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Young, Educated, Unemployed

Sena Coskun ¹

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¹ University of Mannheim, Email: sena.coskun@uni-mannheim.de, Web: <https://sites.google.com/view/senacoskun>

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Young, Educated, Unemployed*

Sena Coskun[†]

University of Mannheim

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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 endogeneous 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 explains a substantial part 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.

Key words: unemployment, labor market frictions, European labor markets, education, productivity, skill premium

JEL Codes: E24, J21, J24, J31, J64

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[†]Email: sena.coskun@uni-mannheim.de. Web: <https://sites.google.com/view/senacoskun>

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, young college graduates 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 graduates 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 graduates always have lower unemployment rates in all states, but also the gap is large (Figure 2).

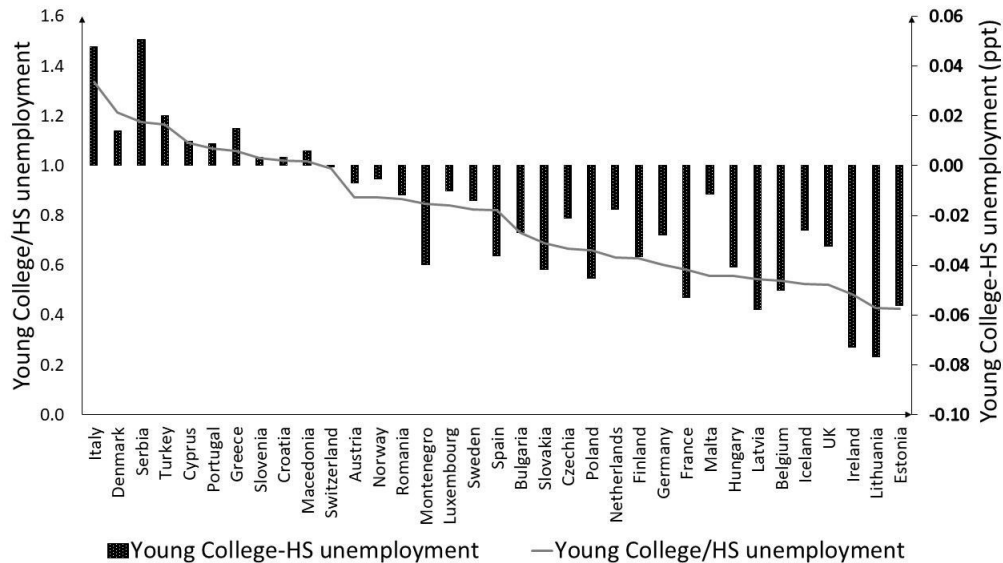


Figure 1: Europe Average Unemployment Rate Differences

Note: The unemployment rates for the 25-29 age group have been averaged from 2004-2017 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.

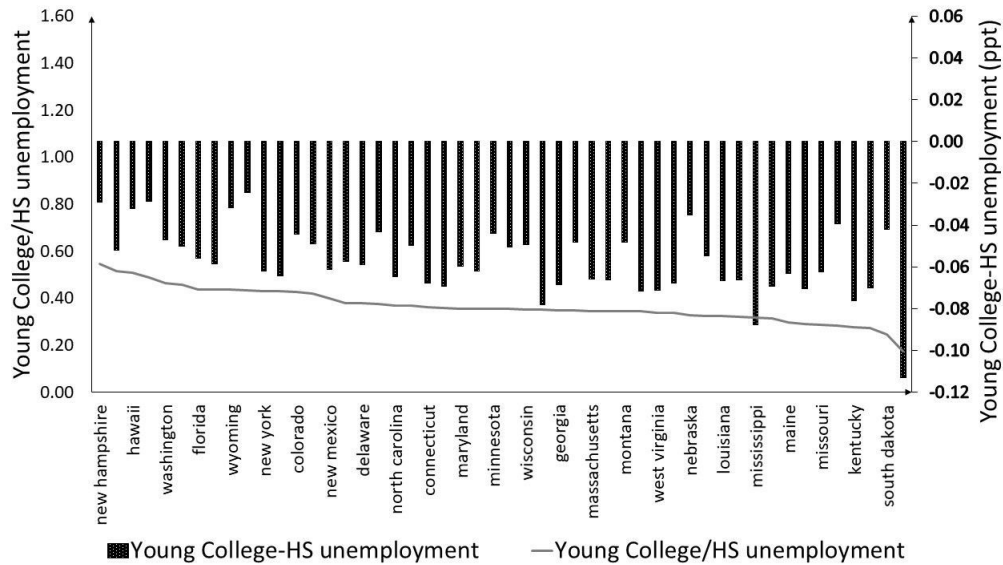


Figure 2: US Average Unemployment Rate Differences

Note: The unemployment rates for the 25-29 age group have been averaged from 2004-2017 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 graduates 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); Freeman & Wise (1982); Freeman (1976); Cuadras-Morató & Mateos-Planas (2013)). This happens when college graduates cannot find suitable jobs and accept 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); Gautier et al. (2002); Arseneau & Epstein (2019); Barnichon & Zylberberg (2019)). 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

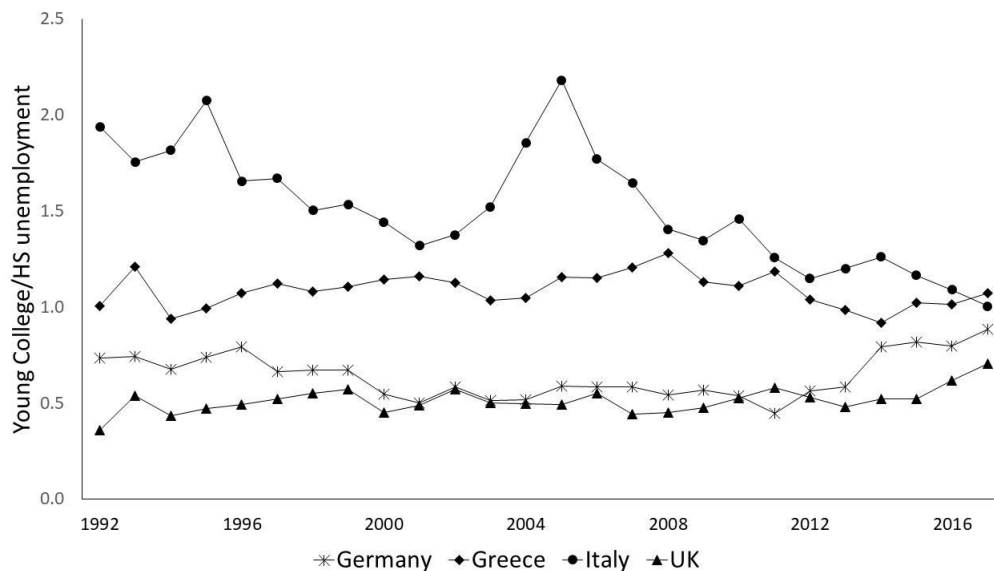


Figure 3: Time Series of Unemployment Rates

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); Saint-Paul (1994)). The “*Labor market frictions hypothesis*” claims that frictions contribute young educated people to be more unemployed. However, there is a second possibility that the cause not 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), Obiols-Homs & Sánchez-Marcos (2018)). In contrast, under the “*Labor market frictions hypothesis*”, wages would not be necessarily be depressed as much. 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. Hence it is not straightforward to draw implications from college wage premium in a setting with high frictions (Figure 4)¹.

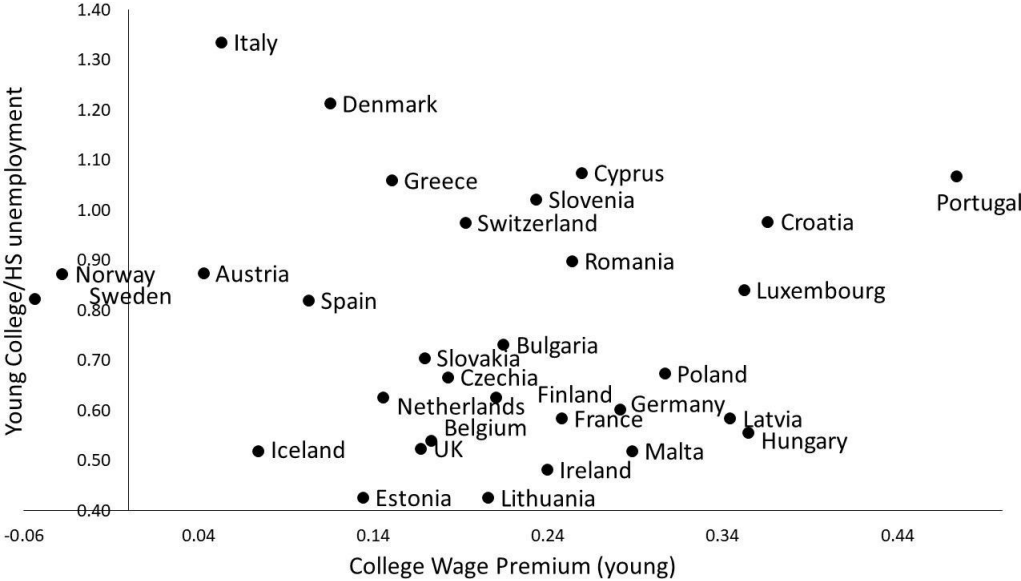


Figure 4: Relative Unemployment vs. Relative Wage

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 2004-2017 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 2004-2017.

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, and use the struc-

¹I am going to use the structure of the model to filter out the effect of frictions on observed wages to determine relative productivities of workers.

ture of the model to back out marginal product of labor from the data. 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. Friction parameters are estimated within the model after country specific macroeconomic and efficiency parameters are incorporated. Hence, friction parameters act as residuals that explain the part of the unemployment rate differences that productivities or observable country-specific factors cannot explain. 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 are estimated from the wage data at country level and labor market frictions are 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 rates². To disentangle the effects of two explanations, I 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 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, mismatch rates and job destruction 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.

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 the demand side of the labor market concerning education, mismatch, frictions, and productivity. We can draw several important conclusions from my analysis. In countries with

²Mismatch 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 C.

the “*young, educated, unemployed*” phenomenon³, 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-skilled relative to low-skilled vacancy creation is positively correlated with high skilled relative to low skilled efficiency as also found by Obiols-Homs & Sánchez-Marcos (2018) with education quality. The available vacancy data also favors 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. 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 equilibrium⁴ can exist; secondly, it affects unemployment rates of subgroups asymmetrically. I also contribute to the literature by developing a framework through which any type of unemployment differences can be analyzed⁵. Finally, in addition to labor market frictions, I draw attention to “education” in determining cross-country differences in labor market outcomes (Krueger & Kumar (2004)). In this paper, I not only address the “*young, educated, unemployed*” phenomenon but also highlight deeper issues affecting the labor market in these countries. The results suggest that improving education policy and fostering firms’ demand for skills may have important roles to play in ameliorating labor market outcomes of the “*young, educated, unemployed*”.

³Apart from unemployment rates, one should also consider the participation margin of different groups in such an analysis. In Appendix E, Figure 19, I plot cross-country relative employment rates. Although employment rates of highly educated people are generally higher than low educated people (except Italy), the gap in employment rates are small in favor of highly educated people in countries with “young, educated, unemployed” phenomenon, suggesting the same pattern with employment rates as well.

⁴Cross-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)).

