Determining Gender Differences in Education and Labor Market Outcomes*

Carla Varona Cervantes† and Russell Cooper‡

April 27, 2023

Abstract

This paper studies gender differences in educational attainment and labor market compensation. Across a group of OECD countries, though men are paid more than women, the college attainment rates and college premia are higher for women. The gap in the college premium is positively correlated with the gender difference in college attainment rates. This paper explores potential explanations for these patterns. The approach is to estimate the parameters of a dynamic model of education choice and labor market outcomes that allows for information frictions, and then decompose the observed gender gaps through a series of counterfactual exercises. These gaps are driven mainly by gender differences in the average compensation at non-college jobs. For Germany and Italy, where the college premium is higher for men, the gaps are largely explained through taste shocks capturing the influence of family and peers.

1 Motivation

This paper starts from two frequent observations about gender differences in education and labour outcomes.[1] First, the fraction of women obtaining a college degree 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: on average women get a fraction of the salary paid to men conditional on educational attainment. Importantly, college rates are higher for

*We are grateful to seminar participants at the EUI, NYU Abu Dhabi, the HSBC Business School at Peking University, the Tiomkin School of Economics, the University of Haifa, the Central Bank of Chile and the University of Essex. A special thanks to and Carlos Carrillo-Tudela, Andrea Ichino, Claudia Olivetti, Zvi Eckstein, Christian Haefke, Kevin Lang, Alex Monge, Michael Manove, Yona Rubinstein and Eric Smith for keeping us on path.

†Department of Economics, the European University Institute and NYU Abu Dhabi, Carla.Varona@eui.eu

‡Department of Economics, the European University Institute, russellcoop@gmail.com

[1] The accompanying data analysis shows these patterns for our sample of OECD countries.

women in the same countries where college educated men earn more than college educated women.

These differences in college rates may seem inconsistent with the gender wage gaps. However, coupling these observations on wage gaps and educational attainment ignores the college wage premium which provides the marginal incentive for educational attainment: **differences in** the education choice depends on the **differences in** returns to education and not gender differences in pay *per se*. Across our sample of 21 OECD countries the higher rates of college attainment for women compared to men are positively associated with higher returns to college.[2]

But, of course, these are only associations as both educational attainment and the college premium are endogenous variables, reflecting more fundamental differences across genders that manifest themselves in these correlations. The main point of the paper is to determine the underlying economic factors that generate these patterns. We consider a number of alternative explanations.

Focusing initially on the returns to education and college attainment rates, college wage premia might directly reflect the effect of education on human capital and productivity. Moreover, labor market opportunities for non-college educated individuals are also an important determinant of productivity (wage) gains from college. Specifically, gender differences in the return to college could emerge from lower compensation for women in jobs which do not require a college degree.

There are also indirect effects arising from the role of education as a signal of ability, along the lines of Spence (1973), and more generally associated with statistical discrimination. This applies in settings where firms are unable to directly observe workers ability and thus productivity. From this perspective, the larger return to education might indicate that education is more informative about ability for women compared to men.

Finally, differences in tastes for college and consequent high skilled jobs can impact the college decision. These tastes, also termed non-pecuniary effects, might reflect a variety of factors, such as peers and family, marriage prospects and others, that can influence the value of education beyond the return in direct compensation. If the distribution of this perceived value of college differ by gender, then differences in college rates, college premia and mean wages can emerge.

[2]This is shown in further detail by a regression of gender differences in college attainment on gender differences in the returns to college across those countries presented in Appendix 8.1.

There are three phases in the analysis. The first, section 2, sets out the basis facts and serves two purposes. First, it establishes the aforementioned facts on gender differences in education experiences and labor market outcomes in our data, the OECD based Program of International Assessment of Adult Competences (hereafter PIAAC). Second, the data generates moments that are eventually used for model estimation.

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 differences in education and labor market outcomes in the quantitative analysis, allowing the assessment of the aforementioned hypotheses. The model relies on the inability of firms to observe workers ability. Instead, ability and hence productivity are inferred from a noisy signal and the education attainment of the worker. This is an equilibrium model: the individual return to education depends on the distribution of ability conditional on educational attainment and the signal of ability.

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 (SMM). 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.

Section 5 presents our baseline estimation. Much of the quantitative analysis highlights on four leading OECD countries: Germany, Italy, Japan and the US. Overall the estimated model succeeds in matching the data patterns for these four key countries. We estimate the model for 21 countries and summarize the findings through the cross-country association between the gaps in college attainment rates and returns to education, measured through a Mincer wage regression. We find that the patterns in the data are quite closely matched in the simulated data for the 21 countries, even though these cross country correlations were not among the moments targeted.

Based on the estimated model, we conduct a series of counterfactuals to determine the sources of these gender differences in the four key countries. For Japan and the US, these gaps are driven mainly by gender differences in the productivity of workers without college. Women are estimated to receive a lower level of compensation in non-college jobs. In this way, the college premium can be larger for women than men, as in the data. This low productivity also creates a higher incentive for women to attend college through a lower opportunity cost of college relative to men. The outcome is that women have a higher college rate despite being paid less for both college and non-college jobs. Using detailed data from the US, almost half of the difference in compensation for non-college jobs is driven by job composition across genders.

This explanation does not hold for Germany and Italy as the data patterns are different. For Germany, there is a large wage gap but a negative college premium gap, so that men have a higher return from college than women. For Italy, in contrast to Japan and the US, there is no differences in compensation for non-college workers. For these two countries the gaps are largely explained through tastes for college (and for the jobs associated with higher education attainment). In Germany the gender wage gap for non-college workers is small compared to that in Japan and US.

These exercises make clear that there is not a single explanation for the observed data patterns. Instead, gender differences in productivity, of both college and non-college educated, as well as gender specific distributions of tastes play important roles. Informational frictions are present but by themselves do not explain much of the gender differences across countries.

Section 6 explores some model extensions. Our data show that the labor force participation rate is lower for women at each level of education in our four countries. To the extent that this participation leads to the sorting of women with higher potential wages into the labor market, the participation dimension makes it more difficult to match observed wage gaps. This selection effect is modelled by the inclusion of an option to work at home, estimating both the mean and the standard deviation of the home productivity shock. The expanded model is able to match the participation rates as well as the education attainment, college premia and wage gap moments. A second extension introduces gender and country specific time costs of college, allowing us to consider the hypothesis that differences in college rates reflect a lower opportunity cost of education for women. Through these exercises, our main findings are robust. Differences in education and labor market outcomes by gender can be attributed to differences in wages for non-college workers in Japan and the US and to taste differences in Germany and Italy. Again, these are not the only forces at work but rather the ones that are most important.

A final section introduces and studies a form of direct discrimination: the perception by all firms that women are less productive than men. We estimate this model, assuming all other parameters are common across genders. Overall, the model with discrimination alone does not match the data moments very well.

Related Literature

This paper is clearly related to the vast literature on education and labor experiences by gender. While that literature touches on each of our motivating observations - i.e gender differences in college education rates, college premium and wages, there is no single contribution that captures them jointly.

The interaction of gender and education builds upon the canonical framework laid out in the vast literature growing out of Becker (1962) and Becker (2009). This includes the basic model of education choice and the empirics of gauging the returns to education. Specifically associated with our focus on gender, Becker, Hubbard, and Murphy (2010a) and Becker, Hubbard, and Murphy (2010b) study the worldwide boom of college education together with the reversal of the gender college gap from 1970 to 2010.

Our approach also builds upon the literature that explains gender gaps in education and/or labor market outcomes through information frictions and statistical discrimination. 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 as well as differences in the perceived value of education.

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. Nielsson and Steingrimsdottir (2010) applied that model to explain the gender gap in schooling attainment in the US and present evidence supporting the role of statistical discrimination.

Lundberg and Startz (1983) studies the effects of labor market outcomes on education, also with an emphasis on gender. They posit a model of statistical discrimination in the labor market and use it to determine the effects of eliminating discriminatory measures. Their focus is on the welfare effects of these interventions. Our model shares some components with theirs, particularly an information structure in which firms observe a noisy signal about worker ability. But, there is an important difference here as well. For Lundberg and Startz (1983), the signal is not separate from but rather includes education.

For us, education is observed in addition to a noisy signal of ability. Thus the effects of noisy signals on education attainment, which is a key channel in our analysis, is not present in their formulation. In contrast, our focus is on using this model to study the determinants of the gaps across gender in education and college premia.

Focusing on gender differences in labor market outcomes, Mulligan and Rubinstein (2008) note that the reduction over time in the US of the gender wage gap has coincided with an increase in wage inequality within genders. At the same time, the labor force participation rates of women rose. Their main hypothesis links these change over time to the increased return to human capital accumulation for 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 document a significant convergence across cohorts in the labor market outcomes of married compared to single women. This is seen in part of increased labor market participation but also human capital accumulation. Continuing on this theme of labor force participation choices by women. Olivetti and Petrongolo (2008) link employment status with wage gaps across a broad range of OECD countries. They find that the gender wage gap is negatively correlated with the gender employment gap seen in the data.

A useful starting point for the literature on discrimination is Cain (1986). That paper lays out the basic framework of the discussion, both in terms of theory and evidence. Some of the basic regressions for our analysis mimic those described by Cain (1986).

Hsieh, Hurst, Jones, and Klenow (2019) use a Roy model of occupational choice, augmented to allow for frictions in the form of: (i) labor market discrimination (ii) barriers to the acquisition of human capital, and (iii) occupation-specific preferences. They 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. Our approach is different in that we focus on how labor market frictions impact differentially education (not occupation) decisions of men and women and how these choices relate to the various gaps in education rates and labor market compensation. Further our model has a very explicit foundation in imperfect information about worker ability and thus an emphasis on statistical discrimination. Their framework, in contrast, has no such information friction. Hsieh, Hurst, Jones, and Klenow (2019) link discrimination to labor market frictions. Our analysis can be viewed as a way to understand those frictions, allowing them to arise from a variety of sources.

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. We use the estimation, joint with counterfactuals, to interpret these, and related, facts.

2.1 Data

Data source and sample selection. The PIAAC data underlying this study is from the first round of the OECD Survey of Adult Skills. We restrict our sample to individuals aged between 25 and 34 that we classified as early workers as information frictions might be more important in this stage of the working life. Self-employed individuals are excluded. To avoid outliers and to 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.[3]

We have data for 21 countries (shown in Figure 6) but 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.

PIAAC assesses individual's proficiency in three main domains: numeracy, literacy and problem solving in technology-rich environment. For our analysis we use PIAAC numeracy scores as (noisy) signals of individual's ability.[4] 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. To do so, we rely on the International Standard Classification

[3]Through this selection we are comparable to other studies.

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

of Education (ISCED).[5]

2.2 College Rates

The college rates are higher for women in each of the four countries.[6] An empirical model summarizing 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.[7]

The moments used in the structural estimation come from estimating (1) by gender for each country.[8] The results are presented in Table 3 with the data moments for the structural estimation. 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.

2.3 Returns to Education

We present the returns to education in two complementary forms. The first presents a breakdown of wages by education and gender that underlies the pattern displayed in Figure 6. We then report results from Mincer regressions. This section establishes key patterns of compensation by gender and educational attainment.

[5]Specifically, we define a dichotomous variable indicating two levels: (i) below college (ISCED 1 through 4) and (ii) college and beyond (ISCED 5 and above). See `https://ilostat.ilo.org/resources/concepts-and-definitions/classification-education/` for a discussion. The college measure includes some trade and technical school degrees in Germany and Italy, as discussed in Cooper and Liu (2019).

[6]This is shown in Figure 6 and is clear from the moments, Table 20.

[7]Appendix sub-section 8.2.1 contains detailed information on these scores as well as gender specific distributions.

[8]Appendix Table 10 shows the results from (1) pooling men and women with 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 education decision is less correlated with our proxy of ability for women, though the gender difference is statistically significant only in Italy. Except for Japan, the inclusion of the interactive term increases the gender dummy.

2.3.1 Wage Gaps and College Premia

Table 1 reports the log of mean wages. 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. 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. These results are consistent with Figure 6. 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, particularly for the non college-educated group. The gender gap in non-college wages is much higher in both Japan and the US compared to Germany and Italy.

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
0.070		0.008		**0.263**		**0.181**	
College							
3.123	2.958	2.700	2.647	2.633	2.523	3.092	3.043
0.165		0.053		**0.110**		**0.049**	
College Premium							
.397	.302	.294	.248	.092	.244	.334	.466
-0.095		-0.046		**0.152**		**0.132**	

This table reports the log of mean wages by gender, education for early workers along with the differences for those without and with college. The college premium is the log of mean wages for those with college minus the log of mean wages for those without a college degree.

Table 1: College Premia and Wage Gaps

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 college wage premium, independent of gender gaps.

2.3.2 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_{ik} is a dummy for college attainment, s_{ik} is the numeracy test score, and age_{ik} is the individual age, a proxy for experience.[9]

The effects of gender can be introduced into this regression in a couple of ways. First, one can add a gender dummy. Thus, the interaction of gender and the coefficients on education and/or the test score would uncover gender specific responses of wages to these variables. Finally, one can run separate regressions by gender.

Appendix Table 11 presents results using dummy variables in two ways.[10] The first includes a dummy (set to 1 for women) for the constant, thus uncovering average gender effects. The second adds to this gender interactions with both education and the test score. From the first regression without interaction effects, there are significant negative effects of being a female on average wages in Germany, Japan and the US. This effect is not significant in Italy. Wages, on average, are about 10% lower for women in Germany and the US and nearly 16% lower in Japan. This is the magnitude of the aforementioned wage gap in our data. From this regression, the wage gap in Germany is not that different from that in the US. But once interactions with education and the test score are allowed, the gender effects change dramatically. Gender matters for both the intercept of the relationship and the slope with respect to education in Japan and the US. For both countries, the negative effect of being female on the constant almost doubles. At the same time, the interaction of gender and college is significantly positive on these two countries. In some sense, the direct effect of being a women on wages is larger than it appears if the interaction effects are excluded. However, for Germany as in Italy, the individual coefficients are statistically insignificant. Importantly, there are no statically significant differences in the returns to ability, as measured by the numeracy score. This accords with the findings in Hanushek, Schwerdt, Wiederhold, and Woessmann (2015).[11]

[9]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 results. We do not see any top coding in these data in contrast to the concerns about the US CPS data raised in Hubbard (2011).

[10]While PIAAC contains other potentially interesting covariates, samples sizes become very small with the additional conditioning.

