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LABOR MARKET IMPLICATIONS OF EDUCATION MISMATCH

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Labor Market Implications of Education MisMatch*

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Abstract

This project studies the impact of education mismatch on labor outcomes. Across our sample of OECD countries, there is evidence of mismatch in education choices and labor markets. Labor market outcomes are not independent of education mismatch. Our framework for analysis is a dynamic choice model, focusing on decisions on education and training. From the estimation of model parameters, the main factor explaining education mismatch is a shock to the perceived value of education. In Germany, imperfect information about ability at the time of the education decision creates mismatch as well. From simulations of lifecycle dynamics and counterfactual experiments, among four key countries, education undermatch in Japan is sustained through labor market mechanisms while in Germany, Italy and the US, education undermatch is resolved. Training plays a key role in these dynamics.

1 Motivation

Productive efficiency requires the matching of high ability individuals to appropriate education levels and eventually to jobs commensurate with their ability and training. Inefficiencies can arise in the form of education mismatch, job mismatch or both. The output loss from mismatch can be substantial. Mitigating mismatch has been a policy goal for individual countries and international organizations, such as the OECD and the International Labor Organization.[1] Absent an understanding of the sources of mismatch and their interaction, designing policy remedies is quite difficult. While there is a large and insightful literature on education and job mismatch in isolation, the point of this paper is to study their joint determination with a particular emphasis on isolating the effects of education mismatch on labor market outcomes.

Throughout, education mismatch refers to the lack of assortative matching between education and ability: that is, it occurs when high ability agents are not always the most educated while some low ability agents have high educational attainment. Imperfect capital markets, different tastes for education and information frictions about education opportunities and individuals' ability are possible sources of (measured) education mismatch. Job (labor market) mismatch refers to the efficiency loss relative to assortative matching between skills and types of occupation. It can arise from frictions in labor market reallocation like imperfect information, discrimination, training decisions and labor market regulations.

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[1]MisMatch was part of a hot issues discussion by the OECD in March 2016 and there is a dashboard dedicated to ongoing research and topics on skills development: `http://www.oecd.org/skills/`. For the International Labor Organization see `https://www.ilo.org/skills/Whatsnew/WCMS_740388/lang--en/index.htm`.

Earlier work, such as Pellizzari and Fichen (2013), McGowan and Andrews (2015), Dillon and Smith (2017) and Cooper and Liu (2019), study these forms of mismatch in isolation. Education mismatch might imply labor market misallocations since the information value of a degree could be reduced and distorted. In this sense, education mismatch can create further information frictions in the allocation of individuals to jobs. The causality could run the other way. The extent to which the labor market is able to efficiently allocate skills into occupations, for example, affects the return to the acquisition of those skills through education. Thus, labor market mismatch might impact education decisions.

Our main goal is to evaluate the extent that labor market institutions offset or perpetuate education mismatch. Focusing specifically on those undermatched in education, what are their labor market outcomes? We find that indeed labor market institutions do overcome this mismatch in Germany, Italy and the US. This is not the case in Japan. The mechanism for these labor market transitions, highlighted by the paper, is informal training.

The first part of the paper, Section 2, provides evidence of both forms of mismatch using data from the OECD Program of International Assessment of Adult Competences (hereafter PIAAC). Individuals' jobs are divided into two categories: (i) skilled and (ii) unskilled occupations. For educational attainment, we define a dichotomous variable indicating two levels: (i) below college and (ii) college and above. PIAAC scores are used as noisy measures of ability.

The distributions of PIAAC scores conditional on educational attainment overlap: there are individuals with a low level of education but a higher PIAAC score than those with high education. A similar pattern is observed for the distributions conditional on types of occupation: there are individuals in an unskilled occupation but with a higher PIAAC score than those with a skilled one. Our methodology for characterizing labor market mismatch is not a statement about job satisfaction but rather the assignment of workers to skilled jobs based upon their ability.[2]

Our initial empirical analysis brings together evidence on the labor market implications of education outcomes. A first exercise adds the measures of education mismatch to standard Mincer wage regressions, building on Hanushek, Schwerdt, Wiederhold, and Woessmann (2015). Pooled regressions find positive and significant wage coefficients for individuals undermatched in education and negative for those who were overmatched in education. This means that an individual overmatched (undermatched) in education have a lower (higher) return to education. But at the individual country level these effects are not statistically significant though our dynamic simulations uncover these differences in compensation, particularly for the education undermatched group.

A second exercise looks at job flows, drawing upon the PIAAC data, to analyze the effect of education mismatch on job assignment in early employment. In our pooled sample, around 39% (37%) of the individuals that were overmatched (undermatched) in education, are also overmatched (undermatched) in the job. Similarly, around 39% (33%) of the individuals undermatched (overmatched) in the job, were also undermatched (overmatched) in education. This is part of the evidence that labor market outcomes are impacted by education mismatch.

The last section of the empirical analysis studies assignment to informal training for early workers.[3] Offering training to high-ability individuals, initially undermatched in education, would allow them to acquire the necessary skills and then efficiently use them in the labor market. The key issue is selection into training. We find that the type of occupation in early employment is an important determinant in the assignment

[2] Similarities and differences with the approach of McGowan and Andrews (2015) are discussed below.
[3] We discuss our measure of training in some detail below.

to informal training, with college and specially our proxy for ability, playing a minor role. Specifically, individuals with skilled jobs in our sample in early employment are more likely to receive informal training than individuals with unskilled jobs.

To understand the sources of education and job mismatch, their interaction and dynamic implications, we construct a model economy, presented in Section 3, combining heterogeneous individuals, differing in ability, and jobs with different skill requirements. Individuals make education and labor market decisions. Education choices are influenced by tastes for education, capital market frictions and the labor market institutions that will ultimately determine the return to college. A strong negative taste for education may induce, for example, high ability agents to choose not to go to college.[4] This case would indicate mismatch but the allocation may still be efficient, though not output maximizing. In a setting with imperfect capital markets, relatively high ability agents may choose a low level of education simply because of a binding borrowing constraint. So both variations in tastes and binding borrowing constraints can induce education mismatch. As in Cooper and Liu (2019), there is another source of education mismatch in the model associated with ability being measured instead of observed: individuals make education decisions based upon their true ability but PIAAC score are imperfect signals of ability.

The allocation of workers in the labor market is based, in part, on the education choice: educated workers are more likely to be assigned to skilled jobs and workers with no education are more likely to be allocated to unskilled jobs. However, the flows into skilled and unskilled jobs observed in the data indicate that educational attainment is not the only factor determining job. Thus, the assignment of individuals to jobs will be indirectly influenced also by individuals' ability. To do so, the model allows for informal training during an early work phase of life. As with education, training increases individuals skills at the cost of devoting less time to productive activities. Further, training and education will impact both productivity and individuals job assignment in the late work phase of life.

Country specific parameters of the model are estimated using simulated method of moments capturing mismatch in both education and labor allocation and their interconnection. A main outcome of the estimation, presented in Section 4, is a quantitative assessment of the sources of education mismatch and the consequences for labor market outcomes. The analysis addresses these points through the choice of appropriate moments and counterfactual exercises.

From the estimation, a main cause of educational mismatch are taste shocks.[5] For Germany, this is supplemented with noise about ability at the time of the education decision, consistent with the discussion of early sorting into education.[6]

The estimated model is used in Section 6 to generate dynamics that are not directly seen in the PIAAC data, as it is a single cross section. This allows us to determine, for example, the probability an agent is mismatched in the job, both early and late, given, say, education undermatch. This is an important thought experiment as it makes clear the extent to which labor market flows compensate for education mismatch.

From the perspective of resolving education undermatch, there are marked differences across countries. At one extreme is Japan where undermatch in education is sustained through job assignments and training. Specifically, almost 80% of individuals undermatched in education are assigned low skilled jobs and none of them choose to train. As a consequence they remain trapped in these jobs through their working lifetimes. In contrast, in Germany, Italy and the US, the undermatched in education fare better, in part because they

[4]As developed below, there are a number of interpretations for this taste shock, both in terms of its representation in the model and potential sources.

[5]This result differs from that of Cooper and Liu (2019). The source of these differences in results are discussed in detail below.

[6]For a discussion of this system and an emphasis on it flexibilities, see Dustmann, Puhani, and Schönberg (2017).

are assigned a high skill job with higher probability than in Japan. Moreover, those assigned a low skill job are very likely to train and are subsequently placed in a high skill job. In the US, for example, about 70% of undermatched individuals are eventually placed in high skilled jobs. And, in these three countries, the compensation to the undermatched in education is considerably higher than the average paid to the well matched, in education, with no college.

As for the education overmatched, in Italy almost none of these individuals remain in skilled jobs through their working lives. In the US, more than 80% of overmatched in education individuals are assigned skilled jobs late in their careers. This rate is slightly lower in Germany and Japan.

The estimation is supplemented by a counterfactual exercise that considers alternative labor market institutions. Specifically, we make two important modifications. First, all individuals with college are assigned to skilled jobs and cannot be reassigned to unskilled ones. Second, non-college education individuals are assigned to unskilled jobs and can only be reassigned to skilled jobs in late employment through training. We find, as in the baseline analysis, that, for these alternative institutions, training continues to correct for education undermatch in Germany, Italy and the US.

A final discussion, Section 7, provides a country perspective. That is, instead of looking at the model and its predictions from the viewpoint of sources and consequences of mismatch, the outcomes by country are discussed. This facilitates an understanding of how education and labor market institutions that differ across countries might impact mismatch.

Related Literature

This project is obviously related to the vast literature on the sources and consequences of education mismatch and labor market misallocations: including Dillon and Smith (2017), Abbott, Gallipoli, Meghir, and Violante (2019), McGowan and Andrews (2015), Pellizzari and Fichen (2013), Cooper and Liu (2019) and Garibaldi, Gomes, and Sopraseuth (2020).

We contribute to this literature in three important ways. First, our theoretical model allows both sources of mismatch allowing us to evaluate the effects of education mismatch on labor market allocations. Studies of education mismatch generally focus on its effects on the economy production capacity and ignore the presence of other labor market frictions. At the same time, studies of labor market mismatch focus only on frictions happening in the labor market and do not take into account distortions to the education choice. Second, we add to the literature related to labor market inefficiencies from training decisions by evaluating the role of training in overcoming education undermatch. Third, the use of PIAAC data, allows us to conduct a cross-country comparison of the interconnection of both types of mismatch and discuss aspects of institutional structures that underlie the observed relationship.

Flinn and Mullins (2015) also look at the interaction of education choices and labor market outcomes. Their emphasis is on the role of labor market frictions and worker bargaining power on education choices. There is no education mismatch in their model. Our emphasis, in contrast, in on the effects of education frictions, leading to mismatch, on labor market outcomes without the presence of additional labor market frictions. From their analysis, it is clear how labor market frictions impact education rates without creating education mismatch.

Our paper also adds to the literature on the importance of pre-labor market conditions for lifetime earnings. Huggett, Ventura, and Yaron (2011) find that, as of age 23, differences in ability to learn, human capital, and wealth account for more of the variation in lifetime earnings, lifetime wealth, and lifetime utility than do differences in shocks received over the working lifetime. Our paper also assumes that difference in human capital are crucial in determining the life cycle position in the labor market although the focus and methodology are very different.

There are numerous papers that focus on training, both selection into training and its effects on future earnings and job assignment. Our contribution is to stress the role of training in overcoming education mismatch. The existing literature stresses the role of the hold-up problem as a disincentive for the accumulation of human capital, including training. In a setting with education and labor frictions, Flinn, Gemici, and Laufer (2017) study the determinants into training. But education is exogenous and there is no education mismatch. Thus the interaction between mismatch and training is not studied.

Given the interest in lifelong learning, it is not surprising that the PIAAC data has been used as a source of information on training and its consequences. A few of those studies relate directly to our goal of understanding the interaction between mismatch and training.

Martin (2018) provides a general assessment of the use of the PIAAC data, with some emphasis on both skill mismatch and lifelong learning. Martin (2018) notes that "In all countries, those workers with the most education and skills participate far more in learning opportunities than their peers with less education and skills."

Brunello and Rocco (2015) study the Adult Education and Training (AET) in the PIAAC data. In terms of selection into training, they discuss evidence that training is more likely for individuals with higher educational attainment and more likely for younger individuals. As for the effects of training on labor market outcomes, they argue that training leads to both higher wages and present limited evidence that skills improve.

Cabrales, Dolado, and Mora (2017) study training in Spain and in other PIAAC countries. Their focus is on the interaction of job protection measures and training. They emphasize the interaction between training and the type of employment contract, temporary vs. permanent. Some of their findings for Spain are relevant for our model and its implications. They find a positive association between training and the accumulation of skills, measured by the PIAAC tests. On job assignment, they find that higher test scores are positively related to permanent jobs. And, perhaps most importantly, they argue that workers with temporary jobs are less likely to receive training.

The result that the type of contract is linked to training is most intriguing for us as it indicates another potential channel for the resolution of mismatch. However, using data for our 4 countries, there is no evidence that mismatch in education is related to the assignment of permanent versus temporary contracts.[7]

Another related study is Gauly and Lechner (2019) which focuses on selection bias and the evaluation of training outcomes. Like studies of the return to formal education, determining the effects of training requires some control for selection. Gauly and Lechner (2019) study this for Germany, supplementing the PIAAC data for Germany with a follow-up longitudinal study specifically for Germany. Combining these data sets allows them to distinguish selection effects from the impact of training on skills. They conclude that the selection effects are quite strong and essentially accounts for the positive correlation of training and skills.

There is another related literature, such as Kawaguchi and Murao (2014) for OECD countries, that focuses on the effects of aggregate conditions at the top of an individual's first job on labor market outcomes later in life.[8] The discussion there points to the effects of differences in labor market institutions on the persistent effects of initial conditions. While our study is not about aggregate conditions, the same persistent effect of initial conditions such as education mismatch may depend on labor market institutions. We return

[7] This was also largely the case in Spain as well, the focus of Cabrales, Dolado, and Mora (2017), though overmatched individuals had a slightly higher rate of permanent attachment.

[8] Liu, Salvanes, and Sørensen (2016) provide a detailed account for Norway.

to this point below specifically in the case of Japan.

Finally, to be clear on language, throughout we refer to education mismatch as reflecting the misallocation of individuals with respect to educational outcomes. And we refer to labor mismatch as denoting the misallocation of individuals with respect to job assignment. Some of the literature uses the terms education mismatch to denote the misallocation of workers, based upon their education, to jobs. And, some of the literature studies the co-existence of vacancies and unemployed workers as mismatch.

2 Facts

This section provides initial evidence on education and labor market mismatch and their interaction. It also includes evidence on the selection to training. These facts are used in part to motivate our analysis and also to provide a basis for the structural estimation that follows.

The main data source for this analysis is the Survey of Adult Skills from PIAAC. The use of PIAAC data is crucial to conduct a cross-country comparison of the relationship between ability, educational attainment and labor market allocations. The survey assesses the proficiency of adults aged 16-65 in three domains: literacy, numeracy and problem solving in technology-rich environments.

Before the skill assessment, all participants responded to a background questionnaire that provides information in four main areas: (i) basic demographic characteristics of respondents, (ii) education attainment and participation in learning activities, (iii) labor force status and employment and (iv) the use of skills at work and in daily life. Our analysis includes participants aged 25 to 54, excludes self-employed individuals and uses data from 21 participating countries from the first round of the survey: Austria, Belgium, Canada, Czech Republic, Denmark, England, Estonia, Finland, Germany, France, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Slovak Republic, Spain, Sweden and the United States (US).[9] We report results for pooled sample and for 4 individual countries: Germany, Italy, Japan and the US.[10]

To study the relationship between ability and educational choices, we use the PIAAC numeracy score as a signal of cognitive ability. For the analysis relating skills and types of occupation, we add individuals' proficiency in literacy and problem solving. Thus, we use the average of the three dimensions as signal of individuals' skills in the labor market.

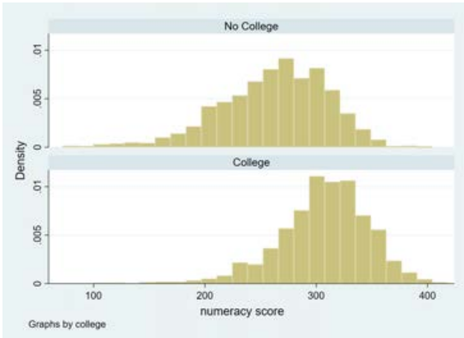
There are standard concerns with the use of PIAAC scores as measures of ability. First, as with all tests, scores signal ability with noise. Second, and more importantly for the education mismatch analysis, the exam is not taken prior to education but is given during working years, so that the test results might also reflect education, and training and work experience. These concerns are dealt with in the quantitative analysis by adding noise to test scores, disciplined by model moments, and by a treatment allowing reverse causality.

For educational attainment we rely on the International Standard Classification of Education (ISCED). We define a dichotomous variable indicating two levels: (i) below college (ISCED 1 through 4) and (ii) college and beyond (ISCED 5 and above). For individual's occupations we rely on the International Standard Classification of Occupations from 2008 (ISCO 08) and define two types of jobs: (i) unskilled (first to third ISCO skill levels) and (ii) skilled jobs (fourth ISCO skill level).

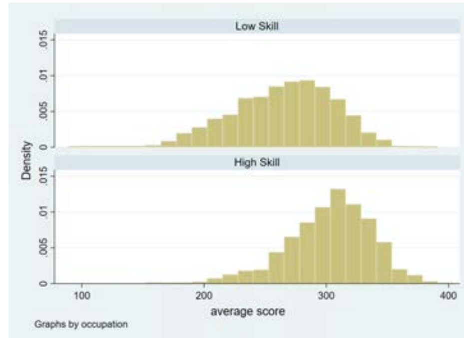
Figure 1 illustrates, for Germany and Italy, the two measures of mismatch that we develop in this paper.

[9] The data collection for the first round took place from August 2011 to November 2012. Individuals aged 25-54 are supposed to had made their education decisions before 2006, so the Great Recession cannot affect their educational choices.

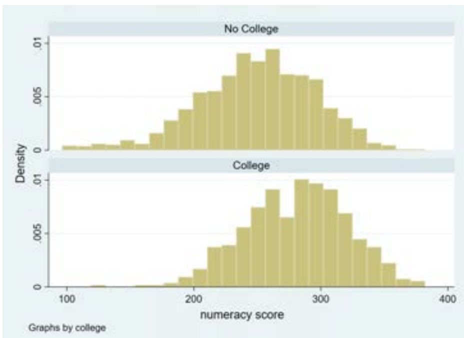
[10] These countries were selected for the detailed study in part because of their differences in both education mismatch, training and labor market institutions. Some of these facts are established for the broader set of countries in Appendix subsection 9.1.



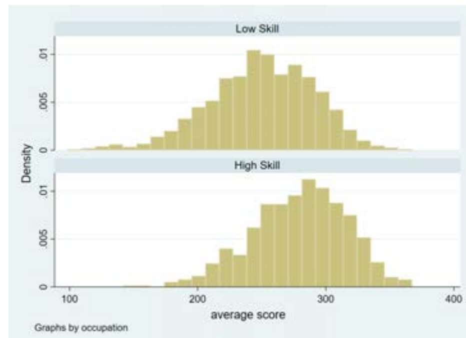
(a) Germany: Education Levels



(b) Germany: Occupations



(c) Italy: Education Levels



(d) Italy: Occupations

Figure 1: Ability, Education Levels and Occupations

Note: Figures in the left panels show the distribution of PIAAC numeracy scores by education by country. For each country, the top row is less than college and the bottom row is college and beyond. Figures in the right panel show the distribution of PIAAC average scores by occupations by country. For each country, the top row is low skilled jobs and the bottom row is skilled jobs.

The left panel shows the distribution of PIAAC numeracy scores by educational attainment for each country while the right panel shows the distribution of PIAAC total average scores by types of occupations. Tables 1 and 2 report moments for those distributions.[11]

	No College			**College**		
	Mean	**Sd**	**N**	**Mean**	**Sd**	**N**
Germany	262.05	48.55	1939	306.73	40.05	1117
Italy	249.45	46.03	2039	280.91	40.62	460
Japan	279.62	37.56	1220	308.71	33.79	1705
United States	231.80	51.39	1492	289.25	42.37	1204
Pooled	256.13	49.21	38013	297.99	41.06	26277

Note: This table reports the moments of the distribution of the numeracy score by country and educational level. Data for all countries are reported in Table 29.

Table 1: PIAAC numeracy score

Some patterns are clear from Figure 1. First, for each of the countries, the distribution of PIAAC scores

[11]These tables condition on education but not age. There were no distinct patterns in the data relating scores to age.

for those with college degrees (skilled occupations) is a rightward shift of the scores for the low education group (workers in low skilled occupations). These differences in means are clear from Tables 1 and 2 and are statistically significant. Second, for every country, we observe significant dispersion of PIAAC scores for each of the educational attainment levels and types of occupation. Third, and most importantly for the purposes of our study, there is considerable overlap in these distributions. This is indicative of mismatch: there are individuals that didn't go to college but whose scores are higher than those with a college degree and there are individuals in low-skilled jobs but whose scores are higher than those in high-skilled ones. These patterns are also apparent for the pooled sample of 21 countries.

