Gender Differences in Education and Labor Market Outcomes: Statistical Discrimination and Human Capital Accumulation.

Carla Varona Cervantes*and Russell Cooper†

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Abstract

This paper studies gender differences in educational attainment and labor market compensation across a group of OECD countries. Across these countries, college attainment rates are higher for women than men, despite a wage gap. The empirical analysis documents a positive correlation between this education gender gap and one related to the effects of education on compensation. The paper explores potential explanations for this pattern. The approach is to first estimate the parameters of a dynamic model of education choice and labor market outcomes, and then decompose gender differences through a series of counterfactual exercises, highlighting the role of statistical discrimination and differences in human capital accumulation.

1 Motivation

This paper starts from two common observations about gender differences in education and labour outcomes.[1] First, the fraction of women obtaining college degrees exceeds that of men. This is the case for a broad range of countries over a long span of time. Second, there is a gender wage gap: women get a fraction of the salary paid to men conditional on education attainment. Importantly, college rates are higher for women in the same countries where college educated men earn more than women.

These observations seem at odds. Are the education choices of woman consistent with their labor market outcomes? If there is labor market discrimination against women, what is the rationale for their high college attainment rates relative to men?

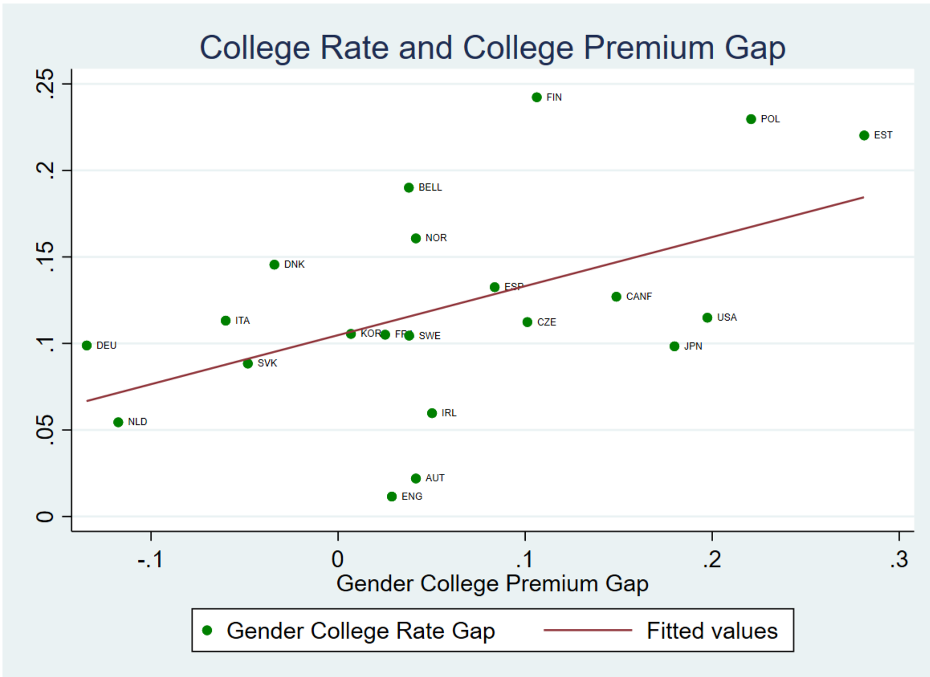
An immediate response is that this evidence alone is not necessarily puzzling. Coupling these observations on wage gaps and education attainment ignores the college wage premium which provides the marginal incentive for educational attainment. That is, **differences in** the education choice depends on the **differences in** returns to education and not gender differences in pay.

Figure 1, which motivates this paper, digs deeper to show the education rates of woman, relative to men, and the marginal return from education, captured through the gender difference in college wage premia.[2] The vertical axis shows country specific differences in college attainment between women and men (the gender college rate gap). Note that these rates are positive, indicating higher college attainment for woman

*Department of Economics, the European University Institute, Carla.Varona@eui.eu
†Department of Economics, the European University Institute, russellcoop@gmail.com
[1] The accompanying data analysis show these for our OECD countries.
[2] The differences in the college wage premia are used here in the motivation. The quantitative analysis goes further to focus on the education coefficients in Mincer wage regressions.

across these 21 OECD countries. The horizontal axis is a measure of the gender difference in the college premium (gender college premium gap). It is largely positive as well for most of the countries, indicating a higher college premium for women.

There is a clear positive relationship between the differences in education rates and differences in the marginal return to education.[3] In countries where the difference in college rates is higher, the differences in college wage premium is also higher. From this regression, the higher rates of college attainment for women compared to men are positively associated with higher returns to college. From this perspective, there is no puzzle explaining the relatively high college rates of women, despite the fact that men are, on average, paid more than women.



Note: The variable on the horizontal axis is the gender difference in the college wage premium. On the vertical axis is the college rate of woman minus that of men.

Figure 1: College Attainment and Returns from Education: Gender Gaps

But of course these are only associations as both educational attainment and the college premium are endogenous variables. The return to education matters for the education decision and at the same time are impacted by selection into education The point of the paper is to determine the underlying economic factors that generate these and related observations about differences by gender in education choices and labor market outcomes.[4] Doing so requires a model to understand and quantify the determinants of the education choice and labor market outcomes.

College wage premia reflect both a direct and an indirect effect of education. The direct effect is simply that education increases human capital and productivity and thus is remunerated. So, if the human capital accumulation is higher for women than men, then the college premium will be larger for woman. The indirect effects come from education as a signal of ability, along the lines of Spence (1973), and more

[3]The slope of the regression line shown in the middle of the figure is 0.283, the p-value is 0.023 and the $R^2 = 0.243$.
[4]The focus here is on the gender specific returns to education and not the aforementioned wage gaps.

generally associated with statistical discrimination. From this perspective, the larger return to education might indicate that education is more informative about ability for women compared to men. This may come directly in that education might be more correlated with ability for women. Or, it might come indirectly insofar as other indicators of ability observed by employers, are less informative for woman so that more weight is placed on education as a signal of ability as a result statistical discrimination. This stems from Lang and Manove (2011) and is explored in some detail below.

The challenge for evaluating these alternative explanations is empirical. Do they generate higher college rates for women and at the same time match the observed gender specific labor market outcomes reflected in the returns to education? That is, can these models rationalize the pattern in Figure 1? In this paper, these explanations are explored through a series of counterfactual exercises based upon the estimation of a dynamic stochastic model of education choice and labor market outcomes that allows for information frictions.

There are three phases in the analysis. The first, section 2, serves two purposes. First, it establishes the aforementioned facts on differences in education experiences and labor market outcomes in our data, the OECD based Program of International Assessment of Adult Competences (hereafter PIAAC). That data includes a test score which we take as a noisy signal of ability. Second, the data generates moments that are eventually used for model estimation. These include the college rates that motivated this paper along with the results of a logistic regression that predicts educational attainment based on the test score and a Mincer style wage regression. Thus the moments capture two main dimensions of the motivation: (i) the choice of education and (ii) the marginal returns to education.

The second phase is the model, Section 3, which determines individual education choices and labor market outcomes. The model provides the structure to understand the driving forces in gender education and labor market outcomes in the quantitative analysis, allowing the assessment of the aforementioned hypothesis.

A couple of properties from the model are noteworthy. First, it allows the education to have an impact on individuals productivity. Second, The model includes various features that capture the information frictions, along the lines of Lang and Manove (2011). In particular, agents make education choices knowing their own ability but knowing that employers will only observe signals of ability such as test scores and educational attainment. The relative weight employers put on education when estimating worker's productivity will be affected by the quality of the signal of ability. In addition, choices are impacted by "taste" shocks, indicating other factors that might influence the perceived returns to education. In this way, the hypotheses advanced above are captured in the model. At one extreme of the model is the Spence (1973) framework in which the only inference about workers ability comes from observed education.[5]

This is not just a model of individual choice, since the marginal return to education depends on the distribution of ability conditional on educational attainment and the signal of ability. This is determined in equilibrium by finding a fixed point such that firms beliefs about workers ability given the observed signal and education level, are consistent with workers education decisions taken those beliefs as given. Thus the estimation includes the determination of a labor market equilibrium to generate wages that are consistent with the inferences drawn about ability from test scores and educational achievement.

The final phase is quantitative, including model estimation and then a series of counterfactual exercises. Specifically, Section 4 presents our estimation strategy of simulated method of moments. It outlines the moments we match, including wage regressions that capture the patterns of Figure 1. In this way, the motivating observations concerning differences in college rates and the return to education are key elements

[5] See Fang (2006) for a detailed discussion and model that goes beyond the Spence (1973) framework by considering other dimensions of worker ability.

of the quantitative exercise.

Section 5 presents our baseline estimation that focuses on the patterns of education and pay differences, along the line of those displayed in Figure 1. Much of the quantitative analysis highlights on four leading OECD countries: Germany, Italy, Japan and the US. With a limited number of countries, we are able to carefully analyze the estimates.

Here we decompose gender outcomes in education and labor markets, highlighting the role of noise about ability. We do find support for the view that signals about the ability of men are more informative than those about women so that education matters more in forming beliefs about women's ability. This is seen in our analysis of the four leading countries as and in the broader range of countries underlying Figure 1.

But there is another important factor. The returns to education through the accumulation of human capital are generally higher for women than men, directly generating both higher education rates for women as well as larger marginal returns to education.

This counterfactual leads to one of our main findings. **The main explanation for the differences in college attainment and education return lies in a higher level of human capital accumulation for women relative to men stemming from attaining a college degree.** Put bluntly, women seem to "get more" out of college, perhaps reflecting differences in college quality, choice of major or in other (unmeasured) components of ability that enhance the education experience.

Section 6 looks at two additional implications of the model. The first returns to the commonly made point about the wage gap. Our estimated model does not produce such a gap though a simple extension shows how it can be created. Second, we look at the estimated model from the perspective of mismatch, studying the extent to which the high education rates of women relative to men is due to a mis-assignment in the education process.

Related Literature

Our study is most closely related to the literature on information frictions and statistical discrimination in labor market outcomes. Spence (1973) is a natural starting point where individual ability is signaled to employers through education. Education does not involve human capital accumulation. In that model, multiple equilibria naturally arise and can perhaps rationalize observed education and labor market outcomes. We explore a less extreme model allowing human capital accumulation during education and introducing a signal to firms about worker's ability.

A leading recent example is Lang and Manove (2011), in the tradition of statistical discrimination, which focuses on the role of the differences in the informativeness of the signal about ability received by employers in explaining the higher education rates for blacks compared to whites, conditional on ability. In this study we test how the same reasoning can help explaining differences in education choices by gender but allowing pre-labor market forces to interact with statistical discrimination. The results in Figure 1 suggest that these forces play an important role in explaining gender differences. Their analysis is specifically on race difference for males, while we study gender differences over a range of countries. Also, our approach is to estimate the underlying sources of differences in Mincer regression coefficients through the lens of a dynamic choice model.

This paper is clearly related to the literature on education and labor experiences by gender. In a recent work, Hsieh, Hurst, Jones, and Klenow (2019) use a Roy model of occupational choice, augmented to allow for labor market discrimination, barriers to the acquisition of human capital, and occupation-specific preferences to study how these three factors has affected the allocation of women and black men into different occupations in the United States from 1960 to 2010. The authors find evidence of large reductions in barriers to occupational choice faced by these two groups, resulting in a better sorting of talented women and black men. Their findings suggest that falling barriers explain roughly 40% of aggregate growth in market GDP per person. Our approach is different in that we focus on how labor market frictions impact differently education decisions of men and women.

Also focusing on US experience over time, Eckstein, Keane, and Lifshitz (2019) study the convergence in labor market outcomes of married and single women. They use CPS data from 1962 to 2015 to study labor, education and marital outcomes for individuals. They document a significant convergence across cohorts in the labor market outcomes of married woman. This is seen in part of increased labor market participation but also human capital accumulation. Through a dynamic choice model, this convergence is explained by four main factors related to education, marriage opportunities, job offers and birth control. Having only a single cross section, we are unable to study the evolution of these factors over time. However, in our focus on differences across countries, some of these factors reappear as institutional features.

Note that one possibility is that our focus on education outcome is too coarse and should be refined to condition on the choice of study area. While we have no measure of this in our data, there is an extensive literature that analyzes gender differences in earnings and education outcomes including the choice of major. Using data from the National Longitudinal Survey from 1972, Altonji (1993) finds that the college premium is higher for women compared to men, but women are more likely to major on fiends that lead to lower paid occupations. Specifically, the author finds that relative to no college, women receive significantly higher payoff to nontechnical fields compared to men, and about the same in technical fields, although slightly higher for women. Moreover, the return (relative to high school) of advance degrees in technical and no technical field is much higher for women than men. These findings suggest that the wage differential between men and women narrows with education. However, conditional on going to college and relative to education, men tend to receive higher returns in business and Science, Technology, Engineering, and Math (STEM) fields. Furthermore, women are much less likely to major in business/communications, engineering, and the physical sciences than men, and much more likely to major in education, and more likely to major in the humanities. According to the author, those gender differences in post secondary outcomes tend to raise the wage gap between educated men and women.