⁵I replicate the same type of analysis with US states in online appendix

2 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 sector⁶, hence allowing them to perform on-the-job search because observed mismatch rates across countries also differ and will be targeted in calibration. Mismatch search intensity is endogenous in the model. Furthermore, stochastic aging has also been introduced to link young and old people in order to reflect the idea of life-cycle decision making. Finally, I allow types of workers to be imperfect substitutes to reflect the inter-dependency 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 (Arseneau & Epstein (2019); Garibaldi et al. (2019)), 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.

A job can be destroyed exogenously or through on-the-job search. Exogenous job destruction rate (δ) is country-specific and estimated from the data. In Figure 18 of Appendix C.4, I show how estimated job separation rates are correlated with “young, educated, unemployed” phenomenon. The data does not support the view that young

⁶This 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.

college graduates are more likely to be unemployed because they are fired more often.

The economy in this model consists of households, production firms, and the bargaining firms⁷. Production firms produce a unique final output by using different types of labor, but they cannot hire workers directly; they need intermediary bargaining firms⁸. 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.

2.1 Households

Households consist of four types of people: young educated, young uneducated, old educated, and old uneducated⁹. Fractions of young people (α), uneducated people within young (μ) and uneducated people within old ($\hat{\mu}$), are exogeneous. They are aging stochastically (de la Croix et al. (2013)): young people become old with probability σ and old people become retired with probability ω ¹⁰. Corresponding labor market tightness functions, job finding and job filling probabilities are given in Appendix B.4.

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 skilled and unskilled market, where her search intensity may be different for unskilled jobs ($\tilde{\lambda}_y$ ¹¹). She finds a skilled job with probability of $f(\theta_{2y})$ ¹² 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 exogeneously with probability δ , and she switches to being unemployed. If she is employed in an unskilled job, hence “mismatched”, she is performing on-the-job search with some λ_y

⁷Distinction between bargaining and production firms is similar to Christiano et al. (2016)

⁸This 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.

⁹Young refers to age 25-29, old refers to age 30-64 when matching the model to the data.

¹⁰Distribution of labor force can be seen in Appendix B2.

¹¹ $\tilde{\lambda}_y$ will be estimated in calibrating the model to target unemployment and mismatch rates observed in data.

¹² θ_{2y} is the tightness of the young skilled market; $f(\theta_{2y})$ is the job finding probability in the corresponding market, in which the function is derived from constant returns to scale matching function. More details can be found in Appendix B.4.

intensity and finds a job in a skilled market with probability $f(\theta_{2y})$. In this case, she switches from a “mismatched” state to an “employed in skilled sector” state. Finally, stochastic aging implies that she may become “old” with probability σ . The decision problem can be described by the following Bellman equations:

- Value of being unemployed:

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

- 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:

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

Young low educated: Young low educated refers to people between 25-29 years old and have a high school degree. A young low educated unemployed person receives an unemployment benefit of b_y . She can only look for jobs in unskilled market. She finds an unskilled job with a probability of $f(\theta_{1y})$ and accepts, thus switching from being unemployed to employed in an unskilled market. When a young low educated person is employed, the job can be destroyed exogeneously with probability δ , and she switches to being unemployed. Finally, stochastic aging implies that she may become “old” with probability σ . (See Appendix B.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 δ and she switches and becomes unemployed. If she is employed in an unskilled job, hence “mismatched”, she is performing on-the-job search with some λ_o intensity and finds a job in skilled market with probability $f(\theta_{2o})$. In this case, she switches from a “mismatched” state to an “employed in skilled sector” state. Finally, stochastic aging implies that she may become “retired” with probability ω and continue

to receive pension benefits, which is a function of her last wage¹³. (See Appendix B.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 δ and she switches to become unemployed. Finally, stochastic aging implies that she may become “retired” with probability ω and continue to receive pension benefits, which is a function of her last wage¹⁴. (See Appendix B.3 for corresponding Bellman equation)

2.2 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 determined¹⁵. 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 probabilities¹⁶. 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

¹³Details of retirement value can be found in Appendix B.4

¹⁴Details of retirement value can be found in Appendix B.4

¹⁵See Appendix B.4 for surplus sharing equations

¹⁶Details of job filling probabilities can be found in Appendix B4

vacancy state to job state. Hence, the value of a vacancy $V(i, j)^{17}$, 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:

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

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

where κ_{ny} is the probability of facing an uneducated young worker and κ_{no} is the probability of facing a low educated old worker. ($\kappa_{ny} = \frac{u(l, y)}{u(l, y) + \lambda_y u(h, y)}$, $\kappa_{no} = \frac{u(l, o)}{u(l, o) + \lambda_o u(h, o)}$) (See Appendix B.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 δ , and the firm switches from job state to vacancy state. Note that for a mismatched worker, the job destruction rate becomes $\delta + \lambda f(\theta_2)$. With δ probability, the job is destroyed exogenously; with $\lambda f(\theta_2)$ probability, the worker will find a job in the skilled sector and quit the job.

¹⁷Free-entry condition implies $V(i, j) = 0$ for all i, j .

- Value of skilled job filled by young:

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

- Value of unskilled job filled by young high educated:

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

- 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 B.3.

2.3 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:

$$Y = Z[\theta_h H^\rho + \theta_l \tilde{L}^\rho]^{1/\rho} \quad (1')$$

H is skilled (high educated) labor, \tilde{L} is effective low skilled labor (high or low educated), θ_h and θ_l are technological efficiency parameters, and $\rho = 1 - \frac{1}{\sigma_E}$ is a function of elasticity of substitution (σ_E) between education levels in the production function. Z is the aggregate productivity. 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.

$$\tilde{L} = \alpha_p M + L \quad (2')$$

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

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

$$H = [\psi_p H_y^\eta + H_o^\eta]^{1/\eta} \quad (3')$$

$$M = [\beta_p M_y^\eta + M_o^\eta]^{1/\eta} \quad (4')$$

$$L = [\gamma_p L_y^\eta + L_o^\eta]^{1/\eta} \quad (5')$$

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 B.4 for more details).

2.4 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 7 for parameter values for each case)

The question of interest in this paper is relative unemployment rates between the educated and uneducated for young and old separately. Throughout the analysis, I am going to focus on these two measures: (u_{hy}/u_{ly} for referring to the ratio of young college unemployment rate to young high school unemployment rate, and u_{ho}/u_{lo} for the old group). First, consider a baseline economy that is completely segregated (no possibility of mismatch) where everything is symmetric between groups (i.e. they are perfect substitutes to each other and there is no stochastic aging, there are equal number of people in each category, they all have the same productivity, vacancy posting costs for different jobs are the same). In this scenario, unemployment rates across groups should be the same. Now, I examine the effect of increasing relative technological efficiency (θ_h/θ_l) on unemployment rates. Relative technological efficiency represents the productivity gap between high skilled and low skilled labor and is the focus of this paper. Hence, I show the implications of (θ_h/θ_l) on unemployment rates in different scenarios. 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.

As a second step, I introduce imperfect substitution between age and education groups as well as stochastic aging. Imperfect substitution makes types of workers interdepen-

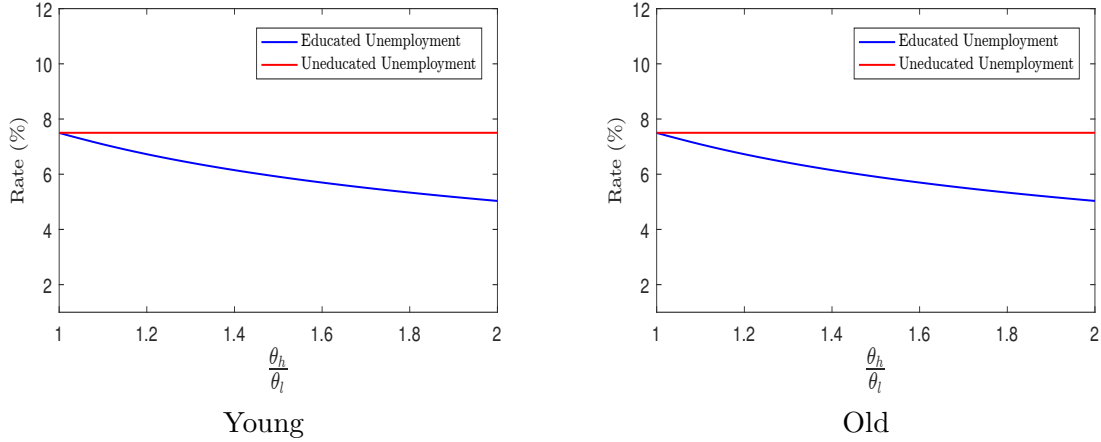


Figure 5: Relative Technological Efficiency vs. Unemployment Rates: Symmetric Case

dent 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-factors into the model: i.e., fraction of young in the labor force (fewer than old) and fraction of educated (fewer than uneducated) among young and old to see the composition effects at unemployment levels and the effects of increasing the relative technological efficiency (θ_h/θ_l) on unemployment rates together with composition effects. There are fewer young people (age 25-29) in the work force than older people. Hence, introducing the characteristics of population structure instead of having equal numbers of young and old produces a relative supply effect, decreases the unemployment rate of young, and increases unemployment rate of old. Moreover, there are more uneducated workers than educated workers in the work force. Hence, decreasing the education ratio again produces a relative supply effect and de-

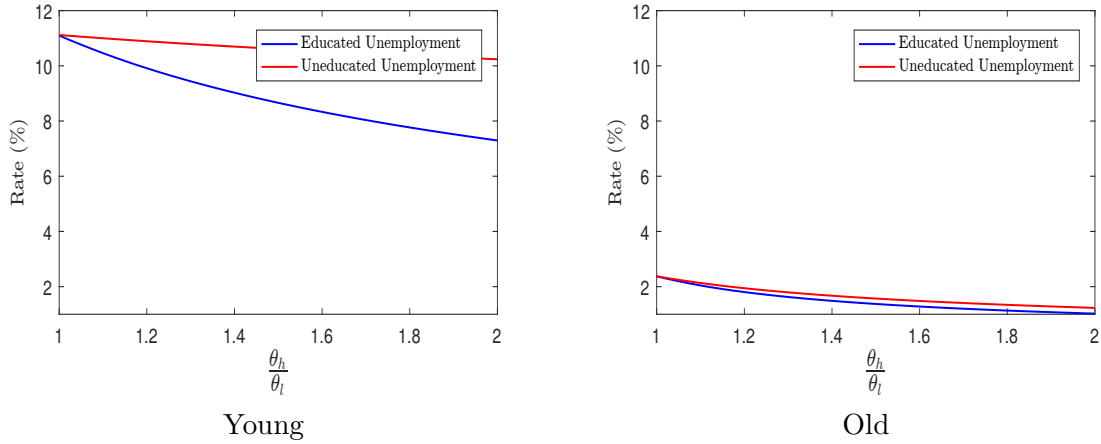


Figure 6: Relative Technological Efficiency vs. Unemployment Rates: Imperfect Substitution, Stochastic Aging

increases 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).

