

# Young, Educated, Unemployed\*

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## Abstract

In a number of European countries, unemployment rates for young college graduates are higher than for young high school graduates. This presents a challenge for canonical models of unemployment that suggest that unemployment should decrease with education. I disentangle two potential explanations for the pattern: “labor market frictions” versus “relative productivity.” Here, labor market frictions are obstacles to labor market flows (such as employment protection regulation), whereas relative productivity refers to features that lower the output of educated workers already matched to firms (such as an education system that does not provide the right skills or a lack of jobs that make good use of workers’ skills). The analysis builds on a search and matching model with endogenous productivity differences and the possibility of mismatch (educated workers working in low skilled jobs). I show that when young educated workers have productivity levels close to uneducated workers, they have higher unemployment rates, because firms create fewer skilled jobs. My counterfactual analysis shows that the relative productivity channel is more important than the labor market frictions channel in accounting for unemployment of young educated workers. The results suggest that improving education policy and fostering firms’ demand for skills may have important roles to play in addressing high unemployment among young workers.

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# 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 1). This pattern is very persistent for the above countries (Figure 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 2).

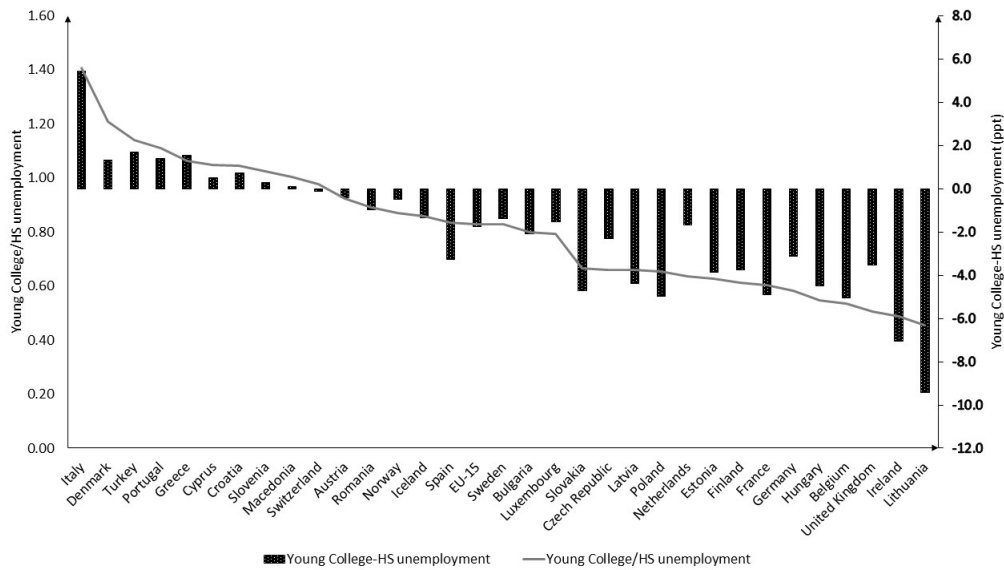


Figure 1: Europe Average Unemployment Rate Differences

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.

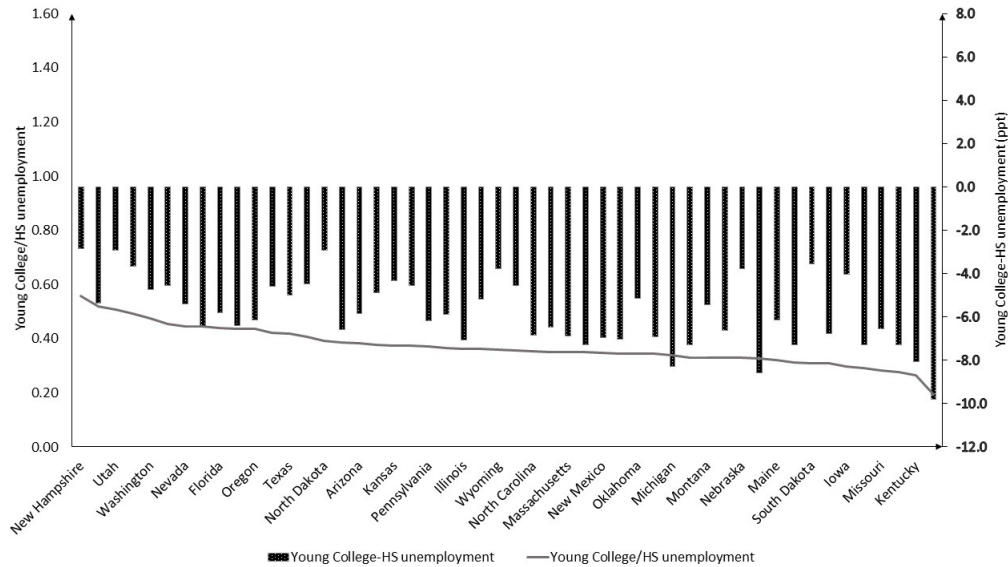


Figure 2: US Average Unemployment Rate Differences

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.

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

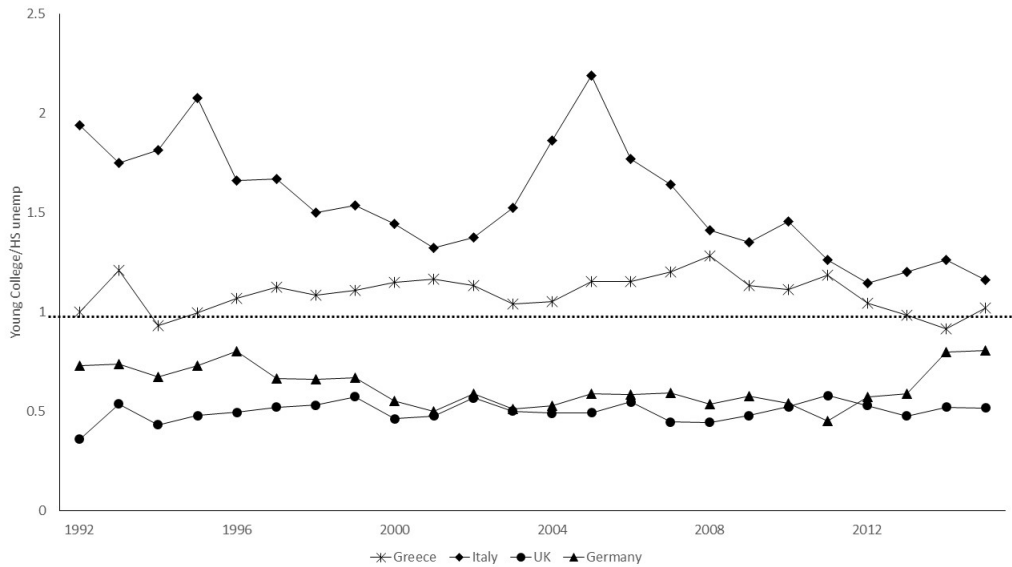


Figure 3: Time Series of Unemployment Rates

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.

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

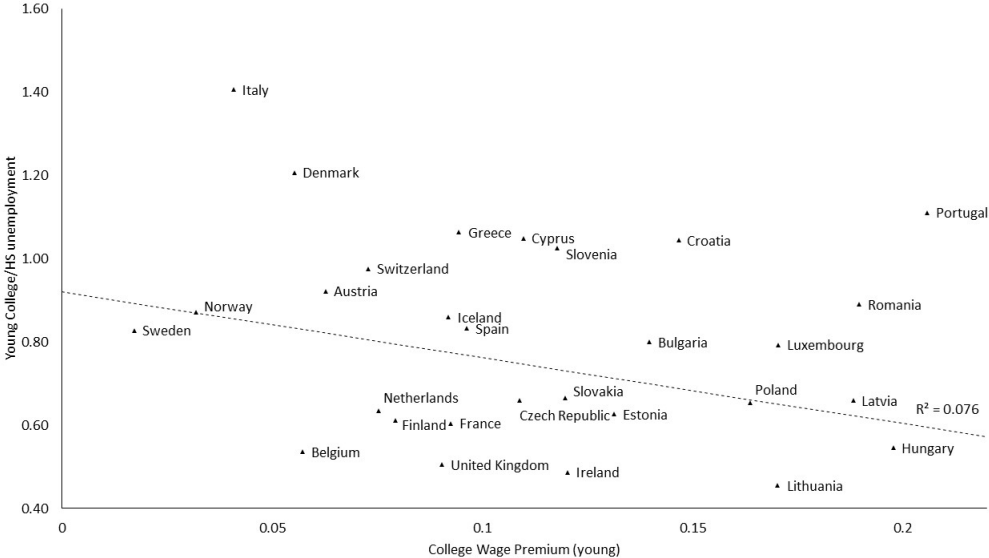


Figure 4: Relative Unemployment vs. Relative Wage

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.

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<sup>1</sup>. 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 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

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<sup>1</sup>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.

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<sup>2</sup> 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

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<sup>2</sup>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)).

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 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 (Guvonen 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)). Schomburg (2004)

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<sup>3</sup>, 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

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<sup>3</sup>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.

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, in which case they will be 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<sup>4</sup>. Production firms produce a unique final output by using different types of labor, but they cannot hire workers directly; they need intermediary bargaining firms<sup>5</sup>. 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 Households

Households consist of four types of people: young educated, young uneducated, old educated, and old uneducated<sup>6</sup>. Fractions of young people ( $\alpha$ ), uneducated people within young ( $\mu$ ) and uneducated people within old ( $\hat{\mu}$ ), are exogenous. They are aging stochastically (de la Croix et al. (2013)): young people become old with probability  $\sigma$  and old people become retired with probability  $\omega$ <sup>7</sup>. Corresponding labor market tightness functions, job finding and job filling probabilities are given in Appendix D.4.

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<sup>4</sup>Distinction between bargaining and production firms is similar to Christiano et al. (2016)

<sup>5</sup>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.

<sup>6</sup>Young refers to age 25-29, old refers to age 30-64 when matching the model to the data.

<sup>7</sup>Distribution of labor force can be seen in Appendix A.1

**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 ( $\tilde{\lambda}_y$ <sup>8</sup>). She finds a skilled job with probability of  $f(\theta_{2y})$ <sup>9</sup> 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 person is employed in a skilled job, the job can be destroyed exogenously with probability  $\delta$ , 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  $\lambda_y$  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  $\sigma$ . The decision problem can be described by the following Bellman equations:

- Value of being unemployed:

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

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<sup>8</sup> $\tilde{\lambda}_y$  will be estimated in calibrating the model to target unemployment and mismatch rates observed in data.

<sup>9</sup> $\theta_{2y}$  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. More details can be found in Appendix D.4.

- Value of working in a skilled market:

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

- Value of working in an unskilled market:

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

**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  $\delta$ , and she switches to being unemployed. Finally, stochastic aging implies that she may become “old” with probability  $\sigma$ . (See Appendix D.3 for corresponding Bellman equation)

**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  $\delta$  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  $\lambda_o$  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  $\omega$  and continue to receive pension benefits, which is a function of her last wage<sup>10</sup>. (See Appendix D.3 for corresponding Bellman equation)

**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  $\delta$  and she switches to become unemployed. Finally, stochastic aging implies that she may become “retired” with probability  $\omega$  and continue to receive pension benefits, which is a function of her last wage<sup>11</sup>. (See Appendix D.3 for corresponding Bellman equation)

## 3.2 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 workers, in which case they will be called mismatched workers. Nash Bargaining occurs between workers and bargaining firms and wage is determined<sup>12</sup>.

