I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12974

Output Costs of Education and Skill Mismatch

Pietro Garibaldi
Pedro Gomes
Thepthida Sopraseuth

FEBRUARY 2020

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12974

Output Costs of Education and Skill Mismatch

Pietro Garibaldi
Collegio Carlo Alberto, University of Torino and IZA

Pedro Gomes
University of London and IZA

Thepthida Sopraseuth
University of Cergy-Pontoise

FEBRUARY 2020

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Output Costs of Education and Skill Mismatch*

We propose a simple theory of under- and over-employment. Individuals of high type can perform both skilled and unskilled jobs, but only a fraction of low-type workers can perform skilled jobs. People have different non-pecuniary values over these jobs, akin to a Roy model. We calibrate two versions of the model to match moments of 17 OECD economies, considering separately education and skills mismatch. The cost of mismatch is 3% of output on average but varies between -1% to 9% across countries. The key variable that explains the output cost of mismatch is not the percentage of mismatched workers but their wage relative to well-matched workers.

JEL Classification: E24, J24
Keywords: education mismatch, skill mismatch

Corresponding author:
Thepthida Sopraseuth
University of Cergy-Pontoise
33 Boulevard du Port
95011 Cergy
France
E-mail: Thepthida.Sopraseuth@u-cergy.fr

* We would like to thank participants at seminars at the London School of Economics, University of Kent, University of Bath, University of York, University of Durham, and at the SAM, BCAM and Nordic annual conferences.

1 Introduction

Education and skill mismatch refers to the workers employed in occupations that typically require different education or skills. In labor statistics and policy circle (OECD, 2018), workers are classified as over- or under-employed, depending on whether their education or skill is below or above the occupation average requirement. The OECD reports that, on average across advanced economies, 25% (18%) of workers are under-employed and 22% (7%) are over-employed vis-à-vis their education (skill).[1]

Despite representing such a large proportion of the work force, and despite the policy effort to measure mismatch, there is no accepted theory of over-education and mismatch. While there are various semi formal economic models of over-education reviewed by McGuinness (2006), we still lack a text-book model of under- and over-employment and quantitative estimates of the costs of mismatch. The paper aims at filling these gaps: we propose a simple macroeconomic model of mismatch and provide model-based cross-country estimates of its cost in terms of output.

The theory is based on four features. First, individuals of high and low type are endowed with one unit of indivisible labor. Second, a representative firm has jobs which differ on their skill requirements. Individuals of high type are able to perform skilled jobs but also unskilled jobs, with perhaps higher efficiency than workers of low type. Conversely, only a fraction of low-type workers can perform the skilled jobs, albeit with lower efficiency than high-type workers. Third, individuals have a different "non-pecuniary" value over these jobs, and optimally sort across them. Fourth, each worker is paid its marginal productivity. This simple variation of Roy (1951) and Borjas (1987) is sufficient to generate a labor market allocation with both endogenous under- and over-employment.

We calibrate the model to 17 OECD economies, based on data from the *Survey of Adult Skills* (PIAAC). The model is very general and fairly parsimonious. We calibrate two different versions of the model to fit empirical measures of either education or skill mismatch.

[1] See Quintini (2011) and McGowan and Andrews (2015). To clarify the semantics, we refer to "mismatch" as the discrepancy between workers' competencies and those required by the job. "Under-employment" is used here as the under-use of workers' competencies. "Over-employment" refers to the converse. We focus on two different dimensions of workers' competencies: education and skills. This phenomenon is also referred to as over(under)-education or over(under)-skilling in OECD reports.

Five structural parameters can be obtained by solving a simple algorithm to match five key moments, including over- and under-employment, and relative wages of well-matched and mismatched workers.

We use the model to quantify the output costs of education and skill mismatch. Eliminating education mismatch completely would raise output by 2.5% on average, with large cross-country differences ranging from -1.5 to 7% of output. Eliminating skill mismatch would raise output on average by 3.2%, ranging from -0.7 to 9% of output across countries. The key variable that explains the output cost of mismatch is not the percentage of mismatched workers, but their wage relative to well-matched workers. In particular, our paper suggests that the policy maker should pay attention to the wage loss of an under-employed college graduate/skilled worker with respect to her well-matched counterpart. Countries with sizeable "wage costs of under-employment" suffer from a scarcity of college/skilled-workers in skilled jobs, thereby they would significantly increase output if they were able to successfully reduce mismatch. Based on regressions with simulated data, a 10 percentage point higher "wage costs of under-employment" is associated with a 1 percentage point higher output cost of mismatch. Our model suggests that mismatch has a sizeable impact on relative wages in the economy. The removal of education mismatch would lead to a lower college premium, but this is not the case with skill mismatch.

The paper contributes to several strands of the literature. First, it proposes an original method to compute the macroeconomic cost of mismatch. The existing literature has documented the impact of mismatch on wages or job satisfaction and other correlates of workers' productivity. However, the empirical evidence seems inconclusive as results are sensitive to the nature of the mismatch measure (education, skill or qualification) or lead to ambiguous conclusions (See McGowan and Andrews (2015) and Grunau (2016) for a survey). We take these discrepancies across measures as given and feed the model to assess the output cost of mismatch. Interestingly, we find that output costs remain large and consistent across different mismatch measures. In addition, our model suggests that over- and under-employment tend to reinforce each other. This interaction is missed in the current literature. Our emphasis of "non-pecuniary dimension" of the job is also coherent with the literature on mismatch that emphasised the role of assignment and job characteristics (See

Sattinger (1993)).

Direct evidence on the impact of mismatch on the aggregate economy is also limited to specific countries using linked employer-employee data (Mahy et al. (2015) for Belgium, Grunau (2016) for Germany). McGowan and Andrews (2015) proposes a cross-country perspective by looking at the impact of mismatch on labor productivity using industry-level regressions. We subscribe to the OECD concern about the need for cross-country macroeconomic assessment. Our originality lies in proposing a model-based method for assessing the cost of mismatch, thereby taking into account endogenous workers' sorting into jobs and general equilibrium effects on wage premia, which is not taken into account in the current empirical studies.

The paper also relates to the recent economics literature on education mismatch, which uses mainly search models and focuses only on under-employment. Our paper suggests that, when assessing the economic consequences of mismatch, over-employment should also be taken into account. A first group of papers applies labor market search with on-the job search and career mobility to explain over-education (Sicherman and Galor (1998) and Dolado et al. (2009)). Chassamboulli (2011) and Barnichon and Zylberberg (2019) study the cyclical dimension of over-education, where over-education arises from workers having higher job-finding rates in lower-ranked occupations. A more theoretical oriented literature focuses on search with multiple applicants (Shimer (1999) and Julien et al. (2000)). Arseneau and Epstein (2014) also measure the welfare cost of eliminating over-education in a search and matching model. Finally, Sahin et al. (2014) propose a model-based measure of the cost of mismatch unemployment. With respect to their paper, we subscribe to the model-based measure. Yet, our paper estimates the cost of mismatch on the job rather than mismatch between unemployment and vacancies. In addition, we look at over- and under-employment separately, and propose a cross-country measure of mismatch.

Our model is neoclassical in spirit and does not require labor market imperfections. The key advantage of our model relative to the above mentioned matching literature, beside its simplicity, is the fact that we consider a production function and the general equilibrium effects of over- and under-employment on marginal productivity and wages. Our model suggests that the two phenomena reinforce each other. If more low-type people take up

skilled jobs, they push the skilled wages down and the unskilled wages up, making under-employment more attractive to high-type workers.

2 Model Set up

Technology and Preferences

Individuals are endowed with 1 unit of indivisible labor and firms require different jobs to produce output. There are two types of individuals. The first type of individual has higher education / high skill while the second type has not. In the presentation of the theoretical model, we will use the words "high-type" (h) and "low-type" (l). We make the empirical distinction between education-based and skilled-based mismatch in the subsequent sections when taking the model to the data.

The supply of high-type individuals in the economy is indicated with n, while the supply of workers with lower education is $1 - n$. There are two jobs in the economy, that we shall call the skilled and the unskilled jobs. In what follows, we shall use a Cobb Douglas specification:

$$Y = (j_h)^{\alpha}(j_l)^{1-\alpha} \tag{1}$$

where $1 > \alpha > 0$ and $j_h(j_l)$ is the number of skilled (unskilled) jobs in efficiency units. Firms produce with a constant return technology in different jobs.

A key assumption in our theory concerns the ability of different individuals to perform different jobs. On the one hand, high-type workers can perform skilled jobs with one efficiency unit, but they are also able to perform unskilled jobs with efficiency units $\zeta \geq 1$. On the other hand, low-type workers can perform unskilled jobs with one efficiency unit, but only a fraction Θ of them can also perform the skilled jobs[2] with lower efficiency units $\chi \leq 1$. The natural asymmetry in the problem between workers with high and low type is captured by $\zeta \geq 1 \geq \chi$ and $\Theta \leq 1$.

[2]This assumption makes the model consistent with the empirical facts that, among non-college graduates / unskilled, there are more well-matched than over-employed workers, while over-employed workers earn more than their well-matched counterparts. Without this assumption, as over-employed workers earn more than their well-matched counterparts, the majority of low-type workers would want to sort into high-type occupations, which is not consistent with the data. Θ can be interpreted as regulatory elements in some occupations. For instance, requirements on experience or degree in some high-type jobs.

Individual preferences are linear, and the model is static. The wage paid per efficiency unit of the skilled job is indicated with w_h while for the unskilled job is indicated with w_l. Workers have heterogeneous "non-pecuniary value" over these jobs, and each individual draws a relative preference for both jobs ϵ_i^h and ϵ_i^l from distributions with cumulative densities $F^h(.)$ and $F^l(.)$, assumed to be extreme type I error distribution with parameters (0,1). Workers utility is thus the sum of the wage and non-pecuniary value, so for an individual i earning a wage w, its utility is $U_i = w + \nu\epsilon_i$, where ν captures the weight of the non-pecuniary value shock in the individual preferences.[3]

Sorting by High-Type Workers and Under-employment

The key decision of a high-type worker i concerns the sector in which to supply her indivisible unit of labor. The problem reads

$$U_i^h = Max\{w_h + \nu\epsilon_i^h, \zeta w_l + \nu\epsilon_i^l\} \tag{2}$$

An high-type worker prefers an unskilled job only if $w_h + \nu\epsilon_i^h < \zeta w_l + \nu\epsilon_i^l$, or if $\epsilon_i^h - \epsilon_i^l < \frac{\zeta w_l - w_h}{\nu}$. In contrast, she takes an unskilled job if its value over the skilled job is large enough to compensate the wage differential. This simple sorting condition implies that there is an endogenously determined value of under-employment defined as:

$$u = n\left[\frac{e^{\frac{\zeta w_l}{\nu}}}{e^{\frac{\zeta w_l}{\nu}} + e^{\frac{w_h}{\nu}}}\right] \tag{3}$$

This expression follows from the fact that the difference between independent extreme type I error distributions has a logistic distribution. Notice that, as ν tends to zero, all individuals will prefer the option which offers the highest wage, meaning that either $u = 0$ or $u = 1$ depending on whether $w_h \gtrless \zeta w_l$.