	Low-Skilled			**High-Skilled**		
	Mean	**Sd**	**N**	**Mean**	**Sd**	**N**
Germany	264.09	43.08	1655	302.60	34.75	1188
Italy	249.79	41.26	1388	279.02	36.49	720
Japan	293.82	33.58	1534	313.08	30.33	1008
United States	249.26	46.22	1248	290.91	39.16	1237
Pooled	258.79	44.88	38013	298.13	36.61	26277

Note: This table reports the moments of the distribution of the average PIAAC score by country and type of occupation. Data for all countries are reported in Table 30.

Table 2: PIAAC average score

2.1 Measuring Mismatch

Figure 1 suggests the presence of important amounts of the two types of mismatch across OECD countries. We now conduct a more formal analysis to measure mismatch and to classify individuals into under, well and overmatched both in education and in the labor market. To do this, we estimate probabilities of (i) obtaining higher education and (ii) getting a skilled job conditional on PIAAC scores. Based on these estimates, an agent is undermatched (overmatched) in education if she didn't (did) complete college but the predicted probability of doing so is sufficiently high (low). Similarly, we say an agent is undermatched (overmatched) in her job if she doesn't (does) have a skilled job but the predicted probability of doing so is sufficiently high (low). The residuals are the well matched.

2.1.1 Education Mismatch

In this section we generate empirical measures of education mismatch. Specifically, consider the following logistic model of educational choice:

$$\Pr\left(e_i = 1 | a_i\right) = \frac{\exp^{\alpha_0+\alpha_1 a_i}}{1+\exp^{\alpha_0+\alpha_1 a_i}} \tag{1}$$

where a_i is the PIAAC numeracy score, considered as a proxy for individual i's ability.[12] Here $e_i = 0$ signifies that individual i has no college degree and $e_i = 1$ signifies college attainment and beyond. The regressions are run at the individual level by country. In order to better compare the results, we normalize the test score within each country to have a mean zero and a standard deviation of unity.

Predicted values from these logistic regressions are used to classify individuals into under- and overmatched. An individual is overmatched in education if e_i=1 but the model's predicted probability of e_i=1 is

[12] The PIAAC data report 10 plausible values for the numeracy score for each individual. We use the mean of these plausible values as a proxy for ability.

lower than the 20th percentile of all predicted values. Similarly, an individual is undermatched in education if e_i=0 but the model's predicted probability of e_i=1 is higher than the 80th percentile of all predicted values.[13] The choice of these specific upper and lower bounds to identify mismatched individuals are clearly arbitrary. The inference of the model comes from using these same cut-offs in the structural estimation.

	College Rate	**Undermatch**	**Overmatch**	α_0	α_1	**Marg. Effect**	**N**
Germany	0.366	0.092	0.061	-0.883	1.274	0.222	3,056
				(0.05)	(0.07)		
Italy	0.184	0.157	0.065	-1.972	1.015	0.113	2,499
				(0.07)	(0.07)		
Japan	0.583	0.071	0.116	0.137	0.919	0.194	2,925
				(0.04)	(0.05)		
United States	0.447	0.065	0.040	-0.465	1.437	0.253	2,696
				(0.05)	(0.07)		
Pooled	0.409	0.083	0.054	-1.561	1.192	0.224	64,290
				(0.047)	(0.013)		

Note: This table reports data moments including α_0 and α_1 from equation 1. Standard errors are provided in parenthesis for the logistic coefficient estimates. The column labeled "Marg. Effects" is the average marginal effect of the normalized numeracy score on college attainment. N is the size for the 25-54 age groups in each sample.

Table 3: Education Mismatch

Results for this exercise are presented in Table 3 for Germany, Italy, Japan, the US and the pooled sample. The estimated coefficients from columns 1-5 are used as moments in the structural estimation.[14]

College attainment, under- and overmatch rates for every country are reported in the first three columns. Here, the undermatch (overmatch) rate represents the proportion of individuals that didn't (did) choose college and are mismatched. The fourth and fifth columns show the estimates of the coefficients from the logistic model while column six represents the average marginal effect of the numeracy score on the probability of college attendance.

From the pooled sample, there is evidence of both forms of mismatch. For this large sample, the marginal effect of the numeracy score on education is about 0.22.

There is important variation across countries. Although college attainment rates are relatively high for these 4 advanced economies, they are considerably lower in Germany and in Italy compared to Japan. Mismatch rates are lowest in the US. The undermatch rate is highest in Italy, where the college attainment is lowest. The overmatch rate is highest is Japan, where the college attainment is higher. In general, this pattern is observed for the whole sample of 21 countries: countries with higher education rates tend to have lower undermatch rates and higher overmatch rates.

2.1.2 Labor Mismatch

We follow the same methodology to generate empirical measures of labor market mismatch.[15] In particular, we now consider the following logistic model:

[13]Appendix sub-section 9.2.1 considers an alternative measure in which these percentiles are calculated within the appropriate reference group by education rather than the entire population.

[14]The sample and thus estimates are a bit different than those reported in Cooper and Liu (2019) since the age group here is 25-54 year old, and we excluded self-employed. In particular, the average college rate is a bit lower.

[15]Other empirical approaches use job satisfaction to measure mismatch as discussed in McGowan and Andrews (2015).

$$\Pr(o_i = 1|\hat{a}_i) = \frac{\exp^{\delta_0+\delta_1\hat{a}_i}}{1+\exp^{\delta_0+\delta_1\hat{a}_i}} \tag{2}$$

where $\hat{a}_i$ is the PIAAC average score of the three dimensions, considered as a proxy for individual i's skills, $o_i = 0$ signifies that individual i has an unskilled occupation and $o_i = 1$ signifies skilled occupation. As in (1), ability is measured as the average of all reported plausible values of the three dimensions. This allows for education and previous job experience to impact, say, the problem solving component of the test score and thus measured ability.[16]

McGowan and Andrews (2015) identify individuals, by occupation, who are well-matched in terms of their self-assessment of their own skills relative to those required to perform their job. From this group, they obtain critical test scores for, say, the 5th and 95th percentiles. All workers in the occupation are evaluated relative to these cutoffs. As with our measure, mismatch is identified as being outside of these values.

For this analysis, we defined two phases of the working life. Individuals aged 25-34 are classified as early workers while individuals aged 35-54 are considered late workers. Regressions are run at the individual level by country and employment phase. As with education mismatch, the average score is normalized within each country and employment group to have a mean zero and a standard deviation of unity.

Predicted values from these logistic regressions are used to classify individuals into under- and over-matched in the labor market. An individual is overmatched in the labor market if o_i=1 but the model's predicted probability of o_i=1 is lower than the 20th percentile of all predicted values. Similarly, we say an individual is undermatched in the labor market if o_i=0 but the model's predicted probability of o_i=1 is higher than the 80th percentile of all predicted values.

Table 4 shows the labor market mismatch rates by employment phase for Germany, Italy, Japan, the US and the pooled sample. These rates are calculated as the ratio of the number of agents in a type of job that are mismatched divided by the number of agents in that type of job.

The pooled sample exhibits a number of important characteristics. There is substantial job mismatch in the early work phase, with the undermatch rate exceeding the overmatch rate. Further, these mismatch rates are slightly lower for older compared to younger workers.

Measures of labor market mismatch also vary significantly across countries. Undermatch rates are higher than overmatch rates for all of them. Similarly, important differences in terms of mismatch rates are observed between the two age groups. In every country, the labor market undermatch rate is significantly higher for the subsample of individuals in early employment, except for Japan in which there is almost no difference. Overmatch rates are higher for late workers in Japan, Germany and the pooled sample, and lower in the US and Italy.

Lower mismatch rates for late workers might be indicative of the presence of labor market mechanisms like training that help in the reallocation of under-matched workers into jobs. Higher mismatch rates, on the other hand, might reflect some failure for the labor market to correct the initial misallocation of workers. However, there is a word of caution in interpreting these differences. The PIAAC data is cross-sectional, not panel. Thus, we cannot distinguish between the cohort effect and the age effect when analyzing the two groups. The differences in overmatch rates, for example, might be indicative of different labor market agreements for that cohort that make it more difficult to separate overmatch individuals from their skilled jobs. Our estimated model will help in uncovering those dynamics.

[16] As suggested to us by Huacong Liu, this timing and choice of test might also allow for the current job to impact the score since we do not know how long the individual was in the current job. We return to this below in a robustness exercise, sub-section 9.2.2.

	under job early	under job late	over job early	over job late
Germany	0.101	0.091	0.038	0.055
Italy	0.165	0.144	0.086	0.070
Japan	0.134	0.133	0.085	0.101
United States	0.091	0.078	0.075	0.055
Pooled	0.102	0.091	0.060	0.057

Table 4: Labor Market Mismatch by Employment Age

2.2 Empirical Effects of Education Mismatch on Labor market outcomes

The evidence indicates both education and job mismatch. A key motivation of this paper is understanding their interaction. Leaving aside the issue of causality, is there evidence that education and labor market outcomes, in terms of mismatch, are correlated? Further, how do these patterns evolve? One intriguing hypothesis is that education undermatch initially leads to labor market undermatch but over time, through training and/or reallocation across jobs, the effects of the initial education undermatch disappear.

A simple correlation analysis, in Table 28, shows positive and significant correlations for all countries between (i) being mismatched -either under or over- in education and in the job, (2) being overmatched in education and overmatched in the job and (3) being overmatched in education and overmatched in the job. The next steps go beyond those correlations by analyzing the impact of education mismatch on compensation, job assignment and selection into training.

2.2.1 Mincer Regressions: The Wage Effects of Education Mismatch

This section analyzes the wage effects of education mismatch. To do so, we add the obtained measures of education mismatch for each individual by country to a standard Mincer wage regressions. Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) use also the PIAAC scores as a measure of cognitive skills in these type of regressions. It is clear from their analysis that both the PIAAC numeracy score as well as education are positively correlated with labor market earnings.

We use the gross hourly earnings of wage and salary workers as the labor income measure.[17] We follow Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) for some sample selection criteria that further restrict our sample. First, in each country, we trim the bottom and top one percent of the wage distribution to limit the influence of outliers. Second, to avoid other influences such as family demands or health limitations that might affect labor-force attachment, we limit the estimation sample to full-time workers, defined as those working at least 30 hours per week.

Some interesting relations are clear from Table 5, both for the individual country and pooled regressions. First, earnings depend positively on PIAAC numeracy scores indicating they are not just noise. Second, all regressions show an obvious college premium. Third, the positive coefficient on late employment signals a seniority effect. These results are in line with findings in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).

Fourth, and more importantly for the purpose of our study, education mismatch appears to have a statistically significant effect on predicting wages for the pooled sample. In particular, the positive coefficient on education undermatch means that those who were undermatched in education get compensated compared

[17] In the Public Use File, earnings data for Austria, Canada, Germany, Sweden, and the United States are reported only in deciles. We thank Marco Paccagnella for running these regressions for us.

	Pooled	Germany	Italy	Japan	US
numeracy score	0.095**	0.149**	0.092**	0.137**	0.159**
	(0.001)	(0.01)	(0.02)	(0.01)	(0.01)
college	0.243**	0.237**	0.276**	0.120**	0.243**
	(0.001)	(0.02)	(0.03)	(0.03)	(0.03)
late_emp	0.143**	0.173**	0.226**	0.268**	0.179**
	(0.001)	(0.02)	(0.02)	(0.02)	(0.02)
gender	-0.161**	-0.116**	-0.136**	-0.298**	-0.117**
	(0.001)	(0.02)	(0.02)	(0.02)	(0.02)
under_educ	0.043**	-0.001	0.018	-0.070	0.099
	(0.01)	(0.04)	(0.04)	(0.05)	(0.06)
over_educ	-0.066**	-0.034	-0.053	-0.005	-0.022
	(0.01)	(0.07)	(0.15)	(0.05)	(0.09)
R^2	0.578	0.302	0.225	0.302	0.310

Note: This table reports the results from Mincer type regressions for our small sample of 4 countries and the pooled sample. The depend variables for all of them is log hourly earnings. Standard errors are reported in parenthesis. The numeracy score is normalized within each country to have zero mean and standard deviation of unity. The variable gender takes the value 1 if the individual is female, and 0 otherwise. The variable late_emp takes the value 0 if the individual is an early employee (25-34 years old) and 1 otherwise. A */** next to the coefficient indicates significance at the 10/5% level. Table 31 includes Mincer regressions for all countries among the moments.

Table 5: Mincer Regressions by Country.

to the well-matched without college. In a similar manner, the negative coefficient for education overmatch implies that those who were overmatched in education get a pay cut relative to the well-matched college graduates. This could represent a way in which education mismatch impacts labor market outcomes. However, at the individual country level, these effects are absent. This is also true for majority of the 21 countries in our sample.[18]

2.2.2 Effects of Education Mismatch on Skill Assignment

	Ed-Job (general)	**Ed-Job (undermatch)**	**Ed-Job (overmatch)**
Germany	0.330*	0.386*	0.179*
Italy	0.420*	0.460*	0.394*
Japan	0.256*	0.330*	0.346*
United States	0.311*	0.412*	0.197*
Pooled	0.339*	0.339*	0.345*

Note: This table reports correlations between different estimates of education and job mismatch. The star indicates significance at the 1% level. Table 28 reports correlations for all countries.

Table 6: Correlations between education and job mismatch.

While there is no evidence of wage effects of educational mismatch at the country level, there is evidence that job assignment is impacted. Table 6 looks at the correlations of education and job mismatch for the four countries.[19] The first column reports the correlation between being mismatched in education and in the job.

[18] Coefficients from these regressions for all countries are shown in Table 31 in the appendix. Just a few countries show statistically significant coefficients for our measures of education mismatch.
[19] Table 28 in the appendix reports the same correlations for all countries.

	Early Job Outcome					
	Undermatch	**Well-match**	**Overmatch**	**Undermatch**	**Well-match**	**Overmatch**
Education Outcome	**Conditional on Educ**			**Conditional on Job**		
GERMANY						
Undermatch	37.70%	62.30%	0.00%	47.92%	4.86%	0.00%
Well-match	3.23%	95.23%	1.55%	52.08%	94.37%	85.71%
Overmatch	0.00%	75.00%	25.00%	0.00%	0.77%	14.29%
ITALY						
Undermatch	44.57%	55.43%	0.00%	64.06%	10.78%	0.00%
Well-match	5.09%	92.70%	2.21%	35.94%	88.58%	71.43%
Overmatch	0.00%	42.86%	57.14%	0.00%	0.63%	28.57%
JAPAN						
Undermatch	60.87%	39.13%	0.00%	21.54%	1.36%	0.00%
Well-match	7.49%	91.04%	1.47%	78.46%	93.37%	45.45%
Overmatch	0.00%	74.47%	25.53%	0.00%	5.27%	54.55%
US						
Undermatch	47.22%	52.78%	0.00%	40.48%	2.33%	0.00%
Well-match	2.97%	93.70%	3.33%	59.52%	96.81%	87.50%
Overmatch	0.00%	63.64%	36.36%	0.00%	0.86%	12.50%
Pooled						
Undermatch	37.03%	62.97%	0.00%	39.36%	4.60%	0.00%
Well-match	4.16%	93.73%	2.10%	60.64%	93.80%	66.79%
Overmatch	0.00%	60.51%	39.49%	0.00%	1.60%	33.21%

Note: This table shows the distribution between different labor market and education outcomes in terms of mismatch. The first three columns represents the distribution across labor market outcomes conditional on the education one (row interpretation). The last three columns condition the distribution on the labor market match (column interpretation.)

Table 7: Distribution of Education and Early Labor Market Outcomes

The second column reports correlations between being undermatched in education and undermatched in the job. The third column shows the correlation between being overmatched in education and overmatched in the job. Clearly mismatch in education is positively correlated with mismatch in jobs.

Table 7 goes further and displays the cross sectional distribution of education and job mismatch, by country, for early employment. Beyond compensation, another dimension of labor market outcomes is the assignment to jobs. In particular, does the labor market assignment overcome or reinforce mismatch in education?

The first three columns of Table 7 show the distribution across labor market outcomes, in terms of job mismatch, conditional on education mismatch for the pooled sample, Germany, Italy, Japan and the US. In the pooled sample, almost 40% (37%) of the individuals that were overmatched (undermatched) in education are also overmatched (undermatched) in the job. Similarly, around 39% (33%) of the individuals undermatched (overmatched) in the job were also undermatched (overmatched) in education. These proportions vary across countries.

Notice that there are no individuals in our sample undermatched (overmatched) in education but overmatch (undermatch) in the labor market. Our methodology requires agents to have relatively high test scores to be considered undermatched and relatively low scores to be considered overmatched. This mechanism, together with the high correlation between our measures of ability and labor market skills, implies a zero probability of opposite types of mismatch in education and the labor market for the same individual.

The moments indicating job outcome conditional on education will be used in the estimation. As the PIAAC is not a panel, the dynamic of job assignment is not well captured. Hence our focus on early

	Germany	Italy	Japan	US	Pooled
			Early emp.		
δ_{cs}	0.773	0.681	0.471	0.743	0.693
δ_{ns}	0.233	0.168	0.120	0.228	0.205
			Late emp.		
δ_{cs}	0.759	0.833	0.578	0.798	0.754
δ_{ns}	0.199	0.246	0.201	0.270	0.240

Note: This table reports flows from education. Here $(\delta_{cs}, \delta_{ns})$ are the probabilities that a college educated (no college educated) individual obtains a skilled job in the designated employment phase.

Table 8: Job Flows

assignment in Table 7 and in the estimation.

Another dimension of labor market outcomes is job assignment by skill. Table 8 indicates these flows in early and late employment. From the top panel, for all countries, $0 < \delta_{cs} < 1$ in early emplloment so that having a college education does not guarantee the attainment of a skilled job. Likewise, $0 < \delta_{ns} < 1$ in all countries as well so that some individuals can obtain a skilled job even without a college degree. The latter effect thus provides a path for undermatched individuals to be selected into a skilled job.

The late employment flows have a similar pattern where a college degree increases the chances of a skilled job but does not guarantee one. Except for Germany, δ_{cs} is larger in the late employment period consistent with a better sorting of individuals over time.[20] And likewise δ_{ns} is lower in the late employment period.

But this interpretation must be taken with caution. As the PIAAC is a single cross section, the dynamics from early to late employment can not be taken directly from the data. Thus for much of the estimation we rely on $(\delta_{cs}, \delta_{ns})$ for early employment as calculated from the data. But we estimate and/or otherwise set the flows for late employment, conditional on training outcomes, as explained below.

2.2.3 Training

The goal of our analysis is to understand not only the interaction between education and labor market mismatch but also how this interaction evolves over time. If education mismatch matters for labor market allocations, does its effect last over time? What are the mechanism at play? In principle, training allows high-ability individuals initially undermatched in education to acquire skills and then efficiently use them in the labor market. In this way, we consider training as a possible mechanism for overcoming education undermatch.

The PIAAC data report different measures of training. Formal training refers to any formal education, job related, received by the employee in the last 12 months before the interview.[21] In contrast, informal training refers to participation in one of the following activities: (i) courses conducted through open or distance education, (ii) organized sessions for on-the-job training or training by supervisors or co-workers, (iii) seminars or workshop and (iv) courses or private lessons. Since PIAAC data does not report the level/type of formal education followed by the respondent, it is difficult to separate the education variable from the formal training one. Thus, the main measure used in our analysis corresponds to informal training, although formal training is also considered as an alternative.

[20] Again, as this is not a panel, we are unable to determine the fraction, for example, of college educated individuals assigned to skilled jobs early retain those jobs in the late employment period.

[21] Specifically, the background questionnaire defines formal education as the one "provided in schools, colleges, universities or other educational institutions and leads to a certification that is taken up in the national educational classification".

	Pooled	Germany	Italy	Japan	USA
non formal training					
numeracy	0.213**	0.313**	0.248*	0.053	0.196
skilled job	0.617**	0.854**	0.579**	0.965**	0.585*
college	0.326**	0.038	0.757**	0.600**	-0.100
gender	-0.372**	-0.517**	-0.147	-0.516**	-0.691**
private	-0.449**	-0.614**	0.311	-0.361	-0.812**
permanent	0.403**	0.506**	0.389	0.451**	0.267
size	0.307**	0.122	0.051	0.368*	0.217

Note: This table reports for each country, the probability of receiving training, conditional on individual and firm characteristics.

Table 9: Training assignment

Our main interest is selection into training. Table 9 reports the results from a logistic regression of the probability of receiving non formal training in early employment, conditional on individuals' and some firm characteristics. Since training is received in less than 12 months prior to the interview we assume that the type of occupation, at the moment of the interview, is not a consequence of training but rather the type of job they held while being trained.