<sup>10</sup>Details of retirement value can be found in Appendix D.4

<sup>11</sup>Details of retirement value can be found in Appendix D.4

<sup>12</sup>See Appendix D.4 for surplus sharing equations

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<sup>13</sup>. 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  $V(i, j)$ <sup>14</sup>, 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:

$$rV(s, y) = \underbrace{-c_{2y}}_{\text{skilled vacancy cost available to young}} + \underbrace{p(\theta_{2y})}_{\text{skilled job filling probability by young}} \underbrace{[J(s, h, y) - V(s, y)]}_{\text{switch from vacancy to job state}} \quad (4)$$

- Value of unskilled vacancy available for young:

$$rV(n, y) = -c_{1y} + \underbrace{\kappa_{ny}}_{\text{prob. of facing low educated}} \underbrace{p(\theta_{1y})}_{\text{unskilled job filling probability}} \underbrace{[J(n, l, y) - V(n, y)]}_{\text{switch from vacancy to job state}} \\ + \underbrace{(1 - \kappa_{ny})}_{\text{probability of facing high educated}} \underbrace{p(\theta_{1y})}_{\text{unskilled job filling probability}} \underbrace{[J(n, h, y) - V(n, y)]}_{\text{switch from vacancy to mismatched job state}} \quad (5)$$

where  $\kappa_{ny}$  is the probability of facing an uneducated young worker and  $\kappa_{no}$  is the

<sup>13</sup>Details of job filling probabilities can be found in Appendix A.2

<sup>14</sup>Free-entry condition implies  $V(i, j) = 0$  for all  $i, j$ .



probability of facing a low educated old worker. ( $\kappa_{ny} = \frac{u(l,y)}{u(l,y)+\lambda_y u(h,y)}$ ,  $\kappa_{no} = \frac{u(l,o)}{u(l,o)+\lambda_o u(h,o)}$ )  
(See Appendix D.3 for Bellman equations describing the vacancy decision for old)

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  $\delta$ , 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  $\delta$  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:

$$\begin{aligned}
rJ(s, h, y) = & \underbrace{MPL(H_y)}_{\text{marginal product of}} - \underbrace{w(s, h, y)}_{\text{young high}} & (6) \\
& \text{young high skilled} & \text{skilled wage} \\
& + \delta \underbrace{[V(s) - J(s, h, y)]}_{\text{switch from job}} + \underbrace{\sigma[J(s, h, o) - J(s, h, y)]}_{\text{switch to old state}} \\
& \text{to vacancy state}
\end{aligned}$$

- Value of unskilled job filled by young high educated:

$$\begin{aligned}
rJ(n, h, y) = & \underbrace{MPL(M_y)}_{\text{marginal product of}} - \underbrace{w(n, h, y)}_{\text{young}} & (7) \\
& \text{young mismatched} & \text{mismatched wage} \\
& + [\delta + \underbrace{\lambda_y f(\theta_{2y})}_{\text{on-the-job search}}] [V(n) - J(n, h, y)] + \sigma[J(n, h, o) - J(n, h, y)]
\end{aligned}$$

- Value of unskilled job filled by young low educated:

$$\begin{aligned}
rJ(n, l, y) = & \underbrace{MPL(L_y)}_{\substack{\text{marginal product of} \\ \text{young low skilled}}} - \underbrace{w(n, l, y)}_{\substack{\text{young low} \\ \text{skilled wage}}} & (8) \\
& + \delta \underbrace{[V(n) - J(n, l, y)]}_{\substack{\text{switch from job} \\ \text{to vacancy state}}} + \underbrace{\sigma[J(n, l, o) - J(n, l, y)]}_{\substack{\text{switch to old state}}}
\end{aligned}$$

For job values filled by old workers, see the Bellman equations in the Appendix D.3.

### 3.3 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),  $\theta_h$  and  $\theta_l$  are technological efficiency parameters, and  $\rho = 1 - \frac{1}{\sigma_E}$  is a function of elasticity of substitution ( $\sigma_E$ ) 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  $\alpha_p$  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  $\psi_p$ ,  $\beta_p$ ,  $\gamma_p$  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 (See Appendix D.4 for more details).

### 3.4 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 mismatch, hence on-the-job search, certainly affects the unemployed pool among the educated, as well as market tightness for the uneducated. (See Table 23 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 ( $\theta_h/\theta_l$ ) on unemployment rates. Figure 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.

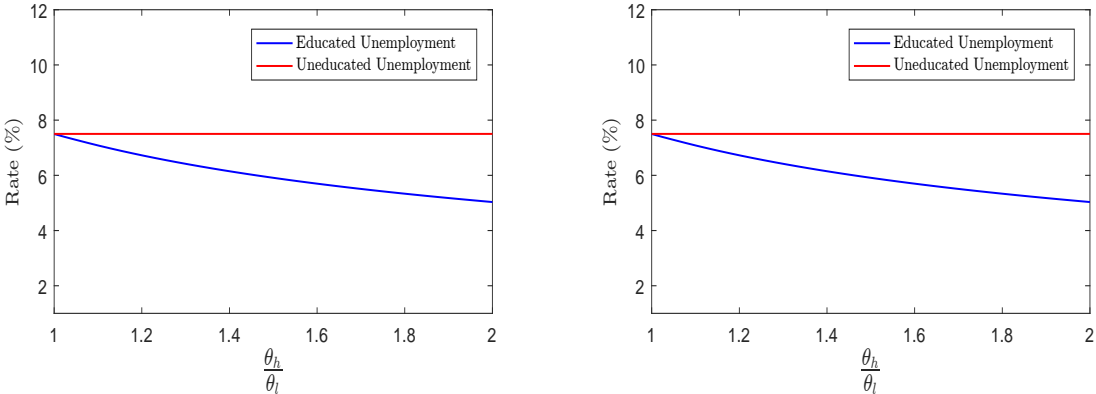


Figure 5: Relative Technological Efficiency vs. Unemployment Rates: Symmetric Case

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

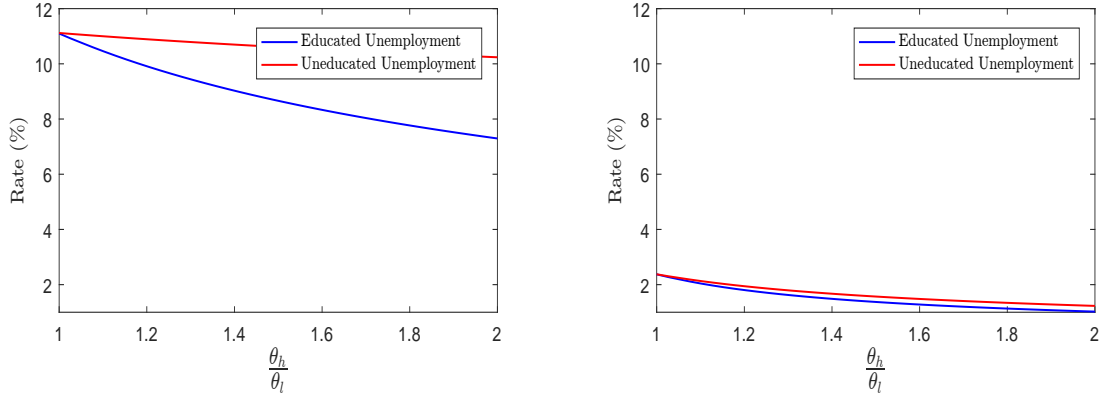


Figure 6: Relative Technological Efficiency vs. Unemployment Rates: Imperfect Substitution, Stochastic Aging

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 technological efficiency ( $\theta_h/\theta_l$ ) 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 7).

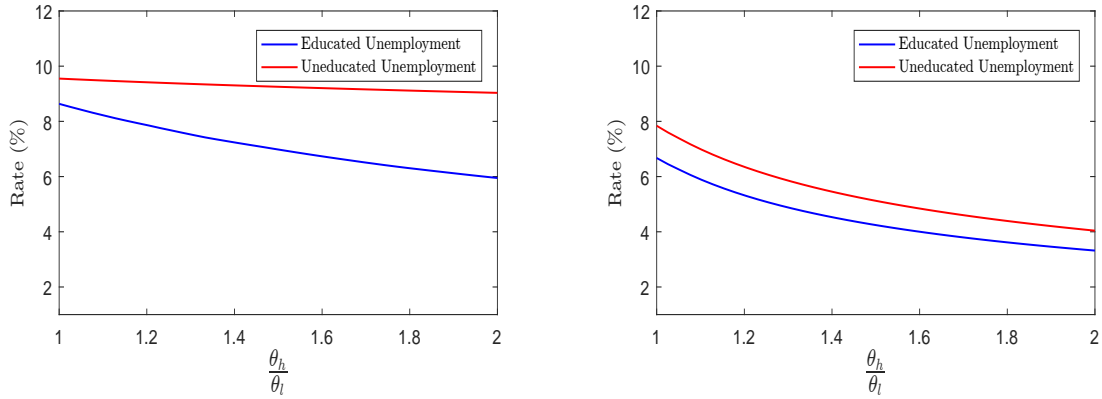


Figure 7: Relative Technological Efficiency vs. Unemployment Rates: Relative Supply

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 8; the slope decreases relative to Figure 7). The mechanism behind that is when educated workers become more and more productive, they 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.

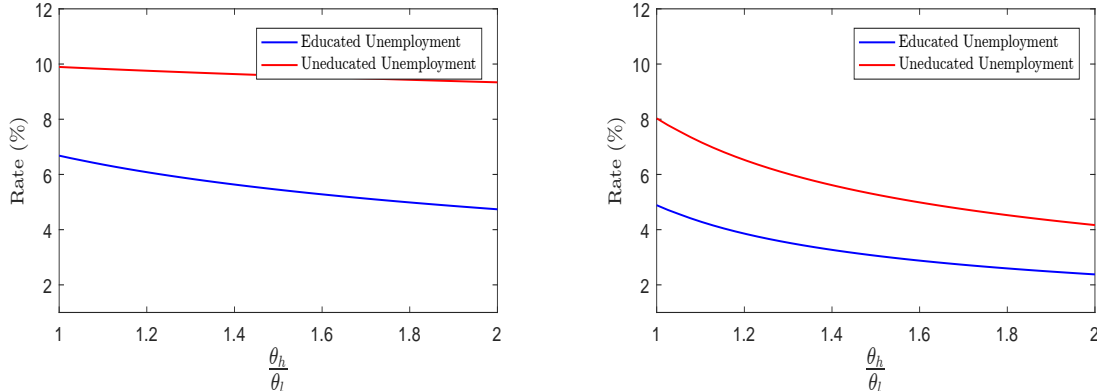


Figure 8: Relative Technological Efficiency vs. Unemployment Rates: Mismatch Channel

Finally, I exogenously increase the vacancy posting cost of skilled jobs available to young. Figure 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.

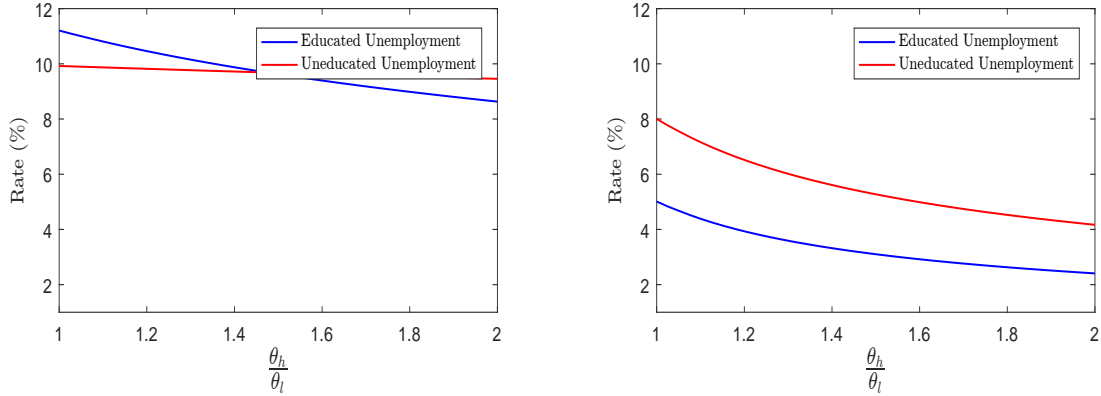


Figure 9: Relative Technological Efficiency vs. Unemployment Rates: Vacancy Cost

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 unemployment 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 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.

### 4.1 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)<sup>15</sup> 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,<sup>16</sup> 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.

