low skilled efficiency (θ_h/θ_l):

Figure II.2 shows how relative vacancy creation (right) and relative unemployment rate of young (left) move with relative technological efficiency in the model. It is intuitive that everything else held constant, relatively more efficient skilled workers are, the economy responds to that by creating relatively more skilled vacancies in equilibrium. This finding

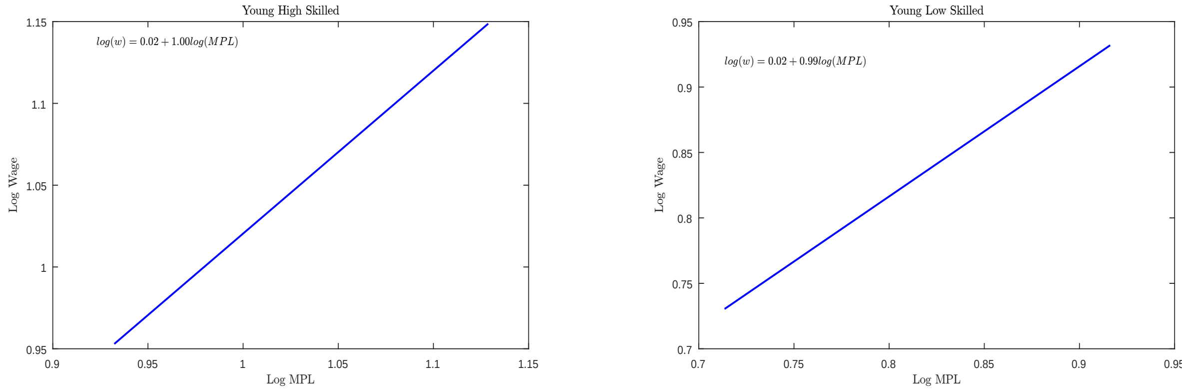


Figure II.1: Wage-Productivity Gap

Note: This figure is produced as an example using UK's parameters and calibration, but the same exercise is repeated throughout the paper.

is in line with the predictions of Acemoglu (1999), who argues that a low productivity gap produces an equilibrium in which there is one single type of job that is more unskilled. But I provide evidence that two types of jobs can co-exist with less skilled jobs when the productivity gap is low, making this evidence empirically more relevant. Moreover, college educated people may have higher unemployment rates if relative skilled efficiency (θ_h/θ_l) is low.

Skilled vacancy creation relative to low skilled vacancy creation negatively correlates with educated young unemployment relative to low educated young unemployment:

Figure II.2 suggests that relative vacancy is negatively correlated with relative unemployment. To show that correlation, I plot relative vacancy ratio versus relative unemployment rate by changing the relative technological efficiency in the economy. Figure II.3 shows that when skilled workers get more productive, the economy moves to an equilibrium where there are more skilled jobs and less educated unemployment. Although the data to identify skilled versus unskilled vacancies for countries of interest is restricted, there is

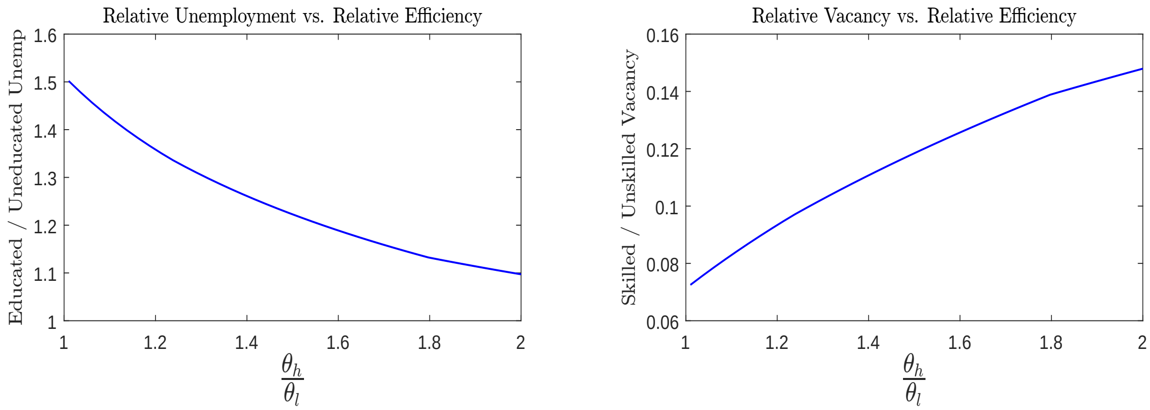


Figure II.2: Relative Unemployment, Vacancy, Efficiency

still some evidence that the data is consistent with the model. In Figure II.4, I show that in countries where skilled vacancy creation is high, young college graduates are less likely to be unemployed than high school graduates. But for the countries where we do observe higher educated unemployment rates like Slovenia and Cyprus, we also observe lower rates of skilled vacancy creation.

3 Results

The aim of this paper is to show the factors that promise to explain unemployment differentials and quantify the relative importance of each factor. The two hypotheses I provided are the "labor market frictions hypothesis" and the "productivity hypothesis". I give supportive evidences for each hypothesis from my analysis first, then I compare two hypotheses.

In terms of the productivity hypothesis, the first piece of evidence is that relative productivity of skilled versus unskilled labor estimated at the country level is negatively correlated with relative unemployment rates. Furthermore, I also estimated relative productivity of young versus old within each skill category, which has potential to explain unemployment rate differences between young and old. There is also a negative correlation between young

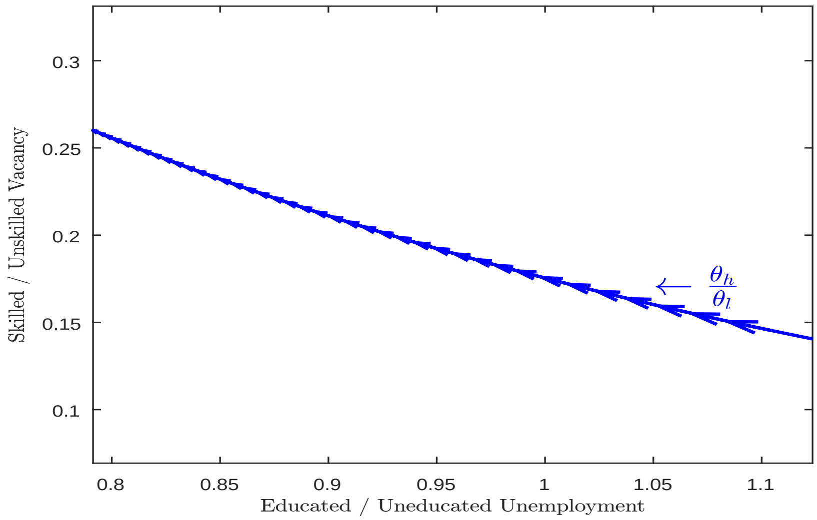


Figure II.3: Relative Unemployment vs. Relative Vacancy

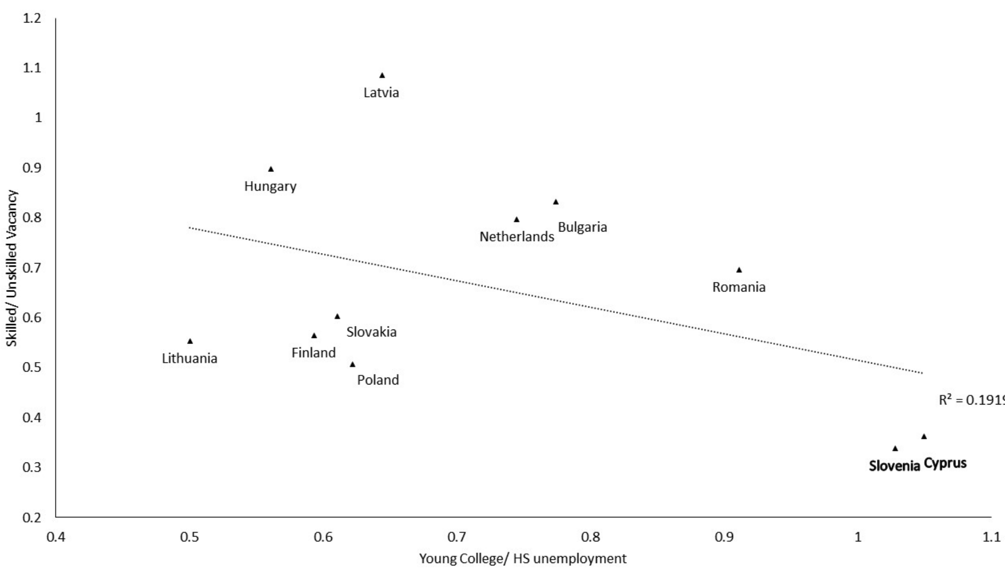


Figure II.4: Relative Vacancy vs. Relative Unemployment

Note: The data is taken from publicly available Eurostat Job Vacancy Statistics. Skilled and unskilled vacancies are calculated according to definition used throughout the paper by using occupation categories and respective college ratio in each occupation category. The ratio both in the x and y axis is the average from 2005 to 2015.

versus old productivity in the high skilled sector and relative unemployment rate.

In terms of the "labor market frictions" hypothesis, my model predicts that low intensity of mismatch contributes to explaining unemployment differentials as well, while mismatch possibility lessens the phenomenon by decreasing educated unemployment and increasing uneducated unemployment. I show that countries with higher young college unemployment also have low mismatch rates, which puts more pressure on job prospects of educated people. Another prediction of my model is that high vacancy costs, especially for the young skilled sector, can also contribute to the explanation by reducing job opportunities for educated people. There is also evidence that conducting business (which can be translated into high vacancy costs) is difficult in countries with higher young educated unemployment.

A more important contribution of my paper is disentangling the "labor market frictions" versus "productivity" hypotheses in explaining unemployment rate differences between groups. To do that, I perform counterfactual analysis with two-country comparisons. I find that the productivity hypothesis is substantial and it is even more important when frictions are high. Productivity hypothesis contributes to 20% to 100% of the gap in relative unemployment rates between countries. In the following subsections, I am going to show the results relating to each hypothesis and counterfactual analysis.

3.1 Results on "Productivity" and "Frictions":

The high vs. low skilled productivity difference is narrower in countries with higher young educated unemployment:

I argued that relative productivity of skilled versus unskilled labor is an important factor in driving the outcome about relative unemployment rates. My first suggestive evidence was the negative relationship between the young college premium and young relative unemployment rate (Figure I.4). However, as I noted before, that figure is not as sharp as

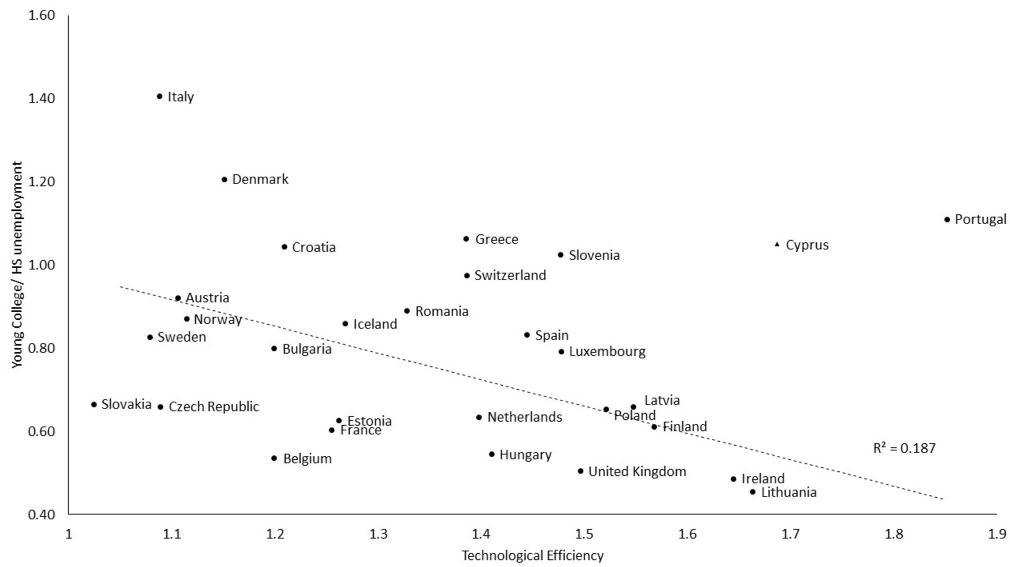


Figure II.5: Relative Technological Efficiency vs. Relative Unemployment Rate
Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2015 and the structural estimation method described in the paper. Regression is weighted by countries' labor force sizes of 25-29 age group.

it should be because of the existing mismatch evidence. In other words, countries with high levels of mismatch will have low college premium due to the fact that educated mismatched workers are not exploiting their full productivity. Hence, college premium is not a good reflection of relative productivity when mismatch is high. To overcome this issue, I used the structural estimation method, which takes into account the mismatched workers; therefore, estimated relative productivity between skilled and unskilled workers (note that it is different than educated and uneducated). Figure II.5 shows the correlation between relative technological efficiency (θ_h/θ_l) and relative unemployment rate, which is higher than in Figure I.4 and significant. More specifically less productive the skilled workers are, the higher unemployment rates they have. Especially when we look at Italy and Denmark, where the unemployment gap is high, we observe that the productivity gap is also low, and when we look at the UK where the unemployment gap is too low, the productivity gap is too high.

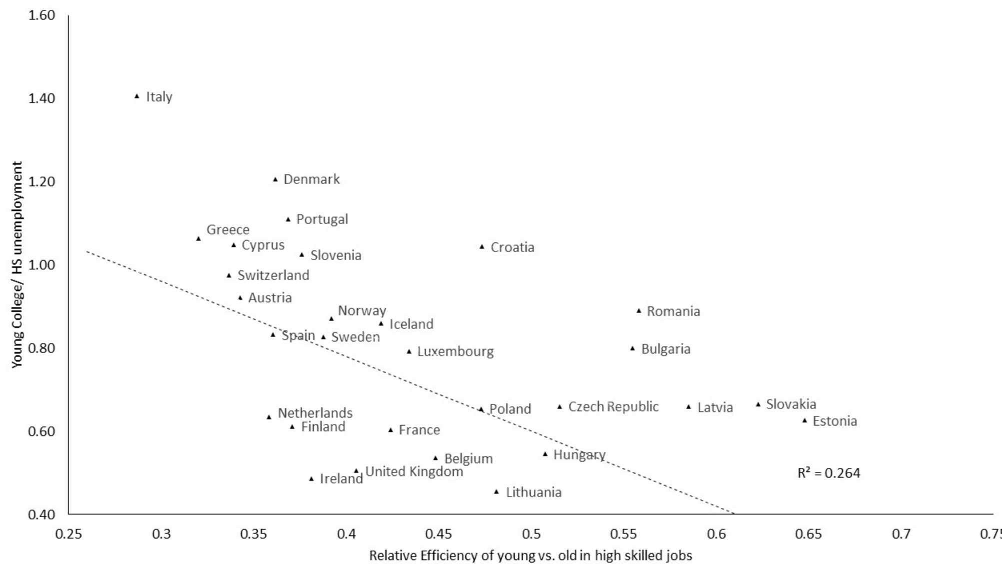


Figure II.6: Relative Efficiency of Young vs. Old in High Skilled Jobs
Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2015 and the structural estimation method described in the paper. Regression is weighted by countries' labor force sizes of 25-29 age group.

Young vs. Old productivity difference within high educated group is wider in countries with higher young educated unemployment:

The second significant evidence about the "productivity hypothesis" is about young versus old within the high educated group. Table II.6 shows ψ_p in which relative efficiency of young with respect to old within high skilled workers negatively correlates with relative unemployment rates. In the countries where young educated people have higher unemployment rates than uneducated people, they also have much lower productivity than their older counterparts in the skilled market. In other words, young high skilled workers enter the labor force with much lower productivity than old worker and have higher returns to skill later on. This observation together with the above observation on relative technological efficiency puts more pressure on young and educated people. They are not particularly different than unskilled workers and they are too different than older skilled workers, hence they are not very attractive to firms either from the skill side or age side.

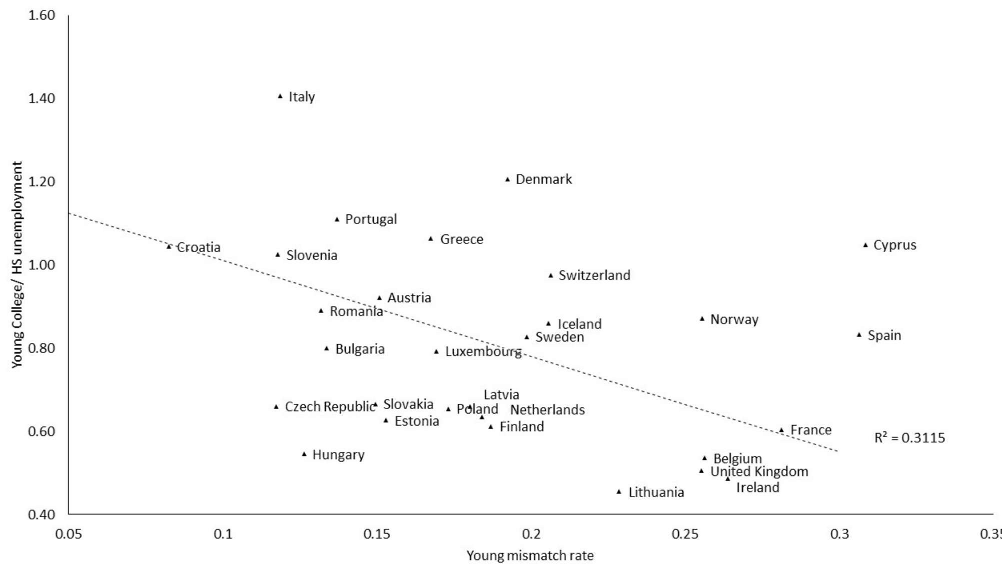


Figure II.7: Young Mismatch Rate vs. Relative Unemployment Rate

Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on education and occupation status of people. The mismatch rates are calculated for every country and every year and have been averaged for years 2004 to 2015. Regression is weighted by countries' labor force sizes of 25-29 age group. More detail on occupations and calculation exists in Appendix E.2.

Mismatch rate is smaller in countries with higher young educated unemployment:

Figure II.7 shows that there is a negative correlation between mismatch rate and relative unemployment rate across countries. More specifically, in countries like Italy, Portugal, and Greece where young college educated people are more unemployed, their propensity to work in unskilled jobs, hence being over-qualified, is also low, which explains part of the story. My model predicts that high mismatch intensity lessens the phenomenon by decreasing educated unemployment and increasing uneducated unemployment. The empirical evidence on mismatch rates is also promising in that explanation.

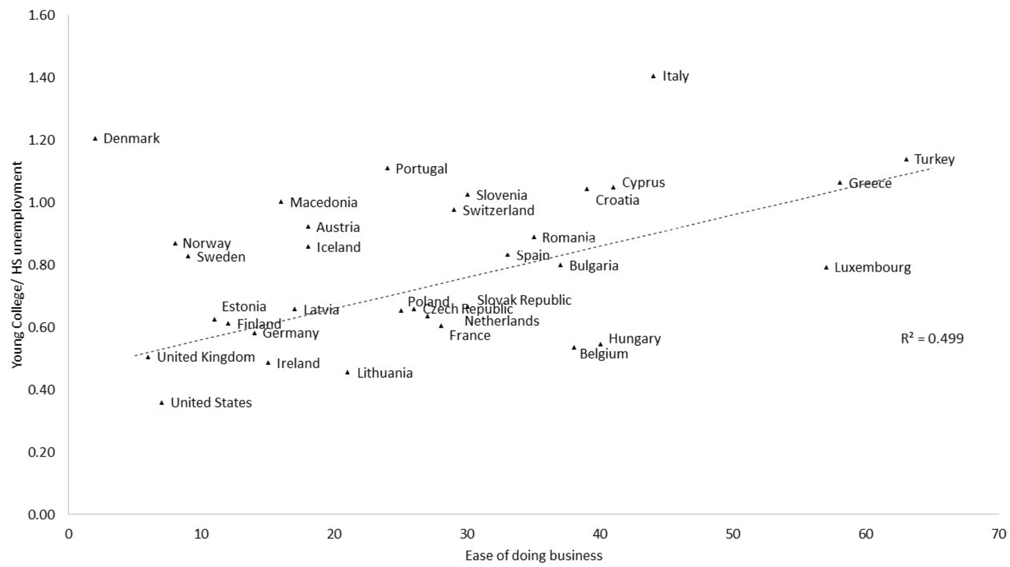


Figure II.8: Ease of Doing Business vs. Relative Unemployment Rate

Note: Ease of Doing Business index is taken from World Bank for 2014. Unemployment rates are based on Eurostat Statistics. Regression is weighted by countries' labor force sizes of 25-29 age group.

Doing business is difficult in countries with higher young educated unemployment:

My model predicts that higher vacancy posting cost is causing unemployment rates to go up, especially for the corresponding group of the type of vacancy. Although a particular empirical measure for skilled vacancy costs does not exist, there is evidence on the difficulty of doing business. Figure II.8 shows that the correlation between the difficulty of doing business and relative unemployment rate is positive and high. It is high particularly in countries where young college educated unemployment is relatively much higher such as Italy, Turkey and Greece. Difficulty of doing business can, in general, be easily translated into high vacancy costs. How it may particularly be more relevant for young skilled workers will be discussed later in the paper in the Case Study section.

3.2 Counterfactual Analysis

To disentangle the effects of productivity versus frictions and to show the results in a more precise way, I am going to conduct a counterfactual analysis with two-country comparison. I am first going to select two countries similar in many dimensions but differ in terms of relative productivity. I am going to do this twice for two countries with relatively low frictions and another two countries with higher frictions to see how friction level affects the response. Then, I am going to select countries from opposite (or different in two dimensions) and do the same exercise. The purpose of this exercise is to show how much each channel contributes to explaining the difference in the relative unemployment rate (u_{hy}/u_{ly}). Candidate countries are: Italy and Denmark, which have higher young educated unemployment but differ in terms of labor market institutions; the UK and Spain, which have lower young educated unemployment but differ in terms of labor market institutions. First, I am calibrating the model to match the four unemployment rates and two mismatch rates for each country separately. The differences in this calibration are: country-specific macro-factors (young ratio, education ratio); estimated relative efficiencies outside of the model; estimated friction parameters inside of the model to match the rates (vacancy posting costs, mismatch intensity). I then ask the question, "What would happen if the UK had the same macro-factors as Denmark, the same frictions as Denmark, and the same relative efficiencies as Denmark?" step by step. When I eventually introduce every set of parameters, I reach to Denmark's value. Then, I calculate how much of the distance from the UK to Denmark has been reduced with macro factors, frictions, and relative productivity. I repeat this exercise for other pairs of countries, too.