In a more recent study, Gemci and Wiswall (2014) document the fact that despite the higher college rate for women relative to men in recent cohorts, a substantial gender difference in college major choices remains, with women from the 1970s births cohort being about two thirds as likely as men to earn a degree in a science or business field. The authors develop and estimate a dynamic overlapping generations model of human capital investment and labor supply that allows for college major selection, heterogeneity in major-specific skills and tastes and rental rates. Their results provide evidence that differences in preferences for majors are the main driving force behind the gender gap in college major choice. Moreover, they find that gender differences in the distribution of major-specific skills, while significant, are far less important in explaining the gap.

2 Facts

This section provides information on the underlying data and establishes some facts that will guide the analysis. These facts are ultimately represented by moments that are used in the structural estimation.

2.1 Data

Data source and sample selection. The data underlying this study is from the OECD Survey of Adult Skills, which is part of the Program of International Assessment of Adult Competencies (PIAAC). We restrict our sample to individuals aged between 25 and 34 that we classified as early workers. Self-employed individuals are excluded. In order to avoid outliers and prevent the influences on the results of sources that might affect labor-force attachment, when we examine wages we limit our estimates to full-time employees and drop the bottom and top one percent of the wage distribution in each country.

For most of the analysis we present details for Germany, Italy, Japan and the US. The choice of countries allows us to link our results to different educational system and labor market institutions. In addition, the relationship between the gender gaps in college rates and return to college differ among these countries: it is positive for Japan and the US, almost nonexistent in Italy, and it's reversed in Germany.

Variables. PIAAC ssesses individual's proficiency in three main domains: numeracy, literacy and problem solving in technology-rich environment. For most of the analysis we use PIAAC numeracy scores as (noisy) signals of individual's ability.[6] However, literacy and problem solving are also considered in some model extensions. In order to make results comparable across countries, we normalize the distribution of scores to have zero mean and standard deviation of unity for each gender-country pair. As for educational attainment we divide our sample into two groups: individuals without a college degree and those with college or a higher degree.

This section is built around three key facts that guide the construction of our theory model and its estimation. These facts are established in the sub-sections that follow.

Fact 1: For individuals between 25 and 34, the college attainment rates of women are larger in all four countries.

Fact 2: The coefficient on education in the Mincer (wage) regression is higher for women than men for Japan and the US, the reverse is true in Germany and Italy.

Fact 3: The college premium is higher for women than men in Japan and the US and lower in Germany and Italy.

2.2 Test Scores

One relatively simple explanation for these gender specific education and labor market outcomes could be differences in underlying ability. Of course, innate ability is not directly and instead researchers resort to using test scores as noisy proxies. Table 1 presents the mean and variance of the test results by gender, occupation and education for each country we study. These statistics relate to the young cohort of workers, aged between 24-35 years.

A couple of features are noteworthy. First, for all countries and gender, the mean numeracy score is higher for those with college education. Although, as emphasized in Figure 2, the distributions have large enough standard deviations, such that some individuals without college have higher scores than those with college, which suggest the presence of sources that distort the education decision.

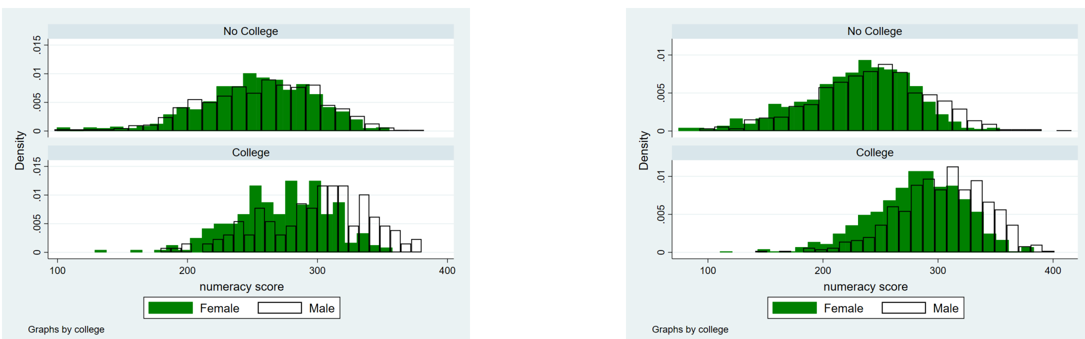
[6]See Hanushek, Schwerdt, Wiederhold, and Woessmann (2015) for a discussion of these tests in the context of Mincer regressions.

	Germany		Italy		Japan		US	
	Men	Women	Men	Women	Men	Women	Men	Women
	Pooled							
Mean	289.201	283.835	267.933	262.010	302.302	297.283	274.135	258.871
Sd.	44.839	43.805	48.790	42.683	38.651	33.700	54.610	52.355
Diff in Mean	5.366*		5.923		5.017*		15.263***	
	No College							
Mean	275.315	267.833	258.753	256.328	284.858	281.383	247.426	228.076
Sd.	44.117	43.202	46.435	43.050	41.003	33.284	50.066	48.723
Diff in Mean	7.482**		2.425		3.476		19.350***	
	College							
Mean	317.273	305.053	307.251	275.106	314.108	304.268	310.660	285.383
Sd.	31.127	34.713	38.104	39.019	32.047	31.494	36.443	39.271
Diff in Mean	12.220***		32.145***		9.840***		25.276***	
College Rate	0.331	0.430	0.189	0.303	0.596	0.695	0.422	0.537

Note: A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 1: PIAAC Numeracy Scores by Gender and Educational Attainment. Younger cohort.

Second, and most importantly for this study, there are differences in test scores by gender. The rows labeled "Diff in Mean" report the differences in mean scores and their significance.[7] For this cohort, there are significant gender differences in average numeracy score (at the 1 or 5% significance level) for those in college and also for those not in college in Germany and the US. These patterns can be also observed from Figure 2.



(a) Italy (b) US

Figure 2: Ability, Education Levels and gender

Note: Figures show the distribution of PIAAC numeracy scores by education and gender for Italy and the US. For each country, the top row is less than college and the bottom row is college and beyond.

Notice that, if the two distributions were the same and sorting into college was solely based on the test score, then the mean test score should be lower for women with a college degree given the higher college rate for women. And, consequently, the mean test score would also be lower for women without college. This is consistent with the data patterns.[8]

[7] A positive sign indicates that the mean score is higher for men.
[8] Similar results are obtained if we analyze the older cohort.

Notice also that, if we look at the unconditional means shown at the top rows of the table, differences by gender are only significant at the 1% significance level in the US, at the 10% in Germany and Japan. They are not significant for Italy at the 1%, 5% or 10% significance level. We come back to this point in Section 4 when we analyze our baseline estimates for the distribution of ability and noise in the test scores.

2.3 College Rates

As stated in Fact 1, the college rates are higher for women in each of the four countries. This is shown in the college rate row of Table 1 and in Figure 1 for our sample of early workers.[9]

Here we go beyond the differences in the unconditional college rates by studying the determinants of the education choice, emphasizing the dependence, at the individual level, of the education choice on the test score. For that analysis, the empirical model of the education choice is:

$$\Pr\left(e_i = 1|s_i\right) = \frac{\exp^{\chi_0+\chi_s s_i}}{1+\exp^{\chi_0+\chi_s s_i}}. \tag{1}$$

The dependent variable is the educational attainment of individual i, where $e_i = 1$ iff individual i has a college education. The regressor, denoted s_i is the standardized numeracy score. This regression is run by gender for each country.

The results are presented in Table 8 where the data moments for the structural estimation are presented. Consistent with higher college rates, the constant is higher for women compared to men in all countries. The coefficients on the test score are all positive but range by country and gender. The coefficients are higher for males than females and are relatively high in the US and considerably lower in Japan. As these are used as moments for the estimation, the structural model will aid in their interpretation.

To further analyze the gender difference in the dependence of the education choices on the score, Table 2 shows the results from a logistic regression as in equation (1) but pooling men and women adding a gender dummy (=1 for women), model (1), and an interaction term, model (2). The positive and significant coefficient on the gender dummy in both models implies that, even when we control for ability, the probability of going to college is higher for women than men in our four countries. In addition, the coefficients on the interaction between gender and the score in model (2) suggest that the dependence on the score of the probability of going to college is lower for women than men, though the effect is statistically significant only in Italy. Except for Japan, the inclusion of the interactive term increases the gender dummy.

2.4 Returns to Education

We present the returns to education in two complementary forms. The first presents a breakdown of wages by occupation that underlie the pattern displayed in Figure 1. We then reports results from Mincer regressions.

2.4.1 Wage Gaps by Education

As noted earlier, it is commonly thought that there is a significant wage gap between men and women. Here that gap is presented across countries, conditioning on education. Table 3 reports the log of mean wages for early workers. A couple of points stand out.

First, for all countries and genders there is a return to college. In Japan the college wage premium for men is positive, but small compared to other countries.

[9]Nor is it specific to the young cohort. Looking at the older cohort, individuals aged 35-55, we also find that the college rates for women exceed those of men for most of the countries.

	Germany		Italy		Japan		US	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Numeracy	1.395***	1.241***	1.734***	0.906***	0.921***	0.833***	1.716***	1.600***
	(0.169)	(0.110)	(0.300)	(0.148)	(0.152)	(0.101)	(0.203)	(.131)
Gender	0.514***	0.447**	1.250***	0.667***	0.463***	0.481***	0.689***	0.665***
	(0.184)	(0.176)	(0.313)	(0.237)	(0.170)	(0.171)	(0.183)	(0.182)
Gender-Score	-0.286	na	-1.291**	na	-0.190	na	-0.216	na
	(0.222)		(0.339)		(0.201)		(0.265)	
Constant	-0.994**	-0.950**	-2.130**	-1.666**	0.243**	0.241**	-0.570**	-0.546**
	(0.137)	(0.125)	(0.269)	(0.166)	(0.116)	(0.114)	(0.136)	(0.133)
Observations	844	844	551	551	751	751	888	888
Pseudo R^2	0.183	0.181	0.149	0.116	0.108	0.107	0.2710	0.270

Note: A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 2: Selection into College: Gender differences

Germany		Italy		Japan		US	
Men	Women	Men	Women	Men	Women	Men	Women
No college							
2.726	2.656	2.406	2.398	2.541	2.278	2.758	2.577
College							
3.123	2.958	2.700	2.647	2.633	2.523	3.092	3.043
College Premium							
1.487	1.352	1.342	1.282	1.097	1.277	1.396	1.594

This table reports the log of mean wages by gender and education for early workers .

Table 3: College Premia and Wage Gaps

Second, for Japan and the US, the college premium for woman exceeds that of men. In Germany and Italy, the opposite is the case. In both countries the college premium is higher for men than women, particularly for Italy. These results are consistent with Figure 1.

Third, there is a gender wage gap, with men paid more than women, for both education levels in all countries. The smallest earning differences are observed in Italy where the mean of log wages for men and women are very close.[10]

To be clear, while considering wage gaps is common in public discourse, it is not the appropriate perspective for understanding individual choice. The decision about college rests upon the wage premium. The underlying calculation is independent of gender gaps.

2.4.2 Mincer Regressions

Mincer regressions provide further insight about the returns to education, controlling for a signal of ability (the numeracy score) as well as experience, proxied here by age. The generic regression is given by

$$\omega_{ik} = \alpha_0 + \alpha_e e_{ik} + \alpha_s s_{ik} + \alpha_a age_{ik} + \zeta_{ik} \tag{2}$$

for individual i in country k. Here ω_{ik} is log gross hourly earnings of workers, e is a dummy for college attainment, s is the numeracy test score, and age is the individual age, a proxy for experience.[11]

[10] As shown in Table 4 in the pooled (across gender) Mincer regressions, Italy is the only country without a significant coefficient on gender.

[11] Throughout log gross hourly earnings of wage and salary workers are used to measure labor income. The sample pertains to full-time workers, defined as those working at least 30 hours per week. We thank Marco Paccagnella for providing these

The effects of gender can be introduced into this regression in a couple of ways. First, one can add a gender dummy. Second, the interaction of gender and the coefficients on education and/or the test score would uncover gender specific responses to these variables. Finally, one can run separate regressions by gender. Here we summarize the data through the first two types of regressions and reserve the third approach to generate moments for our estimation.

As with the college premium, the Mincer coefficient on education reflects both a direct and an indirect effect. The direct effect is simply that education increases human capital and productivity and thus is remunerated. So, if the effect of education on human capital accumulation is higher for women than men, then the college premium will be larger for woman. In this case, all else the same, education rates would be predicted to be higher for women in a simple model of education choice.