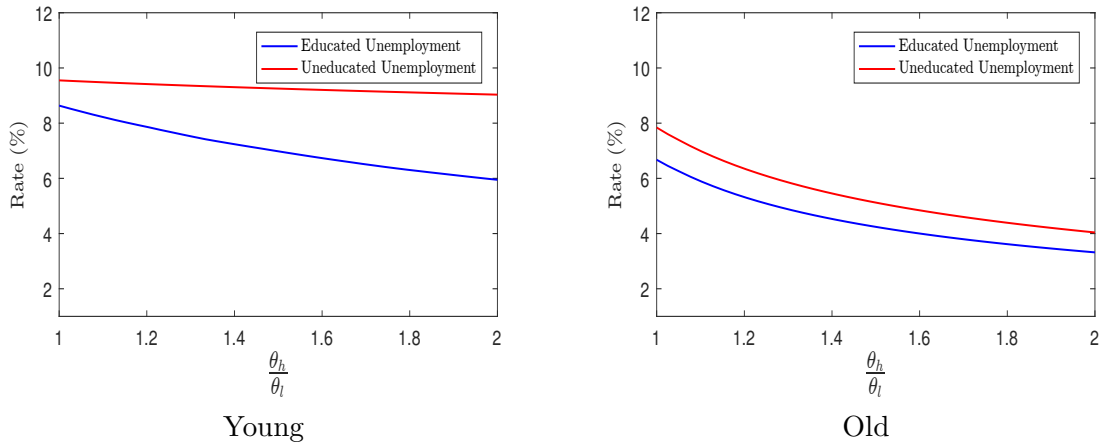


Figure 7: Relative Technological Efficiency vs. Unemployment Rates: Relative Supply

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.

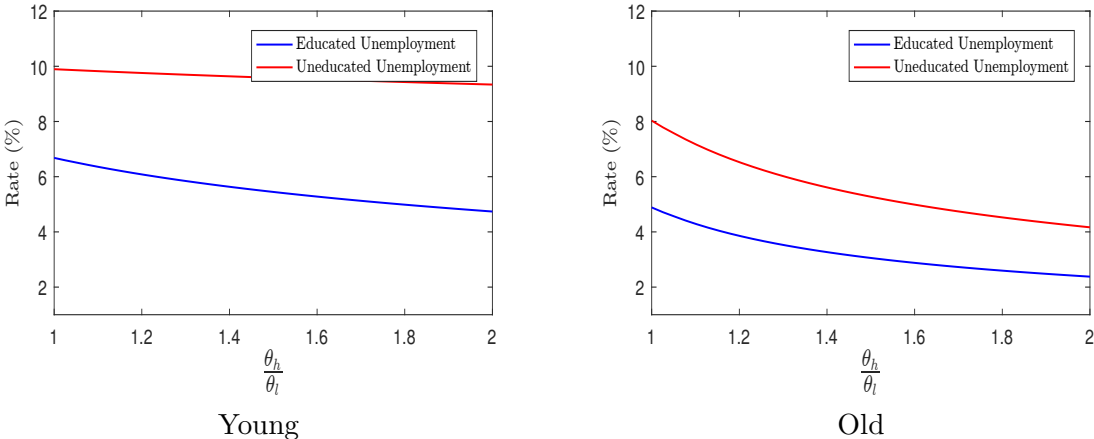


Figure 8: Relative Technological Efficiency vs. Unemployment Rates: Mismatch Channel

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.

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 costs, as well as mismatch intensity, determines the

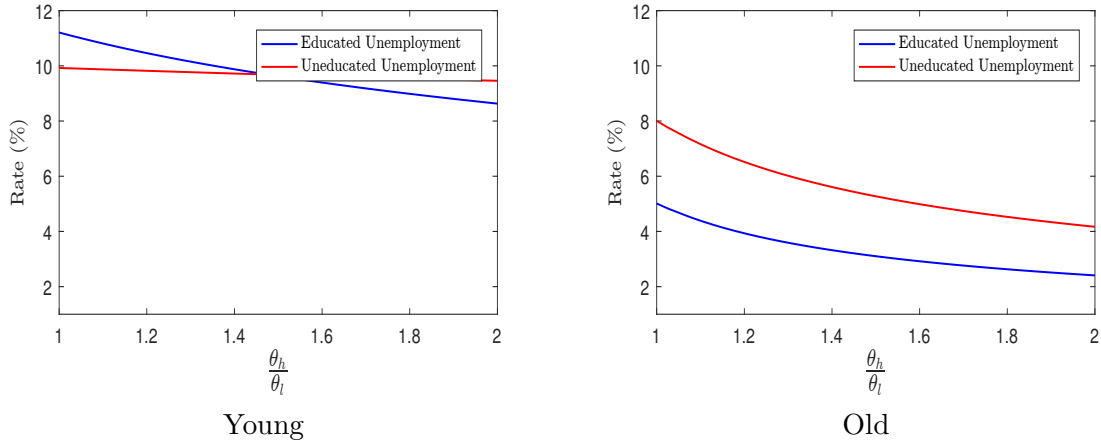


Figure 9: Relative Technological Efficiency vs. Unemployment Rates: Vacancy Cost

level of unemployment. High vacancy costs amplify the “productivity channel”; i.e. to observe “young, educated, unemployed” phenomenon, both the “frictions hypothesis” (high vacancy costs) and the “productivity hypothesis” (low relative productivity) are necessary. In the next sections, I am going to quantify the effect of “frictions” vs. “productivity”.

3 Data

The purpose of my analysis is to quantify the effect “frictions” vs. “productivity” in determining the “young, educated, unemployed” phenomenon. I perform my calibration for every individual country separately by targeting their long term unemployment rate averages. Since wage data is available for years 2004-2017, all the parameters estimated directly from the data will be the averages of the same time period.

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, job destruction rate 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.

3.1 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, relative efficiencies and job destruction rates. 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 (see table 11). Secondly, I assign every individual as young (25-29) or old (30-64)¹⁸ 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 hourly wage (by using annual income and hours worked), 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 14 years and 31 countries,¹⁹ with average hourly wage and employment level of six types of labor to be used in estimation of relative

¹⁸Since the unemployment rates that I am matching is for these age groups specifically, all the analysis is done based on these age groups.

¹⁹A list of countries and coverage years can be found in Appendix C

efficiencies. I restrict myself to full time workers only; i.e. people who report more than 20 hours of weekly work and who worked at least 6 months during the income reference period and whose hourly wages are calculated between 1-100 Euros. Throughout the analysis, I use gross income. However, in EU-SILC gross income is not defined for five countries (ES, GR, IT, LV, PT) in the beginning of the sample period 2004-2006. I use net income instead for those missing years in order to not to decrease the sample years even further by excluding 3 pre-crisis years. However, my analysis is robust to reasonable changes in data selection in terms of coverage, full-time work and mismatch definition. As I show in Table 10, not all the countries are present throughout the full sample period. In order to be consistent in my analysis, when information from other sources is used such as Eurostat, EU-LFS, I calculate the average of the years for which each country exists in EU-SILC, unless otherwise specified.

3.2 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.)²⁰. Moreover, I analyze composition of majors as well as major specific unemployment rates. Furthermore, I estimate on-the-job search intensity of workers who have been mismatched²¹. 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 document differences in the types of first job contracts, the method by which first job is found, to analyze cross-country differences.

4 Model Parameterization and Estimation

I fit the model for each country separately by targeting their long term averages of unemployment, mismatch and wage ratios. The procedure contains several steps. First, I fit externally calibrated parameters. Then, using the structure of the model and observed

²⁰I 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.

²¹Estimation details are given in Appendix C4

wages in the data, I estimate relative efficiencies (more details are below) governing the “productivity hypothesis”. Finally, I estimate friction parameters (governing the “frictions hypothesis”) to fit the unemployment rates. At the end, the model matches unemployment rates, mismatch rates as well as wage ratios observed in the data.

4.1 Parameters

There are four sets of parameters used in the model²². Out of 4 sets of parameters, countries differ in 3 sets of parameters, For each country, I take the standard parameters the same. Remaining parameters can be grouped as “country-specific observable characteristics” (such as job destruction rate) which are used as model inputs, “productivity parameters” which are estimated from wages and the structure of the model and finally “friction parameters” which are estimated to fit the observed unemployment and mismatch rates in each country.

1. Standard search-matching parameters such as bargaining power, discount rate, and elasticity of substitution are taken from the literature (see Table 4).
2. Country-specific observable characteristics such as fraction of young, fraction of college graduates, pension replacement rate, job destruction rate²³ and on-the-job search intensity are parameterized using Eurostat, OECD and EU-LFS (Table 3 in online appendix). The macro-facts to be used as targets, such as age-education specific unemployment rates, are taken from Eurostat (Table 6 in online appendix). Mismatch rate is calculated at country level by using EU-SILC confidential micro-data (Table 6 in online appendix)²⁴. In Figure 18, I show how job separation rates across countries are correlated with relative unemployment rates.
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 (Table 5 in online appendix).

²²Parameter lists and targets are given in Appendix B1 and online appendix.

²³See Appendix C.4 for the estimation procedure and the discussion about how relative unemployment rates are correlated with job separation rates in the data.

²⁴More details about estimation procedure exists in Appendix C.

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 (Table 4 in online appendix).

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.

4.2 Estimation of Relative Efficiencies

I am interested in relative efficiencies between types of workers in order to address the “productivity hypothesis”. However, marginal product of labor is not observable. I propose a way of estimating marginal product of labor by using the wage data and the structure of the model.²⁵

In the model, as production firms are competitive, relative marginal product of labor (young to old) of each type can be written as²⁶:

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

In the data, I observe relative supply (young to old) of each type of workers as well as their relative wages. As a first step, I take observed wages as proxy for marginal product of labor and run the following average estimation for each country separately by using annual variation by taking η fixed²⁷:

²⁵In the long run, relative wages influence relative supply of workers through choice of education. But, as Abraham (2008) shows this happens in the long run.

²⁶All remaining equations for low skilled and mismatched workers are provided in Appendix D

²⁷ η is taken as 0.8 which is in the range of estimates of Card & Lemieux (2001)

$$\log(\hat{\psi}_p)_i = \sum_{t=1}^n \left(\log\left(\frac{\text{wage}(H_y)}{\text{wage}(H_o)}\right)_{it} - (\eta - 1)\log\left(\frac{H_y}{H_o}\right)_{it} \right) / n$$

where i stands for country and t stands for time. The first step of estimation for each type allows me to estimate ψ_p , β_p and γ_p . Using equations 3', 4' and 5', I calculate H, L and M . By the same procedure, relative marginal product of labor between mismatched and low skilled workers can be written as:

$$\frac{MPL(M_y)}{MPL(L_y)} = \frac{\frac{\partial Y}{\partial M_y}}{\frac{\partial Y}{\partial L_y}} = \frac{\alpha_p \beta_p}{\gamma_p} \left(\frac{M}{L}\right)^{1-\eta} \left(\frac{M_y}{L_y}\right)^{\eta-1} \implies$$

$$\log(\alpha_p) = \log\left(\frac{MPL(M_y)}{MPL(L_y)}\right) - (\eta - 1)\log\left(\frac{M_y}{L_y}\right) - (1 - \eta)\log\left(\frac{M}{L}\right) - \log\left(\frac{\hat{\beta}_p}{\hat{\gamma}_p}\right)$$

As all the left hand side variables are either observed or estimated in the first step, I run the following average estimation:

$$\log(\hat{\alpha}_p)_i = \sum_{t=1}^n \left(\log\left(\frac{\text{wage}(M_y)}{\text{wage}(L_y)}\right)_{it} - (\eta - 1)\log\left(\frac{M_y}{L_y}\right)_{it} - (1 - \eta)\log\left(\frac{M}{L}\right)_{it} - \log\left(\frac{\hat{\beta}_p}{\hat{\gamma}_p}\right)_i \right) / n$$

The second step allows me to estimate α_p which then help me to calculate \tilde{L} by using equation 2'. Finally, relative marginal product of labor between high skilled and mismatched workers allows me to write the following equation:

$$\frac{MPL(H_y)}{MPL(M_y)} = \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial M_y}} = \frac{\theta_h}{\theta_l} \frac{\psi_p}{\alpha_p \beta_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{M}\right)^{1-\eta} \left(\frac{H_y}{M_y}\right)^{\eta-1} \implies$$

$$\log\left(\frac{MPL(H_y)}{MPL(M_y)}\right) - (\eta - 1)\log\left(\frac{H_y}{M_y}\right) - (1 - \eta)\log\left(\frac{H}{M}\right) - (\rho - 1)\log\left(\frac{H}{\tilde{L}}\right)$$

$$- \log\left(\frac{\hat{\psi}_p}{\hat{\alpha}_p \hat{\beta}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)$$

I run the following average estimation which allows me to estimate θ_h/θ_l and finally calculate Y by using equation 1' and by taking elasticity of substitution between education

levels (ρ) as fixed²⁸ :

$$\log\left(\frac{\hat{\theta}_h}{\hat{\theta}_l}\right)_i = \frac{1}{n} \sum_{t=1}^n \left(\log\left(\frac{wage(H_y)}{wage(M_y)}\right)_{it} - (\eta - 1)\log\left(\frac{H_y}{M_y}\right)_{it} - (1 - \eta)\log\left(\frac{H}{M}\right)_{it} - (\rho - 1)\log\left(\frac{H}{\bar{L}}\right)_{it} - \log\left(\frac{\hat{\psi}_p}{\hat{\alpha}_p \hat{\beta}_p}\right)_i \right)$$

At the end of this 3-step estimation procedure, country-specific relative efficiencies are estimated which will be used as model inputs in further calibration steps.