It is clear from the table that the type of occupation appears to be a strong determinant in participation into informal training with educational attainment and our proxy of ability playing a less important role. In particular, early workers with skilled jobs have a higher probability of receiving non formal training than the ones with unskilled jobs. Note too that college is significant in only Italy and Japan: for these countries education is positively correlated with training. In all countries, there is a positive correlation with numeracy, though this is not statistically significant in Japan and the US.[22]

It is difficult to directly interpret these estimates since both education attainment and job assignment are endogenous. We return to disentangling these effects after the estimation of the model.

The estimation focuses on training means by type of occupation as shown in Table 10. These means are used as moments in the structural estimation. The training rates are about one-third for unskilled and two-thirds for workers in skilled jobs. The rates are relatively low in Italy.

rate	**Germany**	**Italy**	**Japan**	**US**	**Pooled**
			Informal		
unskilled	0.386	0.195	0.380	0.436	0.372
skilled	0.643	0.364	0.685	0.682	0.626
			Formal		
unskilled	0.126	0.032	0.029	0.141	0.109
skilled	0.183	0.128	0.054	0.207	0.162

Note: This table reports training rates by early workers conditional on the type of occupation and type of training.

Table 10: Training Rates

Since the PIAAC is a single cross-section, as mentioned before, it's not possible to look at the consequences of training dynamically as we do not know which late workers got training in early employment. Thus, we use the estimated model to get at the implications.

[22] Choi (2019) focuses on the impact of permanent vs temporary work status on training. Our model lacks this distinction.

3 Model

There are three phases of the life cycle emphasized in the model that accord with the structure of the data analysis. The first stage allows the individual to obtain formal education. The second and third stages are employment periods. They differ, in part, because of the opportunity for training in the middle period that impacts productivity, earnings and job assignment in the final period.

Figure 3 shows these three periods. These are discussed in turn, starting from employment and working backwards to the education choice.

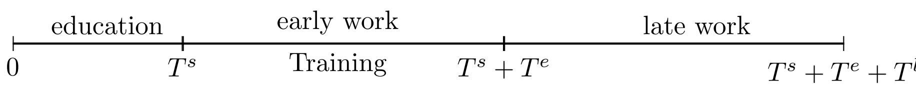


Figure 3: Phases of Household Life Cycle

3.1 Employment Phases

This section summarizes the outcomes and decisions in the employment phases. The key (and only) decision explored here is training, undertaken in the early work period. This highlights a potential path to a skilled job through human capital accumulation, particularly for those who were undermatched in education. Of course, the strength of this will depend on the selection into training and its effects on human capital.

3.1.1 Late Work

In the late work period, the worker is assigned to either a skilled or unskilled job. Let $\delta_2^j(e, \theta, tr)$ be the probability that a type (e, θ) agent is assigned a high skilled job in late work conditional on training (tr). Here $j \in \{s, u\}$ denotes the job assignment for **early employment**. This function is taken as given in determining the training choice. These probabilities depend not only on the worker type and the training decision but also on the type of job in early work. This is a general specification and we return below to its implementation in the quantitative analysis.

As for compensation, workers are paid their marginal product.[23] Compensation depends solely on their human capital, which reflects their innate ability, education and training. By assumption, this is independent of their early work job assignment.[24]

Specifically, the productivity of a worker in a skilled job is given by $H(e, \theta, tr) = h(e)\theta\zeta(e)^{tr}$ where $h(e)$ captures the effects of education, θ is innate ability, $tr \in \{0, 1\}$ indicates if the worker has successfully trained while $\zeta(e)$ parameterizes the effect of training on worker human capital. The specification allows the effects of training to depend on the level of education, e. Here both e and tr are dichotomous reflecting the discrete choices over college and training. Compensation per period in late work for workers in a skilled job is $\omega_2 H(e, \theta, tr)$ where ω_2 is the base wage for late employment.

If a worker is assigned to an unskilled job, then $H(e, \theta, tr) \equiv 1$ regardless of education, ability or training. With this specification, the returns to education and training are dependent on job assignment. In this case, the late worker employed in an unskilled job is paid ω_2 each period.

[23] In contrast to Garibaldi, Gomes, and Sopraseuth (2020) model of labor market mismatch, there is no effect from co-workers to the productivity of a given worker.

[24] Alternatively, assume that ability is not directly observed but rather is signaled by a job test of the worker, described below. In this case, it is as if *ex ante* the worker is paid expected compensation in the event the firm observes an unbiased signal of true ability.

Compensation over the entire late work period is summarized by $Y_2^j(e,\theta,tr)$ where $j \in \{s,u\}$ denotes if the worker is in a skilled or unskilled job. This is the sum of the wages earned in each period, discounted back to the start of the **early** employment period.[25] Here j refers to the type of job in late employment

These income measures as well as the uncertainty over late job assignment can be combined to create a measure of expected income, discounted to the start of early employment, over the late period for a type (e,θ) worker given by:

$$\bar{Y}_2^k(e,\theta,tr) = \delta_2^k(e,\theta,tr)Y_2^s(e,\theta,tr) + (1-\delta_2^k(e,\theta,tr))Y_2^u. \tag{3}$$

Here the $k \in \{s,u\}$ in $\bar{Y}_2^k(e,\theta,tr)$ and $\delta_2^k(e,\theta,tr)$ refers to the early job assignment.

3.1.2 Early Work

Workers are hired by firms at the end of period T^s. At the time a worker is hired, the firm observes each worker's education and ability.

Based upon these two pieces of information, the worker is assigned to either a low or a high skill job.[26] Regardless of the job assignment, as in the late work, the worker is assumed to be paid its marginal product, $H(e,\theta)\omega_1$. There is no effect of training on productivity in early work so that $H(e,\theta) = h(e)\theta$ if the worker with education e and ability θ is in a skilled job. Otherwise $H(0,\theta) = 1$ for all θ so that productivity and the wage for unskilled workers is ω_1 regardless of education and ability.

Compensation in early work is summarized by $Y_1^j(e,\theta)$ where $j \in \{s,u\}$ denotes if the worker is in a skilled or unskilled job. This is the sum of wages per period over the early work period, discounted to the start of early work. Denote the probability of assignment to a skilled job in the early period by $\delta_1(e,\theta)$.

3.1.3 Training

During the early employment phase, agents have an option to receive training. The cost of training is a fraction of time, $0 \leq \bar{e}^t \leq 1$, that must be allocated to the acquisition of skills in place of early work. Further there is a direct payment of p^t for formal training.

The benefit of training is the expected gain in human capital in late employment: $H(e,\theta,tr) = h(e)\theta\zeta(e)^{tr}$. Recall that this gain is realized iff the worker obtains a skilled job. Thus there may be uncertainty over the returns to training due to randomness in the job assignment.[27]

Formally, the expected income gain to training for a type (e,θ) early worker in job of skill $j \in \{s,u\}$ is given by:

$$\begin{aligned} \Delta^j(e,\theta) &\equiv \bar{Y}_2^j(e,\theta,1) - \bar{Y}_2^j(e,\theta,0) \\ &= \delta_2^j(e,\theta,1)(Y_2^s(e,\theta,1) - Y_2^u) - \delta_2^j(e,\theta,0)(Y_2^s(e,\theta,0) - Y_2^u). \end{aligned} \tag{4}$$

[25] To be clear, $Y_2^s(e,\theta,tr) = \omega_2 H(e,\theta,tr)\tilde{R}^{T^l}/R^{T^e}$ and $Y_2^u = \omega_2\tilde{R}^{T^l}/R^{T^e}$. Here and below, $\tilde{R}^x = (1+R+R^2+...+R^{x-1})/R^{x-1}$ where R is the real interest rate and x is the length of the period of the flow that is being discounted.

[26] In our quantitative analysis this is restricted so that assignment in early employment is based only on the education level.

[27] An alternative formulation would allow for a stochastic element to the training outcome as well, with (or without) randomness in the job assignment. Since agents are effectively risk neutral, this uncertainty is fully captured by $\zeta(e)$. So this should not be interpreted solely as human capital accumulation but rather the compound lottery associated with training. For ease of exposition, throughout we refer to $\zeta(\cdot)$ as parameterizing the human capital accumulation from training. Relatedly, Flinn, Gemici, and Laufer (2017) acknowledge measurement error associated with training and its outcomes.

Here the expected income given training, discounted back to the start of the early work period, was taken from (3). From this expression there are two effects of training. The first comes from the dependence of the probability of being in a skilled job on training: $\delta_2^j(e,\theta,1) \neq \delta_2^j(e,\theta,0)$. The second effect comes from productivity in a skilled job: $Y_2^s(e,\theta,1) > Y_2^s(e,\theta,0)$. This gain is characterized by $\zeta(e)$.

A type (e,θ) agent currently in a skilled job will train iff:

$$\omega_1 h(e)\theta\bar{e}^t\tilde{R}^{T^e} + p^t \leq \Delta^s(e,\theta). \tag{5}$$

The left side includes the opportunity cost of training, discounted to the start of the early work period, while the right side is the expected gain from training. The condition for training of an agent in an unskilled job is:

$$\omega_1\bar{e}^t\tilde{R}^{T^e} + p^t \leq \Delta^u(e,\theta). \tag{6}$$

Let $\phi^j(e,\theta) \in \{0,1\}$ be the training choice for a type (e,θ) worker in job type j in early employment.[28] At the individual level this is a discrete choice with $\phi^j(e,\theta) = 1$ indicating a choice to train. With the specification $H(e,\theta,tr) = h(e)\theta\zeta(e)^{tr}$, if $\zeta(\bar{e}) > \zeta(0)$ the training choice will be increasing in both education and ability. In addition, the cost of training is increasing in both ability and education if the agent is assigned a skilled job.

To see these incentive effects more clearly, consider an agent in a skilled job early. Suppose that the agent will remain in the skilled job in the late work period regardless of the training decision. Then (5) can be written as:

$$\omega_1 h(e)\theta\bar{e}^t\tilde{R}^{T^e} \leq \omega_2 h(e)\theta(\zeta(e)-1)\left(\tilde{R}^{T^l}/R^{T^e}\right). \tag{7}$$

In this case, the informal training choice is independent of $h(e)\theta$ since the agents retains a skilled job regardless.

But if the agent is currently in an unskilled job, assuming that the only way to obtain a late skilled job is through training, the condition for informal training is:

$$\omega_1\bar{e}^t\tilde{R}^{T^e} \leq \omega_2(\theta h(e)\zeta(e)-1)\left(\tilde{R}^{T^l}/R^{T^e}\right). \tag{8}$$

In this case, the incentives to train are clearly increasing in both ability and education. This will provide a way for undermatched individuals, assigned to unskilled jobs early, to climb up to skilled jobs.

The choice, $\phi^k(e,\theta)$ can be used to obtain measures of discounted (to the start of the early work phase) expected income that incorporate the optimal training decision. For late income,

$$\bar{Y}_2^k(e,\theta) = \delta_2^k(e,\theta,\phi^k(e,\theta))Y_2^s(e,\theta,\phi^k(e,\theta)) + (1-\delta_2^k(e,\theta,\phi^k(e,\theta)))Y_2^u \tag{9}$$

where $k \in \{s,u\}$ denotes the early assignment. From this, and given the randomness in early work assignment, unconditional expected late income is given by:

$$\bar{Y}_2(e,\theta) = \delta_1(e,\theta)\bar{Y}_2^s(e,\theta) + (1-\delta_1(e,\theta))\bar{Y}_2^u(e,\theta). \tag{10}$$

Using the optimal training decision to incorporate training costs, the expected income from early work

[28] The choice is $\{0,1\}$ given observables as there is no training specific choice shock.

is given by:

$$\bar{Y}_1(e,\theta) = \delta_1(e,\theta)\left[Y_1^s(e,\theta) - [\omega_1 h(e)\theta\bar{e}^t\tilde{R}^{T^e} - p^t]\phi^s(e,\theta)\right] + (1-\delta_1(e,\theta))\left[Y_1^u - [\bar{e}^t\omega_1\tilde{R}^{T^e} - p^t]\phi^u(e,\theta)\right]. \tag{11}$$

3.2 College Choice

Given these labor market flows and the dependence of compensation on ability, education and training, each agent makes an education choice. Here that choice is restricted to no college or college: $e \in \{0, \bar{e}\}$ where $0 \leq \bar{e} \leq 1$ is the fraction of time in school.

There are three direct influences that impact the education choice: ability, taste and borrowing constraints. As ability and education are, by assumption, complements in productivity in skilled jobs, individuals, all else the same, will sort into education based on ability. That is, all agents above a critical ability will choose college.

But there are other factors at play. Agents may differ in their valuation of college, either the experience itself, or the prestige of a degree, etc. This effect is captured by "tastes". In addition, there is an opportunity cost of going to college and tuition must be paid. If agents are unable to borrow against their future income, so that borrowing constraints matter, then the education choice will be impacted.

It is useful to relate the education choice directly to mismatch. In this model, mismatch will arise either from the presence of taste shocks or binding borrowing constraints. In both cases undermatch may occur, high ability individuals may not choose the college option, either because they do not directly value the experience or because of the cost due to limited borrowing possibilities. Further, overmatch can arise from taste shocks that induce a relatively low individual to choose the college path.

Finally, another possibility is that no education mismatch occurs despite its measurement in the data. This would reflect noisy test scores. While individuals sort efficiently based on ability, the test results are noisy enough to produce the levels of mismatch found in the data. As discussed below, this result is not trivial since there is discipline in the estimation on the informativeness of the test score in wage regressions.

Importantly, the assignment of agents to jobs in the early work phase will have an independent impact on the education choice. For example, if either low education agents can be assigned high skilled jobs or high education agents are assigned to low skilled job, then the return to education falls relative to no education. While this impacts the education rate, it does not create education mismatch.

More formally, knowing ability and labor market prospects, an individual at the start of the education phase chooses an education level.[29] Under the no college option, the individual goes to work immediately and earns ω_1 in an unskilled job. As long as $\delta_1(0,\theta) > 0$ this individual will have an opportunity to work in a skilled job after the education phase and even train in that period.

If the agent chooses college, then a fraction of time, denoted $\bar{e}$, is spent at school. Earnings during the school phase are then $\omega_1 * (1-\bar{e})$. In addition, there is a direct tuition cost denoted p. The gain to education, of course, comes in the early and later work phase where high ability agents are compensated for their education as long as they are in skilled jobs.

Let $Y(e,\theta)$ be the discounted value of expected lifetime income for an agent with education e and ability θ:

$$Y(e,\theta) = Y_0(e) + \frac{\bar{Y}_1(e,\theta) + \bar{Y}_2(e,\theta)}{R^{T^s}} \tag{12}$$

[29] An extension below relaxes the assumption that the individual knows θ.

with both $\bar{Y}_2(e,\theta)$ defined in (10) and $\bar{Y}_1(e,\theta)$ defined in (11) including the costs and benefits of training for a type (e,θ) individual. The first term is income, net of tuition, during the education phase:

$$Y_0(e) = \frac{\omega_0(1-e) - pe}{\tilde{R}^{T^s}} \tag{13}$$

with $e \in \{0, \bar{e}\}$.[30]

If capital markets are perfect so that there are no borrowing constraints, agents are able to completely insure themselves over income fluctuations coming from transitions between skilled and unskilled jobs, post education.[31] Thus their consumption each period is proportional to the sum of the discounted present value of their expected income, $Y(e,\theta)$, as given in (14)

$$c(e,\theta) = \frac{Y(e,\theta)}{\tilde{R}^T}. \tag{14}$$

If household utility over consumption is given by $u(c)$, then lifetime utility for an agent of ability θ choosing education e is given by:

$$V(e,\theta) = u(c(e,\theta))\tilde{\beta}^T + \varepsilon(e) \tag{15}$$

Here $\varepsilon(e)$ is a "taste shock" associated with each choice of education, $e \in \{0, \bar{e}\}$.[32] As specified, the taste shock is directly associated with the education choice. It is possible to include additional taste shocks in the model, say for training and for high skilled jobs. The difficulty though is in distinguishing these taste variations. Thus a more generous interpretation of $\varepsilon(e)$ to include other sources of variation is certainty consistent with the analysis.

3.3 Efficiency

The idea that mismatch is inefficient is certainly present in the ongoing policy discussions. This short section describes efficient allocations for our environment. Sub-section 6.6 provides estimates of output loss due to mismatch.

Assuming that risk sharing can be achieved through type specific transfers, the key to efficiency is a mapping from agent type (θ, ε) to education, job assignment outcomes and training outcomes.[33] For this economy, ability influences productivity only for agents who are assigned skilled jobs. Also, assume that the number of skilled (unskilled) jobs is totally elastic rather than predetermined so there are no congestion effects.

In this case, an efficient outcome has the following characteristics:

1. there exists a function $\theta^*(\varepsilon(e))$ such that $e = \bar{e}$ iff $\theta > \theta^*(\varepsilon(e))$. The function $\theta^*(\varepsilon(e))$ comes from an indifference condition with respect to the education decision given that training and job assignments are efficient, as detailed next. If there are no taste shocks, then there is a single θ^*.

2. all agents with $e = \bar{e}$ get skilled jobs. Otherwise, their education is useless.

[30] As above, $\tilde{R}^x = (1 + R + R^2 + ... + R^{x-1})/R^{x-1}$ where R is the real interest rate and x is the length of the period of the flow that is being discounted.

[31] Borrowing constraints during the employment phase are considered in section 5. Our main interest is in the interaction of education and job mismatch and the incompleteness of markets post-education, while potentially influencing the education rate, is not key.

[32] In (15) $\tilde{\beta}^T = 1 + \beta + \beta^2 + ...\beta^{T-1}$.

[33] As we shall see, the estimation does not uncover any role for borrowing constraints so that assuming all agents are risk neutral is consistent with the results.

3. agents with $e = 0$ get unskilled jobs for $\theta < \theta^{**}$ where $H(0, \theta^{**}) = 1$ and those with $e = 0$ get skilled jobs for $\theta \geq \theta^{**}$.

4. given the training technology, the efficient solution is the same as the individual choice expressed in (5) and (6).

5. all agents who train are assigned skilled jobs.

4 Quantitative Analysis

This section of the paper brings the model to the data through a simulated method of moments approach. The moments include those that summarize: (i) education choices, (ii) education mismatch, (iii) wages, (iv) job assignment and (v) training. These moments are topical in that they motivate our analysis and, as verified below, are informative about our parameters.

4.1 Approach and Functional Forms

The estimation finds the parameter vector Θ that solves:

$$\pounds \equiv min_{\Theta}(M^d - M^s(\Theta))W(M^d - M^s(\Theta))'. \tag{16}$$

In this expression, the data moments are given by M^d, the simulated moments, that depend on the parameters are given by $M^s(\Theta)$. W is the conforming identity matrix.

The model plays a prominent role in the analysis since it provides the mapping from the parameters Θ to the moments. This mapping comes from: (i) the policy functions at the individual level characterizing education and training decisions given Θ, (ii) creating a panel by drawing shocks from the estimated processes and simulating the resulting choices and (iii) calculating moments from the simulated data.

For the estimation, the parameter vector is defined by

$$\Theta \equiv (\phi, \bar{\varepsilon}, \sigma_e, h(\bar{e}), w_2, \sigma_j, \zeta(0), \zeta(\bar{e}), \bar{e}^t, \delta_{css}, \delta_{nsu}, nbp, bbar). \tag{17}$$

All parameters from the model are summarized in Table 11.

Here ϕ is the shape parameter for the Pareto distribution of ability, $\bar{\varepsilon}$ parameterizes the taste shocks, σ_e parameterizes the noise in the education test, $h(\bar{e})$ is the human capital accumulated from college, w_2 is the wage in the late period of employment, σ_j parameterizes the noise in the job test.[34]

The parameters $(\zeta(0), \zeta(\bar{e}), \bar{e}^t)$ relate directly to training: $\zeta(0), \zeta(\bar{e})$ are the (expected) human capital accumulation parameters if training occurs, distinguished by education level, e. The opportunity cost of training is $\bar{e}^t$.[35] Under this specification, there is a component of the training choice that is education dependent, $\zeta(e)$, and a component that depends on the job assignment in early employment through the opportunity cost $\bar{e}^t$.

The model allowed a rich specification of flows between skilled and unskilled jobs over time. The estimation places restrictions on those flows to highlight the effects of training on job flows. With that in mind, the parameters $(\delta_{css}, \delta_{nsu})$ control the flows from skilled jobs in early employment to job assignment in the

[34]For the implementation, there is a single taste shock to influences the difference in values between college and no college.

[35]The model with formal training introduces a direct cost of p^t.

late working phase **if training is not chosen**, dependent on education outcome.[36] Further, the likelihood a worker in an unskilled early job is promoted to a skilled job is equal to zero: $\delta_2^u(e, \theta, 0) = 0$ for all θ. In this way, we focus on the role of training to obtain a promotion to a skilled position.[37]

Flows into early employment, $\delta_1(\bar{e}, \theta) = \delta_{cs}$ and $\delta_1(0, \theta) = \delta_{ns}$, are taken directly from the data, as in the top panel of Table 8. Thus, the dependence of these flows on ability is not considered.