Denmark vs. the UK

The UK and Denmark are more similar in terms of labor market institutions to each other than to Italy or Spain. Denmark follows active labor market policies with low levels

	UK	Macro factors	Labor Market Frictions	Relative Productivity	Denmark
u_{hy}/u_{ly}	0.51	0.51	1.08	1.22	1.22
Relative Effect		0%	80%	20%	
u_{ho}/u_{lo}	0.66	0.67	0.73	0.8	0.8
Relative Effect		7%	43%	50%	

Table II.1: UK vs. Denmark

of employment protection but generous unemployment benefits where the UK also has low employment protection but also low unemployment benefits. The UK has high levels of mismatch and Denmark has moderate levels of the mismatch which is an indication of having fewer mismatch frictions and a high education ratio relative to Italy. The major difference between the UK and Denmark is the relative unemployment rate, which is the focus of this exercise. Table II.1 shows that differences in macro-factors have no explanatory power, and differences in frictions explain 80% of the gap in relative unemployment rate of young; relative productivity plays a smaller role where it explains 20% of the gap. For older people, on the other hand, the role of relative productivity becomes more important with 50% contribution. This finding is in line with Figure I.8 where I argued that when there are fewer mismatch frictions (high mismatch), unemployment rates are less responsive to the changes in relative productivity. That's why the relative productivity channel has a smaller explanatory power. (See Appendix H for differences in estimated parameters)

Italy vs. Spain

Italy and Spain are known for having high labor market frictions with high employment protection, passive labor market policies, and moderate levels of unemployment insurance. They are similar to each other more than any other country in Europe. The differences between them are that the education ratio in Spain is higher, and the mismatch rate in Spain is higher (which is partly due to the rapid increase in enrollment rates). More

	Spain	Macro factors	Labor Market Frictions	Relative Productivity	Italy
u_{hy}/u_{ly}	0.84	0.83	1.07	1.4	1.4
Relative Effect		-1%	41%	60%	
u_{ho}/u_{lo}	0.60	0.62	0.69	0.72	0.72
Relative Effect		16%	59%	25%	

Table II.2: Spain vs. Italy

importantly, relative unemployment rates are different[26]. Table II.2 shows that when I introduce Italy's macro-factors to Spain, the relative unemployment moves in the opposite direction from the target, although the effect is very small. When I further introduce Italy's friction parameters, I could proceed 41% of the distance between relative unemployment rates for young. Hence, the majority of the distance, 60%, is captured by the differences in relative productivity. This exercise shows that the effect of productivity is bigger in a setting with higher frictions because the low intensity of the mismatch channel in Italy makes unemployment rates more responsive to the changes in relative productivity, as I showed previously in mechanism section. It is slightly different for older people that the majority of the gap can be explained by frictions. (See Appendix H for differences in estimated parameters.)

UK vs. Italy

Now I select two countries, Italy and the UK, from both ends of the distribution of educated young unemployment (See Figure I.1) and labor market institutions. Italy has the highest relative unemployment rate; the UK has the lowest one. Italy has high labor market frictions with high employment protection, passive labor market policies, and moderate levels of unemployment insurance, whereas the UK has low employment protection and

[26]Note that Spain also used to have higher young college unemployment than young high school unemployment until 2005, but that relationship has been reversed afterwards which is the period for which I am performing my estimation and targeting.

	Italy	Macro factors	Relative Productivity	Labor Market Frictions	UK
u_{hy}/u_{ly}	1.4	1.69	1.27	0.51	0.51
Relative Effect		-32%	47%	85%	
u_{ho}/u_{lo}	0.72	0.71	0.65	0.66	0.66
Relative Effect		17%	100%	-17%	

Table II.3: Italy vs. UK

low unemployment benefits. Italy has low mismatch rates and the UK has high mismatch rates. They also differ in terms of macro-factors; the education ratio in Italy is low whereas it is high in the UK. Table II.3 shows that the effect of macro-factors which mainly speak to educated supply, works the other way around. In other words, if Italy had an educated labor supply as high as in the UK, relative unemployment would have been much less in favor of educated people. Differences in relative productivity still plays a substantial role, and it explains 47% of the distance in unemployment rate differentials for young and 100% of the distance in unemployment rate differentials for old. (See Appendix G for differences in all estimated parameters.)

The lesson from this exercise is that the relative productivity differences across countries are compelling factors in determining relative unemployment rates, and they become even more important in countries with higher frictions.

3.3 Differences in parameter values

I have already pointed out that four main factors differ across countries that promise to explain unemployment rate differences. The factors are relative technological efficiency, young versus old efficiency in high skilled jobs, mismatch intensity, and vacancy posting costs. Table II.4 shows the differences in those parameters across four countries used in calibration exercise [27]. As I mentioned, the main contribution on the productivity side

[27]The whole set of parameter values used in calibration exercise can be found in Appendix B

	Italy	Denmark	UK	Spain
Efficiency Parameters				
θ_h/θ_l	1.11	1.17	1.52	1.41
Friction Parameters				
$\tilde{\lambda}_y$	0.21	0.4	1.5	0.78
c_{2y}	0.35	0.17	0.22	1.21

Table II.4: Estimation Results

comes from relative technological efficiency (θ_h/θ_l), where it is low in Denmark and Italy and high in the UK and Spain. On the frictions side, I mentioned that mismatch rates negatively correlate with the relative unemployment rates. Estimates for mismatch search intensity ($\tilde{\lambda}_y$) shows that Italy and Denmark have lower mismatch search intensity and the UK and Spain have much higher. Final explanation on the frictions side comes from vacancy posting costs, where in Italy, vacancy posting cost for young skilled workers (c_{2y}) is higher than the UK and Denmark. The only exception to this rule is Spain, where it is much higher, but it mostly comes from the fact that Spain has high unemployment rates in general.

3.4 Italy, Denmark, UK, Spain

In this exercise, I first show the location of these countries on a relative productivity versus relative unemployment rate scale. Then, I ask the question, "What would happen to unemployment rates if I only change relative technological efficiency?" Figure II.9 first shows how the prevalence of mismatch in Spain and in the UK lowers the relative unemployment rate for all levels of relative productivity in favor of educated workers. In other words, Spain has higher frictions in terms of vacancy costs, which pushes the curve up but low frictions due to the prevalence of mismatch that pushes the curve down. The UK, on the other hand, has both lower frictions on each side; that's why it lies on the bottom of the figure. Since they also have higher relative technological efficiency, they are located on the right side of the figure with even lower relative unemployment rates. Italy has frictions both due to high vacancy costs and low prevalence of mismatch; that's why Italy's curve is located at the top of the figure. Denmark, on the other hand, has moderate levels of frictions due to low levels of mismatch. They are both located on the left side of the figure because they have low levels of relative technological efficiency.

Next, I move the countries along the relative technological efficiency scale to see where they would have been located if they had a different relative productivity measure. The change in relative unemployment rates in Italy and Denmark is much faster with a steeper curve due to low prevalence of mismatch. In other words, Denmark and Italy could have performed much better in approximating unemployment rates between educated and uneducated groups if they had higher relative technological efficiency. On the other hand, for Spain and the UK, the same is true except the fact that the response of relative unemployment is rate to the changes in relative technological efficiency is much slower due to the high prevalence of mismatch. The mechanism behind this is that when educated workers get more and more productive, not only do they have lower unemployment rates, but there is also switch by previously mismatched workers to the skilled market, which depresses the decreases in educated unemployment decline because the job seeker pool becomes larger.

3.5 Shutting Down the Productivity Channel

One major contribution of my paper is to show the productivity hypothesis is an important factor explaining unemployment rate differences across groups and across countries. Counterfactual analyses above show the contribution of the productivity hypothesis in different cases. Suppose I completely eliminate the productivity hypothesis assuming that it is not relevant. Therefore, I ask the question: "can we explain unemployment gap only with labor

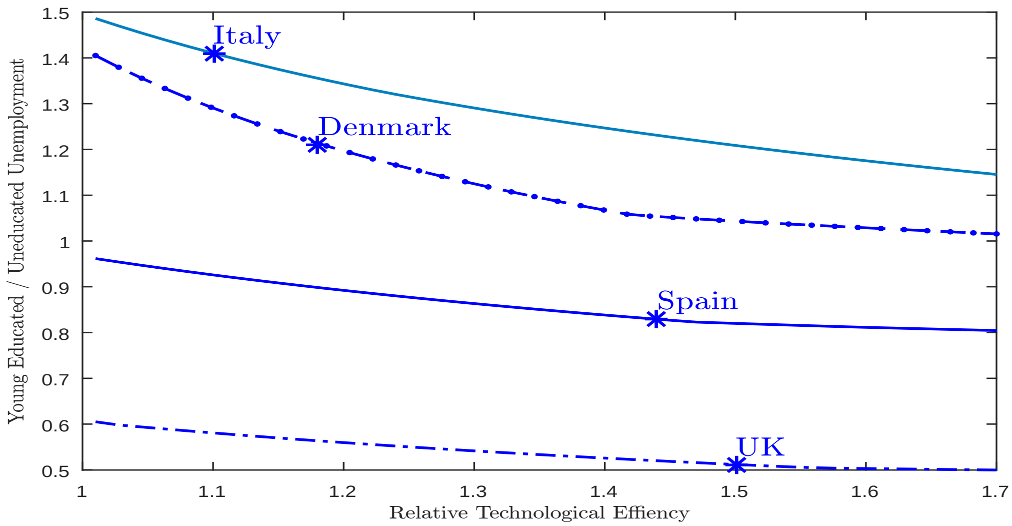


Figure II.9: Location on the relative productivity vs. relative unemployment scale

market frictions?". If I can, then the productivity hypothesis will be irrelevant.

To show the implications of eliminating the productivity channel, I perform another counterfactual analysis. Here, I estimate labor market frictions of Italy to match Italy's unemployment rates, using counterfactual efficiencies of the UK. In other words, I ask the question that "if Italy had the UK's relative productivity levels, what should be necessary to target the observed unemployment rates?". Low college attainment and high college educated unemployment in Italy means that the supply of college educated workers is low in the labor market. Since, college educated workers are scarce resource, the model predicts a counterfactually high college premium. Moreover, in order to achieve Italy's high unemployment with counterfactually high college premium, the model predicts very high labor market frictions (high vacancy posting costs).

The first column of Table II.5 shows UK's estimated wage gap and skilled vacancy posting cost for young and the third column is for Italy. The difference between the UK and Italy is that wage gap is larger in the UK and vacancy posting cost is larger in Italy.

	UK	Italy with UK's relative productivity	Italy
Wage Gap (w_{shy}/w_{nly})	1.24	1.49	0.9
Vacancy Cost (c_{2y}/θ_l)	0.21	0.81	0.34

Table II.5: Shutting down the Productivity Channel

When I shut down the productivity channel and target Italy's unemployment rates, the second column shows what the model predicts. The model predicts not only larger wage gap than what Italy has, even larger than what the UK has. Moreover, the vacancy posting cost is more than twice of what it is initially estimated. Hence, this analysis as well indicates that the productivity hypothesis is crucial to capture both the differences in unemployment rates and the wage gap.

4 Discussion

I would like to discuss some other potential explanations and concerns, and I explain whether they are crucial or not in determining my results.

Duration in college, hence the age entering the labor market, differ across countries

One argument for explaining a higher young college unemployment rate than high school can be about transitioning into the labor market. If college students in certain countries spend more time finishing school, therefore graduating at an older age, they might be in a disadvantageous position because they are going to spend some time finding their first job and will be unemployed. On the other hand, college students in countries where they graduate at a younger age would have already found a job by the time their peers are still searching. Figure V.2 shows that the correlation between age at the end of college education and the young educated unemployment rate is not strong. There are countries that have low rates of college unemployment, although they graduate much later on. Therefore, the duration argument seems not to be a crucial determinant, even if we cannot fully reject the hypothesis that it may produce.

Mother Hypothesis

One argument for higher college unemployment, especially when thinking about Italy, is the "mother hypothesis". It has been argued that young people in Italy have a lot of support from their family, which makes staying unemployed feasible for them. There are also papers discussing this issue for Mediterranean countries (Bentolila & Ichino (2008); Becker et al. (2010)). Hence, the mother hypothesis may be seen as responsible for higher college unemployment. First, I am going to show in a simple supply-demand framework that the "mother hypothesis" implies higher wages for educated people, which is counterfactual. Second, I am going to show through the model that outside option differences cannot generate observed unemployment differentials due to mismatch opportunities.

In figure V.4, I present a simple supply-demand diagram to show the direct partial equilibrium effect of the mother and productivity hypotheses on relative unemployment rates and relative wages. The mother hypothesis means that the mothers of young graduates provide resources to their children so that the children increase their outside options, and they prefer staying unemployed, probably waiting for better jobs. In this case, the supply of college graduates shrinks, which increases their wages and may increase college unemployment rates because there is less supply (left side of the figure). However, empirical findings show that wages of skilled labor relative to low skilled is very low in Italy, which supports the "productivity hypothesis" as represented on the right side of the figure. The productivity hypothesis implies that lower efficiency will lower labor demand, which will lead to a decrease in equilibrium wages of the highly skilled.

I complement the analysis by showing the model's predictions. The parameter that captures the "mother hypothesis" in my model is b_y, which is the outside option of staying unemployed. I exogeneously change the outside option (Figure V.3). I show that higher outside option reduces the relative unemployment rate (u_{hy}/u_{ly}) . Both unemployment rates increase as young people find it more acceptable to stay at home. Educated young can also look for jobs in the unskilled sector, which crowds out uneducated young. Both analyses show that the "mother hypothesis" is unlikely to be behind the observed differences in relative unemployment rates.

Major composition, therefore the characteristics of college supply, differ across countries

Another argument for higher college unemployment might be about what has been taught in the universities. People tend to see STEM majors as more marketable and easier fields to find a job with. On the other hand, humanities and arts are seen as less marketable and might have been blamed for high educated unemployment rates because humanities graduates might not be considered as "skilled" in production terms even though they are technically educated because they have a college degree. With this argument, we may expect lower college unemployment rates in countries with higher rates of STEM majors in colleges. However, Figure V.10 shows that a strong correlation does not exist. Countries with high levels of educated unemployment rates such as Italy, Greece, and Portugal do not particularly have lower STEM ratio among the youth labor force. Another way to look at this concern is to see whether countries with high levels of young college unemployment have higher levels of humanities graduates among the unemployed than in the labor force. In other words, we need to answer the question of whether young college unemployment is mostly caused by if humanities graduates are most likely to be unemployed or not. Figure

V.11 shows whether humanities graduates are differently represented in the unemployed pool than in the labor force and whether it has a link between overall young college unemployment. Although for most countries, humanities graduates are over represented in the unemployed pool than in the labor force (the ratio being larger than 1 on the x-axis shows that they are), this fact does not significantly correlate with high young college unemployment for these countries.

How about migration?

Migration is a big concern in terms of affecting labor market outcomes of source and destination countries and is becoming even more so where people are more mobile within Europe. Migration of skilled versus unskilled workers are two different topics (even not so distinct) that should be considered. For the sake of this paper, migration of skilled workers within Europe is more important to consider in terms of producing "brain drain" and "brain gain". How does migration affect analysis (if it does)? Consider the case where skilled workers are mobile and there is selection in migration patterns. Skilled workers from countries where returns to skill is low migrate to countries where returns to skill is higher. If only the ones who are at the high end of skill distribution are migrating, it will magnify productivity differences. More clearly, it will close the gap between skilled versus unskilled productivity in the sending country and magnify the gap between skilled and unskilled in the hosting country. In terms of my findings, it does not contradict my hypothesis; it can only explain part of the reason of productivity differences within a country among the remaining workers. If there is no selection in migration patterns, it is more difficult to make a prediction, but it is less likely to change the skill distribution in a dramatic way both in the sending and destination country.

The other question is if migration affects equilibrium unemployment rates? If some of the skilled workers from low return countries migrate to high return countries, there should be fewer people looking for skilled jobs in the sending country, which should benefit the remaining educated workers. However, still having high educated unemployment rates in these countries shows that it is not the case. As I previously explained, the link that goes from productivity to the unemployment rates passes through vacancy creation. In other words, losing very high skilled people decreases average productivity in the remaining part and slows down skilled vacancy creation, which leads to higher educated unemployment rate as I previously showed.

Finally, I am going to document migration patterns in OECD countries and show that although there is an increasing trend in high skilled migration, migration rates for many European countries are still very low and unlikely to affect equilibrium unemployment in a significant way. Even through it may, it does not contradict any of the hypotheses I raised. For most OECD countries, emigration rates among high skilled workers are higher than total emigration rates, suggesting that there is a selection in emigration patterns (cite OECD). Some countries are performing well in attracting high skilled workers (brain gain), while some are mostly on the sending side (brain drain). Hence, there are some net winners (US, Australia, Canada) and net losers (UK, Korea) (Boeri et al. (2012)). Among OECD countries, emigration rates of the high skilled is the highest in Luxembourg, Ireland and New Zealand (around 30%) and lowest in Japan and the US (around 1%). Comparison of the UK vs. Italy does not give striking results as the UK has 11% emigration of high skilled and Italy has 7%. In other words, emigration patterns do not strongly correlate with relative unemployment rates. Even if it does, it is in the opposite direction than expected; countries with higher educated unemployment are less likely to send high-skilled labor abroad.

Job Finding Method

There are several channels like friends and family, public services, and online applications that people can search for a job and can find one. The measures that I have constructed from the EU-LFS 2009 ad-hoc module “Entry of Young People into the Labor Market” shows that there are cross-country differences in the methods that the first job is found. Although the causation between the finding method and unemployment rates is not particularly clear, there is still a room to point out some possible market inefficiencies that may also determine unemployment rates in a particular way. Figures V.6 and V.7 together show that in Southern European countries, the majority of people find their first jobs through friends, whereas finding them through education institutions or public services is more common in Western Europe. Finding a job through social connections is not particularly bad, but not finding a job through public services or other means can point out some market inefficiencies in southern countries where unemployment is high.

Type of First Job Contract

Young educated workers in Southern and some Eastern European countries have difficulty in finding a job in the beginning of their career. Figures V.8 and V.9 show that in these countries fewer people report that their first job is permanent full time, and majority of them report that it is temporary part time. These figures give an evidence that job security for young workers continues to be low, even after entering employment status. Hence, the problem of not being able to find a job continues into not being able to work in a permanent full time job.

5 Case Study: Italy

Italy is a country which lies on the extreme for most of the measures that I am looking at, especially for the main question of the paper in terms having so much higher young college unemployment rate than high school unemployment rate. That's why Italy deserves a separate analysis to understand labor market institutions, education policy and industrial composition to find counterparts of model's predictions in real life. I will analyze Italian market from supply and demand side.

5.1 Demand Side

The problems usually having been discussed about demand side of Italy's labor market are concentrated on difficulty of doing business, high prevalence of small family-owned businesses and industrial composition being based on traditional consumer goods which do not require high productivity. While giving evidences about all the above issues, I am going to discuss how one can interpret each of these in terms of model's parameters and the predictions that I am drawing.

- **Doing business is hard:** Both anecdotal and scientific evidence show that running a business is difficult in Italy which is related to both starting a business and hiring workers later on. World Bank's Doing Business project measures several features regarding starting and running a business such as the days required to get electricity, ease of getting credit and paying taxes, days required to enforce a contract etc...An index called "ease of doing business" has been constructed for many countries. Italy lies on the extreme of the distribution which basically suggests that doing business is difficult along with several dimensions aggregated in an index. Starting a business is difficult mainly because of the red tape. Anecdotal evidences show that one should have a great determination to go over procedures which may last a decade. There is also evidence that lending rates are higher in Italy compared to other European countries (ECB data on business loans) which mostly affect small businesses. This also becomes an obstacle towards starting a business in terms of funding. On top of it, hiring workers is very costly in Italy due to high minimum wages and social security contributions. Moreover, the fact that firing is difficult as Italy adopts the labor market system with high employment protection regulations (OECD (2016)), that also puts another pressure on the employer in the decision of hiring workers.

- **Small Business:** A great majority of the firms (among the highest in OECD) in Italy are small businesses (47% of total employment) (OECD (2017)). Moreover, 85% of firms are family owned business which constitutes 70% of total employment. High prevalence of small businesses has other outcomes in the labor market. First, it makes the effect of high lending rates on business creation even more severe because small firms are mostly affected by high lending rates. Secondly, small business are the ones operating in traditional sectors without any complex technology which depresses Italian productivity and creates "low skill equilibrium" and "productivity slowdown" (Pellegrino & Zingales (2017)). On the other hand, Italian graduates cannot find jobs matching to their skills due to high prevalence of SMEs operating with low technology. Hence, it affects the overall productivity of Italian firms as the highly educated workers cannot fully exploit their productivity in firms which do not require high skills. All these help to explain why demand for university graduates is weak. Some research suggests that entrepreneurs who do not themselves hold a tertiary degree have a lower propensity to hire tertiary graduates (Schivardi & Torrini (2010)). Better earnings and employment prospects for Italian graduates working abroad provide further support to the hypothesis that that demand for their skill in Italy may be structurally weak.

- **Industrial Composition:** Majority of industry is composed by traditional sectors specialized in consumer based products. This is also correlated with the firm size discussed above such that evidence suggests that product diversification is strongly correlated to firm size. In 2013, 65.4% of Italian firms were specialized in the production of one single good, 15.4% in that of two and only 7.6% in three different products (Toniolo (2013)). The number of firms showing a much diversified production pattern (e.g. producing 10 or more different goods) was only 0.8%. The relationship between product diversification and employment is such that firms that follow traditional productive patterns have low intensity to hire new workers. Around 30% of firms developing new products or services intend to recruit new workers, whereas the share of firms recruiting new workers decreases substantially (14.4%) among those firms that stick to their traditional productive patterns (OECD (2017)). Hence, industrial composition of Italy puts another downward pressure on job creation. Moreover, it affects employment opportunities of skilled workers even more as they either cannot find jobs or cannot exploit their full productivity in such a business environment.

5.2 Supply Side

- **Supply of Graduates:** Graduate share in Italy has been one of the lowest in Europe. The share of university graduates among young cohorts is 20% which is well below OECD average (30%). It is increasing but at a lower rate than other countries which previously had low attainment levels such as Spain, Portugal and Turkey. The reason for low attainment level can also be due to the fact that Italy allocates the smallest share of public expenditure to tertiary education of all OECD countries (1.0% of GDP, compared to the OECD average of 1.6%) (OECD (2017)).

It has been shown that the increase in graduate share is positively associated with restructuring activities and with productivity growth. However, for Italy the recent increase in graduate share could not been translated to a shift of the productive structure from low to high human capital activities. In other words, the fact that there is a higher share of graduate people employed in the economy is mostly coming from the supply effect not from the demand change by firms. According to OECD (2017) Italy is the only G7 country with a higher share of tertiary educated workers in routine occupations than in non-routine ones which can be thought as a reflection of the low demand for higher levels of skills in Italy. Still, it has been thought that further increase in tertiary educational attainment can in turn foster the demand for skilled workers by firms by changing industrial structure from low to high human capital.

- **Quality of Education:** Italy performs badly relative to other OECD countries in terms of student skills both at secondary and tertiary level. Italian students have low scores in PISA test than majority of the countries. This brings a challenge about the overall education system but mostly addressing to low skill quality. The Survey of Adult Skills 2013 has been produced by OECD Programme for the International Assessment of Adult Competencies (PIAAC) and gives a comprehensive comparative look at adult skills across countries. While a greater portion of Italian population relative to others lacks literacy skills, it is true for every education level. A comparison shows that Italian university graduates have similar literacy skills as Japanese high school graduates (OECD (2013)). Moreover, Italians are the ones who make less use of reading skills at work. Considering the strong correlation between overall labor productivity and use of skills at work, that may also be something which depresses productivity (Schivardi & Torrini (2010)).

- **Emigration:** Brain drain has become an issue in some policy debate. There has been an increasing number of Italian skilled workers emigrating and canceling their Italian residency and Italy is not very successful at attracting skilled work force from abroad to compensate the loss because of red tape and non-transparent recruitment processes. Boeri et al. (2012) claims that 88% of foreign PhD students in Italy leave the country after their studies. Italy has also the lowest R&D investment among EU-15 members which in turn makes less possible for academia to compete globally.

5.3 Relation to Model

Summarizing all the above key points, the issues where Italy is struggling at, seems to affect labor market outcomes of young people and educated people. In terms of the model and analysis that I am providing , they all have a counterpart in my analysis where I am showing that the effects are towards having high unemployment rates, high educated unemployment rates. More specifically, difficulty of running a business and high cost of hiring a worker translate into having less mismatch hence higher educated unemployment rate in my model. Also, high prevalence of small businesses and traditional sectors as well as supply side explanations about the quality of education also explain why the demand for skilled workers is relatively low and why skilled workers cannot exploit their full productivity which can be translated into relative productivity hypothesis in my model. I also show that having low relative productivity between skilled and unskilled workers causes relative unemployment rates to be in favor of less skilled by also increasing overall unemployment rate. Finally, observations about emigration of highly skilled workers can explain why Italy has low levels of relative productivity by assuming that the ones who are emigrating are the ones who are most skilled in the distribution hence lowering the mean productivity of those who stay.