[11]This interaction between intercept and slope coefficients is not entirely new to the literature. Cain (1986) provides a very clear and concise presentation of models of statistical discrimination, which fits very well with the empirical results reported in Table 11. His Figure 13.1(b) illustrates the case in

Gender specific regressions are shown in the table of moments, Table 3, and provided in more detail in Appendix Table 12. For Japan and the US, the coefficient on education for woman is much higher than for men. This is a similar finding to the high college premium for women in these countries reported in Table 1. This differences in returns to education are reversed in Italy (very slightly) and Germany. The Mincer coefficient on education reflects two channels that link education to compensation. One is the direct effect of human capital accumulation. The other comes from education as a signal of ability, along the lines of Spence (1973).

3 Model

We study a dynamic economy populated by workers and firms. The model provides a structure for interpreting the moments and is used, through counterfactuals, to understand the forces behind the gender specific education and labor market outcomes.

Workers are of two gender types and make an education decision. Firms pay workers their expected marginal product given their information. Equating expected productivity and compensation reflects our initial assumption that factor markets are competitive and non-discriminatory. As an extension we introduce discrimination into the model.

3.1 Workers

Workers are active for two phases, shown in Figure 1. Individuals are born with innate ability θ. In the education phase, they make an education decision, $e \in \{0, 1\}$, where $e = 1$ indicates obtaining a college degree. If college is chosen, agents incur two costs of education. One is the direct payment of tuition, p. Second there is an opportunity cost of education due to time spent studying. Let $C(\theta)$ with $C'(\theta) < 0$ represent these costs. The assumption that $C(\theta)$ is decreasing implies that higher ability individuals incur a lower cost of college. In addition, there is an individual choice specific taste shock, denoted $\varepsilon(e)$, that is orthogonal to ability and impacts the education choice.

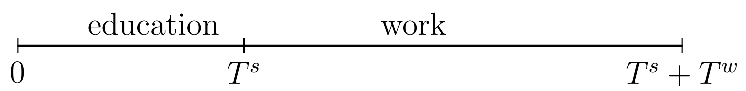


Figure 1: Phases of Household Life Cycle

which there are both level and slope differences by gender, where one group (women) have both a lower informativeness of the signal and a lower mean productivity.

There is a technology stipulating that output of educated workers equals the product of the worker's human capital, conditional on educational attainment, $h(1)$, and ability, i.e. $h(1)\theta$. With this specification, there is an underlying complementarity such that high ability workers have a higher marginal return to education. The output and thus compensation of a worker without education is simply $h(0)$.[12] The technology assumed in quantitative exercise is summarized in Table 2, in the panel labeled Productivity.

	Productivity		Income Flows	
education	Ed. Phase	Work Phase	Ed. Phase	Work Phase
no college	$h(0)$	$h(0)$	$h(0)$	$h(0)$
college	$h(0)$	$h(1)\theta$	$\text{h}(0)(1 - C(\theta)) - p$	$h(1)E[\theta\|s, e = 1]$

Table 2: Job Productivity and Income

3.2 Firms

Firms do not observe workers' ability directly but instead infer ability from observing education and a noisy signal, s, where

$$s = \lambda\theta + (1 - \lambda)\bar{\theta}(1 + \zeta). \tag{3}$$

Here ζ represents noise, with mean 0 and $\lambda \in [0, 1]$ parameterizes the informativeness of the signal. When $\lambda = 1$, the signal is fully informative while with $\lambda = 0$ it is pure noise, with a mean equal to average ability, $\bar{\theta}$.

Markets are competitive. Firms pay educated workers their expected product given the signal: $\omega(1, s) = h(1)E(\theta|s, 1)$. There are two components to the expression. The first is the direct effect of education on productivity, $h(1)$. The second is the conditional expectation of ability, given the signal s and education e. 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. Non-college workers receive compensation of $h(0)$.

[12] We have experimented with specifications in which productivity for non-college is $h(0)\theta^{\zeta}$. Those results are summarized in the extensions section.

3.3 Worker Dynamic Choice

The agent takes as given the compensation function. The income flows are shown on the right panel of Table 2. The time spent working during college years is $(1 - C(\theta))$ so that the opportunity cost of education for a person with ability θ is the product of this time cost and the wage for workers without education, $h(0)$.

The agent does not know s at the time of the education decision. The discrete choice is to go to college or not:

$$W(\theta, \varepsilon) = max(W^{ed}(\theta, \varepsilon), W^{noed}). \tag{4}$$

Here $W^{ed}(\theta, \varepsilon)$ is the value of education given by

$$W^{ed}(\theta, \varepsilon) = \tilde{\beta}^{T^s} (h(0)(1 - C(\theta)) - p) + \beta^{T^s} \tilde{\beta}^{T^w} E_{s|\theta} (max(\omega(e, s), h(0)) + \varepsilon \tag{5}$$

where $\tilde{\beta}^{x} = (1 + \beta + \beta^2 + ...\beta^{x-1})$ creates discounted present values over the school and working periods of life. Net income flow during college years includes earnings from part time work, as a fraction of time $C(\theta)$ is spent in school, less tuition, p. The second term pertains to working years. The agent, upon finishing college obtains the signal s and can choose to work in the sector for educated workers and obtain $\omega(e, s)$ or opt out to the other sector. With enough noise in the signal, it is possible for someone to choose education and, due to an adverse signal, choose not to work in that sector.[13] The model abstracts from other frictions in the labor market associated with search and matching.

The final term is a taste shock that impacts the value of education. As with other discrete choice models, this is a choice specific shock. It can be thought of as a non-pecuniary dimension of education, representing, among other things, peer and parental effects that could be gender specific.

The value without education is simply the lifetime utility from consumption of $h(0)$:

$$W^{noed} = \tilde{\beta}^{(T^s+T^w)} h(0). \tag{6}$$

Here there is no option for a job in the market for those with a college degree.

Let $Z(\theta, \varepsilon) \in \{0, 1\}$ indicate the choice of college over no college, where $Z(\theta, \varepsilon) = 1$

[13]This flow of income is obtained for T^w periods and then discounted to the start of time by β^{T^s}.

iff $W^{ed}(\theta, \varepsilon) \geq W^{noed}$. This choice is summarized by:

Lemma 1 *If $E_{s|\theta}\omega(s, e)$ is increasing in θ for $e = 1$, then there exists a function $\theta^*(\varepsilon)$ such that for all ε, $Z(\theta, \varepsilon) = 1$ iff $\theta > \theta^*(\varepsilon)$. Further, $\theta^*(\varepsilon)$ is decreasing in ε.*

Proof. By assumption, $C(\theta)$ is decreasing in ability. Further, if $E_{s|\theta}\omega(s, e)$ is increasing in θ for $e = 1$, then the expected compensation for college during the work phase is increasing in ability as well. Thus $W^{ed}(\theta, \varepsilon)$ is increasing in θ. W^{noed} is independent of (θ, ε). For each value of ε, $\theta^*(\varepsilon)$ solves $W^{ed}(\theta, \varepsilon) = W^{noed}$. As $W^{ed}(\theta, \varepsilon)$ is monotonically increasing in ε, $\theta^*(\varepsilon)$ is decreasing in ε. ■

This is a very intuitive characterization of the decision rule. As long as expected compensation is increasing in ability, for each value of the taste shock there is a critical level of ability such that those with ability above it go to college. Further, this critical level of ability falls as the taste shock increases.

3.4 Equilibrium

A key component of the model is the compensation function, $\omega(s, e)$. 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, $E(\theta|s, e)$, and the choices of the individuals, $Z(\theta, \boldsymbol{\varepsilon})$.

Through this conditional expectation, the model fits into the "statistical discrimination" approach to understanding gender differences in compensation. That is, differences across parameters by gender will factor into this conditional expectation. So, as a leading example, the informativeness of the signal, λ, could be gender specific. In that case, $E(\theta|s, e)$ will be gender specific for two reasons. First, simply because of the difference in the signal to noise ratio. Second, the choice function, $Z(\theta, \boldsymbol{\varepsilon})$, will generally depend on the parameters, including λ.

Imperfect information about worker ability, i.e. $\lambda < 1$, is necessary for statistical discrimination. Without it, worker ability is known and, through competition, workers would be paid their marginal product of $h(1)\theta$. This compensation might still differ by gender though if the return to college, $h(1)$, is itself gender specific. Related to the discussion of discrimination, if a subset of firms had, say, a distaste for hiring women, that form of discrimination would not appear in wages since those who do not discriminate would offer higher wages.[14]

In the extreme case of no shocks to taste, finding a linear rational expectations equilibrium is relatively straightforward.

Proposition 1 *If there are no taste shocks, then there exists a linear rational expectations equilibrium in which $\omega(s,e)$ is increasing in s given $e = 1$ and individual choices are characterized by a critical value of ability, θ^*, such that $e = 1$ iff $\theta \geq \theta^*$.*

Proof. If the conditions for Lemma 1 hold then, there exists θ^* such that $e = 1$ iff $\theta \geq \theta^*$. Given this decision rule, $\omega(s,e) = E[\theta|s, \theta \geq \theta^*]$ where s is increasing in ability. From the restriction to a linear rational expectations equilibrium, $E[\theta|s] = \tilde{\alpha}s$ where $\tilde{\alpha}$ is a regression coefficient reflecting the covariance between (θ, s) and the overall variance of s. Because $Cov(s,\theta) > 0$, the conditional expectation of ability is increasing in the signal, even conditioning on $e = 1$. ■

This result is helpful in terms of understanding the workings of a simple version of the model. It is not helpful in understanding the data since taste shocks are present and impact the education decision. Further, as we demonstrate, beliefs in the estimated model are not linear in the signal. This absence of a more general existence proof is compensated by finding an equilibrium within the estimation exercise.

3.5 Understanding Data Moments through the Model

Though simple, the model includes a number of rich channels that are useful for understanding the data moments, principally the gaps in the college rate, in the return to education and in wages. The mapping from parameters to these gaps and other moments underlies the inference (from moments to parameters) that is the basis of the estimation.

The gender specific direct effect of education on human capital is captured by $h(1)$. The productivity and thus compensation for non-college individuals, $h(0)$, impacts the magnitude of the college premium, the opportunity cost of attending college and thus the incentives for college attainment. The indirect effect of college attainment as a signal is present as firms observe only a noise signal, parameterized by λ, of worker ability.

The model also includes gender specific differences in the distributions of ability and tastes. Through the optimization problem, these differences will translate into gender specific college rates and, jointly with firm inferences, differences in compensation.

[14]Arrow (1998) discusses this and related general equilibrium points in the context of racial discrimination. Of course, this consequence of competition would not be operative if all firms discriminated.

Given that ability is not observed, statistical discrimination emerges through multiple channels. All of the factors, such as the noise in the signal, the distribution of taste, differences in ability and productivity will factor into the education decision and thus impact $E[\theta|s, e]$, making this conditional expectation gender specific. So, for example, if women have a higher mean taste for college, this will boost the college rate but will reduce, through selection from a given distribution of ability, the conditional expectation of ability given a signal for college educated women relative to men. In this way, the presence of imperfect information about ability allows a rich interaction between the choices of agents through the equilibrium determination of conditional beliefs.

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. These moments are used to distinguish parameters and thus competing explanations of the gaps that are the focus of this study.

4.1 Approach and Functional Forms

The estimation finds the parameter vector Θ that solves:

$$\pounds \equiv min_{\Theta}(M^d - M^s(\Theta))W(M^d - M^s(\Theta))'. \tag{7}$$

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) solving for a (approximate) signalling equilibrium so that firms' beliefs are consistent with workers' choices, (iii) creating a panel by drawing shocks from the estimated processes and simulating the resulting choices, and (iv) calculating moments from the simulated data.

The solution to (7) is obtained by comparing the model generated moments with the data moments. The simulated sample contains $I = 100,000$ individuals, so that simulation error is minimized.

4.2 Parameters

For the baseline estimation, the parameter vector is $\Theta \equiv (\phi, \bar{\varepsilon}, \mu(\varepsilon), \lambda, h^w(0), h(1))$. Though not explicit in the notation, the parameters are estimated by gender and country.

All parameters from the model are summarized in Table 13. Here ϕ is the shape parameter for the Pareto distribution of ability, $\bar{\varepsilon}$ parameterizes the dispersion of the taste shock that is assumed to be uniformly distributed, $\mu(\varepsilon)$ controls the mean of the taste shock, λ parameterizes the noise in the test scores, $h^w(0)$ represents the productivity of women at non-college jobs and $h(1)$ is the human capital accumulated during college. The productivity and thus compensation of men without college is normalized to 1.

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.[15] Second, taste shocks are assumed to be uniformly distributed between $[\mu(\varepsilon) - \bar{\varepsilon}, \mu(\varepsilon) + \bar{\varepsilon}]$ with mean $\mu(\varepsilon)$ and independent of ability in the baseline model.

Third, the baseline specification assumes that agents know their ability and use this for education decisions. As researchers, we do not observe ability directly. Instead, the PIAAC data set reports test scores. These scores were used to create moments such as the regression coefficients in (1), which used the numeracy score as an input.

For the estimation, it is necessary to create a version of the test score in the model. The specification follows (3). As mentioned, λ in (3) parameterizes the noise of the test so that the signal is a mean preserving spread of θ.[16] The shocks in these test scores are assumed to be uncorrelated with ability.

The out of pocket cost is country specific.[17] The time cost of education is inversely related to ability: $C(\theta) = \frac{\bar{e}}{\theta}$. Here $\bar{e}$ is the fraction of time at school for the lowest ability level and is fixed at $\bar{e} = 0.75$.[18]

[15]To be clear, this is not an assumption about the distribution of wages but rather about the distribution of individuals innate ability. The wage distribution is a result of the equilibrium implied by the model estimation.

[16]The noise draws are from a uniform distribution over $[-0.5, 0.5]$.

[17]The prices come from OECD, Education at a Glance.

[18]From `https://www.oecd.org/education/skills-beyond-school/EDIF_23` the time to completion is roughly the same across countries. The robustness exercise in sub-section 6.2 relaxes this and allow $\bar{e}$ to be both gender and country specific.