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<sup>15</sup>Since the unemployment rates that I am matching is for these age groups specifically, all the analysis is done based on these age groups.

<sup>16</sup>A list of countries and coverage years can be found in Appendix E



## 4.2 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.)<sup>17</sup>. 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.

# 5 Model Parameterization and Estimation

## 5.1 Parameters

There are four sets of parameters used in the model. <sup>18</sup>

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 Eurostat, 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 <sup>19</sup>.
3. Relative efficiencies of different types of workers  $(\psi_p, \beta_p, \gamma_p, \alpha_p, \theta_h/\theta_l)$  are estimated by using EU-SILC for Europe and ACS for the US.

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<sup>17</sup>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.

<sup>18</sup>Parameter lists are given in Appendix E and F.

<sup>19</sup>More details about estimation procedure exists in Appendix E.2.

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.

## 5.2 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 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  $\eta$  fixed<sup>20</sup>, relative wage as well as relative supply of young vs. old within each category (skill, unskilled, mismatched) identify  $\psi_p$ ,  $\beta_p$ ,  $\gamma_p$  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)

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<sup>20</sup> $\eta$  is taken as 0.8 which is in the range of estimates of Card & Lemieux (2001)

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 ( $\alpha_p$ ). 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  $\theta_h/\theta_l$  between low skilled and high skilled jobs by taking elasticity of substitution between education levels ( $\rho$ ) as fixed<sup>21</sup>. (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 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 10, 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.

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<sup>21</sup> $\rho$  is taken as 0.75, which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy (1992)

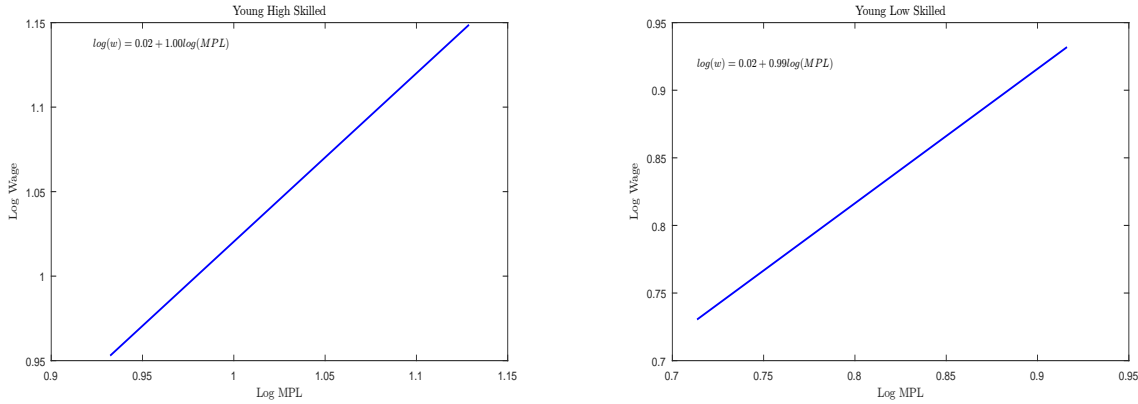


Figure 10: Wage-Productivity Gap

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

### 5.3 Testing the Mechanism

**Skilled vacancy creation relative to low skilled vacancy creation positively correlates with skilled relative to low skilled efficiency ( $\theta_h/\theta_l$ ):**

Figure 11 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 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 ( $\theta_h/\theta_l$ ) is low.

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

Figure 11 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

12 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 still some evidence that the data is consistent with the model. In Figure 13, 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.

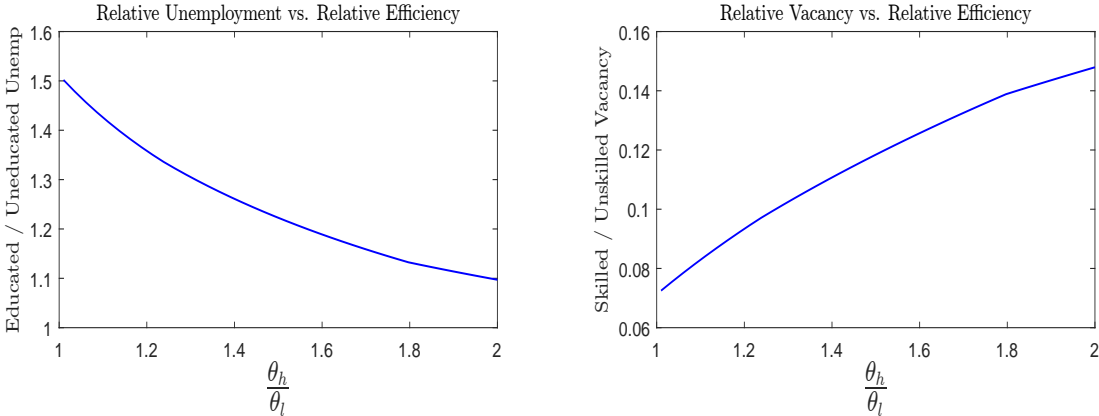


Figure 11: Relative Unemployment, Vacancy, Efficiency

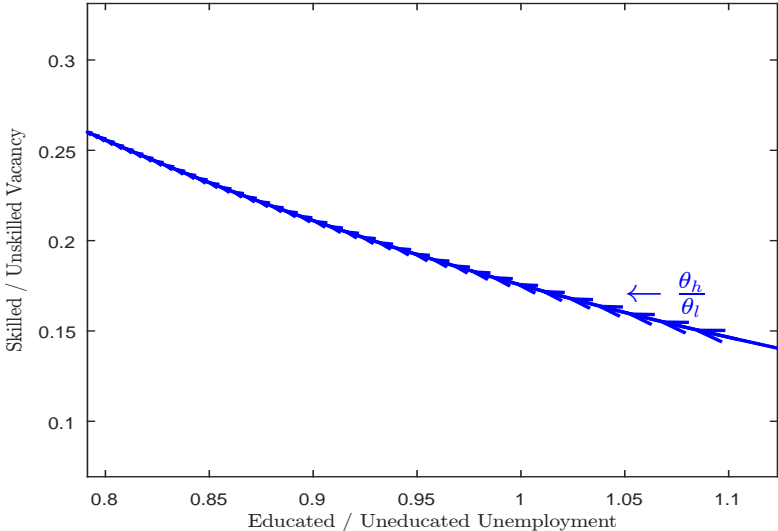


Figure 12: Relative Unemployment vs. Relative Vacancy

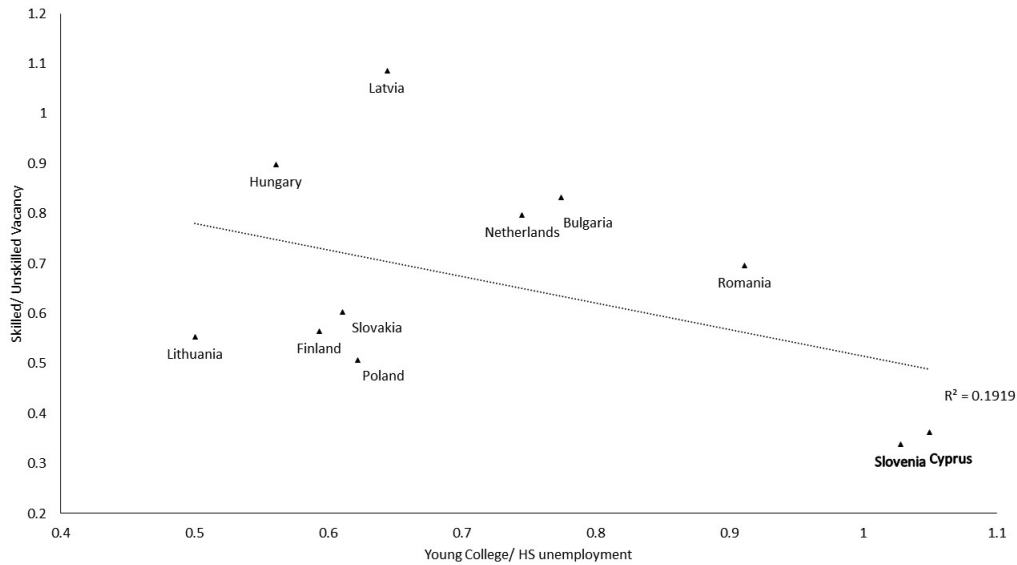


Figure 13: Relative Vacancy vs. Relative Unemployment

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.

## 6 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 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.

## 6.1 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 4). However, as I noted before, that figure is not as sharp as 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 14 shows the correlation between relative technological efficiency ( $\theta_h/\theta_l$ ) and relative unemployment rate, which is higher than in Figure 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.

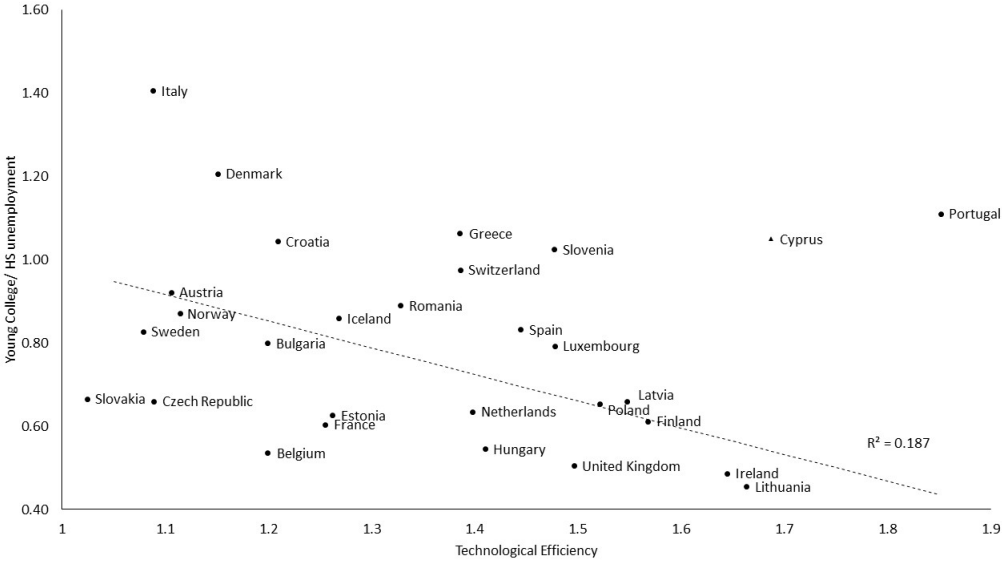


Figure 14: Relative Technological Efficiency vs. Relative Unemployment Rate  
 Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2015 and the structural estimation method described in the paper. Regression is weighted by countries' labor force sizes of 25-29 age group.

**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 15 shows  $\psi_p$  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.



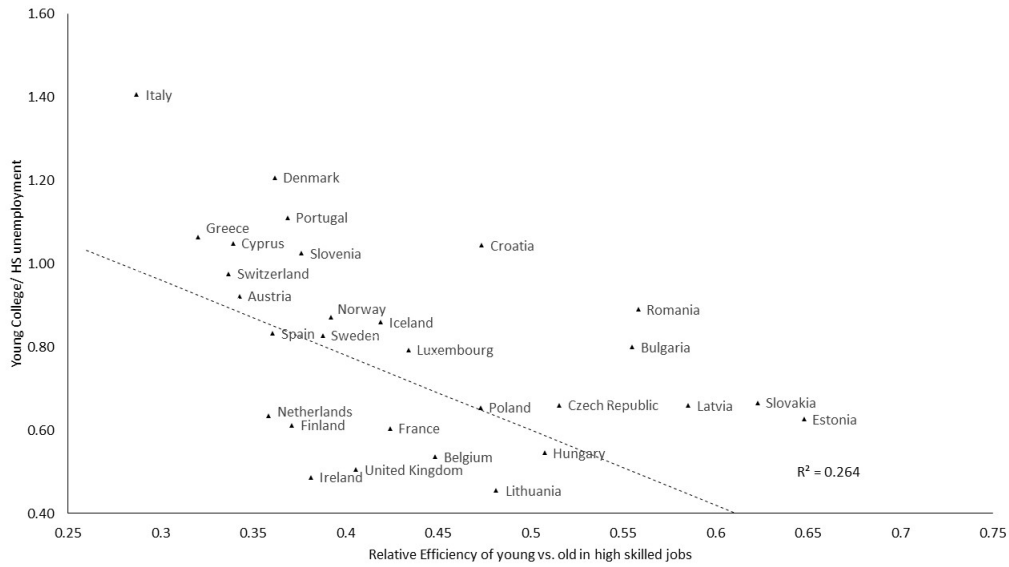


Figure 15: Relative Efficiency of Young vs. Old in High Skilled Jobs  
 Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2015 and the structural estimation method described in the paper. Regression is weighted by countries' labor force sizes of 25-29 age group.