6 US Case

American Community Survey is used to do the same analysis for American states. All the steps explained in EU-SILC section is repeated for the US. The aggregated data for the US is a time series of cross sections for 16 years (2000-2015) and 51 states.

In this paper, I analyzed the question of "why college educated young people have higher unemployment risk than high school graduates in some European countries but not elsewhere?". While answering this question, I developed a framework in which I both used confidential micro-data to estimate relative productivity of different types of workers and a search-matching model to perform counterfactual analysis. With this analysis, I am able to enlighten the differences across types and quantify what factors are more important in determining unemployment differentials.

I claim that this framework can be used to explain other types of unemployment differentials as well. It means that it is not developed to explain only higher college unemployment. To show that, I am going to take US labor market as an example, perform a similar analysis and show the sources of unemployment differentials.

I use American Community Survey through IPUMS micro-data to find unemployment rates across different ages, education groups and different states. Note that we never observe higher college unemployment in the US. Although, the US labor market looks much more homogeneous than Europe, there are still some differences across states. Although there are no major differences in high educated unemployment rates, low educated young unemployment rates range from 5% (North Dakota) to 13% (Mississippi).

I am going to separate the US labor market in two parts according to low educated young unemployment rates. Then, I am going to show the differences across states in which unemployment rates among young HS graduates are lower than US average and higher than US average. I am going to argue that the productivity gap between high and low skilled is bigger in states with high HS unemployment rates. It means that having higher returns to skill promotes skilled vacancy creation by leaving less options for low skilled group, hence increasing low skilled unemployment rates even more.

In Table II.6 shows that states in which young low educated unemployment rate is relatively low, have both mismatch efficiency (α_p) and relative technological efficiency (θ_h/θ_l) lower than the states with higher young low educated unemployment rate. In other words, in states where skilled workers have higher efficiencies relative to unskilled workers both in doing same jobs (mismatch) and in complementary jobs, they have higher advantage over low educated, which fosters skilled vacancy creation and increases low educated unemployment rate.

Estimated Parameters	Low States	High States
ψ_p (relative efficiency of young in high skilled)	0.37	0.39
β_p(relative efficiency of young in mismatched)	0.58	0.59
γ_p(relative efficiency of young in low skilled)	0.49	0.52
α_p(mismatch efficiency relative to low educated)	1.19	1.31
θ_h/θ_l(relative technological efficiency)	1.69	1.79
α(young ratio in labor force)	0.11	0.12
μ(uneducated ratio within young)	0.64	0.62
$\hat{\mu}$(uneducated ratio within old)	0.65	0.64
υ(pension replacement rate)	0.47	0.47

Table II.6: Estimation Results (US)

Note: Low States are the states in which young HS unemployment rates are lower than US average, High states are the states in which young HS unemployment rates are higher than US average.

7 Special Case: Denmark

One of the countries which has higher young college unemployment rate in my analysis is Denmark. Since Denmark looks structurally quite different than other countries with the same observation, that raises questions about what really causes Denmark to experience this.

First of all, average unemployment rate in Denmark is one of the lowest in Europe (around 5%), and the gap between young college and young high school unemployment rate is quite low (1.3 ppt) in terms of percentage points (OECD (2016)). Denmark's labor market regime is mainly characterized by very generous unemployment insurance, active labor market policies and low employment protection regulations. It has been thought that low employment protection together with generous unemployment benefits works well in terms of both creating a flexible labor market which fosters job creation without any fear of hiring workers and in terms of providing employment security to people rather than job security. It is a very common practice in Denmark to fire people, i.e. 20% of people experience unemployment every year (Hendeliowitz (2008)). But, majority of them can find jobs very easily, the rest is financially secured by unemployment insurance which gives 90% of the previous income level. Also, active labor market policies (highest share of expenditure for labor market policies) establish the view of "welfare to workfare" by providing skill upgrading to those who are unemployed to ensure their return to employment.

Denmark's labor market policy is completely the opposite of Southern European regime where I observe higher young college unemployment rates. It is the opposite in the sense that, Southern European regimes are characterized by high employment protection regulations which dampens job creation in the long run and makes costly to hire workers, average unemployment benefit level which cannot give particularly high security to those who are unemployed and passive policies which are not helpful for transition from unemployment to employment.

Denmark's measured relative productivity between skilled and unskilled labor is in line with my hypothesis in the sense that Denmark does have low relative productivity which supports my hypothesis. In terms of labor market institutions, it is possible that high unemployment benefits may give poor incentives to accept short term part time jobs. This may temporarily rise the unemployment rate of newly graduated people until they are settled in a permanent job. But, my analysis shows that the main driver is the relative productivity hypothesis which is completely in line with Denmark case.

8 Conclusion

In this paper, I analyzed the reasons behind unemployment rate differences across different groups following an observation, which is "higher unemployment rates among young college graduates than young high school graduates in some European countries". I developed a framework by which I was able to estimate productivity differences across different groups using confidential micro-data and perform counterfactual analysis in a search-matching model to quantify the importance of relative productivity and/or labor market frictions.

The main findings of the paper are as follows. In countries with the "*young, educated, unemployed*" phenomenon, the productivity difference between high versus low skilled workers is narrower. The productivity difference between young and old within the high educated group is wider. Mismatch rates are also lower. These three facts play a role in determining vacancy creation in favor of unskilled jobs, which worsens the situation of educated workers. In other words, high skilled relative to low skilled vacancy creation positively correlates with high skilled relative to low skilled efficiency. The available vacancy data is also in favor of this result. Moreover, I showed that vacancy costs and/or mismatch search intensity contributes to the fact from the "frictions" side. High vacancy costs and low prevalence of mismatch increases the relative unemployment rate and also makes the changes in unemployment rate differences more vulnerable to productivity changes. Furthermore, my counterfactual analysis shows that the productivity hypothesis explains a substantial part of unemployment differentials and it is even more important when labor market frictions are high. Two-country comparisons show that productivity differences can explain 20% to 60% of differences in relative unemployment rates of young and 25% to 100% of differences in relative unemployment rates of old.

I contributed to the literature in many different ways. First, I analyzed an observation which was not raised before, and I explained the reasons by keeping the conventional wisdom about labor market frictions and providing a new complementary explanation: the "productivity hypothesis". Secondly, I developed a framework through which any type of unemployment differences can be micro-founded. Finally, I showed how to discipline micro-data and import the findings in a theoretical framework to perform counterfactual analysis. My contribution can be used to learn more about the unemployment rate differences both across groups within a country and/or across countries.

The question that I raise has important policy implications. First, I emphasized the importance of relative productivity in creating larger unemployment differences across groups. Those differences are sometimes in favor of old, sometimes less educated, and sometimes high educated depending on the country. Frictions play also an important role in determining mismatch rates, creating a more (less) fluid labor market. Policy makers should understand the reasons why some people have much lower productivity than their counterparts in other countries that impose worse labor market conditions in their countries. The education system and demand for higher education (i.e., skill use at work) should be analyzed extensively.

Chapter III

Fertility Response to Business Cycles: "Gender Asymmetry in Industries"

(with Husnu Dalgic)

1 Introduction

This paper studies cyclical as well as gender asymmetric properties of industries to understand the relationship between fertility trends and economic conditions. The fertility rate in the US had an increasing trend in the beginning of 2000s until the start of the Great Recession. In 2007, total fertility rate was 2.12, the highest number since 1971, then it declined sharply to 1.84 by 2015. We find that 44% of fertility decline can be attributed to gender asymmetric industry employment and different cyclical properties of industries.

Industries have different cyclical properties (Abraham & Katz (1984)). A great majority of women (41%) are employed in industries such as education, health services and government which are acyclical (or even countercyclical) industries. On the other hand, a great majority of men are employed in industries such as construction and manufacturing which are heavily procyclical industries. It is still the women who mostly bear the time cost of a child (Kleven et al. (2018), hence the opportunity cost of having a child is foregone earnings in employment for females. Then, increase in male income increases fertility through income effect, while female income increase has ambiguous effect because it produces both income and substitution effects. However, many evidences show that the substitution effect is dominant and higher female income both at cross section and in time series is correlated with lower fertility rates (Heckman & Walker (1990)). In times of economic downturns, since males are employed in heavily procyclical industries, they lose their jobs which decreases household income and it has a negative impact on fertility. On the other hand, female employment is either not affected or affected positively due to acyclical properties of female dominant industries, better economic prospects of women also have a negative impact on fertility. Hence, we argue that fertility decline is amplified in economic downturns because of these two properties of the economy: 1- gender asymmetric industry employment, 2- cyclical properties of industries.

Our empirical analysis shows that state level birth rates are correlated negatively with the changes in female dominant industry employment (and industry compensation) and positively with the changes in male dominant industry employment (and industry compensation) for the whole sample period of 2002-2016. The correlations are even stronger at post-recession period. We also show that employment (or compensation) changes in gender symmetric industries do not have any effect on fertility rates since the positive effect from men is canceling out by the negative effect from women.

In order to understand the effect of the structural properties of the economy in shaping fertility trends with business cycles, we build a model with the following features: 1-Joint household consumption, saving and fertility decision. 2- Partial specialization. 3-Timing of birth. In our model, male income is positively related to fertility through income effect and female income is negatively related to fertility through substitution effect. We calibrate the model to match pre-recession fertility rates for younger and older women. We compute the changes in industry level total compensation between 2007-2011. Using industry gender composition, we build a measure of gender compensation levels for different age groups. We then apply the observed compensation changes to our model. Our model is able to predict the fertility in response to the changes in industry compensation both qualitatively and quantitatively. We then ask the question of "what would have happened to fertility if industry employment was not gender-biased and/or industries display the same cyclical properties?'. In all the counterfactual scenarios, we predict the fertility changes to be milder.

Fertility decline is becoming an important problem in the developed world. Although, the US did not suffer from this problem as much compared to Europe, the recent data shows that it will in the near future as the current fertility rate is well below the replacement level. We highlight a different aspect of labor market structure and its relation to fertility. Gender asymmetry in labor market affects fertility in an adverse manner. Obviously, it is unfortunate that better labor market outcomes for women worsens fertility. However, one reason why we obtain such a conclusion is that women still incur majority of child-bearing and another reason is that women have to sacrifice hours worked when they have children. Hence, other than gender symmetric labor market conditions, policies which may potentially reduce the opportunity cost of child to mothers may help in rising fertility.

2 Related Literature

In his seminal paper, Becker (1960) analyzes fertility as en economic choice where families have utility from both the number of children they have and quality they invest to them. Later, in Becker & Barro (1988); Becker et al. (1990), fertility has been analyzed in the context of economic growth by introducing altruism of parents, hence as an outcome affecting macro economic outcomes. Doepke (2015b) summarizes the quality-quantity trade-off literature by Gary Becker and points the importance of quality perspective in fertility choice as the income elasticity is stronger for quality by also noting that the desired fertility is still positively correlated with income levels which is an evidence for children being normal goods.

The first attempt to analyze the cyclicality of fertility is by (Butz & Ward, 1979). In their paper, they argue that fertility in the US fertility becomes countercyclical in 60s, after the baby boom period. However, there are other studies later on, which argues that the decrease in fertility in the 60s was due to increase in female labor force participation rate as well as the introduction of “the pill”. (Macunovich, 1995) argues that in recession periods, the negative effect of unemployment surpasses the positive effect of lower opportunity cost. There is also evidence about procyclicality of fertility in a multiple country study by (Sobotka et al., 2011). Finally, (Jones & Schoonbroodt, 2016) proves that fertility is procyclical in a study by incorporating dynastic altruism and productivity shocks.

Understanding the baby boom in 50s and its consequences on the labor market is a prominent feature of the literature. (Greenwood et al., 2000) argue that baby boom in 50s is caused by an atypical burst in technological progress in household sector which lowers the opportunity cost of child. On the other hand, (Doepke et al., 2015) argue that after war baby boom was caused by increased female labor market participation by older generations during the war which persisted and competed out younger generation of women from the labor market in after-war period.

The effects of female and male wages on fertility have been studied empirically by identifying the effects through the panel data. (Heckman & Walker, 1990) identify the effect of an increase in female’s wage on fertility by analyzing Swedish panel data and find that higher female wage leads to delaying childbirth and lower fertility as a result. In order to identify the effect of male income on fertility, unexpected job displacement has been used as an exogeneous shock. Both (Lindo, 2010) and (Amialchuk, 2013) find that an unexpected shock to male income (job displacement) decreases fertility. (Schaller, 2016) attempts to find both effects by using exogenous labor demand shocks and gender employment indices in industries. Consistent with the literature, she finds positive effect for male wage and negative effect of female wage. (Dettling & Kearney, 2014) also shows that house prices (hence business cycles) have a positive impact on fertility.

Not only wage changes but also the effect of unemployment on fertility has been studied in the literature and the results are similar to those of wage changes. (Schmitt, 2011) and (Özcan et al., 2010) find that male unemployment affects fertility negatively whereas female unemployment affects positively.

Until recently, the literature tries to identify the wage effects on fertility and tried to explain long term cycles with economic conditions. Following the papers which study the occupation riskiness by looking at the wage and unemployment volatility ((Saks & Shore, 2005)), (Sommer, 2016) studies the effect of unexpected earnings risk on fertility and finds that higher earnings risk is associated with delay in fertility and lower fertility. A comprehensive study by (Adda et al., 2017) endogenize all life time choices and argue that career choices are made along with fertility choices, hence there is sorting in occupations according to fertility choices during life time.

3 Facts

3.1 Facts on Fertility

The US has relatively high fertility rates but experienced sharpest decline in the Great Recession

Fertility rates have been declining in the 20th century and there is negative correlation between GDP per capita and fertility rates all over the world ((Doepke, 2015a), Doepke & Tertilt (2016)). Increase in female labor participation rate, pill revolution certainly have an impact on this long run decreasing trend. There is however, large baby boom and bust

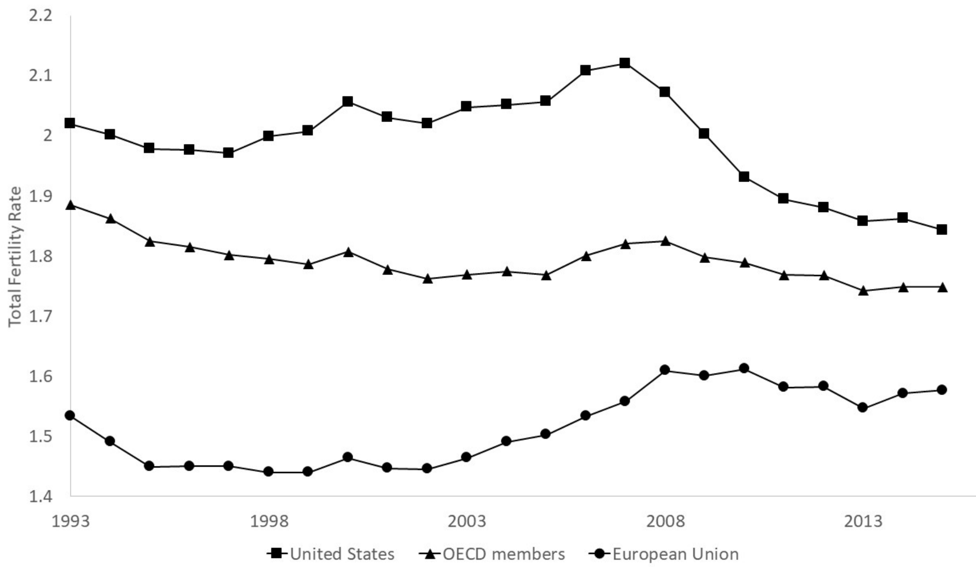


Figure III.1: Total Fertility Rate in Developed World
Source: World Bank

periods in the 20th century driven by economic conditions ((Doepke et al., 2015; Jones & Schoonbroodt, 2016)). Since 80s on, fertility rates become more stable, large baby boom and baby bust periods do not exist anymore as it occurred in the middle of the century. However, there are still cycles correlated with economic conditions.

In the US, fertility had an increasing trend during late 90's and early 2000s with the housing boom. Then, a sharp declining trend started with the Great Recession. OECD countries have been also affected by global conditions and European countries by the Euro Crisis. However, the decline in the US fertility rate was very sharp and lasted long (Figure III.1). Only after 2011, it converged to a plateau.

Fertility declines in recession times

Figure III.2 shows the fertility trend in the US starting from 1975 and the recession periods. For all the recession periods since 80s, fertility drops with the start of the recession and usually recovers by the end of the recession and follows an increasing trend afterwords.

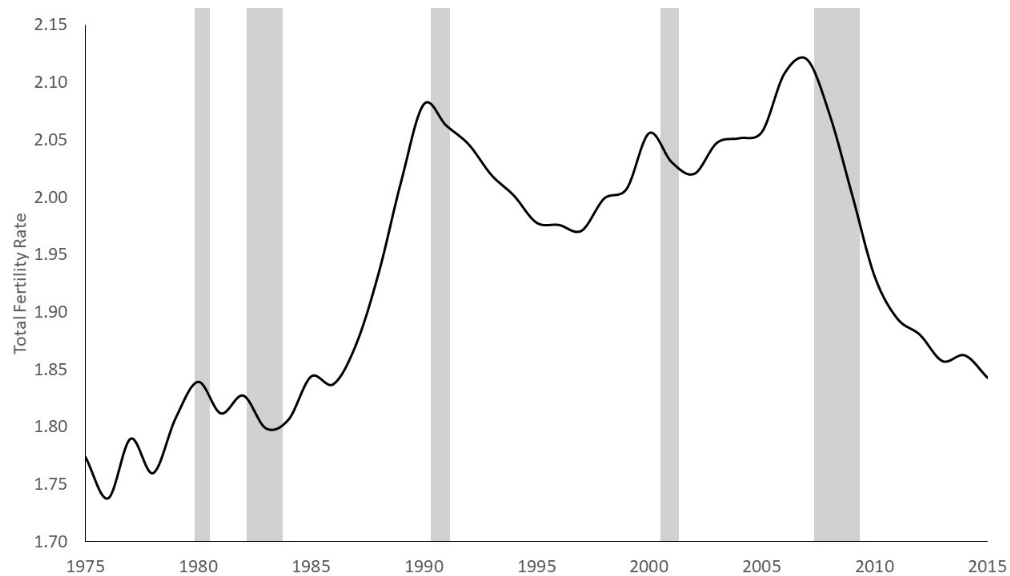


Figure III.2: Fertility and Recessions in the US
Note: Shaded areas areas are recession periods. The data is taken from Fred.

There are two recessions in which fertility continued to drop even after the recession, which are 1990 recession and the Great Recession. One common characteristic of these recessions is that we experience "jobless recoveries" in both (Gordon (1993),Doepke & Tertilt (2016)). Our analysis also shows that fertility is more responsive to employment changes than income changes at aggregate level. Hence, jobless recoveries imply that fertility recovery also takes time.

Fertility change and real GDP per capita change are correlated at state level

Figure III.3 shows that the states which experienced the largest GDP decline also experienced the largest fertility decline and vice versa. Hence, not only at time series but also at cross-section, fertility is positively correlated with income changes. For instance, in California and Florida, during the recession, income declined significantly, so as the fertility. (For a visual representation, see Figure VI.1 in Appendix C)

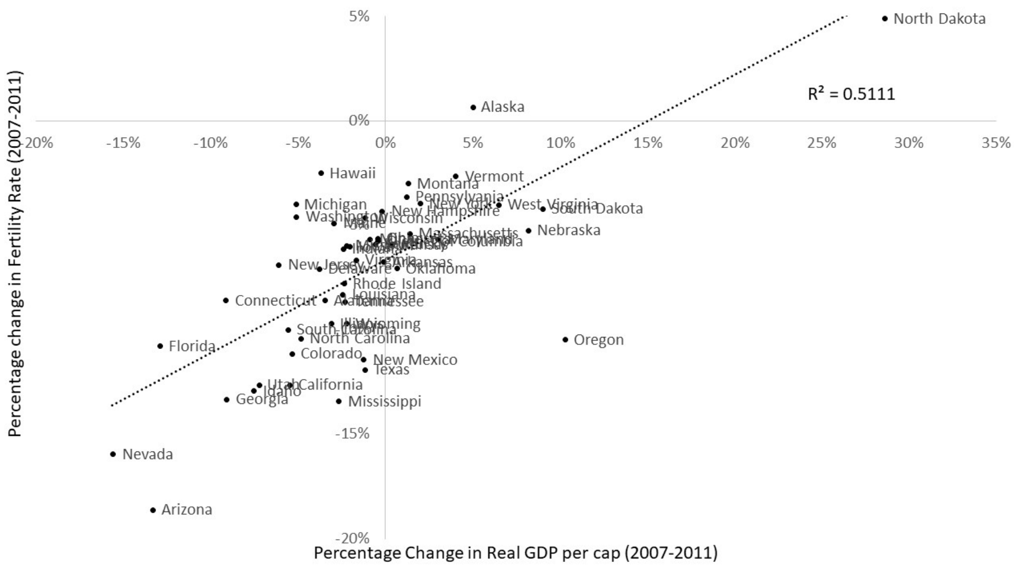


Figure III.3: Fertility vs. Real GDP per capita Change
Note: Fertility data has been taken from National Health Statistics. State level real GDP per capita data has been taken from Bureau of Economic Analysis

Fertility decline was the sharpest among women of age group 20-30

Figure III.4 shows that women of age 25-29 and 20-24 had the highest birth rates. However, they experienced the largest decline after the recession possibly due to delaying motive, hence fertility decline in 20-30 age group has been translated into increase in birth rates of women of age 30-39. As reported by (Kleven et al., 2018), even in Denmark where social system towards families is more powerful with maternity leaves, there is a child penalty in hours worked and earned wages among women. Hence, among younger ages there is a career cost of children ((Adda et al., 2017)), which makes fertility among young more responsive. Moreover, women of age 40-44 have a stable fertility trend. In our model section, we are going to incorporate different trends across age groups.

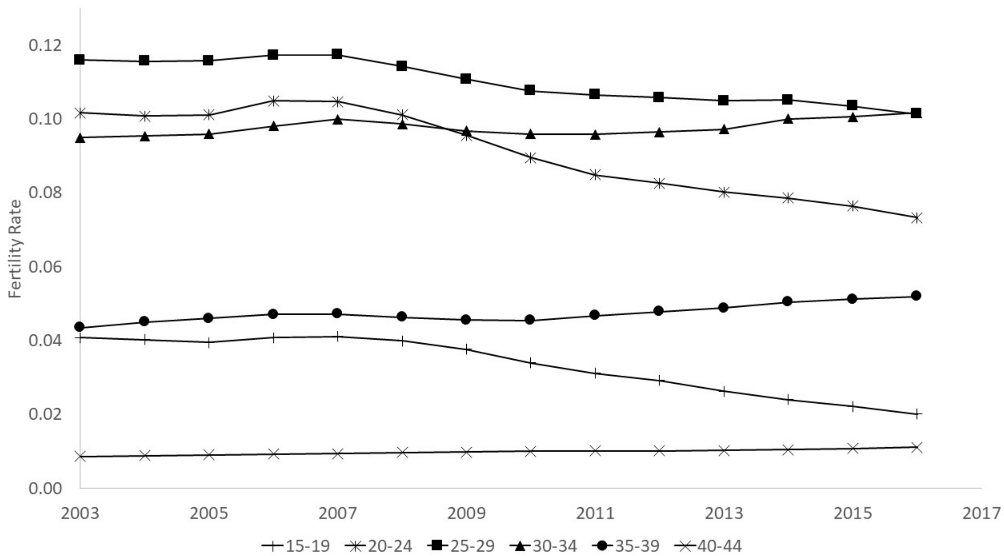


Figure III.4: Fertility Across Age
Source: National Health Statistics

Tempo vs. Quantum Effects

Sobotka (2004) discusses tempo and quantum effects in fertility for Europe. In the developed world, there is a trend towards postponing childbirth to later years of adulthood, which is called "tempo effect". On the other hand, the overall decrease in fertility is called "quantum effect". Figure III.5 shows these effects for the US. In 2007, both tempo and quantum effects are positive relative to 2003. In 2011, there is a significant quantum effect, however we do not observe a tempo effect as there is no right shift in age profile of fertility. In 2015 though, there is a tempo effect as the whole distribution shifts to the right relative to 2011. It means that younger females have lower fertility rates but older females have higher fertility rates. Hence, between 2007-2011, we do observe the pure effect of the recession as there is an overall decline which is mostly pronounced among young females. In 2015, we start observing the recovery of fertility rate among older women who postponed fertility during the recession.