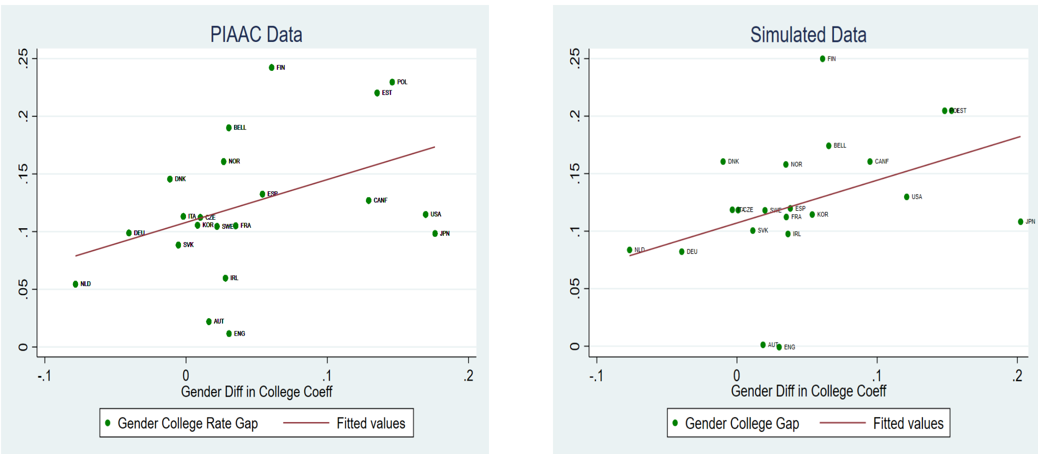
4.3 Moments

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. The baseline moments are summarized in Table 14.[19]

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.

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

The result of these regressions for all countries is shown in Figure 2. The estimated returns to education follow the pattern set out in Figure 6: there is a positive association between the college gap and differences in 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, women minus men, is the estimated values of α_e from (2). On the vertical axis is the college rate of woman minus that of men. The right panel is from the data, the left from simulated data (discussed below).

Figure 2: College Attainment and Marginal Returns from Education: PIAAC Data

[19]Moments for all countries are in presented in Appendix sub-section 8.4.5.

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 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.[20] 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 takes as given a wage function conditional on education and signal. That function, which represents the employer's conditional beliefs about ability given the test s and education e, is given by:

$$\tilde{\omega}(s,e) = h(e)E(\theta|s,e) = h(e)[\tilde{\omega}^e_{con} + \tilde{\omega}^e_s \times s + \tilde{\omega}^e_{sq} \times s^2] \tag{8}$$

where a quadratic specification of $E(\theta|s,e)$ with respect to s is imposed in (8). These beliefs hold for all e though ability only matters in determining compensation for college education individuals.

For a given vector of parameterized beliefs, $\tilde{\omega} \equiv (\tilde{\omega}^e_{con}, \tilde{\omega}^e_s, \tilde{\omega}^e_{sq})$, agents jointly make education decisions. These choices generate a relationship between ability and the signal, conditional on education. From simulated data based upon these choices, we regress ability on the test score to obtain estimated coefficients $\hat{\omega} \equiv (\hat{\omega}^e_{con}, \hat{\omega}^e_s, \hat{\omega}^e_{sq})$. When these regression coefficients and beliefs match, i.e $\hat{\omega}$ is close enough to $\tilde{\omega}$, then an equilibrium obtains. Of course, there is no guarantee that an equilibrium will exist nor be unique.

[20] 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. This turns a fixed point problem into a larger simulated method of moments problem.

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 baseline model is also the foundation for the extended model that confront evidence on gender differences in labor market participation decisions.

The estimation is undertaken for all countries, with a focus on Germany, Italy, Japan and the US. We first present and analyze the results for these four countries and then present the findings for all countries. In this way, we can examine the estimation results and provide detailed interpretations for these particular countries and then use these insights for evaluating the findings for the entire set of countries.

5.1 Estimation Results: Four Countries

We first present the estimated parameters and moments. We then discuss the equilibrium beliefs underlying this outcome. The results reported for the model are those pertaining to an equilibrium outcome.[21]

5.1.1 Moments and Parameters

From the moments reported in Table 3, the fit is very close for all country, gender pairs as indicated in the block labeled “Baseline”. Note that the motivating facts about education rates and returns to education gaps are picked up by the estimated models. Along with those gaps, the model is also capable of reproducing the wage gap difference of the log of mean wage for college educated men and that of women as the column labeled ”wage gaps” shows. From the data panel, the wage gap is positive in all countries, highest in Germany and lowest in the US. The estimated model fits this gap closely. Further, the positive χ_s coefficients in the data, indicating the correlation between college choice and the signal, are positive in the data and are closely matched in the model. Because agents do not know s when they make their education choice, this regression coefficient reflects both the dependence of education on ability and the informativeness of the signal about ability. Despite the presence of taste shocks, the estimated model struggles in matching

[21]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.

the absolute level of college attainment, particularly in Japan and the US.

	Men					Women						
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**			
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
						Data						
G	0.331	-0.994	1.395	0.111	0.239	0.430	-0.480	1.108	0.128	0.199	0.165	na
I	0.189	-2.130	1.734	0.061	0.210	0.303	-0.880	0.443	0.085	0.208	0.053	na
J	0.596	0.243	0.921	0.091	0.022	0.695	0.706	0.732	0.098	0.198	0.110	na
U	0.422	-0.570	1.716	0.155	0.162	0.537	0.119	1.499	0.149	0.331	0.049	na
						Baseline						
G	0.299	-0.992	1.395	0.137	0.251	0.382	-0.472	1.107	0.136	0.192	0.151	0.005
I	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
J	0.545	0.254	0.919	0.086	0.028	0.654	0.716	0.730	0.078	0.196	0.108	0.005
U	0.373	-0.564	1.716	0.120	0.154	0.489	0.131	1.496	0.135	0.332	0.048	0.006

Note: This table reports data and simulated moments for the model matching wage gaps. Here "wage gap" is the difference in the log of mean wages for college educated men and women. In this table and those that follow, G is Germany, I is Italy, J is Japan and U is the United States. See Table 14 for a full list of other variables.

Table 3: Moments: Baseline

The parameters, along with standard errors, for the baseline estimation are reported in Table 4.[22] Leaving aside gender comparisons (for the moment), there are a couple of points to make concerning the parameter estimates. The estimated value of ϕ ranges from a high for Japanese men, indicating relatively low mean ability, to a low for German males. There is variability in tastes in all countries, but much larger than the others in Italy. The mean of the taste shock is positive in all cases except for Italian women. The informativeness of the signal, λ is highest for Italian and US women and lowest for German men and Japanese women. Imperfect information, i.e. $\lambda < 1$, pervades although it is closer to one for US and Italian women. The estimated value of $h(1)$ is less than unity in all gender, country pairs.[23] This does not mean that worker productivity falls with college, else the college rate would be zero. In the model, the expected return from college is $E[\theta|s, e = 1]h(1) - h(0)$, so that the gain to education is not measured by $h(1) - h(0)$ alone, selection based upon ability matters as well. There are some variations in $h(1)$ across countries, with this component of the return being relatively low in Japan compared to Italy. Lastly, the wage for non-college women, $h^w(0)$, are lower than those of men in all countries except in Italy where it is exactly 1. In Germany the estimate

[22]The standard errors were computed by combining the matrix of derivatives of moments with respect to parameters (with a 5% window) and the variance covariance matrix of the moments. The latter was obtained by simulating the baseline model 1000 times. In doing so, we held beliefs fixed for computational reasons. Appendix section 8.4.4 contains a complete discussion of identification, including the responsiveness of moments to parameters that underlie these standard errors.

[23]Recall that $h(0) = 1$ is a normalization for men.

of $h^w(0)$ is smaller than 1 but still much closer to 1 relative to Japan and the US. This is consistent with the data shown in Table 1: the wage gap for non college educated individuals is almost nonexistent in Italy, positive but close to zero in Germany and relatively higher in Japan and the US. Although we do not target those gaps directly the estimation exercise is able to generate values that are close to those observed in the data. Since the education decision depends, in part, on the difference $h(1)E(\theta|s, e = 1) - h(0)$, the estimates of $h(0)$ imply, all else the same, higher return to college for women in Japan and the US.

	Men					**Women**					
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$h^w(0)$
	Baseline										
G	3.774	0.270	0.096	0.522	0.853	5.131	0.443	0.141	0.764	0.942	0.953
	0.779	0.148	0.061	0.146	0.130	0.578	0.114	0.036	0.082	0.028	0.007
I	6.550	0.321	0.114	0.800	0.944	5.826	1.154	-0.208	0.940	1.021	1.000
	1.575	0.115	0.065	0.274	0.110	1.001	0.564	0.234	1.624	0.057	0.008
J	6.972	0.218	0.458	0.757	0.864	6.274	0.030	0.302	0.531	0.775	0.766
	1.208	0.104	0.020	0.099	0.036	2.936	0.147	0.013	0.273	0.113	0.0058
U	5.057	0.169	0.258	0.659	0.908	6.248	0.352	0.108	0.946	1.002	0.814
	0.639	0.075	0.026	0.066	0.045	0.643	0.133	0.016	0.335	0.019	0.007

Note: This table reports parameter estimates for the model matching wage gaps. Standard errors are shown below the point estimates. Here "$h^w(0)$" is the wage for women without college. This wage is normalized to one for men. See Table 13 for other parameter definitions.

Table 4: Parameter Estimates : Baseline

5.1.2 Equilibrium Outcomes: Beliefs and Choices

We use the estimated model to study the equilibrium beliefs and education choices. This ties the baseline to the underlying theory.

Beliefs As noted earlier, the solution of the model contains the beliefs of individuals about the wages paid for college graduates, as given in (8). Table 5 reports the equilibrium beliefs for the baseline model of expected ability conditional on the test score and college education: i.e. $E(\theta|s, e = 1)$. The table shows the regression coefficients as well as the R^2 measure of fit.

One result is that the quadratic model linking ability to the test score fits very well. The fit is close to 95% for Italian men and nearly 100% for Italian women. For both

	Men				Women			
	constant	s	s^2	R^2	constant	s	s^2	R^2
				Baseline				
G	-0.284	1.165	0.084	0.840	-0.120	1.045	0.049	0.939
I	-0.001	0.940	0.069	0.943	-0.062	1.048	0.003	0.996
J	0.420	0.330	0.271	0.850	1.997	-1.827	0.976	0.545
U	0.159	0.727	0.148	0.847	-0.052	1.039	0.004	0.995

Note: This table reports the equilibrium beliefs from a quadratic regression of ability on the test score given college education.

Table 5: Equilibrium Beliefs: Labor Market

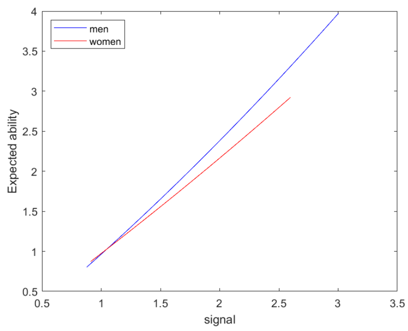
Italian and US women, the constant and coefficient for s^2 are low and the coefficient for the signal is close to 1. This is consistent with the high estimate for λ. The fit falls to 54.5% for Japanese women. Multiple starting points were tried to find these equilibrium outcomes by gender and country. The response of conditional beliefs to the test score are all positive and at an increasing rate, with one exception. For Japanese men the coefficient on s is negative while the coefficient on the quadratic term is positive and relatively large.

Figure 4 shows the mapping by gender and country from signals to compensation.[24] From this figure, expectations are all monotonically increasing and strictly convex.

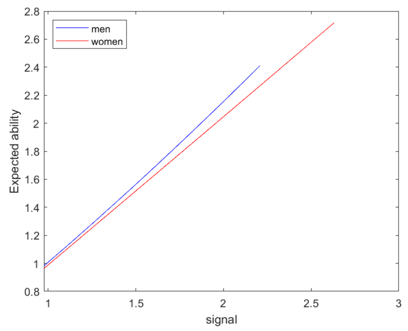
Important to our analysis is that Figure 4 shows evidence of statistical discrimination against women. Two individuals with the same education and test score who differ in gender do not generate the same expected ability. They are viewed differently by employers. And, given the differences in h(1), they will generally not receive the same compensation. Specifically, for all countries, the expected ability of educated men exceeds that of educated women for a given signal, except for the very low and very high signals in Japan. As a result, a wage gap in favour of educated men emerges. Note that the domain of the signal is also gender specific.

To be clear, these beliefs and the consequent statistical discrimination 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. Further, this is an approximate rational expectations equilibrium. This implies that arbitrary beliefs about the productivity of one gender, which might be viewed as an alternative form of discrimination, is ruled out.

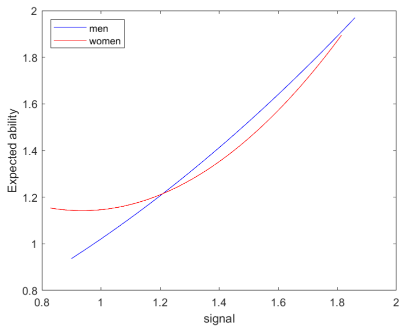
[24]In constructing this figure, the top 1% have been trimmed, just as in the data calculations.



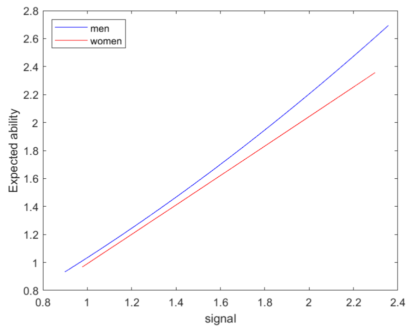
(a) Germany



(b) Italy



(c) Japan



(d) US

These figures show the equilibrium dependence of expected ability on the signal by country and gender for the baseline model.

Figure 4: Dependence of Beliefs on the Signal

Choices From Lemma 1, if beliefs imply that $E_{s|\theta}\omega(s, e)$ is increasing in θ, then they imply choices through a cut-off rule for a given ε. From Figure 4, beliefs are monotone in the signal. From the structure of the signal, higher ability individuals are more likely to obtain higher signals: $E_{s|\theta}\omega(s, e)$ is increasing in θ.

Figure 5 shows the education decisions of women in Italy for pairs of ability and tastes.[25] There are two distinct regions. A lower left area with relatively low ability and taste shocks, shown in red. Above and to the right is the area of the college educated.

These regions underly the coefficients of the logistic regression, (1), which related the test score to the education choice. Differences in parameters, such as the noise in the test score and the dispersion of tastes, impact the response of the education choice to ability and thus the correlation of the test score and education attainment. For example, an increase in the mean taste will, all else the same, lead to a larger constant in the regression. Further, an increase in the dispersion of the taste shock would imply, all else the same, a smaller coefficient on the test score in (1).