In the next step, using the structure of the model, I find a relationship between wages and MPL . For each country, I insert all fixed and externally estimated parameters (standard parameters and country specific parameters) as well as relative efficiencies above. I estimate friction parameters (vacancy posting costs, mismatch search intensities) by targeting four unemployment rates (young educated, old educated, young uneducated, old uneducated) and two mismatch rates (young and old). I simulate the model using the productivity shock Z . For each value of Z , I observe wages produced by the bargaining process and MPLs that the model generates. Then, I ran the following regression using the simulated data,

$$\log(w_i) = b_{0,i} + b_{1,i}\log(MPL_i)$$

where i refers to the type of the worker. I regress wages on MPLs for each country, to estimate the coefficients of the above relationship²⁹. By using estimated coefficients, I calculate MPL from the observed wage in the data using the relationship below (separately for each type).

$$MPL = \exp\left(\frac{\log(w) - b_0}{b_1}\right)$$

Finally, I redo all the steps from the beginning (estimating relative efficiencies) using estimates for MPLs that I obtained in the final step. After second iteration, estimation results do not change, hence I perform the “update” only once through which I eliminate the effect of frictions on wages.

²⁸ ρ is taken as 0.75, which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy (1992)

²⁹I report the coefficients of the estimation in Online Appendix.

One example to show how this method works could be that we do observe that mismatch workers are receiving much lower wages than their productivities. If we just predict productivity differences between types by ignoring this fact, we would have misleading measures, because the existence of mismatch workers depresses wages of college graduates 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 as quantitatively estimated by Arseneau & Epstein (2019) and Garibaldi et al. (2019).

5 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 provide 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. 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.

A compelling 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.

5.1 Results on “Productivity” and “Frictions”:

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

I argue that relative productivity of skilled versus unskilled labor is an important factor in driving the outcome about relative unemployment rates. However, as I noted before, Figure 4 is not a good predictor of relative productivity 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 use a structural estimation method, which takes into account the mismatched workers; therefore, estimate relative productivity between skilled and unskilled workers. Figure 10 shows the correlation between relative technological efficiency (θ_h/θ_l) and relative unemployment rate. 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.

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 11 shows ψ_p in which relative efficiency of young with respect to old within high skilled workers negatively correlates with relative unemployment rates. In the countries where young educated people have higher unemployment rates than uneducated people, they also have much lower productivity than their older counterparts in the skilled market. In other words, young high skilled workers enter the labor force with much lower productivity than old worker and have higher returns to skill later on. This observation together with the above observation on relative technological efficiency puts more pressure on young and educated people. They are not particularly different than unskilled workers and they are too different

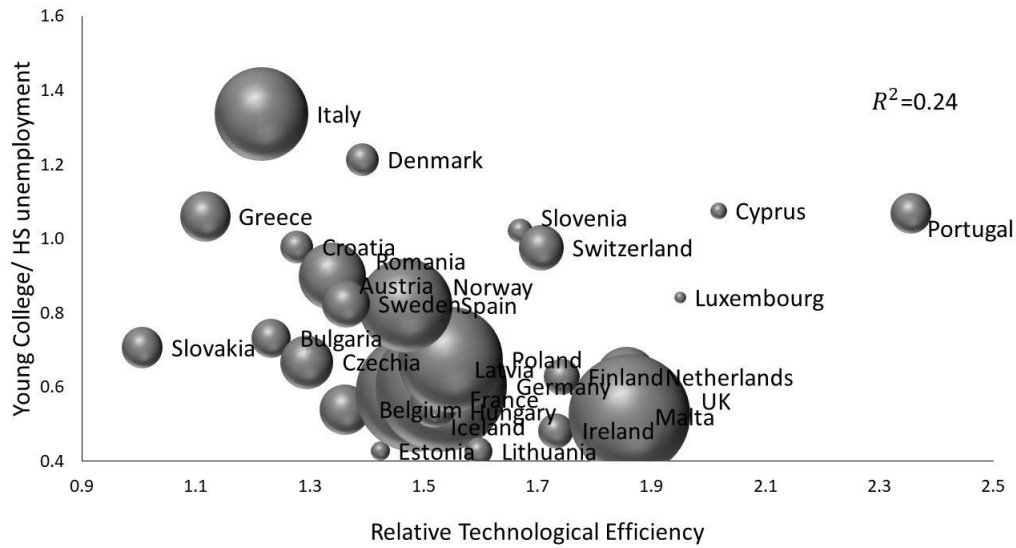


Figure 10: Relative Technological Efficiency vs. Relative Unemployment Rate
 Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2017 and the structural estimation method described in the paper. The size of bubbles represent countries' labor force sizes of 25-29 age group and regression is weighted accordingly.

than older skilled workers, hence they are not very attractive to firms either from the skill side or age side.

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

In an economy where educated people cannot work in unskilled jobs, the two labor markets become completely separate. However, educated people can also work in unskilled jobs which crowd-out people with lower education. Hence, in the presence of mismatch, it becomes even more interesting to observe “young, educated, unemployed” phenomenon. Figure 12 shows that there is a negative correlation between mismatch rate and relative unemployment rate across countries. More specifically, in countries like Italy, Portugal, and Greece where young college educated people are more unemployed, their propensity to work in unskilled jobs, hence being over-qualified, is also low, which explains part of the story. My model predicts that high mismatch intensity lessens the phenomenon by decreasing educated unemployment and increasing uneducated unemployment. The empirical evidence on mismatch rates is also promising in that explanation.

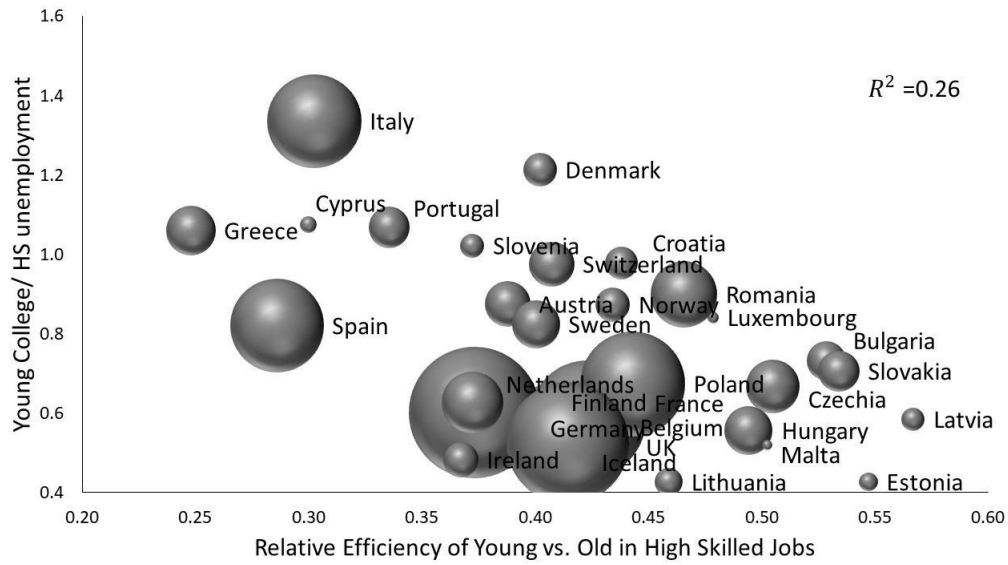


Figure 11: Relative Efficiency of Young vs. Old in High Skilled Jobs
 Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on wages from 2004 to 2017 and the structural estimation method described in the paper. The size of bubbles represent countries' labor force sizes of 25-29 age group and regression is weighted accordingly.

Vacancy posting costs are higher in countries with higher young educated unemployment:

Figure 13 shows the positive correlation between vacancy posting costs (high skilled jobs available for young) and relative unemployment rate. In order to provide a cross-country comparable measure of vacancy cost (c_{2y}), I scale estimated (c_{2y}) with young high skilled wage rate, job finding probability and (θ_l). Hence, reported vacancy costs reflect how much of the return on young high skilled jobs are allocated for corresponding vacancies. As I discuss in the model properties section, countries with “young, educated, unemployed” phenomenon have particularly higher vacancy posting costs.

5.2 Mechanism

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

Figure 14 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

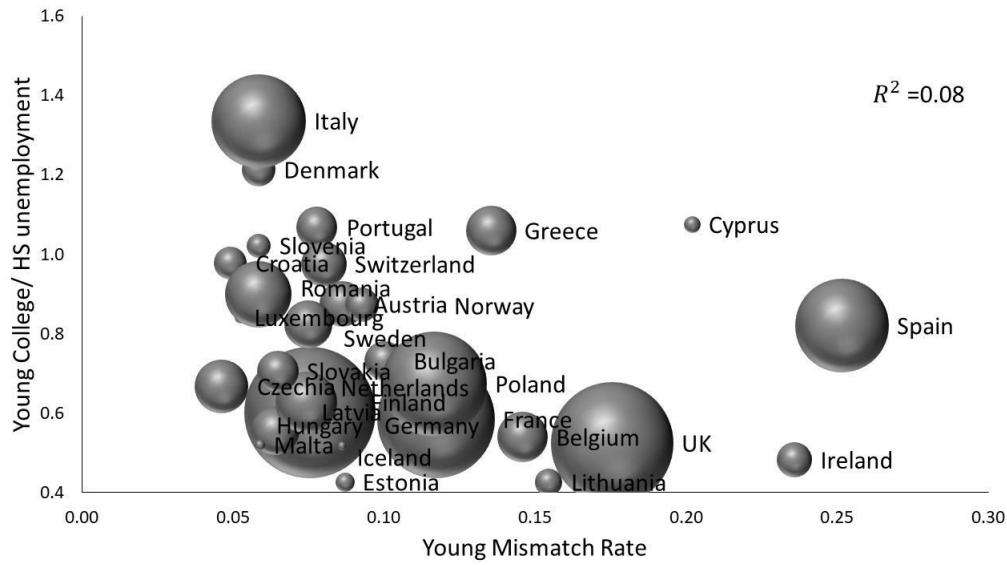


Figure 12: Young Mismatch Rate vs. Relative Unemployment Rate

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 2017. The size of bubbles represent countries' labor force sizes of 25-29 age group and regression is weighted accordingly. More detail on occupations and calculation exists in Appendix E.2.