[3]We take the ν as exogenous. A more general model could micro-found ν depending on labour market conditions and on housing market or transport policies, as well as regulation of specific occupations. The non-pecuniary value is a shortcut and it captures all possible reasons, other than wages, that pushes people to accept a job with lower wages. It is isomorphic to having it as a cost of doing the job i.e. $U = w - \nu\epsilon_i$. As such, the model is not equipped to make any normative statement or to think about optimal policies.

Sorting by Low-Type Workers and Over-employment

We assume an asymmetry between the problem of workers of high and low type: only a fraction Θ of low-type workers receive an opportunity in a skilled job. For a worker i that has an opportunity, the sorting decision reads:

$$U_i^l = Max\{\chi w_h + \nu\epsilon_i^h, w_l + \nu\epsilon_i^l\} \tag{4}$$

The low-type worker takes on the skilled job only if $\chi w_h + \nu\epsilon_i^h > w_l + \nu\epsilon_i^l$, or if $\epsilon_i^h - \epsilon_i^l > \frac{w_l - \chi w_h}{\nu}$. This simple sorting condition implies that there is an endogenously determined value of over-employment defined as

$$o = (1-n)\Theta\left[\frac{e^{\frac{\chi w_h}{\nu}}}{e^{\frac{\chi w_h}{\nu}} + e^{\frac{w_l}{\nu}}}\right] \tag{5}$$

Labor Demand and Market Clearing

A representative firm maximises profits taking as given the wage for both jobs. Labor demand is given by

$$w_h = \alpha\left(\frac{j_l}{j_h}\right)^{1-\alpha} \quad , \quad w_l = (1-\alpha)\left(\frac{j_h}{j_l}\right)^{\alpha}. \tag{6}$$

Wages adjust until the demand for jobs is equal to the supply of efficiency units, such that all workers get paid their marginal productivity. Given the different efficiency units, there are four different wages in the economy. w_h and w_l are the wages paid to "well-matched" high- and low- type workers. The education/skill premium of well-matched workers is given by the ratio of the two ($\frac{w_h}{w_l}$). Over-employed workers get χw_h and under-employed workers get ζw_l. The education/skill premium of under-employed workers is given by ζ. This is a crucial variable in the papers by Arseneau and Epstein (2014) and Barnichon and Zylberberg (2019). Market clearing equilibrium imply

$$j_h = (n-u) + \chi o \quad , \quad j_l = (1-n-o) + \zeta u. \tag{7}$$

Equilibrium

Definition 1 *A steady-state equilibrium consists of wages* $\{w_h, w_l\}$*, skilled and unskilled jobs* $\{j_h, j_l\}$*, under-employment for educated workers* $\{u\}$*, over-employment for low-educated workers* $\{o\}$*, such that*

1. *The representative firm maximizes profits (6).*
2. *High-type workers sort across labour markets according to (2).*
3. *Low-type workers with an opportunity to chose between markets, sort according to (4).*
4. *Markets clear (7).*

We can summarize the model in four equations: under- and over-employment given by equations (3) and (5) respectively and two wage equations (equation (6)) in which the number of skilled j_h and unskilled jobs j_l are replaced by their expressions (equation (7)).

Notice that the model features complementarity between over- and under-employment. Suppose that, in partial equilibrium, over-employment increases, more low-type workers are in complex jobs, the supply of unskilled labor goes down, such that skilled wages fall and unskilled wages increase, thereby reducing the wage differential and increasing under-employment. Conversely, if under-employment increases, it pushes unskilled wages down and skilled wages up, increasing wage differential and, hence raising over-employment. While one might suspect the possibility of multiple equilibria, we show in Appendix A that, given the asymmetries of the model (as long as $\zeta \geq 1 \geq \chi$ does not hold with two equalities), the equilibrium exists and is unique.

3 Calibration

The OECD Survey of Adult Skills is part of the OECD Program for the International Assessment of Adult Competencies (PIAAC). The data were collected between 2011 and 2015. In each country, the survey provides one wave of data with socio-demographic information (gender, education), labor market status and assesses the proficiency of adults aged between

16 and 65 in literacy, numeracy and problem solving. This cross-section sample includes only respondents who are currently employed.

Definition of mismatch: Education and skill mismatch. We want our measure of mismatch to be consistent with the dichotomic nature of the theoretical model with two groups of workers: high-type and low-type. When analysing the data, we develop two different criteria to categorize workers, one based on education and one based on skill.

Finding an appropriate measure of mismatch is a debated issue in the literature (See Flisi et al. (2017) for a survey). Baert et al. (2013) for instance use subjective approaches based on self-reported mismatch. Workers are asked about their feeling about the job match. In contrast, Bauer (2002), among others, rely on objective measures, such as the actual level of education or skill attained by peers working in the same occupation. The workers' education/skill levels within each occupation is used to infer the education/skill level required for a job. Mismatch occurs when the individual's education level deviates from the majority of types (education or skill) within each occupation. Each measure has its advantages and drawbacks: subjective measures may just be a reflection of workers' poor information, but provide up-to-date information that is specific to each respondent; objective measures are based on actual jobs, are easily observed but assume that, within each occupation, the education/skill requirement is the same for all workers.

We want to provide conservative measures of mismatch in order to provide a lower bound on the output costs of mismatch. As such, we measure mismatch as a combination of subjective and objective mismatch.

For the subjective mismatch measure, we follow McGowan and Andrews (2017). To identify well-matched workers, we use two questions in the survey asking workers to compare their skill level and that required for their job: "Do you feel that you have the skills to cope with more demanding duties than those you are required to perform in your current job?" and "Do you feel that you need further training in order to cope well with your present duties?". Workers who neither feel they have the skills to perform a more demanding job nor feel the need for further training in order to be able to perform their current job satisfactorily are considered as well-matched.

As for the objective mismatch measure, we will consider two measures. The first one is based on education, the second one is based on skills.[4] Under the education-based measure, we consider high-type workers as college workers. College workers are those who report an educational attainment of ISCED 5B (first stage of tertiary education: typically shorter, more practical, technical specific programmes leading to professional qualifications) and higher. n is the share of college-educated workers. On average for the 17 countries, there are 40% of workers with college education. We then compute the share of non-college workers within each 2-digit occupation. A college-educated (non-college) worker is classified as under-employed (over-employed) when working in an occupation that is majority non-college (college).

As for skills, we look at the distribution of literacy and numeracy proficiency scores among workers.[5] Under the skilled-based measure, we consider as high-type (low-type) workers that are in the top (bottom) 50% in terms of proficiency scores. The share of high-skilled workers, n, then equals 0.5. We then compute the share of low-skilled workers within each 2-digit occupation. A high-skilled (low-skilled) worker is classified as under-employed (over-employed) when working in an occupation that is majority low-skill (high-skill).

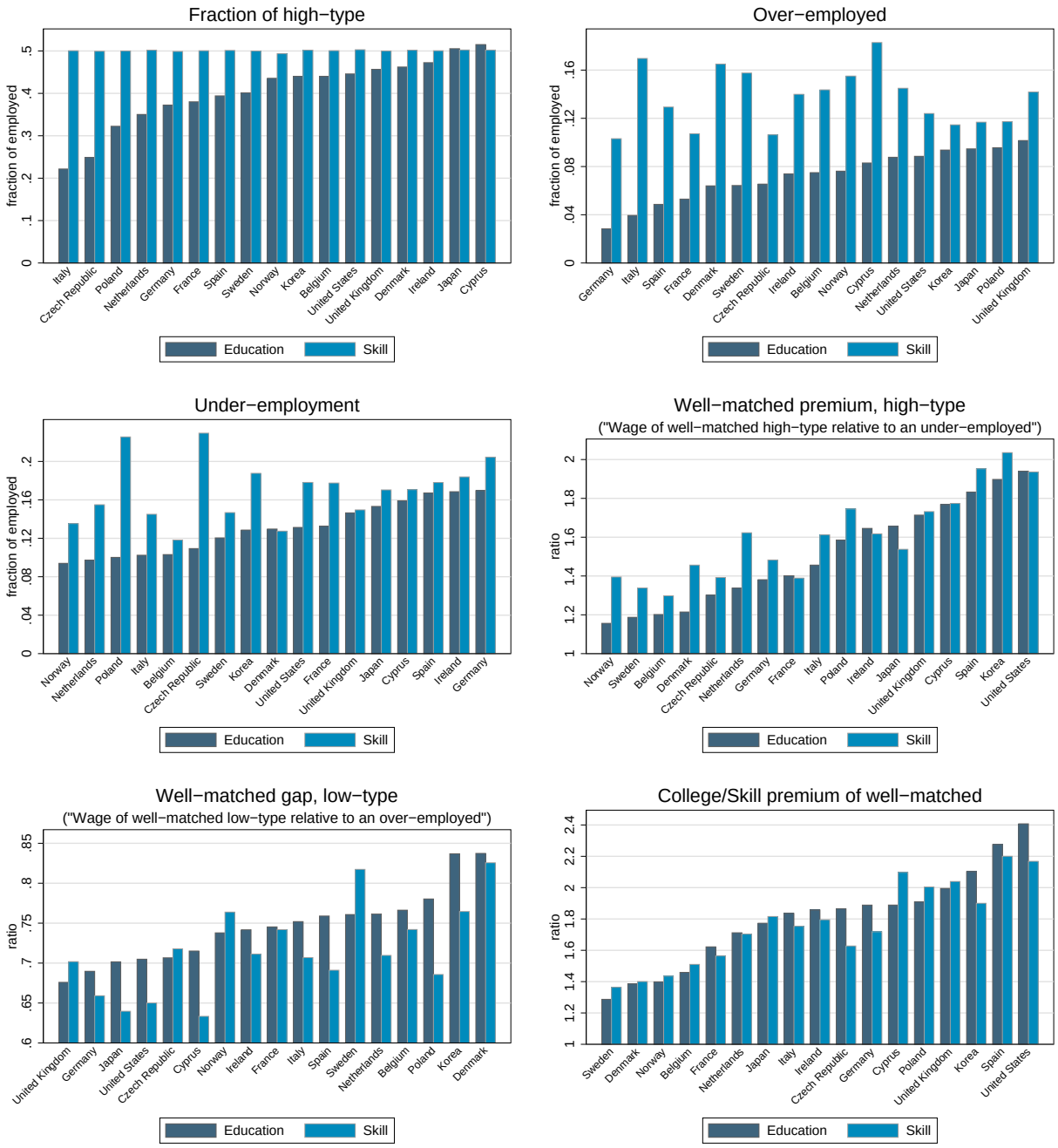
We then present two measures of mismatch based on the intersection of the subjective and objective measures. The first one is referred to as "education mismatch": A worker is considered as under-employed (over-employed) if she views herself as mismatched, college (non-college) graduate and working in 2-digit occupations that are majority non-college (college). The second measured is called below "skill mismatch" : A worker is considered as under-employed (over-employed) if she views herself as mismatched, high-skill (low-skill) and working in 2-digit occupations that are majority low-skill (high-skill).