[25]The figures are comparable in other country and genders.

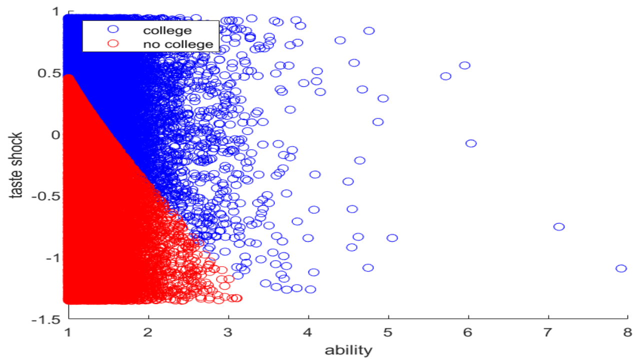


Figure 5: Education Decision: Italian Women

5.2 Explaining 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 those gender differences. This goes beyond the standard errors by studying the economic significance of various experiments.

In particular, what difference by gender generates the observed higher college rates and college premium for women in most of the countries? What is different in Germany and Italy that generates higher college rates for women but higher college premium for men? Are those differences consistent with the observed wage gaps? Our model allows us to consider a number of possible channels: (i) different productivity gains from college either through gender differences in average compensation in jobs that do not require a college degree, $h(0)$, or through gender differences in human accumulation from college, $h(1)$ (ii) non economic factors (role models, gender norms, non economic benefits of college) expressed as gender differences in the perceived value of education, (iii) gender differences in the distribution of ability and (iv) differences in the informativeness of the signal about ability, λ.

From our estimation results, it is clear that, combined, all these factors explain the three gender gaps. Decomposing these results into the contribution of each factor is made difficult by the nonlinearity of the model. There are two findings. First, for Japan and the US, the main factor creating the gender gaps lies in the gender differences in average compensation among non educated individuals, i.e. $h^w(0) < 1$. Second, for Germany and Italy, in contrast, tastes (non economic factors) are the main driving forces. This should not be interpreted as a statement about the only factor. For no countries is there a factor that alone explains all of the gaps.[26]

In order to assess the relative importance of each channel to the observed gender gaps, a number of counterfactual exercises were conducted. For these exercises, the estimated parameters for women were set -one by one- equal to those estimated for men. With these restrictions, the models were simulated. These experiments help to understand how the parameter differences contributed to the gender gaps. While the standard errors are useful for statistical significant, these counterfactuals are informative about what is driving the estimation results.[27] Table 6 summarizes this first experiments in terms of the three gaps.[28]

Building on this, Table 16 studies the interaction of these parameter differences by sequentially changing the parameters characterizing a women into those of a man. The first stage in this decomposition comes from the results in Table 6. This counterfactual goes further by allowing multiple explanations to coexist.

These two types of exercises give similar insights. The key difference, across genders in Japan and the US, is in the lower compensation paid to non-college educated women, $h^w(0) < 1$. With this lower wage and therefore lower opportunity cost of education, it is possible for the model to generate a higher college premium and a higher college rate for women but lower average wages for women with a college degree compared to men. If $h^w(0) = 1$, as in the estimation for Italy, then a larger college wage premium for women is inconsistent with lower average wages for educated women. Still, from Table 16, taste differences are important as well, particularly for explaining the education rate gaps.

Instead, the patterns for Germany and Italy seem best explained by gender difference in the mean and the dispersion of the perceived value of college. From Table 6, eliminating taste differences in Germany reverses the education gap and almost eliminates the college premium and wage gaps. For Italy, this variation reduces the college education gap by about 25% and reverses the college premium and wage gaps. For both countries, no other single variation reduces these gaps more than eliminating taste differences.[29] From Table 16, coupling this change in tastes with equality in $h^w(0)$ further reduces the college

[26]This parallels the statement of results in Eckstein, Keane, and Lifshitz (2019) who also do not find a single factor but concludes that all are needed to rationalize data patterns.

[27]There were other experiments to consider which are more informative about the model. In one, the model is re-estimated allowing gender differences along only one dimension. In another, the model is re-estimated allowing differences in all parameters except one.

[28]Appendix Table 15 presents all of the moments from these simulations.

[29]For example, forcing the ability parameter to be the same in Germany also reduces the college premium and wage gaps but increases the education rate gap.

premium and wage gaps.

Importantly, Tables 6 and 16 show equilibrium outcomes. That is, they show the resulting gaps allowing beliefs and therefore compensation to change with parameters. So the responses shown in these tables couple of direct effects of changing parameters along with the indirect effects on choices as equilibrium beliefs respond to the induced variations in selection.

The following presentation is orgainzed around the potential explanations for these gender gaps. The first two sub-sections, focusing on human capital and tastes respectively, contain the evidence that these are the main sources of gaps.

	Germany	Italy	Japan	US	Germany	Italy	Japan	US
	Data				Baseline			
Ed. Rate Gap	0.099	0.124	0.099	0.135	0.084	0.133	0.109	0.117
College Premium Gap	-0.135	-0.060	0.180	0.198	-0.102	-0.052	0.159	0.158
Wage Gap	0.165	0.053	0.110	0.049	0.151	0.052	0.108	0.048
	Same $h(0)$				Same $(\bar{\varepsilon}, \mu)$			
Ed. Rate Gap	0.042	0.133	-0.362	-0.145	-0.051	0.099	0.304	0.392
College Premium Gap	-0.133	-0.052	0.097	0.059	0.012	0.066	0.112	0.119
Wage Gap	0.133	0.052	-0.097	-0.059	0.036	-0.066	0.155	0.086
	Same λ				Same ϕ			
Ed. Rate Gap	0.113	0.136	-0.070	0.147	0.175	0.120	0.045	0.169
College Premium Gap	-0.134	-0.055	0.212	0.141	0.015	-0.086	0.148	0.216
Wage Gap	0.183	0.055	0.055	0.065	0.033	0.086	0.119	-0.010
	Same Beliefs: Ed Fixed				Same Beliefs: Response			
Ed. Rate Gap	0.084	0.133	0.109	0.117	0.114	0.144	-0.070	0.161
College Premium Gap	-0.054	-0.023	0.146	0.202	-0.108	-0.052	0.211	0.148
Wage Gap	0.103	0.023	0.121	0.003	0.156	0.052	0.056	0.057

This table reports the education. college premia and wage gaps resulting from simulations of the models allowing replacing the parameters of women for those of men.

Table 6: Determinants of Education, College Premia and Wage Gaps

5.2.1 Human Capital

Human capital comes into the analysis through the effects of college, $h(1)$, as well as the productivity of women without college, $h(0)$. Clearly, either a relatively high value of $h(1)$ for women or a relatively low value of $h(0)$ could create a higher marginal return to education for women relative to men, thus creating gaps in both college premia and a college rates in favour of women. Recall that the return to education is $E[\theta|s, e = 1]h(1) - h(0)$ so that choices are not driven by the difference $h(1) - h(0)$ alone. Hence the gap reflects selection into education as well.

Note that an outcome in which the college premium is higher for women but men are paid more in college jobs, as is the case for both Japan and the US, is challenging to match. Several explanations for the college premium gap in favour of women, such as a higher estimate of $h(1)$ or statistical discrimination in favor of women, also imply that educated women are paid more than men, contrary to the data moments. As we shall see, the key is the lower estimated value of $h(0)$ for women. That is, women are estimated to receive a lower level of compensation in non-college jobs. In this way, the college premium during the working phase can be larger for women than men, as in the data. At the same time, it creates a higher incentive for women to attend college through a lower opportunity cost of college relative to men during the schooling phase. The outcome is that women have a higher college rate despite being paid less for both college and non-college jobs.

Of course, in Germany and Italy, the data patterns are a bit different. For those countries, women have a higher college rate, but a lower college premium and, as in the other countries, there is a positive wage gap. So gender differences in $h(0)$ will not be the source of these gender specific outcomes.

From Table 4 the estimated values of $h^w(0)$ are far below those of men in Japan and the US. This difference does not exist in Italy and is quite small in Germany.

Table 6 summarizes the effects of a counterfactual in which $h^w(0) = 1$, leaving other parameters at their baseline values, on the gaps in isolation. The education and wage gaps for Japan and the US are negated by the restriction that $h^w(0) = 1$. Further, note that for these two countries the college premium is reduced by 40 and 65 percent, respectively.[30] For Germany and Italy, forcing $h^w(0) = 1$ does reduce the education rate in Germany but otherwise has a minimal effect on the gaps. For Italy, with the estimate of $h^w(0)$ close to 1, this experiment changes nothing.

From Table 16, if this restriction of $h^w(0) = 1$ is followed by a second restriction that tastes are the same, then for Japan and the US, the gaps are further reduced. Specifically, eliminating these taste differences brings the education rate gap much closer to zero in both countries and reduces the other gaps as well.

It is important to understand the mechanism at hand. The wage gap is simply the

[30]Looking at the full set of moments in Table 15, the reduction in the fit, relative to the baseline, in Japan and the US makes clear the importance of the estimated differences in $h^w(0)$ for those countries.

difference in the log of the mean wage of educated men and that of women. The value of $h^w(0)$ plays no direct role in this calculation. But the wage paid to non-educated women does impact the education choice and thus the conditional expectation of ability that factors into the wage: $\omega(s,e) = h(e)E(\theta|s,e)$ for $e = 1$. From our estimation, a lower value of $h^w(0)$ implies higher college rates for women. With the same ability distribution across genders, this implies lower average ability (and therefore compensation) of female college graduates relative to men. Thus impacting the wage gaps. Of course, this selection effect reduces the wage premium as well, therefore differences in $h^w(0)$ plays both a direct and indirect effect on the observe college premium gap. Recall that Tables 6 and 16 show general equilibrium effects.

External Evidence Given the prominent role of $h^w(0) < 1$ in Japan and the US it is instructive to look at more detailed evidence on the types of jobs and associated compensation of non-college individuals in those countries. Olivetti and Petrongolo (2014) study gender wage gaps across countries from this perspective.[31] They link cross-country differences in labor market outcomes by gender to differences in the relative demand for female work. For the US, Rendall (2017) studies the evolution of the gender wage gap, both within and between education groups. Under the assumption that men have a comparative advantage in jobs that require "brawn", Rendall (2017) argues the shift in labor demand towards jobs that are more "brain" oriented increases the demand for women relative to men.[32] Though her analysis focuses on the dynamics of these gaps, it provides evidence that links these gaps to labor demand factors. In a related study, Ngai and Petrongolo (2017) study the reallocation of labor from manufacturing to the service sector. This transformation, coupled with an assumption that women have a comparative advantage in the service sector, leads to a reduction in the wage gap. This evidence taken together points to the role of industry composition and the implied labor demand in generating gender wage differences.

For our analysis, the main point is that this evidence is consistent with $h^w(0) < 1$ with this gap driven, for example, by composition effects for non-college workers. If men have a comparative advantage in "brawn" and non educated jobs are mainly "brawn"

[31] They also study hours gaps, not available in our data, but do not look at education and college premia gaps.

[32] This requires a way to map occupations into a demand for "brain" or "brawn", as shown in Section 2 of that paper.

intensive such that the price of those skills is higher, then a wage gap in favour of non educated men arises.

The PIAAC data is not detailed enough to study job composition across our sample of countries. Focusing on the US, Appendix 8.4.3 presents median earnings (total and by gender) and gender gaps across the most frequent 10 occupations among non-college educated women and non-college educated men. We decompose the gender wage gap and find that around 42% of the pay gap comes from differences in the composition of occupations. Therefore, it is apparently not the only factor in generating the estimated gender differences in compensation among non-college graduates, gender differences in occupation certainly play a major role.

Looking at Japan, Hara (2018) focuses on the gender wage gap at the establishment level looking at the extremes of the wage distribution. That analysis points to the presence of a large wage gap for low educated workers, consistent with our finding of $h^w(0) < 1$ in Japan. Interestingly, Hara (2018), attribute a large fraction of the wage gap to within compared to between firm effects.

Taking together, this evidence for the US and Japan argues against the view that gender differences in compensation for non-college educated are driven exclusively by composition effects. Surely job characteristics matter, but there is evidently more to be explained. This leaves open other possibilities, including discrimination against women in low education jobs.

5.2.2 Tastes

The blocks labeled "$\bar{\varepsilon}, \mu(\varepsilon)$" show simulation results when the distribution of tastes for women is the same as that of men while the rest or parameters are kept at their baseline values.[33] The baseline parameter estimates reported in Table 4 indicate a larger mean taste for college for men in all countries except for Germany and more dispersion for women except in Japan.

Looking at Table 6, in Germany, the college premium (in favor of men) and wage gaps are almost removed and the college rate gap reverses sign. For Italy, the education rate gap is smaller and the college premia and wage gaps reverse signs compared to the baseline. From Table 15, the fit is worse for these two countries with this experiment

[33]Simulations with eliminating only mean tastes were not informative as education rates of women went to 1 in some countries.

compared to all the others.[34]

Thus, the main source of the gaps for Germany and Italy seems to be gender differences in the distribution of the perceived value of college. Other variations in parameters surely impact the various gaps, such as the effects of differences in ϕ for Germany, but none do as much in terms of eliminating the gaps.

For Japan and the US, this restriction does not eliminate the gaps. In fact the college rate is much higher for women in both countries and the wage gap is larger than the baseline as well.[35] Further, the wage gaps and large college premia remain even if taste differences are removed.

This does not mean that taste differences are not important for the gaps in Japan and the US. As already notes, eliminating taste differences along with the restriction of $h^w(0) = 1$, further reduces the gaps as seen in Table 16.

Different taste distribution have both direct and indirect effects on the gaps. An increase (decrease) in the estimated mean will directly affect the mean value of a college education relative the non college option and therefore will increase (decrease) the college rate. An increase (decrease) in the college rate will lower (raise) the average ability of college graduates and therefore compensation through changes in beliefs. On the other hand, changes in the dispersion of taste will affect directly the education decision and, at the same time, the link between ability and college. Therefore, beliefs about worker's ability conditional on education will change and thus compensation.

External Evidence As in the discussion of human capital, it is useful to evaluate this finding using other sources. As mentioned, differences in the perceived value of education can be the result of role models, gender norms, peer effects, parents education and other characteristics that impact individuals' attitudes about education or about the jobs associated to education. From this perspective, it is thus informative to link social attitudes about gender roles of education and labor market outcomes.