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 (θ_h/θ_l) is low.

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

Figure 14 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 15 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.

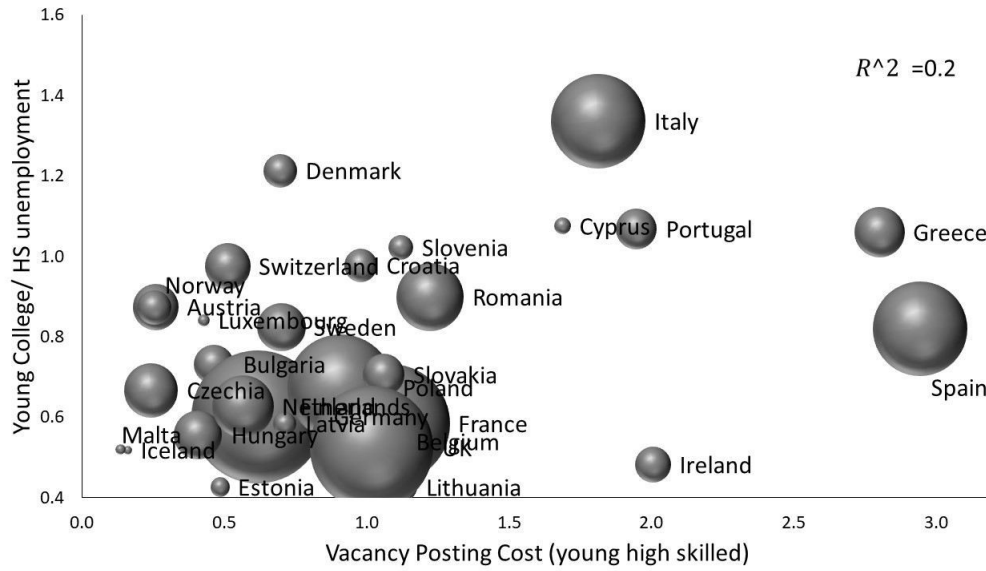


Figure 13: Vacancy Posting Cost vs. Relative Unemployment Rate

Note: Author's own estimates of relative technological efficiency using EU-SILC micro-data on education and occupation status of people. Reported vacancy posting costs are $c_{2y}/w_{shyp}(\theta_{2y})\theta_l$ and details are given in online appendix. The size of bubbles represent countries' labor force sizes of 25-29 age group and regression is weighted accordingly.

In Figure 16, 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.

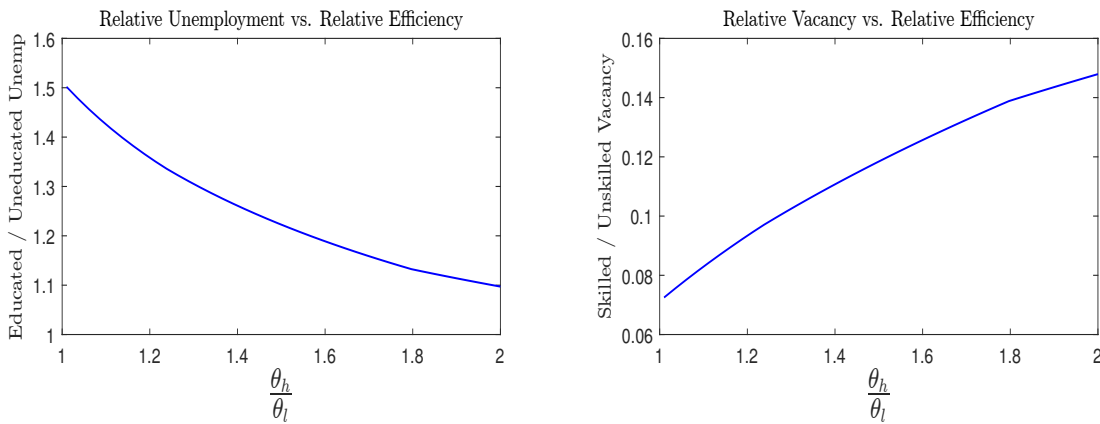


Figure 14: Relative Unemployment, Vacancy, Efficiency

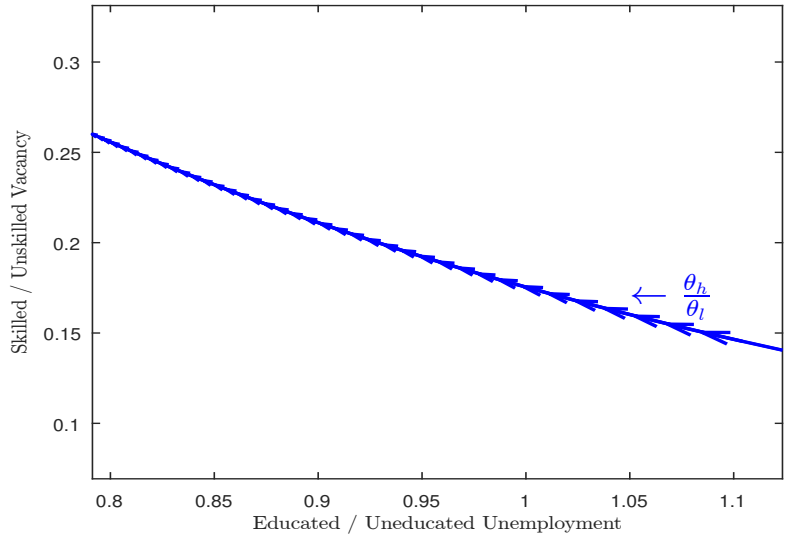


Figure 15: Relative Unemployment vs. Relative Vacancy

5.3 Counterfactual Analysis

To disentangle the effects of productivity versus frictions and to show the results in a more precise way, I conduct a counterfactual analysis with two-country comparison. I select two countries similar in many dimensions but differ in terms of relative productivity. I do this twice for two countries with one high one low friction and two countries with high frictions to see how friction level affects the response. 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 Spain, which both have high frictions but differ in terms of relative unemployment rate and Italy vs. the UK which lie at the opposite sides of the distribution in terms of both frictions and relative unemployment rate. First, I calibrate the model to match the four unemployment rates and two mismatch rates for each country separately. The differences in this calibration are: country-specific parameters (fraction of young, fraction of educated, pension replacement rate, job destruction rate, on-the-job search intensity given in Table 3 of online appendix); estimated relative efficiencies (Table 5 of online appendix); estimated friction parameters inside of the model to match the rates (vacancy posting costs, mismatch intensity given in Table 4 of online appendix). I then ask the question, “What would happen if Italy had the same country-specific parameters as Spain, the same frictions as Spain, and the same relative efficiencies as Spain?”

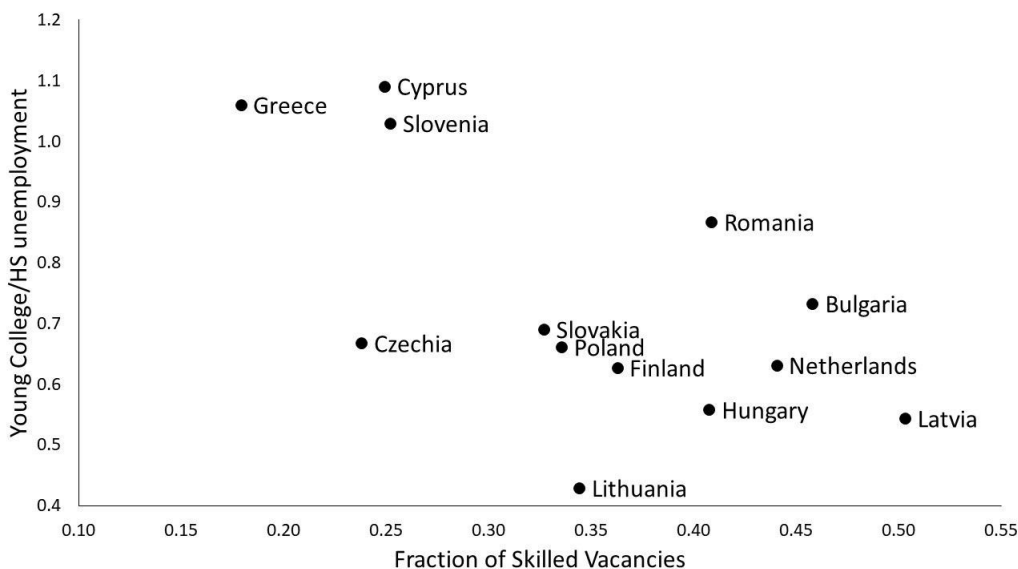


Figure 16: Relative Vacancy vs. Relative Unemployment

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 2004 to 2017.

step by step. When I eventually introduce every set of parameters, I reach to Spain's value. Then, I calculate how much of the distance from the Italy to Spain has been reduced with country-specific parameters, frictions, and relative productivity. I repeat this exercise for other pairs of countries, too.

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 different³⁰. Table 1 shows that when I introduce Spain's country-specific parameters to Italy, the relative unemployment moves in the opposite direction from the target. The most important input in this counterfactual is the demographics of Spain. In other words, if Italy had as much college graduates as Spain had, relative unemployment rate would have been even worse. When I further introduce Spain's productivity parameters, I could proceed

³⁰Note that Spain also used to have higher young college unemployment than young high school unemployment until 2005, but that relationship has been reversed afterwards which is the period for which I am performing my estimation and targeting.

100% of the distance between relative unemployment rates for young. Finally, when I introduce frictions of Spain, most importantly lower mismatch rates in Spain to Italy then relative unemployment could have been further reduced. This exercise shows that the effect of productivity is big 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 show previously in mechanism section.

Country-specific parameters	Italy	Spain	Spain	Spain
Relative Productivity	Italy	Italy	Spain	Spain
Labor Market Frictions	Italy	Italy	Italy	Spain
u_{hy}/u_{ly}	1.34	1.8	1.28	0.82
Relative Effect		-88%	100%	88%

Table 1: Italy vs. Spain

Note: Relative Effect is calculated by taking the distance between Italy’s and Spain’s relative unemployment rates as the baseline and calculating how much of that distance is closed by changing one parameter set at a time. Parameter values are summarized in Online Appendix Table 3,4,5 for each channel.

Italy vs. the UK

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; fraction of college graduates in Italy is low whereas it is high in the UK. Table 2 shows that the effect of macro-factors which mainly speak to supply of college graduates, works the other way around as in Spain. 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 34% of the distance in unemployment rate differentials for young. However, majority of the distance is captured by differences in labor market frictions.

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.

Country-specific parameters	Italy	UK	UK	UK
Relative Productivity	Italy	Italy	UK	UK
Labor Market Frictions	Italy	Italy	Italy	UK
u_{hy}/u_{ly}	1.34	1.64	1.36	0.52
Relative Effect		-37%	34%	102%

Table 2: Italy vs. UK

Note: Relative Effect is calculated by taking the distance between Italy's and Spain's relative unemployment rates as the baseline and calculating how much of that distance is closed by changing one parameter set at a time. Parameter values are summarized in Online Appendix Table 3,4,5 for each channel.