The indirect effects come from education as a signal of ability, along the lines of Spence (1973). From this perspective, the larger coefficient on education in the Mincer regression indicates that education is more informative about ability for women compared to men. This may come directly in that education might be more correlated with ability for women. Or, it might come indirectly insofar as other indicators of ability, such as test scores, are less informative for woman so that more weight is placed on education as a signal of ability. This is motivated by the analysis of differences in education by race in Lang and Manove (2011).

The Mincer wage results are presented in Table 4.[12] The table shows the coefficients from a Mincer regression pooling across genders. One specification includes only a gender dummy while the second has additional interactions between gender and college and the score.

As we can see from the table, the gender variables are not statistically significant in Italy. For Germany there is a significant gender dummy for only one specification, indicating a lower level of compensation for women. Importantly, there is no significant interaction between gender and college in either of these two countries.

In contrast, the interaction between gender and the education variable is positive and significant in the US and Japan implying a higher return to college for women in those countries. Accordingly, the gender dummy is much more negative in this specification compared to the one without interactions.

This evidence is consistent with the motivation as well. There exists both a wage gap between men and women, captured by the dummy. But, at the same time, there is a higher return to education for women. So a specification that ignores these interactions would understate the direct effects of gender on wages. That is, in determining the direct effect of gender of wages, it seems critical to control for any potentially offsetting interaction effects.

Fact 2 is apparent from this table. For Japan and the US, the coefficient on the interaction of college and gender is positive and significant. This is a similar finding to the high college premium for women in these countries reported in Table 3. This interaction is not significant in either Italy or Germany.

Importantly, there are no statically significant differences in the returns to ability, as measured by the numeracy score. This is in accord with the findings reported in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).

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results.

[12] Estimates from other specifications and samples are presented in the Appendix.

	Germany		Italy		Japan		US	
numeracy	0.118***	0.111***	0.071***	0.061**	0.094***	0.092***	0.149***	0.155***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.031)
college	0.221***	0.240***	0.203***	0.206***	0.082**	0.019	0.246***	0.162**
	(0.04)	(0.061)	(0.04)	(0.067)	(0.03)	(0.038)	(0.04)	(0.065)
age	0.028***	0.028***	0.022***	0.021***	0.033***	0.033***	0.031***	0.032***
	(0.01)	(0.007)	(0.01)	(0.006)	(0.01)	(0.005)	(0.01)	(0.006)
gender	-0.098**	-0.081	-0.040	-0.042	-0.159***	-0.275***	-0.099**	-0.181***
	(0.04)	(0.050)	(0.04)	(0.039)	(0.03)	(0.049)	(0.03)	(0.056)
gend_score	na	0.018	na	0.027	na	0.008	na	-0.007
		(0.043)		(0.040)		(0.029)		(0.039)
gend_coll	na	-0.042	na	-0.003	na	0.179***	na	0.170**
		(0.081)		(0.089)		(0.060)		(0.084)
Constant	1.664***	1.664***	1.505***	1.504***	6.156***	6.196***	1.795***	1.817***
	(0.22)	(0.217)	(0.19)	(0.187)	(0.15)	(0.148)	(0.18)	(0.184)
Observations	562	562	328	328	595	595	602	602
R^2	0.239	0.239	0.205	0.207	0.199	0.213	0.312	0.320

Note This table presents the results from Mincer style wage regressions with log gross hourly earnings as dependent variable. Notice that the number of observations is lower compared to Table 2 due to the mentioned further sample selection restrictions. A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 4: Mincer regressions

3 Model

The presentation of the model has three components. The first part explains the essentials of the education choice, neatly summarized through a static optimization problem. The full model, emphasizing dynamics, is explained in the next part. The section also includes a discussion of the empirical implications of the model taken to the data.

3.1 An Illustrative Framework

Individuals are born with innate ability θ. They make an education decision, $e \in [0,1]$, indicating the fraction of their time endowment spent in school. The remainder of time is spent working, at a (normalized) wage of 1, independent of ability. Agents incur a cost of education that is inversely related to their ability. Let $C(e,\theta,\varepsilon)$ with $C_1(e,\theta,\varepsilon) > 0$ and $C_2(e,\theta,\varepsilon) < 0$ represent these costs. Here ε is a random element in the cost of education that plays the role of a taste shock.

There is a technology stipulating that output equals the product of the worker's human capital, conditional on educational attainment, $h(e)$, and ability, i.e. $y = h(e)\theta$ with $h'(e) > 0, h''(e) < 0$.[13] With this specification, there is an underlying complementarity such that high ability workers have a higher marginal return to education.

Firms do not observe workers' ability directly but instead infer ability from education and a noisy signal, s, where $s = \theta + \zeta$ and ζ represents noise. Labor markets are competitive and firms pay workers their expected product of

$$\omega(e,s) = h(e)E(\theta|s,e) \tag{3}$$

[13]For simplicity, the technology omits co-worker effects.

given their information. There are two components to this expression. The first is the direct effect of education on productivity, $h(e)$. The second is the conditional expectation of ability, given the signal s and education. Importantly, the level of education plays two roles: (i) it directly impacts output and (ii) it provides information about ability. This latter effect is determined in equilibrium by the choices of workers that, of course, will depend on how firms perceive the link between education and ability.

These are the roles for education highlighted in the discussion of potential links between college rates and measures of the marginal return to education, for example in the coefficient of education in a Mincer regression. They are central to the model and to the complementary quantitative exercises.

The agent takes as given the compensation function, (3).[14] If the worker knows s at the time of the education decision, then the education choice is determined from

$$max_e \omega(e,s) + (1-e) - C(e,\theta,\varepsilon) \tag{4}$$

This yields an education choice of $e = \phi(\theta, s, \varepsilon)$. Note that by assuming the worker knows s, compensation is independent of ability. Yet ability matters in the education decision insofar as it influences the cost of education. This is similar to the structure assumed in Spence (1973). If $C(\cdot)$ does not depend on θ, then the only link between education and ability is through the correlation between s and θ.

If instead the worker does not know s at the time of the education decision, then the optimization problem is

$$max_e E_{s|\theta} \omega(e,s) + (1-e) - C(e,\theta,\varepsilon) \tag{5}$$

yielding a decision rule of $e = \tilde{\phi}(\theta, \varepsilon)$. In this specification, ability also provides information about the signal and thus it has an additional influence.

Regardless of the information about s, a key component of the model is the compensation function, $\omega(e,s)$, given in (3). It is an equilibrium object, reflecting the perceived productivity of agents as workers. In the empirical implementation of the model, an equilibrium is imposed as a consistency requirement between the beliefs of firms, summarized by $E(\theta|s,e)$, and the choices of the individuals, summarized by $e = \tilde{\phi}(\theta, \varepsilon)$. Through this conditional expectation, the model fits into the "statistical discrimination" approach to understanding gender differences in compensation.

Importantly, the signaling effects of education will depend on the relative informativeness of the signal, s, about ability, θ. Thus, all else the same, a less noisy signal ought to reduce the dependence of compensation on education and increase its dependence on s.

These are indeed properties of this model. But again these effects are driven in part by the choices of agents linking education decisions to both their ability, signal and tastes.

3.2 A Dynamic Discrete Choice Model

The full model that is taken to the data is dynamic. The key mechanisms of the simple model, particularly the informational frictions, are retained. Specifically, the extended model adds a number of elements. First, it is explicitly dynamic, distinguishing education from work periods of life and thus allowing the timing to be closer to that in the data. Second, the education choice is discrete, with $e = 0$ indicating no college and $e = 1$ for those who obtain a college degree.

[14] The complete model includes discounting and is very explicit about distinguishing education and work phases of life. Here, consider a static setting or view $\omega(e,s)$ as a discounted present value.

To understand the first element, there are two phases of the life cycle as shown in Figure 4 that accord with the structure of the data analysis. The first stage allows the individual to obtain formal education. The second is the employment period.

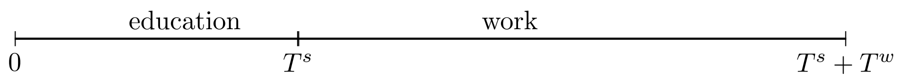


Figure 4: Phases of Household Life Cycle

During the education phase, the agent chooses to go to college, $e = 1$, or not, $e = 0$. Going to college has two costs: (i) the opportunity cost of time at school and (ii) tuition. If a fraction $\bar{e}$ of time is spent in school, then the cost of a college education per period would be $\omega_s \bar{e} + p$, where ω_s is the wage paid to workers during the education period and p is the tuition. We set $\omega_s = 1$.

Given the discrete nature of education, Table 5 shows the output obtained for various combinations of life cycle phase and educational (college or not) attainment. Here there are two levels of human capital stemming from the education choice, $(h(0), h(1))$.

	Productivity	
education	Ed. Phase	Work Phase
no college	1	$h(0)\theta^{\xi}$
college	1	$h(1)\theta$

Table 5: Job Productivity

This discrete choice structure contains a complementarity between education and ability. The return to college is increasing in ability. Further, the dependence of productivity on ability if $e = 0$ is parameterized by ξ so that the extent of the complementarity will be estimated.

The choice of agents compares the discounted present values of costs of education and its benefits to determine the education choice. This decision involves a taste shock that impacts the valuation of going to college.

As in the simple model, the key element of firm inference about worker ability remains. The two channels by which education influences compensation remain and, as in the simple model, provide the incentives for obtaining a college education.

3.3 Going to the Data

This sub-section outlines the models taken to the data and provides a link back to the motivating evidence and additional facts.

3.3.1 Estimated Models

The estimated model studies the discrete education choice of the agent, based upon expectations of compensation in the work period. It combines the solution of an individual choice problem with a rational expectations equilibrium in the labor market that links signals and education to compensation. The baseline estimation assumes agents know s when choosing education. It also imposes that $C(e, \theta, \varepsilon)$ be solely a function of e through a tuition payment and sets $\xi = 0$ so that all uneducated workers obtain a wage of $h(0)$.

After the estimation of the baseline model, there are a number of extensions to the basic framework. One of these involves a change to the information structure: i.e. do agents know s at the time of their education choice. A second explores the affects of allowing the cost of education to depend on ability, as in Spence (1973). Another extension involves a labor participation decision after the education choice, reflecting gender differences in employment rates.

3.3.2 UnderStanding the Facts through the Model

This sub-section looks at the model from the perspective of the various hypotheses concerning the positive relationship between the gender gap in education rates and in the college wage premia. The quantitative analysis that follows uses the model to assess the relative contributions of the factors underlying these hypotheses.

The first hypothesis was a direct effect of education: the human capital accumulated in college differed by gender. From Table 5 that is reflected in differences across gender in $h(1)$, as $h(0) = 1$.

The other two hypotheses focus on information frictions and statistical discrimination. The key to both of these views is the determination of wages given education and the job signal. The information component is captured by $E(\theta|s, e)$. This expectation is directly related to observations of the college wage premium.

The effects of education on this conditional expectation comes from the correlation between education and ability induced by the choice of the individual. Ability can impact this choice from the returns to education and also through the its effect on the cost of education.

There are two important mitigating factor. First, the model contains taste shocks.[15] To the extent that taste shocks weaken the link between education and ability, they impact the inference about ability from the education choice. Of course, these taste shocks have no influence on the direct effect of education on wages through the accumulation of human capital, $h(1)$.

Second, the inference about ability depends not just on education but on the signal as well. The role of education as a signal of ability depends on the informativeness of this signal. If the signal is very noisy, the firm will be led to put more weight on education in predicting ability. If, at the other extreme, the signal is very informative, then there is no signaling power of education.[16] The estimated model will produce estimates of the noise in the signal, allowing an empirical evaluation of this channel.

4 Quantitative Analysis

The models confront the data through a simulated method of moments approach. The moments include those that summarize: (i) college rates, (ii) selection into college and (iii) wages. The moments describing wage premia by job classification and job flows are included in the expanded model presented in Section **??**.

The baseline model is purposefully parsimonious, focusing on the key features of the data motivating the analysis: (i) the gender gap in education and (ii) the gender gap in returns to education, summarized by the Mincer regressions. Estimation results for this model are presented first, in Section 5, and are

[15] In Lang and Manove (2011) productivity depended on a match specific factor. That model element was needed in their framework to limit the informativeness of education about productivity. In our setting, the taste shocks play a similar role since education is not perfectly correlated with ability.

[16] The coefficient on education is like a regression of wages on the part of education that is not related to the signal. That is, consider: 1) a first regression of education on the signal and 2) then a regression of wages on the residuals from the previous regression (the part of education that is not related to the signal). This produces the education coefficient in the Mincer regression, α_{ed}. Therefore, if the signal is very informative about ability, then the relationship between education and ability goes away in the first regression. These points are formalized in the Appendix.

used to understand the motivating patterns of gender differences in education attainment and Mincer wage regression coefficients. These results are the foundation for understanding additional dimensions of gender related education and job outcomes, including job assignments, in Section **??**.

4.1 Approach and Functional Forms

The estimation finds the parameter vector Θ that solves:

$$\pounds \equiv min_{\Theta}(M^d - M^s(\Theta))W(M^d - M^s(\Theta))'. \tag{6}$$

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 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.