Fortin (2005) studies the interrelationship between attitudes about gender roles and labor market outcomes. Her analysis points to the significance of the agreement with the

[34] From Table 15, the fit with these restrictions worsens in all countries. In fact, except for Japan the fit is worse than under the $h^w(0) = 1$ restriction. This tells us that these taste differences by gender matter considerably for the overall moments.

[35] A mean preserving spread in the taste shock impacts the average college rate since additional weight in the tails changes the maximum of the two options. So, if the college rate is relatively low, adding more mass to the tails of the taste shock distribution will increase the college rate.

following statement as indicative of attitudes about gender roles:

> When jobs are scarce, men should have more right to a job than women.

The gender difference in agreement with this statement is positively correlated with the gender pay gap.[36] So, countries in which a large fraction of men relative to women agree with this statement, the gender wage gap is larger.

In our model, these differences in societal attitudes would influence choices through the distribution of taste shocks. As emphasized by Fortin (2005), labor market outcomes are largely determined through education so that these attitudes may have a large influence on the education decision.

Additionally, differences in the perceived value of education can reflect gender differences in non economic benefits from college like improving health, better skills to develop children's human capital and better marriage prospects as argued by Becker, Hubbard, and Murphy (2010a). They provide some evidence supporting that although those benefits have increased for women over time, they are below those of men in many countries.[37]

Riphahn and Schwientek (2015) study the reversal over time of the gender education gap in Germany. Their analysis includes multiple factors that might explain the increase of educational attainment of women relative to men. They argue that economic factors, such as the labor market outcomes, including the (wage) return to education and female participation, are not key determinants of these patterns. Instead, they find that the gap for tertiary education is associated with demographic changes and social norms, the latter measured as attitudes about women's role in the home, through the ALLBUS survey.[38] They argue that these measures of social norms are associated with the intertemporal changes in the gender gaps.

5.2.3 Other Sources of Gender Differences

Based on Lang and Manove (2011), a natural conjecture was the differences in λ impacted the education rate and the coefficient on education Mincer wage regression: for women,

[36] This is seen in panel B in Figure 2 of Fortin (2005).

[37] Specifically, they argue that (i) the effect of college on life expectancy is higher for men compared to women, (ii) the difference in the marriage rate for college-educated men relative to high school–educated men still exceeds the difference for women (iii) the positive effect of college on family income for married individuals is not different between genders and (iv) there is no evidence proving that the effect of fathers' college education on the children's education is greater than that of mother's .

[38] These questions are similar to those in the survey underlying the results reported in Fortin (2005).

more noise in the score (λ low) implies both a higher college rate and more weight on education in inferring ability by firms. In the estimated model, λ is higher for women in all countries except for Japan. So the idea that increased sensitivity of wages to education would generate both a higher return to education and a higher college rate is not operative in the Germany, Italy and the US. In those countries, raising the level of λ to that of men, increases education rates slightly while preserving the college premia and wage gaps. Differences in λ are not key to explaining the gaps in these countries. In Japan, where the estimated λ is higher for men, increasing the informativeness to this level has substantial effects on the education gap in Japan, reversing the sign. The wage gap is cut in half. From Table 15, the worsening of the fit is almost as bad as forcing equality in $h(0)$. But, the reduced education rate for women, increases the college premium. So in this dimension, increasing λ does eliminate the gaps in Japan.

The estimation allows the distribution of ability, controlled by a single parameter ϕ, to be gender specific. The estimated value of ϕ is higher for women (so lower mean and less dispersion in ability) in Germany and the US while lower in Italy and Japan. Setting the values for women equal to those of men has the largest effects on model fit in Germany and the US. From Table 15, for both of these countries, the sensitivity of education choice to the signal is increased relative to the baseline and this contributes to the worsening of the fit. Looking at the gap, in these two countries, this counterfactuals eliminate the wage gaps and increase the education rate and college premia gaps. The education rate gap is also reduced in Japan. Compared to the other parameter differences, the role of the gender specific ability distribution is small.

While beliefs are not an independent source of these gaps, clearly they matter for the outcome through statistical discrimination. The bottom row of Table 6shows two experiments to evaluate the role of beliefs. In both, the beliefs about women are replaced by those of men. Therefore, the signal of an educated women will lead to the same expected ability as that of an educated with the same value.In one experiment, "Same Beliefs: Ed Fixed" the resulting gaps are calculated given baseline education choices of women. In the second experiment, "Same Beliefs: Response" those education choices responded to the imposed change in beliefs. To differing degrees these are both partial equilibrium exercises in that beliefs and outcomes are disjoint. Overall, even if differences in beliefs are removed, here by forcing women's signals to be treated as those of men, the gaps largely remain intact. This makes clear that it is not just beliefs alone that matter, but the underlying distribution of signals that those beliefs are applied to.

5.3 Estimation Results: All Countries

Figure 6 indicated patterns of education and college premia gaps for a large number of OECD countries. Though the discussion has focused on only four countries, the estimation was extended to others and broadened to introduce the Mincer test score regressions across countries, as in the left panel of Figure 2.[39] One way to summarize the results is to look at the relationship between the college attainment and college premia gaps.

The right panel of Figure 2 shows a positive correlation across countries in the gender gaps of college rates and Mincer wage education coefficients produced by the model, resembling that from the data. Note that this pattern is a by-product of the estimation: these gaps were not in the targeted moments.

Table 7 provides the specific regression results across all of the countries, where the dependent variable is the gender difference in educational attainment and the right side is the gender difference in the coefficient on education. In the data, there is a positive association between the college gap and the gap in the Mincer education coefficient across the broader set of countries. Both the estimate on the gap in the Mincer education coefficients as well as the R^2 are very close to the (un-targeted) data moments. The estimated model picks up this data pattern 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.

Table 7 also includes the estimated results based upon from a simulation of the models in which the returns for non-college women were set equal to those of men, i.e. $h^w(0) = 1$, in all countries. From that simulation, the positive association between these gaps disappears. The coefficient estimate falls to 0.079 and is not statistically significantly different from zero while the R^2 falls to essentially zero, 0.002.

[39]Moments and parameter estimates are provided in Tables 20, 21 and 22. The models for these 21 countries were estimated imposing linear beliefs, reflecting the computational time solving for an equilibrium with non-linear beliefs.

Source	Mincer Ed.	R^2
Data	0.367	0.165
	0.189	
Model	0.372	0.171
	0.1874	
Same $h(0)$	0.079	0.002
	0.412	

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

Table 7: Regressions of Differences Across Countries

6 Extensions

Here we consider three key extensions of the model.[40] The first includes a labor force participation decision after the education choice. This is made non-trivial by the introduction of a taste shock from home production. The second allows the opportunity cost of education to depend on gender and country. The final extension estimates a model with explicit discrimination.

6.1 Selection into Employment

The analysis thus far ignores labor force participation decisions.[41] This is an important margin particularly because empirically labor force participation is dependent upon both education and gender and thus this omission might underlie some of the estimated parameter differences by gender.

There is a long literature on selection, growing out of Heckman (1974). Relative to our exercise, Olivetti and Petrongolo (2008) report an important finding: across OECD countries there is a negative correlation between the gaps (men minus women) in wages and in participation.[42] If, for example, there was positive selection in a country, so that only high ability agents worked, then a low female participation rate, relative to

[40]Returning to the specification of technology in Table 2, we also experimented with specifications in which productivity for non-college is $h(0)\theta^{\zeta}$. We selected a couple of values of $\zeta \in [0,1]$ and re-estimated the parameters for the US baseline model. We assumed that for non college workers the job signal was perfectly informative, thus isolating the effects of imperfect information in the college labor market. The fit did not improve.

[41]Conversations with Zvi Eckstein, Kevin Lang, Michael Manove, Claudia Olivetti and Yona Rubinstein on the development of this section are much appreciated.

[42]Their study is not based upon PIAAC data but rather the European Community Household Panel Survey.

men, would be associated with a lower gender wage gap, all else the same. This logic is certainly suggestive that controlling for participation is important for understanding the determinants of wage gaps in our data and perhaps also the college attainment and college premia gaps as well.

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.

Our focus here is on two questions. First can our model with the addition of participation still match the evidence on the three gaps? Second, how does the addition of the participation decision influence the factors that determine these gaps? Unfortunately, our data is not rich enough for us to explore the complex factors impacting participation such as marital status. Our approach is consequently much more modest.

First, we use a two-step procedure to control for labor market participation in the Mincer regression. With this two-step procedure, we re-estimate the Mincer regression to determine if the inverse Mills ratio is significant. We find that it is, but only for US men. The structural model, with the revised coefficients from the Mincer regression, is then re-estimated for US men, which is the sole country/gender pair where the inverse Mills ratio is statistically significant in the second stage. After the re-stimation, the parameter estimates are quite close to the baseline results.

Second, we supplement the moments to include labor market participation rates by gender and education across our countries. We add to the model a random value of home production, thus allowing agents an outside option. Estimating the parameters of the distribution of these home production allows us to match the participation rates. This is viewed as an alternative methodology.

Both of these exercises are limited by data availability. In terms of instruments that could impact participation but not the wage regression, we rely on marital status and whether an individual has children or not. These factors comes into play in the two-step procedure. As marriage and fertility are not part of the structural model, marital status and the impact of children are assumed to underlie the home production shocks in the labor force participation choice.

6.1.1 Controlling for Participation

The baseline model uses moments from a Mincer regression that does not control for participation in the labor market. One common approach to dealing with any resulting bias in parameter estimates follows the two-step procedure from Heckman (1979). We use that procedure, setting marital status and whether or not an individual has a child as variables that impact the labor force participation decision but not the wages paid.

The results for the two stage estimation are reported by gender and country in Appendix sub-section 8.5.1. The first stage regressions, indicate the dependence of participation decisions on marital status (German men, Italian men, Japanese women, US men) and the presence of children (Germany women, Japanese women, US women). Also note that numeracy impacts participation for German and Italian women but not for males in those countries. It also matters for Japanese men.

Except for US men, the inverse Mills ratio is not significant in any of the second stage Mincer regressions. This implies that there is no selection bias for the other country gender pairs.[43]

For the US only, we re-estimated the model using these coefficients as alternative moments. The results are reported in Appendix Tables 27 and 28. Compared to the baseline data moments, with the two-step procedure the Mincer regression coefficients on both education and the signal are slightly larger. Re-estimating the model with these revised moments, the fit and parameter estimates are very close to the baseline. Importantly, the estimated model continues to match the gaps in college attainment, Mincer education coefficients and the wage gap.

6.1.2 Extending the Model to include Participation

For the estimation exercise, the model is extended to include a labor force participation choice after the education stage. This is not the choice by college educated individuals to take a job with the non-college educated group. Rather, this is an additional option that allows anyone to choose to work at home (enjoy leisure) rather than participating in the labor market.

We assume that agents after entry into the labor force draw a shock that determines their home production. This shock is realized for the non-college agents during the

[43] Clearly though our data is a bit sparse with regards to other variables that might impact participation such as wealth and information about a spouse.

schooling phase as they are not in school. For those going to college, the shock is realized at the start of the work phase. Importantly, this shock is not known when the education choice is made, rather it is understood by agents as generating a future option.[44]

Specifically, the values of college and no college are modified to include this option.

$$W^{ed}(\theta, \varepsilon) = \tilde{\beta}^{T^s} (h(0)(1 - C(\theta)) - p) + \beta^{T^s} \tilde{\beta}^{T^w} E_{\zeta_h, s|\theta} (max(\omega(e, s), h(0), h(0) + \zeta_h) + \varepsilon \tag{9}$$

where ζ_h is the value of home production.[45] By construction, the realized value of home production is not correlated with ability nor with the tastes for education. For those not obtaining a college degree,

$$W^{noed} = \tilde{\beta}^{(T^s + T^w)} E_{\zeta_h} max(h(0), h(0) + \zeta_h) \tag{10}$$

Before discussing results, it is straightforward to understand some of the implications of introducing this stochastic home production. First, it will induce selection out of employment for both education groups. This selection will be dependent on the job market signal as that determines compensation.[46] All else the same, this selection will increase the college premium since the compensation for the non-college group is independent of the signal. To the extent the effects of endogenous participation are stronger for women, in terms of a lower participation rate and/or more selection on the job market signal, then the lower participation rate of women will tend to reduce the wage gap and increase the college premium.

The home production option also impacts the education decision. Reducing the mean of the home production distribution will increase the college rate since the alternative to college is less attractive. Reducing the dispersion of the home production shock, from simulation, increases the education rate as there is less mass in the tails and thus home production is a less attractive option.[47] The higher college rate for women will decrease

[44]There are other timings to consider. The model was specified and re-estimated assuming that the non-college agents had the home production shock realized at the start of the work phase as well. The main findings about the presence of the gaps in wages, education, participation and the college premium remained though the fit of the model deteriorated.

[45]It is added to $h(0)$ for interpretation purposes.

[46]Much of the literature focuses on selection based upon ability. But in our model, compensation does not depend directly on ability. Of course, if the signal received by firms is informative about ability, then higher ability individuals are more likely to remain in educated jobs.

[47]This is true for both the college and non-college choices but the reduction in the dispersion has a larger effect on the non-college value.

the mean expected ability of college graduates increasing even more the gender wage gap and decreasing the college premium further. This magnifies the effects on wages of the participation decision.

6.1.3 Estimation Results

The parameters $(\mu_h, \overline{h})$, represent the mean and dispersion of the home productivity shocks added to the baseline model.[48] They are estimated by gender and country, but do not vary by education. The moments are supplemented to include the participation rates by gender and education.[49]

The moments are presented in Appendix Table 29. The fit remains very good for all countries. The basic data patterns of higher participation rates for men and for those with a college education are matched by the estimated model. The simulated model produces participation rates that are higher than in the data for educated men and women and participation rates that are lower than the data for non-college educated individuals. The gaps in college rates and education coefficients on the Mincer regression remain well matched. Further, the simulated model continues to generate wage gaps that are in accord with the data. That said, the introduction of the participation choices leads to some interesting differences in parameter estimates compared to the model without this choice.

From the parameter estimates in Appendix Table 30, the mean value of the home productivity shocks are negative though the mean value of home production, $h(0)+\mu_h$, is positive. Further the mean values of the shock are higher for women which is consistent with their lower participation rates. With the exception of Germany, the dispersion of this shock, and thus its option value, is larger for women. Since, as noted above, higher dispersion in the home productivity shock reduces education, the higher estimated dispersion for women implies that differences in the distribution of the home productivity shock does not contribute to the college rate gap.