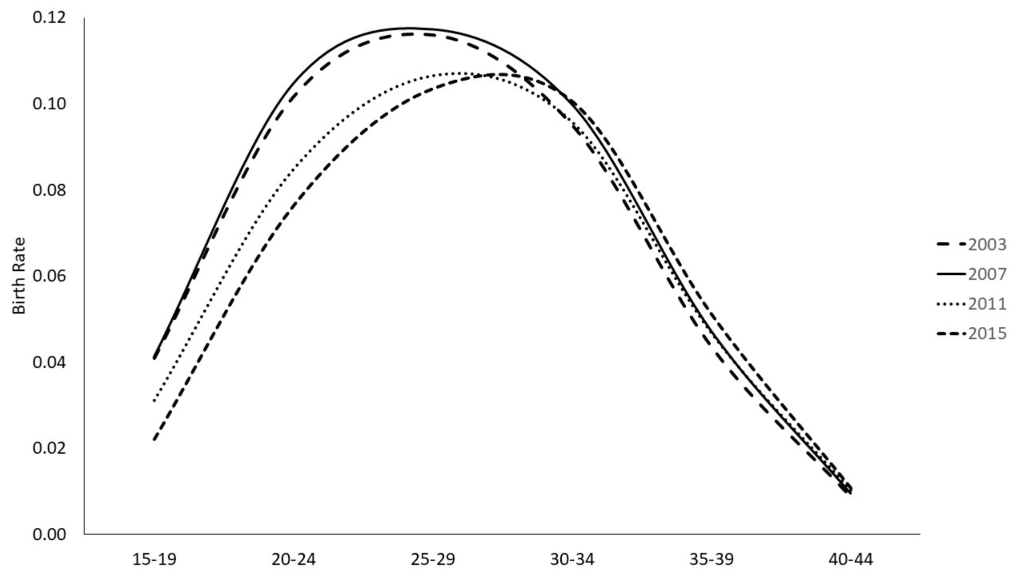


Figure III.5: Tempo vs. Quantum Effects

Fertility decline vary across races

In order to understand the heterogeneity across individuals, we do present the outcomes for different race groups in Figure III.6. All the race groups had an increase in fertility until 2007 and decline afterwords but Hispanic women experienced the largest decline in fertility. The convergence in fertility rates of Hispanic vs. non-Hispanic women over time may have contributed to the decline. However, Hispanic fertility also starts declining after the Great Recession.

3.2 Facts on Labor Market

Female employment share within industry ranges from 13% to 77%

Figure III.7 shows that female versus male employment within each industry vary significantly. Some industries such as education and health services, financial activities and government are female dominant where construction, manufacturing and mining industries

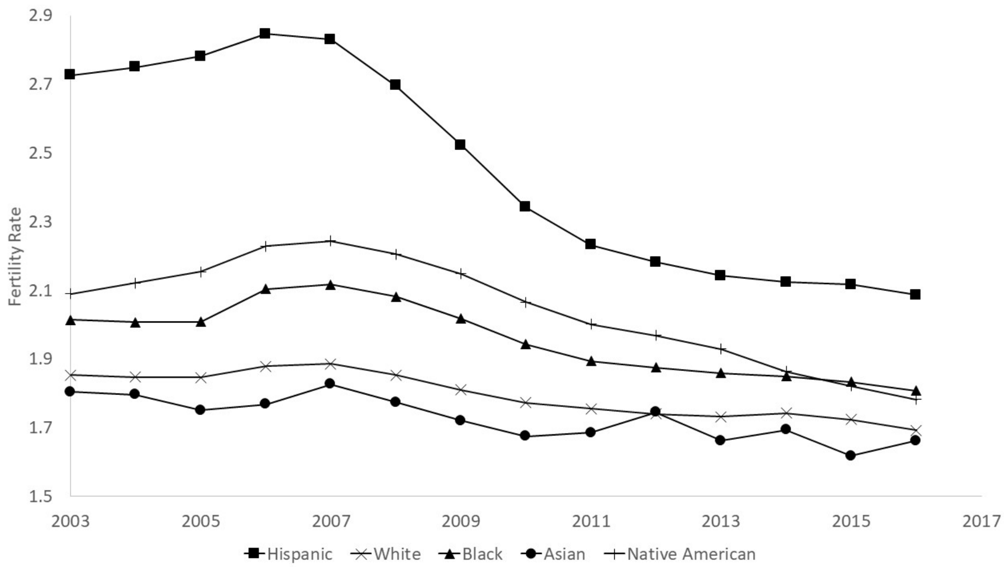


Figure III.6: Fertility Across Races
Source: National Health Statistics

are heavily male dominant. Especially education and health services industry is the most female dominant industry where 77% percent of industry employment is female. On the other hand, construction and mining industries are most male dominant industries where 87% of employment is male. Furthermore, these changes do not change over time (see Appendix C Figure VI.2).

Half of women are employed in education, health and government industries

Not only education and health services industry is female dominant but also a large fraction (22%) of females are working in that industry. Figure III.8 shows that almost half of employed women are working in two major industries; education and health services and government. Also, industry trends in female employment is stable over time (see Appendix C Figure VI).

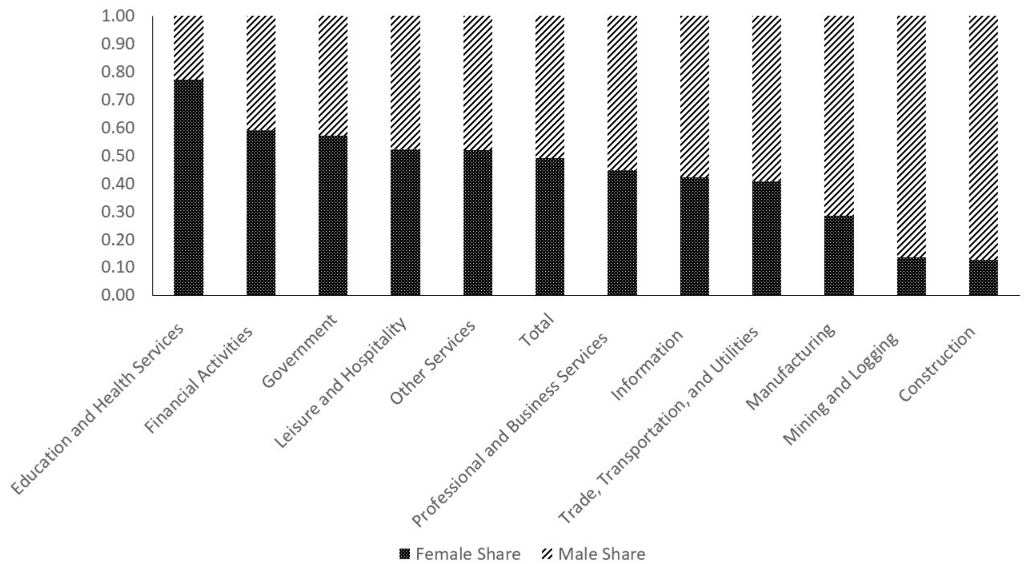


Figure III.7: Gender Bias in Industries
Note: The data is taken from Bureau of Labor Statistics. Women shares are averages across years 2002-2015.

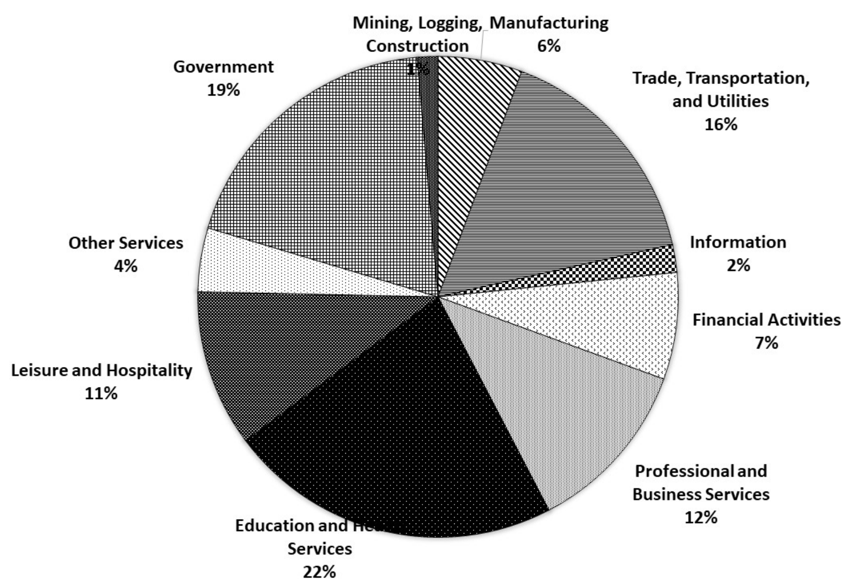


Figure III.8: Female Employment
Note: The data is taken from Bureau of Labor Statistics. Industry shares are averages across years 2002-2015.

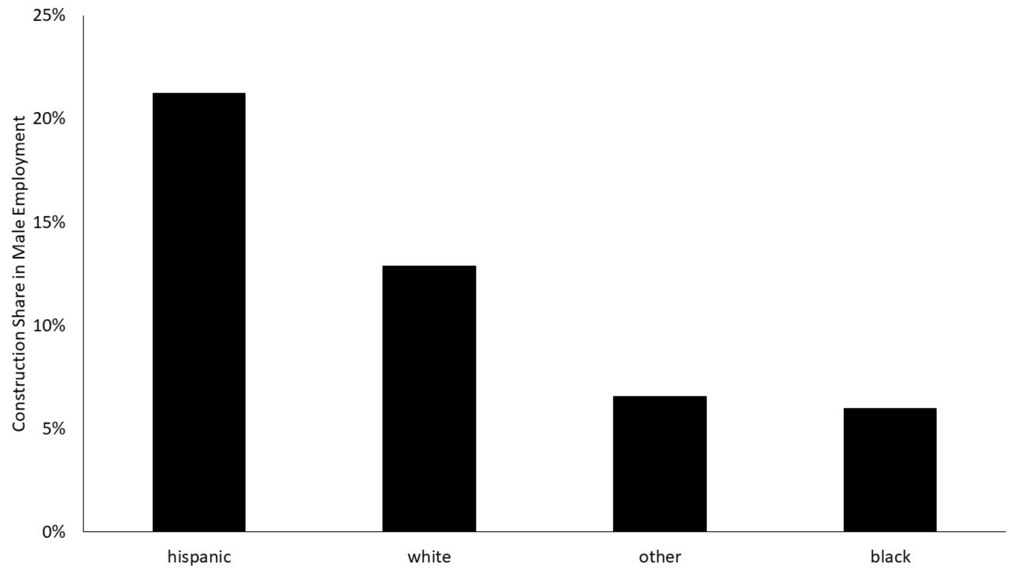


Figure III.9: Construction Share in Male Employment

Employment share vary across races

Figure III.9 documents the variation of construction industry share in male employment. Hispanic men are predominantly employed in construction industry. Previously, we documented that Hispanic fertility decline was the sharpest relative to other races. The fact about Hispanic men's high employment share in construction gives additional evidence why Hispanic fertility might have been declined much.

Male dominated industries are procyclical and female dominated industries are acyclical

In terms of number of people each industry employs, male dominated industries experience a large employment decline during recessions where female dominated industries do not deviate from the long term trend. Hence, Figure III.10 shows that construction and manufacturing industries are procyclical whereas education, health services and government industries are acyclical. Employment changes for all industries are shown in Figure VI.4.

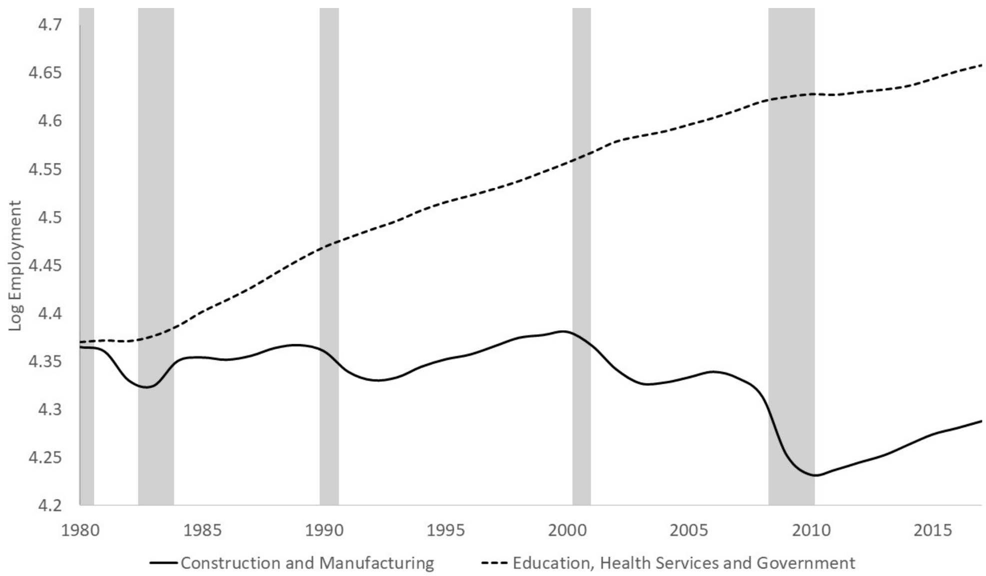


Figure III.10: Male vs. Female Dominated Industries
Note: Data is taken from Bureau of Labor Statistics.

4 Data

4.1 National Health Statistics

Fertility data; ratio of number of births to total population and to female population of 15-44 age for every state between years 2003-2016 is taken from National Health Statistics. Age and race specific fertility rates are also taken from National Health Statistics database.

4.2 Bureau of Labor Statistics

Industry employment numbers at state level between years 2002-2015 as well as female and male employment at industry level are taken from Bureau of Labor Statistics database. Monthly data has been used to calculate the correlation between total employment changes and industry level employment changes. To calculate female employment share in each industry and industry share in total female employment, the annual data has been used.

To form the birth rate-employment matched data set between years 2002-2016, state level annual industry employment levels have been used.

4.3 Bureau of Economic Analysis

Regional Statistics from Bureau of Economic Analysis has been used to get the total employee compensation at industry and state level. CPI index has been used to get real employee compensation to be consistent in yearly changes. The data is matched to state level birth rate data.

4.4 Current Population Survey

Current Population Survey has been used to estimate earnings gap between female and male, as well as between young and old workers. These estimates have been used as model inputs when constructing compensation of four different agents. Moreover, industry employment composition for different race and education groups have been also estimated as robustness check.

5 Empirical Analysis

5.1 Cyclical Properties

The first step of the empirical analysis is to identify the cyclical properties of industries. To do that, we use monthly employment data from BLS and look at the percentage changes in industry employment and calculate the correlation of industry employment changes to the total employment changes between years 2002-2015. Table III.1 shows that the correlation between industry employment changes to the total employment changes ranges from 0.18

Industry	Correlation	Within Industry Women Share	Industry Share in Women Employment
Trade, Transportation, and Utilities	0.86	0.41	0.16
Professional and Business Services	0.86	0.45	0.12
Manufacturing	0.85	0.28	0.06
Construction	0.84	0.13	0.01
Financial Activities	0.72	0.59	0.07
Leisure and Hospitality	0.71	0.52	0.11
Other Services	0.56	0.52	0.04
Information	0.48	0.42	0.02
Mining and Logging	0.41	0.13	0.00
Government	**0.21**	**0.57**	**0.19**
Education and Health Services	**0.18**	**0.77**	**0.22**

Table III.1: Correlation of Industry Employment Changes and Total Employment Changes
Note: Monthly employment data is taken from Bureau of Labor Statistics. The first column represents the correlation between monthly employment changes at industry level to the national employment changes. The second column is the average within industry female share over the years of 2002-2015. The third column is the average industry share of women over the years 2002-2015.

to 0.86. Moreover, procyclical industries have lower female share and vice versa. The exceptions are trade, transportation and utilities and professional and business services industries where the procyclicality is the highest and gender bias does not exist. However, construction and manufacturing industries have the correlation 0.84 and 0.85 respectively and they have the lowest female share in employment. Furthermore, industries with the highest female share are education, health services and government, with shares 77% and 57% respectively and those are the industries with the lowest correlation between industry employment and total employment (0.18 and 0.21)[28]. There is another exception to this, which is financial activities industry with relatively high female share (59%) and high correlation (0.72).

[28](Charles et al., 2017) find that college attendance decreased during boom times and increased in recession times. This finding can be also thought as a reason why education, health services are acyclical, and even countercyclical sometimes.

5.2 Gender Asymmetry and Cyclicality: How to decide?

The hypothesis that we are arguing in this paper is that female dominated industries are acyclical and male dominated industries are heavily procyclical. As described in the previous part, there are some exceptions to this rule. Hence, we are going to analyze how important these irregularities are. First exception is that two heavily procyclical industries; "Trade, Transportation, and Utilities" and "Professional and Business Services" are relatively gender balanced; i.e. displays 41% to 45% women share respectively. Hence, we think negative effect on fertility from male side and positive effect of fertility from female side will cancel out each other[29]. Another exception is "Financial Activities" industry which has relatively high cyclicality (0.72) and relatively high female share (0.59). However, Figure III.8 shows that this industry captures only 7% of total female employment. Therefore, it is a relatively small industry and excluding that from the analysis does not change the analysis qualitatively[30].

As a result, major industries which are significantly procyclical and male dominant and significantly acyclical and female dominant are the ones which also employ a large majority of labor force. Hence, in our empirical analysis, we are going to focus on these industries; Construction and Manufacturing to represent male income effects, Education, Health and Government to represent female income effects. However, results including all the industries will be shown as well. Employment changes in gender equal industries do not have a significant impact on fertility as male and female effects cancel out each other. In our model, we incorporate employment and cyclicality of all industries when constructing the measure for men and women wages.

[29]Robustness checks are done and presented in Appendix C Table VI.1

[30]Robustness checks are done and presented in Table VI.1

5.3 Regression Analysis

The classical assumption of time cost of childbearing is only on female side implies that male income changes produce income effect, female income changes produce both income and substitution effects. However, previous studies and cross sectional evidences show that substitution effect is dominant for female as high wage earner women have lower fertility rates. To test this hypothesis, we construct a dataset which includes birth rates and industry employment at state level. For male income effects, we use employment of male dominant industries (construction, manufacturing) as a proxy and for female income, we use employment of female dominant industries (education, health services and government). Table III.2 shows that employment changes in female dominant industries have negative impact on fertility changes, whereas employment changes of male dominant industries have positive impact as we argued. In other words, 1% employment increase in male dominant industries leads to 0.22 ppt increase in fertility and 1% employment increase in female dominant industries leads to 0.31 ppt decrease in fertility at state level.

If we think that employment changes may not be a good proxy for income changes, we have also used total industry compensation changes as it captures both the changes in employment and changes in earnings. Table VI.1 shows the results for different specifications. Coefficients for male and female income effects remains qualitatively same and significant. Moreover, regression results for post-recession period give larger effects.

Finally, in order to rule out potential problem which may arise from excluding industries other than the ones we defined as female and male dominant industries, we have included all the industry compensation changes in our analysis. Consistent with our hypothesis, compensation changes of gender equal industries do not have significant effect on fertility as positive male effect and negative female effect cancel out each other. Nevertheless, male dominant and female dominant industry compensation changes still have significant effect

Baseline Specification		
Dependent Variable: $\Delta Fertility\ Rate_{t,t-1,s}$		
$\%\Delta Employment\ Female\ Dominant\ Industries_{t-1,t-2,s}$	-0.31***	-0.50***
	(0.108)	(0.098)
$\%\Delta Employment\ Male\ Dominant\ Industries_{t-1,t-2,s}$	0.22***	0.19***
	(0.015)	(0.021)
Year Fixed Effects	No	Yes
R^2	0.35	0.73
n	576	576

Table III.2: Birth Rate and Gender Biased Industry Employment
Note: The data includes state level industry employment and birth rates for years 2002-2016. Female dominant industries are education, health services and government, male dominant industries are construction and manufacturing. Birth data is from NHS and industry employment data is from BLS. The regression is weighted by state employment level.

on fertility outcomes, where the signs are the same as in the baseline specification (Table VI.1).

6 Model

We formalize the idea of heterogeneous impact of female and male earnings in fertility and we conduct counterfactual scenarios such as "What would have happened if industry employment was gender balanced?" or "What would have happened if different industrial cyclical properties did not exist?". To address these issues, we build a household fertility choice model with partial specialization(Jones et al., 2010). Partial specialization feature allows both genders to work in the market, however only female incur the time cost of childbearing. We first derive the static model and we build a 3-period model in order to address the fertility gap between younger and older women, but more importantly larger fertility decline among younger women in recession times.

6.1 Static Model

A representative household solve the maximization problem in (1) by choosing how much to consume (c) and how many kids to have (n). σ_c is curvature of the utility function with respect to consumption, σ_n is curvature of the utility function with respect to fertility. α_n represents preference towards children with respect to consumption. Household has income from male (w_m) and from female (w_f). However, female has to sacrifice her time from working when they have a kid by a factor γ. There is no labor force participation decision. Both genders work full time, female works less when they have a kid.

$$\max_{c,n} \frac{c^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{n^{1-\sigma_n}}{1-\sigma_n} \quad s.t. \; c \leq w_m + (1-\gamma n) w_f$$

Optimality Condition:

$$\left(\frac{[w_m + (1-\gamma n*) w_f]}{n*^{\sigma_n/\sigma_c}} \right) = \left(\frac{\gamma w_f}{\alpha_n} \right)^{1/\sigma_c}$$

Special Case $\sigma_c = \sigma_n = 1$:

$$n* = \frac{w_m + w_f}{\left(\gamma w_f + \left(\frac{\gamma w_f}{\alpha_n} \right) \right)} \tag{III.1}$$

$$\partial n^* / \partial w_m = \frac{\alpha_n}{\gamma w_f (\alpha_n + 1)} > 0 \tag{III.2}$$

$$\partial n^* / \partial w_f = \frac{-w_m \alpha_n}{\gamma (\alpha_n + 1) w_f^2} < 0 \tag{III.3}$$

$$\partial n^*/\partial w_m \partial w_f = \frac{-\alpha_n}{\gamma w_f^2(\alpha_n + 1)} < 0 \tag{III.4}$$

$$\partial n^*/\partial^2 w_f = \frac{2 w_m \alpha_n}{\gamma(\alpha_n + 1) w_f^3} > 0 \tag{III.5}$$

Fertility is an increasing function of male income and decreasing function of female income. Moreover, female income has a negative impact on the response of fertility to the male income changes. It means that fertility changes less to a shock to the male income if female income is high. On the other hand, fertility responds more to a shock to the female income if male income is high and less if female income is high.

6.2 3-Period Model

Representative household lives 3 periods. In the first period she is young, in the second period she is old and in the last period she is retired. Having a kid is only possible in the first 2 periods. In the third period, the agent consumes her savings. Female incur the time cost of the kid only when the kid is young. The young agent face borrowing constraints.