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

Figure 16 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.

**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 17 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

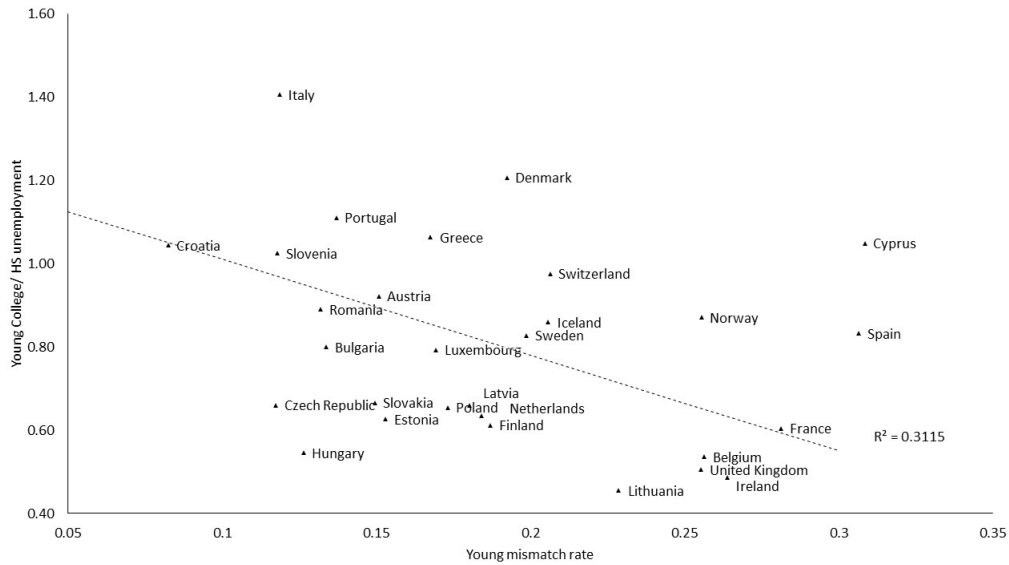


Figure 16: Young Mismatch Rate vs. Relative Unemployment Rate

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.

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.

## 6.2 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

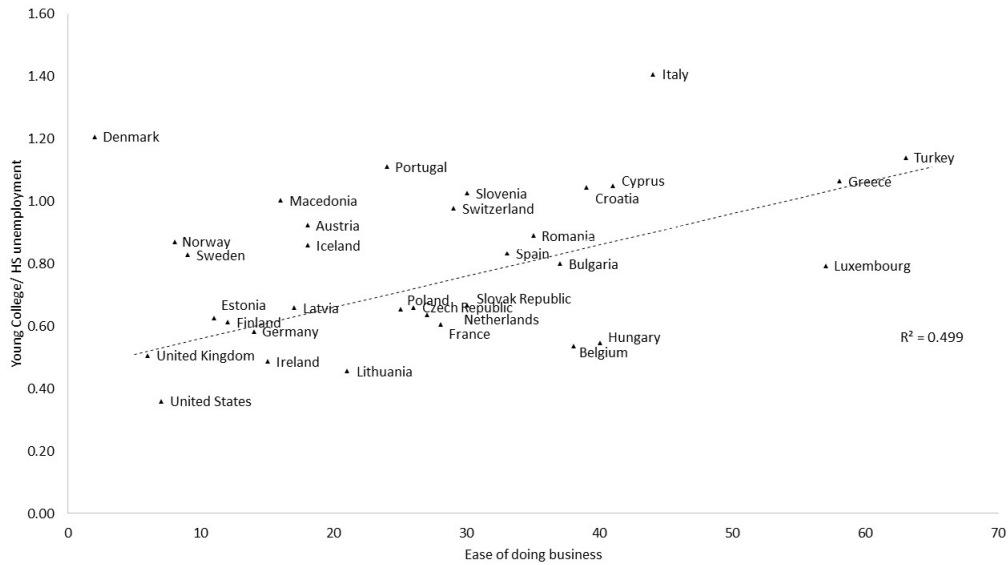


Figure 17: Ease of Doing Business vs. Relative Unemployment Rate  
 Note: Ease of Doing Business index is taken from World Bank for 2014. Unemployment rates are based on Eurostat Statistics.  
 Regression is weighted by countries' labor force sizes of 25-29 age group.

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 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 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 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)

	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 1: UK vs. Denmark

### 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 importantly, relative unemployment rates are different<sup>22</sup>. Table 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.)

<sup>22</sup>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

	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 2: Spain vs. Italy

### UK vs. Italy

Now I select two countries, Italy and the UK, from both ends of the distribution of educated young unemployment (See Figure 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 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 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.

	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 3: Italy vs. UK

which I am performing my estimation and targeting.

### 6.3 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 4 shows the differences in those parameters across four countries used in calibration exercise <sup>23</sup>. As I mentioned, the main contribution on the productivity side comes from relative technological efficiency ( $\theta_h/\theta_l$ ), 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.

	Italy	Denmark	UK	Spain
Efficiency Parameters				
$\theta_h/\theta_l$	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 4: Estimation Results

### 6.4 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 18 firsts 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

<sup>23</sup>The whole set of parameter values used in calibration exercise can be found in Appendix H

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.

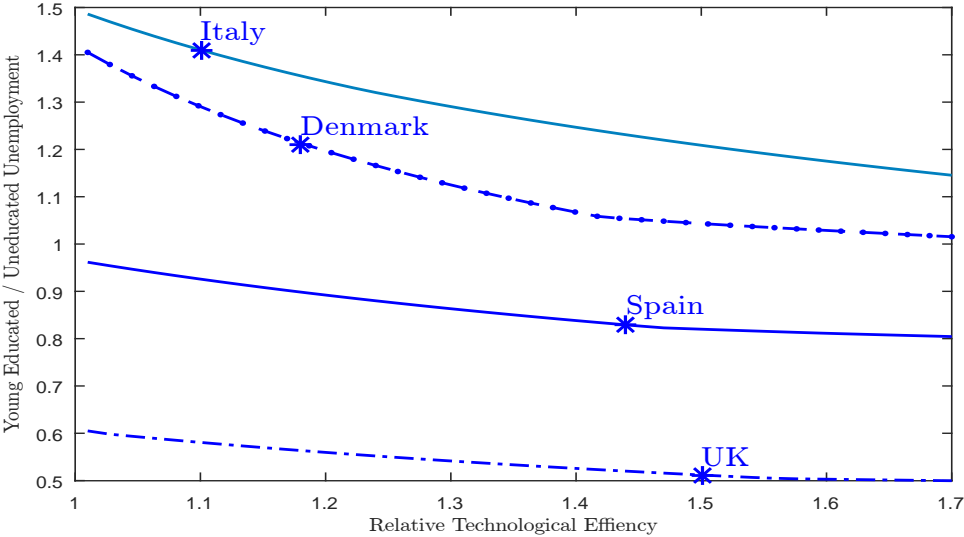


Figure 18: Location on the relative productivity vs. relative unemployment scale

## 6.5 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 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 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. 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.

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

Table 5: Shutting down the Productivity Channel



## 7 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 21 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 23, 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 22). 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 29 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 30 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 25 and 26 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 27 and 28 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.

## 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.

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## A 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.

### A.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 opportuni-

ties of skilled workers even more as they either cannot find jobs or cannot exploit their full productivity in such a business environment.

## A.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 be 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.

### A.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.

## B 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 6 shows that states in which young low educated unemployment rate is relatively low, have both mismatch efficiency ( $\alpha_p$ ) and relative technological efficiency ( $\theta_h/\theta_l$ ) 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
$\psi_p$ (relative efficiency of young in high skilled)	0.37	0.39
$\beta_p$ (relative efficiency of young in mismatched)	0.58	0.59
$\gamma_p$ (relative efficiency of young in low skilled)	0.49	0.52
$\alpha_p$ (mismatch efficiency relative to low educated)	1.19	1.31
$\theta_h/\theta_l$ (relative technological efficiency)	1.69	1.79
$\alpha$ (young ratio in labor force)	0.11	0.12
$\mu$ (uneducated ratio within young)	0.64	0.62
$\hat{\mu}$ (uneducated ratio within old)	0.65	0.64
$v$ (pension replacement rate)	0.47	0.47

Table 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.

## C 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.

## D Model Details

### D.1 Definitions

Parameter	Definition
$\alpha$	Young ratio in the population
$\mu$	Uneducated ratio among young
$\hat{\mu}$	Uneducated ratio among old
$\beta$	Workers' share in the Nash Bargaining
$r$	Discount rate
$\delta$	Exogenous job destruction rate
$\nu$	Pension replacement rate
$b_y$	Unemployment benefit of young
$b_o$	Unemployment benefit of old
$\sigma$	Probability of becoming old
$\omega$	Probability of becoming retired
$\lambda_y$	On-the-job search intensity of young
$\lambda_o$	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
$\alpha_p$	Relative efficiency of mismatched wrt low educated
$\psi_p$	Relative efficiency of young high educated wrt old high educated
$\gamma_p$	Relative efficiency of young low educated wrt old low educated
$\beta_p$	Relative efficiency of young mismatched wrt old mismatched
$\theta_h/\theta_l$	Relative technological efficiency in the production

Table 7: 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 8: 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 9: Variable Definitions

## Unemployment and Mismatch Rates:

- $u_{hy} = u(h, y)/\alpha(1 - \mu)$
- $u_{ho} = u(h, o)/(1 - \alpha)(1 - \hat{\mu})$
- $u_{ly} = u(l, y)/\alpha\mu$
- $u_{lo} = u(l, o)/(1 - \alpha)\hat{\mu}$
- $mismatch_y = m(n, h, y)/\alpha(1 - \mu)$
- $mismatch_o = m(n, h, o)/(1 - \alpha)(1 - \hat{\mu})$

## D.2 Distribution of Labor Force

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

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

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

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

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

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

### D.3 Bellman Equations

- Value of being unemployed (young educated):

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

- Value of working in skilled market (young educated):

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

- Value of working in unskilled market (young educated):

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

- Value of being unemployed (young low educated):

$$\begin{aligned}
rU(l, y) = & b_y + \underbrace{f(\theta_{1y})}_{\substack{\text{job finding probability} \\ \text{in unskilled market}}} [W(n, l, y) - U(l, y)] + \sigma[U(l, o) - U(l, y)] \quad (9)
\end{aligned}$$

- Value of working in unskilled market (young low educated):

$$rW(n, l, y) = w(n, l, y) + \delta[U(l, y) - W(n, l, y)] + \sigma[W(n, l, o) - W(n, l, y)] \quad (10)$$

- Value of being unemployed (old educated):

$$\begin{aligned}
rU(h, o) = & b_o + \underbrace{f(\theta_{2o})}_{\substack{\text{job finding probability} \\ \text{in skilled market}}} [W(s, h, o) - U(h, o)] \quad (11) \\
& + \underbrace{\tilde{\lambda}_o}_{\substack{\text{mismatch search} \\ \text{intensity}}} \underbrace{f(\theta_{1o})}_{\substack{\text{job finding probability} \\ \text{in unskilled market}}} \underbrace{\max[0, W(n, h, o) - U(h, o)]}_{\substack{\text{switch from unemp} \\ \text{to employment} \\ \text{if worthwhile}}} \\
& + \omega \underbrace{[ \underbrace{R(h, u)}_{\substack{\text{value of retirement} \\ \text{for high educated unemployed}}} - U(h, o) ]}_{\text{switch to "retirement" state}}
\end{aligned}$$