Relative to the baseline, the variability of the taste shocks, parameterized by $\bar{\varepsilon}$, for the "Gap" model is much larger than that for the model with a participation decision. In this sense, the taste shock of the baseline model without a participation choice might

[48] The distribution of taste shocks was uniform so that $\overline{h}$ controls the limits of the domain of the uniform, as in the specification of the education taste shock.

[49] Adding additional moments that link participation to marital status, as in the estimates reported in sub-section 8.5.1, is not feasible without a marriage decision within the model.

incorporate the home productivity shock added in this specification.[50] Note too that in the specification of the model with participation, the informativeness of the signal, λ, is estimated to be much lower for women. This accords with some of the earlier discussion of statistic discrimination based upon noisier signals for women supporting a higher college attainment rate. It also has an implication for selection into employment: the lower participation rate of women means only those with high job market signals work, but this does not directly translate into selection on ability given the low estimate of λ.

Building on this, Appendix Table 29 presents some counterfactuals which provide insight into the sources of these gender differences. As before, these are simulations in which a parameter for women is set at the estimated value of men keeping the rest of the parameters at their baseline values. As in the baseline without participation, the point estimate of non-college productivity for women, $h^w(0)$, is well below that of men, particularly in Japan and the US. Removing differences in $h(0)$, the fit for these two countries falls considerably. The education and wage gaps are both reversed. In contrast, the biggest effects on Germany and Italy come from removing taste differences. As in the earlier estimation, $h^w(0)$ is close to 1 in Italy. Removing the taste differences in these two countries, reverses both the college attainment and wage gaps. This is not the case for either Japan or the US. Setting the informativeness of the signal, λ, equal across genders leads to a deterioration of fit in all countries. But the changes in the Mincer education coefficient are very small. For example, in Japan, increasing the estimated value of λ to the much higher value for men reduces the coefficient on education from 0.226 to 0.215. Consistent with theory, the more informative signal reduces the education coefficient but the effect is small.

6.2 Gender and Country Specific Opportunity Cost of College

Here we extend the model to allow the time cost of education to be both gender and country specific.[51] This experiment is related to the findings reported in Becker, Hubbard, and Murphy (2010a) who argue that a significant factor explaining the increase college gap for women is a reduction, over time, in the cost of education for women.[52]. In order to

[50]But note that the taste shock was only for college educated while the home production shock is common though its incidence can be education specific.

[51]Thanks for Morgan Hardy and Yona Rubinstein for comments that led to this exercise.

[52]These cost differentials would be termed "barriers to human capital accumulation" in Hsieh, Hurst, Jones, and Klenow (2019).

	$h(0)$	$h(0) * \bar{e}$	$\mathrm{E}(\frac{\bar{e}}{\theta}\|e=1)$	oc	$h(0)$	$h(0) * \bar{e}^w$	$\mathrm{E}(\frac{\bar{e}}{\theta}\|e=1)$	oc
		Men			Women			
G	1	0.75	0.470	0.470	0.932	0.659	0.539	0.502
I	1	0.75	0.533	0.533	0.992	0.748	0.614	0.609
J	1	0.75	0.617	0.617	0.769	0.419	0.451	0.346
U	1	0.75	0.522	0.522	0.834	0.691	0.659	0.550

Note: This table reports the average time cost, defined as $h(0)E(\frac{\bar{e}}{\theta}|e=1)$, of education by gender and country. "oc" is the opportunity cost of college.

Table 8: Average Opportunity Cost of College

maintain the same number of moments as parameters, we do not estimate $h^w(0)$. Instead we set this productivity at the levels shown in Table 1.

The results from this robustness check are shown in Appendix sub-section 8.5.2. Looking at the moments in Table 31, the fit is as good as the baseline for Italy and Japan and slightly worse for Germany and the US. Again, the estimated model creates wage gaps for all countries that are close to the data. Further, as in the baseline estimates, there are college education gaps in favor of women of about the same magnitude as in the data. Finally, the differences in coefficients on education in the Mincer wage regressions match the data patterns.

Looking at the parameter estimates in Appendix Table 32, the estimated amount of time in college for the lowest ability level is about 10% higher for US women compared to US men and almost 28% lower for Japanese women compared to men. In this case, the mean taste for education is estimated to be higher than the baseline for US women to offset the increased cost of education. For Japanese women, the mean taste for education is lower than the baseline.

Table 8 provides measures of the opportunity cost of college by country and gender. The product $h(0)*\bar{e}^w$ measures the time cost of college for the lowest ability women, thus ignoring selection. Comparing this to the comparable measure of 0.75 for men, it is lower for women than for men in all countries, though only slightly in Italy. So, for a man and a women of comparable ability, the cost of college would be lower for the women.

The realized time cost incurred, of course, depends on the selection into college. Table 8 shows the computed values of the time cost of education, $E(\frac{\bar{e}}{\theta}|e=1)$ by gender and country as well as the opportunity cost, $h(0)*E(\frac{\bar{e}}{\theta}|e=1)$. From this table, the **realized** time cost of education is higher for women in all countries other than Japan. The higher average cost of education reflects the selection effects coming from the higher college rate of women. For Japan there is both a relatively low value of $h^w(0)$ and a low estimated time cost parameter for women.

6.3 Discrimination

This section introduces discrimination into the model. Our approach is to consider a model in which the only difference across genders is in the perception of productivity. Here perception is what matters since this determines the compensation paid and thus the incentives for human capital accumulation. Specifically, suppose that firms view the expected output of a man with education e and a signal s as $\omega(e, s)$ while a women with the same fundamentals would be paid $\omega(e, s) - z$.[53] Note that z is not indexed by (e, s) so that discrimination is not type specific. Allowing, for example, $z(e)$ would essentially return us to the estimated model in which both $(h(0), h(1))$ were gender specific.

Though we define z as beliefs about productivity, it has a broader interpretation. If women were viewed as more costly to employ, then this added cost would be indistinguishable from a productivity loss. Likewise, if firms had a "distaste" for hiring women, that too is captured by the perceived productivity reduction.

With this specification of discrimination, we estimate the model under the restriction that no other parameters differ by gender. This allows us to gauge how far a model with discrimination alone can match moments.

Appendix Tables 33 and 34 present the results. From the table of moments, the fit is much worse for the model with discrimination compared to the baseline. It is not surprising that this model struggles between generating a wage gap, through $z < 0$, and creating a college premium and a college rate that are both higher for women. The estimated z is negative in three countries, but positive in Italy, thus creating a wage gap in Germany, Japan and the US. If $z < 0$, then the non-college wage is lower for women and this reduces the opportunity cost of education. This is why the college rate is higher for women than men in Germany, Japan and the US and lower in Italy. But these effects are very small. This slightly higher college rate translates, through selection, into a slightly smaller college premium for women, given that $(h(0), h(1))$ are not gender specific. This model with discrimination alone fails to match the moments.

[53]This formulation appears in section 3.1.2 of Cain (1986) and is attributed to Becker.

7 Conclusions

This paper studies gender differences in education and compensation. In addition to the frequently cited 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 across countries.

The goal of the paper was to uncover the sources of these gaps in educational attainment, college premia and wages of college educated workers. A model allowing for gender specific differences in tastes, technology and the informativeness of signals was specified and estimated using simulated method of moments. The baseline model focused on gender differences in educational attainment, college premia and wage gaps. The analysis was broadened to include participation rates as moments. The structural model was able to match these moments quite closely.

Through a series of counterfactual exercises, we find that the gaps in Japan and the US are largely explained by differences in the productivity of workers without a college degree. For Germany and Italy, taste differences play a more prominent role. In contrast, gender differences in the informativeness of signals about worker ability and/or gender differences in the distribution of ability do not explain these gaps. The same is true for a model in which employers believe in a productivity difference between men and women.

There are a couple of interesting model extensions to consider.[54]. First, the model can be extended to include a second dimension of heterogeneity across agents, allowing a formalization of "brain, brawn" distinction. With more detailed data, it would be possible to estimate this expanded model and use it to generate further insights into the nature of compensation differences for non-college individuals. Second, building on this, technological advance may reduce the demand for brawn relative to brain, thus impacting the gender gaps studied here. Understanding the magnitudes of this interaction would be important to more fully understand the gender implications of technology progress.

References

Arrow, K. J. (1998): "What has economics to say about racial discrimination?," *Journal of economic perspectives*, 12(2), 91–100.

[54] Thanks to Eric Smith for conversations on both of these points.

Becker, G. S. (1962): "Investment in human capital: A theoretical analysis," *Journal of political economy*, 70(5, Part 2), 9–49.

——— (2009): *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago press.

Becker, G. S., W. H. Hubbard, and K. M. Murphy (2010a): "Explaining the worldwide boom in higher education of women," *Journal of Human Capital*, 4(3), 203–241.

——— (2010b): "The Market for College Graduates and the Worldwide Boom in Higher Education of Women," *American Economic Review*, 100(2), 229–233.

Cain, G. G. (1986): "The economic analysis of labor market discrimination: A survey," *Handbook of labor economics*, 1, 693–785.

Cooper, R., and H. Liu (2019): "MisMatch in Human Capital Accumulation," *International Economic Review*, 60(3), 1291–1328.

Eckstein, Z., M. Keane, and O. Lifshitz (2019): "Career and family decisions: Cohorts born 1935–1975," *Econometrica*, 87(1), 217–253.

Fortin, N. M. (2005): "Gender role attitudes and the labour-market outcomes of women across OECD countries," *oxford review of Economic Policy*, 21(3), 416–438.

Hanushek, E. A., G. Schwerdt, S. Wiederhold, and L. Woessmann (2015): "Returns to Skills around the World: Evidence from PIAAC," *European Economic Review*, 73, 103–130.

Hara, H. (2018): "The gender wage gap across the wage distribution in Japan: Within- and between-establishment effects," *Labour Economics*, 53, 213–229.

Heckman, J. (1974): "Shadow prices, market wages, and labor supply," *Econometrica: journal of the econometric society*, pp. 679–694.

Heckman, J. J. (1979): "Sample selection bias as a specification error," *Econometrica: Journal of the econometric society*, pp. 153–161.

Hsieh, C.-T., E. Hurst, C. I. Jones, and P. J. Klenow (2019): "The Allocation of Talent and US Economic Growth," *Econometrica*, 87(5), 1439–1474.

Hubbard, W. H. (2011): "The phantom gender difference in the college wage premium," *Journal of Human Resources*, 46(3), 568–586.

Kricheli-Katz, T., and T. Regev (2021): "The effect of language on performance: do gendered languages fail women in maths?," *NPJ science of learning*, 6(1), 1–7.

Lang, K., and M. Manove (2011): "Education and labor market discrimination," *American Economic Review*, 101(4), 1467–96.

Lundberg, S. J., and R. Startz (1983): "Private discrimination and social intervention in competitive labor market," *The American Economic Review*, 73(3), 340–347.

Mulligan, C. B., and Y. Rubinstein (2008): "Selection, investment, and women's relative wages over time," *The Quarterly Journal of Economics*, 123(3), 1061–1110.

Ngai, L. R., and B. Petrongolo (2017): "Gender gaps and the rise of the service economy," *American Economic Journal: Macroeconomics*, 9(4), 1–44.

Nielsson, U., and H. Steingrimsdottir (2010): "The signalling value of education across genders," *Empirical Economics*, 54(4), 1827–1854.

Olivetti, C., and B. Petrongolo (2008): "Unequal pay or unequal employment? A cross-country analysis of gender gaps," *Journal of Labor Economics*, 26(4), 621–654.

——— (2014): "Gender gaps across countries and skills: Demand, supply and the industry structure," *Review of Economic Dynamics*, 17(4), 842–859.

Rendall, M. (2017): "Brain versus brawn: the realization of women's comparative advantage," Discussion Paper 491, University of Zurich, Institute for Empirical Research in Economics, Working Paper.

Riphahn, R. T., and C. Schwientek (2015): "What drives the reversal of the gender education gap? Evidence from Germany," *Applied Economics*, 47(53), 5748–5775.

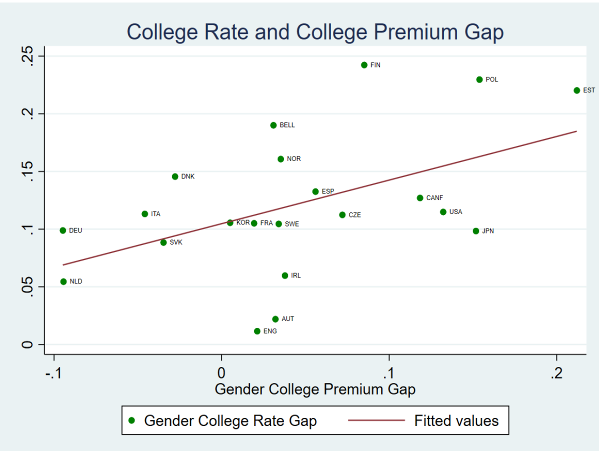
Spence, M. (1973): "Job market signaling," *The Quarterly Journal of Economics*, pp. 355–374.

8 Online Appendix

8.1 College Rates and Returns

Figure 6 displays the education rates of woman, relative to men, and gender differences in the marginal return from education, captured by the college wage premia.[55] The vertical axis shows country specific differences in college attainment between women and men (the gender college rate gap). Note that these gaps are positive, indicating higher college attainment for woman 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.

From the regression displayed in the graph, the higher rates of college attainment for women compared to men are positively associated with higher returns to college.[56] From this perspective, for most countries, there is no puzzle explaining the relatively high college rates of women, despite the fact that men are, on average, paid more than women. As discussed in detail as the paper progresses, Germany and Italy are exceptions with a higher college rate for women but negative college premium gaps.



Note: The variable on the horizontal axis is the gender difference in the college wage premium. The college wage premium for men (women) is the log of the mean wage for college educated individuals minus the log of the mean wage of those without college. On the vertical axis is the college rate of woman minus that of men.

Figure 6: College Attainment and Returns from Education: Gender Gaps

[55]The differences in the college wage premia are used here in the motivation. The college premium is the log of mean wages for those with college minus the log of mean wages for those without a college degree. The quantitative analysis goes further to focus on differences in the education coefficients in Mincer wage regressions.

[56]The slope of the regression line shown in the middle of the figure is 0.378(0.154), the p-value is 0.024 and the $R^2 = 0.241$.

8.2 App: Facts

8.2.1 Scores

Table 9 presents more information on numeracy scores.