In the cases with capital market imperfections, *nbp* is the fraction of agents unable to borrow and *bbar* is a borrowing limit. Our adoption of this formulation of a borrowing constraint is explained below.

The model assumes that agents know their ability and use this for education, employment and training decisions. As researchers, we do not observe ability directly. Instead, through the PIAAC data set, we have test scores. These scores have already been used to create moments such as the regression coefficients in (1), which used the numeracy score as an input, and the regression coefficients in (2), which used an average of scores, in order to measure labor market mismatch.

For the estimation, it is necessary to create versions of these test scores in the model. There are two noisy test scores, one for education and the other for the job. The score in test k for agent i, denoted ts^{ik}, is a noisy signal of worker ability:

$$ts^{ik} = \theta_i + \sigma_k \zeta^{ik}. \tag{18}$$

Here σ_k for $k \in \{e, j\}$ parameterizes the noise in test k, denoted ζ^{ik}, and these are elements of Θ, where e denotes the education test score and j is the job test score. The shocks in these test scores are assumed to be uncorrelated.

There are some functional form assumptions, as in Cooper and Liu (2019), that underlie Θ. First, ability has a Pareto distribution, with a shape parameter denoted ϕ. So the CDF of ability, θ, is given by $1 - \theta^{-\phi}$ with a mean of $\frac{\phi}{\phi-1}$, decreasing in ϕ. Taste shocks are assumed to be uniformly distributed in the interval $[-\bar{\varepsilon}, \bar{\varepsilon}]$ and independent of ability in the baseline model.

Throughout the estimation, the fraction of time at school is fixed at $\bar{e} = 0.75$, for all countries. But the out of pocket cost is country specific. Relative to the US, the cost in Germany is 0, is 26.06% in Italy and 92.91% in Japan.[38] Finally, $\omega_1 = 1$ is a normalization.

4.2 Moments

For the estimation, there are three types of moments. They are chosen with a couple of criteria in mind. First and foremost, they are informative about underlying structural parameters in Θ. Second, since the PIAAC is a single cross section, the moments do not reflect any dynamics between individuals of different ages. All moments are summarized in Table 12.[39]

The first five moments in Table 13 summarize educational outcomes. These include, in order, the college rate, the undermatch rate and the overmatch rate. The coefficients (α_0, α_1) are from the logistic regression in (1) that relates the educational decision to a constant and the education test score. For the data, this regression uses the PIAAC numeracy score. In creating the simulated data, this test score comes from (18) for $k = e$, parameterized by σ_e. This is used as a regressor in (1) and the mismatch rates are calculated as in the data.

The labor market outcomes include wage patterns and the assignment of workers to job types. The

[36] Relative to the earlier more general notation, $\delta_{css} = \delta_2^s(\bar{e}, \theta, 0)$ and $\delta_{nsu} = (1 - \delta_2^s(0, \theta, 0))$ for all θ.
[37] Recall that we only have a cross section and thus cannot directly follow the dynamic effects of training in our data.
[38] These come from Cooper and Liu (2019).
[39] Moments for all countries are in Table 31.

Parameters	Description
Set	
$\bar{e}$	fraction of time at school
p	Tuition for college
ω_1	Wage in education and early work phases
$h(0)$	Human capital accumulation in case of no college in skilled jobs
δ_{cs}	Flows from college to skilled job in early employment
δ_{ns}	Flows from no college to skilled job in early employment
Estimated	
ϕ	Shape parameter for the Pareto distribution of ability
$\bar{\varepsilon}$	Taste shocks
σ_e	Noise in the education test
$h(\bar{e})$	Human capital accumulation from college
ω_2	Wage in the late period of employment
σ_j	Noise in the job test
$\zeta(0)$	Gain from training for individuals with no college
$\zeta(\bar{e})$	Gain from training for individuals with college
p^t	Direct cost for formal training
$\bar{e}^t$	Time cost of training
δ_{css}	Flow from skilled job in early employment to skilled job in late for individuals with college
δ_{nsu}	Flow from skilled job in early employment to unskilled job in late for individuals with no college
nbp	Fraction of agents unable to borrow
$bbar$	Borrowing Limit

Table 11: Parameters: Description

coefficients for the wage regressions are taken from Table 5. The moments are the estimated coefficients on the test score (numeracy), education attainment, period of employment (early,late) and dummy variables indicating either undermatch or overmatch in education. Here the inclusion of the period of employment helps to pin down the second period wage, w_2.

As for job assignment, the moments are the distribution across labor market outcomes, in terms of under- and overmatch, conditional on education outcomes, again in terms of under- and overmatch. These flows are displayed in Table 7. In addition, the early work phase mismatch rates, from Table 4, are included as well.[40] For the simulated data, the test score for the job mismatch rates comes from (18) for $k = j$, thus parameterized by σ_j, and used as an input into (2) to calculate job mismatch rates.

The training outcomes are captured by the frequency of informal training by early workers. These moments reflect our emphasis on training as a source of upward mobility. The robustness section includes estimates with formal training.

4.3 Estimation Results

This section presents the baseline estimation results. There are a couple of main findings. First, education mismatch is largely due to taste shocks. Second, there is no evidence of capital market imperfections.

To be clear, this section of the paper is intended to report the results. The economic interpretation and implications are brought out in section 6.

[40]Mismatch in late employment is not included, consistent with the view of minimizing moments that enforce a steady state on the data.

Moments	Description
Education	
ed	Education rate
un	Education Undermatch rate
ov	Education Overmatch rate
α_0	Constant in logistic regression 1
α_1	Coefficient for education test in logistic regression 1
Labor market	
test	Coefficient for education test in mincer regression by country
ed	Coefficient for education level in mincer regression by country
late	Coefficient for employment age indicator in mincer regression by country
ed un	Coefficient for education undermatch indicator in mincer regression by country
ed ov	Coefficient for education overmatch indicator in mincer regression by country
uu	Flow from education to job undermatch in early employment
uo	Flow from education undermatch to job overmatch in early employment
ou	Flow from education overmatch to job undermatch in early employment
oo	Flow from education to job overmatch in early employment
ue	Labor market undermatch rate for early workers
oe	Labor market overmatch rate for early workers
Training	
unsk	Fraction of early workers with unskilled jobs receiving training
sk	Fraction of early workers with skilled jobs receiving training

Table 12: Moments: Description

The moments are reported in Table 13 and parameter estimates in Table 14. For the baseline model, there are 18 moments and 11 parameters, so the model is overidentified.

From Table 13, the baseline model matches quite well the education moments, including the differences across countries in education rates. The model captures the low education and high undermatch rate in Italy as well as the relatively high education and high overmatch rates in Japan. The logistic coefficients, including the sign switch for α_0 in Japan are picked up as well.

In terms of the Mincer regressions, the model generates positive wage responses to the test score as well as to education and seniority.[41] But the responses to both the score and education are muted compared to the data. These results reflect, in part, the inclusion of under and overmatch in education as regressors.[42]

Looking at the moments summarizing labor flows, the estimated model matches very well the interactions between education and job mismatch, with the exception of Italy. So, for example, the "uu" rate of 0.393 of Germany in the simulated data comes from the 9.5% of individuals who are undermatched in education who are assigned unskilled jobs. These individuals test well in those jobs and are thus viewed as undermatched in employment. This predicted rate is quite close to that of 0.377 found in the actual data.

The model does not capture that the frequency of early labor undermatch and overmatch, denoted ue, oe respectively. In particular, the labor overmatch rates are considerably higher in the model than in the data. This is not because the model creates an excessive amount of overmatch in education. Rather this is produced through the labor markets, i.e. $(\delta_{cs}, \delta_{ns})$.

The moments that summarize the training rates are well matched. The estimated model captures the

[41] In both actual and simulated data, the test here is the education not the job score.

[42] The estimated model in Cooper and Liu (2019) included the coefficient on the test score in a Mincer regression with and without education and did not include education under and overmatch. For that estimation, the coefficients on the test score were well matched.

differences in training rates across countries as well as the fact that training is more likely for those in high skilled jobs. As discussed later, this is a key element in the contribution of training to offsetting education mismatch.

There are a couple of noteworthy features of the parameter estimates in Table 14. First, the returns to education and seniority are present with estimates of $h(\bar{e})$ and ω_2 above unity. Second, the noise in the education test, σ_e, is much smaller than the job test noise, σ_j. Third, these appears to be substantial variation in taste through a large estimate of $\bar{\varepsilon}$, made clear below by the restricted re-estimation as discussed below.

As for the training process, for Germany and Italy the human capital accumulation is lower for college educated than for the non-college group. The opposite is the case in Japan and the US. Also, for each of the countries either $\zeta(0)$ or $\zeta(\bar{e})$ lie below one.[43] This does not imply though that workers will not train. Recall from (9) that training not only increases human capital but also impacts job assignment. These forces are reflected in training decisions conditional on education and thus the simulated average training rates.

As for the flows associated with job transitions conditional on not training, $(\delta_{css}, \delta_{nsu})$ vary considerably across the countries. These probabilities have direct effects on the training decision by job assignment, thus distinct from $\zeta(e)$, since they apply if the agent chooses not to train. Indirectly they also impact the education decision. The estimate of δ_{css} is low in Germany and Italy. The estimate of δ_{nsu} is very high in Germany and relatively low in Italy. Thus individuals without college degrees who initially are assigned a skilled job are unlikely to retain that job, particularly in Germany.

For Japan and the US, $(\delta_{css}, \delta_{nsu})$ were not identified by the variation in the PIAAC data. That is, at the baseline parameter estimates, variations in these parameters did not impact the moments.[44] For the baseline moments and parameter estimates, as well as the analysis that follows, the lack of identification is remedied in two distinct ways.

In Japan, we set $(\delta_{css} = 1, \delta_{nsu} = 0)$ so that workers who do not train do not lose their position in a skilled job. This can be viewed as extreme job protection of workers in skilled jobs, a characteristic of labor markets in Japan.. In this way, there is no additional randomization in job assignment. To be clear, the setting of these two parameters is inconsequential for the analysis of Japan except for the dynamics of employment flows studied in section 6.3.

For the US, we turned to the NLSY97, a panel data set, to study the skill assignment over time of workers conditional on training. Following the procedures presented in Appendix sub-section 9.3, these flows were calculated as $\delta_{css} = 0.423, \delta_{nsu} = 0.576$.

The next experiments study the sources of education mismatch. By eliminating one shock at a time, the results provide some intuition on identification. Here we find one of our main results: the taste shock is critical for generating education mismatch and thus matching data moments.

The panel labeled "No Taste Shock" shows the re-estimated model with the restriction that $\bar{\varepsilon} == 0$, thus eliminating taste shocks. Clearly the fit of the model deteriorates for all countries, most noticeably in Italy. Note that in this case, the model produces mismatch as a consequence of noisy test scores: the σ_e. This is seen in the parameter estimates, Table 14, where the noise in the education test score is much higher than the baseline for all the countries, particularly Japan and the US. Further the estimated noise in the job test increases as well, particularly for Italy. From this experiment, there is a tradeoff between noise in the tests

[43] Recall that these are the expected productivity gains to training, incorporating the likelihood training succeeds as well as job assignment to take advantage of the increased human capital. If we re-estimate the model imposing $\zeta(e) \geq 1$, the fit worsens a bit in all countries.

[44] At the baseline estimates, individuals without a college degree in Japan and in unskilled jobs do not train, regardless of the size of δ_{nsu}.

and taste shocks. The baseline results indicate that the presence of the taste shocks is more effective in matching moments.

The fit worsens largely because of the model's inability to match the flows between education and job mismatch. For example, in Japan, the undermatch rate in education is 7.5% but none of these individuals are undermatched in the job. This occurs because the education and job mismatch are largely driven by uncorrelated noise in the test scores. Eliminating the taste shock improves the fit of the Mincer regression, particularly the education regressor since, in the absence of taste shocks, education is more closely correlated with ability. The coefficient on the test score is relatively low reflecting the added noise in the education test.

The importance of the taste shock is further reinforced by the case which eliminates noise in the education score, denoted "No Noise in Ed Test". The fit of the model does deteriorate without the noise, but not by very much. Interestingly, the job mismatch flows do not collapse to zero without noise in the education score indicating that the job mismatch is driven by both the education mismatch and the assignment of workers to jobs by skill. From Table 14, eliminating the noise in the education test has a small positive effect on the estimated variability of taste shocks.

	Education					**Mincer Reg.**					**Ed → Early Job**				**Emp. Mismatch**		**Training**		
	ed	un	ov	α_0	α_1	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
										Data									
Germ.	0.366	0.092	0.061	-0.883	1.274	0.149	0.237	0.173	-0.001	-0.034	0.377	0.000	0.000	0.250	0.101	0.038	0.386	0.643	na
It.	0.184	0.157	0.065	-1.972	1.015	0.092	0.276	0.226	0.018	-0.053	0.446	0.000	0.000	0.571	0.165	0.086	0.195	0.364	na
Jap.	0.583	0.071	0.116	0.137	0.915	0.137	0.120	0.270	-0.070	-0.005	0.609	0.000	0.000	0.255	0.134	0.085	0.380	0.685	na
US.	0.447	0.065	0.040	-0.465	1.437	0.159	0.243	0.179	0.099	-0.022	0.472	0.000	0.000	0.364	0.091	0.075	0.436	0.682	na
										Baseline									
Ger.	0.313	0.095	0.069	-0.871	1.280	0.097	0.176	0.173	-0.067	0.001	0.393	0.004	0.008	0.200	0.138	0.150	0.408	0.645	0.032
It.	0.150	0.141	0.040	-1.940	1.024	0.118	0.120	0.167	-0.039	-0.047	0.549	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.135
Jap.	0.512	0.080	0.141	0.115	0.928	0.070	0.234	0.321	-0.089	0.000	0.611	0.000	0.000	0.232	0.168	0.155	0.387	0.807	0.048
US	0.379	0.080	0.055	-0.458	1.439	0.071	0.276	0.187	-0.037	-0.023	0.494	0.000	0.000	0.330	0.140	0.155	0.443	0.707	0.044
										No Taste Shock									
Ger.	0.329	0.089	0.060	-0.873	1.273	0.055	0.291	0.206	-0.089	0.013	0.131	0.048	0.047	0.138	0.175	0.168	0.340	0.680	0.128
It.	0.154	0.149	0.052	-2.010	1.009	0.021	0.346	0.252	-0.032	-0.027	0.133	0.036	0.132	0.000	0.161	0.137	0.066	0.426	0.482
Jap.	0.524	0.075	0.107	0.130	0.931	0.023	0.280	0.344	-0.039	0.012	0.000	0.044	0.051	0.000	0.151	0.078	0.399	0.813	0.507
US	0.405	0.060	0.060	-0.451	1.441	0.036	0.316	0.241	-0.054	0.015	0.044	0.061	0.059	0.063	0.110	0.121	0.185	0.690	0.398
										No Noise In Ed Test									
Ger.	0.305	0.102	0.038	-0.875	1.281	0.096	0.151	0.160	-0.058	-0.026	0.387	0.000	0.001	0.255	0.156	0.163	0.413	0.645	0.038
It.	0.149	0.140	0.039	-1.944	1.029	0.117	0.119	0.171	-0.038	-0.049	0.570	0.000	0.000	0.301	0.170	0.161	0.268	0.290	0.139
Jap.	0.510	0.088	0.138	0.115	0.928	0.065	0.232	0.321	-0.084	-0.019	0.619	0.000	0.000	0.234	0.173	0.172	0.385	0.805	0.052
US	0.377	0.078	0.056	-0.465	1.443	0.072	0.275	0.187	-0.037	-0.023	0.501	0.000	0.000	0.329	0.139	0.154	0.447	0.677	0.043
										Capital Market Imperfections									
Ger.	0.313	0.094	0.069	-0.874	1.281	0.097	0.178	0.172	-0.069	0.001	0.385	0.005	0.009	0.198	0.137	0.150	0.403	0.645	0.032
It.	0.150	0.141	0.040	-1.940	1.024	0.118	0.120	0.167	-0.039	-0.047	0.549	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.135
. Jap.	0.512	0.080	0.141	0.114	0.925	0.070	0.234	0.322	-0.089	-0.000	0.616	0.000	0.000	0.234	0.168	0.155	0.386	0.807	0.048
US	0.378	0.079	0.055	-0.463	1.443	0.072	0.276	0.187	-0.038	-0.023	0.499	0.000	0.000	0.333	0.140	0.154	0.445	0.701	0.043
										Formal Training									
Ger.	0.313	0.093	0.073	-0.871	1.279	0.086	0.153	0.161	-0.090	0.014	0.384	0.006	0.009	0.212	0.138	0.151	0.158	0.181	0.041
It.	0.148	0.142	0.046	-1.952	0.996	0.117	0.114	0.150	-0.052	-0.043	0.570	0.000	0.000	0.323	0.171	0.164	0.165	0.219	0.150
Jap.	0.503	0.082	0.140	0.080	0.934	0.065	0.192	0.301	-0.071	-0.004	0.627	0.000	0.000	0.232	0.168	0.157	0.379	0.046	0.152
US	0.367	0.073	0.067	-0.529	1.453	0.053	0.257	0.209	-0.054	-0.016	0.495	0.000	0.000	0.334	0.137	0.155	0.178	0.655	0.259

Note: This table reports data and simulated moments for the estimated models. See Table 12 for a full list of variables.

Table 13: Moments

5 Extensions and Robustness

This section explores the robustness of our results.[45] Throughout the focus is on the sensitivity of our main findings regarding the role of taste shocks rather than noisy test scores as well as the limited role of

[45] Some additional exercises are reported in Appendix sub-section 9.2.

	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	p^t	$\bar{e}^t$	δ_{css}	δ_{nsu}
						Baseline						
Ger.	6.392	2.517	0.101	1.246	1.000	0.496	1.031	0.937	na	0.219	0.156	0.994
It.	4.511	4.951	0.017	1.127	1.110	0.825	0.834	0.772	na	0.137	0.001	0.315
Jap.	8.968	5.793	0.050	1.352	1.004	0.003	0.693*	1.165	na	0.210	0.993	0.992
US	10.682	2.457	0.004	1.132	1.000	0.236	0.974	1.351	na	0.059	0.423	0.576
						No Taste Shock						
Ger.	6.056	na	0.288	1.236	1.030	2.990	1.034	0.975	na	0.232	0.143	1.000
It.	6.135	na	0.498	1.151	1.274	1.092	0.767	0.832	na	0.071	0.044	0.238
Jap.	14.313	na	0.113	1.441	1.015	0.000	0.794	1.147	na	0.210	0.986	0.686
US	11.630	0.004	0.106	1.147	1.028	0.317	0.940	1.387	na	0.121	0.423	0.576
						No Noise in Ed Test						
Ger.	7.235	2.665	na	1.248	1.004	0.694	1.029	0.932	na	0.199	0.149	0.999
It.	4.590	4.935	na	1.126	1.118	0.727	0.834	0.773	na	0.129	0.000	0.323
Jap.	10.130	5.995	na	1.374	1.000	0.189	0.817	1.164	na	0.220	0.950	0.991
US	10.632	2.459	0.002	1.132	1.001	0.229	0.975	1.351	na	0.059	0.423	0.576
						Imperfect Capital Markets						
Ger.	6.371	2.498	0.105	1.246	1.000	0.499	1.030	0.937	na	0.220	0.156	0.996
It.	4.511	4.951	0.017	1.127	1.110	0.825	0.834	0.772	na	0.137	0.001	0.315
Jap.	9.037	5.787	0.049	1.357	1.004	0.003	0.692	1.162	na	0.212	0.992	0.993
US	10.657	2.454	0.004	1.132	1.000	0.231	0.975	1.351	na	0.059	0.423	0.576
						Formal Training						
Ger.	6.184	2.552	0.110	1.207	1.147	0.555	0.967	0.914	1.960	0.276	0.269	0.994
It.	4.572	4.969	0.010	1.128	1.119	0.725	0.824	0.772	1.823	0.147	0.003	0.338
Jap.	8.293	5.673	0.052	1.535	1.000	0.027	0.899	1.102	0.448	0.446	0.606	0.017
US	14.275	2.494	0.003	1.144	1.024	0.162	0.934	1.380	0.426	0.107	0.423	0.576

Note: This table reports parameter estimates for the baseline models.

Table 14: Parameter Estimates

capital market imperfections. Some of these extensions are continued in our study of the implications of the estimated models for explaining education mismatch and the implications for labor market outcomes.

As we shall see, the extension of the model to include imperfect information about ability leads to a better fit for Germany, though not for other countries. This is of interest since among the countries Germany is known for its early tracking system, consistent with the findings reported below.

5.1 Imperfect Capital Markets

The estimation was extended to include two models of borrowing constraints. In the first case, all agents are subject to an upper bound, *bbar*, on the amount they can borrow during the education phase. If this constraint binds, then, due to the assumed concavity of utility, the cost of education is increased and undermatch can occur. The economic significance of this constraint depends on the outside resources of young agents. For this case, the estimation includes a parameter for the maximal level of borrowing during the education phase.