- Value of working in skilled market (old educated):

$$rW(s, h, o) = w(s, h, o) + \delta[U(h, o) - W(s, h, o)] + \omega[\underbrace{R(s, h)}_{\substack{\text{value of retirement} \\ \text{for high skilled}}} - W(s, h, o)] \quad (12)$$

- Value of working in unskilled market (old educated):

$$\begin{aligned} rW(n, h, o) = & w(n, h, o) + \delta[U(h, o) - W(n, h, o)] \\ & + \underbrace{\lambda_o}_{\substack{\text{on-the-job search} \\ \text{intensity}}} \underbrace{f(\theta_{2o})}_{\substack{\text{job finding probability} \\ \text{in skilled market}}} [W(s, h, o) - W(n, h, o)] \\ & + \omega[\underbrace{R(n, h)}_{\substack{\text{value of retirement} \\ \text{for mismatched}}} - W(n, h, o)] \end{aligned} \quad (13)$$

- Value of being unemployed (old low educated):

$$rU(l, o) = b_o + f(\theta_{1o})[W(n, l, o) - U(l, o)] + \omega[\underbrace{R(l, u)}_{\substack{\text{value of retirement} \\ \text{for low educated unemployed}}} - U(h, o)] \quad (14)$$

- Value of working in unskilled market (old low educated):

$$rW(n, l, o) = w(n, l, o) + \delta[U(l, o) - W(n, l, o)] + \omega[\underbrace{R(n, l)}_{\substack{\text{value of retirement} \\ \text{for low skilled}}} - W(n, l, o)] \quad (15)$$

- Value of skilled vacancy available for young:

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

- Value of skilled vacancy available for old:

$$rV(s, o) = \underbrace{-c_{2o}}_{\text{skilled vacancy cost available to old}} + \underbrace{p(\theta_{2o})}_{\text{skilled job filling probability by old}} \underbrace{[J(s, h, o) - V(s, o)]}_{\text{switch from vacancy to job state}} \quad (16)$$

- Value of unskilled vacancy available for young:

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

- Value of unskilled vacancy available for old:

$$rV(n, o) = -c_{1o} + \underbrace{\kappa_{no}}_{\text{prob of facing low educated}} \underbrace{p(\theta_{1o})}_{\text{unskilled job filling prob}} \underbrace{[J(n, l, o) - V(n, o)]}_{\text{switch from vacancy to job state}} \quad (17) \\ + \underbrace{(1 - \kappa_{no})}_{\text{probability of facing high educated}} \underbrace{p(\theta_{1o})}_{\text{unskilled job filling probability}} \underbrace{[J(n, h, o) - V(n, o)]}_{\text{switch from vacancy to mismatched job state}}$$

where  $\kappa_{ny}$  is the probability to face an uneducated young worker and  $\kappa_{no}$  is the probability to face an low educated old worker. ( $\kappa_{ny} = \frac{u(l, y)}{u(l, y) + \lambda_y u(h, y)}, \kappa_{no} = \frac{u(l, o)}{u(l, o) + \lambda_o u(h, o)}$ )



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

- Value of skilled job filled by young:

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

- Value of skilled job filled by old:

$$\begin{aligned}
 rJ(s, h, o) = & \underbrace{MPL(H_o)}_{\text{marginal product of}} - \underbrace{w(s, h, o)}_{\text{old high}} \tag{18} \\
 & \text{old high skilled} \quad \text{skilled wage} \\
 & + ( \underbrace{\delta}_{\text{exogeneous}} + \underbrace{\omega}_{\text{retirement}} ) \underbrace{[V(s) - J(s, h, o)]}_{\text{switch from job}} \\
 & \text{job destruction} \quad \text{probability} \quad \text{to vacancy state}
 \end{aligned}$$

- Value of unskilled job filled by young low educated:

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

- Value of unskilled job filled by old low educated:

$$\begin{aligned}
rJ(n, l, o) = & \underbrace{MPL(L_o)}_{\text{marginal product of}} - \underbrace{w(n, l, o)}_{\text{old low}} \tag{19} \\
& \text{old low skilled} \quad \text{skilled wage} \\
& + ( \underbrace{\delta}_{\text{exogenous}} + \underbrace{\omega}_{\text{retirement}} ) \underbrace{[V(n) - J(n, l, o)]}_{\text{switch from job}} \\
& \text{job destruction} \quad \text{probability} \quad \text{to vacancy state}
\end{aligned}$$

- Value of unskilled job filled by young high educated:

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

- Value of unskilled job filled by old high educated:

$$\begin{aligned}
rJ(n, h, o) = & \underbrace{MPL(M_o)}_{\text{marginal product of}} - \underbrace{w(n, h, o)}_{\text{old}} \tag{20} \\
& \text{old mismatched} \quad \text{mismatched wage} \\
& + [\delta + \underbrace{\lambda_o f(\theta_{2o})}_{\text{on the job search}} + \underbrace{\omega}_{\text{retirement probability}}] [V(n) - J(n, h, o)]
\end{aligned}$$

## D.4 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  $\theta$  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  $\lambda$ . There are 4 labor market tightness parameters determined endogenously.  $\theta_{1y}$  is for young low skilled market,  $\theta_{1o}$  is for old low skilled market,  $\theta_{2y}$  is for young skilled market,  $\theta_{2o}$  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  $\nu$  fraction<sup>24</sup> of their last income (except the case of switching from being unemployed to employed where they receive the same benefit) where:

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<sup>24</sup>Country specific pension replacement rates are used in calibration. See Appendix for details.

$$R(h, u) = b_o/r, R(l, u) = b_o/r, R(n, l) = vw(n, l, o)/r, R(s, h) = vw(s, h, o)/r, R(n, h) = vw(n, h, o)/r$$

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

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

$$(1 - \beta)[W(s, h, y) - U(h, y)] = \beta[J(s, h, y) - V(s, y)] \quad (21)$$

$$(1 - \beta)[W(s, h, o) - U(h, o)] = \beta[J(s, h, o) - V(s, o)] \quad (22)$$

$$(1 - \beta)[W(n, h, y) - U(h, y)] = \beta[J(n, h, y) - V(s, y)] \quad (23)$$

$$(1 - \beta)[W(n, h, o) - U(h, o)] = \beta[J(n, h, o) - V(s, o)] \quad (24)$$

$$(1 - \beta)[W(n, l, y) - U(l, y)] = \beta[J(n, l, y) - V(n, y)] \quad (25)$$

$$(1 - \beta)[W(n, l, o) - U(l, o)] = \beta[J(n, l, o) - V(n, o)] \quad (26)$$

**Steady state conditions** for each market are as follows where the left-hand sides are for people entering the market and right-hand sides are people leaving the market.

- **Skilled Market:**

$$\underbrace{f(\theta_{2y})(u(h, y) + \lambda_y M_y)}_{\text{inflow to emp by unemp and mismatched high educated young}} = \underbrace{(\delta + \sigma)[\alpha(1 - \mu) - u(h, y) - M_y]}_{\text{outflow from employment}} \quad (27)$$

$$\begin{aligned}
& \underbrace{f(\theta_{2o})(u(h, o) + \lambda_o M_o)}_{\text{due to job finding}} + \underbrace{\sigma[\alpha(1 - \mu) - u(h, y) - M_o]}_{\text{due to switch to old state}} = & (28) \\
& \underbrace{(\delta + \omega)[(1 - \alpha)(1 - \hat{\mu}) - u(h, o) - M_o]}_{\text{outflow from employment}}
\end{aligned}$$

inflow to emp by unemp and mismatched high educated old

• **Unskilled Market:**

$$\begin{aligned}
& \underbrace{f(\theta_{1y})u(l, y)}_{\text{inflow to emp by unemployed low educated}} = \underbrace{(\delta + \sigma)(\alpha\mu - u(l, y))}_{\text{outflow from employment}} & (29)
\end{aligned}$$

$$\begin{aligned}
& \underbrace{f(\theta_{1o})u(l, o)}_{\text{due to job finding}} + \underbrace{\sigma[(\alpha\mu - u(l, y))]}_{\text{due to switch to old state}} = \underbrace{(\delta + \omega)((1 - \alpha)\hat{\mu} - u(l, o))}_{\text{outflow from employment}} & (30) \\
& \text{inflow to emp by low educated old}
\end{aligned}$$

• **Mismatch Market:**

$$\begin{aligned}
& \underbrace{f(\theta_{1y})u(h, y)\tilde{\lambda}_y}_{\text{inflow to mismatch by high educated young}} = \underbrace{[\delta + f(\theta_{2y})\lambda_y + \sigma]M_y}_{\text{outflow from mismatch}} & (31)
\end{aligned}$$

$$\begin{aligned}
& \underbrace{f(\theta_{1o})u(h, o)\tilde{\lambda}_o}_{\text{due to job finding}} + \underbrace{\sigma M_y}_{\text{due to switch to old state}} = \underbrace{[\delta + f(\theta_{2o})\lambda_o + \omega]M_o}_{\text{outflow from mismatch}} & (32) \\
& \text{inflow to mismatch by high educated old}
\end{aligned}$$

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:

$$MPL(H_y) = \frac{\partial Y}{\partial H_y} = \theta_h \psi_p Y^{1-\rho} H^{\rho-\eta} H_y^{\eta-1} \quad (33)$$

$$MPL(H_o) = \frac{\partial Y}{\partial H_o} = \theta_h Y^{1-\rho} H^{\rho-\eta} H_o^{\eta-1} \quad (34)$$

$$MPL(M_y) = \frac{\partial Y}{\partial M_y} = \theta_l \alpha_p \beta_p Y^{1-\rho} \tilde{L}^{\rho-1} M^{1-\eta} M_y^{\eta-1} \quad (35)$$

$$MPL(M_o) = \frac{\partial Y}{\partial M_o} = \theta_l \alpha_p Y^{1-\rho} \tilde{L}^{\rho-1} M^{1-\eta} M_o^{\eta-1} \quad (36)$$

$$MPL(L_y) = \frac{\partial Y}{\partial L_y} = \theta_l \gamma_p Y^{1-\rho} \tilde{L}^{\rho-1} L^{1-\eta} L_y^{\eta-1} \quad (37)$$

$$MPL(L_o) = \frac{\partial Y}{\partial L_o} = \theta_l Y^{1-\rho} \tilde{L}^{\rho-1} L^{1-\eta} L_o^{\eta-1} \quad (38)$$

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.