Mismatch is sizeable, with an average of around 20% based on education measure (30% based on skills). These numbers are consistent with OECD (Quintini, 2011). Educational under-employment (at 13% on average) is larger than over-employment(at 7%). This also the case for skill under-employment (17%) that is higher than skill over-employment (13%).

[4]We explore a third definition - qualification mismatch in Appendix D.

[5]We also considered problem solving scores in addition to literacy and numeracy but, in this case, four countries drop out of the sample. The main results on output costs carry through. Results are available upon request.

Figure 1: Calibration targets



Note: All calculated from PIAAC data. "Education mismatch" : A worker is considered as under-employed (over-employed) if she views herself as mismatched, college (non-college) graduate and working in 2-digit occupations that are majority non-college (college). "Skill mismatch": A worker is considered as under-employed (over-employed) if she views herself as mismatched, high-skill (low-skill) and working in 2-digit occupations that are majority low-skill (high-skill). The correlation between the measures for education and skill are: 0.03 for over-employment, 0.22 for underemployment, 0.91 for the well-match premium of the high type, 0.67 for the well-matched gap of low-type and 0.91 between the college and the skill premium.

In most countries, over-employment is smaller than under-employment.

Figure 1 sheds light on the differences between educational mismatch and skill mis-

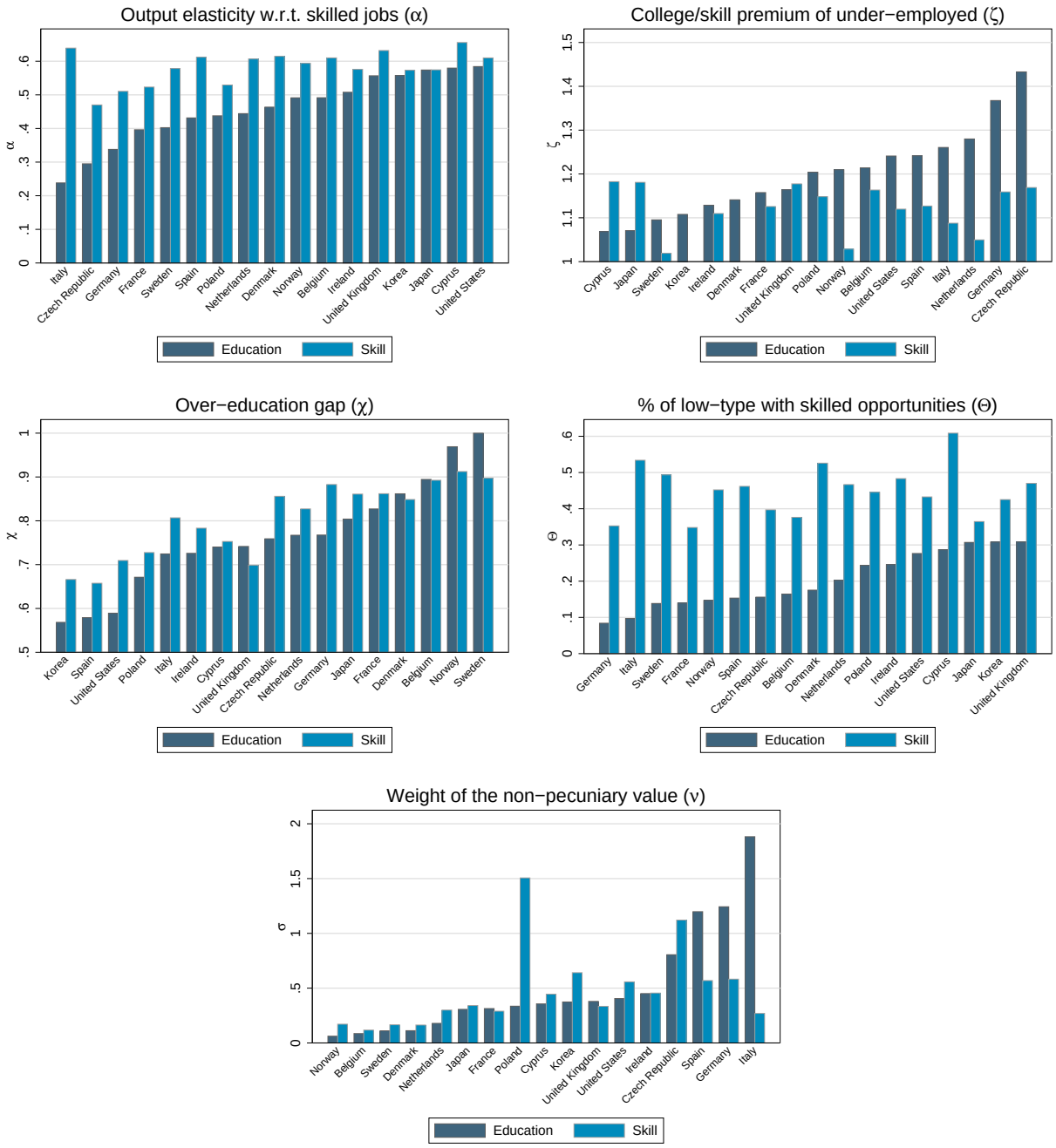
match. The skill-based measure predict higher levels of mismatch, whether in over- or under-employment. The correlation of mismatch across the two measures is low (0.22 for under-employment, 0.03 for over-employment). This echoes the differences across mismatch measures that have been documented in the literature (Flisi et al. (2017)). Our contribution does not lie in further elucidation of the reasons behind these discrepancies. We take these discrepancies as given and feed the model to assess the output cost of mismatch.

Wage. The wage refers to gross hourly earnings. Earnings data for Germany, Sweden, and the United States are reported only in deciles. We use Hanusek et al. (2015) procedure to assign the decile median to each respondent belonging to the respective decile of the country-specific wage distribution. In each country, we trim the bottom and top one percent of the wage distribution to limit the influence of outliers. We compute average gross hourly earnings for each worker group (high/low type, under- over-employed).

The average college or skill premium of well-matched workers hovers around 80%, and has a correlation of 0.9 across mismatch measures. The well-matched premium for college workers (skill workers) is large: they earn 50% (60%) more than under-employed college (skill) workers. This variable $\frac{w_h}{\zeta w_l}$ is inversely related to the wage loss incurred by an under-employed high-type worker relative to a well-matched counterpart. This is called the "wage cost of under-employment" in Barnichon and Zylberberg (2019). It is substantial on average, varying from 15% in Norway (education-based) to 90% in the US (whether under education or skill mismatch). Finally, mismatch of low-type workers lead to a wage gain with respect to their well-matched counterparts : well-matched low-type earn on average around 70% of the wage of over-employed low-type (education based or skill based) workers. $\frac{w_l}{\chi w_h}$ relates to the "wage gain of over-employment".

Interestingly, while the two indicators of mismatch do not yield the same prevalence of mismatch across countries, these two measures yield similar wage outcomes, in particular for the wage cost of under-employment and wage gain of over-employment (with a correlation across mismatch measures of 0.91 and 0.67, respectively).

Figure 2: Calibrated parameters



Note: Estimated to fit empirical targets.

Calibration based on empirical targets. The model has then five parameters $\{\alpha, \zeta, \chi, \Theta, \nu\}$, that are determined for the model to match five targets that we can get from PIAAC: $\left\{u, o, \frac{w_h}{w_l}, \frac{w_h}{\zeta w_l}, \frac{w_l}{\chi w_h}\right\}$. The targets are: the fraction of under-employment and over-employment in total employment. The last three targets relate to wages: the college/skill premium of well-matched workers ($\frac{w_h}{w_l}$), the well-matched premium of high-type workers ($\frac{w_h}{\zeta w_l}$) and the

well-matched gap of low-type workers ($\frac{w_l}{\chi w_h}$). They are shown in Figure 1.

Figure 2 displays the parameter values. The values in all countries meet the theoretical restrictions to ensure existence and uniqueness. Appendix B displays the model fit. The baseline economy does fit the empirical targets.