The young agent solves the following problem:

$$\max_{c_y, a_y, c_o, a_o, n_y, n_o, c_r} \quad U_y + \beta U_o + \beta^2 U_r \ s.t.$$

$$\begin{aligned}
c_y + a_y &\leq w_{my} + (1 - \gamma_0 n_y) w_{fy} \\
c_o + a_o &\leq (1+r) a_y + w_{mo} + (1 - \gamma_0 n_o - \gamma_1 n_y) w_{fo} \\
(1+r) a_o &= c_r \\
a_y &\geq 0
\end{aligned}$$

where

$$U_y = \frac{c_y^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{(\nu + n_y)^{1-\sigma_n}}{1-\sigma_n}$$

$$U_o = \frac{c_o^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{(n_y + n_o)^{1-\sigma_n}}{1-\sigma_n}$$

$$U_r = \frac{c_r^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{(n_y + n_o)^{1-\sigma_n}}{1-\sigma_n}$$

The old agent solves the following problem:

$$\max_{c_y, a_y, c_o, a_o, n_y, n_o, c_r} \quad U_o + \beta U_r \ s.t.$$

$$\begin{aligned} c_o + a_o &\leq (1+r)a_y + w_{mo} + (1 - \gamma_0 n_o - \gamma_1 n_y) w_{fo} \\ (1+r)a_o &= c_r \\ a_y &\geq 0 \end{aligned}$$

where

$$U_o = \frac{c_o^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{(n_y + n_o)^{1-\sigma_n}}{1-\sigma_n}$$

$$U_r = \frac{c_r^{1-\sigma_c}}{1-\sigma_c} + \alpha_n \frac{(n_y + n_o)^{1-\sigma_n}}{1-\sigma_n}$$

In the 1st period utility of the agent (U_y), the utility from children has a different structure. The agent derives utility from kids (if any when young) but they have a preference parameter (ν) which can be thought as the utility from being childless and which allows them to postpone fertility if necessary. (Baudin et al., 2015) finds that 2.5% of women remain childless due to poverty and 8.1% due to high opportunity cost. Hence, this parameter can serve to both purposes faced by young women. Hence even if young agent does not have a kid, they still have some positive utility. a_y and a_o represent saving when young and old respectively.

Assumption 1 Agents face borrowing constraints when they are young which implies $a_y \geq 0$.

Assumption 2 Time cost associated to young and older kids are different.

Assumption 3 There is an implicit assortative mating in terms of age groups. Young women are mating to young men and old women are mating to old men.

6.3 Gender Asymmetry in Industries and Income Cyclicality

Female and male workers have different weights in industry employment and industries have different cyclicality in total compensation. Empirically, sticky wage rule implies that wages do not change much with business cycles but employment does. Hence, a good measure of earning changes in a model without incorporating unemployment would be total compensation which implicitly captures the changes in both earnings and employment at industry level. Hence, we provide an empirically tractable way of measuring the total compensation of men vs. women, its time series movement as well as gender bias in employment. Equations below are used to estimate total compensation of men vs. women weighted by industry employment using industry compensation. ω_{fi} and ω_{mi} represent fraction of female and male employment in industry i respectively. These shares do not depend on time, as they are independent of time as shown previously. w_{it}[31] represents total compensation of industry i, γ_{fi} represents the gender gap in earnings in industry i. Finally, η_{fi} and η_{mi} represent earnings gap between young and old workers. Hence w_{yft} , w_{oft}, w_{ymt} and w_{omt}

[31]Total compensation levels are divided by CPI index to remove price effects.

become total female and male compensation for young and old workers separately. The advantage of such an analysis is that it allows us to observe: 1-The effect of changes of industrial compensation on female and male earnings. 2- The effect of gender weights on cyclicality of male and female earnings.

$$w_{yft} = \Sigma_{i=1}^{i=n} \omega_{fi} w_{it} \gamma_{fi} \eta_{fi} \tag{III.6}$$

$$w_{oft} = \Sigma_{i=1}^{i=n} \omega_{fi} w_{it} \gamma_{fi} (1 - \eta_{fi}) \tag{III.7}$$

$$w_{ymt} = \Sigma_{i=1}^{i=n} \omega_{mi} w_{it} (1 - \gamma_{fi}) \eta_{mi} \tag{III.8}$$

$$w_{omt} = \Sigma_{i=1}^{i=n} \omega_{mi} w_{it} (1 - \gamma_{fi})(1 - \eta_{mi}) \tag{III.9}$$

Assumption 4 Industry weights in employment are stable over time but different for genders.

Assumption 5 Gender earnings gap is stable over time but vary across industries.

Assumption 6 Age earnings gap is different across genders and industries but stable over time.

6.4 Estimating Model Parameters

In this paper, we are not only looking at theoretical implications of female and male wage changes on fertility but also estimate those changes as well as relative earnings between agents using industry compensations. Hence, these estimates are crucial in approximating income shocks to the observed shocks in the Great Recession.

$i = industry$	ω_{fi}	ω_{mi}
Mining and Logging	0.1%	0.9%
Construction	1.2%	8.3%
Manufacturing	5.7%	13.7%
Trade, Transportation, and Utilities	15.8%	22.3%
Information	1.9%	2.5%
Financial Activities	7.2%	4.8%
Professional and Business Services	11.8%	14.1%
Education and Health Services	22.4%	6.4%
Leisure and Hospitality	10.5%	9.3%
Other Services	4.3%	3.8%
Government	19.0%	13.8%

Table III.3: Industry Shares in Male vs. Female Employment

Note: The data on gender specific employment at industry level is taken from BLS for the sample years of 2002-2015.

6.4.1 Gender Bias Industry Employment

Table III.3 documents the percentage of people employed in each industry separately for male and female. Since these shares do not change significantly over time, the average of the sample year 2002-2015 has been reported and has been used for the analysis. Almost half of employed women are working in education, health services and government. More than half of employed men on the other hand, are working in the most procyclical industries; construction, manufacturing, trade-transportation and professional and business services. These shares are used to construct male and female compensation and also to perform counterfactual compensation scenarios.

6.4.2 Age Profile in Earnings

Since we are constructing compensation changes using macro level data and age-specific compensation changes are not available, we developed a measure of difference in earnings according to age groups. Table III.4 represents the fraction of compensation captured by younger workers (20-30 age group) differently for men and women. We estimated η_{fi} and

$i = industry$	η_{fi}	η_{mi}
Mining and Logging	0.40	0.42
Construction	0.44	0.41
Manufacturing	0.40	0.37
Trade, Transportation, and Utilities	0.38	0.35
Information	0.37	0.34
Financial Activities	0.40	0.33
Professional and Business Services	0.41	0.34
Education and Health Services	0.40	0.29
Leisure and Hospitality	0.40	0.36
Other Services	0.44	0.40
Government	0.41	0.40

Table III.4: Age Profile in Industry Earnings

Note: Current Population has been used to calculate earnings difference across age, gender, industries. η_{fi} represents the fraction of earnings captured by young female and $(1 - \eta_{fi})$ represents the fraction captured by old female.

η_{mi} by using Current Population Survey for the years 2002-2015 and averaged across years. We have estimated average earnings of men and women of different age groups at industry level. Finally, we took the ratio of young to old by normalizing the sum to 1.

6.4.3 Gender Gap in Industry Earnings

Since we are not able to observe the actual compensation captured by each gender at industry level, we construct a measure of gender gap (γ_{fi}) which represents the fraction of compensation captured by female in each industry. We used Current Population Survey for the years 2002-2015 and estimated average earnings of men and women at industry level. Finally, we took the ratio of women to men by normalizing the sum to 1 and averaged across years.(see Table III.5)

$i = industry$	γ_{fi}
Mining and Logging	0.40
Construction	0.46
Manufacturing	0.41
Trade, Transportation, and Utilities	0.38
Information	0.41
Financial Activities	0.36
Professional and Business Services	0.39
Education and Health Services	0.38
Leisure and Hospitality	0.40
Other Services	0.38
Government	0.42

Table III.5: Gender Gap in Industry Earnings

6.4.4 Aggregated Compensation Changes

By using the estimates reported in Table III.3,III.4,III.5 and equations 4 through 7, we have constructed earnings of four agents (young women, old women, young men, old men) in the model. This measurement captures the effect of: 1- industry shares in earnings, 2-industry compensation changes, 3- gender gap in earnings, 4- age gap in earnings. Then, we report the annual changes in compensation levels of four agents in the model in Table III.6. In the last row, we show the changes for the recession period 2007-2011 for which we observe the sharpest decline both in fertility, employment and compensation levels. As argued before, male compensation levels show a significant (5%) decline during that period, even after taking into account the changes in all the industries. However, the compensation change for female income is relatively small (around 0.7%).

6.4.5 Fertility of Young and Old

Table III.7 documents the average number of children for the age group of 20-29 and 30-40 to be used as the targets in the model. In order to obtain this measure, the birth rates of 5-year bracket age groups are multiplied by 5. The fertility of both groups are the highest

	w_{yft}	w_{oft}	w_{ymt}	w_{omt}
2003	1.5%	1.5%	0.3%	0.4%
2004	2.9%	2.9%	2.4%	2.5%
2005	1.4%	1.4%	1.2%	1.3%
2006	2.9%	2.9%	2.6%	2.7%
2007	2.8%	2.8%	2.3%	2.4%
2008	-0.4%	-0.5%	-1.7%	-1.7%
2009	-1.4%	-1.4%	-4.2%	-4.2%
2010	0.8%	0.8%	0.2%	0.3%
2011	0.3%	0.4%	0.7%	0.9%
2012	2.0%	2.0%	2.0%	2.2%
2013	0.9%	0.9%	0.9%	0.9%
2014	2.9%	2.9%	3.3%	3.4%
2015	4.8%	4.9%	4.8%	4.9%
2007-2011	-0.7%	-0.8%	-5.0%	-4.7%

Table III.6: Computed Measures of Model Earnings

in 2007, then decline afterwards until 2011. After 2011, the changes are relatively modest. Comparing younger and older women's fertility show us that younger women respond more to the economic shocks, i.e. the average number of children decreases from 1.11 to 0.96 for the age group 20-29, whereas it decreases from 0.74 to 0.71 for age group 30-40. This is partly due to delaying motive for younger women, and also borrowing constraints for young families.

6.4.6 Relative Compensation between Agents

When calibrating the model, we need to determine a relative measure between wages of four different agents, then the changes will follow according to Table III.6. We use computed model earnings according to the structure described in section 6.3 and summarize in Table VI.2. In order to find the relative measure between compensation levels when calibrating the model, we take the averages across years, normalize w_{fy} to 1 and calculate w_{my}, w_{mo} and w_{fo} as summarized in Table III.8.

	n_y	n_o	n_{total}
2003	1.09	0.69	1.78
2004	1.08	0.70	1.78
2005	1.08	0.71	1.79
2006	1.11	0.73	1.84
2007	**1.11**	**0.74**	**1.85**
2008	1.08	0.72	1.80
2009	1.03	0.71	1.74
2010	0.99	0.71	1.69
2011	**0.96**	**0.71**	**1.67**
2012	0.94	0.72	1.66
2013	0.93	0.73	1.66
2014	0.92	0.75	1.67
2015	0.90	0.76	1.66
2016	0.87	0.77	1.64

Table III.7: Average number of kids per age group
Note: The data is from National Health Statistics. The birth rates for 5-year bracket age groups are multiplied by 5 to get the average number of child at every age group. n_y represents the average number of children for the group of age 20-29, n_o is the average number of children for the group of age 30-40.

Variable	Definition	Value
w_{my}	Young male wage	$1.37w_{fy}$
w_{mo}	Old male wage	$2.44w_{fy}$
w_{fo}	Old female wage	$1.49w_{fy}$
w_{fy}	Young female wage	1

Table III.8: Relative Compensation
Note: The data on compensation levels is from BEA. Computed model wages is shown in Table VI.2

7 Results

We parameterized the model as summarized in Table III.9. The discount rate and the intertemporal elasticity of substitution are taken as standard from the literature. For the curvature parameters, σ_c and σ_n, we have selected within the range used in the literature. Setting them equal to 1, leads to log-utility case in which income ans substitution effects cancel out each other, hence we observe no change in fertility when incomes of all agents change equally. In order to get rid of that effect, we set them greater than 1. Moreover, when both curvature parameters equal to each other, gender differentiated wage shocks produce the same effect. However, we are confident that our qualitative results do not depend on the choice of curvature parameters.

In order to determine the level of fertility, as well as the difference between young and old, we calibrated α_n and ν. If young families do not derive any utility from being childless, then everybody would be having babies when young because there is higher return due to having them for a long time. However, this is not compatible with the data. To address this issue, we use two source of variation. The purpose of ν is that it gives flexibility to young families to postpone childbearing as they are financially constrained. Having ν positive, allows young families to have some utility from being childless. Also, we allocate different time cost for younger and older children as shown by Kleven et al. (2018). They find that hours worked decline by 20% following the first birth, then increase by time but still remain 0.97% lower than women without children. Hence, we took these estimates as the time cost of children (γ_o and γ_1).

Finally, we normalized wage of young female to 1 and estimate the ratio of compensations between four agents in the model. More details are given in section 6.4.6. Hence, we calibrate two parameters α_n and ν to target fertility of young and old women. The results of the calibration are shown in Table III.9.

Parameters	Definition	Value	Source
r	Discount rate	0.01	
β	Intertemporal elasticity of substitution	0.99	
σ_n	Curvature of utility wrt fertility	1.5	
σ_c	Curvature of utility wrt consumption	2	
w_{fy}	Young female wage	1	
γ_0	Time cost of young children	0.2	Kleven et al. (2018)
γ_1	Career cost of children	0.097	Kleven et al. (2018)
w_{my}	Young male wage	$1.37w_{fy}$	CPS, BEA
w_{mo}	Old male wage	$2.44w_{fy}$	CPS, BEA
w_{fo}	Old female wage	$1.49w_{fy}$	CPS, BEA
Calibrated Parameters			
α_n	Preference of fertility wrt consumption	0.1	Target $n_y = 1.1$
ν	Childlessness utility when young	2.76	Target $n_o = 0.74$

Table III.9: Calibration Results

7.1 Calibration Results

7.2 Counterfactual Analysis

We argue that the fertility decline is amplified during recessions due to gender biased industry employment and cyclical properties of industries. In order to show this amplification mechanism, we perform counterfactual analysis. First, we apply the computed compensation changes from Table III.6 to the model and observe how well we can approximate the fertility changes in the data. The model performs well in delivering the fertility outcomes in 2011 (Figure III.11). Hence, observed changes in industry compensations as well as gender-specific employment are crucial in explaining fertility trends. Then, instead of applying observed changes which is larger decline in male-dominant industries, smaller decline in female-dominant industries, we apply the average decline in compensation at national level after taking into account all the industry compensation changes. In that case, fertility decline would have been milder. It is because of 2 effects: 1- Male income loss is smaller, hence affects fertility less. 2- Female income loss is larger, due to lower opportunity cost,

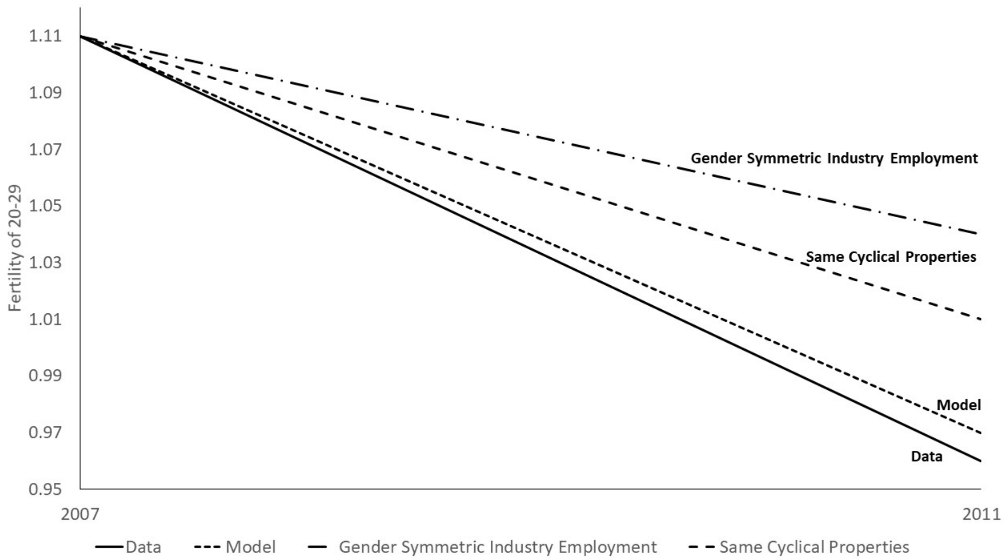


Figure III.11: Model Fit and Counterfactuals

	2007 Data	2011 Data	2011 Model	Gender Symmetric Employment	Same Cyclicality
n_y	1.11	0.96	0.97	1.04	1.01
n_o	0.74	0.71	0.68	0.71	0.7
$\%\Delta w_{fy}$		-0.7%	-0.7%	-2.8%	-4.4%
$\%\Delta w_{fo}$		-0.8%	-0.8%	-2.8%	-4.4%
$\%\Delta w_{my}$		-5.0%	-5.0%	-3.3%	-4.4%
$\%\Delta w_{mo}$		-4.7%	-4.7%	-2.8%	-4.4%

Table III.10: Counterfactual Analysis

fertility increases.

As a result, in such a scenario where genders are equally employed in industries, everybody would experience the same average decline in earnings. Thus, fertility would not decline as much. A simple accounting gives an estimate of 28% as the amplification effect. Hence, 28% of fertility decline can be explained by gender-biased industry employment.

Employment change of men versus women have different effect on fertility

We showed in our empirical analysis that employment change in male-dominant industries affect fertility positively and employment change in female-dominant industries affect fertility negatively at state level. Moreover, in our theoretical framework, we showed that under reasonable assumption, male income has positive impact on fertility whereas female income has negative impact on fertility. In order to incorporate both employment and wage changes during the recession, we used compensation data and we got the same results.

Part of fertility decline can be explained by gender-biased industry employment and industrial cyclical properties:

Our quantitative model predicts that 44% of the fertility decline can be explained by the fact that women and men are employed in different industries with different cyclical properties. Hence, in an hypothetical world where everything is symmetric across genders, fertility decline should have been milder during recessions.

8 Conclusion

This paper attempts to give a complementary explanation for procyclical feature of fertility. We argue that part of the reason why fertility is procyclical is due to gender asymmetry in industries as well as different cyclical properties of industries. Men are employed in heavily procyclical industries whereas women are employed in acyclical industries. In recession times, worse labor market outcomes of men negatively affect fertility. On the other hand, better or stable labor market outcomes of women also negatively affect fertility due to substitution effect of female wage. Hence, gender asymmetry feature of the labor market aggravates the fertility response to business cycles.

We show that increases in employment (and total compensation) in male dominant industries have positive impact on fertility at state level whereas increases in female dominant industries have negative impact on fertility. Our empirical analysis shows that the results are robust to the measure used (either employment or compensation) and also robust when all industry changes are incorporated. The outcome changes in gender-equal industries do not seem to have a significant effect on fertility.

We build a model of household fertility choice with partial specialization. We show qualitatively that under reasonable parameters, female wage affects fertility negatively and male wage affects fertility positively. With a 3-period model, we are able to present quantitative results by also incorporating fertility differences among age groups. Our quantitative model predicts well the fertility change among younger and older women as a result of compensation changes in male and female income measured from the data.

In order to quantify the importance of gender asymmetry in industries, we perform a counterfactual analysis by asking the question " what would be the fertility after the recession if industries were gender-equal and/or genders experience same cyclical shocks?". In all scenarios, we find that fertility decline would have been milder. Our accounting shows that 44% of the fertility decline in the Great Recession can be attributed to gender-biased industry employment and cyclical properties of industries.

We believe that our findings are important in order to understand why fertility is procyclical, what feature of the labor market causes this phenomenon and finally why better labor market outcomes of women means lower fertility. One reason why we obtain such a conclusion is that women still incur majority of childbearing and another reason is that women have to sacrifice hours worked when they have children. Hence, other than gender symmetric labor market conditions, policies which may potentially reduce the opportunity cost of child to mothers may help in rising fertility.

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Appendix A

Model Details

Definitions

Parameter	Definition
α	Young ratio in the population
μ	Uneducated ratio among young
$\hat{\mu}$	Uneducated ratio among old
β	Workers' share in the Nash Bargaining
r	Discount rate
δ	Exogenous job destruction rate
ν	Pension replacement rate
b_y	Unemployment benefit of young
b_o	Unemployment benefit of old
σ	Probability of becoming old
ω	Probability of becoming retired
λ_y	On-the-job search intensity of young
λ_o	On-the-job search intensity of old
$\tilde{\lambda}_y$	Mismatch search intensity of young
$\tilde{\lambda}_o$	Mismatch search intensity of old
c_{1y}	Vacancy cost in young unskilled market
c_{1o}	Vacancy cost in old unskilled market
c_{2y}	Vacancy cost in young skilled market
c_{2o}	Vacancy cost in old skilled market
α_p	Relative efficiency of mismatched wrt low educated
ψ_p	Relative efficiency of young high educated wrt old high educated
γ_p	Relative efficiency of young low educated wrt old low educated
β_p	Relative efficiency of young mismatched wrt old mismatched
θ_h/θ_l	Relative technological efficiency in the production

Table IV.1: Parameter Definitions

Abbreviation	Meaning
nly	young low skilled
nlo	old low skilled
shy	young high skilled
sho	old high skilled
nhy	young mismatched
nho	old mismatched

Table IV.2: Abbreviations

Variable	Definition
$u(h, y)$	number of high educated young unemployed
$u(h, o)$	number of high educated old unemployed
$u(l, y)$	number of low educated young unemployed
$u(l, o)$	number of low educated old unemployed
$v(s, y)$	number of young skilled vacancies
$v(s, o)$	number of old skilled vacancies
$v(n, y)$	number of young unskilled vacancies
$v(n, o)$	number of old unskilled vacancies
$w(s, h, y)$	wage of young high educated
$w(s, h, o)$	wage of old high educated
$w(n, h, y)$	wage of young mismatched
$w(n, h, o)$	wage of old mismatched
$w(n, l, y)$	wage of young low educated
$w(n, l, o)$	wage of old low educated
H_y	number of young high educated employed
H_o	number of old high educated employed
M_y	number of young mismatched employed
M_o	number of old mismatched employed
L_y	number of young low educated employed
L_o	number of old low educated employed
H	aggregate number of high skilled employed
M	aggregate number of mismatched employed
L	aggregate number of low educated employed
$\tilde{L}$	effective number of low skilled employed
Y	aggregate product

Table IV.3: Variable Definitions

Model Properties

	Symmetric Case	Imperfect Substitution, Stochastic Aging	Relative Supply	Mismatch Channel	Vacancy Cost
β	0.7				
r	0.01				
δ	0.1				
b_y	0.1				
b_o	0.1	0.3			
θ_l	1				
υ	0.5				
ρ	1	0.8			
η	1	0.75			
σ	0	0.1			
ω	0	0.028			
α	0.5		0.1		
μ	0.5		0.7		
$\hat{\mu}$	0.5		0.8		
$\tilde{\lambda}_y$	0			0.5	
$\tilde{\lambda}_o$	0			0.5	
λ_y	0			1	
λ_o	0			1	
c_{1y}	0.1				
c_{2y}	0.1				0.6
c_{1o}	0.1				
c_{2o}	0.1				
α_p	1				
ψ_p	1				
β_p	1				
γ_p	1				
θ_h/θ_l	[1,2]				

Table IV.4: Model Properties (Parameter Values)

Appendix B

Data

Country Code	Country Name	Frequency	Years
AT	Austria	12	2004-2015
BE	Belgium	11	2004-2014
BG	Bulgaria	9	2007-2015
CH	Switzerland	7	2008-2014
CY	Cyprus	10	2005-2014
CZ	Czechia	10	2005-2014
DK	Denmark	12	2004-2015
EE	Estonia	11	2004-2014
ES	Spain	12	2004-2015
FI	Finland	12	2004-2015
FR	France	11	2004-2014
GR	Greece	12	2004-2015
HR	Croatia	5	2010-2014
HU	Hungary	11	2005-2015
IE	Ireland	11	2004-2014
IS	Iceland	12	2004-2015
IT	Italy	11	2004-2014
LT	Lithuania	10	2005-2014
LU	Luxembourg	11	2004-2014
LV	Latvia	11	2005-2015
NL	Netherlands	11	2005-2015
NO	Norway	12	2004-2015
PL	Poland	10	2005-2014
PT	Portugal	11	2004-2014
RO	Romania	8	2007-2014
SE	Sweden	11	2004-2014
SI	Slovenia	11	2004-2015
SK	Slovakia	10	2004-2014
UK	United Kingdom	10	2004-2014

Table V.1: European Countries and data availability in EU-SILC

Observable Country-Specific Characteristics

On the job search intensity λ_y and λ_o:

On the job search intensity parameters are estimated from EU-LFS microdata using variables "lookoj" which is asking whether the respondent is looking for another job and "seekdur" which is asking the duration of seeking. The duration (less than 6 months, 6 months-11 months, more than 1 year) is considered as the intensity of searching and each category is weighted accordingly. If a person who is performing on-the-job search (said yes to lookoj) is searching for another job since less than 6 months, the weight is 0.3 (0.6 and 0.9 for more duration). Hence, to be consistent with the model, on-the-job search intensity is calculated by taking the average of duration weights only among mismatched and the ones who are looking for another job. This ratio is calculated for young and old, country and year separately and averaged out across year for every country (from 2004 to 2015). The difference between young and old is not statistically significant. Southern European countries have higher intensities than Central and Northern Europe. For convenience, I used 0.4 for countries where college educated have higher unemployment rates and 0.3 for other countries. But the results are robust to changes in this range.