## E 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 10: European Countries and data availability in EU-SILC

### E.1 Observable Country-Specific Characteristics

On the job search intensity  $\lambda_y$  and  $\lambda_o$ :

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	$\lambda_y$	$\lambda_o$	Country	$\lambda_y$	$\lambda_o$
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 11: On-the-job Search Intensity

**Young ratio  $\alpha$ , Uneducated ratio within young  $\mu$ , 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 ( $\alpha$ ) 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 ( $\mu$ ) 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	$\alpha$	$\mu$	$\hat{\mu}$	Country	$\alpha$	$\mu$	$\hat{\mu}$
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 12: Young and Uneducated Ratio in Europe

State	$\alpha$	$\mu$	$\hat{\mu}$	State	$\alpha$	$\mu$	$\hat{\mu}$
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 13: Young and Uneducated Ratio in the US

### Pension replacement rate $v$ :

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  $v$ . 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 14: Pension Replacement Rates

## E.2 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 also 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.

	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech Republic	Denmark	Estonia	Finland	France
1	0.51	0.59	0.58	0.51	0.74	0.42	0.58	0.48	0.64	0.55
2	0.82	0.89	0.93	0.84	0.95	0.82	0.85	0.75	0.88	0.87
3	0.42	0.59	0.61	0.30	0.54	0.28	0.55	0.41	0.71	0.55
4	0.34	0.44	0.36	0.10	0.26	0.16	0.39	0.35	0.47	0.33
5	0.37	0.26	0.35	0.05	0.31	0.14	0.48	0.21	0.46	0.18
6	0.34	0.07	0.32	0.03	0.09	0.10	0.34	0.16	0.34	0.12
7	0.36	0.13	0.29	0.01	0.19	0.02	0.28	0.12	0.31	0.12
8	0.24	0.08	0.24	0.02	0.10	0.01	0.25	0.08	0.26	0.06
9	0.34	0.16	0.40	0.02	0.11	0.01	0.34	0.07	0.35	0.09
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	Greece	Hungary	Iceland	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherlands
1	0.55	0.60	0.41	0.63	0.20	0.59	0.63	0.52	0.58	0.58
2	0.95	0.91	0.79	0.84	0.71	0.86	0.83	0.90	0.86	0.87
3	0.75	0.43	0.31	0.70	0.23	0.52	0.56	0.38	0.22	0.54
4	0.59	0.35	0.31	0.47	0.13	0.40	0.38	0.18	0.12	0.47
5	0.59	0.31	0.16	0.43	0.12	0.34	0.19	0.10	0.07	0.45
6	0.57	0.25	0.05	0.42	0.06	0.32	0.08	0.04	0.00	0.28
7	0.44	0.19	0.07	0.25	0.05	0.29	0.14	0.04	0.03	0.32
8	0.40	0.19	0.06	0.27	0.04	0.23	0.08	0.06	0.00	0.25
9	0.61	0.36	0.09	0.25	0.07	0.17	0.07	0.05	0.02	0.48
<hr/>										
	Norway	Poland	Portugal	Romania	Slovakia	Slovenia	Spain	Sweden	Switzerland	United Kingdom
1	0.57	0.47	0.57	0.59	0.69	0.54	0.66	0.39	0.63	0.47
2	0.87	0.91	0.72	0.95	0.70	0.83	0.99	0.79	0.83	0.80
3	0.66	0.28	0.26	0.23	0.35	0.26	0.69	0.39	0.49	0.54
4	0.42	0.19	0.17	0.16	0.13	0.10	0.65	0.20	0.22	0.35
5	0.38	0.13	0.07	0.07	0.04	0.09	0.53	0.25	0.40	0.32
6	0.34	0.03	0.01	0.01	0.03	0.04	0.53	0.07	0.22	0.19
7	0.28	0.04	0.03	0.02		0.03	0.55	0.08	0.23	0.21
8	0.19	0.04	0.02	0.02	0.01	0.01	0.50	0.07	0.15	0.15
9	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
<b>1</b>	<b>Legislators, senior officials and managers</b>	Skilled
11	Legislators, senior officials and managers	Skilled
12	Corporate managers	Skilled
13	Managers of small enterprises	Skilled
<b>2</b>	<b>Professionals</b>	Skilled
21	Physical, mathematical and engineering science professionals	Skilled
22	Life science and health professionals	Skilled
23	Teaching professionals	Skilled
24	Other professionals	Skilled
<b>3</b>	<b>Technicians and associate professionals</b>	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
<b>4</b>	<b>Clerks</b>	Unskilled
41	Office clerks	Unskilled
42	Customer services clerks	Unskilled
<b>5</b>	<b>Service workers and shop and market sales workers</b>	Unskilled
51	Personal and protective services workers	Unskilled
52	Models, salespersons and demonstrators	Unskilled
<b>6</b>	<b>Skilled agricultural and fishery workers</b>	Unskilled
61	Skilled agricultural and fishery workers	Unskilled
<b>7</b>	<b>Craft and related trades workers</b>	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
<b>8</b>	<b>Plant and machine operators and assemblers</b>	Unskilled
81	Stationary-plant and related operators	Unskilled
82	Machine operators and assemblers	Unskilled
83	Drivers and mobile plant operators	Unskilled
<b>9</b>	<b>Elementary occupations</b>	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 16: 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 17: 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 18: 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 16. 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 19 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 19: Skilled/ Unskilled Vacancies

## F Parameters

### F.1 Standard Parameters from the Literature

Parameters from the Literature			
Parameter	Definition	Value	Source
$r$	Discount rate	0.01	Shimer (2007)
$\delta$	Exogenous job destruction rate	0.1	Shimer (2007)
$\beta$	Worker's bargaining power	0.7	Shimer (2007)
$\eta$	Elasticity of substitution between age groups	0.75	Card & Lemieux (2001)
$\rho$	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)
$\sigma$	Probability of becoming old	0.2	Author's own calculation
$\omega$	Probability of becoming retired	0.028	Author's own calculation

Table 20: Standard Parameters

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

## F.2 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
$\theta_l$	Efficiency of low skilled sector

Table 21: 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.

Estimated Relative Efficiency Parameters	
Parameter	Definition
$\alpha_p$	Relative efficiency of mismatched wrt low educated
$\psi_p$	Relative efficiency of young high educated wrt old high educated
$\gamma_p$	Relative efficiency of young low educated wrt old low educated
$\beta_p$	Relative efficiency of young mismatched wrt old mismatched
$\theta_h/\theta_l$	Relative technological efficiency in the production

Table 22: Estimated Relative Efficiency Parameters

### F.3 Model Properties

	Symmetric Case	Imperfect Substitution, Stochastic Aging	Relative Supply	Mismatch Channel	Vacancy Cost
$\beta$	0.7				
$r$	0.01				
$\delta$	0.1				
$b_y$	0.1				
$b_o$	0.1	0.3			
$\theta_l$	1				
$v$	0.5				
$\rho$	1	0.8			
$\eta$	1	0.75			
$\sigma$	0	0.1			
$\omega$	0	0.028			
$\alpha$	0.5		0.1		
$\mu$	0.5		0.7		
$\hat{\mu}$	0.5		0.8		
$\tilde{\lambda}_y$	0			0.5	
$\tilde{\lambda}_o$	0			0.5	
$\lambda_y$	0			1	
$\lambda_o$	0			1	
$c_{1y}$	0.1				
$c_{2y}$	0.1				0.6
$c_{1o}$	0.1				
$c_{2o}$	0.1				
$\alpha_p$	1				
$\psi_p$	1				
$\beta_p$	1				
$\gamma_p$	1				
$\theta_h/\theta_l$	[1,2]				

Table 23: Model Properties (Parameter Values)

## G Structural Estimation

I take weighted mean of the left hand sides<sup>25</sup> 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

<sup>25</sup>Subscript  $i$  refers to the country and  $t$  refers to year.

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.

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

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

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

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 ( $\alpha_p$ ). Below 2 equations identify  $\alpha_p$  together. Hence,  $\tilde{L}$  which is the effective number of low skilled workers in the economy can be calculated.

$$\begin{aligned} \frac{MPL(M_y)}{MPL(L_y)} &= \frac{\frac{\partial Y}{\partial M_y}}{\frac{\partial Y}{\partial L_y}} = \frac{\alpha_p \beta_p}{\gamma_p} \left(\frac{M}{L}\right)^{1-\eta} \left(\frac{M_y}{L_y}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(M_y)}{MPL(L_y)}\right)_{it} - (\eta - 1)\log\left(\frac{M_y}{L_y}\right)_{it} - (1 - \eta)\log\left(\frac{M}{L}\right)_{it} - \log\left(\frac{\hat{\beta}_p}{\hat{\gamma}_p}\right) = \log(\alpha_p) \end{aligned}$$

$$\begin{aligned} \frac{MPL(M_o)}{MPL(L_o)} &= \frac{\frac{\partial Y}{\partial M_o}}{\frac{\partial Y}{\partial L_o}} = \alpha_p \left(\frac{M}{L}\right)^{1-\eta} \left(\frac{M_o}{L_o}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(M_o)}{MPL(L_o)}\right)_{it} - (\eta - 1)\log\left(\frac{M_o}{L_o}\right)_{it} - (1 - \eta)\log\left(\frac{M}{L}\right)_{it} = \log(\alpha_p) \end{aligned}$$

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 ( $\rho$ ) as fixed<sup>26</sup>. These 4 equations identify  $\theta_h/\theta_l$  together.

$$\begin{aligned}\frac{MPL(H_y)}{MPL(M_y)} &= \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial M_y}} = \frac{\theta_h}{\theta_l} \frac{\psi_p}{\alpha_p \beta_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{M}\right)^{1-\eta} \left(\frac{H_y}{M_y}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(H_y)}{MPL(M_y)}\right)_{it} - (\eta-1)\log\left(\frac{H_y}{M_y}\right)_{it} - (1-\eta)\log\left(\frac{H}{M}\right)_{it} - (\rho-1)\log\left(\frac{H}{\tilde{L}}\right)_{it} \\ &\quad - \log\left(\frac{\hat{\psi}_p}{\hat{\alpha}_p \hat{\beta}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)\end{aligned}$$

$$\begin{aligned}\frac{MPL(H_o)}{MPL(M_o)} &= \frac{\frac{\partial Y}{\partial H_o}}{\frac{\partial Y}{\partial M_o}} = \frac{\theta_h}{\theta_l} \frac{1}{\alpha_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{M}\right)^{1-\eta} \left(\frac{H_o}{M_o}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(H_o)}{MPL(M_o)}\right)_{it} - (\eta-1)\log\left(\frac{H_o}{M_o}\right)_{it} - (1-\eta)\log\left(\frac{H}{M}\right)_{it} - (\rho-1)\log\left(\frac{H}{\tilde{L}}\right)_{it} \\ &\quad - \log\left(\frac{1}{\hat{\alpha}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)\end{aligned}$$

$$\begin{aligned}\frac{MPL(H_y)}{MPL(L_y)} &= \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial L_y}} = \frac{\theta_h}{\theta_l} \frac{\psi_p}{\gamma_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{L}\right)^{1-\eta} \left(\frac{H_y}{L_y}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(H_y)}{MPL(L_y)}\right)_{it} - (\eta-1)\log\left(\frac{H_y}{L_y}\right)_{it} - (1-\eta)\log\left(\frac{H}{M}\right)_{it} - (\rho-1)\log\left(\frac{H}{\tilde{L}}\right)_{it} \\ &\quad - \log\left(\frac{\hat{\psi}_p}{\hat{\gamma}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)\end{aligned}$$

$$\begin{aligned}\frac{MPL(H_o)}{MPL(L_o)} &= \frac{\frac{\partial Y}{\partial H_o}}{\frac{\partial Y}{\partial L_o}} = \frac{\theta_h}{\theta_l} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{L}\right)^{1-\eta} \left(\frac{H_o}{L_o}\right)^{\eta-1} \implies \\ &\log\left(\frac{MPL(H_o)}{MPL(L_o)}\right)_{it} - (\eta-1)\log\left(\frac{H_o}{L_o}\right)_{it} - (1-\eta)\log\left(\frac{H}{M}\right)_{it} - (\rho-1)\log\left(\frac{H}{\tilde{L}}\right)_{it} \\ &\quad = \log\left(\frac{\theta_h}{\theta_l}\right)\end{aligned}$$

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<sup>26</sup> $\rho$  is taken as 0.75 which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy (1992)

With the above procedure and with iteration to correct wage-MPL gap, I am able to estimate relative efficiencies of workers ( $\psi_p, \beta_p, \gamma_p, \alpha_p, \theta_h/\theta_l$ ) to be used in the model to explain unemployment rate differentials.