4 Output gains of removing mismatch

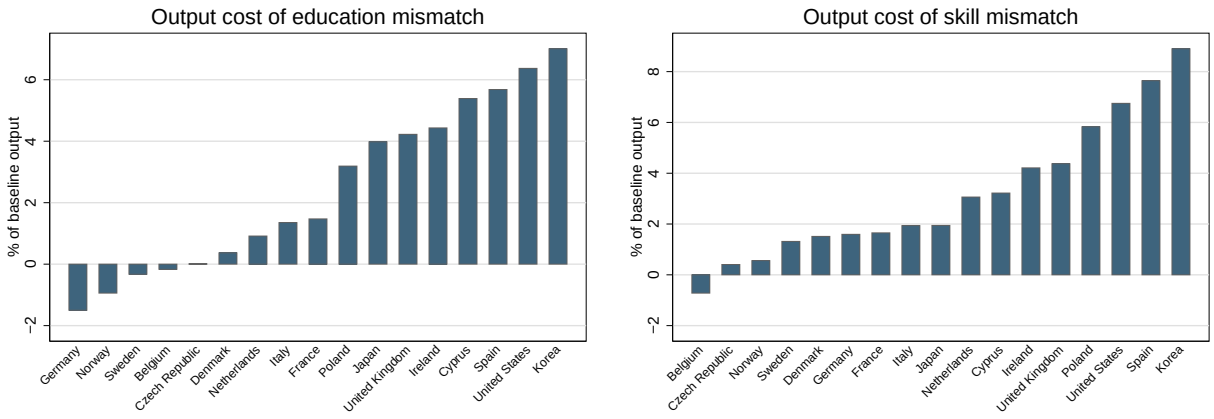
The main exercise is to quantify what are the gains in terms of output of eliminating mismatch by setting both over- and under-employment to zero in the model. The results are shown in Figure 3. When we set under- and over-employment outright to zero, the output gains are on average 2.5 % based on education mismatch (3.2% based on skill mismatch), but vary substantially across countries, with low or negative output costs of mismatch in Belgium and Norway to output costs hovering around 7 to 9% in the US and Korea.[6]

Interestingly, the two measures of mismatch, based on education or skill, deliver very similar predictions regarding output costs. While both measures displays different magnitudes of under- and over-employment and shares of high-type workers, the correlation of output costs across measures equals 0.85. This suggests that the model delivers robust measurement of output cost.

For the sake of illustrating our results, let us have a closer look at the US and Belgium. The US output cost of mismatch hovers around 6% versus -1% to -.2% in Belgium. One might think that the prevalence of over- and under-employment *per se* are good predictors of output costs. Focussing on educational mismatch, over-employment in the US is 9%, which is higher than the Belgian over-employment (7.5%), while 13% of US workers are under-employed versus 10% in Belgium. The extent of educational mismatch is rather similar across the two countries while output costs are very different. It is also the case for skill-based mismatch. So the extent of mismatch is not a primary driver for output costs. Similarly, the two countries are also characterized by the same share of high-type workers, whether college educated (44% of workers) or high-skill (50% in all countries, by definition,

[6]By setting $u = o = 0$, we have $j_h = n$, $j_l = 1 - n$ (equation (7)). It can be shown that, given our empirical targets and parameter values, in all economies, after ending mismatch, j_h increases and j_l goes down with respect to the baseline economy. The net effect of ending mismatch on output (equation (1)) is therefore ambiguous.

Figure 3: Output costs of mismatch ($u = o = 0$)



Note: Model simulations. The graph plots the percentage variation of output relative to baseline when setting $u = o = 0$.

in the skill based measure).

In order to confirm this intuition, we run univatiate regression of output costs on either the fraction of college graduates or the extent of (educational or skill) mismatch. We want to base our result on a dataset that is larger than a scatter plot of 17 points. As such, we build simulated data. For each parameter we give nine equally distributed numbers between the minimum and the maximum of our set of 17 countries. We simulate a fictitious country for each possible combination of parameters. We only keep simulations for which the five empirical targets are between the minimum and the maximum of our set of 17 countries. In total, we have around 23 thousand observations for the education mismatch and 15 thousand for the skill mismatch (n is always kept at 0.5).

Using simulated data, we regress output costs on each observable variables used in the calibration (Table 1) in turn. When all empirical targets are included, the OLS regression accounts for around 96% of the variance in output costs (shown in Appendix C). When we include the share of high-type workers n the R-squared is only 0.05. We get the even lower R-squared when regressing the gains on the extent of mismatch is (whether over- or -under employment). This confirms that output costs are not driven by the percentage of mismatched workers per se.

Interestingly, the wage premium of well-matched college workers alone accounts for 91% of output costs variance (80% for skill mismatch). In other words, countries, such as the

Table 1: Regression of output cost of mismatch on observable variables

	Education mismatch		***Skill mismatch***	
Variable	**coef. (t-stat)**	**[R-squared]**	**coef. (t-stat)**	**[R-squared]**
n	6.98 (33.43)	[0.046]		
o	15.22 (21.96)	[0.021]	-5.75 (-6.52)	[0.003]
u	-7.18 (-10.48)	[0.005]	4.67 (5.85)	[0.002]
$\frac{w_h}{w_l}$	6.30 (164.64)	[0.541]	9.25 (139.64)	[0.555]
$\frac{w_h}{\zeta w_l}$	10.58 (474.05)	[0.907]	11.61 (252.30)	[0.803]
$\frac{w_l}{\chi w_h}$	4.11 (12.81)	[0.007]	1.47 (4.40)	[0.001]
Obs.		(22,996)		(15,625)

The table shows coefficient, t-statistic and R-squared of the univariate regression of the model-based output costs of mismatch on all observable variables in turn. n share of high-type workers in employment. u and o, share of under-employed and over-employed workers, respectively, in total employment. $\frac{w_h}{w_l}$ high-type wage premium of well-matched workers. $\frac{w_h}{\zeta w_l}$ well-matched premium of high-type workers relative to under-employed. $\frac{w_l}{\chi w_h}$ well-matched loss of low-type workers relative to over-employed.

US, with sizeable wage losses of under-employment (of more than 90%), would benefit from eliminating mismatch, while countries, such as Belgium, with more moderate wage cost of under-employment (of around 20% - 25%) would not. The magnitude of the coefficient, quite similar in both regressions in Table 1, suggests that a 10 percentage point increase in the wage cost of under-employment is associated with a cost of 1% of output. It is easier to understand why this variable is so related to the welfare costs if we compute the derivative of output with respect to under-employment: $\frac{\partial Y}{\partial u} = -w_h + \zeta w_l$. This partial derivative tell us that reducing under-employment at the margin would raise output by $w_h - \zeta w_l$, which dividing by ζw_l is exactly the wage loss of under-employment. Given our calibration, reducing under-employment, at the margin, always raises output.

Our estimates hint that the cut-off value hovers around $\frac{w_h}{\zeta w_l} = 1.4$. Whatever the mismatch measure, output costs start building up (starting at 2% to 3% of output loss) in countries where the wage premium of well-matched high-type workers relative to under-employed counterparts is larger than 40%. Policy makers in countries, such as the US, should be concerned that too few educated/skilled workers are actually working on well-matched jobs. This scarcity of labor away from more productive jobs is very likely to be costly in terms of output. In contrast, countries, such as Belgium, with more moderate wage cost of under-employment should not be concerned about high-type workers taking up jobs as plumber or electricians because this does not create too much scarcity in the market of

skilled jobs.

Table 1 suggests that the wage gain of over-employment is not strongly associated with the output costs. Appendix C provides further insight as we present output costs from ending under- and over-employment separately. For education mismatch, the output gain of removing over-employment are on average -3%. Ending over-employment reallocates non-educated workers away from more productive jobs, which lowers output. On the other hand, the output gains of removing under-employment alone are only 1.4 percent. The reason why the sum of the two effects separatly is lower than the effect of removing both at the same time points to their interdependence. When removing over-employment, the wage loss of under-employment shoots up, which raises the gains of eliminating under-employment. Similarly, eliminating underemployment, lowers the college/skill premium so it reduces the cost of over-employment.

Finally, our model has predictions on the effect of mismatch on wage dispersion. In the case of the education-based measure, in all countries, removing mismatch raises the number of high-type jobs while lowering the number of low-type jobs, which results in lower wage inequality in the zero-mismatch economy compared with the baseline model. The average college premium [7] is 53% in the baseline economy versus 27% in the zero-mismatch economy.

With the skill-based measure, the aggregate skill premium of 39% in the baseline goes up to 42% on average after removing mismatch. Indeed, under the baseline calibration, the high over-employment pushes the wages of the unskilled upward. This effect disappears when skill mismatch is removed. This result illustrates the difference between educational mismatch and skill mismatch. Despite the divergence in predictions on wage inequality, the two measures provide consistent predictions on output costs. We view this point as providing another illustration that our model-based measure of output costs of mismatch provides robust estimates.

We present in Appendix D the results with a third measure of mismatch, qualification mismatch, based on alternative subjective measure of the right qualification in the occupa-

[7] Notice that the average college premium in the economy is the ratio of average wage earned by college-graduates (well-matched and under-employed) relative to the average wage earned by non-college workers (well-matched and over-employed): $\frac{\frac{(n-u)w_h+u\zeta w_l}{n}}{\frac{(1-n-o)w_l+o\chi w_h}{1-n}}$.

tion. Consistent with the education mismatch, the output costs are around 2.5 percent. In Appendix E we extend our theory to endogeneize education to address some of the concerns of the early literature on education mismatch that was mainly concerned with over-education in the context of the return to schooling (Freeman (1975); McGuinness (2006)). We find that the average output costs of 1.7 percent, 0.8 percent lower than the benchmark case where education is exogenous. Given that OECD economies spend on average only 1.2 percent of GDP on tertiary education, the larger quantitative effect of mismatch does not work through the education investment costs. Finally, we estimate the output cost of mismatch with the CES production function with an elasticity of substitution of 2, in between the range of values provided by Acemoglu and Autor (2011) (between 1.6 and 2.9). We show in Appendix F that, when high-type and low-type jobs are more substitutes in the production function, output costs of mismatch increase from 2.5% to 6.3% for education mismatch, and from 3.2% to 4.5% for skill mismatch.

5 Conclusion and Discussion

We propose a simple theory of under- and over-employment using a variation of a Roy sorting mechanism. The model matches key moments of 17 OECD economies. The output costs of mismatch lies between 2.4% and 3.2% on average but vary between -1.5 to 9% of output across countries. The key variable that explains the output cost of mismatch is not the percentage of mismatched workers but their wage relative to well-matched workers. In particular, output cost of mismatch is positive and sizeable in countries with large wage cost of under-employment. In the US, well-matched college-graduates earn 90% more than under-employed college-educated workers. This high "wage cost of under-employment" signals a sizeable scarcity of college-educated workers in skilled jobs and/or that a college degree does not improve significantly the productivity of workers in unskilled occupations. Our results then suggest that removing mismatch in the US would raise output by 6%, which appears sizeable as the US spend 2.5 % of GDP on tertiary education. Our exercise of removing all mismatch is very stylized. At the margin, reducing under-employment increases output in all the countries, but this marginal gain is related to the wage cost of under-employment.