The solution to (6) is obtained by comparing the model generated moments with the data moments. The simulated sample contains $I = 100,000$ individuals, so that sampling error is minimized.

4.2 Parameters

For the baseline estimation, the parameter vector is defined by

$$\Theta \equiv (\phi, \bar{\varepsilon}, \mu(\varepsilon), \lambda, h(1)). \tag{7}$$

All parameters from the model are summarized in Table 6. Here ϕ is the shape parameter for the Pareto distribution of ability, $\bar{\varepsilon}$ parameterizes the dispersion of the taste shock, $\mu(\varepsilon)$ controls the mean of the taste shock, λ parameterizes the noise in the test scores and $h(1)$ is the human capital accumulated from college.

Parameters	Description
Set	
$\bar{e}$	fraction of time at school
p	Tuition for college
ω_s	Wage in education and early work phases
$h(0)$	Human capital accumulation if no college
Estimated	
ϕ	Shape parameter for the Pareto distribution of ability
$\bar{\varepsilon}$	Taste shocks Dispersion
$\mu(\varepsilon)$	Taste shocks Mean
λ	Noise in the test: weight on true ability
$h(1)$	Human capital accumulation from college

Table 6: Parameters: Description

The baseline specification assumes that agents know their ability as well as their signal and use this for education decisions.[17] 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

[17] The alternative is explored below.

coefficients in (1), which used the numeracy score as an input. 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 for agent i, denoted ts^i, is a noisy signal of worker ability:

$$ts^i = \lambda\theta_i + (1-\lambda)\bar{\theta}\zeta^i. \tag{8}$$

Here ζ^i is noise in the test score with mean and standard deviation of 1 such that ts^i is a mean preserving spread of θ.[18] In (8), λ parameterizes the noise of the test. The shocks in these test scores are assumed to be uncorrelated with ability.

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. Second, taste shocks are assumed to be uniformly distributed with mean $\mu(\varepsilon)$ 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 and gender specific. Relative to the US, the cost in Germany for males and females is 0, is 26% (male) and 27% (female) in Italy and 93% (male) and 104% (female) in Japan.[19]

Notably missing from the parameters is ξ from the specification of technology in Table 5. For the baseline estimation, we set $\xi = 0$ so that workers without education obtain a wage of $h(0) = 1$ to focus the initial estimation on the informativeness of signals.

4.3 Moments

Moments	Description
Education	
ed	Education rate
χ_0	Constant in logistic regression (1)
χ_1	Coefficient for education test in logistic regression (1)
Labor market	
α_s	Coefficient for education test in mincer regression by country and gender
α_e	Coefficient for education level in mincer regression by country and gender

Table 7: Moments: Description

For the estimation, the moments are chosen with a couple of criteria in mind. First and foremost, they relate directly to the research questions of understanding the gender gaps in education and compensation. Second, they are informative about underlying structural parameters in Θ. Third, since the PIAAC is a single cross section, the moments do not reflect any dynamics of individuals over the lifecycle. The baseline moments are summarized in Table 7.[20]

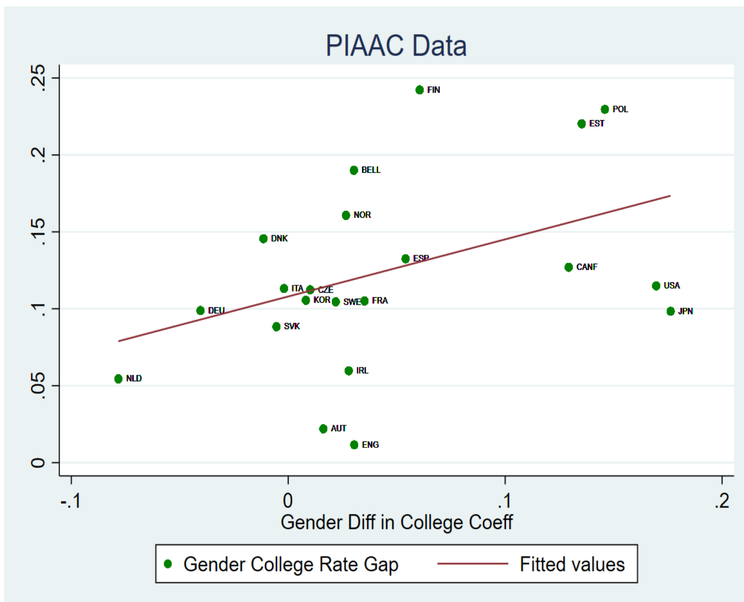
The first set of moments relate to educational attainment, measured as the college attainment rate, and the selection into education. The selection is captured by the coefficients, (χ_0, χ_1), from (1), by gender and country. The model will not generate perfect sorting on ability both because the test score is noisy and also because of the presence of taste shocks that also influence the education decision.

[18]The noise draws are from a uniform distribution over $[-0.5, 0.5]$.
[19]These come from OECD, Education at a Glance.
[20]Moments for all countries are in presented in sub-section 5.4.

Also, keep in mind that the signal *per se* is not informative to the individual about ability, since the agent knows θ at the time of the education decision. Here the signal comes into play for two reasons. First, it affects compensation and thus the return to education. Second, as researchers we do not directly observe ability so that the signal proxies for that in this regression.[21]

The second set of moments are the regression coefficients from the wage equations, (2). For these moments, the regressions are run by gender and country rather than with gender dummy variables.

The result for all countries is shown in Figure 5. The estimated returns to education follow the pattern set out in Figure 1: there is a positive association between the college gap and the estimated values of α_e from (2). In the discussion that follows, the earlier focus on the college wage premium is replaced by the differences in the education coefficients in these gender specific Mincer regressions.



Note: The variable on the horizontal axis is the difference in the estimated values of α_e from (2). On the vertical axis is the college rate of woman minus that of men.

Figure 5: College Attainment and Marginal Returns from Education: PIAAC Data

Together the moments include both the college rate and the coefficient on education in the Mincer regression, allowing us to explore within the structural model the interactions between these two prominent moments. In this way, the estimated model will clarify the underlying economic forces that drive the differences in these coefficients across gender by country.

4.4 Imposing Equilibrium Beliefs

The estimation involves both the solution of an individual choice problem over education as well as an equilibrium condition for the determination of the wage function. The first of these components, given beliefs about the compensation function, is relatively straightforward. For a given set of parameters, the agents make a choice between college and no college by comparing the discounted expected returns from the

[21] In principle this could justify the inclusion of a separate measure of noise related to this regression and independent of the labor market signal. This is part of the error in this regression.

two alternatives and incorporating the taste shock. The agents are fully rational, using all the information available to them in making this choice.

But the choice of an individual depends upon beliefs about compensation which need to be model consistent.[22] The equilibrium dimension arises because the wages, through competition, will equal the expected productivity of the worker. This depends critically on the information about ability contained by the education decision, reflected by $E(\theta|s,e)$. As in Spence (1973), this inference is determined by the choices of all agents.

Specifically, in making the education decision, the worker is assumed to hold beliefs over wages given by:

$$\tilde{\omega}(s,e) = h(e)E(\theta|s,e) = h(e)[\tilde{\omega}^e_{con} + \tilde{\omega}^e_s \times s] \tag{9}$$

where $E(\theta|s,e)$ represents the employer's conditional beliefs about ability given the test s and education e. Linearity of $E(\theta|s,e)$ with respect to s is imposed in (9).

So for a given vector of parameterized beliefs, $(\tilde{\omega}^e_{con}, \tilde{\omega}^e_s)$, agents jointly make education decisions. These choices generate a relationship between ability and the signal conditional on education. Thus, the last step runs a regression of true ability on test scores for the resulting educated workers, $(\hat{\omega}^e_{con}, \hat{\omega}^e_s)$. When these regression coefficients and beliefs match i.e $(\hat{\omega}^e_{con}, \hat{\omega}^e_s)$ is close enough to $(\tilde{\omega}^e_{con}, \tilde{\omega}^e_s)$, then an equilibrium obtains. Of course, there is no guarantee that an equilibrium will be found nor that it is unique.[23] The results reported for the model are those pertaining to an equilibrium outcome.[24]

Notice that $\tilde{\omega}^e_s$ determines the weight employers put on the signal when constructing expected ability of workers. Similarly, $\tilde{\omega}^e_{con}$ captures the part of the expected ability that is common to all educated individual, independently of their signal. The values of this two coefficients are driven mainly by the informativeness of the test score, λ. A perfect signal of ability ($\lambda = 1$) implies $\tilde{\omega}^e_s = 1$ and $\tilde{\omega}^e_{con} = 0$. A signal that is only noise ($\lambda = 0$) implies $\tilde{\omega}^e_s = 0$ and $\tilde{\omega}^e_{con} = \bar{\theta}^e$.

Since equilibrium wages in the simulated data are constructed according to (9), changes in λ impacts the Mincer coefficients through $\tilde{\omega}^e_s$ and $\tilde{\omega}^e_{con}$. All else the same, a higher value of $\tilde{\omega}^e_s$ (high λ) for example, implies a higher dependence of wages paid on the signal that might increase the estimate of α_s in (2). Similarly, all else the same, a low $\tilde{\omega}^e_s$ (low λ) might imply a higher mincer coefficient for education through a higher relative weight of $\tilde{\omega}^e_{con}$ in workers expected ability and therefore on wages.

But of course all is not the same. Mincer coefficients are more complex objects affected by other factors like the covariance between education and the signal. Changes in the informativeness of the signal have also equilibrium effects on selection into education. Thus Mincer regression coefficients are not always monotone functions of λ.

[22] An alternative is the make the beliefs data consistent. In that case, the beliefs are fixed by a regression on the data and then the model is required to match the regression coefficients from the data regression. As discussed in Cooper, Haltiwanger, and Willis (2007), this turns a fixed point problem into a larger simulated method of moments problem.

[23] Through simulations we have found instances of multiple equilibria. In particular, with very noisy signals, an equilibrium emerges in which education has no value as a signal and the education rate is very low, driven solely by taste shocks. An example of this occurs in some of the counterfactuals.

[24] This procedure brings us close to the Mincer regressions used as moments. It would seem that we could frame beliefs directly from those regressions. But that is not the case as the Mincer regressions contain another regressor, age, and are also in very different units. Hence we solve for a fixed point and match moments.

5 Baseline Estimation

This section first presents the baseline estimation results. It then uses the estimated model to determine the key factors in generating gender specific education and labor market outcomes. The section concludes with a discussion of robustness, including a labor force participation choice.

5.1 Estimation Results

The baseline model assumes that agents know the signal s when deciding on education, solving the dynamic analogue to (4). Further in the baseline specification, the cost of education is just tuition and the opportunity cost of education, assumed to be independent of ability. And there is no match shock. These restrictions are relaxed below.

	Education			**Mincer Reg.**		
	ed	χ_0	χ_s	α_s	α_e	fit
			Data			
GM	0.331	-0.994	1.395	0.111	0.239	na
GW	0.430	-0.480	1.108	0.128	0.199	na
IM	0.189	-2.130	1.734	0.061	0.210	na
IW	0.303	-0.880	0.443	0.085	0.208	na
JM	0.596	0.243	0.921	0.091	0.022	na
JW	0.695	0.706	0.732	0.098	0.198	na
UM	0.422	-0.570	1.716	0.155	0.162	na
UW	0.537	0.119	1.499	0.149	0.331	na
			Baseline			
GM	0.315	-0.991	1.395	0.107	0.238	0.000
GW	0.401	-0.475	1.109	0.122	0.201	0.001
IM	0.174	-2.129	1.734	0.064	0.209	0.000
IW	0.298	-0.879	0.444	0.084	0.208	0.000
JM	0.547	0.254	0.920	0.086	0.030	0.003
JW	0.653	0.714	0.730	0.098	0.198	0.002
UM	0.403	-0.566	1.716	0.146	0.166	0.001
UW	0.520	0.122	1.500	0.140	0.332	0.000

Note: This table reports data and simulated moments for the estimated models. See Table 7 for a full list of variables.

Table 8: Moments

Moments and Parameters The moments are in Table 8 and the parameter estimates are reported in Table 9. From the moments, the fit of the model is very good. This is particularly the case for German men, Italians (both men and women) and US women where the distance between moments and data is essentially zero.[25] For the other countries and genders there are differences between moments and data but these are small given the metric in (6).

For all countries, the model reproduces the higher college rates for women. But, for all countries and genders, the model prediction of education attainment is lower than in the data.

For the selection into college, note that in the data the constant of the logistic regression is always higher for women and the coefficient on the test score is higher for men although very close to those of women.

[25]Note that the model is just identified.

This pattern is reproduced in the estimated model as well.

Matching the pattern of the Mincer regression coefficients is an important element of the analysis. For both Japan and the US, the estimated model generates much higher coefficients for woman than men in the Mincer regressions. At the same time, and despite the differences across genders in educational attainment, for Germany and Italy, gender differences across the Mincer regression coefficients are not large. Further the coefficient on education is lower for women than men in these two countries. Sub-section 5.2 looks carefully at gender differences in parameters to explain these moments.