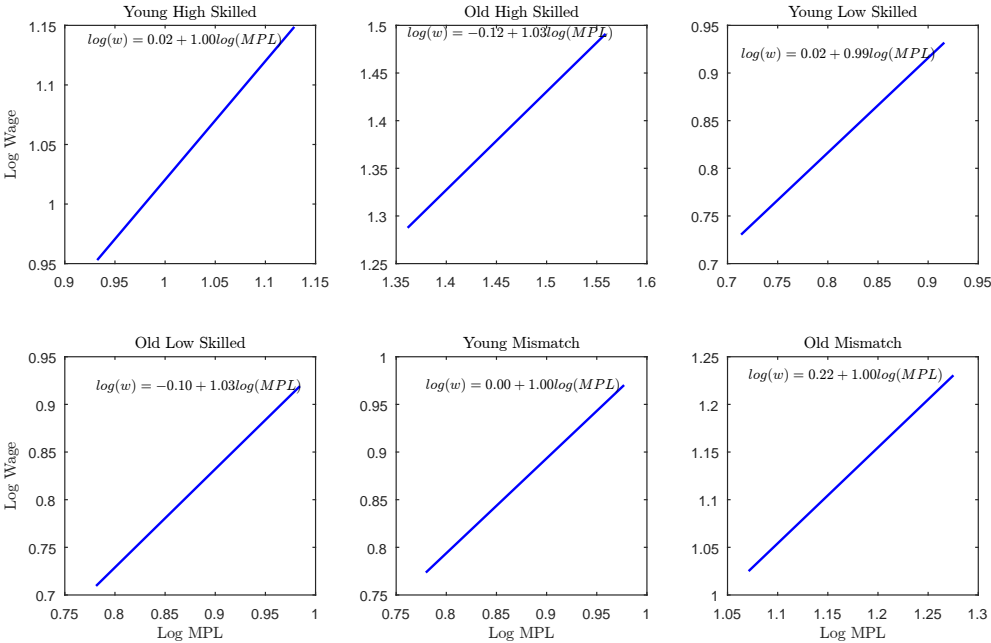


Figure 19: Wage-MPL Gap

## H Estimation Results

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

Table 24: First and Second Estimation, Europe (Wage Update)

	UK	Denmark	Italy	Spain
Efficiency Parameters				
$\alpha_p$	1.02	1.06	0.96	0.94
$\psi_p$	0.39	0.35	0.29	0.34
$\gamma_p$	0.55	0.46	0.50	0.42
$\beta_p$	0.65	0.50	0.64	0.59
$\theta_h/\theta_l$	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
$\theta_l$	3.7	3.4	0.98	0.67
Macro Factors				
$\alpha$	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
$v$	0.42	0.75	0.82	0.8

Table 25: Estimation Results Europe

1st Stage		
Estimated Parameters	Low States	High States
$\psi_p$ (relative efficiency of young in high skilled)	0.40	0.39
$\beta_p$ (relative efficiency of young in mismatched)	0.45	0.45
$\gamma_p$ (relative efficiency of young in low skilled)	0.53	0.51
$\alpha_p$ (mismatch efficiency relative to low educated)	1.53	1.59
$\theta_h/\theta_l$ (relative technological efficiency)	1.67	1.76
Updated		
Estimated Parameters	Low States	High States
$\psi_p$ (relative efficiency of young in high skilled)	0.37	0.39
$\beta_p$ (relative efficiency of young in mismatched)	0.58	0.59
$\gamma_p$ (relative efficiency of young in low skilled)	0.49	0.52
$\alpha_p$ (mismatch efficiency relative to low educated)	1.19	1.31
$\theta_h/\theta_l$ (relative technological efficiency)	1.69	1.79

Table 26: 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.



# I Descriptive Statistics

## I.1 Unemployment Rates

County	(ISCED 3-4)	(ISCED 5-6)	(ISCED 3-4)	(ISCED 5-6)
	Upper Secondary	Tertiary Education	Upper Secondary	Tertiary Education
	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 27: Unemployment Rates in Europe (average of 2004-2015)

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

Table 28: Unemployment Rates in the US (average of 2000-2015)

## I.2 Tertiary Enrollment Rates

Country	Gross Tertiary Enrolment Rate	Country	Gross Tertiary Enrolment 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 29: Tertiary Enrollment Rates

### I.3 Employment Rates

County	(ISCED 3-4)	(ISCED 5-6)	Employment Ratio
	Upper Secondary	Tertiary Education	College/HS
	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 30: Employment Rates in Europe (average of 2004-2015)

# J Figures

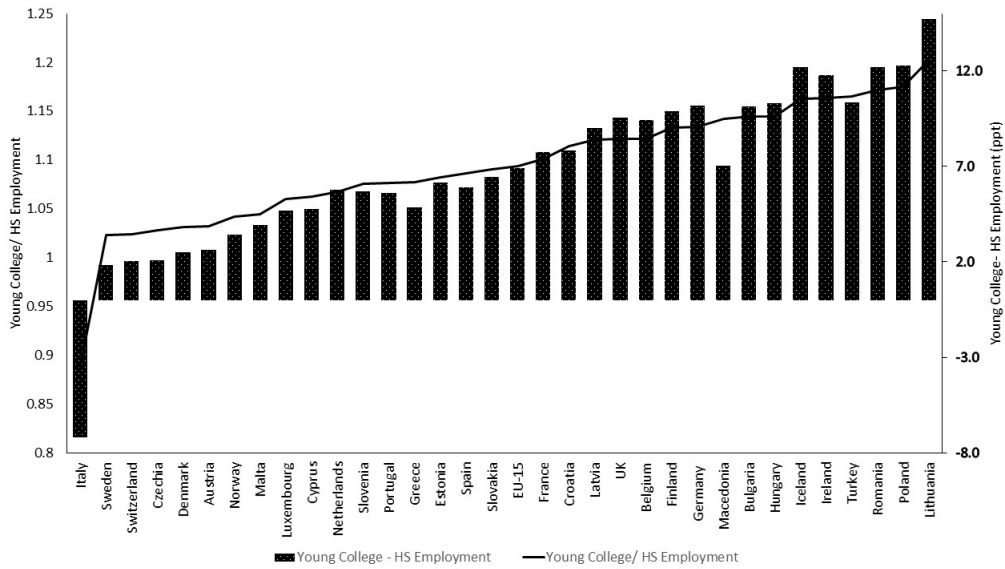


Figure 20: Employment Rates in Europe (average of 2004-2015)

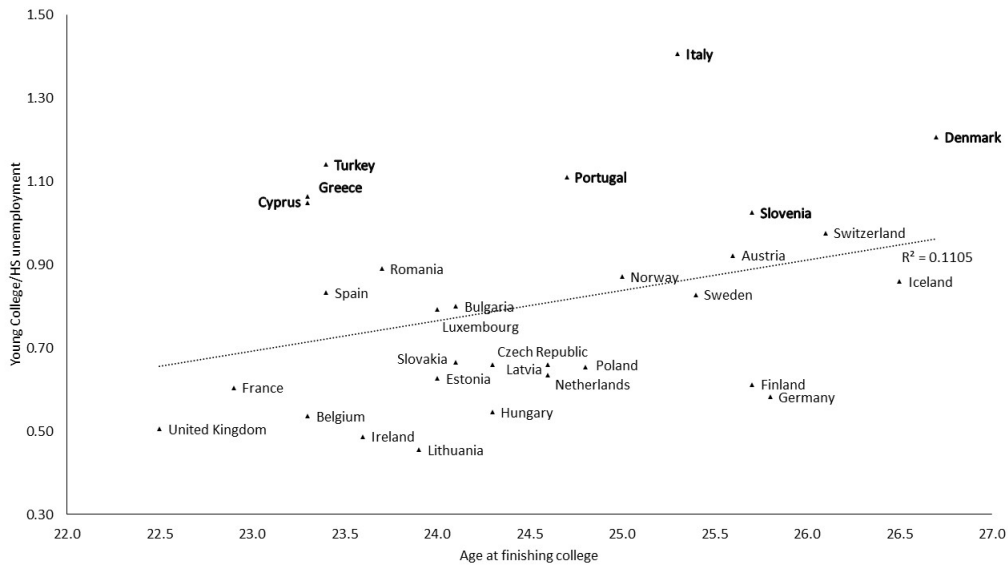


Figure 21: Duration in College

Note: The data for average age at the end of college is taken from Eurostat website (reference year is 2009).

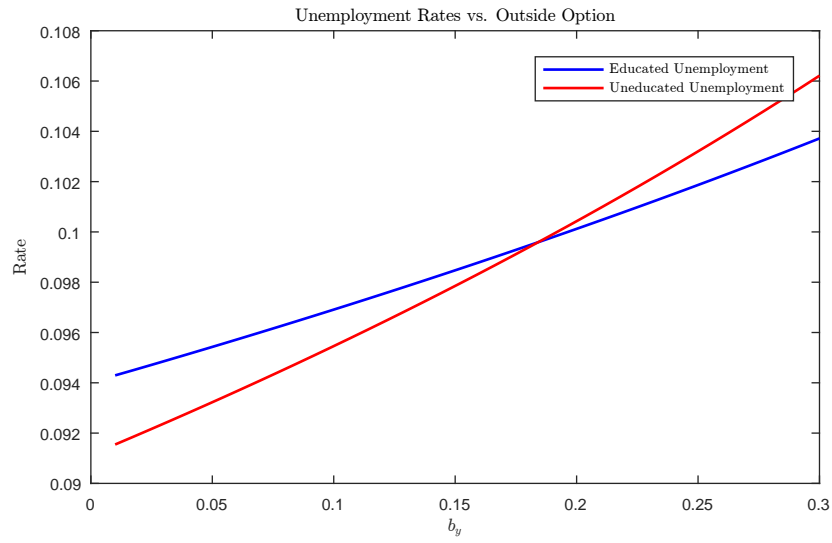


Figure 22: Mother Hypothesis

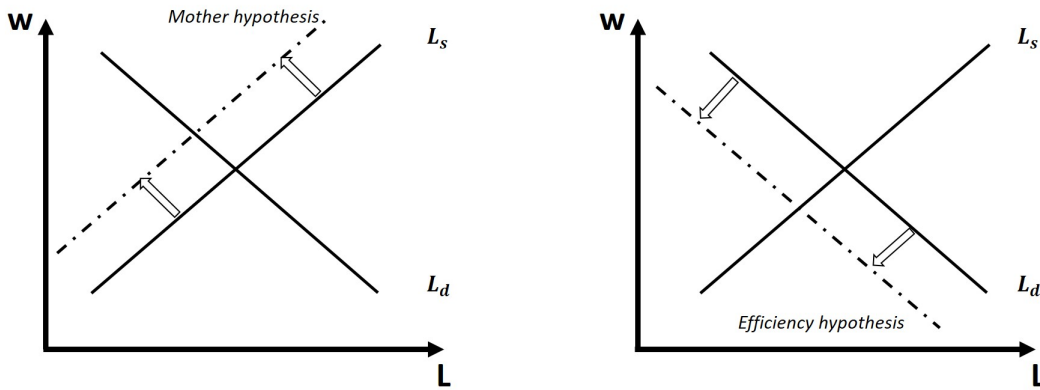


Figure 23: Mother vs. Efficiency Hypothesis

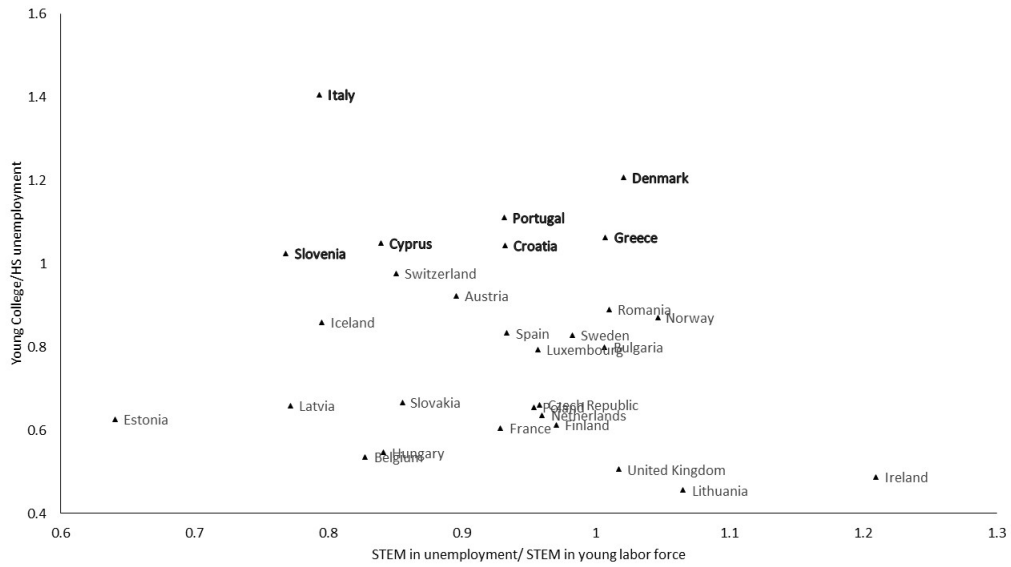


Figure 24: STEM in unemployment vs. in labor force

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.