References

Acemoglu, D. and D. Autor (2011): "Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings," Elsevier, vol. 4 of *Handbook of Labor Economics*, 1043 – 1171.

Arseneau, D. and B. Epstein (2014): "The Welfare Costs of Skill-Mismatch Employment," Finance and Economics Discussion Series 2014-042, Washington: Board of Governors of the Federal Reserve System.

Baert, S., B. Cockx, and D. Verhaest (2013): "Overeducation at the start of the career: Stepping stone or trap?" *Labour Economics*, 25, 123–140.

Barnichon, R. and Y. Zylberberg (2019): "Underemployment and the Trickle-Down of Unemployment," *American Economic Journal: Macroeconomics*, 11, 40–78.

Bauer, T. (2002): "Education mismatch and wages: A panel analysis," *Economics of Education Review*, 21, 221–229.

Borjas, G. J. (1987): "Self Selection and the Earnings of Immigrants," *The American Economic Review*, 77, 531–553.

Chassamboulli, A. (2011): "Cyclical Upgrading of Labor and Employment Differences across Skill Groups," *The B.E. Journal of Macroeconomics*, 11, 1–42.

Dolado, J. J., M. Jansen, and J. F. Jimeno. (2009): "On-the-Job Search in a Matching Model with Heterogeneous Jobs and Workers," *Economic Journal*, 119, 200–228.

Flisi, S., V. Goglio, E. C. Meroni, M. Rodrigues, and E. Vera-Toscano (2017): "Measuring Occupational Mismatch: Overeducation and Overskill in Europe:Evidence from PIAAC," *Social Indicators Research*, 131, 1211–1249.

Freeman, R. B. (1975): *The Overeducated American*, New York: Academic Press.

Grunau, P. (2016): "The impact of overeducated and undereducated workers on establishment-level productivity: First evidence for Germany," *International Journal of Manpower*, 37, 372–392.

Hanusek, E. A., G. Schwerdt, S. Wiederhold, and L. Woessmann (2015): "Returns to skills around the world : Evidence from PIAAC," *European EconomicReview*, 73, 103–130.

Julien, B., J. Kennes, and I. King (2000): "Bidding for Labor," *Review of Economic Dynamics*, 3, 619–49.

Mahy, B., F. Rycx, and G. Vermeylen (2015): "Educational Mismatch and Firm Productivity: Do Skills, Technology and Uncertainty Matter?" IZA Discussion Paper 8885.

McGowan, M. A. and D. Andrews (2015): "Labour Market Mismatch and Labour Productivity: Evidence from PIAAC Data," OECD Economics Department Working Papers 1209, OECD Publishing.

——— (2017): "Skills mismatch, productivity and policies: Evidence from the second wave of PIAAC," OECD Economics Department Working Papers 1403, OECD Publishing.

McGuinness, S. (2006): "Overeducation in the Labour Market," *Journal of Economic Surveys*, 20, 387–418.

Quintini, G. (2011): "Right for the job: over-qualified or under-skilled?" OECD Social, Employment and Migration Working Papers 120, Organisation for Economic Co-operation and Development.

Roy, A. D. (1951): "Some Thoughts On The Distribution Of Earnings," *Oxford Economic Papers*, 3, 135–146.

Sahin, A., J. Song, G. Topa, and G. Violante (2014): "Mismatch Unemployment," *The American Economic Review*, 104, 3529–3564.

Sattinger, M. (1993): "Assignment models of the distribution of earnings," *Journal of Economic Literature*, 31, 101–122.

Shimer, R. (1999): "Job Auctions." *https://pdfs.semanticscholar.org/2fb6/b8bbcb4287266b4f06ae30dc826a75dc1dc0.pdf*.

Sicherman, N. and O. Galor (1998): "A Theory of Career Mobility," *Journal of Political Economy*, 169–192.

APPENDIX: For publication if requested

A Existence and uniqueness

Substituting the wage equations on the expressions of over- and under-employment:

$$u = n\left[\frac{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-u)+\chi o}{(1-n-o)+\zeta u}\right)^{\alpha}}}{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-u)+\chi o}{(1-n-o)+\zeta u}\right)^{\alpha}} + e^{\frac{\alpha}{\nu}\left(\frac{(1-n-o)+\zeta u}{(n-u)+\chi o}\right)^{1-\alpha}}}\right] \tag{8}$$

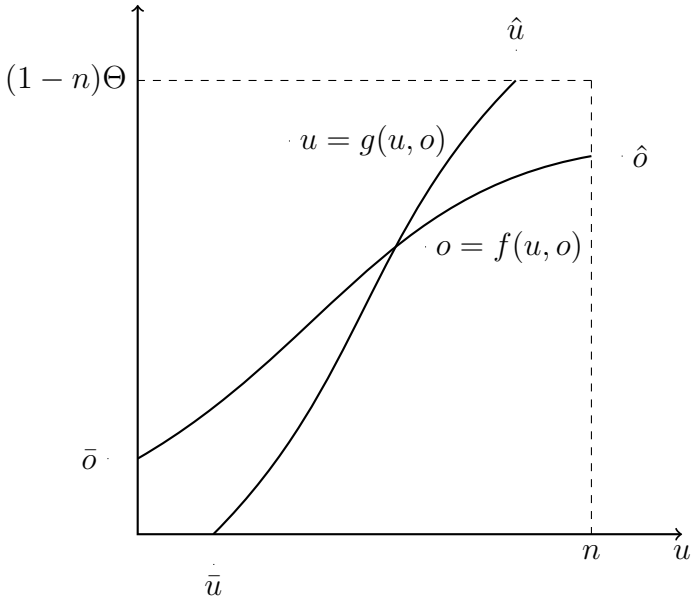
$$o = (1-n)\Theta\left[\frac{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-o)+\zeta u}{(n-u)+\chi o}\right)^{1-\alpha}}}{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-o)+\zeta u}{(n-u)+\chi o}\right)^{1-\alpha}} + e^{\frac{(1-\alpha)}{\nu}\left(\frac{(n-u)+\chi o}{(1-n-o)+\zeta u}\right)^{\alpha}}}\right] \tag{9}$$

So we end up having two equations and two unknowns

$$u = g(u(-), o(+))$$
$$o = f(u(+), o(-))$$

When evaluated at the origin, $g(0,0) = n\left[\frac{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{n}{1-n}\right)^{\alpha}}}{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{n}{1-n}\right)^{\alpha}} + e^{\frac{\alpha}{\nu}\left(\frac{1-n}{n}\right)^{1-\alpha}}}\right] > 0$ and $f(0,0) = (1-n)\Theta\left[\frac{e^{\frac{\chi\alpha}{\nu}\left(\frac{1-n}{n}\right)^{1-\alpha}}}{e^{\frac{\chi\alpha}{\nu}\left(\frac{1-n}{n}\right)^{1-\alpha}} + e^{\frac{(1-\alpha)}{\nu}\left(\frac{n}{1-n}\right)^{\alpha}}}\right] > 0$, which means the solution is above the 45 degree plane. As $g(n,0) = 0$, the solution is below the 45 degree plane and both functions are continuous, there exists an equilibrium.

The figure below plots the two functions



where $\bar{u}$, $\hat{u}$, $\bar{o}$ and $\hat{o}$ are implicitly defined by

$$\bar{u} = n\left[\frac{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-\bar{u})}{(1-n)+\zeta\bar{u}}\right)^{\alpha}}}{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-\bar{u})}{(1-n)+\zeta\bar{u}}\right)^{\alpha}} + e^{\frac{\alpha}{\nu}\left(\frac{(1-n)+\zeta\bar{u}}{(n-\bar{u})}\right)^{1-\alpha}}}\right] \tag{10}$$

$$\hat{u} = n\left[\frac{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-\hat{u})+\chi(1-n)\Theta}{(1-n)(1-\Theta)+\zeta\hat{u}}\right)^{\alpha}}}{e^{\frac{\zeta(1-\alpha)}{\nu}\left(\frac{(n-\hat{u})+\chi(1-n)\Theta}{(1-n)(1-\Theta)+\zeta\hat{u}}\right)^{\alpha}} + e^{\frac{\alpha}{\nu}\left(\frac{(1-n)(1-\Theta)+\zeta\hat{u}}{(n-\hat{u})+\chi(1-n)\Theta}\right)^{1-\alpha}}}\right] \tag{11}$$

$$\bar{o} = (1-n)\Theta\left[\frac{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-\bar{o})}{(n)+\chi\bar{o}}\right)^{1-\alpha}}}{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-\bar{o})}{(n)+\chi\bar{o}}\right)^{1-\alpha}} + e^{\frac{(1-\alpha)}{\nu}\left(\frac{(n)+\chi\bar{o}}{(1-n-\bar{o})}\right)^{\alpha}}}\right] \tag{12}$$

$$\hat{o} = (1-n)\Theta\left[\frac{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-\hat{o})+\zeta n}{\chi\hat{o}}\right)^{1-\alpha}}}{e^{\frac{\chi\alpha}{\nu}\left(\frac{(1-n-\hat{o})+\zeta n}{\chi\hat{o}}\right)^{1-\alpha}} + e^{\frac{(1-\alpha)}{\nu}\left(\frac{\chi\hat{o}}{(1-n-\hat{o})+\zeta n}\right)^{\alpha}}}\right] \tag{13}$$

To show that they only cross once, it is sufficient that the slope of the $u = g(u, o)$ is always steeper than the other. Applying the total differentiation to the condition of under-employment

$$\frac{du}{do}\mid_g = \frac{\chi j_l + j_h}{\Omega_1 + j_l + \zeta j_h} \tag{14}$$

and doing the same to the condition of over-employment

$$\frac{do}{du}\mid_f = \frac{j_l + \zeta j_h}{\Omega_2 + \chi j_l + j_h} \tag{15}$$

where $\Omega_1 = \frac{n j_h j_l \nu}{(n-u)u(\zeta\alpha w_l + (1-\alpha)w_h} > 0$ and $\Omega_2 = \frac{(1-n)\Theta j_h j_l \nu}{((1-n)\Theta - o)o(\alpha w_l + \chi(1-\alpha)w_h} > 0$.
Calculating the ratio we can show it is always larger than 1.

$$\frac{\frac{1}{\frac{du}{do}\mid_g}}{\frac{do}{du}\mid_f} = 1 + \frac{\Omega_1}{j_l + \zeta j_h} + \frac{\Omega_2}{\chi j_l + j_h} + \frac{\Omega_1\Omega_2}{(j_l + \zeta j_h)(\chi j_l + j_h)} > 1 \tag{16}$$

B Model fit

Table 2 displays the model fit for the education mismatch and the skill mismatch, respectively. The model fit is very good.