Country	λ_y	λ_o	Country	λ_y	λ_o
Austria	0.23	0.29	Latvia	0.26	0.33
Belgium	0.29	0.32	Lithuania	0.27	0.31
Bulgaria	0.32	0.35	Luxembourg	0.26	0.29
Croatia	0.41	0.43	Malta	0.34	0.31
Cyprus	0.39	0.37	Netherlands	0.29	0.33
Czech Republic	0.30	0.31	Norway	0.23	0.28
Denmark	0.24	0.28	Poland	0.31	0.32
Estonia	0.27	0.30	Portugal	0.40	0.41
Finland	0.23	0.25	Romania	0.31	0.35
France	0.31	0.35	Slovakia	0.37	0.38
Greece	0.39	0.41	Slovenia	0.36	0.37
Hungary	0.31	0.35	Spain	0.36	0.35
Iceland	0.17	0.20	Sweden	0.21	0.22
Ireland	0.30	0.31	Switzerland	0.25	0.31
Italy	0.36	0.37	United Kingdom	0.26	0.28

Table V.2: On-the-job Search Intensity

Young ratio α, Uneducated ratio within young μ, Uneducated ratio within old $\hat{\mu}$:

These parameters are taken from Eurostat website using labor force numbers with education and age categories for every country and every year separately. Young ratio (α) is the ratio of people who are in the labor force and at least high school degree aged 25-29 to people who are in the labor force and at least high school degree aged 25-64. Uneducated ratio within young (μ) is calculated by taking the ratio of people whose highest educational attainment is upper secondary (ISCED level 3-4) and in the labor force aged 25-29 to people with ISCED level 3 and above in the labor force aged 25-29. Finally, uneducated ratio within old is calculated by taking the ratio of people whose highest educational attainment is upper secondary (ISCED level 3-4) and in the labor force aged 30-64 to people with ISCED level 3 and above in the labor force aged 30-64.

Country	α	μ	$\hat{\mu}$	Country	α	μ	$\hat{\mu}$
Austria	0.13	0.77	0.77	Latvia	0.14	0.66	0.72
Belgium	0.14	0.55	0.61	Lithuania	0.13	0.51	0.67
Bulgaria	0.12	0.70	0.73	Luxembourg	0.13	0.57	0.63
Croatia	0.14	0.74	0.79	Netherlands	0.12	0.58	0.65
Cyprus	0.16	0.48	0.64	Norway	0.12	0.55	0.60
Czech Republic	0.13	0.76	0.83	Poland	0.16	0.60	0.76
Denmark	0.11	0.59	0.64	Portugal	0.13	0.72	0.83
Estonia	0.14	0.63	0.62	Romania	0.14	0.75	0.85
Finland	0.12	0.65	0.57	Slovakia	0.15	0.74	0.83
France	0.13	0.55	0.69	Slovenia	0.14	0.68	0.72
Germany	0.11	0.75	0.71	Spain	0.14	0.59	0.66
Greece	0.14	0.65	0.73	Sweden	0.12	0.59	0.65
Hungary	0.14	0.71	0.77	Switzerland	0.12	0.63	0.63
Iceland	0.13	0.65	0.66	Turkey	0.19	0.74	0.84
Ireland	0.16	0.48	0.62	United Kingdom	0.13	0.56	0.63
Italy	0.11	0.80	0.82				

Table V.3: Young and Uneducated Ratio in Europe

State	α	μ	$\hat{\mu}$	State	α	μ	$\hat{\mu}$
Alabama	0.11	0.67	0.69	Montana	0.09	0.68	0.67
Alaska	0.12	0.75	0.68	Nebraska	0.11	0.63	0.68
Arizona	0.12	0.68	0.64	Nevada	0.12	0.73	0.71
Arkansas	0.12	0.72	0.73	New Hampshire	0.09	0.60	0.61
California	0.13	0.61	0.57	New Jersey	0.10	0.51	0.54
Colorado	0.12	0.57	0.55	New Mexico	0.11	0.73	0.65
Connecticut	0.10	0.52	0.54	New York	0.12	0.51	0.58
Delaware	0.11	0.59	0.63	North Carolina	0.11	0.62	0.64
District of Columbia	0.19	0.23	0.35	North Dakota	0.11	0.65	0.70
Florida	0.11	0.66	0.65	Ohio	0.11	0.64	0.69
Georgia	0.12	0.62	0.62	Oklahoma	0.12	0.71	0.70
Hawaii	0.12	0.69	0.62	Oregon	0.11	0.64	0.63
Idaho	0.12	0.74	0.70	Pennsylvania	0.10	0.59	0.67
Illinois	0.12	0.56	0.62	Rhode Island	0.11	0.55	0.59
Indiana	0.11	0.67	0.71	South Carolina	0.12	0.65	0.67
Iowa	0.11	0.66	0.73	South Dakota	0.11	0.67	0.71
Kansas	0.11	0.63	0.65	Tennessee	0.12	0.65	0.68
Kentucky	0.12	0.68	0.70	Texas	0.12	0.65	0.63
Louisiana	0.12	0.67	0.70	Utah	0.15	0.69	0.64
Maine	0.09	0.68	0.68	Vermont	0.08	0.61	0.61
Maryland	0.11	0.53	0.54	Virginia	0.12	0.54	0.55
Massachusetts	0.11	0.44	0.51	Washington	0.11	0.63	0.61
Michigan	0.11	0.66	0.68	West Virginia	0.11	0.71	0.74
Minnesota	0.10	0.62	0.67	Wisconsin	0.10	0.67	0.71
Mississippi	0.12	0.72	0.72	Wyoming	0.11	0.73	0.71
Missouri	0.12	0.63	0.68				

Table V.4: Young and Uneducated Ratio in the US

Pension replacement rate υ:

In the model, the old becomes retired with stochastic probability and get a fixed pension depending on their last wages. Hence, their last wage is replaced with a rate υ. To find country-specific pension replacement rates, I referred to OECD (2013) and I used average earners net replacement rate in my analysis.

Country	Pension Replacement rate	Country	Pension Replacement rate
Austria	0.9	Luxembourg	0.7
Belgium	0.62	Netherlands	1.01
Czech Republic	0.75	Norway	0.63
Denmark	0.75	Poland	0.6
Estonia	0.62	Portugal	0.68
Finland	0.63	Slovakia	0.85
France	0.71	Slovenia	0.6
Greece	0.71	Spain	0.8
Hungary	0.95	Sweden	0.55
Iceland	0.76	Switzerland	0.65
Ireland	0.45	United Kingdom	0.42
Italy	0.82	US	0.47

Table V.5: Pension Replacement Rates

Occupation Categories and Mismatch:

The mismatch definition that I am using in this paper is vertical mismatch or being overqualified for a job which results from university graduates are working in unskilled jobs. First of all, deciding which occupation should be considered skilled and unskilled is a challenge, especially in a cross country analysis. First of all, there are time changes, such as being a banker doing basic daily transactions should have been considered as a skilled job 20 years ago although it does not require much skills now with computers etc.. This is not a major concern for my analysis because the time period that I am using is 2004-2015. The second concern is that countries differ in terms of their overall education level which in turn affect average education level at a certain occupation. In order to maintain consistency in defining “mismatch measure”, I used the same assigning rule for all the countries. The only problem it creates, mismatch can be measured a little higher than people perceive in high educated countries and vice versa. But by keeping that in mind, a consistent measure would benefit me in terms of observing how labor force is allocated to different occupations. By using EU-SILC microdata, I calculated college educated ratio at every 2 digit occupation categories (ISCO-88) for every country separately to alo observe any significant cross-country differences and considered the occupation as skilled if more than half of the workers are college educated. Note that having still some high school workers working in a skilled occupation can be because of generational differences (a 55 year old man doing that job since years hence developed on the job skills). However, most important thing is that in a such a skilled occupation, the new comers should be asked to have at least university degree. Another shortcoming is that having high college educated ratio can mean two things: 1- overall education level of the country hence abundance of college educated workers. 2- likelihood of mismatch which causes originally low skilled occupation to have relatively higher college educated ratio. Therefore, 50% threshold is a reasonable measure both to capture generational differences in skilled occupation and mismatch problem in low skilled occupations.

Table V.6: College Educated Ratio in 1 digit occupation categories by countries

		Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech Republic	Denmark	Estonia	Finland	France
1	**Legislators, senior officials and managers**	0.51	0.59	0.58	0.51	0.74	0.42	0.58	0.48	0.64	0.55
2	**Professionals**	0.82	0.89	0.93	0.84	0.95	0.82	0.85	0.75	0.88	0.87
3	**Technicians and associate professionals**	0.42	0.59	0.61	0.30	0.54	0.28	0.55	0.41	0.71	0.55
4	**Clerks**	0.34	0.44	0.36	0.10	0.26	0.16	0.39	0.35	0.47	0.33
5	**Service workers and shop and market sales workers**	0.37	0.26	0.35	0.05	0.31	0.14	0.48	0.21	0.46	0.18
6	**Skilled agricultural and fishery workers**	0.34	0.07	0.32	0.03	0.09	0.10	0.34	0.16	0.34	0.12
7	**Craft and related trades workers**	0.36	0.13	0.29	0.01	0.19	0.02	0.28	0.12	0.31	0.12
8	**Plant and machine operators and assemblers**	0.24	0.08	0.24	0.02	0.10	0.01	0.25	0.08	0.26	0.06
9	**Elementary occupations**	0.34	0.16	0.40	0.02	0.11	0.01	0.34	0.07	0.35	0.09

		Greece	Hungary	Iceland	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands
1	**Legislators, senior officials and managers**	0.55	0.60	0.41	0.63	0.20	0.59	0.63	0.52	0.58	0.58
2	**Professionals**	0.95	0.91	0.79	0.84	0.71	0.86	0.83	0.90	0.86	0.87
3	**Technicians and associate professionals**	0.75	0.43	0.31	0.70	0.23	0.52	0.56	0.38	0.22	0.54
4	**Clerks**	0.59	0.35	0.31	0.47	0.13	0.40	0.38	0.18	0.12	0.47
5	**Service workers and shop and market sales workers**	0.59	0.31	0.16	0.43	0.12	0.34	0.19	0.10	0.07	0.45
6	**Skilled agricultural and fishery workers**	0.57	0.25	0.05	0.42	0.06	0.32	0.08	0.04	0.00	0.28
7	**Craft and related trades workers**	0.44	0.19	0.07	0.25	0.05	0.29	0.14	0.04	0.03	0.32
8	**Plant and machine operators and assemblers**	0.40	0.19	0.06	0.27	0.04	0.23	0.08	0.06	0.00	0.25
9	**Elementary occupations**	0.61	0.36	0.09	0.25	0.07	0.17	0.07	0.05	0.02	0.48

		Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden	Switzerland	United Kingdom
1	**Legislators, senior officials and managers**	0.57	0.47	0.57	0.59	0.69	0.54	0.66	0.39	0.63	0.47
2	**Professionals**	0.87	0.91	0.72	0.95	0.70	0.83	0.99	0.79	0.83	0.80
3	**Technicians and associate professionals**	0.66	0.28	0.26	0.23	0.35	0.26	0.69	0.39	0.49	0.54
4	**Clerks**	0.42	0.19	0.17	0.16	0.13	0.10	0.65	0.20	0.22	0.35
5	**Service workers and shop and market sales workers**	0.38	0.13	0.07	0.07	0.04	0.09	0.53	0.25	0.40	0.32
6	**Skilled agricultural and fishery workers**	0.34	0.03	0.01	0.01	0.03	0.04	0.53	0.07	0.22	0.19
7	**Craft and related trades workers**	0.28	0.04	0.03	0.02		0.03	0.55	0.08	0.23	0.21
8	**Plant and machine operators and assemblers**	0.19	0.04	0.02	0.02	0.01	0.01	0.50	0.07	0.15	0.15
9	**Elementary occupations**	0.44	0.03	0.03	0.02	0.04	0.03	0.48	0.11	0.14	0.19

ISCO-88 Codes	Occupation Descriptions	Model Status
1	**Legislators, senior officials and managers**	Skilled
11	Legislators, senior officials and managers	Skilled
12	Corporate managers	Skilled
13	Managers of small enterprises	Skilled
2	**Professionals**	Skilled
21	Physical, mathematical and engineering science professionals	Skilled
22	Life science and health professionals	Skilled
23	Teaching professionals	Skilled
24	Other professionals	Skilled
3	**Technicians and associate professionals**	Unskilled
31	Physical and engineering science associate professionals	Unskilled
32	Life science and health associate professionals	Unskilled
33	Teaching associate professionals	Unskilled
34	Other associate professionals	Unskilled
4	**Clerks**	Unskilled
41	Office clerks	Unskilled
42	Customer services clerks	Unskilled
5	**Service workers and shop and market sales workers**	Unskilled
51	Personal and protective services workers	Unskilled
52	Models, salespersons and demonstrators	Unskilled
6	**Skilled agricultural and fishery workers**	Unskilled
61	Skilled agricultural and fishery workers	Unskilled
7	**Craft and related trades workers**	Unskilled
71	Extraction and building trades workers	Unskilled
72	Metal, machinery and related trades workers	Unskilled
73	Precision, handicraft, craft printing and related trades workers	Unskilled
74	Other craft and related trades workers	Unskilled
8	**Plant and machine operators and assemblers**	Unskilled
81	Stationary-plant and related operators	Unskilled
82	Machine operators and assemblers	Unskilled
83	Drivers and mobile plant operators	Unskilled
9	**Elementary occupations**	Unskilled
91	Sales and services elementary occupations	Unskilled
92	Agricultural, fishery and related labourers	Unskilled
93	Labourers in mining, construction, manufacturing and transport	Unskilled
01	Armed forces	Dropped

Table V.7: Skilled and Unskilled Occupations in the Model

Mismatch Rates:

Mismatch rates have been estimated by using EU-SILC microdata. Every working individual aged between 25-64 is assigned to being mismatched, skilled or unskilled according to procedure described in section "occupation categories". Then mismatch rate for young and old have been calculated for every year and every country separately, then averaged out across years. Mismatch rate for young is the ratio of mismatched young workers with respect to all young workers (aged 25-29) who at least have high school degree in the labor force. Mismatch rate for old is the ratio of mismatched old workers with respect to all old workers (aged 30-64) who at least have high school degree in the labor force. Country specific values are given below.

Country	Mismatch rate (young)	Mismatch rate (old)	Country	Mismatch rate (young)	Mismatch rate (old)
Austria	0.24	0.23	Latvia	0.23	0.20
Belgium	0.20	0.18	Lithuania	0.19	0.09
Bulgaria	0.21	0.21	Luxembourg	0.12	0.11
Croatia	0.07	0.07	Malta	0.08	0.06
Cyprus	0.26	0.17	Netherlands	0.24	0.21
Czech Republic	0.08	0.06	Norway	0.30	0.25
Denmark	0.22	0.21	Poland	0.13	0.05
Estonia	0.10	0.11	Portugal	0.10	0.07
Finland	0.19	0.21	Romania	0.10	0.05
France	0.23	0.14	Slovakia	0.11	0.08
Greece	0.26	0.31	Slovenia	0.16	0.18
Hungary	0.17	0.17	Spain	0.36	0.34
Iceland	0.30	0.25	Sweden	0.16	0.11
Ireland	0.24	0.21	Switzerland	0.20	0.18
Italy	0.08	0.08	United Kingdom	0.23	0.16

Table V.8: Mismatch rates in Europe

State	Mismatch rate (young)	Mismatch rate (old)	State	Mismatch rate (young)	Mismatch rate (old)
Alabama	0.10	0.08	Montana	0.10	0.09
Alaska	0.08	0.08	Nebraska	0.11	0.09
Arizona	0.09	0.09	Nevada	0.10	0.09
Arkansas	0.08	0.07	New Hampshire	0.12	0.10
California	0.12	0.10	New Jersey	0.14	0.11
Colorado	0.14	0.12	New Mexico	0.08	0.07
Connecticut	0.13	0.11	New York	0.14	0.10
Delaware	0.11	0.09	North Carolina	0.11	0.09
District of Columbia	0.14	0.10	North Dakota	0.11	0.08
Florida	0.11	0.10	Ohio	0.10	0.08
Georgia	0.11	0.10	Oklahoma	0.09	0.08
Hawaii	0.11	0.12	Oregon	0.12	0.09
Idaho	0.09	0.08	Pennsylvania	0.11	0.08
Illinois	0.13	0.10	Rhode Island	0.14	0.10
Indiana	0.10	0.08	South Carolina	0.11	0.09
Iowa	0.10	0.07	South Dakota	0.11	0.08
Kansas	0.11	0.09	Tennessee	0.11	0.08
Kentucky	0.10	0.08	Texas	0.10	0.09
Louisiana	0.10	0.07	Utah	0.09	0.09
Maine	0.12	0.08	Vermont	0.13	0.10
Maryland	0.12	0.09	Virginia	0.12	0.10
Massachusetts	0.15	0.11	Washington	0.11	0.10
Michigan	0.10	0.08	West Virginia	0.08	0.06
Minnesota	0.12	0.09	Wisconsin	0.10	0.08
Mississippi	0.08	0.07	Wyoming	0.09	0.08
Missouri	0.11	0.09			

Table V.9: Mismatch rates in the US

Skilled vs. Unskilled Vacancy:

I used publicly available Eurostat Job Vacancy Statistics. Unfortunately, vacancy statistics for every occupation separately is only available for few countries. I used the same definition of skilled vs. unskilled as presented in Table V.7. Then I calculated skilled/unskilled vacancy ratio for each country by dividing the number of skilled job vacancies over unskilled job vacancies. Note that this measure is different than vacancy rate which is the ratio of job vacancies to all jobs (occupied+vacant). Table V.10 shows skilled vs. unskilled vacancy ratio for countries averaged from 2005 to 2015.

Country	Skilled/ Unskilled Vacancy
Bulgaria	0.83
Cyprus	0.36
Latvia	1.08
Lithuania	0.55
Hungary	0.9
Netherlands	0.8
Poland	0.5
Romania	0.7
Slovenia	0.34
Slovakia	0.6
Finland	0.56

Table V.10: Skilled/ Unskilled Vacancies

Parameters

Standard Parameters from the Literature

Parameters from the Literature			
Parameter	Definition	Value	Source
r	Discount rate	0.01	Shimer (2007)
δ	Exogenous job destruction rate	0.1	Shimer (2007)
β	Worker's bargaining power	0.7	Shimer (2007)
η	Elasticity of substitution between age groups	0.75	Card & Lemieux (2001)
ρ	Elasticity of substitution between skill groups	0.8	Card & Lemieux (2001)
b_y	Unemployment benefit of young	0.1	Albrecht & Vroman (2002)
b_o	Unemployment benefit of old	0.1	Albrecht & Vroman (2002)
σ	Probability of becoming old	0.2	Author's own calculation
ω	Probability of becoming retired	0.028	Author's own calculation

Table V.11: Standard Parameters

Note: Young represents the 25-29 age bracket, hence one can think that 20% (σ=0.2) of the young population get old every period. Old represents the 30-64 age bracket, hence we can think of 2.8% (ω=0.028) get retired every period.

Estimated Relative Efficiency Parameters	
Parameter	Definition
α_p	Relative efficiency of mismatched wrt low educated
ψ_p	Relative efficiency of young high educated wrt old high educated
γ_p	Relative efficiency of young low educated wrt old low educated
β_p	Relative efficiency of young mismatched wrt old mismatched
θ_h/θ_l	Relative technological efficiency in the production

Table V.13: Estimated Relative Efficiency Parameters

Estimated Parameters

Estimated Parameters within the Model	
Parameter	Definition
c_{1o}	Vacancy cost in old unskilled market
c_{2y}	Vacancy cost in young skilled market
c_{2o}	Vacancy cost in old skilled market
$\tilde{\lambda}_y$	Mismatch search intensity of mismatched young
$\tilde{\lambda}_o$	Mismatch search intensity of mismatched old
θ_l	Efficiency of low skilled sector

Table V.12: Estimated Parameters within the Model

In estimating relative efficiency parameters, I used EU-SILC confidential microdata for Europe and ACs for the US for the working population aged 25-64 who at least have high school degree. I iterated the estimation once by using the model prediction about wage-productivity gap. Below, I document estimation results for some countries alone and grouped according to similar characteristics.

Estimation Results

	1st Stage			
Estimated Parameters	Italy	UK	Denmark	Spain
ψ_p (relative efficiency of young in high skilled)	0.29	0.41	0.36	0.36
β_p(relative efficiency of young in mismatched)	0.47	0.53	0.44	0.46
γ_p(relative efficiency of young in low skilled)	0.48	0.56	0.46	0.47
α_p(mismatch efficiency relative to low educated)	1.16	1.31	1.15	1.23
θ_h/θ_l(relative technological efficiency)	1.09	1.50	1.15	1.44
	Updated			
Estimated Parameters	Italy	UK	Denmark	Spain
ψ_p (relative efficiency of young in high skilled)	0.29	0.39	0.35	0.34
β_p(relative efficiency of young in mismatched)	0.64	0.65	0.50	0.59
γ_p(relative efficiency of young in low skilled)	0.50	0.55	0.46	0.42
α_p(mismatch efficiency relative to low educated)	0.96	1.02	1.06	0.94
θ_h/θ_l(relative technological efficiency)	1.11	1.52	1.17	1.41

Table V.14: First and Second Estimation, Europe (Wage Update)

	UK	Denmark	Italy	Spain
Efficiency Parameters				
α_p	1.02	1.06	0.96	0.94
ψ_p	0.39	0.35	0.29	0.34
γ_p	0.55	0.46	0.50	0.42
β_p	0.65	0.50	0.64	0.59
θ_h/θ_l	1.52	1.17	1.11	1.41
Friction Parameters				
c_{1o}	0.4	0.47	0.15	0.53
c_{2y}	0.8	0.57	0.34	0.81
c_{2o}	3.6	2.4	0.42	1.83
$\tilde{\lambda}_y$	1.5	0.4	0.21	0.78
$\tilde{\lambda}_o$	1	0.8	0.77	1.05
θ_l	3.7	3.4	0.98	0.67
Macro Factors				
α	0.13	0.11	0.11	0.14
$1-\mu$	0.46	0.41	0.2	0.41
$1-\hat{\mu}$	0.37	0.36	0.18	0.34
υ	0.42	0.75	0.82	0.8

Table V.15: Estimation Results Europe

	1st Stage	
Estimated Parameters	Low States	High States
ψ_p (relative efficiency of young in high skilled)	0.40	0.39
β_p(relative efficiency of young in mismatched)	0.45	0.45
γ_p(relative efficiency of young in low skilled)	0.53	0.51
α_p(mismatch efficiency relative to low educated)	1.53	1.59
θ_h/θ_l(relative technological efficiency)	1.67	1.76
	Updated	
Estimated Parameters	Low States	High States
ψ_p (relative efficiency of young in high skilled)	0.37	0.39
β_p(relative efficiency of young in mismatched)	0.58	0.59
γ_p(relative efficiency of young in low skilled)	0.49	0.52
α_p(mismatch efficiency relative to low educated)	1.19	1.31
θ_h/θ_l(relative technological efficiency)	1.69	1.79

Table V.16: First and Second Estimation, US (Wage Update)

Note: Low States are the states in which young HS unemployment rates are lower than US average, High states are the states in which young HS unemployment rates are higher than US average.