	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 9: PIAAC Numeracy Scores by Gender and Educational Attainment

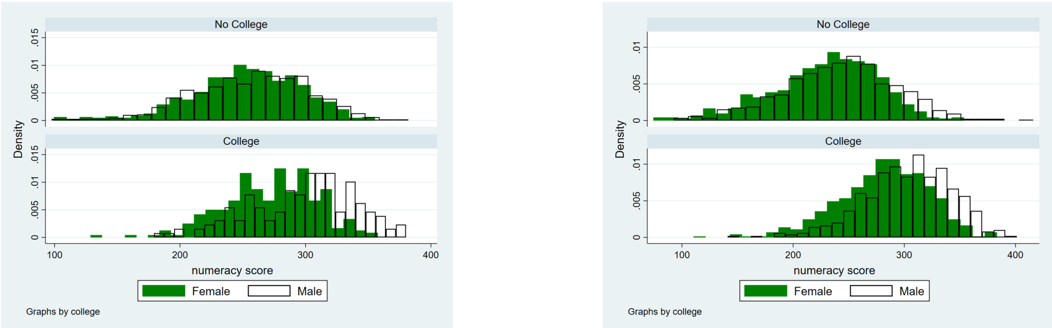
One relatively simple explanation for these gender specific education and labor market outcomes could be differences in underlying ability. Of course, innate ability is not directly observed and instead researchers resort to using test scores as noisy proxies. Table 9 presents the mean and variance of PIAAC test results by gender 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 7, the distributions have large enough standard deviations such that some individuals without college have higher scores than those with college, suggesting the presence of sources that distort the education decision.

Second, and most importantly for this study, there are differences in test scores by gender.[57] The rows labeled "Diff in Mean" report the differences in mean scores and

[57]See Kricheli-Katz and Regev (2021) and references therein for a discussion of the interaction of gender, language and test score results. Our analysis does not compare the test distributions of test scores by gender.

their significance.[58] 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 7.



(a) Italy (b) US

Figure 7: Ability, Education Levels and Gender

Note: These 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.

8.2.2 Selection into College

Table 10 provides estimates of selection into college through a specification with gender interactions.

	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 10: Selection into College: Gender differences

[58] A positive sign indicates that the mean score is higher for men.

8.3 Mincer Regressions

This section presents Mincer regression results with interactions, Table 11, and estimated separately by gender, Table 12.

	Germany		Italy		Japan		US	
	Men	Women	Men	Women	Men	Women	Men	Women
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 wage regressions with log gross hourly earnings as dependent variable. Notice that the number of observations is lower compared to Table 10 due to the mentioned further sample selection restrictions. A */**/*** next to the difference in means indicates significance at the 10/5/1% level

Table 11: Mincer regressions

8.4 App: Baseline Estimation

This section provides further detail on the baseline estimation.

8.4.1 Moments and Parameters

The following tables describe the parameters, Table 13, and the moments, Table 14.

8.4.2 Moments from Decompositions

Table 15 presents moments when parameters are restricted to be gender independent. These cases are used for the decomposition exercise presented in the text. Table 16 presents a recursive decomposition.

	Germany		Italy		Japan		US	
	Men	Women	Men	Women	Men	Women	Men	Women
num score	0.111**	0.128**	0.061**	0.085**	0.091**	0.098**	0.155**	0.149**
	(0.029)	(0.032)	(0.027)	(0.027)	(0.022)	(0.019)	(0.030)	(0.025)
college	0.239**	0.199**	0.210**	0.208**	0.022	0.198**	0.162**	0.331**
	(0.062)	(0.054)	(0.067)	(0.055)	(0.038)	(0.047)	(0.065)	(0.054)
age	0.028**	0.027**	0.008	0.046**	0.039**	0.024**	0.032**	0.032**
	(0.010)	(0.009)	(0.007)	(0.010)	(0.007)	(0.006)	(0.008)	(0.009)
r2	0.239	0.231	0.163	0.321	0.172	0.213	0.273	0.367
N	321	241	193	135	334	261	296	306

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.

Table 12: Mincer Regressions by Country.

Parameters	**Description**
Set	
$\bar{e}$	fraction of time at school
p	Tuition for college
$h^m(0) = 1$	Average productivity if no college for men
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
$h^w(0)$	Human capital accumulation if no college for women

Table 13: Parameters: Description

8.4.3 Occupations of Non College Individuals

Tables 17 and 18 present data on earnings for key occupations of non-college workers in the US.

Tables 17 and 18 present data from the American Community Survey (ACS) from 2016 and present median earnings (total and by gender) and gender gaps across the most frequent 10 occupations among non-college educated women and non-college educated men in the US.[59] A couple of observations are noteworthy. First, there is a sizeable wage gap in all occupations. Second, non educated men and women do not have the same

[59]These tables with additional explanation appear in Appendix sub-section 8.4.3.

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
wage gap	log of mean wages for college educated men minus that of women

Table 14: Moments: Description

occupations in general. For example, the most common occupational category among non educated women is "Secretaries and administrative assistants" with median annual earnings of \$36,653 while for non educated men it is "Drivers/sales workers and truck drivers" with median annual earnings of \$43,384. Moreover, the occupations shown in Table 17 seem to be relatively brawn intensive while occupations shown in Table 18 seem to be relatively brain intensive. Given this, one might wonder whether the gender gap among this educational group is coming mainly through gender differences in the type of occupations that they perform or due to other factors that affect wages conditional on occupation.

Following this idea, we decompose the gender gap using 330 occupational categories from ACS 2016:

$$W^m - W^w = \sum_i (s_i^m - s_i^w) w_i^m - \sum_i (w_i^m - w_i^w) s_i^w \tag{11}$$

where s_i^w (s_i^m) represent the fraction of non educated women (men) allocated to the occupational category i and w_i^w (w_i^m) in the median earnings for non college educated women (men) associated to the occupational category i. We interpret the first term as the part of the wage gap associated to differences in type of jobs while the second one is the part of the wage gap that can be attributed to within occupations differences.

8.4.4 Identification

There are a couple of ways to see the identification of parameters based upon the selected moments. Based upon starting the estimation procedure at different values for both parameters and beliefs, we have not found multiple parameters generating the same

	Men					Women						
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**			
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
						Data						
G	0.331	-0.994	1.395	0.111	0.239	0.430	-0.480	1.108	0.128	0.199	0.165	na
I	0.189	-2.130	1.734	0.061	0.210	0.303	-0.880	0.443	0.085	0.208	0.053	na
J	0.596	0.243	0.921	0.091	0.022	0.695	0.706	0.732	0.098	0.198	0.110	na
U	0.422	-0.570	1.716	0.155	0.162	0.537	0.119	1.499	0.149	0.331	0.049	na
						Baseline						
G	0.299	-0.992	1.395	0.137	0.251	0.382	-0.472	1.107	0.136	0.192	0.151	0.005
I	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
J	0.545	0.254	0.919	0.086	0.028	0.654	0.716	0.730	0.078	0.196	0.108	0.005
U	0.373	-0.564	1.716	0.120	0.154	0.489	0.131	1.496	0.135	0.332	0.048	0.006
						Same $h(0)$						
G	0.299	-0.992	1.395	0.137	0.251	0.340	-0.689	1.119	0.127	0.162	0.133	0.056
I	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
J	0.545	0.254	0.919	0.086	0.028	0.182	-2.001	1.462	0.031	0.145	-0.097	8.177
U	0.373	-0.564	1.716	0.120	0.154	0.228	-1.471	1.887	0.097	0.207	-0.059	2.808
						Same $h(0), h(1)$						
G	0.299	-0.992	1.395	0.137	0.251	0.265	-1.122	1.125	0.106	0.111	0.189	0.449
I	0.164	-2.127	1.735	0.067	0.207	0.269	-1.028	0.450	0.083	0.142	0.118	0.033
J	0.545	0.254	0.919	0.086	0.028	0.310	-0.969	1.120	0.046	0.163	-0.121	3.162
U	0.373	-0.564	1.716	0.120	0.154	0.143	-2.425	1.954	0.073	0.181	-0.032	6.877
						Same $\bar{\varepsilon}, \mu(\varepsilon)$						
G	0.299	-0.992	1.395	0.137	0.251	0.248	-1.422	2.368	0.114	0.261	0.036	2.528
I	0.164	-2.127	1.735	0.067	0.207	0.263	-1.193	2.221	0.114	0.221	-0.066	3.274
J	0.545	0.254	0.919	0.086	0.028	0.848	1.783	0.441	0.095	0.160	0.155	1.274
U	0.373	-0.564	1.716	0.120	0.154	0.764	2.635	3.768	0.152	0.282	0.086	11.534
						Same λ						
G	0.299	-0.992	1.395	0.137	0.251	0.412	-0.365	0.453	0.099	0.229	0.183	0.447
I	0.164	-2.127	1.735	0.067	0.207	0.300	-0.864	0.389	0.084	0.213	0.055	0.004
J	0.545	0.254	0.919	0.086	0.028	0.475	0.211	2.904	0.114	0.165	0.055	5.021
U	0.373	-0.564	1.716	0.120	0.154	0.520	0.102	0.589	0.105	0.372	0.065	0.838
						Same ϕ						
G	0.299	-0.992	1.395	0.137	0.251	0.474	0.081	1.751	0.207	0.234	0.033	0.757
I	0.164	-2.127	1.735	0.067	0.207	0.285	-0.942	0.397	0.074	0.189	0.086	0.009
J	0.545	0.254	0.919	0.086	0.028	0.589	0.407	0.691	0.060	0.198	0.119	0.107
U	0.373	-0.564	1.716	0.120	0.154	0.541	0.516	1.998	0.172	0.353	-0.010	0.414

Note: This table reports data and simulated moments for the model matching wage gaps. Here "wagegap" is the difference in the log of mean wages for college educated men and women. See Table 14 for a full list of other variables. august 20, 2022

Table 15: Moments: Wage Gap

moments.[60]

Further, Table 19 shows the response of moments to variations in parameters.[61] These are, by construction, partial effects with one parameter changing at a time, evaluated

[60] This comes from the search for a global minimum to (7), which was accomplished by trying different initial values for parameters and beliefs.

[61] The derivative of the moments with respect to parameters underlie the standard errors calculated for the baseline estimates.

Moments	Germany Baseline	$(\bar{\varepsilon}, \mu)$	$h(0)$	λ	Men/$(h(1), \phi)$
Ed. Rate Gap	0.084	-0.051	-0.096	-0.035	0
College Premium Gap	-0.102	0.012	0.002	-0.078	0
Ed. Wage Gap	0.151	0.036	-0.002	0.078	0

Moments	Italy Baseline	$(\bar{\varepsilon}, \mu)$	$h(0)$	λ	Men/$(h(1), \phi)$
Ed. Rate	0.133	0.099	0.099	0.121	0
College Premium Gap	-0.052	0.066	0.066	0.045	0
Ed. Wage Gap	0.052	-0.066	-0.066	-0.045	0

Moments	Japan Baseline	$h(0)$	$(\bar{\varepsilon}, \mu)$	λ	Men/$(h(1), \phi)$
Ed. Rate	0.109	-0.362	-0.042	-0.036	0
College Premium Gap	0.159	0.097	-0.047	-0.030	0
Ed. Wage Gap	0.108	-0.097	0.047	0.030	0

Moments	US Baseline	$h(0)$	$(\bar{\varepsilon}, \mu)$	λ	Men/$(h(1), \phi)$
Ed. Rate	0.117	-0.145	-0.037	0.061	0
College Premium Gap	0.157	0.059	0.038	-0.019	0
Ed. Wage Gap	0.048	-0.059	-0.038	0.019	0

This table reports **all the gaps** in education, college premia and wage across gender resulting from simulations of the models sequentially (cummulative) replacing the parameters of women with those of men, as indicated by the columns. The column marked baseline reports the baseline gap. Moving to the right, the columns indicate which sets of parameters of women are set to the value of men. By the last column, all parameters are at the value of men so that all gaps are removed. This decomposes the simulated not the actual data.

Table 16: Determinants of Education, College Premia and Wage Gaps: Sequential Version

Occupational Category	Estimated Median Earnings				Percentage	
	Total	Men	Women	Gap	Men	Women
Driver/sales workers and truck drivers	43,384	44,340	33,224	11,116	8.84	0.68
First-line supervisors of retail sales workers	39,352	45,234	32,368	12,866	3.94	5.01
Janitors and building cleaners	28,365	31,028	22,989	8,039	3.83	2.42
Construction laborers	34,080	34,427	30,868	3,559	3.68	0.15
Laborers and freight, stock, and material movers	31.764	32.781	26.979	5.802	3,37	1,23
Carpenters	37.176	37.272	31.222	6.050	2,79	0,09
Retail salespersons	32.392	38.872	26.834	12.038	2,58	2,68
Grounds maintenance workers	26.171	26.325	22.507	3.818	2,40	0,19
Cooks	22.246	24.123	20.430	3.693	2,28	2,31
Production workers, all other	35.812	39.570	27.498	12.072	2,26	1,35
Total					**35.96**	**16.12**

Table 17: Main Occupations for Non-College Educated Men

at the baseline estimates. Given the nonlinearities in the model, these elasticities will generally depend on the point estimates. These elasticities are themselves gender specific, allowing a change in a parameter to have differential effects on moments. The last column, “Wage gap” is an exception since this is a joint moment.