Table 2: Education and Skill Mismatch: Model Fit

	o		u		$\frac{w_1}{\zeta w_2}$		$\frac{w_2}{\chi w1}$		$\frac{w_1}{w_2}$	
country	data	model	data	model	data	model	data	model	data	model
Education Mismatch										
Belgium	0.0750	0.0750	0.1031	0.1031	1.2017	1.2017	0.7663	0.7663	1.4590	1.4590
Cyprus	0.0830	0.0830	0.1591	0.1591	1.7680	1.7680	0.7151	0.7151	1.8889	1.8890
Czech Rep.	0.0654	0.0654	0.1093	0.1093	1.3012	1.3012	0.7067	0.7066	1.8645	1.8645
Denmark	0.0640	0.0640	0.1297	0.1297	1.2146	1.2146	0.8373	0.8373	1.3860	1.3860
France	0.0530	0.0530	0.1326	0.1326	1.4013	1.4013	0.7453	0.7453	1.6220	1.6221
Germany	0.0284	0.0284	0.1696	0.1696	1.3811	1.3813	0.6898	0.6896	1.8887	1.8891
Ireland	0.0739	0.0739	0.1685	0.1685	1.6454	1.6454	0.7417	0.7417	1.8572	1.8573
Italy	0.0394	0.0394	0.1024	0.1024	1.4563	1.4563	0.7519	0.7519	1.8357	1.8357
Japan	0.0947	0.0947	0.1532	0.1532	1.6557	1.6557	0.7016	0.7016	1.7729	1.7729
Korea	0.0937	0.0937	0.1286	0.1286	1.8977	1.8977	0.8369	0.8369	2.1024	2.1024
Netherlands	0.0877	0.0877	0.0972	0.0972	1.3376	1.3376	0.7614	0.7614	1.7120	1.7120
Norway	0.0762	0.0762	0.0940	0.0940	1.1561	1.1561	0.7379	0.7379	1.3986	1.3985
Poland	0.0956	0.0956	0.1002	0.1002	1.5853	1.5853	0.7803	0.7803	1.9090	1.9090
Spain	0.0486	0.0486	0.1672	0.1672	1.8326	1.8328	0.7590	0.7589	2.2753	2.2755
Sweden	0.0643	0.0643	0.1205	0.1205	1.1872	1.1873	0.7608	0.7689	1.2871	1.3006
UK	0.1016	0.1016	0.1465	0.1465	1.7139	1.7139	0.6759	0.6759	1.9950	1.9950
Usa	0.0885	0.0885	0.1313	0.1313	1.9400	1.9400	0.7049	0.7049	2.4076	2.4075
Skill Mismatch										
Belgium	0.1436	0.1436	0.1182	0.1182	1.2979	1.2979	0.7420	0.7420	1.5100	1.5100
Cyprus	0.1829	0.1829	0.1706	0.1706	1.7738	1.7737	0.6333	0.6333	2.0974	2.0974
Czech Rep.	0.1063	0.1063	0.2294	0.2294	1.3922	1.3922	0.7179	0.7179	1.6276	1.6276
Denmark	0.1650	0.1650	0.1275	0.1274	1.4562	1.4273	0.8256	0.8256	1.4005	1.4273
France	0.1072	0.1072	0.1775	0.1775	1.3892	1.3892	0.7419	0.7419	1.5640	1.5640
Germany	0.1031	0.1031	0.2045	0.2045	1.4826	1.4827	0.6591	0.6591	1.7185	1.7185
Ireland	0.1399	0.1399	0.1839	0.1839	1.6173	1.6173	0.7113	0.7113	1.7949	1.7949
Italy	0.1697	0.1697	0.1450	0.1450	1.6119	1.6120	0.7069	0.7069	1.7533	1.7534
Japan	0.1168	0.1168	0.1704	0.1704	1.5376	1.5376	0.6397	0.6397	1.8158	1.8158
Korea	0.1146	0.1146	0.1876	0.1876	2.0357	1.9631	0.7646	0.7646	1.9001	1.9631
Netherlands	0.1449	0.1449	0.1550	0.1550	1.6228	1.6228	0.7096	0.7096	1.7035	1.7034
Norway	0.1551	0.1551	0.1353	0.1353	1.3952	1.3952	0.7639	0.7639	1.4349	1.4349
Poland	0.1172	0.1172	0.2255	0.2255	1.7457	1.7456	0.6857	0.6857	2.0043	2.0044
Spain	0.1294	0.1294	0.1780	0.1780	1.9525	1.9525	0.6911	0.6911	2.2003	2.2003
Sweden	0.1576	0.1576	0.1467	0.1467	1.3382	1.3382	0.8174	0.8174	1.3637	1.3637
UK	0.1418	0.1418	0.1496	0.1496	1.7319	1.7319	0.7018	0.7018	2.0393	2.0394
Usa	0.1240	0.1240	0.1782	0.1782	1.9362	1.9362	0.6501	0.6501	2.1681	2.1682

C Further results

We regress output costs on the deep parameters using simulated data (Table 3). We also perform multivariate regression on observable variables (Table 4). With multivariate regression, we include all variables in the regression and report the change in R-squared when one variable is excluded. The main take away is consistent with the message from the main text: well-matched wage premium for high-type workers is the primary drivers for output costs. When this variable is excluded from the regression, the drop in R-squared is sizeable (25.6 to 34.4 percentage points).

Table 3: Univariate Regression Of Output Cost Of Mismatch On Parameters

	Education mismatch		***Skill mismatch***	
Variable	**coef. (t-stat)**	**[R-squared]**	**coef. (t-stat)**	**[R-squared]**
n	6.98 (33.43)	[0.046]		
ν	0.05 (2.10)	[0.000]	2.06 (46.74)	[0.123]
Θ	9.60 (39.98)	[0.065]	3.24 (13.67)	[0.012]
χ	-14.30 (-159.72)	[0.526]	-23.29 (-165.38)	[0.636]
ζ	-5.11 (-40.59)	[0.066]	-13.67 (-47.99)	[0.128]
α	14.59 (194.45)	[0.280]	21.65 (48.02)	[0.129]
Obs.		(22,996)		(15,625)

The table shows coefficient, t-statistic and R-squared of the univariate regression of the model-based output costs of mismatch on each observable variable separately. n share of high-type workers in employment. u and o, share of under-employed and over-employed workers, respectively, in total employment. $\frac{w_h}{w_l}$ *high-type wage premium of well-matched workers.* $\frac{w_h}{\zeta w_l}$ *well-matched premium of high-type workers relative to under-employed.* $\frac{w_l}{\chi w_h}$ *well-matched loss of low-type workers relative to over-employed.*

Table 4: Multivariate Regression of Output Cost Of Mismatch On Observable Variables and Parameters

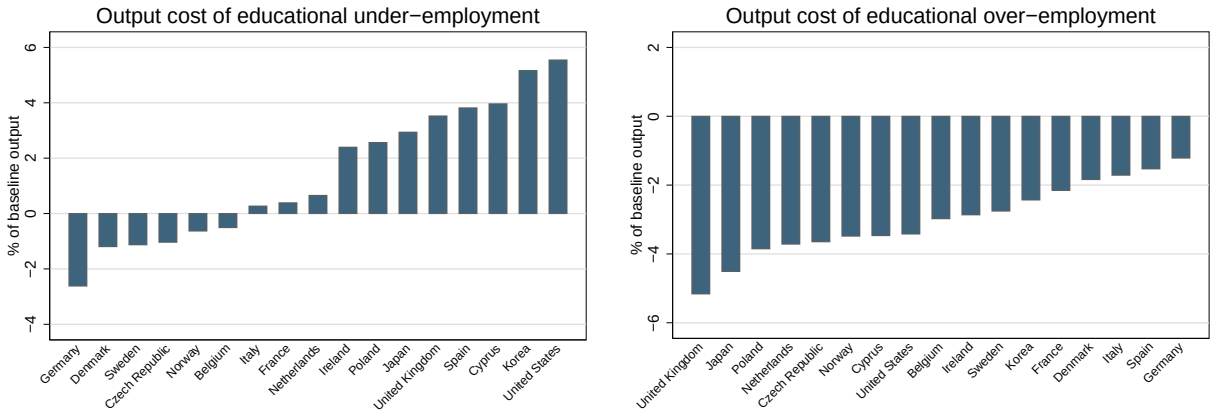
	Education mismatch		***Skill mismatch***	
Variable	**coef. (t-stat)**	**[Δ R-squared]**	**coef. (t-stat)**	**[Δ R-squared]**
n	2.29 (39.56)	[0.003]		
o	17.40 (121.38)	[0.027]	4.17 (27.67)	[0.001]
u	-5.43 (-29.76)	[0.002]	17.51 (127.71)	[0.003]
$\frac{w_h}{w_l}$	-0.13 (-7.17)	[0.000]	0.66 (18.87)	[0.001]
$\frac{w_h}{\zeta w_l}$	10.68 (435.71)	[0.344]	13.17 (372.30)	[0.256]
$\frac{w_l}{\chi w_h}$	7.19 (108.63)	[0.021]	17.37 (277.78)	[0.142]
$cons$	-20.38 (-322.85)		-34.79 (-439.51)	
R^2 (obs.)	0.958	(22,996)	0.971	(15,625)
n	-16.84 (-118.91)	[0.040]		
ν	0.61 (60.04)	[0.010]	2.12 (129.53)	[0.076]
Θ	-1.25 (-15.04)	[0.001]	-2.31 (-31.81)	[0.005]
χ	-13.11 (-239.88)	[0.164]	-20.64 (-282.82)	[0.360]
ζ	-11.03 (-296.47)	[0.250]	-15.89 (-191.61)	[0.165]
α	22.27 (136.66)	[0.053]	16.57 (91.92)	[0.038]
$cons$	22.44 (136.66)		28.47 (161.61)	
R^2 (obs.)	0.935	(22,996)	0.930	(15,625)

The table shows coefficient, t-statistic, R-squared of the multivariate regression of the model-based output costs of mismatch on all parameters. In square brackets, we show the reduction of the R-squared when removing the explanatory variable.