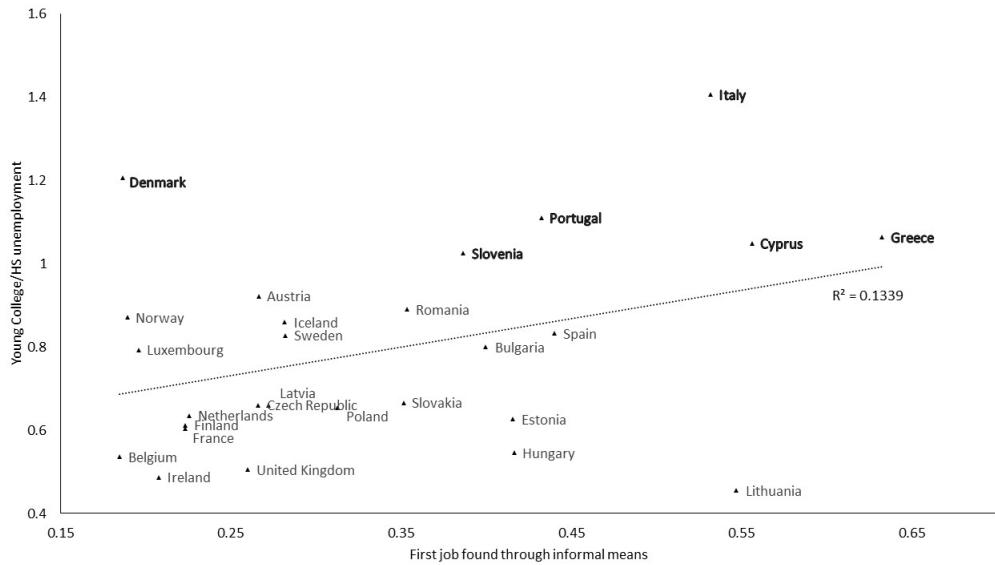
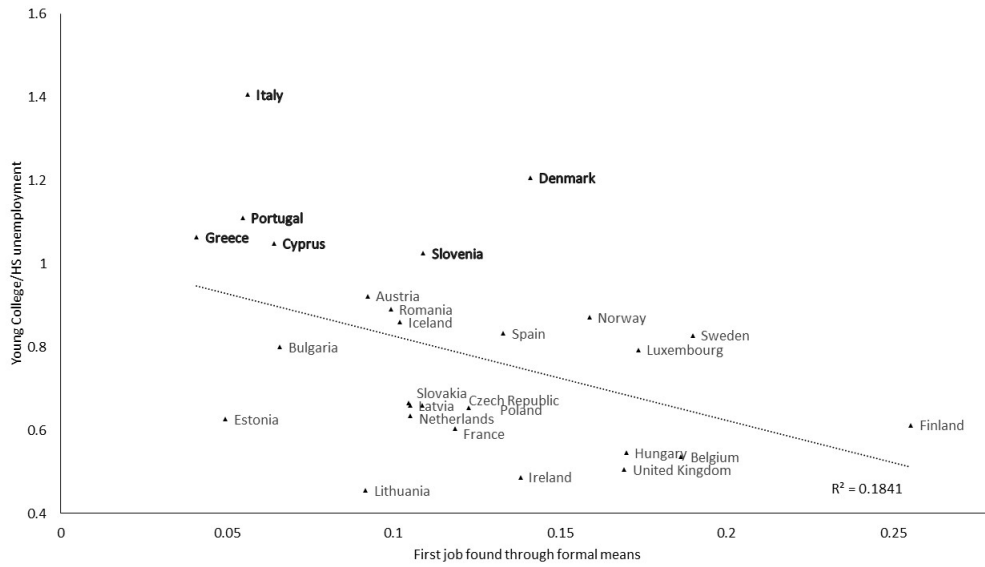
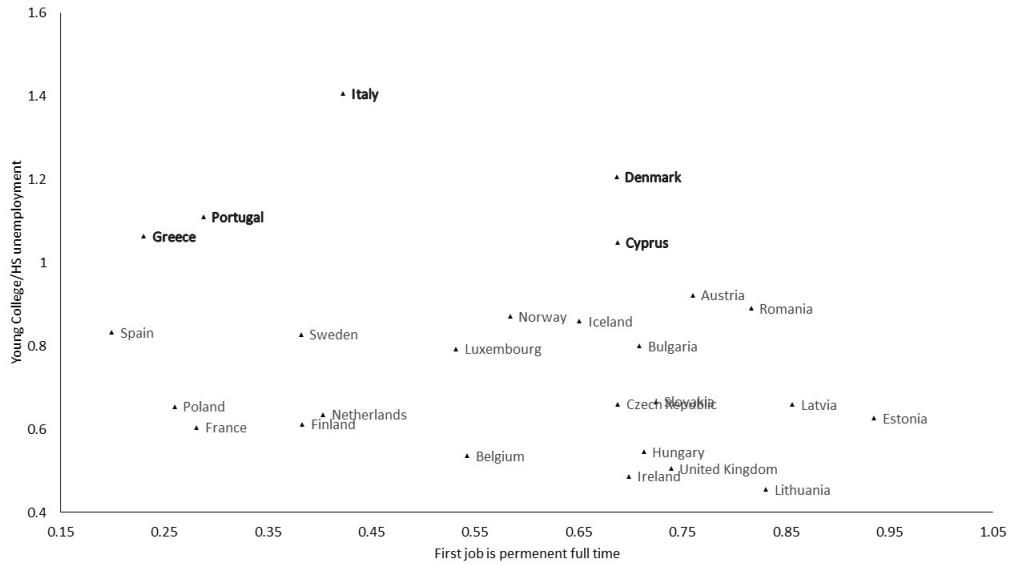


Figure 25: First job is found through friends and family

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 26: 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 27: First job is permanent 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.



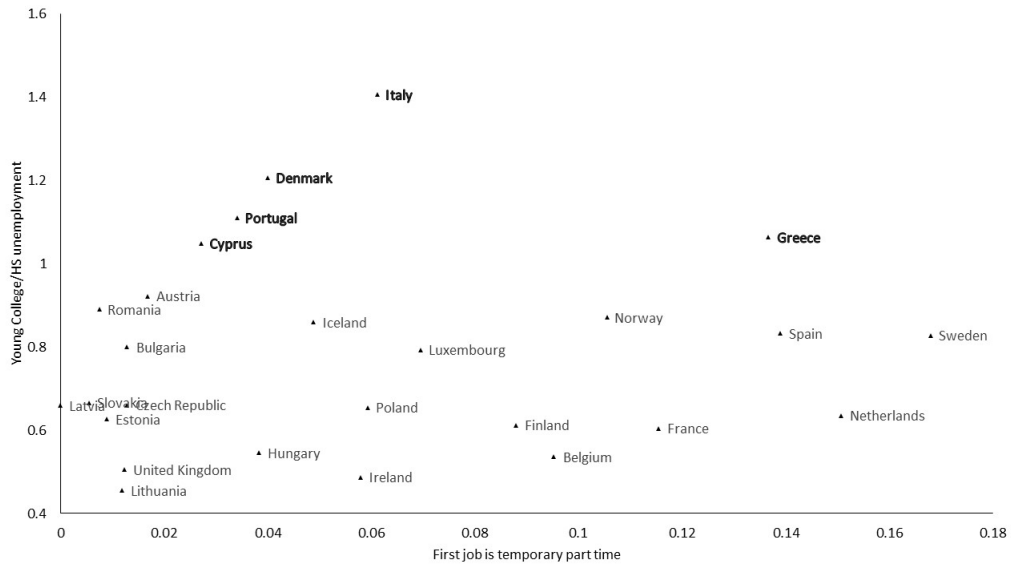


Figure 28: First job is temporary part time

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.

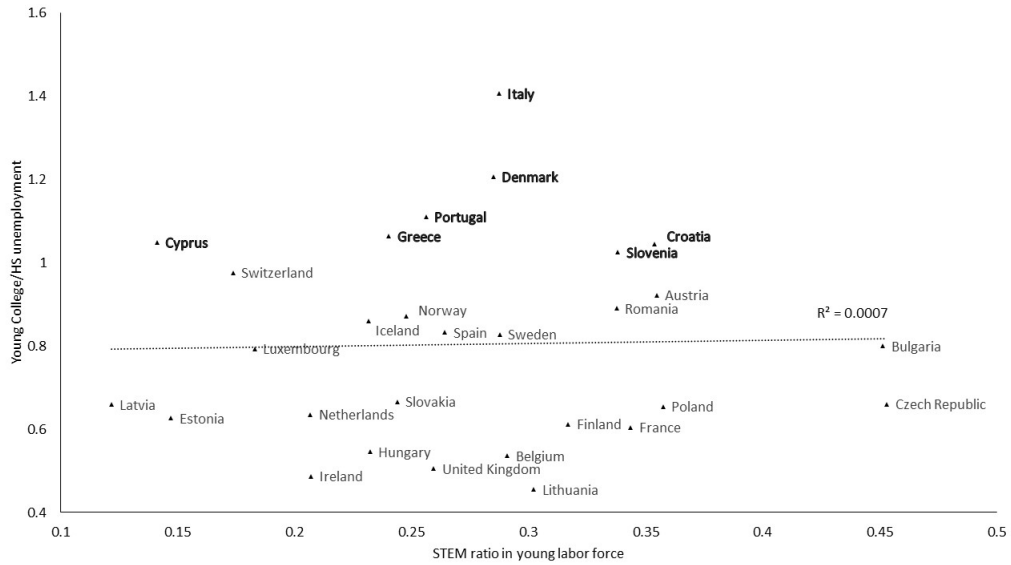


Figure 29: STEM ratio vs. College Unemployment

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.

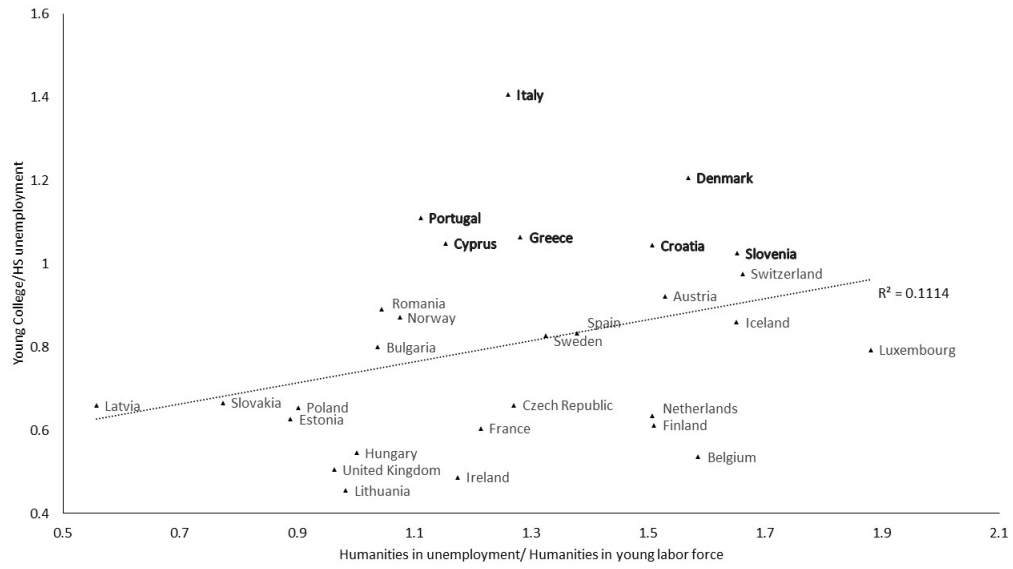


Figure 30: Humanities in unemployment vs. in labor force

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.