Italy, Spain, Denmark and the UK

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 17 first shows how the prevalence of mismatch in Spain and in the UK lowers the relative unemployment rate for all levels of relative productivity in favor of educated workers. In other words, Spain has higher frictions in terms of vacancy costs, which pushes the curve up but low frictions due to the prevalence of mismatch that pushes the curve down. The UK, on the other hand, has both lower frictions on each side; that’s why it lies on the bottom of the figure. Since they also have higher relative technological efficiency, they are located on the right side of the figure with even lower relative unemployment rates. Italy has frictions both due to high vacancy costs and low prevalence of mismatch; that’s why Italy’s curve is located at the top of the figure. Denmark, on the other hand, has moderate levels of frictions due to low levels of mismatch. They are both located on the left side of the figure because they have low levels of relative technological efficiency.

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

lower unemployment rates, but there is also switch by previously mismatched workers to the skilled market, which depresses the decreases in educated unemployment decline because the job seeker pool becomes larger.

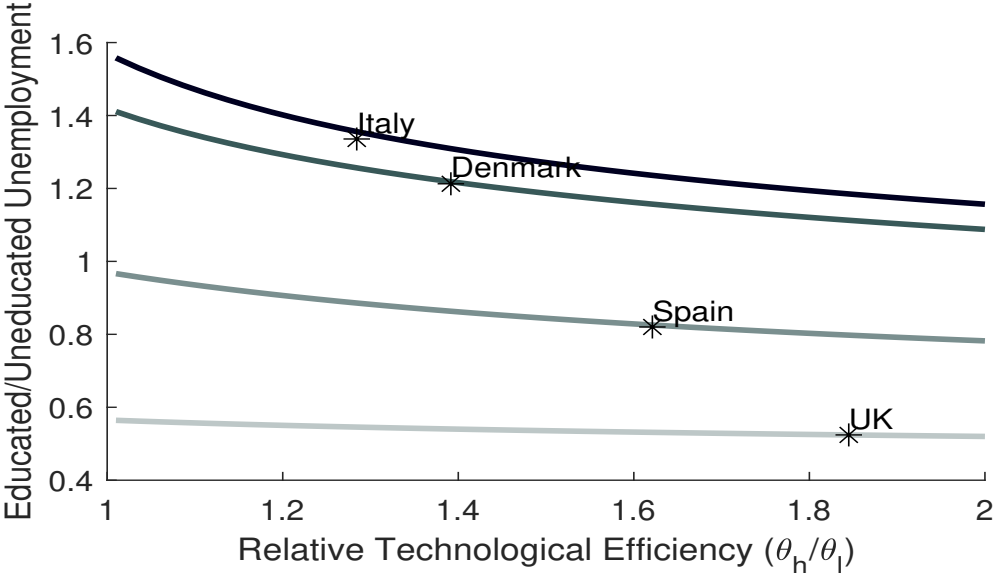


Figure 17: Location on the relative productivity vs. relative unemployment scale

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 3 shows Italy’s estimated wage gap and skilled vacancy posting cost for young and the third column is for the UK. 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 with UK’s relative productivity, 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 needs to be much larger than 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.

	Italy	Italy with UK’s relative productivity	UK
Wage Gap (w_{shy}/w_{nly})	1.2	1.93	1.5
Vacancy Cost (\tilde{c}_{2y}/θ_l)	1.96	2.9	1

Table 3: Shutting down the Productivity Channel
Note: \tilde{c}_{2y} reflects scaled vacancy cost as discussed in Figure 13.

6 Discussion of Alternative Hypotheses

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

College duration differs 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 20 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. I show through the model that outside option differences cannot generate observed unemployment differentials due to mismatch opportunities. 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 21). 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 differs across countries

Another argument for higher college unemployment might be about what has been taught in the universities. 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. 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 24 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.

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.

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. 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. Figure 22 shows that in Southern European countries, the majority of people find their first jobs through friends. 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.

Young educated workers in Southern and some Eastern European countries have difficulty in finding a job in the beginning of their career. Figure 23 shows 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. This gives 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.

7 Conclusion

In this paper, I analyze 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 develop a framework by which I am 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. Moreover, I show 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.

I contribute to the literature in many different ways. First, I analyze a novel observation and explain the reasons by keeping the conventional wisdom about labor market frictions and providing a new complementary explanation: the “productivity hypothesis”. Secondly, I develop a framework through which any type of unemployment differences can be micro-founded. Finally, I show 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 countries³¹.

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³¹As a robustness check, I apply my methodology to the US to understand differences in unemployment rates of high school graduates across US states. I discuss my predictions in the online appendix.

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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)). Guner et al. (2018) find that differences in managerial quality explains significant part of productivity difference between Italy and the US. On the other hand, Italian graduates cannot find jobs matching to their skills due to high prevalence of SMEs operating with low technology. Hence, it affects the overall productivity of Italian firms as the highly educated workers cannot fully exploit their productivity in firms which do not require high skills. All these help to explain why demand for university graduates is weak. Some research suggests that entrepreneurs who do not themselves hold a tertiary degree have a lower propensity to hire tertiary graduates (Schivardi & Torrini (2010)). Better earnings and employment prospects for Italian graduates working abroad provide further support to the hypothesis that that demand for their skill in Italy may be structurally weak.
- **Industrial Composition:** Majority of industry is composed by traditional sectors specialized in consumer based products. This is also correlated with the firm size discussed above such that evidence suggests that product diversification is strongly correlated to firm size. In 2013, 65.4% of Italian firms were specialized in the production of one single good, 15.4% in that of two and only 7.6% in three different products (Toniolo (2013)). The number of firms showing a much diversified production pattern (e.g. producing 10 or more different goods) was only 0.8%. The relationship between product diversification and employment is such that firms that follow traditional productive patterns have low intensity to hire new workers. Around 30% of firms developing new products or services intend to recruit new workers, whereas the share of firms recruiting new workers decreases substantially (14.4%) among those firms that stick to their traditional productive patterns (OECD (2017)). Hence, industrial composition of Italy puts another

downward pressure on job creation. Moreover, it affects employment opportunities of skilled workers even more as they either cannot find jobs or cannot exploit their full productivity in such a business environment.

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)). 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. 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 Model Details

B.1 Parameters

Parameter	Definition	Estimation	Source
α	Young ratio in the population	Country-specific	Eurostat
μ	Uneducated ratio among young	Country-specific	Eurostat
$\hat{\mu}$	Uneducated ratio among old	Country-specific	Eurostat
β	Workers' share in Nash Bargaining	0.7	Shimer (2007)
r	Discount rate	0.01	Shimer (2007)
δ	Exogenous job destruction rate	Country-specific	EU-SILC
ν	Pension replacement rate	Country-specific	OECD
b_y	Unemployment benefit of young	0.1	Albrecht & Vroman (2002)
b_o	Unemployment benefit of old	0.1	Albrecht & Vroman (2002)
σ	Probability of becoming old	0.1	Author's calculation
ω	Probability of becoming retired	0.028	Author's calculation
λ_y	On-the-job search intensity of young	Country-specific	EU-LFS
λ_o	On-the-job search intensity of old	Country-specific	EU-LFS
$\tilde{\lambda}_y$	Mismatch search intensity of young	Unobserved frictions	Model
$\tilde{\lambda}_o$	Mismatch search intensity of old	Unobserved frictions	Model
c_{1y}	Vacancy cost in young unskilled market	Unobserved frictions	Model
c_{1o}	Vacancy cost in old unskilled market	Unobserved frictions	Model
c_{2y}	Vacancy cost in young skilled market	Unobserved frictions	Model
c_{2o}	Vacancy cost in old skilled market	Unobserved frictions	Model
θ_l	Efficiency of low skilled sector	Unobserved frictions	Model
η	Elasticity of substitution between age groups	0.75	Card & Lemieux (2001)
ρ	Elasticity of substitution between skill groups	0.8	Card & Lemieux (2001)
α_p	Relative efficiency of mismatched wrt low educated	Relative Efficiency	EU-SILC+Model
ψ_p	Rel eff of young high educated wrt old high educated	Relative Efficiency	EU-SILC+Model
γ_p	Rel eff of young low educated wrt old low educated	Relative Efficiency	EU-SILC+Model
β_p	Rel eff of young mismatched wrt old mismatched	Relative Efficiency	EU-SILC+Model
θ_h/θ_l	Rel technological efficiency in the production	Relative Efficiency	EU-SILC+Model

Table 4: 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 5: 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 6: Variable Definitions

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

Table 7: Model Properties (Parameter Values)

Unemployment and Mismatch Rates:

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

B.2 Distribution of Labor Force

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

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

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

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

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

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

B.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):

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

- Value of being unemployed (young low educated):

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

- 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):

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

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

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

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

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

- Value of being unemployed (old low educated):

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

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

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

- 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 κ_{ny} is the probability to face an uneducated young worker and κ_{no} is the probability to face an low educated old worker. ($\kappa_{ny} = \frac{u(l, y)}{u(l, y) + \bar{\lambda}_y u(h, y)}$, $\kappa_{no} = \frac{u(l, o)}{u(l, o) + \bar{\lambda}_o u(h, o)}$)

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 δ , and firm switches from job to vacancy state. Note that for mismatched worker, job destruction rate becomes $\delta + \lambda f(\theta_2)$. With δ 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:

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

- 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:

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

B.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 θ is labor market tightness. $v(i, j)$ stands for number of vacancies where $i \in \{n, s\}$ for low skilled, skilled jobs and mismatch jobs and $j \in \{y, o\}$ for young and old. $u(i, j)$ stands for number of unemployed people where $i \in \{l, h\}$ for low educated and high educated and $j \in \{y, o\}$ for young and old. Finally, M_y and M_o stands for educated workers working in low skilled market. Note that since educated workers search in mismatched market less intensely, the actual number of job seekers in mismatched market becomes $\tilde{\lambda}_y u(h, y)$ for young where $\tilde{\lambda}_y$ is search intensity in low skilled market. Also, the actual number of job seekers in skilled market is $u(h, y) + \lambda_y M_y$ where both unemployed educated people are seeking for a job and mismatched workers are performing on-the-job search with intensity λ . There are 4 labor market tightness parameters determined endogenously. θ_{1y} is for young low skilled market, θ_{1o} is for old low skilled market, θ_{2y} is for young skilled market, θ_{2o} is for old skilled market:

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

Value of being retired is fixed and depends on worker's last job where people receive ν fraction³² of their last income (except the case of switching from being unemployed to employed where they receive the same benefit) where:

³²Country 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:**

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

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

• **Unskilled Market:**

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

$$\underbrace{f(\theta_{1o})u(l, o)}_{\text{inflow to emp by low educated old}} + \underbrace{\sigma[(\alpha\mu - u(l, y))]}_{\text{outflow from employment}} = \underbrace{(\delta + \omega)((1 - \alpha)\hat{\mu} - u(l, o))}_{\text{outflow from employment}} \quad (30)$$

due to job finding due to switch to old state

• **Mismatch Market:**

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

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

due to job finding due to switch to old state

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.