The parameter estimates appear in Table 9. For all countries, there is evidence of taste shocks and noise in the test score, as the point estimate of $\bar{\varepsilon}$ exceeds zero and λ^e is less than one. Also the mean of the taste shock is positive, which helps the model match the college rates.

	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ^e	$h(1)$
		Baseline			
GM	4.246	0.370	0.221	0.426	0.955
GW	3.641	0.389	0.280	0.326	0.878
IM	6.113	0.311	0.253	0.652	0.958
IW	6.277	0.830	0.017	0.961	1.037
JM	5.559	0.127	0.554	0.619	0.804
JW	4.878	0.379	0.436	0.340	1.017
UM	2.665	0.224	0.373	0.187	0.700
UW	2.751	0.362	0.184	0.086	1.006

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

Table 9: Parameter Estimates

There are no standard errors associated with these parameter estimates. Doing so is useful for understanding the statistical significance of a particular parameter.

Looking first at the distribution of ability, all else the same, higher mean ability would imply a higher college rate and a higher return to college in the Mincer regression. The mean of ability is higher for women in Germany and Japan. The college choice is also directly impacted by the mean of the taste shock which is higher for men than women, except in Germany.

The dispersion in tastes matters as it impacts the inference about ability from observing education and thus the education coefficient in the Mincer regression. A larger value of $\bar{\varepsilon}$ implies a lower value of the score coefficient in the logistic regression predicting the education choice and a lower coefficient on education in the Mincer wage regression. There is more variability in tastes for women than men in all countries, though the difference is small in Germany.

Education decisions are also dependent on the returns to human capital accumulation, $h(1)$.[26] Except for Germany, the estimate of $h(1)$ is higher for women than men. It is noteworthy that most of these estimates are less than one, except for females in Italy, Japan and in the US. This is not inconsistent with the high college rates, since the wages paid to college graduates depends as well on the conditional ability given education. The model generates a positive return to college through this second mechanism. Further, for this baseline model, $h(1)$ incorporates job assignment probabilities and compensation in those jobs, which are flows outside of this model.

[26]In Cooper and Liu (2019), the estimate of $h(1)$ was less than 1 in a number of countries. But, as the model was enriched to include job flows, as in Cervantes and Cooper (2020), $h(1) < 1$ no longer arises.

Finally, the noise of the signal has multiple effects on model moments. From Table 9, a key difference across countries and genders is the amount of noise in the test score, λ^e. For all countries except Italy, there is more noise in the test score for women than men. This difference is largest, in percentage terms, in Japan and the US.

A key point of the analysis is understanding the mapping from gender specific parameters to differences in outcomes. The discussion above and inspection of Table 9 document parameter differences. But how these matter for education and labor market outcomes is less clear. This is taken up in sub-section 5.2.

Equilibrium Beliefs As noted earlier, the solution of the model contains the beliefs of individuals about the wages paid for college graduates, as given in (9). Table 10 reports the equilibrium beliefs for the baseline model of expected ability conditional on the test score: i.e. $E(\theta|s)$. The table shows the constant and the coefficient on the test score as well as the conditional expectation of ability. Here beliefs are about the ability of workers with college education. Thus education is not a regressor.

	Baseline			counterfactual: λ^e			counterfactual: $h(1)$			counterfactual: $\bar{\varepsilon}$		
C/G	constant	score	$E(\theta\|s)$	constant	score	$E(\theta\|s)$	constant	score	$E(\theta\|s)$	constant	score	$E(\theta\|s)$
GM	-0.879	1.571	1.490	-0.879	1.571	1.490	-0.879	1.571	1.490	-0.879	1.571	1.490
GF	-0.814	1.512	1.527	-1.020	1.668	1.565	-0.705	1.436	1.501	-0.873	1.544	1.536
IM	-0.618	1.442	1.428	-0.618	1.442	1.428	-0.618	1.442	1.428	-0.618	1.442	1.428
IF	-0.045	1.038	1.262	-0.174	1.137	1.243	-0.045	1.038	1.275	-0.049	1.040	1.722
JM	-0.175	1.137	1.287	-0.175	1.137	1.287	-0.175	1.137	1.287	-0.175	1.137	1.287
JF	0.408	0.667	1.288	-0.328	1.246	1.320	0.304	0.755	1.298	0.360	0.688	1.290
UM	-2.552	2.320	1.839	-2.552	2.320	1.839	-2.552	2.320	1.839	-2.552	2.320	1.839
UF	-0.013	0.924	1.655	-2.389	2.231	1.766	-29.992	14.221	3.603	-30.296	14.323	2.779

Note: This table reports the equilibrium beliefs from a regression of ability on a constant and the test score for the baseline model and some counterfactuals.

Table 10: Equilibrium Beliefs: Labor Market

Note that the equilibrium beliefs and the Mincer wage regressions share a pattern since they both reflect, in part, the relative informativeness of test scores and education when predicting ability. Looking at German, Japanese and US women the coefficient on the test score is much lower and the constant much higher compared to men. This is indicative of education being more informative about ability relative to the signal, as suggested by lower value of λ^e for women in those countries. As opposed to Germany, for Japan and the US, this effect together with a higher estimate of $h(1)$ translate into a higher coefficient for education in the Mincer wage regression. As for Italian women, the coefficient for the test score in the equilibrium beliefs is close to one as a consequence of the high λ^e. These beliefs are the key link in the choices of individuals about education and the dependence of compensation on education and the test score.

Notice that in the US and Japan the estimated variation in taste is higher for women than for men. This can potentially reduce the information value of education when predicting ability thus offsetting the effect of a lower λ^e. However the higher constant and lower coefficient for the score observed in Table 10 suggest that the effects on beliefs of the lower value of λ^e for women dominates the higher $\bar{\varepsilon}$.

Looking at the conditional expectation of ability in the baseline, all else the same, the mean ability of those in college should fall as the college rate rises. So, for example, the mean ability given college should be lower for US woman than US men. But, of course, all is not the same. First, from the estimate of ϕ, the ability distributions differ by gender and country. Second, the selection into college depends on more than ability, reflecting taste as well as information about wages.

But these are endogenous objects so that variations in parameters influence all the coefficients in the beliefs and wage regressions. As in other models of statistical discrimination, there is a feedback between the beliefs held by, in this case, firms and the education choices of individuals.

5.2 Evaluating Gender Differences

A key point of the paper is to understand the driving forces behind differences in the education and labor market outcomes by gender. Using the estimated model, we provide additional evidence regarding the gender differences. First, what is the source of the positive relationship between the education attainment gap and that on the wage effects of college expressed as differences in the education coefficients in the Mincer regression? Second, what explains differences in the overall moments by gender?

To pursue these issues, we simulate the models for women in each country, replacing one parameter at a time with that parameter for men in the same country. The results are shown in Table 11, including one case in which two parameters are altered. The results are for women only as the simulations for the men simply repeat the moments from the baseline estimates.

So, for example, in the second row of the block labeled $\mu(\varepsilon)$ the estimated value of the mean taste shock for men in Italy of 0.253 is used instead of the estimate for women in Italy of 0.017. All other parameters are held fixed at their estimated values for Italian women. The results indicated how the various moments as well as the fit change for each parameter substitution. Here the results do not entail re-estimation, just simulation.

	Education			**Mincer Reg.**			**Education**			**Mincer Reg.**		
	ed	χ_0	χ_s	α_s	α_e	**fit**	ed	χ_0	χ_s	α_s	α_e	**fit**
			Baseline						ϕ			
G	0.401	-0.474	1.109	0.122	0.201	0.001	0.333	-0.796	0.870	0.072	0.179	0.169
I	0.298	-0.879	0.444	0.084	0.208	0.000	0.301	-0.861	0.460	0.088	0.212	0.001
J	0.653	0.714	0.730	0.098	0.198	0.002	0.616	0.499	0.487	0.065	0.196	0.110
U	0.519	0.122	1.499	0.149	0.331	0.000	0.520	0.124	1.372	0.136	0.340	0.017
			λ^e						$h(1)$			
G	0.402	-0.440	1.235	0.151	0.191	0.019	0.474	-0.106	1.222	0.149	0.221	0.156
I	0.297	-0.886	0.411	0.064	0.215	0.002	0.247	-1.149	0.455	0.074	0.143	0.080
J	0.643	0.769	1.161	0.164	0.163	0.197	0.395	-0.440	0.375	0.040	0.072	1.551
US	0.446	-0.345	2.104	0.213	0.305	0.595	0.028	-45.671	28.240	0.008	0.742	2,812.00
			$\bar{\varepsilon}$						$\mu(\varepsilon)$			
G	0.390	-0.540	1.184	0.121	0.202	0.011	0.314	-0.998	1.319	0.107	0.237	0.327
I	0.070	-3.987	2.058	0.042	0.452	12.375	0.442	-0.230	0.423	0.106	0.189	0.444
J	0.746	2.175	2.503	0.127	0.092	5.311	0.806	1.690	0.978	0.111	0.163	1.044
US	0.049	-95.634	62.745	0.011	0.848	12920.00	0.835	2.235	1.460	0.153	0.294	4.568
			Beliefs						$h(1), \mu(\varepsilon)$			
G	0.418	-0.390	1.146	0.126	0.192	0.010	0.387	-0.584	1.374	0.133	0.253	0.086
I	0.262	-1.081	0.625	0.089	0.213	0.075	0.390	-0.449	0.404	0.096	0.122	0.203
J	0.682	0.973	1.128	0.109	0.165	0.230	0.541	0.170	0.330	0.047	0.059	0.494
US	0.466	-0.242	2.013	0.150	0.307	0.400	0.414	-0.385	0.696	0.068	0.141	0.958

Table 11: Moments: Evaluating Gender Differences

There are two perspectives in considering this table. The first looks specifically at the factors determining education rates and the Mincer wage coefficients. The second focuses on model fit to discern which are the key differences in parameters across the genders.

5.2.1 College Rates and Mincer Wage Regressions

The hypothesis explaining the gender differences in education rates and marginal returns to education, here through the education coefficient in the Mincer regression, are useful in interpreting these decompositions. Hence we focus on the experiments associated with variations in the test noise, λ^e, the direct return to college, $h(1)$, and the noise in tastes, $\bar{\varepsilon}$.

Noise in the Test Score The importance of noise in the test scores is directly evaluated by a substitution of the estimated value of λ^e for men for that of women, as in the middle left block of Table 11. For Japan and the US, the signal was estimated to be less informative for women than men, suggesting the presence of statistical discrimination as a possible source of differences in the marginal returns to education by gender. Thus the exercise consists of giving women the higher λ^e of men, keeping the rest of the parameters constant. That way, the labor market signal of ability for women becomes as noisy as that of men. The substitution does indeed lead to a reduction in the education coefficient and an increase in the score coefficient in the Mincer regression. In addition, the education rates get closer, particularly in the US. But these changes are relatively minor so that the counterfactual Mincer regression results for women are not close to those of the men.

In Germany too the estimated value of λ^e is higher for men, but the Mincer education coefficient and the education rate barely change. In that case, the less informative signal for women is offset by the higher estimates for men of the direct effects of education on wages, $h(1)$, as mentioned later. In Italy the mincer coefficient for education for women increases with this experiment as the test score was more informative for women in the baseline. The education rate does not change.

Again, the theory predictions are verified in the estimated model: equating the informativeness of the labor market signal about ability for men and women closes the gap in education rates and marginal returns to college. But the effects are not large.

The channel for these changes is the equilibrium beliefs. From Table 10, the block labeled "counterfactual: λ^e" shows the changes in equilibrium beliefs. For both Japan and the US, once we reduce the noise in the test score of women to that of men the coefficient on the test score increases and the constant decreases. Those changes translate into the aforementioned movements in Mincer coefficients and the education rate..[27] Note that the conditional expectation of ability is higher in Japan and the US reflecting the fall in the education rate. This effect is relatively small in Germany. It is important to note that in Germany beliefs move in the same direction as in US and Japan since the movement in λ^e is also the same. But again, since $h(1)$ for women remains low relative to men, education rate and Mincer coefficients barely change.

Italy is an interesting case. As noted, the estimate of λ^e is higher for women in Italy. Moreover, the variance of tastes is much higher for women as well. Both things suggest that education has little information value when predicting ability for Italian women. However, if we look at beliefs, we see that the constant is higher and the coefficient on the test score is lower for women. Moreover, when we give women the lower λ of men, the coefficient increases. It looks like beliefs move in the "wrong" direction.

But it is necessary to keep in mind that the coefficient on the score in beliefs depends on two objects: (i) the covariance between true ability and the signal and (ii) the variance of the signal. The covariance is of course increasing in λ. But the effect of λ on the variance of the signal depends on the variance of ability for the educated individuals relative to the variance of the noise.[28] It is possible for this variance to increase

[27] From various experiments, the expectation of ability conditional on the test score is not monotone in λ^e .