In the second case, a fraction of agents, *nbp*, are unable to borrow at all, while the remainder face no constraint. In a more general setting, the probability of borrowing might depend on a range of individual characteristics, including parental education, income and wealth. But those covariates are not available in the PIAAC data.

The identification of capital market imperfects comes largely from its asymmetric effects on mismatch. In particular, a binding borrowing constraint can produce undermatch in education but not overmatch. This differs from the symmetric, by assumption, effects of tastes shocks.

There was no evidence of either form of borrowing constraint. Though out of pocket tuition is thought to be relatively low in these countries, there remains an opportunity cost of college through foregone income during the education phase. Thus, in principle, borrowing constraints might have mattered. They did not.

5.2 Imperfect Information

	Education						**Mincer Reg.**				**Ed → Early Job**				**Emp. Mismatch**		**Training**			
	ed	un-mat	over-mat	α_0	α_1	$\hat{\alpha}_{et}$	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
Data																				
Ger.	0.366	0.092	0.061	-0.883	1.274	0.940	0.149	0.237	0.173	-0.001	-0.034	0.377	0.000	0.000	0.250	0.101	0.038	0.386	0.643	na
It.	0.184	0.157	0.065	-1.972	1.015	0.847	0.092	0.276	0.226	0.018	-0.053	0.446	0.000	0.000	0.571	0.165	0.086	0.195	0.364	na
Jap.	0.583	0.071	0.116	0.137	0.915	0.778	0.137	0.120	0.270	-0.070	-0.005	0.609	0.000	0.000	0.255	0.134	0.085	0.380	0.685	na
US.	0.447	0.065	0.040	-0.465	1.437	1.062	0.159	0.243	0.179	0.099	-0.022	0.472	0.000	0.000	0.364	0.091	0.075	0.436	0.682	na
Noisy Ability																				
Baseline																				
Ger.	0.314	0.091	0.087	-0.872	1.280	na	0.112	0.192	0.167	-0.079	-0.012	0.382	0.005	0.000	0.227	0.120	0.141	0.413	0.644	0.026
It.	0.150	0.141	0.040	-1.940	1.024	na	0.118	0.120	0.167	-0.039	-0.047	0.548	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.134
Jap.	0.512	0.080	0.141	0.117	0.927	na	0.072	0.235	0.319	-0.091	-0.000	0.617	0.000	0.000	0.235	0.168	0.156	0.387	0.807	0.048
US	0.378	0.079	0.056	-0.463	1.438	na	0.071	0.276	0.187	-0.038	-0.021	0.495	0.000	0.000	0.330	0.140	0.154	0.441	0.706	0.044
No Taste Shocks																				
Ger.	0.313	0.092	0.088	-0.874	1.278	na	0.111	0.183	0.170	-0.079	-0.008	0.390	0.004	0.001	0.204	0.124	0.141	0.421	0.629	0.030
No Noise in Ed Test																				
Ger.	0.306	0.095	0.080	-0.867	1.278	na	0.107	0.149	0.163	-0.051	-0.039	0.392	0.000	0.000	0.279	0.152	0.165	0.408	0.645	0.037
Imperfect Capital Markets																				
Ger.	0.313	0.091	0.087	-0.873	1.283	na	0.112	0.191	0.166	-0.079	-0.012	0.383	0.004	0.000	0.228	0.120	0.141	0.412	0.644	0.026
Reverse Causality																				
Baseline																				
Ger.	0.320	0.089	0.074	-0.860	1.263	0.971	0.060	0.171	0.186	-0.052	-0.008	0.392	0.005	0.001	0.203	0.124	0.140	0.392	0.611	0.034
It.	0.148	0.147	0.010	-1.954	0.838	1.035	0.029	0.113	0.096	-0.086	-0.025	0.588	0.000	0.000	0.392	0.173	0.157	0.147	0.000	0.323
Jap.	0.511	0.077	0.125	0.111	0.967	0.695	0.044	0.228	0.311	-0.060	0.004	0.597	0.000	0.000	0.229	0.170	0.159	0.385	0.805	0.060
US	0.374	0.085	0.008	-0.479	1.476	0.931	0.095	0.225	0.300	-0.070	-0.043	0.500	0.000	0.000	0.336	0.153	0.164	0.461	0.700	0.088

Note: This table reports data and simulated moments for the estimated models. See Table 12 for a full list of variables.

Table 15: Moments: Imperfect Information and Reverse Causality

This section explores a variant of the model which introduces imperfect information at the stage of the education choice.[46] In the baseline model, individuals make education choices based on observed ability. In this extension, individuals choose college having only a signal of their ability: $s_i = \theta_i + \sigma_{ed}\eta_i$.[47] In this specification, the parameter σ_{ed} controls the impact of the noise, η_i on the agent's perceived ability, s_i.

To be clear, the signal is only used for the education choice: compensation and training decisions are made using actual ability. So this specification introduces an information friction at the time of the education decision to produce mismatch but then removes the friction at the time of training. Depending on selection, training may overcome the education mismatch.

The panel labeled "Noisy Ability" in Tables 15 and 16 report the parameter estimates and moments for this case. The moments to be matched are the same as in the baseline with σ_{ed} as an additional parameter.

Comparing Table 15 with Table 13, the fit of the model with imperfect information is better for Germany, but not for the other countries. From Table 16, the estimated noise in Germany is 0.506 which means that individuals are very uncertain about their ability, much more than the noise created from the education test score alone. Further, compared to the baseline, the variability in the taste shock, a competing source of mismatch, is lower. There is also a large reduction in the estimate of σ_j relative to the baseline. This uncertainty in ability is either zero or close to zero in the other countries.

[46] This extension as well as the reverse causality case builds on Cooper and Liu (2019).

[47] Here η^i is a mean zero, uniform random variable in the $[-0.5, 0.5]$ interval.

Further, from Table 15 this good fit remains after eliminating the taste shocks and/or the noise in the test score. As before, there is no evidence of the effects of imperfect capital markets. Evidently, imperfect information about ability is key to understanding mismatch and its labor market implications in Germany.

It is interesting that the imperfect information matters in Germany. As discussed in Dustmann, Puhani, and Schönberg (2017) and Brunello and Checchi (2007), among other studies, Germany has more earlier tracking compared to other countries such as the US and Italy. Early tracking is a natural sources of imperfect information about ability.

5.3 Reverse Causality: Dependence of Test Score on Education

The test score has been assumed to reflect the ability of the individual agent but not education. This assumption is easy to question in the PIAAC data as the test is taken after educational achievement. To the extent that the test score reflects some of the effects of schooling, there is the potential for reverse causality.

Our choice of the numeracy score as indicative of ability was made with this concern in mind. This extension of the model goes further and allows the test score to depend on education. In particular, **for the model** assume the education test score is given by,

$$ts_i = \theta_i + \alpha_{ed} e_i + \sigma_{ed} \zeta^{ie}. \tag{19}$$

Here α_{ed} parameterizes the dependence of the test score on education. As in the baseline model, the test score does not impact the education decision. But, building on the previous section, the education decision is made using a noisy signal of ability. Among other things, this guarantees that education and ability are not perfectly correlated.[48] The parameter α_{ed} is included in the set of structural parameters for this case.

It is not possible to create a data counterpart to (19) since ability is not observed. Thus to obtain some measure of the correlation between the test score and education, (20) is run on the PIAAC data and the coefficient $\hat{\alpha}_{et}$, estimated by OLS, is used as an additional moment.

$$ts_i = \hat{\alpha}_{et} e_i + \zeta^{ie}. \tag{20}$$

To be clear, there is no reason to believe that $\alpha_{ed} = \hat{\alpha}_{et}$, as the latter is obtained from a regression without ability as a regressor, so that there is omitted variable bias by construction. The argument here is that by including $\hat{\alpha}_{et}$ as a moment, it will be informative about the structural parameter α_{ed}.

The panel labeled "Reverse Causality" in Tables 15 and 16 report the parameter estimates and moments for this case. Note that here α_{ed} is in the set of parameters and $\hat{\alpha}_{et}$ is an additional moment.

Looking first at the moments, the estimates of $\hat{\alpha}_{et}$ range from around 0.78 to 1.06, indicating the positive correlation between education and test score. Of course this is not causal since education depends on ability which is not observed. For the "Reverse Causality" block, this moment is obtained by an OLS regression on the simulated data to obtain the model produced counterpart of $\hat{\alpha}_{et}$. In this manner, the omitted variable bias is present in the regression from simulated data as well.

The structural estimate, α_{ed} indicates the estimated impact of education on the test score. As indicated in Table 16, these estimates are near zero for all of the countries.

As in the baseline results, the mismatch seems to be driven largely by taste shocks: eliminating them reduces the fit considerably. And, once again, borrowing constraints have negligible impact.[49]

[48] This could otherwise occur, for example, if there are no taste shocks.

[49] As this alternative model does not dominate the baseline, these other experiments are not reported in the table.

c	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	$\bar{e}^t$	δ_{css}	δ_{nsu}	σ_{ed}	α_{ed}
							Noisy Ability						
		Baseline											
Ger.	5.485	1.923	0.147	1.242	1.050	0.002	0.978	0.871	0.174	0.030	0.995	0.506	na
It.	4.512	4.951	0.017	1.127	1.110	0.826	0.834	0.772	0.137	0.002	0.314	0.000	na
Jap.	8.819	5.944	0.050	1.353	1.000	0.000	0.688	1.165	0.211	0.884	1.000	0.013	na
US.	10.708	2.449	0.007	1.131	1.000	0.235	0.975	1.352	0.060	0.432	0.576	0.001	na
		No Taste Shocks											
Ger.	5.548	na	0.143	1.241	1.041	0.086	0.991	0.875	0.188	0.042	1.000	0.821	na
		No Noise in Test Score											
Ger.	6.659	2.351	na	1.216	1.071	0.706	0.968	0.895	0.139	0.052	0.923	0.468	na
		Imperfect Capital Markets											
Ger.	5.492	1.927	0.146	1.242	1.049	0.002	0.978	0.871	0.174	0.028	1.000	0.503	na
							Reverse Causality						
		Baseline											
Ger.	10.186	1.434	0.069	1.223	1.031	0.118	1.043	1.021	0.180	0.343	0.120	0.137	0.003
It.	15.758	3.309	0.003	1.171	1.007	0.166	1.127	1.091	0.397	0.893	0.265	0.001	0.000
Jap.	14.108	0.516	0.036	1.553	1.001	0.002	0.617	1.038	0.253	0.028	2.998	0.389	0.008
US	7.957	3.890	0.001	1.201	1.000	0.437	1.053	1.287	0.213	0.432	0.576	0.012	0.030

Table 16: Parameter Estimates: Imperfect Information and Reverse Causality

5.4 Job Flows

	Education					**Mincer Reg.**					**Ed → Early Job**				**Emp. Mismatch**		**Training**		
	ed	un-mat	over-mat	α_0	α_1	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
									Data										
Germ.	0.366	0.092	0.061	-0.883	1.274	0.149	0.237	0.173	-0.001	-0.034	0.377	0.000	0.000	0.250	0.101	0.038	0.386	0.643	na
It.	0.184	0.157	0.065	-1.972	1.015	0.092	0.276	0.226	0.018	-0.053	0.446	0.000	0.000	0.571	0.165	0.086	0.195	0.364	na
Jap.	0.583	0.071	0.116	0.137	0.915	0.137	0.120	0.270	-0.070	-0.005	0.609	0.000	0.000	0.255	0.134	0.085	0.380	0.685	na
US.	0.447	0.065	0.040	-0.465	1.437	0.159	0.243	0.179	0.099	-0.022	0.472	0.000	0.000	0.364	0.091	0.075	0.436	0.682	na
									Baseline										
Ger.	0.313	0.095	0.069	-0.871	1.280	0.097	0.176	0.173	-0.067	0.001	0.393	0.004	0.008	0.200	0.138	0.150	0.408	0.645	0.032
It.	0.150	0.141	0.040	-1.940	1.024	0.118	0.120	0.167	-0.039	-0.047	0.549	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.135
Jap.	0.512	0.080	0.141	0.115	0.928	0.070	0.234	0.321	-0.089	0.000	0.611	0.000	0.000	0.232	0.168	0.155	0.387	0.807	0.048
US.	0.379	0.080	0.055	-0.459	1.439	0.072	0.276	0.187	-0.037	-0.023	0.493	0	0	0.330	0.140	0.155	0.443	0.707	0.044
									$\delta_{cs}=1, \delta_{ns}=0$										
Ger.	0.314	0.090	0.082	-0.880	1.277	0.098	0.232	0.164	-0.107	0.012	0.380	0.000	0.000	0.241	0.090	0.084	0.399	0.651	0.022
It.	0.149	0.150	0.015	-1.942	0.982	0.113	0.140	0.151	-0.088	-0.043	0.587	0.000	0.000	0.356	0.157	0.081	0.261	0.417	0.116
Jap.	0.509	0.081	0.142	0.088	0.872	0.074	0.287	0.168	-0.106	0.032	0.566	0.000	0.000	0.391	0.073	0.137	0.000	0.727	0.228
US.	0.382	0.073	0.073	-0.457	1.441	0.078	0.295	0.165	-0.056	-0.011	0.496	0.000	0.000	0.335	0.095	0.108	0.443	1.000	0.143
									$\delta_{css}=1, \delta_{nus}=0$										
Ger.	0.312	0.096	0.072	-0.874	1.286	0.115	0.204	0.150	-0.064	-0.000	0.395	0.006	0.008	0.188	0.135	0.148	0.405	0.000	0.442
It.	0.150	0.143	0.001	-1.948	1.011	0.096	0.147	0.187	-0.063	-0.073	0.584	0.000	0.000	0.421	0.169	0.151	0.254	0.000	0.213
Jap.	0.511	0.080	0.142	0.114	0.926	0.074	0.235	0.322	-0.085	0.000	0.618	0.000	0.000	0.235	0.168	0.156	0.386	0.806	0.048
US.	0.378	0.079	0.057	-0.462	1.435	0.074	0.275	0.192	-0.033	-0.021	0.495	0.000	0.000	0.329	0.140	0.155	0.438	0.666	0.042

Note: This table reports data and simulated moments for the estimated models with alternative job flows.

Table 17: Moments: Alternative Flows

The baseline model put some restrictions on job flows. First, from Table 8, the estimation imposed the flows from education into skilled and unskilled early jobs in a data consistent manner. Second, the estimated parameters δ_{css} and δ_{nsu} determined the probability of flows in late employment by education if there was no training.

In this sub-section we study two cases with alternatives restrictions. For the first, we set $\delta_{cs} = 1$ and $\delta_{ns} = 0$ so that an individual is assigned to a skilled job iff they went to college. Thus there is no initial job randomization. In the second case, we impose $\delta_{css} = 1$ and $\delta_{nsu} = 0$ so that the only gain from training is through human capital accumulation, not job retention.

From Table 17, imposing $\delta_{cs} = 1$ and $\delta_{ns} = 0$ leads to an improvement in fit for Germany and Italy but a deterioration for Japan and the US. This is perhaps not so surprising for Japan since in the data $\delta_{cs} = 0.471$, much lower than the other countries. This stochastic job assignment was creating some early job mismatch that is removed when $\delta_{cs} = 1$. From the parameter estimates in Table 18, for Japan, this restriction leads to a large increase in the noise of the job test score. For the US, the training rate for skilled workers climbs to 100%, far over the data moment. As with Germany and Italy, the "ue,oe" flows are much closer to the data than the baseline. This is not an improvement over the baseline estimates since the estimation takes δ_{cs} and δ_{ns} from the data.

For the second case of $\delta_{css} = 1$ and $\delta_{nsu} = 0$, the fit deteriorated in Germany and Italy. In Germany and Italy, once the incentive to train brought about by job loss is removed, the training rates of skilled workers go to zero. Interestingly, the return to training by low education workers is higher compared to the baseline, particularly in Italy, in order to maintain incentives. But this supports training by unskilled workers.

For the US, the fit did not change. For Japan, the baseline estimation already set $\delta_{css} = 1$ and $\delta_{nsu} = 0$. This is again indicative of the lack of identification of these two parameters for these countries.

	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	$\bar{e}^t$	δ_{css}	δ_{nsu}
						Baseline					
Ger.	6.392	2.517	0.101	1.246	1.000	0.496	1.031	0.937	0.219	0.156	0.994
It.	4.511	4.951	0.017	1.127	1.110	0.825	0.834	0.772	0.137	0.001	0.315
Jap.	8.968	5.793	0.050	1.352	1.004	0.003	0.693	1.165	0.210	0.993	0.992
US.	10.682	2.457	0.004	1.132	1.000	0.236	0.974	1.351	0.059	0.432	0.576
						$\delta_{cs} = 1, \delta_{ns} = 0$					
Ger.	6.199	2.025	0.134	1.243	1.004	0.488	1.070	0.898	0.257	0.118	0.995
It.	4.972	4.720	0.030	1.068	1.085	0.919	0.884	0.755	0.168	0.001	0.328
Jap.	10.109	5.898	0.056	1.299	1.000	0.112	0.691	1.177	0.254	0.978	0.998
US.	10.704	2.669	0.029	1.116	1.000	0.334	0.985	1.331	0.047	0.725	0.010
						$\delta_{css} = 1, \delta_{nsu} = 0$					
Ger.	5.407	2.661	0.135	1.107	1.000	0.519	1.040	0.949	0.257	1	0
It.	5.282	4.271	0.020	1.038	1.052	0.578	0.969	0.804	0.300	1	0
Jap.	8.556	5.737	0.052	1.353	1.000	0.000	0.680	1.167	0.208	1	0
US.	10.345	2.402	0.008	1.135	1.001	0.240	0.973	1.352	0.062	1	0

Table 18: Parameter Estimates: Alternative Flows

5.5 Training: Formal

The analysis of training focuses on informal training in order to have a clear distinction between formal education and training. The model was re-estimated to match the rates of formal rather than informal training. Those training rates are shown in Table 10 and used as the last two moments in the estimation. Note that these rates of formal training are much lower in all countries but do retain the pattern that workers in skilled jobs are more likely to be trained.

The moments are reported in the bottom panel of Tables 13. The model fit for this case is not as good as the baseline. The decline in fit is coming from two sources: (i) the coefficients on mismatch in the Mincer regression and (ii) the training rates. The latter are either inconsistent with the pattern of larger training rates for skilled workers (Germany, Japan) or, as in the US, have very large training rates.

For this estimation the direct cost of training is added along with the opportunity cost, reported in Table 14. The formal cost of formal training is relative to the cost of US tuition. The cost is very large for most countries other than the US, consistent with the high training rates in the US. The estimated time cost is also considerable. As with the baseline, the estimated model has almost no noise in the test score.

5.6 Taste Shocks: the Role of Parental Influence

	Education Outcome (all)			Job Outcome (early)		
	Undermatch	**Well-match**	**Overmatch**	**Undermatch**	**Well-match**	**Overmatch**
GERMANY						
No parents with tertiary	6.11%	91.78%	2.11%	3.49%	94.34%	2.18%
At least one with tertiary	6.11%	91.42%	2.47%	8.64%	91.05%	0.31%
ITALY						
No parents with tertiary	12.97%	86.04%	0.98%	11.16%	86.06%	2.79%
At least one with tertiary	11.03%	84.14%	4.83%	17.78%	82.22%	0.00%
JAPAN						
No parents with tertiary	3.18%	90.84%	5.98%	6.06%	90.36%	3.58%
At least one with tertiary	2.32%	89.01%	8.67%	11.02%	86.72%	2.26%
US						
No parents with tertiary	3.39%	94.85%	1.76%	3.20%	91.99%	4.81%
At least one with tertiary	4.04%	94.04%	1.92%	6.18%	91.45%	2.38%
Pooled						
No parents with tertiary	5.77%	91.71%	2.52%	5.90%	91.17%	2.93%
At least one with tertiary	5.49%	91.11%	3.40%	7.24%	90.18%	2.58%

Table 19: Distribution of Education and Labor Market Outcomes, conditional on Parents' Education

Given the significance of taste variations as a source of mismatch, it is worth exploring further potential sources of these differences in the valuation of a college degree. Table 19 provides some initial evidence on the relationship between parents education and both education and job mismatch. By country, the rows indicate the educational attainment of parents. The blocks report the education and early labor outcomes.

For the pooled sample, parent's educational attainment does not have a large impact on education undermatch. For Italy and to a lesser extent in Japan, the undermatch rate is higher for those with low parental education. Overmatch in education is higher in both Italy and Japan for those whose parents have higher educational attainment. Interestingly, the job outcome effects are much larger. In all four countries, parental educational attainment is positively associated with higher levels of early job undermatch. Whether these are direct effects or arising through education choices will be clearer from the estimated model.