C Data

C.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	5.5%	4.8%	4.0%	2.6%
Belgium	10.9%	5.9%	5.8%	3.3%
Bulgaria	10.2%	7.4%	7.1%	3.4%
Croatia	20.4%	19.9%	11.7%	6.1%
Cyprus	11.5%	12.4%	8.0%	4.9%
Czechia	6.4%	4.3%	4.9%	1.7%
Denmark	6.5%	7.9%	4.3%	3.6%
Estonia	9.8%	4.2%	8.7%	5.0%
Finland	9.8%	6.1%	7.0%	4.3%
France	12.8%	7.5%	6.6%	4.5%
Germany	7.0%	4.2%	6.7%	3.1%
Greece	25.1%	26.6%	15.4%	9.1%
Hungary	9.5%	5.3%	6.5%	2.3%
Iceland	5.5%	2.8%	3.1%	2.4%
Ireland	14.1%	6.8%	8.4%	4.4%
Italy	14.3%	19.0%	5.6%	3.9%
Latvia	12.7%	7.4%	11.9%	4.9%
Lithuania	13.6%	5.8%	11.6%	3.4%
Luxembourg	6.4%	5.4%	3.9%	3.1%
Malta	2.9%	1.5%	2.5%	1.3%
Netherlands	4.8%	3.0%	4.4%	2.8%
Norway	4.1%	3.6%	2.3%	1.8%
Poland	12.6%	8.5%	8.2%	2.7%
Portugal	12.8%	13.7%	8.7%	5.5%
Romania	8.7%	7.9%	5.3%	2.1%
Slovakia	13.1%	9.2%	9.8%	3.4%
Slovenia	11.9%	12.2%	6.2%	3.2%
Spain	20.1%	16.5%	14.1%	8.5%
Sweden	7.9%	6.5%	4.6%	3.6%
Switzerland	4.9%	4.8%	3.5%	2.6%
UK	6.9%	3.6%	4.3%	2.6%

Table 8: Unemployment Rates in Europe

Note: The unemployment rates are averages of 2004-2017 for college and high school graduates if the country exists in EU-SILC for the whole sample period. Otherwise, the average of corresponding years have been reported and used in the model estimation.

C.2 Employment 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	82%	85%	75%	86%
Belgium	78%	87%	73%	84%
Bulgaria	70%	80%	73%	84%
Croatia	68%	76%	65%	82%
Cyprus	75%	81%	75%	84%
Czechia	76%	78%	77%	86%
Denmark	79%	81%	80%	87%
Estonia	76%	81%	75%	84%
Finland	74%	84%	75%	84%
France	76%	84%	74%	84%
Germany	77%	86%	76%	87%
Greece	62%	66%	63%	78%
Hungary	72%	82%	70%	81%
Iceland	77%	88%	88%	92%
Ireland	71%	84%	70%	83%
Italy	62%	55%	74%	84%
Latvia	75%	84%	71%	86%
Lithuania	73%	88%	71%	89%
Luxembourg	78%	83%	71%	85%
Macedonia	50%	57%	61%	78%
Malta	89%	93%	79%	87%
Montenegro	54%	70%	58%	81%
Netherlands	85%	91%	79%	87%
Norway	81%	85%	81%	90%
Poland	71%	83%	65%	86%
Portugal	73%	79%	81%	87%
Romania	71%	83%	70%	87%
Serbia	52%	57%	58%	74%
Slovakia	72%	77%	72%	84%
Slovenia	76%	81%	72%	87%
Spain	67%	74%	71%	82%
Sweden	80%	82%	84%	89%
Switzerland	86%	88%	81%	89%
Turkey	62%	72%	61%	77%
UK	79%	88%	79%	86%

Table 9: Employment Rates in Europe (average of 2004-2017)

C.3 Data Coverage

Country Code	Country Name	Frequency	Years
AT	Austria	14	2004-2017
BE	Belgium	14	2004-2017
BG	Bulgaria	11	2007-2017
CH	Switzerland	11	2007-2017
CY	Cyprus	13	2005-2017
CZ	Czechia	13	2005-2017
DE	Germany	13	2005-2017
DK	Denmark	14	2004-2017
EE	Estonia	14	2004-2017
ES	Spain	14	2004-2017
FI	Finland	14	2004-2017
FR	France	14	2004-2017
GR	Greece	14	2004-2017
HR	Croatia	8	2010-2017
HU	Hungary	13	2005-2017
IE	Ireland	14	2004-2017
IS	Iceland	13	2004-2016
IT	Italy	14	2004-2017
LT	Lithuania	13	2005-2017
LU	Luxembourg	14	2004-2017
LV	Latvia	13	2005-2017
NL	Netherlands	13	2005-2017
NO	Norway	14	2004-2017
PL	Poland	13	2005-2017
PT	Portugal	14	2004-2017
RO	Romania	11	2007-2017
SE	Sweden	14	2004-2017
SI	Slovenia	11	2005-2017
SK	Slovakia	13	2005-2017
UK	United Kingdom	13	2005-2017

Table 10: European Countries and data availability in EU-SILC

C.4 Observable Country-Specific Characteristics

On the job search intensity λ_y and λ_o :

On the job search intensity parameters are estimated from EU-LFS microdata using variables “lookoj” which is asking whether the respondent is looking for another job and

“seekdur” which is asking the duration of seeking. The duration (less than 6 months, 6 months-11 months, more than 1 year) is considered as the intensity of searching and each category is weighted accordingly. If a person who is performing on-the-job search (said yes to lookoj) is searching for another job since less than 6 months, the weight is 0.5 (1 and 2 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. The inverse of the average duration gives the intensity of on-the-job search. This ratio is calculated for young and old, country and year separately and averaged out across year for every country (from 2004 to 2017). As pointed out by Carrillo-Tudela et al. (2015), employed workers tend not to report that they are looking for jobs as I also find a relatively low fraction of “looking for another job”. Hence, calculating intensity out of people who report searching for another job is a more appropriate measure rather than the fraction of people who are looking. If the calculated intensity exceeds 1 which means that mismatched workers are spending more effort in job search than currently unemployed workers, the intensity is assumed to be 1. The results of the estimation can be seen in online appendix.

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

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

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.

Exogeneous Job Destruction Rate δ :

EU-SILC data has a panel dimension as well and it consists of information whether the person had a change in the employment status since last interview time. Hence, I can calculate the fraction of people who switched from being employed to unemployed relative to total number of employed people which gives me the job destruction rate. Since the data size is not appropriate for further heterogeneity, I restrict myself to estimate one single destruction rate for each country which does not depend on the type. I document estimation results in online appendix which are compatible with the estimates of Hobijn & Sahin (2009). In Figure 18, I document estimated separation rates and show that it is not correlated with “young, educated, unemployed” phenomenon. The data does not support the view that young college graduates are more likely to be unemployed because they are fired more often.

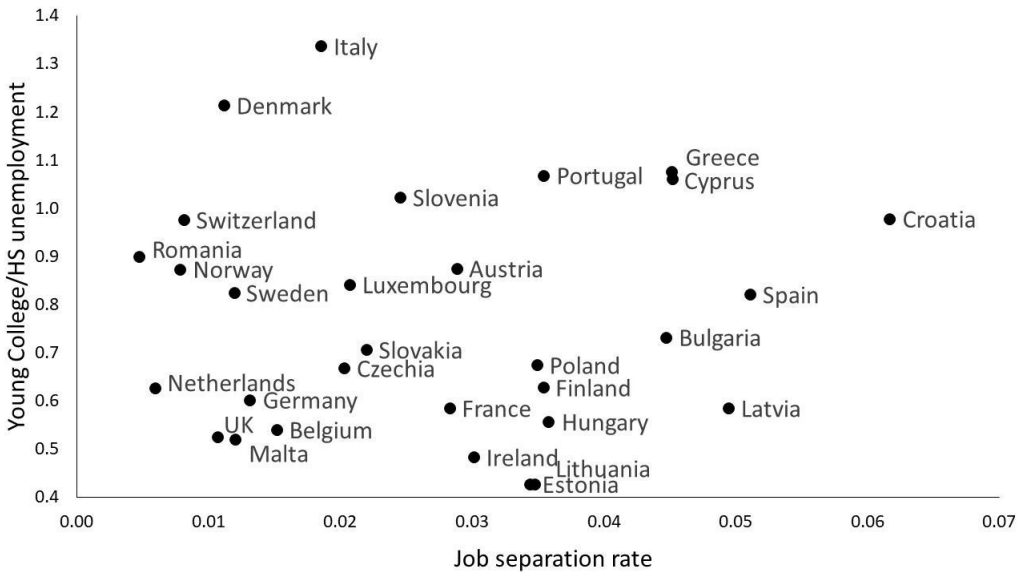


Figure 18: Job Separation Rate

C.5 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 2004-2017. 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. I report the fraction of college graduates at occupation-country level in online appendix.

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 in the online appendix.

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 11. 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). The results are reported in Figure 16.

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

Table 11: Skilled and Unskilled Occupations in the Model

D Structural Estimation

I take weighted mean of the left hand sides³³ of the second equations to get estimates of right hand sides. The regressions are weighted according to the aggregated employment level of every country. Hence H , M , L which are the aggregate number of high educated working in high skilled jobs, low educated working in low skilled jobs and mismatched workers (high educated working in low skilled jobs) in the economy can be calculated.

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

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

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

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

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

³³Subscript i refers to the country and t refers to year.

$$\frac{MPL(M_o)}{MPL(L_o)} = \frac{\frac{\partial Y}{\partial M_o}}{\frac{\partial Y}{\partial L_o}} = \alpha_p \left(\frac{M}{L}\right)^{1-\eta} \left(\frac{M_o}{L_o}\right)^{\eta-1} \implies$$

$$\log\left(\frac{MPL(M_o)}{MPL(L_o)}\right)_{it} - (\eta - 1)\log\left(\frac{M_o}{L_o}\right)_{it} - (1 - \eta)\log\left(\frac{M}{L}\right)_{it} = \log(\alpha_p)$$

The ratio of marginal product of labor of high educated workers to low skilled and mismatched workers helps to identify technological efficiency between low skilled and high skilled jobs by taking elasticity of substitution between education levels (ρ) as fixed³⁴. These 4 equations identify θ_h/θ_l together.

$$\frac{MPL(H_y)}{MPL(M_y)} = \frac{\frac{\partial Y}{\partial H_y}}{\frac{\partial Y}{\partial M_y}} = \frac{\theta_h}{\theta_l} \frac{\psi_p}{\alpha_p \beta_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{M}\right)^{1-\eta} \left(\frac{H_y}{M_y}\right)^{\eta-1} \implies$$

$$\log\left(\frac{MPL(H_y)}{MPL(M_y)}\right)_{it} - (\eta - 1)\log\left(\frac{H_y}{M_y}\right)_{it} - (1 - \eta)\log\left(\frac{H}{M}\right)_{it} - (\rho - 1)\log\left(\frac{H}{\tilde{L}}\right)_{it}$$

$$- \log\left(\frac{\hat{\psi}_p}{\hat{\alpha}_p \hat{\beta}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)$$

$$\frac{MPL(H_o)}{MPL(M_o)} = \frac{\frac{\partial Y}{\partial H_o}}{\frac{\partial Y}{\partial M_o}} = \frac{\theta_h}{\theta_l} \frac{1}{\alpha_p} \frac{H^{\rho-1}}{\tilde{L}^{\rho-1}} \left(\frac{H}{M}\right)^{1-\eta} \left(\frac{H_o}{M_o}\right)^{\eta-1} \implies$$

$$\log\left(\frac{MPL(H_o)}{MPL(M_o)}\right)_{it} - (\eta - 1)\log\left(\frac{H_o}{M_o}\right)_{it} - (1 - \eta)\log\left(\frac{H}{M}\right)_{it} - (\rho - 1)\log\left(\frac{H}{\tilde{L}}\right)_{it}$$

$$- \log\left(\frac{1}{\hat{\alpha}_p}\right) = \log\left(\frac{\theta_h}{\theta_l}\right)$$

³⁴ ρ is taken as 0.75 which is in the range of estimates of Card & Lemieux (2001) and Katz & Murphy (1992)

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

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

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.