Descriptive Statistics

Unemployment Rates

	(ISCED 3-4) Upper Secondary	(ISCED 5-6) Tertiary Education	(ISCED 3-4) Upper Secondary	(ISCED 5-6) Tertiary Education
County	Age 25-29		Age 30-64	
Austria	5.3%	4.9%	3.9%	2.5%
Belgium	10.9%	5.8%	5.8%	3.3%
Bulgaria	10.5%	8.4%	7.6%	3.7%
Croatia	16.9%	17.6%	10.6%	5.3%
Cyprus	10.4%	10.9%	7.1%	4.3%
Czech Republic	6.8%	4.5%	5.2%	1.7%
Denmark	6.3%	7.7%	4.4%	3.5%
Estonia	10.3%	6.5%	9.0%	5.2%
EU-15	10.4%	8.6%	6.7%	4.3%
Finland	9.7%	5.9%	6.9%	4.1%
France	12.4%	7.5%	6.4%	4.5%
Germany	7.5%	4.4%	7.2%	3.3%
Greece	24.1%	25.6%	14.3%	8.3%
Hungary	10.0%	5.4%	6.9%	2.4%
Iceland	9.4%	8.1%	3.1%	2.4%
Ireland	13.7%	6.7%	8.2%	4.4%
Italy	13.4%	18.8%	5.3%	3.8%
Latvia	12.9%	8.5%	12.1%	5.2%
Lithuania	17.3%	7.9%	11.9%	3.8%
Luxembourg	7.5%	5.9%	3.7%	3.0%
Macedonia	37.9%	38.0%	26.6%	13.6%
Netherlands	4.7%	3.0%	4.3%	2.8%
Norway	4.0%	3.5%	2.2%	1.7%
Poland	14.4%	9.4%	9.4%	2.9%
Portugal	12.6%	14.0%	8.7%	5.4%
Romania	8.9%	7.9%	5.6%	2.1%
Slovakia	14.1%	9.4%	10.6%	3.4%
Slovenia	11.6%	11.9%	6.0%	2.8%
Spain	19.5%	16.3%	13.9%	8.4%
Sweden	8.1%	6.7%	4.7%	3.6%
Switzerland	4.8%	4.7%	3.2%	2.4%
Turkey	12.0%	13.6%	7.4%	4.5%
United Kingdom	7.1%	3.6%	4.4%	2.6%

Table V.17: Unemployment Rates in Europe (average of 2004-2015)

Table V.18: Unemployment Rates in the US (average of 2000-2015)

	Age 25-29		Age 30-64			Age 25-29		Age 30-64	
State	HS Degree	C and up	HS Degree	C and up	State	HS Degree	C and up	HS Degree	C and up
Alabama	11.2%	3.9%	6.2%	2.6%	Montana	8.1%	2.7%	5.0%	2.2%
Alaska	12.2%	2.4%	8.5%	2.4%	Nebraska	5.6%	1.8%	3.2%	1.6%
Arizona	9.5%	3.6%	6.9%	3.3%	Nevada	9.7%	4.3%	8.2%	4.4%
Arkansas	9.8%	3.0%	5.8%	2.2%	New Hampshire	6.5%	3.6%	4.5%	2.6%
California	11.2%	5.8%	8.1%	4.5%	New Jersey	11.6%	5.1%	7.5%	4.1%
Colorado	7.9%	3.3%	5.8%	3.3%	New Mexico	10.7%	3.7%	6.5%	3.2%
Connecticut	10.7%	4.1%	7.0%	3.4%	New York	11.3%	4.9%	6.4%	3.7%
Delaware	8.3%	3.8%	6.0%	2.7%	North Carolina	10.6%	3.7%	7.2%	3.2%
District of Columbia	18.4%	3.2%	12.6%	3.3%	North Dakota	4.8%	1.9%	2.6%	1.4%
Florida	10.3%	4.5%	7.5%	4.0%	Ohio	10.3%	3.0%	6.6%	2.9%
Georgia	10.7%	3.7%	7.1%	3.6%	Oklahoma	7.9%	2.7%	4.8%	2.2%
Hawaii	7.2%	3.5%	5.0%	2.5%	Oregon	10.8%	4.7%	7.7%	3.9%
Idaho	7.5%	3.1%	5.5%	2.7%	Pennsylvania	9.8%	3.6%	5.7%	3.0%
Illinois	11.1%	4.0%	7.4%	3.6%	Rhode Island	10.0%	3.5%	6.4%	3.1%
Indiana	10.1%	2.8%	6.4%	2.8%	South Carolina	10.9%	3.6%	7.3%	3.0%
Iowa	5.7%	1.7%	3.9%	1.8%	South Dakota	5.1%	1.6%	3.1%	1.5%
Kansas	6.9%	2.6%	4.4%	2.1%	Tennessee	10.6%	3.3%	6.6%	2.9%
Kentucky	11.0%	2.9%	6.0%	2.6%	Texas	8.6%	3.6%	5.6%	3.0%
Louisiana	9.9%	3.2%	5.7%	2.5%	Utah	5.9%	3.0%	4.5%	2.3%
Maine	9.1%	2.9%	5.3%	2.5%	Vermont	7.3%	2.7%	4.3%	2.1%
Maryland	9.2%	3.4%	5.7%	2.6%	Virginia	8.1%	2.9%	4.7%	2.4%
Massachusetts	10.6%	3.7%	6.7%	3.6%	Washington	9.1%	4.3%	6.4%	3.4%
Michigan	12.5%	4.2%	8.6%	3.8%	West Virginia	10.5%	3.6%	5.4%	2.4%
Minnesota	7.1%	2.5%	4.6%	2.5%	Wisconsin	7.8%	2.9%	5.0%	2.4%
Mississippi	12.7%	4.2%	6.8%	2.6%	Wyoming	5.9%	2.1%	3.7%	1.8%
Missouri	9.1%	2.6%	5.9%	2.6%					

Tertiary Enrollment Rates

Country	Gross Tertiary Enrollment Rate	Country	Gross Tertiary Enrollment Rate
Austria	64%	Macedonia	37%
Belgium	67%	Malta	37%
Bulgaria	57%	Netherlands	65%
Croatia	55%	Norway	75%
Cyprus	45%	OECD members	65%
Czech Republic	59%	Poland	68%
Denmark	78%	Portugal	62%
Estonia	69%	Romania	57%
Finland	92%	Russian Federation	75%
France	57%	Slovak Republic	51%
Germany	65%	Slovenia	83%
Greece	99%	Spain	78%
Iceland	75%	Sweden	72%
Ireland	64%	Switzerland	51%
Italy	65%	Turkey	56%
Latvia	73%	United Kingdom	58%
Lithuania	80%	United States	87%
Luxembourg	15%		

Table V.19: Tertiary Enrollment Rates

Employment Rates

	(ISCED 3-4) Upper Secondary	(ISCED 5-6) Tertiary Education	Employment Ratio College/HS
County	Age 25-29		
Austria	81.8%	84.5%	1.03
Belgium	77.8%	87.2%	1.12
Bulgaria	70.3%	80.5%	1.14
Croatia	68.2%	76.0%	1.11
Cyprus	76.9%	81.7%	1.06
Czech Republic	75.7%	77.8%	1.03
Denmark	79.3%	81.8%	1.03
Estonia	75.4%	81.6%	1.08
EU-15	74.0%	80.9%	1.09
Finland	74.1%	83.9%	1.13
France	76.2%	84.0%	1.10
Germany	76.0%	86.2%	1.13
Greece	62.6%	67.5%	1.08
Hungary	71.2%	81.5%	1.14
Iceland	75.1%	87.3%	1.16
Ireland	72.1%	83.9%	1.16
Italy	62.8%	55.6%	0.89
Latvia	74.6%	83.6%	1.12
Lithuania	72.6%	87.3%	1.20
Luxembourg	78.0%	82.7%	1.06
Macedonia	49.7%	56.7%	1.14
Netherlands	85.2%	91.0%	1.07
Norway	81.6%	85.0%	1.04
Poland	70.0%	82.3%	1.18
Portugal	72.8%	78.4%	1.08
Romania	71.0%	83.2%	1.17
Slovakia	71.3%	77.7%	1.09
Slovenia	75.6%	81.3%	1.08
Spain	68.1%	74.0%	1.09
Sweden	79.9%	81.7%	1.02
Switzerland	85.5%	87.6%	1.02
Turkey	62.4%	72.8%	1.17
United Kingdom	78.8%	88.3%	1.12

Table V.20: Employment Rates in Europe (average of 2004-2015)

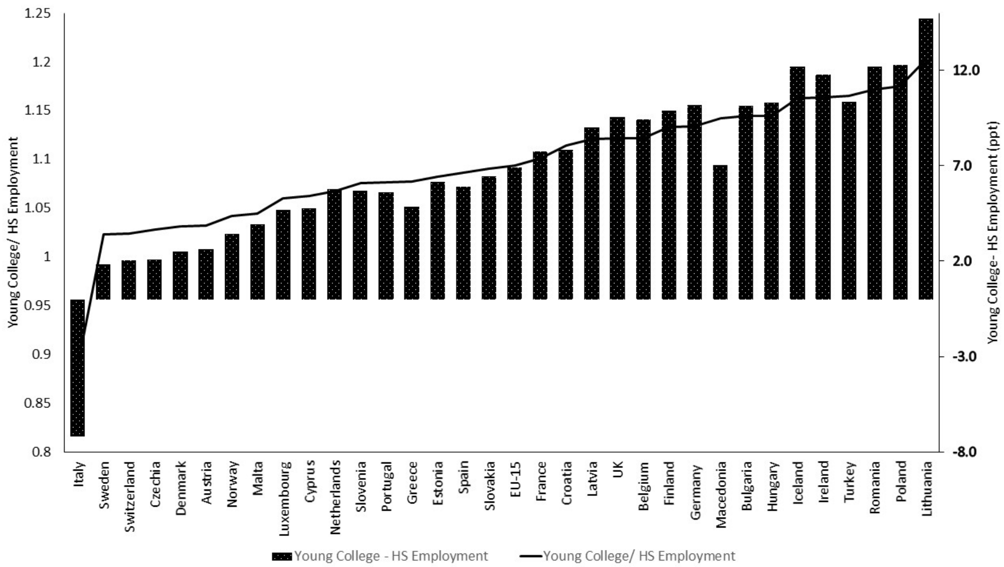

Figure V.1: Employment Rates in Europe (average of 2004-2015)

Figures

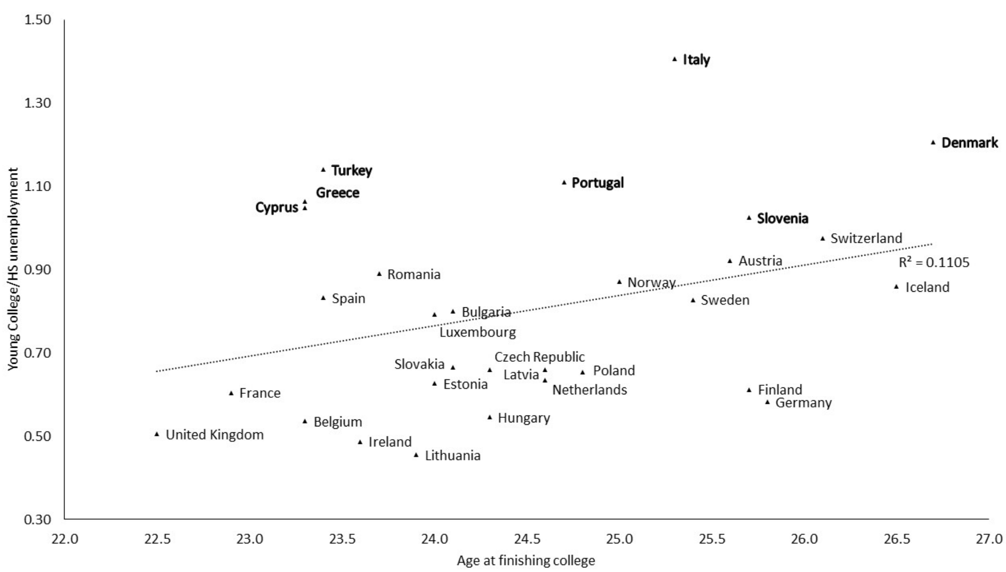

Figure V.2: Duration in College
Note: The data for average age at the end of college is taken from Eurostat website (reference year is 2009).

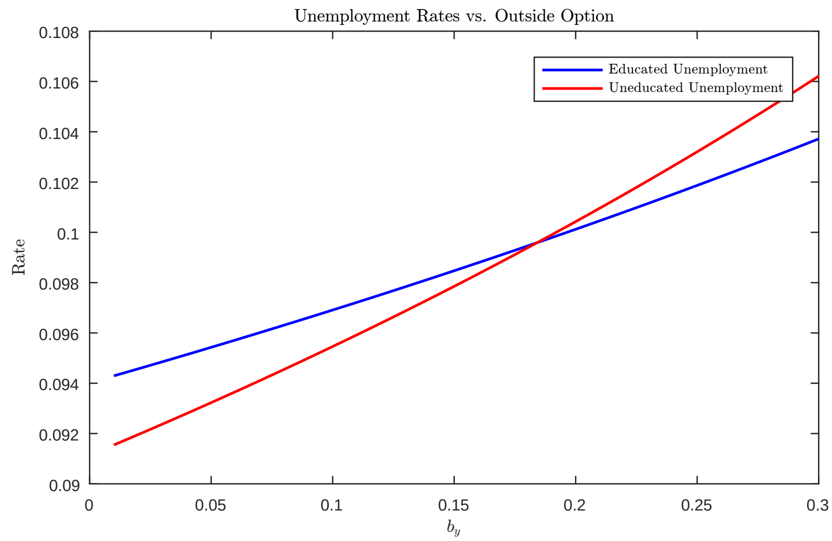

Figure V.3: Mother Hypothesis

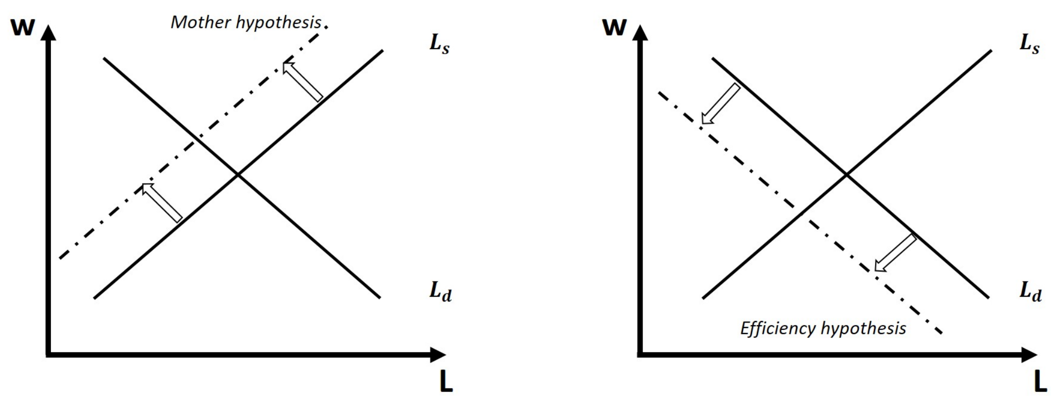

Figure V.4: Mother vs. Efficiency Hypothesis

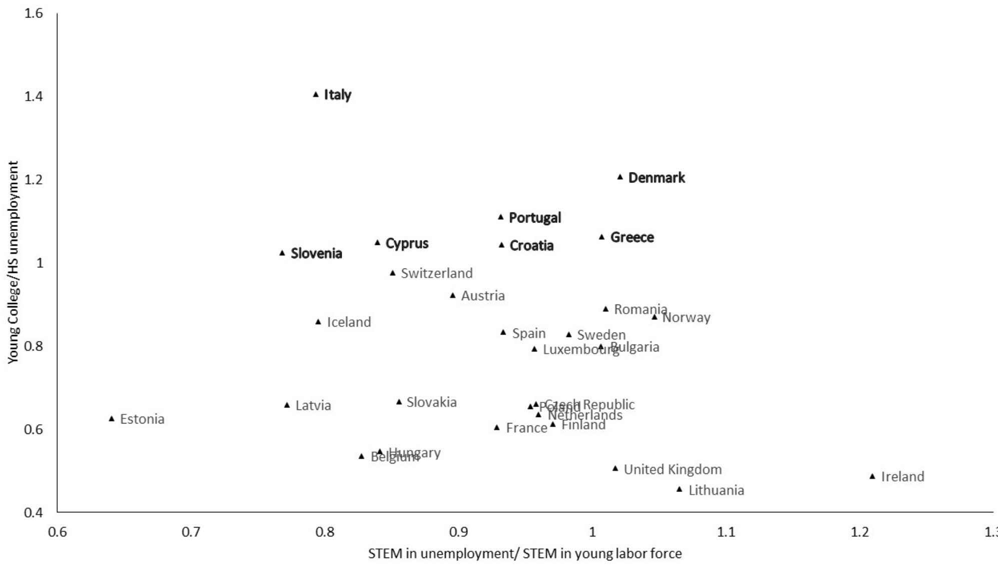

Figure V.5: STEM in unemployment vs. in labor force

Note: The data for STEM ratio is from confidential EU-LFS. Young labor force is from 25 to 29, I used STEM definition by National Science Foundation. The ratio is the average of 2004-2015. The ratio is x-axis represents the selection to unemployment across fields. If the ratio is 1, it means that STEM majors are equally likely to stay unemployed as others in the labor force.

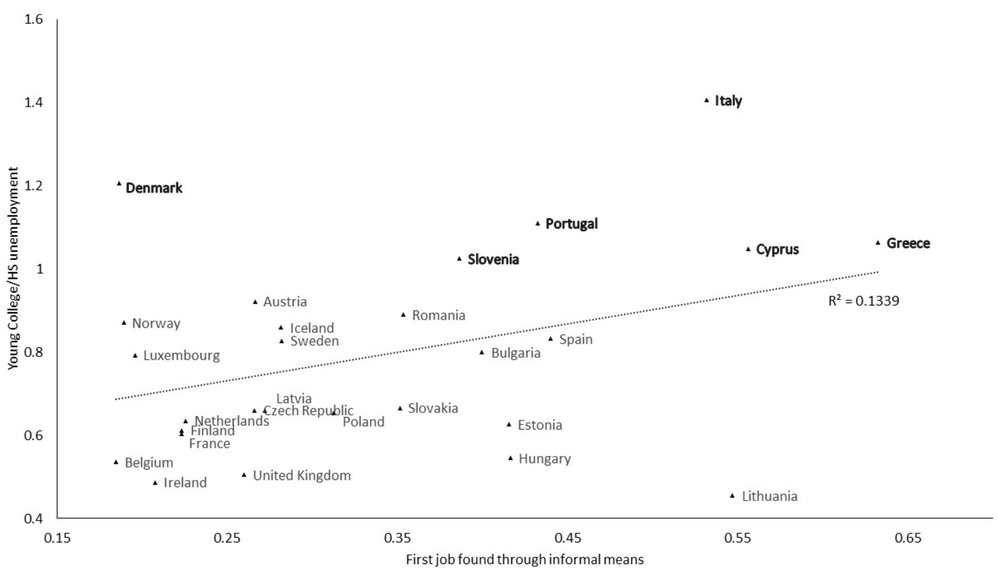

Figure V.6: First job is found through friends and family

Note: The data is for job finding methods is from confidential EU-LFS 2009 ad-hoc module "Entry of Young People into the Labor Market". The ratio is percentage of young people who reported that they found their first job through friends and family.

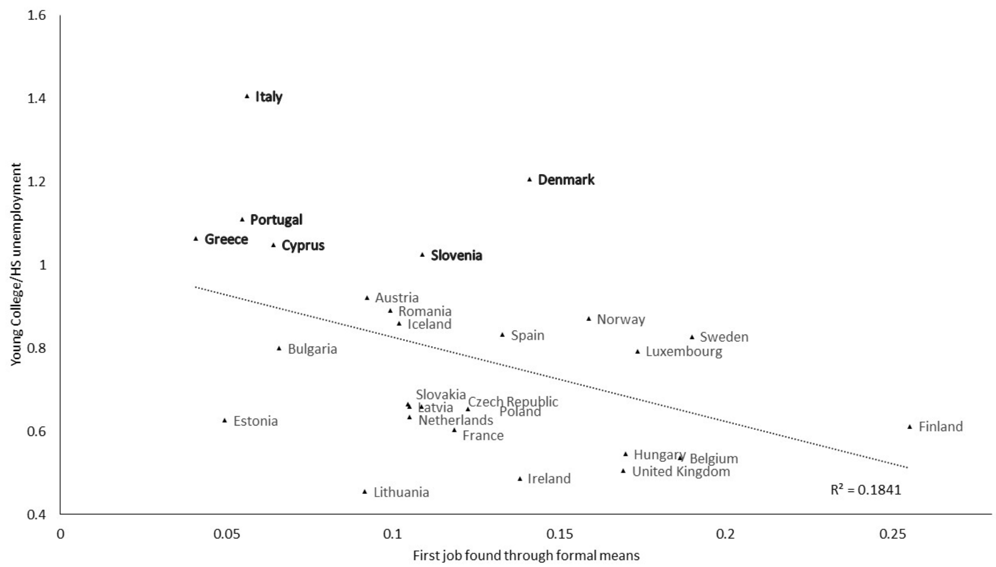

Figure V.7: First job is found through education institution and public services
Note: The data is for job finding methods is from confidential EU-LFS 2009 ad-hoc module "Entry of Young People into the Labor Market". The ratio is percentage of young people who reported that they found their first job through education institutions and public services.

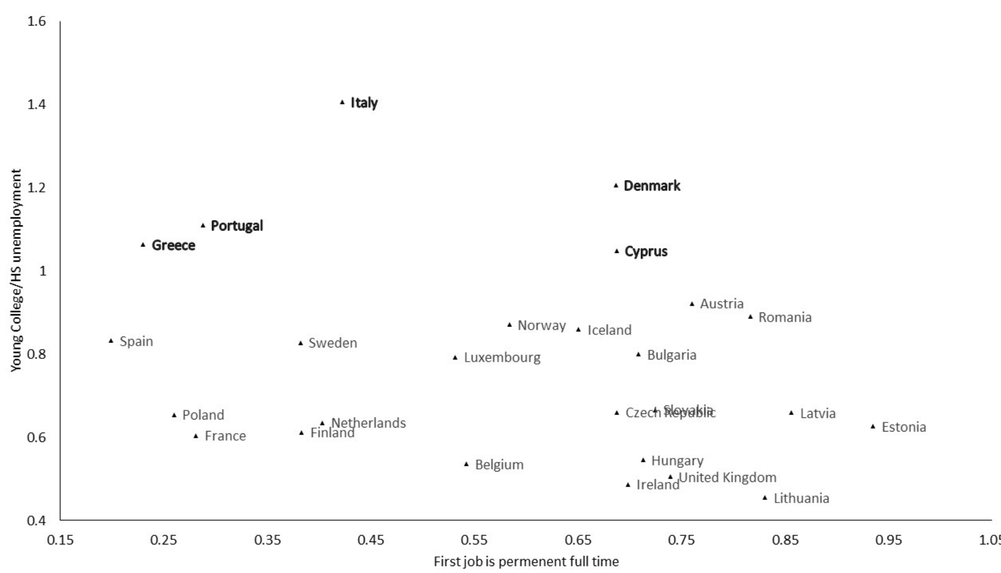

Figure V.8: First job is permenant full time
Note: The data is for job finding methods is from confidential EU-LFS 2009 ad-hoc module "Entry of Young People into the Labor Market". The ratio is percentage of young people who reported that their first job is permanent full time.