[28] More formally, a higher λ has two effects on the weight employers put on the signal when constructing beliefs about ability: (i) it increases the covariance between true ability and the score (covariance effect) and (ii) it gives more weight to the true ability compared to the noise in the variance of the signal (variance effect). When the dispersion of tastes is high, the variance of the ability among educated individuals is also high. In that case, a higher λ leads to a significant increase in the variance of the signal among the educated group. Therefore this variance effect dominates the covariance effect (less noisy signal) when predicting ability. This is more clear from equations (10) and (11).

$$\hat{w_s} = \frac{cov(\theta^e, s^e)}{var(s_e)} = \frac{\lambda\sigma^2_{\theta_e}}{\lambda^2\sigma^2_{\theta_e} + (1-\lambda)^2\bar{\theta}^2\sigma^2_{\varepsilon}} \tag{10}$$

with λ and offset the increase in then numerator, driving the coefficient on the score down.

Accumulation of Human Capital The role of $h(1)$ is evaluated by substituting these parameter for men into the choice problem of women. In the baseline estimation, $h(1)$ was estimated to be lower for men than woman except in Germany. From Table 11, replacing the women's estimate with the men's reduces the college rate to about 3% in the US and by almost 40% in Japan. Further, the education coefficient falls from 0.198 to 0.072 in Japan. The same patterns hold in Italy: both the education rate and the Mincer coefficient on education decrease with the lower $h(1)$, though the effects are not as strong. The opposite occurs in Germany as the change of parameters gives a higher return to women. For the US, the coefficient in the Mincer regression more than doubles, just the opposite of Japan.

The effects of $h(1)$ on the Mincer regression coefficient on education combines both direct and indirect effects. Looking at Italy, Japan and the US, the direct effects move in the same direction: the lower $h(1)$ for men compared to women would imply a reduction in α_e. The indirect effects operate through changes in the conditional expectation of ability given the signal and the education level due to changes in selection. The "counterfactual: $h(1)$" block of Table 10 reports the revised equilibrium beliefs. For Japanese women there is a fall in the constant and modest increase in the coefficient on the test score. Also, there is an increase in the expected ability for those going to college. This is all consistent with the lower education rate: all else the same, the lower return to education imposed in this experiment should imply that only individuals with a high signal continue to select into college. Thus, in this case the indirect effect of $h(1)$ on the Mincer regression coefficient on education acts in the opposite direction of the direct effect, tough the last one dominates.

But, for US women the constant falls from -0.01 to nearly -30 while the coefficient on the score goes from 0.924 to 14.221. Here we see that the conditional expectation of ability rises quite a lot for US female, again coming from the drastic reduction in the college rate. This is an interesting example in which the change in parameters, this case the reduction in $h(1)$, seems to alter the set of equilibria so that the only equilibrium is one with this very low value of education and associated with it a low education rate.

The large increase of the α_e coefficient for US women can then be attributed to this response of beliefs in this counterfactual. That is, if beliefs are held at their baseline equilibrium values, then the reduction in $h(1)$ lowers the education rate for US women and slightly reduces α_e in the Mincer wage regression, closing the gaps. The increases reported for this counterfactual are therefore the consequence of a change in equilibrium beliefs, as reported in Table 10. Clearly, the indirect effect dominates.

Taste Shocks Taste shocks play a role in the informativeness of education about ability. This is seen in the third row of the left panel. For Italy, Japan and the US, tastes were noisier for women compared to men. Under the counterfactual, reducing the variability of tastes should have two effects. First it should lead to an increase in the test score coefficient in the logistic regression. This is indeed the outcome, reflecting an increase in the correlation of the signal of ability and education. Second, it can potentially affect equilibrium beliefs by changing the correlation between education and ability and/or the corresponding selection.

therefore:

$$\lambda \uparrow \implies \hat{w_s} \uparrow \text{ iff } \lambda \leq \sqrt{\frac{\bar{\theta}\sigma_\varepsilon^2}{\sigma_{\theta_e}^2 + \bar{\theta}\sigma_\varepsilon^2}} \tag{11}$$

When $\sigma_{\theta_e}^2$ is low enough, the covariance effect dominates and $\hat{w_s}$ is always increasing in λ. By contrast, if $\sigma_{\theta_e}^2$ is too big then the variance effect dominates and $\hat{w_s}$ is decreasing in λ.

Note that for Germany and Italy, there were essentially no changes in equilibrium beliefs. For Germany this reflects the fact that the variability in tastes were very close for both genders. For Italy, with the high value of λ, variations in the education choice induced by the alternative distribution of tastes does not matter for the inference of ability. However, the reduction in taste does affect selection: it decreases considerable the education rate to nearly 7%. The low education rate leads to an increase in the expected ability conditional on college attendance, and therefore in the education coefficient in the Mincer regression.

For the US, this is a second counterfactual in which it appears that the only equilibrium involves the shutdown of education as a signal, leading to the low education rate. [29] While the earlier case involved a large change in $h(1)$, here the difference between the dispersion in tastes is not large but evidently large enough to have a big effect on the equilibrium outcome . From experiments, if λ was much closer to 1, putting less reliance on education as a signal, then an equilibrium with high education rates and data consistent wage coefficients emerges. It is in this sense that these equilibria with low education rates seem to depend on λ.

Japan is more puzzling. There is again little change in equilibrium beliefs despite the large difference in the dispersion of the taste shocks.

Beliefs Another interesting experiment is simply to replace the beliefs of women for those of men, holding the parameters fixed.[30] As seen from Table 10, there are certainly differences in beliefs by gender within a country. These differences are not large for Germany but they are in Japan and the US.

The bottom left panel shows the results of this experiment. The fit certainly worsens, considerably for Japan and the US. The changes are largely in the logistic regression and thus the selection into college rather than in the wage regression coefficients.

Other Variations Experiments with ability and the mean of the tastes are also reported. Overall, the biggest contributor of the Mincer wage education coefficient is coming from the direct effect of education on human capital, $h(e)$. Differences in the noisiness of the test, parameterized by λ, impact both of the Mincer wage regression coefficients, but the effects are not large enough to explain the differences across genders.

Together, altering the human capital accumulation and the mean tastes provided a variation that brought the moments of males and females much closer than any single variation. This is reported in the bottom right panel of the table. For Japanese women, the college rate and α_e coefficient are close to these moments for men of 54% and 0.030 in the baseline. For US women, these moments are close to the 40% college rate and even lower than the 0.166 estimate of α_e for men.

Recall that for the US women, introducing the lower estimate of $h(1)$ lead to an equilibrium with almost no college attainment. Here that does not arise since the lower $h(1)$ is partly offset by a mean taste that is almost double that of women.

5.2.2 The Fit

These counterfactuals are also useful for understanding the source of differences between the moments by gender. Looking at the fit measures for these treatments, a big difference between men and woman is in the dispersion of tastes, $\bar{\varepsilon}$. From the bottom left panel of Table 11, replacing the noise in tastes for women with the estimate for men has a big impact on the model fit for Italy, Japan and the US. In Germany, there were

[29] With these parameters we were unable to find another equilibrium with higher education rates.

[30] To be clear, the beliefs and actions are not consistent. The moments are not generated from an equilibrium. In some ways, the response here is similar to λ.

not big gender differences in the baseline estimates so not much happens in the experiment. For the other countries, particularly Italy, there was much more dispersion in taste shocks for woman.

Differences in mean tastes matter in all countries. For Germany, the switch to a lower mean taste leads to both a lower college rate for woman and a higher coefficient on education in the Mincer regression. Still, the fit remains good for Germany indicating relatively small gender differences.

The model fit for the US also worsens considerably when the relatively high estimated value of $h(1)$ for women is replaced with the lower value for men. The deterioration in the fit comes through the low college rate and the logistic regression coefficients.

In sum, in terms of the fit measure, for three of the four countries, replacing the female with the male dispersion of the taste shock leads to the biggest deterioration in model fit. This is not the case for Germany, where the mean of the taste shock matters most.

5.3 Robustness

Here we explore the robustness of our findings to a couple of key modeling assumptions. The first is that the Mincer regressions have not included the effects of the decision to work or not by agents. Second, we have assumed that agents know the signal for the labor market at the time of the education decision. Finally, as in Spence (1973), we allow the cost of education to be dependent on ability.

5.3.1 Selection into Employment

The analysis thus far ignores labor force participation decisions.[31] This is an important margin particularly because labor force participation is different for men and women and might underlie some of the reported differences in the education coefficient in the Mincer regression.

There is a long literature on selection, growing out of Heckman (1974). A recent contribution by Eckstein, Keane, and Lifshitz (2019) looks at the interaction between education and labor market outcomes for females in the US. An important point in that paper is that the labor force participation gap between men and women is larger driven by martial status: single women behave much like men in terms of the work/no work margin.

The point here is not the standard selection concern but rather understanding the effects of differential selection by gender on the Mincer wage coefficients. To confront these issues, we conduct a number of exercises. In the end, we conclude that the labor force participation of women is not explaining the differences in the Mincer wage regressions by gender.[32]

The first is empirical, studying the participation decision in the PIAAC data. Results are presented in Table 15. The insignificance of the interaction terms of gender with the score and the education variable, suggest that selection into employment does not depend differently on ability and education by gender. However, the significance of the interaction between gender and the marital status suggests that married women have lower participation in the labor force.

The second looks at the interaction between the Mincer wage regressions and marital status. The empirical specification adds martial status into (2), allowing it to interact with education. Table 16 presents our findings.

As seen here, marital status does not impact the education coefficient in the Mincer regression. For Japan and the US, this coefficient is much larger for woman than men and this pattern remains even when marital status interacts with education in this regression.

[31] Conversations with Zvi Eckstein, Kevin Lang and Michael Manove that provoked this section are much appreciated.
[32] These tables are in the appendix.

The final exercise enlarges the estimated model to include a choice of employment after the education stage. To do so, a second taste shock is added to the model to create a choice between employment and home work (leisure). Further, there are two additional moments, summarizing the labor force participation rates by education and gender in each country. The specification is discussed in more detail and the results are reported in the Appendix. The model fit remains very good. The estimated model still captures gender differences in college rates and in the education coefficient in the Mincer regression. The estimated model produces the data pattern of higher labor force participation by those with a college degree though it generally understates the participation rate of those without college.

5.3.2 Alternative Information Structures

The baseline model assumes that the agent knows the job market signal, s, at the time of the education decision. This section relaxes that assumption so that the education decision is made based on knowing ability but not knowing the perception of firms in the labor market about the worker's ability. This optimization problem was shown earlier as (5) in the illustrative model.

The construction of the compensation function remains the same: $\omega(e,s) = h(e)E(\theta|s,e)$. Regardless of the information held by the worker, compensation is still equal to expected productivity. But in this alternative information structure, the education decision depends only on *ability*, not the test score that the firm will receive.

The moments for this exercise, shown in Table 19, are the same as in the baseline. In particular, the moments still include the logistic regression relating the education choice to the test score. The fit for this specification remain very good, particularly for the Italian women. The estimated model still generates a larger coefficient on education in the Mincer regression for women compared to men in Japan and the US. Though in the US, the difference is much smaller than in the baseline estimated model and in the data.

From the parameters reported in Table 20, we see a large change in parameter values for US women, where the estimated variability in the taste shock is much larger and $h(1)$ is much lower... With the exception of Italian men, the test score is much less noisy.

One way to understand these parameter changes is to consider a model simulation using baseline parameters where agents do not know s when choosing education. In that case, the coefficient on education in the Mincer regression gets quite large, reaching, for example, 0.495 for US women and 0.702 for US men. This is intuitive since education has an added role of a signal about ability when s is not known. To fit the moments better, the re-estimation, again emphasizing the US, adds more variability in tastes to reduce the role of education as a signal. This also increases the college rates, which is why $h(1)$ is so much lower for US women compared to the baseline.

5.3.3 Ability Specific Cost of Education

The model of Spence (1973) is directly related to the interaction of education and information. While our model has a signal that the Spence model excludes and allows education to be productive, both of these effects could be negated in the estimation. But, in our model, the cost of education is not inversely related to ability, which is fundamental to the role of education as a signal in Spence (1973).

To study this we amend the model so that the time cost of education is be inversely related to ability: $C(e,\theta) = \frac{\bar{e}}{\theta}$. In this way, education becomes more informative about ability, all else the same. This is seen by a simulation with baseline parameters, but allowing ability to inversely impact the cost of education. In that case, the Mincer wage coefficient on education is higher in Japan and in the US for both genders.