E Figures

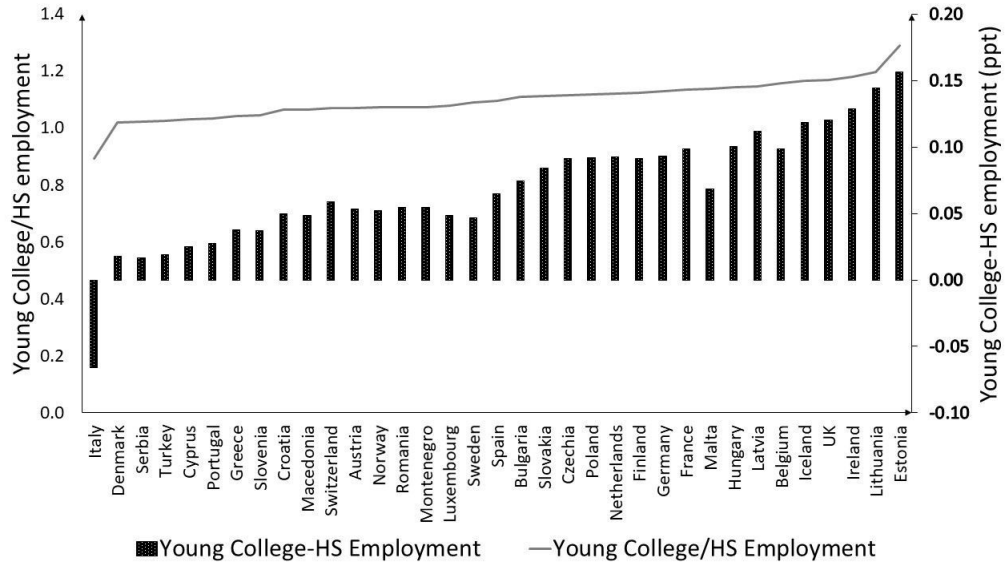


Figure 19: Employment Rates in Europe (average of 2004-2017)

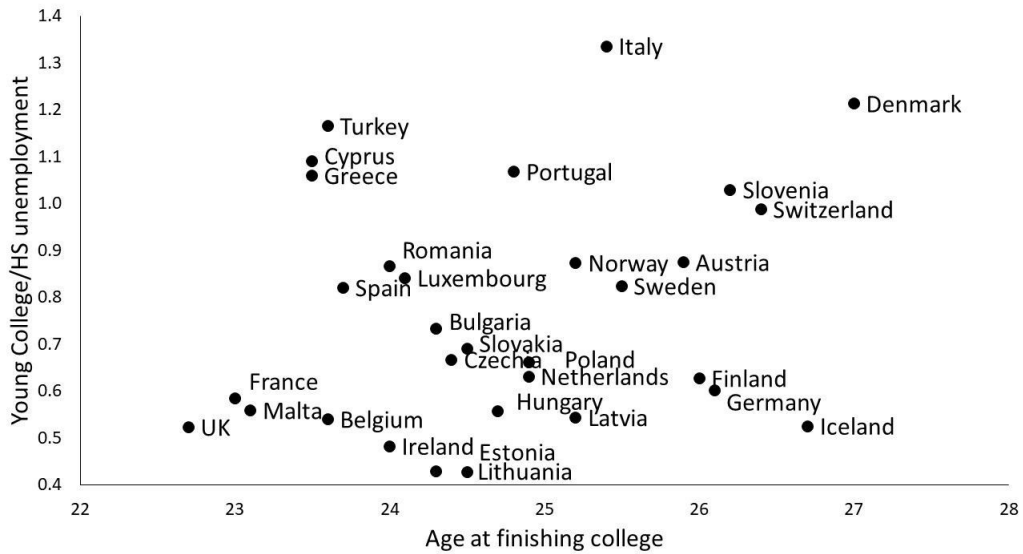


Figure 20: Duration in College

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

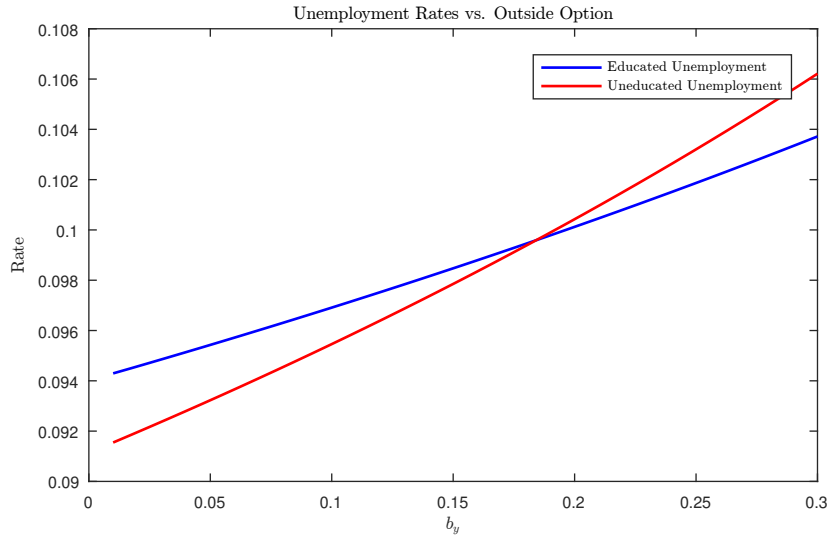


Figure 21: Mother Hypothesis

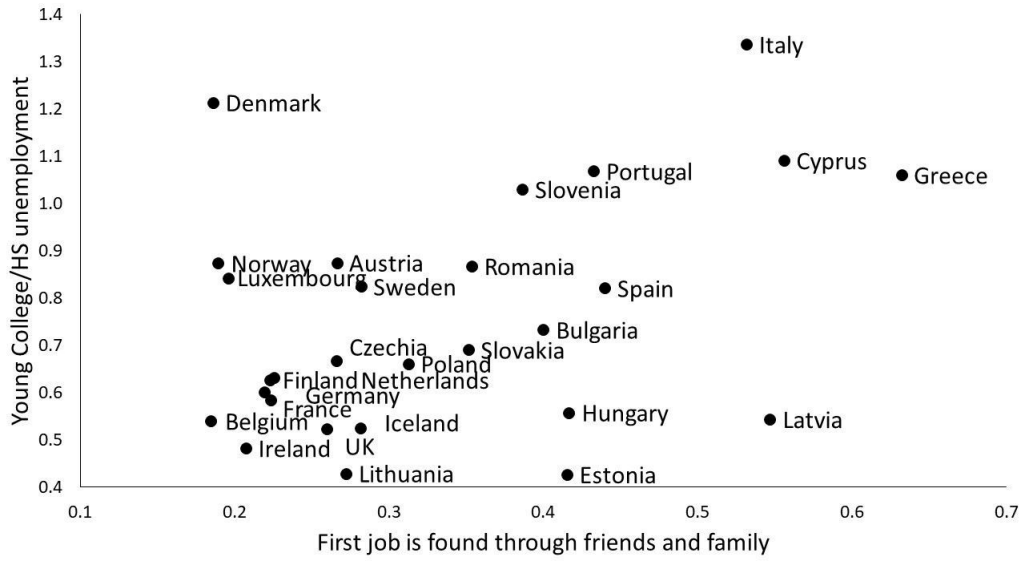


Figure 22: First job is found through friends and family

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.

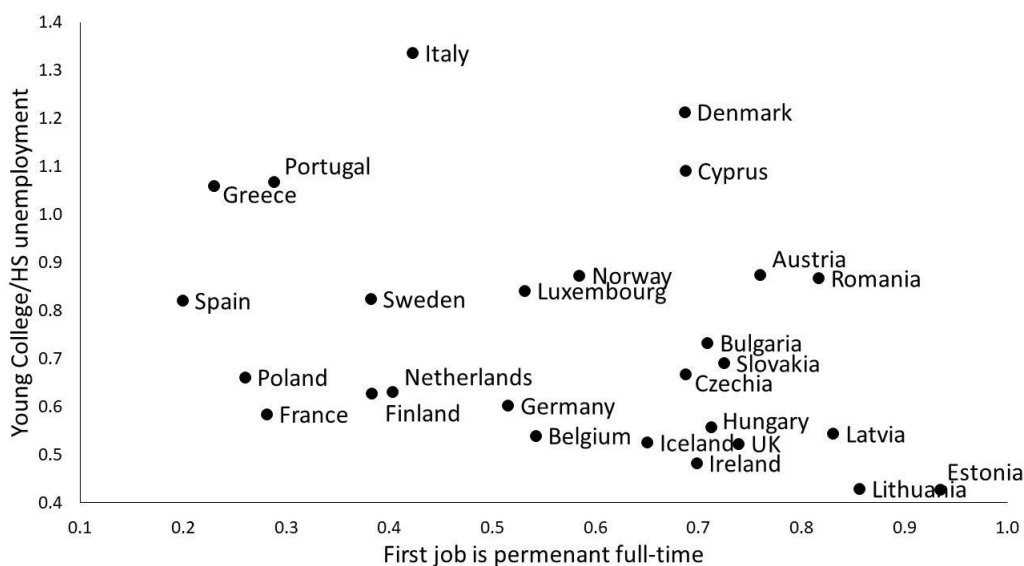


Figure 23: First job is permanent full time

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.

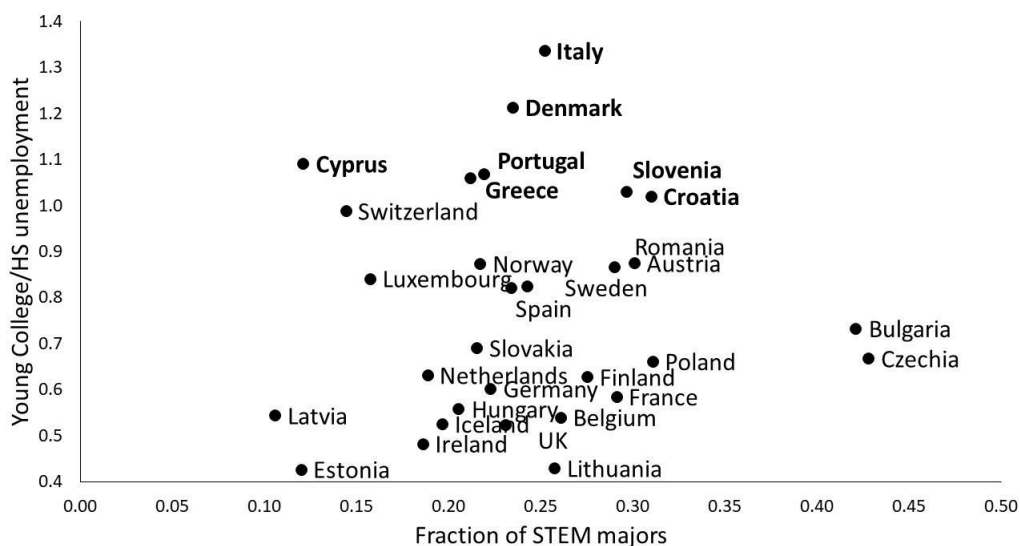


Figure 24: STEM ratio vs. College Unemployment

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.