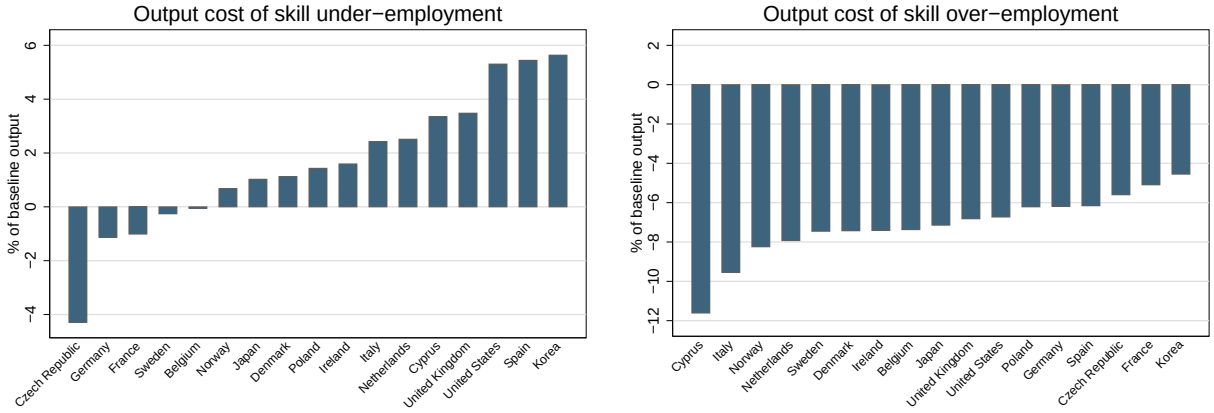
Finally, Figure 4 shows the output costs of under-employment and over-employment, by shutting each one in turn.

Figure 4: Baseline calibration: Output costs of mismatch

Education: Removing under- and over-employment separately



Skill: Removing under- and over-employment separately



Note: Model simulations. The graphs plot the percentage variation of output relative to baseline when setting $u = 0$ *(left-hand graph) and* $o = 0$ *(right-hand graph).*

D Qualification mismatch

D.1 Calibration

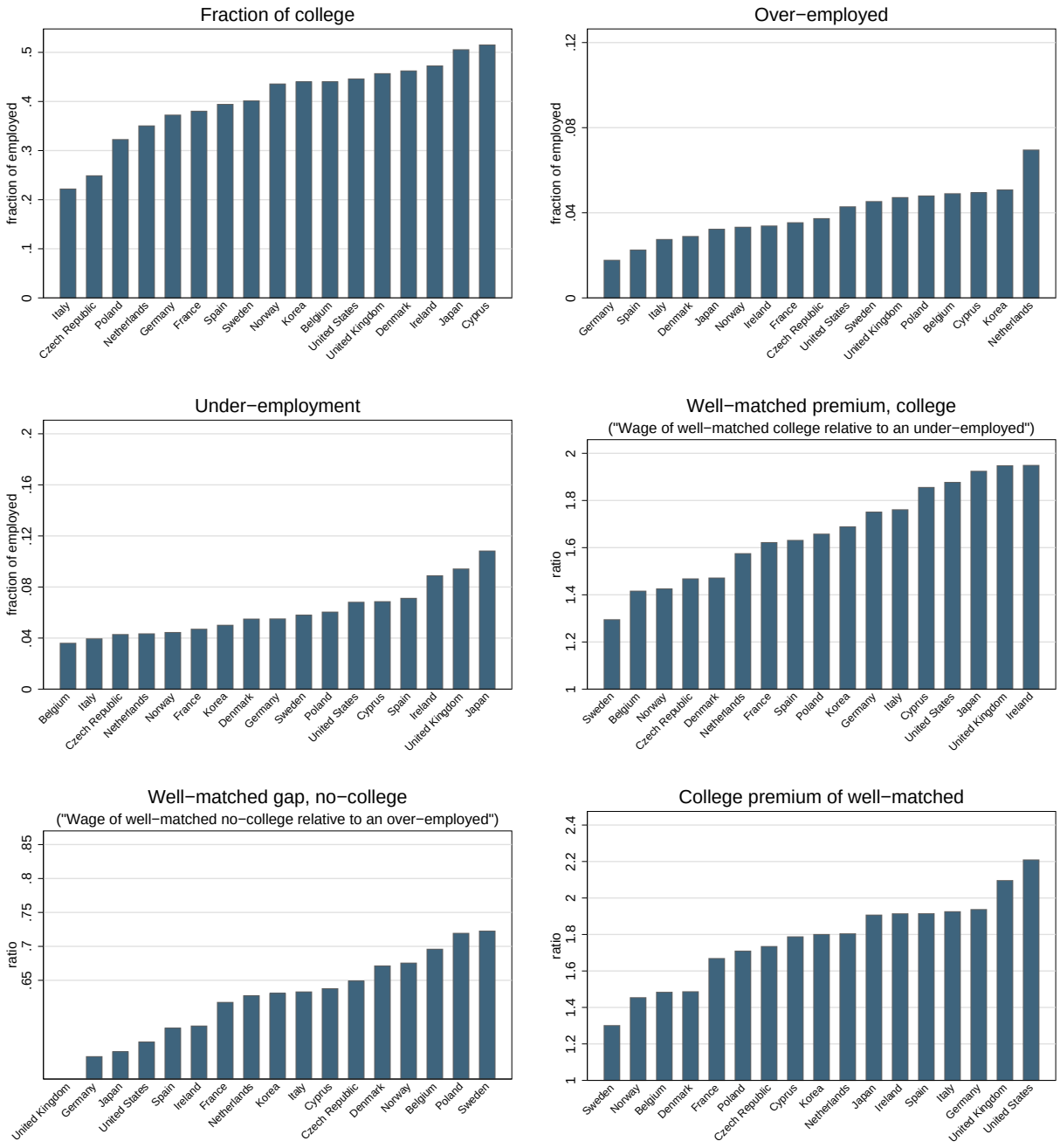
Following McGowan and Andrews (2017), we explore qualification mismatch. We use a benchmark of "appropriate" qualifications required to get the job is based on the following question: "*If applying today, what would be the usual qualifications, if any, that someone would need to get this type of job?*". The respondent's reply is a qualification measured by the International Standard Classification of Education (ISCED) level. This self-reported required education is compared to actual educational attainment. Any respondent with educational attainment above (below) this benchmark are classified as over-qualified (under-qualified).

Consistently with our conservative approach, we combine this subjective measure of mismatch with an objective measure. The education-based objective measure appears as a natural candidate.

Consistently with the model, we consider 2 levels of qualification: college versus non-college. An over-qualified (under-qualified) worker is a college graduate (non-college) who thinks that her job requires non-college (college) education and works in an occupation that is majority non-college (college). The share of high-type workers n is similar to the education-based mismatch in the main text.

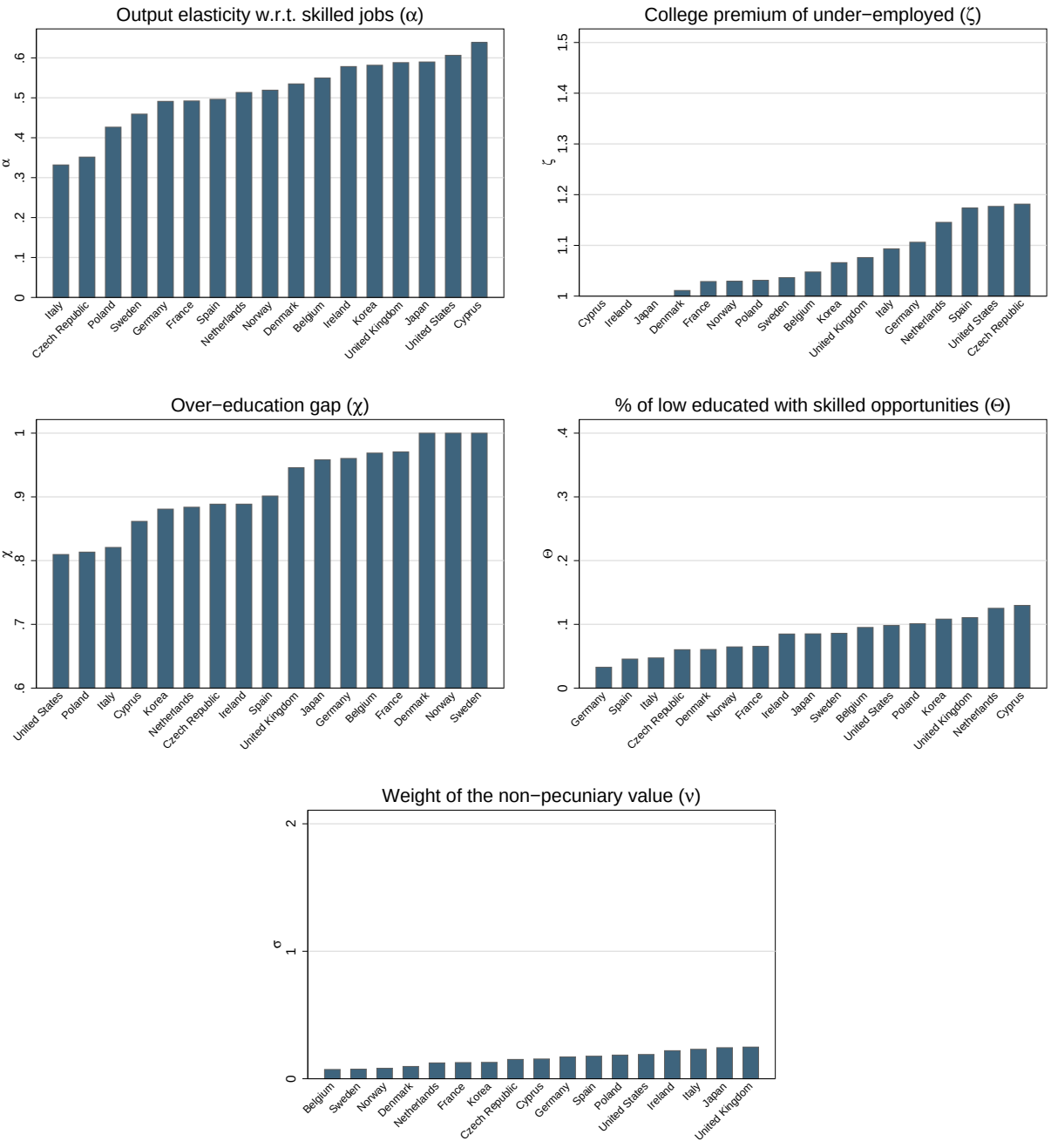
Figures 5 and 6 report the empirical targets and calibrated parameters. The average incidence of under-employment (over-employment) is 6% (3%), which is lower than the incidence found using education-based or skill-based measure.