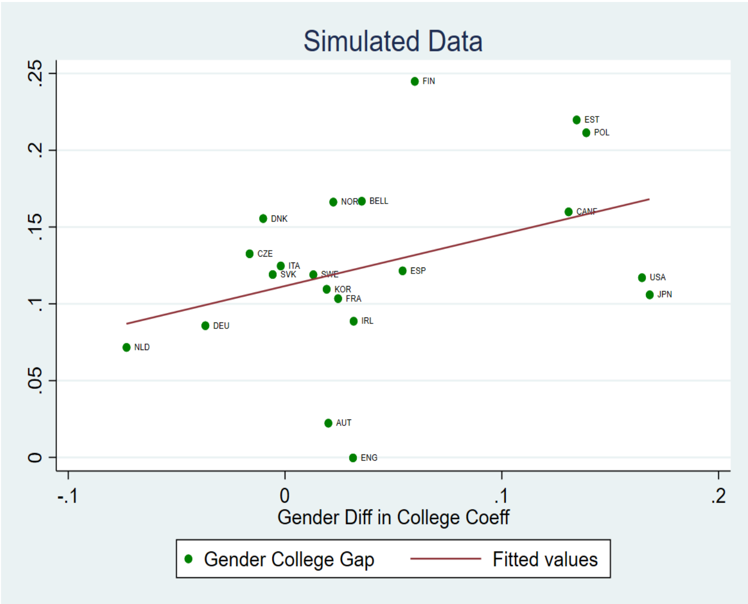
The results for the re-estimated model are reported in the bottom panel of Tables 19 and 20. There are a couple of key points. The fit of the model remains very good and the patterns associated with α_e continue to hold. As before, these differences are quite stark with response to Japanese and US women. For the parameter estimates, the noise in the test score remains larger for Japanese and US women relative to men. The informativeness of the signal for Italian women is lower.

5.3.4 Productivity Differences and Education

The baseline model imposes $\xi = 0$ so that all individuals without college have the same productivity. This sub-section relaxes that assumption so that ξ is estimated. To do so, the moments include measures of wage dispersion for those with and without college education.

[to be completed]

5.4 All Countries



Note: The variable on the horizontal axis is the difference in the estimated values of α_e from (2). On the vertical axis is the college rate of woman minus that of men.

Figure 6: College Attainment and Marginal Returns from Education

Figure 1 indicated patterns of education and college premia gaps for a large number of OECD countries. Though the discussion has focused on 4 of these, the estimation can easily be extended to others and be broadened to introduce the Mincer test score regressions across countries, as in Figure 5.

The baseline model was estimated for all countries. Moments and parameter estimates are provided in Tables 22 and 24.

Figure 6 shows the counterpart to Figure 5 using simulated data from the estimated model. As in the PIAAC data, there is a positive correlation across countries in the college rate and Mincer wage education coefficient produced by the model, as in the data.

Table 12 provides the specific regression results across all of the countries, where the dependent variable is the difference in educational attainment and the right side is either the difference in the coefficient on education or the test score in the Mincer wage regression.

Source	Mincer Ed.	R^2	Mincer Test	R^2
Data	0.367	0.165	0.046	0.001
	0.189		0.482	
Model	0.336	0.1485	0.031	0.016
	0.187		0.580	
λ	0.133	0.011	0.170	0.017
	0.282		0.295	

Note: This table reports the regression results across countries. The LHS is the gender difference in college rates and the RHS is either the gender difference in the Mincer wage education or test score coefficient.

Table 12: Regressions of Differences Across Countries:

There are two distinct patterns in the data. First, there is the positive association between the college gap and the gap in the Mincer education coefficient across the broader set of countries. Second, there is, in the data, a weak association between the Mincer test score coefficient and the college gap.

The estimated model picks up these data patterns across the broader set of countries. But, as with the focus on the four countries, these are associations between endogenous variables in the data and reproduced in the model.

The λ block in Table 12 comes from a decomposition exercise where the informativeness of the signal for women was replaced by the estimated λ for men, in that country. The model was simulated under this counterfactual and then the regressions of the wage gap on the gap in the Mincer coefficients was run again. The results are in stark contrast with the baseline estimation. Now the education gap coefficient is much smaller and not signficiant. While the coefficient on the test score gap is larger and much more significant. So, across the broader set of countries, it is clear that the differential in the noise in the test score contributes to the correlation between the education gap and the education coefficient in the Mincer wage regression.

6 Other Implications

[to be completed]

This section looks at additional implications of the model. Both of these exercises focus explicitly on differences across genders, looking at wage gaps and at mismatch.

6.1 Wage Differences: The Role of Discrimination

6.2 MisMatch

7 Conclusions

This paper studies gender differences in education and compensation. Despite the presence of wage gaps across genders, there are also gender specific returns to education. In most of the countries in our sample, women have higher college attainment rates **and** higher marginal returns to college. These measures are positively correlated.

The point of the paper was to uncover the sources of these gaps in educational attainment and college premia. A model allowing for gender specific human capital accumulation as well as statistical discrimination was specified and estimated using simulated method of moments.

Through a series of counterfactual exercises, we find that statistical discrimination does underlie some of the positive relationship between the observed gaps in college attainment and premia. But this magnitudes are not very large compared to the gender differences in human capital accumulation.

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8 Appendix

8.1 Facts

	Germany		Italy		Japan		US	
Men	Women	Men	Women	Men	Women	Men	Women	
				Young Cohort. No College				
Mean Lit.	271.185	273.024	253.083	256.199	295.829	297.669	257.420	255.128
Sd. Lit.	41.881	41.353	41.771	41.716	36.374	30.995	46.463	41.470
Diff in Mean	-1.838		-3.116		-1.839		2.291	
				Young Cohort. College				
Mean Lit.	310.141	305.997	302.585	277.546	320.501	317.091	310.907	304.567
Sd. Lit.	31.535	32.742	31.992	35.134	26.557	27.276	34.174	35.184
Diff in Mean	4.144		25.039***		3.410		6.341*	

Note: A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 13: PIAAC Literacy Scores by Gender and Education. Younger cohort.

	Germany		Italy		Japan		US	
Men	Women	Men	Women	Men	Women	Men	Women	
				Older Cohort. No College				
Mean Num.	265.233	258.171	255.135	251.130	285.216	278.218	239.527	229.806
Sd. Num.	47.077	47.547	46.531	44.416	37.842	33.008	51.142	47.488
Diff in Mean	7.061***		4.005		6.998***		9.721***	
Mean Lit.	258.064	261.790	252.160	256.335	291.404	291.842	252.195	254.289
Sd. Lit.	43.400	41.784	40.263	39.475	31.652	29.980	43.655	43.002
Diff in Mean	-3.726		-4.174*		-.438		-2.094	
				Older Cohort. College				
Mean Num.	318.330	295.458	292.904	271.166	320.329	300.127	298.911	279.247
Sd. Num.	39.095	38.215	42.827	36.482	34.307	32.238	41.095	41.025
Diff in Mean	22.872***		21.738***		20.202***		19.663***	
Mean Lit.	302.775	294.298	284.894	277.713	319.010	312.090	301.518	295.874
Sd. Lit.	36.199	35.001	35.395	34.665	29.184	28.864	36.501	36.301
Diff in Mean	8.477***		7.180*		6.920***		5.643**	

Note: A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 14: PIAAC Scores by Gender and Education. Older cohort

8.2 Robustness

8.2.1 Selection into Employment

Here we present the estimation results, controlling for participation as well as the re-estimation of the structural model.

	Germany	Italy	Japan	US
Numeracy	0.3378*	0.2197	-0.2996	0.0194
	(0.1853)	(0.2308)	(0.3305)	(0.2189)
College	-0.0198	0.7388	0.2493	0.5288
	(0.4389)	(0.8032)	(0.5602)	(0.5032)
Gender	0.3664	-1.3384***	0.7925	0.0986
	(0.4095)	(0.4028)	(0.6364)	(0.3939)
Marriage	1.4422***	0.3617	2.5722**	1.5186***
	(0.3511)	(0.4650)	(1.0461)	(0.3892)
Gend-Score	0.0055	-0.1085	0.1832	0.1139
	(0.2485)	(0.2721)	(0.3777)	(0.2566)
Gend-college	0.0503	-0.2444	0.0879	0.0275
	(0.5653)	(0.8714)	(0.6880)	(0.5764)
Gend-Marriage	-1.0304**	-0.1321	-4.4294***	-1.8520***
	(0.4901)	(0.5517)	(1.1439)	(0.4661)
Constant	1.0970***	2.0007***	2.2961***	1.0392***
	(0.2579)	(0.3174)	(0.4075)	(0.3217)
Observations	675	464	651	710

Table show the coefficients from a logistic regression on the probability of participating into employment conditional on individuals characteristics. Standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$

Table 15: Selection into employment.

Participation Decision

	Germany		Italy		Japan		US	
	Men	Women	Men	Women	Men	Women	Men	Women
Numeracy	0.141***	0.119***	0.055*	0.079***	0.103***	0.099***	0.166***	0.154***
	(0.032)	(0.041)	(0.028)	(0.027)	(0.022)	(0.02)	(0.0319)	(0.0257)
College	0.083	0.302*	0.151*	0.124	-0.007	0.188***	0.1992	0.3460***
	(0.160)	(0.169)	(0.091)	(0.083)	(0.053)	(0.06)	(0.124)	(0.079)
Age	0.028**	0.024**	0.005	0.045***	0.038***	0.025***	0.027***	0.037***
	(0.012)	(0.011)	(0.009)	(0.011)	(0.008)	(0.01)	(0.009)	(0.009)
Marriage	0.049	0.230	0.015	-0.037	0.162***	0.090	0.2455***	-0.0036
	(0.081)	(0.146)	(0.051)	(0.071)	(0.055)	(0.09)	(0.083)	(0.062)
College-Marriage	0.148	-0.078	0.263**	0.208*	0.006	0.003	-0.078	0.019
	(0.174)	(0.183)	(0.115)	(0.108)	(0.078)	(0.11)	(0.123)	(0.097)
Observations	254	191	166	111	275	230	230	242

Note: This table reports the results from Mincer type regressions for our small sample of 4 countries. These regressions are for the younger cohorts and use the numeracy test score as a measure of ability. These regressions control for marital status

Table 16: Mincer Regressions: Controlling for Marital Status

Mincer Regressions

Re-estimation . Here we report on the re-estimation of the model allowing selection into employment. Importantly, in this specification the job taste shock, denoted $\bar{\varepsilon}^j$, is not known at the time of the education decision so that some agents may indeed choose to go to college and later decide not to work. Allowing the distribution of these shocks to be gender specific, allows us to match labor force participation.[33]

The model with the taste shock is supplemented with moments regarding the labor force participation decision by gender and education. The labor force participation rates are lower for women than men and also lower for non-college grads. The gender differences are largest in Italy, Japan and the US and are almost non-existent in Germany. The results from the estimation are shown in Tables 17 and 18.

	Education			**Mincer Reg.**		**Labor Force Part.**		
	ed	χ_0	χ_s	α_s	α_e	lfnoed	lfed	fit
					Data			
GM	0.331	-0.994	1.395	0.111	0.239	0.855	0.907	na
GW	0.430	-0.480	1.108	0.128	0.199	0.829	0.890	na
IM	0.189	-2.130	1.734	0.061	0.210	0.868	0.868	na
IW	0.303	-0.880	0.443	0.085	0.208	0.714	0.805	na
JM	0.596	0.243	0.921	0.091	0.022	0.948	0.965	na
JW	0.695	0.706	0.732	0.098	0.198	0.875	0.902	na
UM	0.422	-0.570	1.716	0.155	0.162	0.868	0.916	na
UW	0.537	0.119	1.499	0.149	0.331	0.721	0.846	na
					Estimation			
GM	0.332	-0.984	1.414	0.136	0.242	0.657	0.903	0.040
GW	0.410	-0.462	1.128	0.098	0.176	0.662	0.891	0.030
IM	0.204	-2.113	1.750	0.040	0.193	0.612	0.869	0.067
IW	0.305	-0.867	0.464	0.064	0.198	0.558	0.800	0.026
JM	0.554	0.269	0.963	0.050	0.013	0.701	0.965	0.067
JW	0.653	0.722	0.767	0.071	0.205	0.693	0.903	0.037
UM	0.414	-0.560	1.736	0.176	0.101	0.725	0.912	0.025
UW	0.519	0.120	1.496	0.139	0.333	0.749	0.847	0.001

Note: This table reports data and simulated moments for the estimated models with labor force participation.

Table 17: Moments: Labor Force Participation

	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$\bar{\varepsilon}^j$	$h(1)$
			Baseline			
GM	2.458	0.396	0.092	0.084	0.979	0.855
GW	3.280	0.259	0.254	0.150	0.631	0.908
IM	2.639	0.211	0.271	0.068	0.449	0.730
IW	3.548	0.446	0.125	0.142	0.626	0.927
JM	5.251	0.102	0.547	0.291	0.158	0.842
JW	4.059	0.210	0.346	0.164	0.544	0.992
UM	2.038	0.279	0.310	0.043	0.864	0.643
UW	2.968	0.285	0.108	0.125	1.198	1.091

Note: This table reports parameter estimates for the selection into employment model.

Table 18: Parameter Estimates: Labor Force Participation

[33]Given the above results on marital status, only gender is taken into account.