Building upon the evidence in Table 19, this section reports the estimated model extended to include the influence of parental education. To do so, we introduce parental education into the analysis in two ways. First, the regression used to predict the education outcome, (1), is supplemented to include parental education, pe_i:

$$\Pr\left(e_i = 1 | a_i, pe_i\right) = \frac{\exp^{\alpha_0 + \alpha_1 a_i + \alpha_2 pe_i}}{1 + \exp^{\alpha_0 + \alpha_1 a_i + \alpha_2 pe_i}}. \tag{21}$$

The regression coefficient on this additional variable, denoted α_2, appears in the moments given in Table 20.[50] Note that this parameter is positive for all the countries and about the same magnitude as the effects of the test score, α_1.[51] Compared to the baseline model, the estimated α_1 is a bit lower due to the inclusion of parental education.

[50]Other moments are left untouched, and thus we match the baseline moments.
[51]This points to a positive correlation between parents' education and test scores.

Second, the effects of parental education must be included in the model. To do so, the individual taste shock is assumed to be a proxy for parental education. In this way, we are allowing parental education to have a maximal impact on the education choice but not to directly impact mismatch in the labor market.

	Ed Moms						Labor Moms											Training Moms		
	ed	un-mat	over-mat	α_0	α_1	α_2	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
									Data											
Ger.	0.366	0.092	0.061	-1.250	1.150	1.109	0.149	0.237	0.173	-0.001	-0.034	0.377	0.000	0.000	0.250	0.101	0.038	0.386	0.643	na
It.	0.184	0.157	0.065	-2.147	0.953	2.243	0.092	0.276	0.226	0.018	-0.053	0.446	0.000	0.000	0.571	0.165	0.086	0.195	0.364	na
Jap.	0.583	0.071	0.116	-0.235	0.837	1.291	0.137	0.120	0.270	-0.070	-0.005	0.609	0.000	0.000	0.255	0.134	0.085	0.380	0.685	na
US	0.447	0.065	0.040	-0.761	1.286	0.840	0.159	0.243	0.179	0.099	-0.022	0.472	0.000	0.000	0.364	0.091	0.075	0.436	0.682	na
										Baseline										
Ger.	0.313	0.095	0.069	-0.871	1.280	na	0.097	0.176	0.173	-0.067	0.001	0.393	0.004	0.008	0.200	0.138	0.150	0.408	0.645	0.032
It.	0.150	0.141	0.040	-1.940	1.024	na	0.118	0.120	0.167	-0.039	-0.047	0.549	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.135
Jap.	0.512	0.080	0.141	0.115	0.928	na	0.070	0.234	0.321	-0.089	0.000	0.611	0.000	0.000	0.232	0.168	0.155	0.387	0.807	0.048
US	0.379	0.080	0.055	-0.459	1.439	na	0.072	0.276	0.187	-0.037	-0.023	0.493	0	0	0.330	0.140	0.155	0.443	0.707	0.044
									Parents Education: Baseline											
Ger.	0.362	0.092	0.078	-1.253	1.149	1.098	0.047	0.264	0.199	-0.072	0.005	0.129	0.048	0.047	0.135	0.173	0.170	0.361	0.717	0.126
It.	0.312	0.126	0.106	-2.206	0.939	2.200	0.051	0.172	0.220	-0.076	-0.021	0.157	0.033	0.062	0.128	0.183	0.171	0.153	0.648	0.422
Jap.	0.569	0.083	0.130	-0.282	0.845	1.273	0.058	0.339	0.301	-0.094	0.029	0.141	0.028	0.093	0.091	0.189	0.181	0.443	0.838	0.355
US	0.423	0.070	0.077	-0.777	1.274	0.832	0.046	0.341	0.273	-0.069	0.014	0.134	0.045	0.054	0.143	0.184	0.182	0.430	0.706	0.252

Note: This table reports data and simulated moments for the estimated models with parents education influencing the test score.

Table 20: Moments: Parents Education

The model is re-estimated with this added moment, captured by α_2. As indicated by the moments in Table 20, the fit is significantly worse than the baseline (shown as well), reflecting, of course, the added moment. The estimated model continues to match well all of the education moments, including the dependence of the education choice on parents education through the associated taste shock. The estimated model does not match very well the moments summarizing the flow between education mismatch and job mismatch. For all countries, the flows from undermatch in education to undermatch in early employment are much lower than in the data and in the baseline model.

This deterioration in the fit is linked to the parameter estimates. Using the taste shock to proxy for parental influence leads to a large reduction in the variability of the taste shock, $\bar{\varepsilon}$, relative to the baseline estimate. While this reduction in noise helps to match the α_2 parameter in the education choice regression, it is coupled with a large increase, relative to the baseline, in noise in the test score, σ_e. The large amount of noise in the test score reduces the link between education and job mismatch, as evidenced by the deterioration in those moments.

	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	$\bar{e}^t$	δ_{css}	δ_{nsu}
					Baseline						
Ger.	6.392	2.517	0.101	1.246	1.000	0.496	1.031	0.937	0.219	0.156	0.994
It.	4.511	4.951	0.017	1.127	1.110	0.825	0.834	0.772	0.137	0.001	0.315
Jap.	8.968	5.793	0.050	1.352	1.004	0.003	0.693	1.165	0.210	0.993	0.992
US	10.682	2.457	0.004	1.132	1.000	0.236	0.974	1.351	0.059	0.432	0.576
					Parents Education: Baseline						
Ger.	7.680	0.565	0.221	1.212	1.141	2.069	0.970	0.938	0.089	0.104	0.908
It.	6.571	3.842	0.318	0.999	1.010	2.735	0.819	1.318	0.267	0.034	0.355
Jap.	6.523	1.519	0.294	1.352	1.000	2.999	0.507	1.130	0.118	0.256	0.514
US	9.162	0.466	0.152	1.086	1.001	2.979	1.013	1.500	0.101	0.432	0.576

Table 21: Parameter Estimates: Parents Education

From this exercise, it is clear that parental education matters for mismatch, both in education and in labor market outcomes. The model studied here can incorporate the effects of parental education on education alone but this does not carry over to labor market outcomes.

Clearly, from Table 19, the effects of parental education could also impact job outcomes directly. That is outside of the scope of this analysis as it pertains to labor market mismatch that is not a consequence of education mismatch.

6 Interpretation and Implications

This sections uses the estimated models to study the determinants and implications of mismatch.[52] It returns to one of the central theme of the paper: the effects of education mismatch on labor market outcomes.

To do so, we first isolate the source(s) of education mismatch. We then trace mismatch to labor market outcomes: (i) wages, (ii) job assignment and (iii) training.

A key contribution is using the model to generate dynamics. As mentioned numerous times, the data has no dynamic component. But once the model is estimated, we are able to simulate and study the dynamics of mismatch. Thus this section relies entirely on simulation of these dynamics using the estimated model.

Tables 22 provides a summary of results. It highlights the wage, job assignment and training experiences of both under- and overmatched in education individuals by country. It is explained in detail in the subsections that follow.

	MM Rate	wre	wrl	$pr(ske)$	$pr(tr\|ske)$	$pr(tr\|unske)$	$pr(skl\|ske)$	$pr(skl\|unske)$
Germany								
undermatch ed	0.091	0.936	1.244	0.229	0.882	0.895	0.545	0.540
overmatch ed	0.087	0.852	0.722	0.778	0.486	0.714	0.429	0.597
Italy								
undermatch ed	0.141	0.998	1.404	0.168	0.000	1.000	0.680	0.675
overmatch ed	0.040	0.782	0.688	0.718	0.000	0.000	0.000	0.000
Japan								
undermatch ed	0.079	1.020	1.020	0.117	0.000	0.000	1.00	0.0
overmatch ed	0.141	0.916	0.862	0.464	1.000	1.000	0.578	0.578
United States								
undermatch ed	0.079	0.989	1.163	0.221	1.000	1.000	0.704	0.692
overmatch ed	0.055	0.888	0.858	0.749	1.000	1.000	0.814	0.797

Note: This table shows the life cycle path for under- and overmatched in education individuals by country from the baseline model. Here: (i) MM rate is the education mismatch rate, (wrj) is the ratio of the wage paid to mismatched and average wage in employment period j, (iii) ske is skilled in early employment, (iv) skl is skilled in late employment, (v) $unske$ is unskilled in early employment. And $pr(x|y)$ is the probability of x given y.

Table 22: Simulated LifeCycle

6.1 Sources of Education Mismatch

The starting point of the analysis is the determination of the source of education mismatch. If, for example, the main source of education mismatch is noise in the test score, then this is likely to have a minimal impact on labor market outcomes. This is because the education test score has no direct impact on the allocation

[52]It uses the baseline parameter estimates for Italy, Japan and the US from Table 14 and the parameter estimated from the model with imperfect information about ability for Germany from Table 16.

of individuals across schooling and jobs. And, with sufficient noise in the test score, it will not be very correlated with the job test and thus measured labor market mismatch. But, if education mismatch reflects either taste shocks, borrowing constraints or noise about ability, then there can be implications for labor market outcomes.

As argued, education mismatch, joint with other moments, is best explained through taste shocks for Italy, Japan and the US. The fit of the baseline model is essentially maintained when there is no noise in the education test score and allowing capital market imperfections does not improve the fit either. For Germany, the introduction of noisy ability at the time of the education decision improved the model fit relative to the baseline.

As indicated in Table 22, the baseline model generates mismatch in education and captures the patterns across the countries. Note the asymmetry in Italy where undermatch dominates as well as the opposite for Japan where overmatch in education is larger than undermatch.

6.2 Wages

From the Mincer regressions reported in Table 5, the coefficients on both under- and overmatch in education were not significantly different from zero and their point estimates were all small. Thus, there was no direct offset in wages for education mismatch. Put differently, there was no correction in wages for education mismatch.

This is brought out further in Table 22. The columns labeled wre and wrl report the average wage of an individual mismatched in education relative to a well matched individual with the same education in early and late employment. The idea is to summarize the effects of education mismatch on wages conditional on education. So, for example, in the early work period, an undermatched individual in Germany receives about 7% less than an average well-matched individual who also did not go to college. But in late employment, the under-matched individuals obtain nearly a 25% bonus.

This seems to be a general pattern. The wage ratio for undermatched individuals is either below or very close to 1 in the early period. The ratio exceeds one in the late period, except for Japan. And the wage ratio is considerably below one for overmatched in education individuals. Thus the model does predict some wage correction, but mostly in the late period. These corrections are much smaller in Japan and the US compared to Italy.

Note that the wages income in both periods also reflects training. In the early period, the time cost of training reduces labor income while the benefits of training appear in the late employment income.

Overall, education mismatch matters for subsequent labor compensation. This is made clear by these wage ratios. The next task is to uncover the contribution of labor market dynamics and training for this connection.

6.3 Labor Market Mismatch

One way to overcome education undermatch is to assign high (low) ability workers to skilled (unskilled) jobs, regardless of their education. But the actual early job assignment process taken from the data, recall Table 8, allocates some individuals with college degrees to unskilled jobs and some without college to skilled jobs. Afterwards, there is the potential for reallocation of workers across job types joint with training.

Our focus here is on the job mismatch created by education mismatch. For that purpose we follow individuals both under and overmatched in education, through the two work phases.

Recall that the return to training, summarized by $\zeta(\cdot)$, incorporates both the human capital associated with training as well as the likelihood of assignment to a skilled job. For the estimation and the theory model it is based upon, decomposing this compound lottery was not needed.

But to determine the likelihood an individual transits, say, from an unskilled to a skilled job does require this information. The bottom panel of Table 8 provides data moments summarizing late job assignment by education attainment. Taking these as given along with the training probabilities from the model and the estimates of $(\delta_{css}, \delta_{nsu})$, it is possible to calculate the probability an individual is assigned a skilled job conditional on training.[53]

Using these flows, the last two columns of Table 22 shows the transitions in terms of job assignment by education mismatch. So, for example, an undermatched individual in Germany is assigned a skilled job with probability 0.229. That individual trains with probability 0.882 and remains in a skilled job with probability 0.545. This latter probability reflects not just the training decision but also the likelihood of being assigned a skilled job conditional on training which is about 0.60 for those without college in Germany.

For all countries, those undermatched in education are less likely to obtain a skilled job in the early work phase compared to those who are overmatched. But in all the countries except Japan, there are forces to overcome this by late employment. In particular, for Germany, Italy and the US, the undermatched assigned to unskilled jobs early choose to train (the rate is 100% in Italy and the US). These individuals are likely to obtain late skilled jobs. For the undermatched initially assigned skilled jobs, in Italy, they choose not to train and thus risk their skilled job assignment as training is most costly for them. This reduces the fraction of undermatched in education individuals who ultimately have skilled jobs.

In Japan this correction of undermatch through labor flows does not happen. The education undermatched assigned to an unskilled job do not train and so have no avenue for promotion to a skilled job.[54] The 11.7% of the undermatched in education assigned to skilled jobs do retain those jobs in the late work phase.

Looking in more detail at these transitions, Table 23 focuses specifically on the dynamics of job mismatch given education mismatch. It builds on the "uu" and "oo" moments used in the estimation to study the implications for job mismatch in the later period. This is not the same as, but is consistent with, the job assignment studied in Table 22. The columns labeled "ueuj late" and "oeoj late", represent the fraction of individuals mismatched both in education and in the labor market in early employment that continue to be mismatched in the late period. That is, these are **conditional probabilities** to highlight the flows given early mismatch.

To be clear about the forces at work, consider an individual who is undermatched in early employment. By definition, this is someone assigned to an unskilled job with a relatively high job test score. This person might have been undermatched in education and thus did not attend college despite having a high education test score. This individual was then assigned an unskilled job according to their country specific value of δ_{nu}. Alternatively, this individual could be well matched in education, obtaining a college degree. But, with $\delta_{cs} < 1$ and a high correlation between the education and job test, the individual would be deemed undermatched in early employment. As mentioned before, our focus here is on the first case i.e. the job mismatch created by education mismatch.

From this table, the model predicts that education mismatch, both under and over, is largely resolved in Germany and Italy. For those two countries, the "ueuj late" rates are about a third and the "oeoj late"

[53] These calculations are used in Tables 22 and 23. Derivations are shown in Appendix sub-section 9.4.

[54] Here is where setting $(\delta_{css} = 1, \delta_{nsu} = 0)$ could matter. But in Japan, unskilled workers do not train, so the finding that $pr(skl|ske) = 0$ is independent of δ_{nsu}.

rates are almost zero. In Japan none of the education undermismatch is corrected: all the individuals that are undermatched in education and the labor market in early employment, are also undermatched in the late job. Further over half of the overmatch in early by individuals overmatched in education remain. Finally, in the US, education mismatch is partly. Individuals undermatched in education and in the early job, are very likely not to remain undermatched in late employment. Thes flows are similar to those in Germany and Italy. But, as in Japan, individuals overmatched in education and in the early job keep their skilled jobs thus continue to be overmatched in late employment. Note that the training rates in the US are 1 for both skilled and unskilled workers. But these efforts are muted by the fact that not all individuals who train are placed in skilled jobs.[55]

	ueuj early	ueuj late	oeoj early	oeoj late
Germany	0.382	0.386	0.227	0.034
Italy	0.549	0.327	0.304	0.000
Japan	0.611	1.000	0.233	0.571
United States	0.493	0.310	0.330	0.812

Note: This table shows labor market flows from education mismatch. "ueuj early" are the fraction of undermatched in education who are undermatched in their early job. "ueuj late" are the fraction of those from the preceding column who remain undermatched in their late job. "oeoj early" and "oeoj late" are defined analogously.

Table 23: Labor Mismatch Dynamic

6.4 Training: Selection and Effects

Underlying these job transitions is training. Here again the emphasis is on the role of informal training, both through selection into training and its effects on job assignment and compensation.

The moments used in the baseline estimation were the training rates. These were matched well. Table 22 shows the training rates, conditional on early job assignment, for the under- and overmatched in education group. The group of individuals well-matched in education is not shown. Except for Germany, the training rates are extreme, either all agents in a group train or none train. This highlights the incentives to train but also indicates that the model does not include a choice specific shock associated with the training choices.

6.4.1 Selection

The selection into training depends, in part, on the return which itself has two components. First, there is human capital accumulation captured by $\zeta(e)$. By construction, this part of the return depends on education. This return surely provides a way for undermatched individuals to climb the job ladder. Second, there is job assignment which depends on the likelihood an individual who does not train can remain in a skilled job. This is controlled by the estimated parameters $(\delta_{css}, \delta_{nsu})$.

The model has some clear predictions about selection into training. First, all else the same, higher education individuals have a bigger return to training and thus are more likely to train. Second, all else the same, the return to training also increases in ability and thus in the test score.

Table 24 adds to the training rates from Table 22 individuals well-matched in education. Recall that, by definition, individuals undermatched in education do not have a college education while the overmatched do. Some of the well-matched have a college degree and others do not.

[55] As indicated in Table 36, only about 80% (69%) of individuals with (without) a college degree who trained are assigned a late skilled job in the US.

	$pr(tr\|sk)$	$pr(tr\|unsk)$
Germany		
undermatch ed	0.882	0.895
well-matched no college	0.230	0.286
overmatch ed	0.486	0.714
well-matched college	0.912	0.970
Italy		
undermatch ed	0.000	1.000
well-matched no college	0.000	0.109
overmatch ed	0.000	0.000
well-matched college	0.713	0.765
Japan		
undermatch ed	0.000	0.000
well-matched no college	0.000	0.000
overmatch ed	1.000	1.000
well-matched college	1.000	1.000
United States		
undermatch ed	1.000	1.000
well-matched no college	0.049	0.272
overmatch ed	1.000	1.000
well-matched college	1.000	1.000

Note: This table shows the probabilities of receiving training in early employment, conditional on the type of job and the education match.

Table 24: Selection into training

Selection into training varies across the four countries. In Japan, for example, it depends solely on the level of education: all individuals with college train, while none of the individuals without college do. This can be explained by differences in the estimated return to training $\zeta(\cdot)$ for the two groups, reported in Table 14.[56] It is consistent with the evidence in Table 9 that the likelihood of training in Japan did not depend on the numeracy score, given education and job assignment.

In Germany, Italy and the US, the education level impacts the training decision as well. Except for the group assigned to early unskilled jobs in Italy, a higher proportion of educated individuals receive training compared to the non educated ones with the same occupation and ability group. In Germany, 97% of the well matched who went to college with unskilled jobs train, while 90% of those undermatched with unskilled jobs receive training.

Similar to Japan, all individuals with college in the US train as a result of a relatively high $\zeta(\bar{e})$. However, high ability individuals with no college who are placed at unskilled jobs choose to train as well. Thus, education is not the only determinant in participation into informal training.

For Germany, Italy, and the US, there are other factors at play. For instance, conditional on early job assignment and the level of education, in those three countries training is more frequent for the group whose individuals have on average higher ability. The undermatched (overmatched) train more (less) than the well matched who also didn't (did) go to college and are assigned to the same occupation. So, for example, around 88% of the individuals undermatched in education in Germany, who are assigned to unskilled jobs in early employment, receive training. In contrast, only 23% of the well matched group with the same level of education and type of occupation, train. This is due to the fact that, if allocated to skilled jobs, the gain

[56] This points to another issue of identification for Japan since any lower level of $\zeta(0)$ will generate the same moments given that no one without a college degree trains. This has no bearing on any of our findings.

from training is increasing on ability and thus is higher for the undermatched.

Finally, conditional on the education outcome, training is more frequent across the group assigned to unskilled jobs. This is true in all countries.

6.4.2 Implications

These training outcomes are key to understanding wages and labor market flows. Look first at undermatched in education individuals. If these individuals are placed in low skill jobs, they decide to train in all countries except for Japan. This training leads to a proportion of them to obtain high skill jobs in late employment, thus offsetting their education mismatch.[57] This is consistent with the high wage ratio for the undermatched in late employment, as the well matched with no college train much less. Moreover, it explains the mechanism through which the "ueuj late" rates are about a third in Germany, Italy and the US.

In Japan, in contrast, the undermatched do not train and thus do not progress to skilled jobs. Consequently, they receive no wage premium in late employment and the labor market cannot offset their education mismatch. These results are consistent with the "ueuj late" rate of unity reported in Table 23 for Japan.

As for the overmatched in education, they receive training if their initial job assignment is unskilled in all countries except Italy (in Germany the rate is 71%). All of them receive training as well if assigned to an early skilled job in early in Japan and the US, while in Germany only about 50% receive training. Since training leads to the possibility of assignment to skilled jobs in the late period of work, part of the education overmatch is reinforced by training in all countries except for Italy.

As mentioned before, these high training rates for overmatched individuals reflects the estimated return to training for college educated individuals, $\zeta(\bar{e})$. From Table 14, $\zeta(\bar{e}) > \zeta(0)$ for Japan and the US while for Italy and Germany the opposite is true. Recall that $\zeta(\cdot)$ captures the return to the compound lottery associated with training and job assignment and is not just a narrow measure of human capital accumulation. So, college graduates in the US and Japan might have a much higher probability of a skilled job assignment and take advantage of this compared to individuals with no college education.