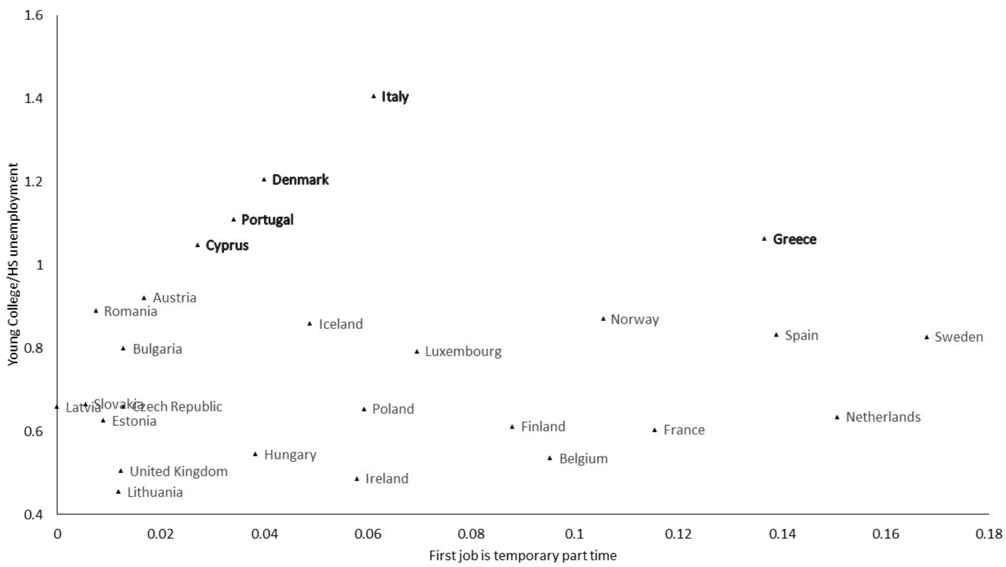

Figure V.9: First job is temporary part time

Note: The data is for job finding methods is from confidential EU-LFS 2009 ad-hoc module "Entry of Young People into the Labor Market". The ratio is percentage of young people who reported that their first job is permanent full time.

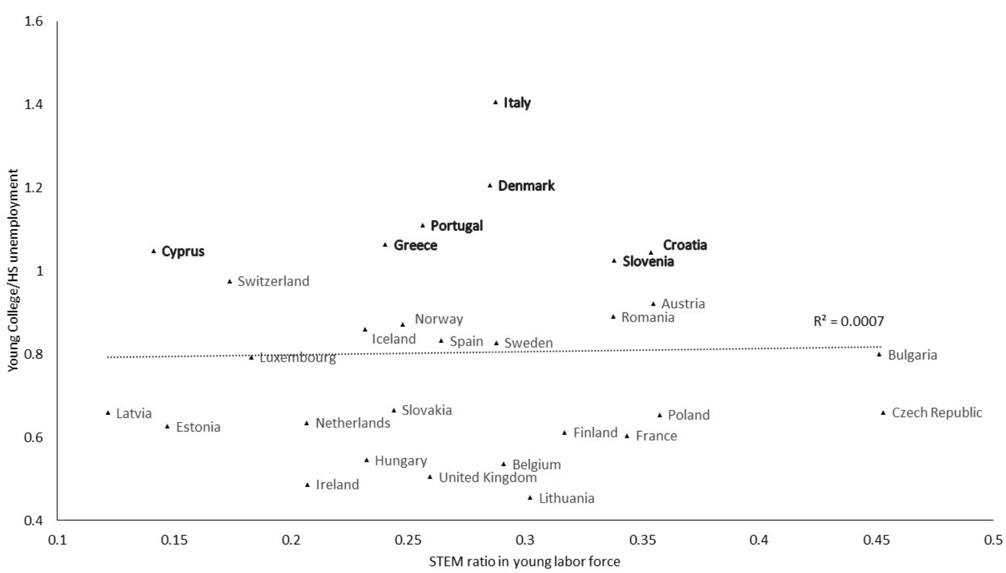

Figure V.10: STEM ratio vs. College Unemployment

Note: The data for STEM ratio is from confidential EU-LFS. Young labor force is from 25 to 29, I used STEM definition by National Science Foundation. STEM ratio is calculated among college labor force and averaged across years 2004-2015.

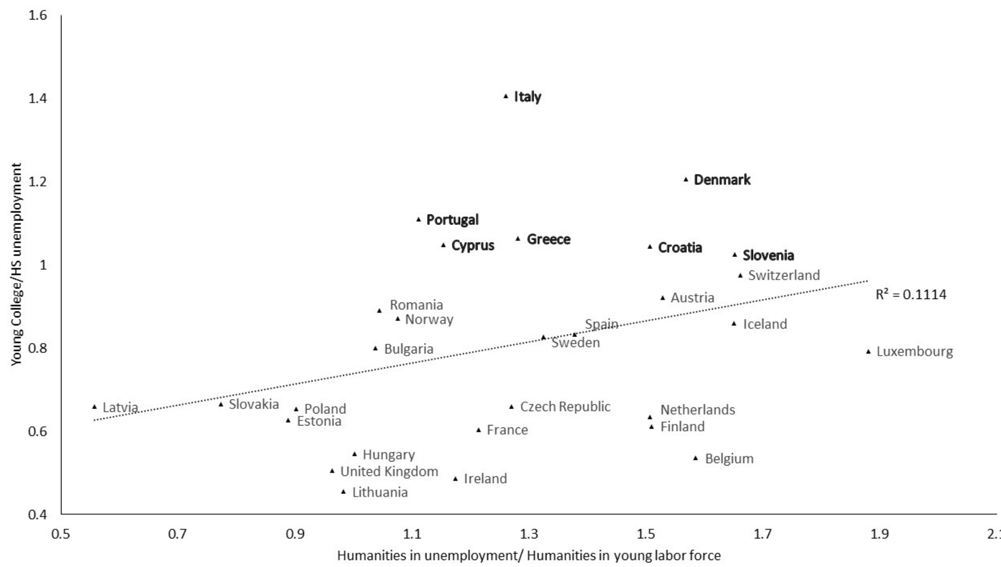

Figure V.11: Humanities in unemployment vs. in labor force

Note: The data for STEM ratio is from confidential EU-LFS. Young labor force is from 25 to 29. The ratio is the average of 2004-2015. The ratio is x-axis represents the selection to unemployment across fields. If the ratio is 1, it means that humanities majors are equally likely to stay unemployed as others in the labor force.

Appendix C

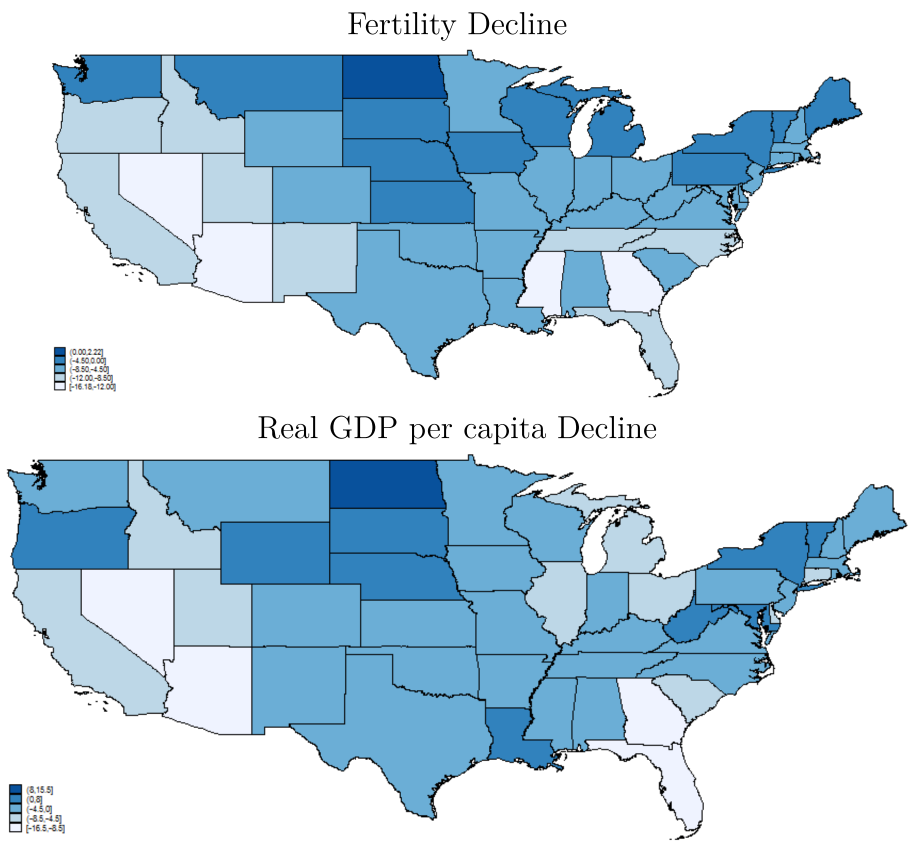

Figure VI.1: Fertility and Real GDP per capita

Note: Upper figure shows the fertility decrease from 2007 to 2010. Below figure shows the real GDP per cap decrease for the same period. The data is taken from National Health Statistics for fertility and Bureau of Economic Analysis for real GDP per capita.

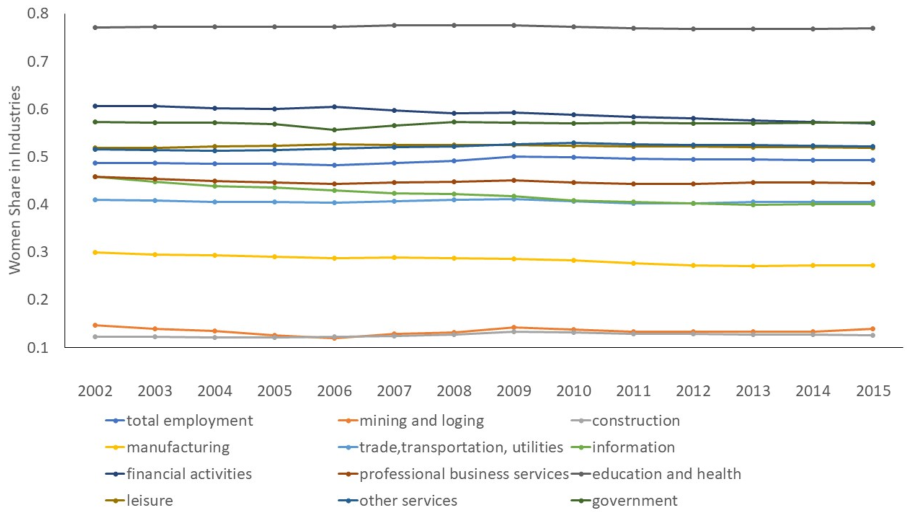

Figure VI.2: Women Share in Industries over time

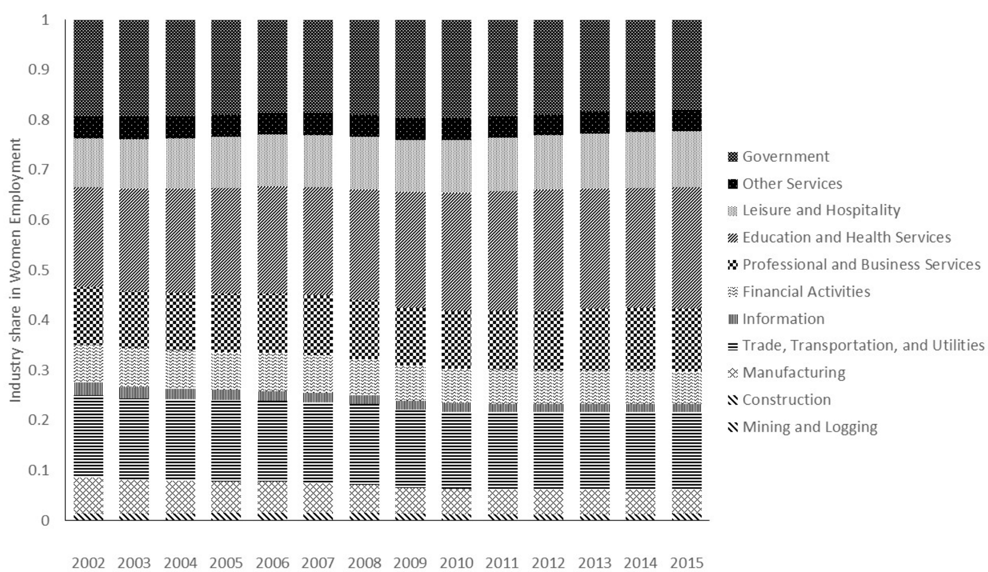

Figure VI.3: Industry Shares in Women Employment over time

	(2002-2016)				(2007-2011)		
Dependent Variable: $\Delta Birth\ Rate_{t,t-1,s}$	1	2	3	4	5	6	7
$\%\Delta Employment\ Female\ Dominant\ Industries_{t-1,t-2,s}$	-0.31***	-0.22*			-0.64***		
	(0.11)	(0.13)			(0.09)		
$\%\Delta Employment\ Male\ Dominant\ Industries_{t-1,t-2,s}$	0.22***	0.30***			0.17***		
	(0.01)	(0.06)			(0.01)		
$\%\Delta Total\ Employment_{t-1,t-2,s}$		-0.21					
		(0.18)					
$\%\Delta Total\ Compensation\ Female\ Dominant\ Industries_{t-1,t-2,s}$			-0.22***			-0.35***	
			(0.06)			(0.04)	
$\%\Delta Total\ Compensation\ Male\ Dominant\ Industries_{t-1,t-2,s}$			0.11***			0.16***	
			(0.04)			(0.02)	
$\%\Delta Total\ Compensation\ in\ Mining_{t-1,t-2,s}$				-0.01			-0.01
				(0.01)			(0.01)
$\%\Delta Total\ Compensation\ in\ Construction_{t-1,t-2,s}$				0.18***			0.1***
				(0.02)			(0.01)
$\%\Delta Total\ Compensation\ in\ Manufacturing_{t-1,t-2,s}$				0.03			0.02
				(0.03)			(0.03)
$\%\Delta Total\ Compensation\ in\ Trade_{t-1,t-2,s}$				0.1			0.11
				(0.07)			(0.07)
$\%\Delta Total\ Compensation\ in\ Information_{t-1,t-2,s}$				-0.03**			0.01
				(0.01)			(0.01)
$\%\Delta Total\ Compensation\ in\ Finance_{t-1,t-2,s}$				0.11***			0.01
				(0.03)			(0.03)
$\%\Delta Total\ Compensation\ in\ Business_{t-1,t-2,s}$				-0.05**			-0.06**
				(0.03)			(0.03)
$\%\Delta Total\ Compensation\ in\ Education, Health_{t-1,t-2,s}$				-0.17***			-0.29***
				(0.06)			(0.05)
$\%\Delta Total\ Compensation\ in\ Leisure_{t-1,t-2,s}$				-0.13***			-0.04
				(0.05)			(0.06)
$\%\Delta Total\ Compensation\ in\ OtherServices_{t-1,t-2,s}$				-0.3***			-0.06
				(0.04)			(0.05)
$\%\Delta Total\ Compensation\ in\ Government_{t-1,t-2,s}$				0.0414			-0.11**
				(0.05)			(0.04)
Constant	0.00*	0.00**	-0.01***	0.01***	-0.00**	-0.01***	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
n	576	576	611	579	384	408	383
R^2	0.352	0.355	0.201	0.512	0.566	0.514	0.567

Table VI.1: Robustness Checks

Note: The dataset is a merged dataset using state level compensation levels from BEA, state level fertility rates from National Health Statistics and state-industry level employment from BLS. All the regressions are weighted by state total employment.

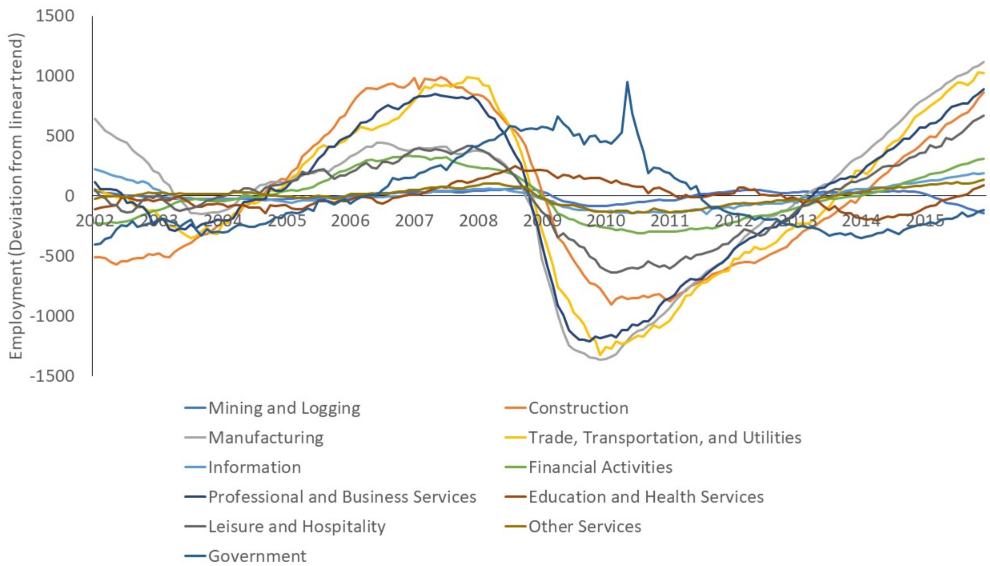

Figure VI.4: Cyclicality of Industry Employment

	w_{yft}	w_{oft}	w_{ymt}	w_{omt}
2002	2116312	3150660	3026713	5378163
2003	2147601	3196593	3037111	5397823
2004	2209960	3289543	3109446	5532591
2005	2241752	3336533	3147912	5605351
2006	2307246	3433944	3228804	5754043
2007	2372942	3531621	3302874	5892843
2008	2362429	3513974	3245149	5789971
2009	2330380	3464231	3109303	5547075
2010	2348195	3490988	3114752	5565495
2011	2355309	3503298	3136468	5614329
2012	2401544	3573281	3199908	5738855
2013	2423357	3606557	3227163	5792470
2014	2493418	3711474	3335110	5989864
2015	2614058	3891777	3494359	6281531
Average	2337464	3478177	3193934	5705743

Table VI.2: Compensation Levels

$i = industry$	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
	%Δ from previous year												
Mining and Logging	0.1%	6.5%	9.9%	12.1%	7.7%	9.6%	-10.5%	5.9%	11.4%	7.7%	2.6%	6.9%	-7.3%
Construction	-0.1%	3.7%	4.2%	7.5%	1.3%	-5.2%	-15.2%	-8.5%	-1.5%	2.8%	4.3%	6.7%	8.8%
Manufacturing	-2.6%	0.0%	-0.7%	0.0%	-0.7%	-4.8%	-10.9%	0.8%	1.6%	1.6%	0.0%	3.1%	3.0%
Trade, Transportation, and Utilities	0.0%	2.1%	0.5%	2.1%	2.0%	-3.5%	-5.2%	-0.5%	1.6%	2.2%	1.1%	3.6%	5.0%
Information	-4.1%	0.5%	-1.7%	1.3%	2.1%	-3.8%	-5.2%	-0.6%	1.5%	2.8%	5.1%	4.1%	5.5%
Financial Activities	2.5%	5.9%	2.8%	5.5%	3.4%	-5.0%	-9.6%	1.9%	2.9%	2.8%	0.0%	5.4%	5.1%
Professional and Business Services	0.0%	5.0%	4.8%	5.1%	5.4%	0.0%	-5.6%	2.7%	3.2%	5.6%	1.9%	4.8%	6.4%
Education and Health Services	4.1%	4.0%	1.5%	3.8%	3.6%	2.1%	4.8%	2.0%	0.0%	2.6%	1.9%	1.8%	5.4%
Leisure and Hospitality	1.7%	3.1%	1.1%	3.4%	2.7%	-0.7%	-3.4%	0.7%	1.7%	4.3%	3.2%	5.4%	6.8%
Other Services	2.4%	1.8%	-1.3%	2.2%	2.0%	-0.4%	-2.0%	-1.1%	0.2%	2.1%	1.5%	4.6%	4.4%
Government	2.1%	1.5%	0.5%	1.5%	2.0%	1.4%	2.9%	-0.5%	-2.8%	-1.4%	-1.0%	1.0%	2.9%

Table VI.3: Change in Total Industry Compensation

	Black		Hispanic		Other		White	
	male	female	male	female	male	female	male	female
agriculture	0.52%	0.06%	1.10%	0.14%	0.73%	0.17%	1.48%	0.19%
mining and loging	0.52%	0.06%	1.10%	0.14%	0.73%	0.17%	1.48%	0.19%
construction	5.97%	0.58%	21.23%	1.38%	6.54%	1.02%	12.86%	1.63%
manufacturing	13.12%	5.83%	12.83%	8.94%	12.10%	7.21%	14.26%	5.76%
trade, transportation, utilities	26.38%	15.95%	19.51%	16.95%	19.77%	15.72%	21.49%	15.37%
information	2.91%	2.35%	1.62%	1.58%	3.10%	2.02%	2.90%	2.06%
financial activities	5.44%	7.88%	3.79%	7.03%	6.53%	8.19%	6.39%	8.57%
business services	11.17%	8.70%	11.34%	10.83%	16.13%	11.31%	11.62%	10.14%
education and health services	13.64%	38.49%	5.68%	27.49%	13.70%	31.08%	10.14%	37.15%
leisure services	10.17%	9.07%	12.15%	14.82%	11.99%	11.93%	7.25%	9.34%
other services	4.36%	3.99%	4.65%	6.27%	4.12%	5.92%	4.05%	5.06%
government	5.88%	7.02%	2.89%	3.51%	4.47%	5.07%	5.35%	3.98%
armed forces	0.52%	0.06%	1.10%	0.14%	0.73%	0.17%	1.48%	0.19%

Table VI.4: Industry Shares across Gender- Race

	Less than HS		HS degree		Some College		College Degree		More than College	
	male	female	male	female	male	female	male	female	male	female
agriculture	1.16%	0.15%	1.26%	0.16%	1.28%	0.17%	1.31%	0.18%	1.28%	0.18%
mining and loging	1.16%	0.15%	1.26%	0.16%	1.28%	0.17%	1.31%	0.18%	1.28%	0.18%
construction	17.27%	1.34%	13.57%	1.39%	13.00%	1.42%	12.47%	1.46%	11.97%	1.45%
manufacturing	13.23%	7.54%	13.70%	6.50%	13.78%	6.34%	13.84%	6.20%	13.73%	6.19%
trade, transportation, utilities	20.48%	16.28%	21.43%	15.78%	21.53%	15.69%	21.46%	15.59%	21.34%	15.58%
information	2.14%	1.84%	2.64%	2.00%	2.72%	2.03%	2.81%	2.04%	2.85%	2.05%
financial activities	4.77%	7.66%	5.75%	8.14%	5.92%	8.23%	6.12%	8.33%	6.19%	8.35%
business services	11.63%	10.42%	11.81%	10.16%	11.87%	10.14%	12.04%	10.20%	12.34%	10.21%
education and health services	7.79%	31.81%	9.76%	35.01%	10.07%	35.48%	10.36%	35.78%	10.64%	35.79%
leisure services	10.58%	12.36%	8.90%	10.56%	8.61%	10.29%	8.35%	10.07%	8.54%	10.05%
other services	4.43%	5.64%	4.21%	5.21%	4.17%	5.17%	4.13%	5.17%	4.12%	5.17%
government	3.85%	4.14%	4.82%	4.38%	4.97%	4.37%	5.08%	4.30%	5.07%	4.34%
armed forces	1.16%	0.15%	1.26%	0.16%	1.28%	0.17%	1.31%	0.18%	1.28%	0.18%

Table VI.5: Industry Shares across Gender-Education