8.2.2 Alternative Information Structure and Cost of Education

	Education			**Mincer Reg.**		
	ed	log(1)	log(2)	test	ed	fit
			Data			
GM	0.331	-0.994	1.395	0.111	0.239	na
GW	0.430	-0.480	1.108	0.128	0.199	na
IM	0.189	-2.130	1.734	0.061	0.210	na
IW	0.303	-0.880	0.443	0.085	0.208	na
JM	0.596	0.243	0.921	0.091	0.022	na
JW	0.695	0.706	0.732	0.098	0.198	na
UM	0.422	-0.570	1.716	0.155	0.162	na
UW	0.537	0.119	1.499	0.149	0.331	na
			No Know Job Signal			
GM	0.304	-0.990	1.398	0.119	0.237	0.001
GW	0.387	-0.474	1.107	0.177	0.209	0.004
IM	0.109	-2.103	0.002	0.001	0.104	3.021
IW	0.298	-0.879	0.443	0.090	0.210	0.000
JM	0.542	0.255	0.918	0.101	0.004	0.004
JW	0.652	0.715	0.729	0.102	0.197	0.002
UM	0.353	-0.564	1.697	0.235	0.291	0.028
UW	0.520	0.123	1.498	0.191	0.359	0.003
			$C(e,\theta)$			
GM	0.317	-0.992	1.395	0.107	0.240	0.000
GW	0.401	-0.475	1.109	0.124	0.200	0.001
IM	0.198	-2.130	1.734	0.011	0.204	0.003
IW	0.300	-0.880	0.443	0.085	0.208	0.000
JM	0.548	0.253	0.922	0.069	0.012	0.003
JW	0.653	0.714	0.730	0.098	0.198	0.002
UM	0.399	-0.565	1.717	0.147	0.166	0.001
UW	0.519	0.123	1.499	0.149	0.331	0.000

Note: This table reports data and simulated moments for the robustness exercises.

Table 19: Robustness: Moments

8.3 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.

	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$
			No Know Job Signal		
GM	4.197	0.153	0.327	0.523	0.866
GW	3.290	0.263	0.346	0.484	0.796
IM	7.884	0.321	0.223	0.088	0.968
IW	5.794	0.831	0.016	0.813	1.017
JM	4.483	0.016	0.584	0.839	0.643
JW	8.458	0.361	0.440	0.891	1.113
UM	2.293	0.656	0.127	0.537	0.698
UW	1.501	6.688	0.278	0.972	0.600
			$C(e,\theta)$		
GM	3.747	0.402	0.083	0.351	0.866
GW	3.270	0.403	0.138	0.272	0.790
IM	5.875	0.066	0.240	0.333	0.815
IW	3.485	1.103	-0.220	0.306	0.789
JM	4.130	0.107	0.436	0.443	0.636
JW	4.498	0.398	0.335	0.291	0.973
UM	2.694	0.237	0.196	0.222	0.652
UW	3.159	0.353	0.078	0.178	1.026

Note: This table reports parameter estimates for the robustness exercises.

Table 20: Robustness: Parameter Estimates

8.3.1 Scores

8.3.2 Estimation Results

	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 21: PIAAC numeracy score. Moments.

	Education			Mincer Reg.		
	ed	log(1)	log(2)	test	ed	fit
	Data					
Aus. M.	0.267	-1.612	1.131	0.092	0.132	na
Aus. W.	0.289	-1.677	1.629	0.112	0.148	na
Bel. M.	0.392	-0.742	1.678	0.051	0.119	na
Bel. W.	0.582	0.388	1.792	0.074	0.149	na
Can. (F) M.	0.500	-0.138	1.034	0.097	0.090	na
Can. (F) W.	0.627	0.521	0.749	0.093	0.219	na
Cz.R M.	0.287	-1.982	2.221	0.034	0.263	na
Cz.R W.	0.400	-0.801	1.635	0.112	0.273	na
Ger. M.	0.331	-0.994	1.395	0.111	0.239	na
Ger W	0.430	-0.480	1.108	0.128	0.199	na
Den. M	0.482	-0.375	0.837	0.058	0.146	na
Den. W.	0.625	0.397	0.875	0.083	0.135	na
Eng. M.	0.513	0.168	0.572	0.150	0.193	na
Eng. W.	0.524	0.159	0.551	0.162	0.224	na
Spa. M.	0.336	-0.984	1.401	0.107	0.240	na
Spa. W.	0.469	-0.265	1.058	0.122	0.294	na
Est. M.	0.335	-0.766	0.863	0.111	0.125	na
Est. W.	0.555	0.265	1.154	0.119	0.260	na
Fin. M.	0.395	-0.692	1.057	0.045	0.124	na
Fin. W.	0.638	0.534	0.936	0.071	0.184	na
Fra. M.	0.416	-0.834	1.958	0.072	0.151	na
Fra. W.	0.521	-0.104	1.896	0.064	0.186	na
Ire. M.	0.466	-0.342	1.361	0.084	0.161	na
Ire. W.	0.527	0.153	1.047	0.145	0.189	na
It. M	0.189	-2.130	1.734	0.061	0.210	na
It. W.	0.303	-0.880	0.443	0.085	0.208	na
Jap. M	0.596	0.243	0.921	0.090	0.022	na
Jap. W	0.695	0.706	0.732	0.098	0.198	na
Kor. M.	0.649	0.458	0.869	0.100	0.215	na
Kor. W.	0.753	1.127	1.162	0.089	0.223	na
Neth. M.	0.399	-0.705	1.521	0.084	0.205	na
Neth. W.	0.455	-0.241	1.260	0.040	0.127	na
Nor. M.	0.451	-0.452	0.872	0.099	0.075	na
Nor. W.	0.611	0.289	0.985	0.070	0.104	na
Pol. M.	0.365	-0.591	1.259	0.105	0.195	na
Pol. W.	0.595	0.401	0.865	0.104	0.341	na
Slov. M.	0.253	-1.348	1.138	0.121	0.249	na
Slov. W.	0.341	-0.747	0.976	0.078	0.243	na
Swed. M.	0.457	-0.681	1.031	0.036	0.055	na
Swed. W.	0.561	-0.081	1.083	0.057	0.077	na
US M.	0.422	-0.570	1.716	0.155	0.162	na
US. W	0.537	0.119	1.499	0.148	0.331	na

Note: This table reports data baseline model.

Table 22: Data Moments: All Countries

	Education			Mincer Reg.		
	ed	log(1)	log(2)	test	ed	fit
	Baseline					
Aus. M.	0.204	-1.604	1.134	0.081	0.142	0.004
Aus. W.	0.227	-1.668	1.634	0.089	0.162	0.005
Bel. M.	0.360	-0.733	1.679	0.060	0.113	0.001
Bel. W.	0.527	0.398	1.789	0.079	0.149	0.003
Can. (F) M.	0.453	-0.126	1.033	0.098	0.090	0.002
Can. (F) W.	0.613	0.524	0.748	0.096	0.220	0.000
Cz.R M.	0.234	-1.979	2.218	0.090	0.291	0.007
Cz.R W.	0.367	-0.797	1.637	0.107	0.274	0.001
Ger. M.	0.313	-0.995	1.395	0.110	0.246	0.000
Ger. W.	0.401	-0.474	1.110	0.122	0.201	0.001
Den. M	0.422	-0.362	0.838	0.053	0.145	0.004
Den. W.	0.577	0.407	0.873	0.083	0.135	0.003
Eng. M.	0.535	0.163	0.572	0.152	0.192	0.001
Eng. W.	0.534	0.156	0.551	0.162	0.223	0.000
Spa. M.	0.326	-0.982	1.402	0.104	0.240	0.000
Spa. W.	0.447	-0.261	1.058	0.121	0.295	0.000
Est. M.	0.330	-0.764	0.862	0.110	0.125	0.000
Est. W.	0.549	0.265	1.155	0.119	0.260	0.000
Fin. M.	0.363	-0.687	1.059	0.041	0.125	0.001
Fin. W.	0.608	0.540	0.935	0.065	0.184	0.001
Fra. M.	0.379	-0.829	1.958	0.069	0.150	0.001
Fra. W.	0.482	-0.098	1.894	0.091	0.174	0.002
Ire. M.	0.440	-0.337	1.361	0.090	0.158	0.001
Ire. W.	0.529	0.152	1.047	0.145	0.189	0.000
It. M.	0.172	-2.132	1.737	0.069	0.207	0.000
It. W.	0.300	-0.880	0.444	0.084	0.208	0.000
Jap. M.	0.547	0.253	0.920	0.085	0.027	0.003
Jap. W.	0.652	0.714	0.730	0.098	0.198	0.002
Kor. M.	0.598	0.470	0.867	0.101	0.206	0.003
Kor. W.	0.708	1.136	1.158	0.088	0.225	0.002
Neth. M.	0.384	-0.701	1.518	0.098	0.201	0.000
Neth. W.	0.456	-0.238	1.259	0.054	0.127	0.000
Nor. M.	0.393	-0.443	0.871	0.087	0.082	0.004
Nor. W.	0.560	0.298	0.984	0.069	0.104	0.003
Pol. M.	0.366	-0.591	1.259	0.113	0.202	0.000
Pol. W.	0.577	0.404	0.864	0.104	0.341	0.000
Slov. M.	0.227	-1.345	1.139	0.119	0.249	0.001
Slov. W.	0.346	-0.748	0.976	0.079	0.243	0.000
Swe. M.	0.367	-0.663	1.036	0.036	0.049	0.008
Swe. W.	0.486	-0.066	1.083	0.064	0.062	0.006
US M.	0.394	-0.565	1.719	0.140	0.168	0.001
US W,	0.518	0.122	1.496	0.148	0.334	0.000

Note: This table reports simulated moments for the estimated baseline model.

Table 23: Simulated Moments: All Countries

	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	λ^j	$h(1)$
	Baseline					
Aus. M.	4.198	0.341	0.289	0.490	0.490	0.751
Aus. W.	3.555	0.233	0.362	0.367	0.367	0.706
Bel. M.	9.507	0.144	0.431	0.739	0.739	1.013
Bel. W.	11.198	0.113	0.397	0.999	0.999	1.093
Can. (F) M.	8.065	0.263	0.438	0.968	0.968	0.984
Can. (F) W.	5.025	0.372	0.384	0.361	0.361	1.045
Cz.R. M.	3.689	0.318	0.235	0.330	0.330	0.892
Cz.R. W.	3.861	0.335	0.228	0.287	0.287	1.001
Ger. M.	4.246	0.370	0.221	0.426	0.426	0.955
Ger. W.	3.641	0.389	0.280	0.326	0.326	0.878
Den. M.	5.601	0.254	0.390	0.354	0.354	0.954
Den. W.	10.291	0.256	0.447	0.997	0.997	1.063
Eng. M.	4.121	0.774	0.375	0.518	0.518	0.937
Eng. W.	3.455	0.869	0.343	0.368	0.368	0.898
Spa. M.	3.211	0.360	0.245	0.228	0.228	0.829
Spa. W.	2.919	0.458	0.195	0.125	0.125	0.929
Est. M.	4.459	0.421	0.304	0.576	0.576	0.832
Est. W.	3.858	0.341	0.282	0.236	0.236	1.040
Fin. M.	7.674	0.186	0.417	0.500	0.500	0.981
Fin. W.	10.547	0.192	0.395	0.748	0.748	1.123
Fra. M.	4.720	0.166	0.409	0.310	0.310	0.925
Fra. W.	4.926	0.190	0.366	0.327	0.327	1.016
Ire. M.	2.502	0.244	0.378	0.056	0.056	0.717
Ire. W.	2.683	0.406	0.340	0.118	0.118	0.796
It. M.	6.113	0.311	0.253	0.652	0.652	0.958
It. W.	6.277	0.830	0.017	0.962	0.962	1.036
Jap. M.	5.559	0.127	0.554	0.619	0.619	0.804
Jap. W.	4.878	0.379	0.436	0.340	0.340	1.017
Kor. M.	2.340	0.351	0.379	0.034	0.034	0.747
Kor. W.	6.041	0.220	0.368	0.425	0.425	1.117
Neth. M.	2.411	0.279	0.326	0.061	0.061	0.709
Neth. W.	3.537	0.171	0.431	0.112	0.112	0.828
Nor. M.	6.952	0.277	0.427	0.769	0.769	0.922
Nor. W.	4.952	0.200	0.471	0.295	0.295	0.909
Pol. M.	5.814	0.336	0.262	0.700	0.700	1.039
Pol. W.	8.118	0.344	0.231	0.907	0.907	1.279
Slov. M.	4.954	0.520	0.051	0.955	0.955	1.003
Slov. W.	4.785	0.410	0.212	0.384	0.384	1.008
Swe. M.	4.302	0.090	0.533	0.267	0.267	0.728
Swe. W.	2.544	0.133	0.515	0.072	0.072	0.600
US M.	2.665	0.224	0.372	0.187	0.187	0.700
US W.	2.751	0.362	0.184	0.086	0.086	1.006

Note: This table reports parameter estimates for the baseline model for all countries. The rows are obvious.

Table 24: Parameter Estimates: All Countries