For Italy, the overmatched do not receive training and thus do not transit to skilled jobs from unskilled jobs. In fact, the overmatched in Italy, while initially placed in skilled jobs, do not retain those jobs. From Table 14, the estimate of δ_{css} is near zero in Italy so that those who do not train lose their skilled job. These results are consistent with the "oeoj late" rate equal to zero for Italy.

6.5 Counterfactual

Some of the initial job mismatch reflects the feature, taken from the data, that $\delta_{cs} < 1, \delta_{ns} > 0$. Thus some individuals well matched in education can be mismatched in their early employment. This randomness in job assignment becomes both a source of job mismatch and impacts education decision.

Here we consider a counterfactual that eliminates this initial job mismatch while keeping education decisions intact. Thus, this counterfactual highlights the role of the two economic decisions: education and training.

To conduct this experiment, assume that $\delta_{cs} = 1, \delta_{ns} = 0$. Further, for late job assignment, the counterfactual assumes that skilled workers do not lose their job assignment even if they do not train. Thus this source of job mismatch, as well as their incentive to train, are removed. To be more clear, with this labor market structure all undermatched individuals are placed at unskilled jobs in early employment and training

[57] As indicated before, these proportions are reported in Table 36.

is the only path to skilled jobs. In contrast, all overmatched individuals are placed at skilled jobs in both periods so training is only chosen if the return $\zeta(\bar{e})$ is high enough. This is a simulation exercise, in contrast to sub-section 5.4 which involved re-estimation of model parameters.

Table 25 shows the transitions through the employment phases conditional on education mismatch. The counterfactual exercise eliminates the possibility for an individual undermatched (overmatched) in education to be assigned to a skilled (unskilled) job. Thus "uu early" and "oo early" rates are now substantially higher compared to the baseline. However, they are lower than one since the education and job test are not perfectly correlated due to different noises. Thus some individuals might appear to be undermatched (overmatched) in education but not in the labor market.

Looking at individuals undermatched in education, in Germany, Italy and the US, the labor market corrects for the education undermatch. There is no correction in Japan. This is similar to the baseline findings. It indicates that the propagation of undermatch in education is not driven by initial job assignments.

	uu early	uu late (cond)	oo early	oo late (cond)
		Baseline		
Germany	0.382	0.386	0.227	0.034
Italy	0.549	0.327	0.304	0
Japan	0.611	1	0.233	0.571
United States	0.493	0.310	0.330	0.812
		Counterfactual		
Germany	0.497	0.383	0.295	1
Italy	0.662	0.328	0.410	1
Japan	0.695	1	0.508	1
United States	0.635	0.310	0.432	1

Note: This table reports the dynamics of labor mismatch under the counterfactual with $\delta_{cs} = 1, \delta_{ns} = 0$.

Table 25: Counterfactual: Labor Mismatch Dynamic

6.6 Earnings Loss from MisMatch

Using the baseline estimates, Table 26 computes earnings over the three phases of the lifecycle.[58] These calculations are for the baseline model and another treatment, called "Maximal Output".[59] Given baseline parameters, this latter allocation was obtained by removing two key sources of mismatch:(i) taste shocks and (ii) the randomness in the allocation to early jobs, i.e. ($\delta_{cs} = 1, \delta_{ns} = 0$). This is the allocation that generates the most earnings, and hence output, in the early and late work phases.

The first three entries are mean earnings over each of the three phases. Note that these earnings are net of lost income and tuition due to schooling and training. Hence, for example, as the education rate changes across treatments, so do mean earnings in the education phase. Thus low earnings in the education phase indicate high college rates. The last entry is total income from the three phases. All of these measures are discounted to the start of the education phase.

Compared to the maximal output allocation, the earning in the education phase are higher in the baseline model. This reflects the lower returns to education when there is randomness in the early job assignment.

[58] Garibaldi, Gomes, and Sopraseuth (2020) also calculates output loss from labor market mismatch. Their formulation allows an interaction between over and undermatched workers, through the production function, that is absent in our model.

[59] For purposes of comparison, this is the baseline taken from Table 14 for all countries.

These low returns translate into a lower college rate than in the maximal output calculation. This is particularly true for Japan: in the maximal output allocation the education rate is over 70%.

The output cost of education mismatch is seen by comparing between the baseline and the maximal output allocation, for each country, the mean earnings in early and late work. For Japan, this difference is substantial, over 12%, indicating the loss associated with undermatch in both education and jobs. This loss is most pronounced in the early work period. For the other countries, these differences in earnings are present but are smaller. In fact, for Italy, the mean earnings in late work are higher than in the maximal output allocation and the total is only slight lower. For Italy, the education mismatch rate is high, as is the value of δ_{ns} in late employment.

	Ed Phase	Early Work	Late Work	Total
		Maximal Output		
Ger.	0.457	8.708	13.535	22.700
It.	0.572	8.691	13.520	22.783
Jap.	0.024	9.100	17.220	26.344
US.	0.239	8.654	14.776	23.670
		Estimated Model		
Ger.	0.516	8.004	13.306	21.825
It.	0.580	8.285	13.604	22.469
Jap.	0.211	7.803	15.441	23.454
US	0.311	8.213	14.217	22.741

This table shows discounted present value of earnings over the education and work phases using baseline parameters.

Table 26: Earnings Net of Education and Training Costs

7 Cross-Country Perspective

Countries differ in both educational and labor market institutions. As discussed already, Germany is known for its early sorting into education. As discussed in evaluating labor market outcomes in the PIAAC data, Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) point to various differences in labor market institutions across countries.

Here we interpret our results from a country perspective, rather than emphasizing the channels linking education to job mismatch. This perspective allows us to introduce institutional features that differ across countries.

7.1 Germany

There are a couple of features of the German education and labor markets that stand out. First, as noted earlier, higher education decisions in Germany are made earlier and thus with limited information about individual ability. This was confirmed in our estimation. Second, there are the effects on education and labor market outcomes of parents education noted by Dustmann (2004) and others. This in part motivated our analysis linking parental education to tastes. These features underlie our account of education and labor market outcomes in Germany.

In Germany, there is considerable education mismatch, partly due to noise about ability at the time of the education decision. Undermatched in education individuals receive training

and about half succeed in being placed in skilled jobs. Part of the overmatch in education is solved by other labor market reallocation mechanisms.

In particular, around 90% of the individuals undermatched in education in Germany decide to train and many are placed at skilled jobs in late employment. This is true for undermatched individuals in both types of jobs in early employment. As a results, flows from education to job undermatch decreases in late employment. In this sense, training helps overcome education undermatch.

The decision to train comes from three main factors. First the estimated return to training for the undermatched in education, $\zeta(0)$, is a bit lower but close to one. Second, the relatively high ability of undermatched individuals implies a relatively large gain from training when assigned to skilled jobs. Third δ_{nsu} close to one implies that not only training is source of upward mobility across jobs but also is the only way for undermatched individuals in skilled jobs to remain there.

In the case of education overmatched individuals, training rates are lower due to lower estimated return to training i.e $\zeta(\bar{e}) < \zeta(0)$, and lower gains from training due to relatively low ability. Around 50% of overmatched individuals with skilled jobs in early employment, and around 70% of those with unskilled jobs, decide to train.[60] In this sense, training might also help to further create/reinforce the flows from education to job overmatch. However, δ_{css} is almost zero. Thus, the other half of overmatched individuals loose their skilled jobs and are reallocated to unskilled ones in late employment, through other labor market reallocation mechanisms.

7.2 Italy

In Italy, the college education rate is relatively low. There is considerable education undermatch which largely reflects taste shocks. There is no evidence of capital market imperfections. Labor market mechanisms in Italy create a path for the undermatched in education and reallocate overmatched to unskilled jobs in late employment.

The transition from school to work in Italy is close to the pooled average, with about 68% of individuals with a college degree obtaining a skilled job and only about 17% of those without college are in a comparable job. Those who are overmatched in education are paid less than average in both early and late employment, while the undermatched are paid considerably more.

Looking specifically at the path of the undermatched. About 83% of them are initially placed in unskilled jobs. All of them decide to train. As a result, around 68% are reassigned to skilled jobs in late employment. In this sense, training helps solving the initial misallocation of undermatched individuals. In contrast, none of those allocated to skilled jobs in early employment choose to train. However the estimated value of δ_{nsu} implies that almost 70% of them keep anyways their skill jobs.

As Table 22 shows, none of the individuals overmatched in education receive training. In addition, δ_{css} is almost zero. Thus, overmatched individuals assigned to skilled jobs in early are reallocated to unskilled jobs in late employment. In this way, the labor market solves the education overmatch. As a result, flows from education to job mismatch decrease substantially in late employment for both types of mismatch. As with Germany, differences in training decisions between over- and undermatched individuals come from differences in the estimated return to training ($\zeta(\bar{e}) < \zeta(0)$) and the relatively low ability of overmatch individuals.

In a comparison of OECD countries, Kawaguchi and Murao (2014) study how a cohort specific scarring effect, which itself depends on labor market conditions at the time of labor market entry, influences unem-

[60] The higher training rate for individuals with unskilled jobs, compared to those with skilled ones, might be explained by a lower opportunity cost.

ployment rates in later years. From that study, Italy stands out as one of the OECD countries, along with Portugal and Spain, with the highest employment protection index. In contrast, the US is the lowest. The argument in Kawaguchi and Murao (2014) is that high employment protection is positively associated with larger scarring effects.

The results for Italy reported in Table 22 are, in some ways, in conflict with this view. Individuals undermatched in education are not likely to get skilled jobs. Those that do get obtain skilled jobs, do not train. Evidently the estimate of $\delta_{nsu} = 0.315$ implies that the penalty for not training is not large. Also, overmatched individuals do not train despite the estimate values of $\delta_{css} = 0.001$. From this perspective, there is not much mobility in Italy. But, this misses an important element: the training of the undermatched in unskilled jobs. These individuals train at a very high rate and succeed in obtaining skilled jobs in late employment. So, for Italy, unlike Japan, the undermatched are not trapped in unskilled jobs.

7.3 Japan

In Japan, the education rate is very high and there is more education overmatch than undermatch. As with the other countries, education mismatch reflects taste shocks. Labor market mechanisms in Japan perpetuate the effects of education undermatch throughout the lifetime employment.

Specifically, and in stark contrast to Italy, none of the undermatched in education individuals train, regardless of their job assignment in early employment. The point estimate of $\zeta(0) = 0.693$ for Japan makes clear that those without education do not have an incentive to train.[61] Thus these agents are trapped. From Table 4, the fraction of late workers undermatched in employment is high in Japan, compared to the pooled sample, reflecting the limited incentives to train.

The opposite is true for the education overmatched. They train, regardless of initial job assignment. This is driven mainly by the estimated return to training of $\zeta(1) = 1.165$.

Recall that these estimates of the return to training incorporates the human capital accumulated through training as well as job assignment to take advantage of the increased human capital. Thus, the estimates for Japan implies that those likelihoods are much higher for college graduates than for the non-educated individuals.

This persistence of initial effects is perhaps not surprising given the nature of labor market institutions in Japan.[62] Kondo (2007) uses micro data to study the effects of first jobs on future labor market outcomes, including training. The paper concludes that the probability of regular full time employment is adversely impacted by initial job placement.[63] Given the estimated value of $\delta_{ns} = 0.12$, those who are undermatched in education in our model are unlikely to obtain a skilled job and thus find the path to training and a future skilled job difficult at best.

Genda, Kondo, and Ohta (2010) specifically compares US and Japan and find that the conditions at graduation have a more persistent effect in Japan than in the US. They highlight two key features in the Japanese system. The first is the role played by high schools in the process of matching graduates with jobs. Evidently, colleges pay a role as well but to a lesser degree. The second are job protection measures that severely limit flexibility in terms of firing full time regular workers. They argue that these features are central to the persistent effects of unemployment rate when the individual entered the labor market

[61] Though lower values of $\zeta(0)$ in Japan do not change these moments, if $\zeta(0)$ is high enough, then individuals without education will train and the fit will worsen.

[62] We are grateful to Masao Ogaki for suggesting this link to the literature on persistent effects of labor market conditions.

[63] In Kondo (2007), a distinction is made between permanent and temporary attachments.

on subsequent earnings. These effects of the initial unemployment rate are more pronounced in Japan and larger for less-educated individuals.

7.4 US

In the US, like Italy and Japan, education mismatch is attributed to taste shocks. The training serves as a device so that agents undermatched in education are unlikely to be trapped in a low skilled job. Overmatched individuals also train and by doing so protect their job status.

Specifically, for the US, there is no evidence of imperfect capital markets creating undermatch in education. The undermatch reflects taste shocks.

Training rates are high for all mismatched individuals in the US. The training pays off. The undermatched individuals placed at unskilled jobs in early employment all train, and almost 70% of them are reassigned to skilled jobs in late employment. The undermatched allocated to skilled jobs in early employment also choose to train and about 70% retain skilled jobs.

As for the overmatched, because of the particularly high estimated value of the expected return to training, $\zeta(\bar{e})$, all of them decide to train regardless of their job assignment in early employment. As a result, a large fraction of overmatched individuals are placed at skilled jobs in late employment. Thus, flows from education to job overmatched persist during late employment.

Returning to Kawaguchi and Murao (2014), the US is often viewed as a country with a minimal level of employment protection. The three measures of labor market rigidity reported by the authors - EPL, Union Coverage and benefit duration of Unemployment Insurance- are considerably low in the US. Thus, the persistence on education mismatch does not seem to be a result of lack of labor market flexibility. In the case of the undermatched, it might be harder for the employers to learn about the true ability when workers are initially placed at unskilled jobs.

8 Conclusions

The goal of the paper was to determine the impact of education mismatch on labor market outcomes. The paper provides evidence of under- and over-match both in education and in the labor market among OECD countries. In fact, these types of mismatch interact with a correlation of about 0.40 between education and job mismatch, pooling across countries.

A key step in the analysis was to determine the causes of educational mismatch, taking into account labor market outcomes. Education mismatch largely reflects taste shocks and not noise in the test score. For Germany, mismatch is also attributed to education choices based upon imperfect information about ability.

The analysis was structured to highlight the impacts of education mismatch rather than autonomous labor market mismatch. From this perspective, we find evidence that education mismatch does indeed have labor market effects through wages, job assignment and training.

From Table 22, relative wages in late employment offset the lost education of undermatched individuals in Germany, Italy and the US. This effect is particularly strong in Italy. In a similar way, the relative wage of overmatched in education individuals is suppressed by late employment.

For training, the selection into training is very much country specific and education dependent. In Germany and the US, undermatched in education leads to high training rates, regardless of initial job assignment. In Italy, these high training rates for education undermatched are high only for those assigned to unskilled job in early employment. In Japan, the undermatched in education do not have training opportunities.

Finally, looking the job assignment, in all countries even a college degree does not guarantee a skilled job. Workers without a college degree, including undermatched individuals, are usually assigned to unskilled jobs. In Germany, Italy and the US nearly 70% of the education undermatch is resolved by late employment insofar as these workers are placed in skilled jobs. For Japan, in contrast, education undermatch persists. Also, for both the US and Japan (to a lesser degree), individuals overmatched in education retain skilled jobs without demotion. For Germany and Italy, this is not the case.

As structure, the analysis excludes independent sources of labor market mismatch.[64] Through this focus, the analysis omits additional frictions, associated with search and matching as well as informal frictions, government regulations and so forth, that certainly impede the job assignment process and thus impact education decisions. These factors are surely important in understanding education rates alone. What remains to be better understood is how these frictions create education mismatch.

The paper began with a broad statement about the economic effects of mismatch from the policy perspective. At this point, the paper does not address explicitly the sources of inefficiency and potential policy actions to remedy them. This is of intense interest as well.

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[64]The point of the counterfactual exercise in section 6.5 was to eliminate all mismatch from the labor market alone.

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9 OnLine Appendix

9.1 Facts for All Countries

Here we present some of the calculations and moments for all countries, not just the four major ones of our analysis.

9.1.1 Mincer Regressions

	numeracy		literacy		average	
	(1)	(2)	(3)	(4)	(5)	(6)
score	0.095**	0.095**	0.082**	0.082**	0.107**	0.107**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
college	0.243**	0.243**	0.260**	0.260**	0.225**	0.225**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
late_emp	0.143**	0.143**	0.148**	0.147**	0.155**	0.155**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
gender	-0.161**	-0.161**	-0.178**	-0.178**	-0.168**	-0.168**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
under_educ	0.043**	0.033**	0.078**	0.066**	0.026**	0.016
	(0.008)	(0.013)	(0.008)	(0.013)	(0.008)	(0.013)
over_educ	-0.066**	-0.042**	-0.103**	-0.082**	-0.037**	-0.005
	(0.012)	(0.021)	(0.012)	(0.021)	(0.012)	(0.021)
late_under		0.015		0.018		0.014
		(0.015)		(0.015)		(0.015)
late_over		-0.034		-0.030		-0.047*
		(0.025)		(0.025)		(0.025)
r2	0.578	0.578	0.574	0.574	0.581	0.581
N	39,521	39,521	39,521	39,521	39,521	39,521

Note: This table reports the results from 6 different Mincer regressions. The depend variables for all of them is log hourly earnings. The first two columns consider the numeracy score as a measure of ability while column 3 and 4 consider the literacy score and column 5 and 6 the average of the three dimensions. Standard errors are reported in parenthesis. PIAAC scores are normalized to have mean zero and standard deviation of unity for the whole sample. The variable gender takes the value 1 if the individual is female, and 0 otherwise. The variable late_emp takes the value 0 if the individual is an early employee (25-34 years old) and 1 otherwise. The variables late_under and late_over represent interactions between late_emp and education under- and overmatch. All regressions control for country specific characteristics. A */** next to the coefficient indicates significance at the 10/5% level.

Table 27: Mincer Regressions. Cut-offs: 20th and 80th percentile

9.1.2 Education and Job Mismatch: Correlations

	Ed-Job (general)	**Ed-Job (undermatch)**	**Ed-Job (overmatch)**
Germany	0.330*	0.386*	0.179*
Italy	0.420*	0.460*	0.394*
Japan	0.256*	0.330*	0.346*
United States	0.311*	0.412*	0.197*
Austria	0.270*	0.280*	0.4549*
Belgium	0.244*	0.261*	0.308*
Canada	0.307*	0.396*	0.302*
Czech Republic	0.281*	0.306*	0.405*
Denmark	0.466*	0.337*	0.662*
England	0.372*	0.441*	0.324*
Spain	0.393*	0.451*	0.093*
Estonia	0.292*	0.314*	0.357*
Finland	0.282*	0.274*	0.399*
France	0.186*	0.217*	0.181*
Ireland	0.154*	0.194*	0.170*
Korea	0.191*	0.249*	0.206*
Netherlands	0.091	0.146*	0.175*
Norway	0.408*	0.355*	0.495*
Poland	0.363*	0.387*	0.403*
Slovak Republic	0.460*	0.482*	0.467*
Sweden	0.404*	0.385*	0.497*
Pooled	0.339*	0.339*	0.345*

Note: This table reports correlations between different estimates of education and job mismatch. The first column reports the correlation between being mismatched in education and in the job. The second column reports correlations between being undermatched in education and undermatched in the job. The third column shows the correlation between being overmatched in education and overmatched in the job. The star indicates significance at the 1% level.

Table 28: Correlations between education and job mismatch.

9.1.3 Scores

	Low-Skilled			**High-Skilled**		
	Mean	**Sd**	**N**	**Mean**	**Sd**	**N**
Germany	264.09	43.08	1655	302.60	34.75	1188
Italy	249.79	41.26	1388	279.02	36.49	720
Japan	293.82	33.58	1534	313.08	30.33	1008
United States	249.26	46.22	1248	290.91	39.16	1237
Austria	264.46	41.52	1376	298.56	31.51	1258
Belgium	265.13	42.13	1280	302.94	32.29	1145
Canada (F)	253.04	44.35	1343	287.69	38.44	1582
Czech Republic	270.05	35.95	1522	298.80	33.62	1030
Denmark	258.60	49.75	1577	298.08	37.90	1713
England	261.93	42.78	1373	298.04	35.68	1106
Spain	243.04	44.91	2162	282.55	35.35	861
Estonia	262.24	36.55	2116	293.04	34.86	1675
Finland	282.47	41.37	1350	314.68	33.454	1332
France	247.62	46.90	1835	289.47	38.06	1596
Ireland	259.37	41.65	1784	289.06	35.88	1299
Korea	265.35	37.71	1988	291.77	29.82	953
Netherlands	273.53	41.50	1094	305.57	32.97	1363
Norway	267.88	45.23	1066	306.18	33.63	1361
Poland	258.25	40.09	1797	292.31	37.12	1092
Slovak Republic	269.46	35.88	1612	292.29	29.59	922
Sweden	268.65	50.60	1026	309.37	38.12	1199
Pooled	258.79	44.88	38013	298.13	36.61	26277

Note: This table reports the moments of the distribution of the average PIAAC score by country and type of occupation.

Table 30: PIAAC average score. Moments.