Figure 5: Qualification mismatch: Calibration targets



Note: All calculatedd from PIAAC data.

Figure 6: Qualification mismatch: Calibrated parameters

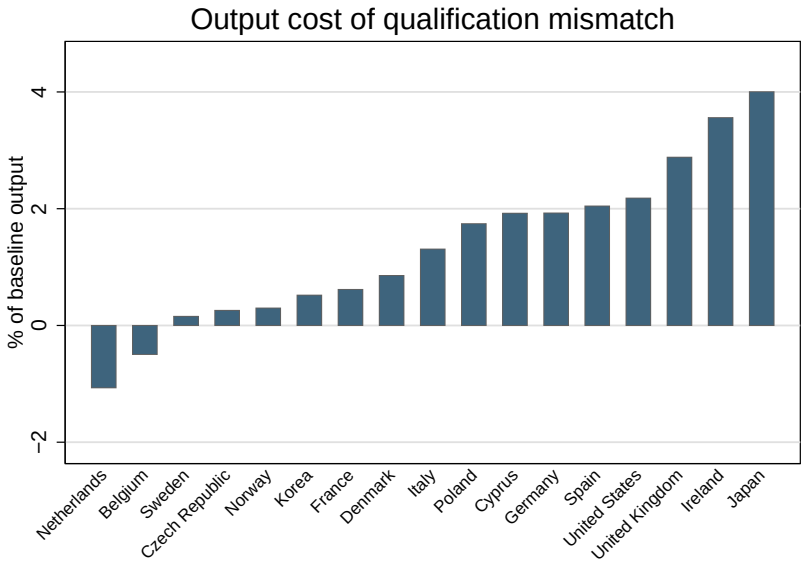


Note: Estimated to fit empirical targets.

D.2 Output costs of qualification mismatch

Figure 7 displays the output costs of mismatch. The average output cost of mismatch is 1.3%, with large cross-country differences (-1%, -0.5% in the Netherlands versus 3.5% to 4% in Ireland and Japan). Using our conservative measure, under- and over-employment appear limited (3% and 6% of employed workers, respectively), such that, in all countries, the baseline economy is close to the zero-mismatch economy. In spite of this apparently limited scope for mismatch, the output costs could be as large as 2% to 4% of output for 7 of our 17 countries.

Figure 7: Output costs of qualification mismatch ($u = o = 0$)



Note: Model simulations. The graph plots the percentage variation of output relative to baseline when setting $u = o = 0$.

E Extension: Endogenous Education

To have a better understanding of how the costs of education mismatch are amplified or mitigated by the presence of endogenous education, we introduce it in a very reduced form. We assume that prior to the market, agents decide whether to invest in higher education by comparing the returns of education with its cost. We assume the returns of education are calculated under the veil of ignorance i.e. without knowing the "non-pecuniary" value of different jobs. The cost of education c is drawn from a log-normal distribution G that has mean μ and variance σ. The values of having or not education are given by:

$$V_h = \left(1 - \frac{u}{n}\right) w_h + \frac{u}{n} \zeta w_l + \nu \Psi_h \tag{17}$$

$$V_l = \left(1 - \Theta \frac{o}{1-n}\right) w_l + \Theta \frac{o}{1-n} \chi w_h + \nu \Psi_l \tag{18}$$

Where Φ_i refers to conditional expected value for "non pecuniary" job value ϵ_i, which are give by

$$\Psi_h = \int_{-\infty}^{\infty} \int_{\frac{\zeta w_l - w_h}{\nu} + \epsilon^l}^{\infty} \epsilon^h f(\epsilon^h) d\epsilon^h f(\epsilon^l) d\epsilon^l + \int_{-\infty}^{\infty} \int_{-\frac{\zeta w_l - w_h}{\nu} + \epsilon^h}^{\infty} \epsilon^l f(\epsilon^l) d\epsilon^l f(\epsilon^h) d\epsilon^h$$

$$\Psi_l = (1-\Theta)(\int_{-\infty}^{\infty} \epsilon^l f(\epsilon^l) d\epsilon^l) + \Theta \left(\int_{-\infty}^{\infty} \int_{\frac{w_l - \chi w_h}{\nu} + \epsilon^l}^{\infty} \epsilon^h f(\epsilon^h) d\epsilon^h f(\epsilon^l) d\epsilon^l + \int_{-\infty}^{\infty} \int_{-\frac{w_l - \chi w_h}{\nu} + \epsilon^h}^{\infty} \epsilon^l f(\epsilon^l) d\epsilon^l f(\epsilon^h) d\epsilon^h \right)$$

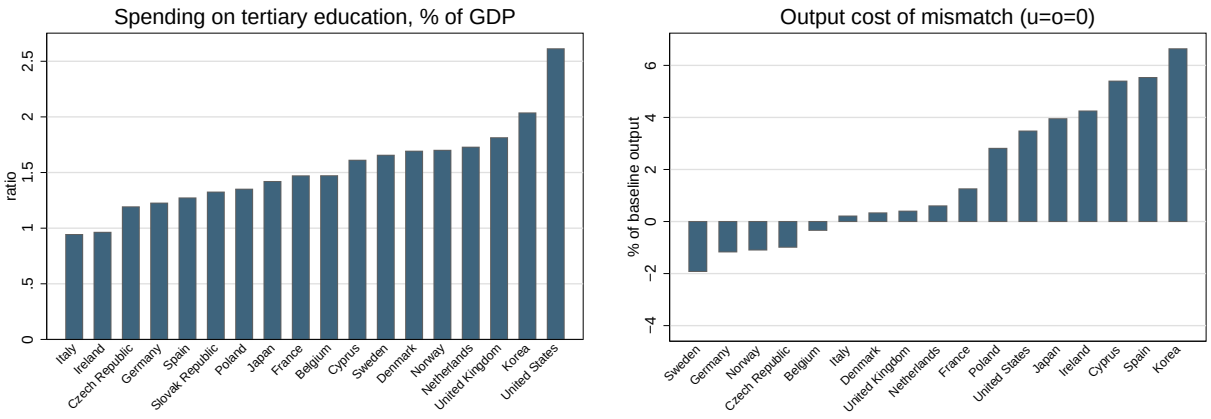
In equilibrium the cost cut-off, c^* above which people decide not to get educated equate $V_h - V_l$, and the fraction of educated worker, now endogenous, is given by

$$n = G(V_h - V_l) \tag{19}$$

which adds to the previous four equilibrium conditions.

For calibration, the mean of the distribution to match the fraction of college graduates (which was previously exogenous) and the variance of the distribution to target an average spending on tertiary education relative to GDP, taken from OECD Statistics (average over 2011-2015, the same period as PIIAC data). We succeed in matching well fairly both statistics for 17 countries. Our results are robust to the introduction of endogenous education, although the average output cost of mismatch is lower by 0.8 percentage points.

Figure 8: Model with endogenous education: calibration target and output cost

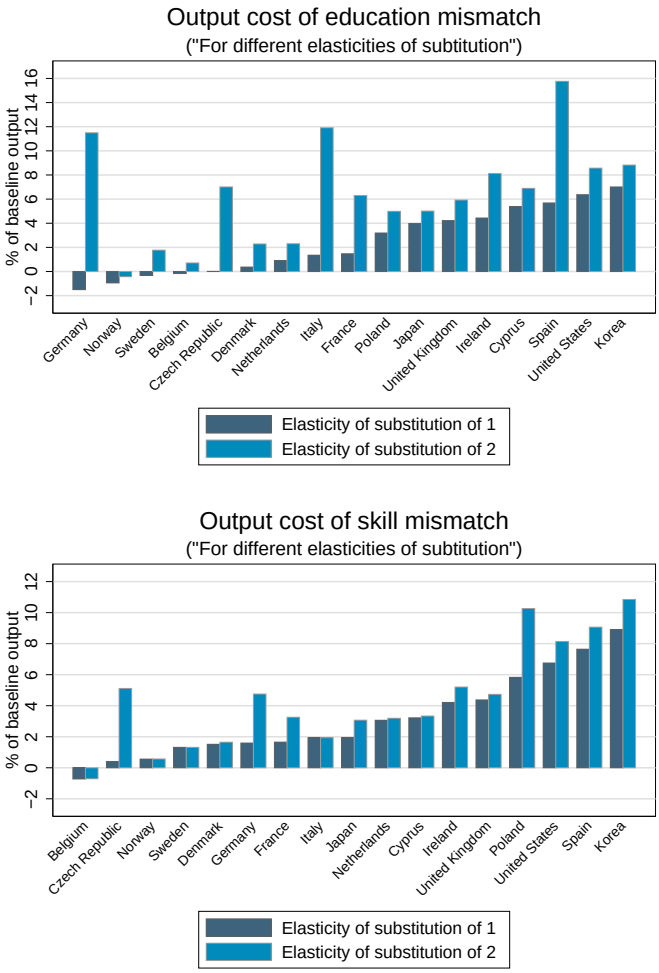


Note: The data of spending on tertiary education relate to GDP is taken from OECD statistics is used as target in calibration. The output cost, based on the model simulations, refers to total output net of education cost when setting $u = o = 0$ relative to baseline.

F CES production function

Figure 9 displays output costs of mismatch when the production function is CES. We present results when the elasticity of substitution between high-type and low-type jobs is 1 (baseline model) and 2. We show that output costs of mismatch, whether education or skill mismatch, increase when high- and low-type jobs are more substitutes.

Figure 9: Output cost of mismatch with CES production function



Note: Model simulations. The graph plots the percentage variation of output relative to baseline when setting $u = o = 0$.