	No College			College		
	Mean	**Sd**	**N**	**Mean**	**Sd**	**N**
Germany	262.05	48.55	1939	306.73	40.05	1117
Italy	249.45	46.03	2039	280.91	40.62	460
Japan	279.62	37.56	1220	308.71	33.79	1705
United States	231.80	51.39	1492	289.25	42.37	1204
Austria	273.30	45.28	2106	311.13	37.50	716
Belgium	264.98	45.94	1527	312.80	34.98	1128
Canada (F)	243.45	48.31	1488	285.30	40.86	1691
Czech Republic	269.44	39.07	2025	309.79	33.56	741
Denmark	260.78	53.24	1776	299.99	47.15	1730
England	244.19	51.76	1566	289.04	43.71	1277
Spain	230.16	48.75	2206	278.53	36.30	1228
Estonia	259.97	41.34	2339	292.38	37.24	1730
Finland	275.47	46.71	1350	312.78	39.36	1482
France	238.64	51.04	2341	297.83	39.48	1400
Ireland	240.75	48.62	2010	286.52	40.95	1580
Korea	248.13	39.70	1699	287.07	31.68261	1784
Netherlands	248.13	39.70	1699	312.24	33.80	977
Norway	269.50	50.16	1466	308.37	44.90	1394
Poland	249.25	44.65	2113	289.64	38.38	1251
Slovak Republic	265.89	45.53	2307	305.42	33.49	639
Sweden	268.57	56.70	1333	309.35	50.53	1043
Pooled	256.13	49.21	38013	297.99	41.06	26277

Note: This table reports the moments of the distribution of the numeracy score by country and educational level.

Table 29: PIAAC numeracy score. Moments.

9.1.4 All Countries, All Moments

	Ed.					Labor											Training		
	ed	un	ov	α_0	α_1	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
									Data										
Ger.	0.366	0.092	0.061	-0.883	1.274	0.149	0.237	0.173	-0.001	-0.034	0.377	0.000	0.000	0.250	0.101	0.038	0.386	0.643	na
It.	0.184	0.157	0.065	-1.972	1.015	0.092	0.276	0.226	0.018	-0.053	0.446	0.000	0.000	0.571	0.165	0.086	0.195	0.364	na
Jap.	0.583	0.071	0.116	0.137	0.915	0.137	0.120	0.270	-0.070	-0.005	0.609	0.000	0.000	0.255	0.134	0.085	0.380	0.685	na
US	0.447	0.065	0.040	-0.465	1.437	0.159	0.243	0.179	0.099	-0.022	0.472	0.000	0.000	0.364	0.091	0.075	0.436	0.682	na
Aus	0.254	0.132	0.043	-1.613	1.123	0.119*	0.201*	0.152*	0.053	0.061	0.244	0.000	0.000	0.750	0.107	0.055	0.371	0.638	na
Bel.	0.425	0.080	0.0381	-0.502	1.492	0.085*	0.168*	0.185*	0.039	-0.049	0.250	0.000	0.000	0.500	0.075	0.040	0.317	0.639	na
Can.	0.532	0.079	0.082	0.045	1.013	0.130*	0.198*	0.154*	0.016	0.036	0.315	0.000	0.000	0.435	0.076	0.084	0.297	0.602	na
CzR.	0.268	0.111	0.032	-1.804	1.725	0.077*	0.247*	0.027	0.007	0.390*	0.287	0.000	0.000	0.727	0.110	0.071	0.401	0.559	na
Den.	0.493	0.092	0.095	-0.363	0.984	0.084*	0.150*	0.132*	0.016	-0.032	0.390	0.000	0.000	0.537	0.098	0.074	0.465	0.730	na
Eng.	0.449	0.094	0.070	-0.343	0.902	0.142*	0.236*	0.181*	0.009	-0.138*	0.500	0.00	0.000	0.250	0.119	0.053	0.449	0.673	na
Est.	0.425	0.095	0.085	0.361	0.903	0.119*	0.210*	-0.026	0.042	-0.021	0.263	0.000	0.000	0.454	0.081	0.056	0.383	0.613	na
Fin.	0.523	0.093	0.080	-0.033	0.918	0.089*	0.181*	0.167*	-0.043	-0.087*	0.275	0.000	0.000	0.440	0.101	0.065	0.484	0.710	na
Fra.	0.374	0.066	0.036	-1.002	1.747	0.102*	0.182*	0.182*	-0.016	0.059	0.256	0.000	0.000	0.273	0.078	0.047	0.290	0.511	na
Ire.	0.440	0.074	0.058	-0.552	1.289	0.118*	0.202*	0.247*	0.079	0.042	0.308	0.000	0.000	0.214	0.118	0.075	0.371	0.619	na
Kor.	0.512	0.076	0.056	-0.145	1.293	0.125*	0.300*	0.197*	-0.150*	0.001	0.450	0.000	0.000	0.242	0.148	0.089	0.491	0.605	na
Net.	0.369	0.101	0.047	-0.725	1.212	0.100*	0.219*	0.224*	-0.020	-0.093	0.140	0.000	0.000	0.429	0.088	0.089	0.471	0.756	na
Nor.	0.487	0.084	0.089	-0.266	1.016	0.079*	0.137*	0.131*	0.039	-0.027	0.379	0.000	0.000	0.488	0.078	0.091	0.480	0.681	na
Pol.	0.372	0.097	0.061	-0.833	1.233	0.112*	0.354*	0.096*	-0.008	0.154	0.457	0.000	0.000	0.360	0.123	0.059	0.276	0.544	na
Slo.	0.217	0.131	0.033	-1.542	1.193	0.116*	0.302*	0.013	-0.080*	-0.028	0.482	0.00	0.00	0.714	0.151	0.047	0.205	0.484	na
Sp.	0.358	0.085	0.035	-0.900	1.382	0.089*	0.374*	0.163*	0.142*	-0.161	0.576	0.000	0.000	0.083	0.130	0.027	0.342	0.625	na
Swe.	0.439	0.084	0.086	-0.672	1.152	0.086*	0.072*	0.117*	-0.042	0.030	0.381	0.000	0.000	0.536	0.098	0.084	0.478	0.721	na

Table 31: Moments

9.2 Additional Robustness Exercises

9.2.1 Alternative Measures of MisMatch

An alternative definition of mismatch evaluates an agent relative to others with the same education rather than compared to the entire population. An agent is undermatched if: (i) the individual does not obtain a college degree and (ii) the predicted probability of going to college exceeds the 80th percentile of the predicted probability of going to college **among college going individuals**. The same point applies to the labor mismatch calculations: an individual in an unskilled job is viewed as undermatched relative to those with that same job assignment. This alternative measure has an important property: if there is perfect sorting by ability into education and jobs, then there will be zero mismatch.

	Education					Mincer Reg.					Ed → Early Job				Emp. Mismatch		Training		
	ed	un-mat	over-mat	α_0	α_1	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
									Data										
Ger.	0.365	0.029	0.027	-0.883	1.274	0.177	0.248	0.188	-0.068	-0.004	0.400	0.000	0.000	0.000	0.046	0.027	0.386	0.643	na
It.	0.184	0.068	0.046	-1.972	1.015	0.097	0.270	0.226	0.009	-0.040	0.410	0.000	0.000	0.429	0.062	0.068	0.195	0.364	na
Jap.	0.583	0.034	0.058	0.137	0.915	0.135	0.127	0.269	-0.079	-0.030	0.571	0.000	0.000	0.286	0.065	0.065	0.380	0.685	na
US.	0.447	0.024	0.014	-0.465	1.437	0.203	0.295	0.238	-0.058	0.209	0.615	0.000	0.000	0.500	0.035	0.042	0.436	0.682	na
									Baseline										
Ger.	0.319	0.012	0.050	-0.868	1.283	0.088	0.225	0.184	-0.069	-0.006	0.391	0.001	0.000	0.003	0.055	0.089	0.387	0.643	0.015
It.	0.154	0.024	0.040	-1.9132	1.021	0.102	0.124	0.211	-0.037	-0.049	0.460	0.000	0.013	0.218	0.136	0.165	0.224	0.309	0.096
Jap.	0.514	0.022	0.105	0.122	0.928	0.067	0.245	0.318	-0.106	0.003	0.578	0.000	0.000	0.210	0.109	0.139	0.389	0.808	0.059
US.	0.382	0.015	0.037	-0.441	1.409	0.072	0.279	0.191	-0.040	-0.025	0.780	0.000	0.000	0.509	0.077	0.111	0.429	0.670	0.080
US. (nlsy)	0.378	0.016	0.035	-0.465	1.403	0.069	0.279	0.187	-0.042	-0.026	0.776	0.000	0.000	0.498	0.078	0.111	0.439	0.705	0.080
									No Taste Shock										
Ger.	0.330	0.013	0.038	-0.871	1.279	0.041	0.297	0.177	-0.087	0.004	0.000	0.028	0.012	0.000	0.040	0.087	0.374	0.639	0.188
It.	0.164	0.026	0.041	-1.953	1.064	0.013	0.343	0.135	-0.027	-0.027	0.130	0.034	0.055	0.094	0.147	0.155	0.165	0.444	0.244
Jap.	0.523	0.030	0.063	0.126	0.923	0.019	0.285	0.338	-0.037	0.010	0.000	0.041	0.012	0.000	0.096	0.061	0.398	0.813	0.478
US.	0.411	0.008	0.035	-0.411	1.468	0.050	0.382	0.198	-0.096	0.022	0.000	0.039	0.012	0.0375	0.053	0.089	0.430	0.696	0.664
US. (nlsy)	0.407	0.008	0.036	-0.432	1.447	0.052	0.353	0.223	-0.101	0.021	0.000	0.033	0.004	0.000	0.052	0.076	0.186	0.692	0.752

This table reports data and simulated moments for the estimated models with alternative mismatch measures.

Table 32: Moments: Alternative MisMatch

This alternative method of mismatch was used to characterize educational and labor market outcomes and the model was re-estimated. The results are shown in Tables 32 and 33.

Looking first at the data moments, the mismatch rates for both education and jobs with this alternative definition are lower for all countries. Still the patterns noted earlier remain: the education undermatch rate is larger than the overmatch in Italy, Germany and the US while overmatch dominates in Japan. One striking difference is that none of the individuals overmatched in education in Germany are overmatched in their early job assignment. This is not the case in other countries.

	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	$\bar{e}^t$	δ_{css}	δ_{nsu}	nbp
						Baseline						
Ger.	5.725	2.386	0.182	1.248	1.002	0.059	1.027	0.940	0.231	0.046	0.619	na
It.	5.113	4.808	0.019	1.128	1.205	2.022	0.800	0.761	0.074	0.001	0.245	na
Jap.	8.912	5.450	0.061	1.355	1.000	0.0000	0.702	1.163	0.208	1.000	0.988	na
US.	10.556	2.426	0.002	1.134	1.002	0.049	0.969	1.352	0.059	0.836	0.032	na
US.(nlsy)	10.758	2.497	0.003	1.131	1.001	0.050	0.974	1.351	0.060	0.432	0.576	na
						No Taste Shock						
Ger.	7.028	na	0.237	1.267	1.030	0.132	1.038	0.951	0.199	0.382	0.748	na
It.	7.924	na	0.331	1.319	1.111	2.597	0.909	0.815	0.128	0.050	0.852	na
Jap.	15.746	na	0.103	1.223	1.000	0.006	0.717	1.376	0.153	0.867	0.984	na
US.	8.065	na	0.159	1.129	1.014	0.531	0.956	1.351	0.030	0.829	0.039	na
US. (nlsy)	7.624	na	0.173	1.136	1.012	0.256	0.949	1.350	0.122	0.432	0.576	na

Table 33: Parameter Estimates: Alternative MisMatch

The fit of the models is better for Germany and Italy but not as good for Japan and the US. The match with the mismatch rates is not as good as the baseline and the model still struggles to match the education coefficient in the Mincer regression. The flows from education to job mismatch are close to the data as are the training rates. The model continues to overstate the job mismatch rates, particularly the overmatch rate.

Removing the taste shocks and re-estimating the model leads to a large deterioration of the fit. So, as in the baseline, the mismatch is largely a consequence of taste shocks. The experiment with random borrowing constraints did not improve the fit for any country and is not shown.

9.2.2 Re-evaluating Job MisMatch

As noted earlier, the job mismatch is calculated from (2) using the average of the three PIAAC test scores. And, like the education decision, there is the potential for reverse causation, i.e. someone placed in a skilled job might acquire the knowledge to score high.

These concerns were present and examined by Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), where the main focus was the estimation of the return to skill. Their main empirical model used the numeracy score as a measure of skill, rather than a composite score.[65] Further, Section 5 of Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) uses an IV approach to control for endogenous variations in the numeracy score, leaving their main findings intact.

Following Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), the model is re-estimated using the numeracy score as the measure of ability in (2) and thus in the calculation of job mismatch. The data panel in Table 13. Compared to the baseline measures, the fraction of undermatch (overmatch) in education to undermatch (overmatch) in early employment, “uu” and “oo” respectively, is much larger in the revised data

[65]As discussed in section 4.4 of Hanushek, Schwerdt, Wiederhold, and Woessmann (2015), the literacy and numeracy scores are very highly correlated, but the problem solving score is less correlated.

	Education					Mincer Reg.					Ed → Early Job				Emp. Mismatch		Training		
	ed	un-mat	over-mat	α_0	α_1	test	ed	late	ed un	ed ov	uu	uo	ou	oo	ue	oe	unsk	sk	fit
	Data: Using Numerical Score for Job MisMatch																		
	0.366	0.092	0.061	-0.883	1.274	0.149	0.237	0.173	-0.001	-0.034	0.541	0.000	0.000	0.250	0.110	0.065	0.386	0.643	na
	0.184	0.157	0.065	-1.972	1.015	0.092	0.276	0.226	0.018	-0.053	0.511	0.000	0.000	0.714	0.162	0.074	0.195	0.364	na
	0.583	0.071	0.116	0.137	0.915	0.137	0.120	0.270	-0.070	-0.005	0.870	0.000	0.000	0.277	0.142	0.077	0.380	0.685	na
	0.447	0.065	0.040	-0.465	1.437	0.159	0.243	0.179	0.099	-0.022	0.528	0.000	0.000	0.545	0.091	0.078	0.436	0.682	na
	Baseline																		
Ger.	0.313	0.095	0.069	-0.871	1.280	0.097	0.176	0.173	-0.067	0.001	0.393	0.004	0.008	0.200	0.138	0.150	0.408	0.645	0.032
It.	0.150	0.141	0.040	-1.940	1.024	0.118	0.120	0.167	-0.039	-0.047	0.549	0.000	0.000	0.303	0.171	0.161	0.267	0.284	0.135
Jap.	0.512	0.080	0.141	0.115	0.928	0.070	0.234	0.321	-0.089	0.000	0.611	0.000	0.000	0.232	0.168	0.155	0.387	0.807	0.048
US.	0.379	0.079	0.057	-0.460	1.437	0.074	0.275	0.192	-0.034	-0.021	0.495	0.000	0.000	0.329	0.140	0.155	0.438	0.666	0.042
	Job MM Num																		
	0.311	0.097	0.065	-0.869	1.276	0.098	0.167	0.170	-0.063	-0.004	0.542	0.001	0.000	0.231	0.134	0.139	0.412	0.638	0.023
	0.150	0.140	0.039	-1.940	1.031	0.121	0.122	0.206	-0.034	-0.051	0.816	0.000	0.000	0.660	0.166	0.149	0.275	0.290	0.144
	0.507	0.087	0.138	0.103	0.937	0.066	0.234	0.313	-0.085	-0.015	0.795	0.000	0.000	0.350	0.171	0.159	0.382	0.804	0.061
	0.378	0.079	0.056	-0.463	1.444	0.074	0.276	0.191	-0.033	-0.022	0.664	0.000	0.000	0.472	0.134	0.142	0.441	0.665	0.061

This table reports data and simulated moments for the estimated models with alternative mismatch measures.

Table 34: Moments: Job MisMatch

since the measures of ability underlying the education and job mismatch moments are the same. But the job mismatch rates in early employment themselves are about the same, with the exception of the high level of job overmatch in Germany.

The model fit reported in Table 34 is better for Germany compared to the baseline as well as the model estimated with noisy ability. This improved fit seems to come mainly from the ability of the estimated model to match the higher "uu" and "oo" flows The fit is worse for the other countries.

The baseline parameter estimates are reported in the top panel of Table 35 and the estimates using the revised data moments are reported in the bottom panel. One interesting difference relative to the baseline is that the noise in the education test is estimated to be lower for all countries except the US, where it is nearly zero anyways. Relatedly the job test noise in Germany is much lower and in Italy it is much higher For Germany, this is what allows the model to produce the higher "uu" and "oo" flows. For Italy these flows are much higher as well in the estimated model but this does not lead to an improvement in the fit.

	ϕ	$\bar{\varepsilon}$	σ_e	$h(\bar{e})$	ω_2	σ_j	$\zeta(0)$	$\zeta(\bar{e})$	$\bar{e}^t$	δ_{css}	δ_{nsu}	nbp
	Baseline											
Ger.	5.725	2.386	0.182	1.248	1.002	0.059	1.027	0.940	0.231	0.046	0.619	na
It.	5.113	4.808	0.019	1.128	1.205	2.022	0.800	0.761	0.074	0.001	0.245	na
Jap.	8.912	5.450	0.061	1.355	1.000	0.0000	0.702	1.163	0.208	1.000	0.988	na
US.	10.556	2.426	0.002	1.134	1.002	0.049	0.969	1.352	0.059	0.836	0.032	na
	Job MM Num											
	6.581	2.586	0.077	1.245	1.001	0.170	1.031	0.936	0.215	0.159	0.999	na
	4.432	4.875	0.010	1.125	1.150	0.008	0.833	0.771	0.136	0.000	0.267	na
	9.829	5.976	0.016	1.341	1.005	0.004	0.680	1.180	0.201	0.994	0.978	na
	10.392	2.386	0.004	1.135	1.001	0.076	0.972	1.352	0.060	0.776	0.000	na

Table 35: Parameter Estimates: Job MisMatch

9.3 NLSY: Calculating US Job Flows

Cohort and sample selection: PIAAC data was collected mainly in 2011. Thus, early workers in our sample -individuals aged aged 25-34 in 2011- were born between 1977 and 1986. Individuals in the NLSY97

country	college	no college
Germany.	0.849	0.603
Italy	1.0	0.672
Japan	0.578	na
US	0.798	0.690

Table 36: Inferring Late Flows

data were born between 1980 and 1984 while individuals in the NLSY79 data were born between 1957 and 1964. Therefore, our US sample of early employees in PIAAC is closer to the NLSY97 cohort.

In order to identify the job assignment probabilities in late employment for individuals allocated to skilled jobs in early that do not train, we need information about their job allocation in late employment. Data for the NLSY97 cohort is available from round 1 (1997-98) through round 18 (2017-18). Respondents were 32 to 38 at the time of their round 18 interviews. We restrict our sample to individuals that were already in late employment by that time. [66]

College. The NLSY97 data report the highest degree completed by the respondents at each interview date. Consistent with our PIAAC education variable, we define two education levels according to the highest degree reported in 2011: (ii) below college and (ii) college and beyond.

Occupation. In every round of the survey, NLSY97 respondents answer questions about every occupation they had since the last interview. We use the information on their most recent occupation at the time of the round 15 interview in 2011-2012, in order to define their early job type. Similarly, use information on their most recent occupation at the time of the round 18 interview in 2017-2018, in order to define their late job type.

Respondents' verbatim descriptors of their occupations are coded using a three-digit Census code frame. In order to have a closer comparison with occupations reported in PIAAC, we mapped the 2002 Census codes reported in the NLSY97 to (two-digit) ISCO88 codes. We then matched those codes to the ISCO skill levels to define our occupation variable. Same as with PIAAC, we define two types of jobs: (i) unskilled (first to third ISCO skill levels) and (ii) skilled jobs (fourth ISCO skill level).

Training. Information on training programs in which respondents participated since the last interview is also collected in every round of the survey. These data refers to training experiences of respondents outside of their regular schooling. Our training measure from PIAAC refers to any informal training received within the 12 months prior to the interview date. Thus, we said an individual in our NLSY97 sub-sample trained in early employment if he reported any training experience within one year before the round 15 interview in 2011-2011.

9.4 Inferring Late Flows

Table 36 provides the inferred probability that an individual who trains is assigned a late skilled job, by education. The inference requires the imposition of a steady state assumption to link the early and late assignments in Table 8.

The procedure amounted to generating a single equation with a single unknown, the probability an individual with training was assigned a skilled job. The inputs into this were the training decisions along

[66]As with PIAAC, we excluded respondents that reported to be self-employed in 2011. In addition, the NLSY97 data includes oversamples of Hispanics and non-Hispanic black which we dropped for this analysis. Our final sample is composed of 2,789 individuals.

with the estimated probabilities that an individual without training would be remain in a skilled job.

It is important to keep in mind that this decomposition of the return to training only matters for the post-estimation analysis. The estimation itself only identifies the compound effects of the human capital accumulated in training and the late job assignment.