Focusing on Germany, from this table, an increase in mean ability (lower ϕ) leads to an increase in college rates, a higher the constant in the logit regression and a higher coefficients on both the score and education in the Mincer regressions. An increase in the dispersion of taste shocks leads to an increase in the college rate. There is an asymmetry here because the increased dispersion causes more agents to switch to college who otherwise would not have gone. More dispersion of the taste shock also reduces the informativeness of education about ability, as seen by the lower coefficient on education in the Mincer regression. The increased noise in education as a signal of ability implies that more weight in put on the test score in determining wages so that the Mincer score coefficient increases. If the mean taste shock increases, then the college rate will increase. As with the dispersion in tastes, the coefficient on education in the Mincer regression will fall. As with the increase in dispersion, the coefficient of the test score in the Mincer regression increases. An increase in the informativeness of the signal about ability reduces the college rate since agents will be paid more based upon true ability so that taste shocks matter less. The score coefficient in the logit regression is much higher, as is the signal in the Mincer regression. Since the signal is more informative, less weight is placed on education in the determination of wages. An increase in the human capital accumulation

Occupational Category	Estimated Median Earnings				Percentage	
	Total	Men	Women	Gap	Men	Women
Secretaries and administrative assistants	36.784	41.394	36.653	4.741	0,25	10,04
First-line supervisors of retail sales workers	39.352	45.234	32.368	12.866	3,94	5,01
Customer service representatives	32.396	35.920	31.898	4.022	1,34	4,93
Maids and housekeeping cleaners	21.562	26.300	21.070	5.230	0,43	3,84
Office clerks, general	34.134	40.013	33.063	6.950	0,34	3,32
Cashiers	21.833	23.956	21.373	2.583	0,69	3,25
Personal care aides	22.723	26.249	22.211	4.038	0,37	2,79
Receptionists and information clerks	29.828	31.587	29.588	1.999	0,13	2,78
Retail salespersons	32.392	38.872	26.834	12.038	2,58	2,68
Janitors and building cleaners	28.365	31.028	22.989	8.039	3,83	2,42
Total					**13.89**	**41.06**

Table 18: Main Occupations for Non-College Educated Women

in college has a very large impact on the college rate. The score becomes less of a determinant of education since agents can obtain higher human capital for lower ability, allowing them to respond to taste variations. The score and education coefficients are both larger when $h(1)$ is higher. Finally, an increase in $h(0)$, has essentially the opposite effect of an increase in $h(1)$.[62] The higher $h(0)$ will reduce the college rate since the college premium is reduced and the opportunity cost of college is higher. The college coefficient in the Mincer regression is lower because the human capital accumulation in college, given ability, is lower. Of course, there is also a selection effect at play as the college rate is lower so that, given tastes, the cut-off value of ability will be higher. As for the wage gap, clearly the wage gap is lower when $h(0)$ is increased. This is consistent with the theme of this section explaining the wage gap through a lower value of $h(0)$ for women.

8.4.5 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.

[62] There are no elasticities reported for men since $h(0) = 1$ is a normalization.

Parm.	Men					Women					
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**		
	College Rate ed	Logit (constant) χ_0	Logit (score) χ_s	Mincer score α_s	Mincer college α_e	College Rate ed	Logit (constant) χ_0	Logit (score) χ_s	Mincer score α_s	Mincer college α_e	Wage gap
						Germany					
ϕ	-1.312	2.792	-0.930	-2.773	-0.204	-0.673	3.325	-1.416	-1.700	-0.504	-0.250
$\bar{\varepsilon}$	0.354	-0.936	-1.000	0.267	-0.506	0.289	-1.200	-1.132	0.009	-0.132	-0.385
$\mu(\varepsilon)$	0.346	-0.767	-0.293	0.218	-0.341	0.351	-1.565	-0.108	0.165	-0.202	-0.277
λ	-0.578	1.433	2.758	0.576	-0.190	-0.242	0.562	2.121	0.589	-0.546	0.888
$h(1)$	2.585	-5.736	-1.802	2.126	1.110	2.069	-9.378	-0.286	1.363	3.263	-2.482
$h(0)$	NaN	NaN	NaN	NaN	NaN	-2.092	9.374	0.308	-1.326	-3.340	-2.123
						Italy					
ϕ	-1.457	1.299	-0.779	-2.848	0.036	-0.393	0.656	-1.088	-1.734	-0.799	1.537
$\bar{\varepsilon}$	0.823	-1.285	-1.391	0.655	-0.960	0.679	-1.213	-1.285	0.081	-0.201	-2.541
$\mu(\varepsilon)$	0.563	-0.641	-0.253	0.476	-0.503	-0.299	0.515	0.069	-0.178	0.077	-2.320
λ	-0.689	1.083	1.892	0.720	-0.101	-0.031	0.056	0.354	0.156	-0.074	3.475
$h(1)$	4.582	-4.832	-1.421	3.767	0.861	1.274	-2.194	-0.231	0.951	4.148	-12.365
$h(0)$	NaN	NaN	NaN	NaN	NaN	-1.296	2.217	0.265	-0.926	-4.216	-2.321
						Japan					
ϕ	-0.686	-8.773	-1.611	-1.895	-0.687	-0.865	-4.284	-0.622	-2.003	0.164	-0.527
$\bar{\varepsilon}$	-0.025	-0.680	-0.678	-0.087	0.774	-0.014	-0.090	-0.101	0.020	0.002	-0.087
$\mu(\varepsilon)$	1.546	17.066	-0.474	0.302	-3.769	1.355	6.305	-0.871	0.744	-1.175	0.954
λ	-0.097	1.106	3.013	1.145	-4.410	-0.480	-1.737	2.518	0.928	-0.323	-0.298
$h(1)$	1.709	19.859	1.151	3.044	14.200	4.430	21.022	-3.109	2.462	1.235	2.481
$h(0)$	NaN	NaN	NaN	NaN	NaN	-4.446	-21.171	3.091	-2.464	-1.238	-6.850
						US					
ϕ	-1.156	5.521	-0.842	-1.590	0.106	-0.455	-13.766	-1.343	-1.113	-0.244	0.569
$\bar{\varepsilon}$	0.179	-0.864	-0.772	0.096	-0.279	0.085	-1.050	-1.097	-0.050	0.045	-0.640
$\mu(\varepsilon)$	1.110	-5.005	-1.012	0.429	-1.219	0.272	6.092	0.022	0.086	-0.067	-4.336
λ	-0.676	2.410	3.768	0.527	-0.576	-0.065	1.469	0.926	0.153	-0.111	3.518
$h(1)$	3.337	-15.227	-2.213	1.580	1.856	2.217	51.343	0.034	0.755	2.418	-9.266
$h(0)$	NaN	NaN	NaN	NaN	NaN	-2.199	-50.806	-0.137	-0.722	-2.446	-5.595

Note: This table reports the elasticity of moments with respect to parameters for Germany. The wage gap column indicates the effects of changes in the parameter for both men and women on that moment.

Table 19: Identification

	Men					Women					
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**		
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap
						Data					
Aut.	0.266	-1.612	1.131	0.092	0.132	0.289	-1.677	1.629	0.112	0.148	0.066
Belg.	0.392	-0.742	1.678	0.051	0.119	0.582	0.388	1.792	0.074	0.149	0.080
Can. (F)	0.500	-0.138	1.034	0.097	0.090	0.627	0.521	0.749	0.093	0.219	0.100
Cze.	0.288	-1.982	2.221	0.034	0.262	0.400	-0.801	1.635	0.112	0.273	0.154
Germ.	0.331	-0.994	1.395	0.111	0.239	0.430	-0.480	1.108	0.128	0.199	0.165
Denm.	0.481	-0.382	0.842	0.058	0.147	0.626	0.397	0.871	0.083	0.135	0.121
Engl.	0.513	0.167	0.572	0.150	0.193	0.524	0.159	0.551	0.162	0.224	0.032
Spain.	0.336	-0.984	1.402	0.107	0.240	0.469	-0.265	1.058	0.122	0.294	0.170
Est.	0.335	-0.766	0.863	0.111	0.125	0.555	0.265	1.154	0.119	0.260	0.334
Fin.	0.395	-0.692	1.057	0.045	0.124	0.638	0.534	0.936	0.071	0.184	0.087
Fra.	0.416	-0.834	1.958	0.072	0.151	0.521	-0.104	1.896	0.064	0.186	0.084
Irl.	0.466	-0.342	1.361	0.083	0.161	0.526	0.146	1.060	0.147	0.189	-0.037
Ita.	0.189	-2.130	1.734	0.061	0.210	0.303	-0.880	0.443	0.085	0.208	0.053
Jpn.	0.596	0.243	0.921	0.091	0.022	0.695	0.706	0.732	0.098	0.198	0.111
Kor.	0.648	0.455	0.870	0.100	0.215	0.754	1.127	1.162	0.089	0.223	0.087
Nld.	0.399	-0.705	1.521	0.084	0.205	0.453	-0.246	1.254	0.040	0.127	0.152
Norw.	0.450	-0.455	0.853	0.098	0.077	0.611	0.286	0.991	0.069	0.104	0.106
Pol.	0.365	-0.591	1.259	0.105	0.195	0.595	0.401	0.865	0.104	0.341	0.167
Svk	0.253	-1.348	1.138	0.121	0.249	0.341	-0.747	0.976	0.078	0.243	0.231
Swe	0.457	-0.681	1.031	0.036	0.055	0.561	-0.081	1.083	0.057	0.077	0.084
USA	0.422	-0.570	1.716	0.155	0.162	0.537	0.119	1.499	0.149	0.331	0.048

Note: This table reports data moments for the 21 countries in our sample

Table 20: Data moments: All countries.

	Men					Women						
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**			
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
						Baseline Estimation						
Aut.	0.206	-1.602	1.135	0.068	0.136	0.208	-1.669	1.630	0.105	0.154	0.064	0.011
Belg.	0.357	-0.734	1.664	0.086	0.105	0.531	0.392	1.789	0.131	0.170	0.093	0.009
Can. (F)	0.456	-0.129	1.032	0.181	0.084	0.617	0.520	0.746	0.223	0.179	0.094	0.028
Cze.	0.215	-1.976	2.223	0.057	0.275	0.334	-0.792	1.634	0.134	0.276	0.157	0.011
Germ.	0.299	-0.992	1.395	0.137	0.251	0.382	-0.472	1.107	0.136	0.192	0.151	0.005
Denm.	0.419	-0.362	0.836	0.066	0.141	0.580	0.408	0.872	0.079	0.131	0.121	0.007
Engl.	0.535	0.161	0.572	0.151	0.194	0.534	0.158	0.551	0.161	0.224	0.032	0.001
Spn.	0.308	-0.981	1.402	0.110	0.252	0.428	-0.259	1.057	0.121	0.290	0.166	0.003
Est.	0.329	-0.766	0.858	0.124	0.107	0.534	0.270	1.155	0.142	0.260	0.343	0.002
Fin.	0.357	-0.685	1.058	0.059	0.118	0.607	0.539	0.933	0.069	0.179	0.084	0.003
Fra.	0.347	-0.823	1.958	0.075	0.147	0.460	-0.093	1.893	0.075	0.182	0.086	0.009
Irl.	0.423	-0.335	1.359	0.105	0.150	0.521	0.153	1.048	0.156	0.187	-0.035	0.003
Ita.	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
Jpn.	0.545	0.254	0.919	0.086	0.028	0.654	0.716	0.730	0.078	0.196	0.108	0.005
Kor.	0.598	0.458	0.861	0.212	0.167	0.713	1.132	1.159	0.169	0.221	0.086	0.026
Nld.	0.360	-0.701	1.521	0.098	0.209	0.444	-0.240	1.259	0.066	0.133	0.150	0.003
Norw.	0.398	-0.442	0.872	0.091	0.073	0.559	0.310	0.980	0.070	0.107	0.109	0.007
Pol.	0.374	-0.593	1.259	0.107	0.194	0.578	0.399	0.865	0.082	0.342	0.166	0.001
Svk	0.239	-1.344	1.141	0.096	0.232	0.340	-0.748	0.974	0.101	0.244	0.234	0.002
Swe	0.362	-0.664	1.033	0.041	0.056	0.481	-0.065	1.082	0.046	0.076	0.082	0.016
USA	0.373	-0.564	1.716	0.120	0.154	0.489	0.131	1.496	0.135	0.332	0.048	0.006

Note: This table reports simulated moments for baseline estimation for the 21 countries in our sample

Table 21: Simulated moments: All countries.

	Men					**Women**					
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$h^w(0)$
Aut.	4.478	0.266	0.189	0.494	0.708	4.144	0.333	0.122	0.596	0.641	0.856
Belg.	5.470	0.000	0.343	0.595	0.829	6.530	0.231	0.287	0.851	0.885	0.836
Can. (F)	2.024	1.514	0.103	0.999	0.400	2.000	1.283	0.443	0.342	0.400	0.817
Cze.	6.137	0.035	0.192	0.635	0.941	4.609	0.246	0.111	0.630	0.787	0.792
Germ.	3.774	0.270	0.096	0.522	0.853	5.131	0.443	0.141	0.764	0.942	0.953
Denm.	5.502	0.024	0.327	0.460	0.849	9.996	0.238	0.389	0.834	0.941	0.896
Engl.	3.934	0.365	0.236	0.453	0.879	3.745	0.371	0.202	0.425	0.832	0.934
Spn.	4.366	0.157	0.156	0.516	0.884	6.159	0.377	0.110	0.787	0.964	0.841
Est.	2.671	0.303	0.184	0.315	0.479	5.961	0.493	0.206	0.989	0.706	0.621
Fin.	6.571	0.086	0.348	0.574	0.870	9.479	0.076	0.333	0.724	0.939	0.870
Fra.	6.742	0.002	0.327	0.676	0.927	8.189	0.001	0.316	0.740	0.934	0.895
Irl.	4.992	0.033	0.301	0.549	0.873	4.358	0.208	0.244	0.562	0.910	0.974
Ita.	6.550	0.321	0.114	0.800	0.944	5.826	1.154	-0.208	0.940	1.021	1.000
Jpn.	6.972	0.218	0.458	0.757	0.864	6.274	0.030	0.302	0.531	0.775	0.766
Kor.	2.084	0.128	0.254	0.245	0.459	5.383	0.656	0.468	0.893	1.016	0.926
Nld.	4.992	0.007	0.243	0.552	0.903	7.386	0.015	0.361	0.639	0.925	0.978
Norw.	4.301	0.201	0.325	0.485	0.709	8.172	0.062	0.396	0.667	0.859	0.886
Pol.	4.706	0.115	0.238	0.527	0.880	9.956	0.266	0.183	0.856	1.010	0.778
Svk	4.765	0.360	0.067	0.582	0.896	4.818	0.209	0.158	0.514	0.741	0.799
Swe	6.921	0.018	0.426	0.555	0.801	9.716	0.013	0.441	0.681	0.842	0.901
USA	5.057	0.169	0.258	0.659	0.908	6.248	0.352	0.108	0.946	1.002	0.814

Note: This table reports parameter estimates for the baseline model for all countries. Here "$h^w(0)$" is the wage for women without college. This wage is normalized to one for men. See Table 13 for other parameter definitions.

Table 22: Parameter Estimates : All Countries

8.5 App: Extensions

8.5.1 Selection into Employment

Here we present the estimation results for the two-step procedure by country. For these regressions, marriage equals 1 if the person is married and children equals 1 if they have children.

VARIABLES	(1) Men Logit First Step	(2) Men Mincer Second Step	(3) Women Logit First Step	(4) Women Mincer Second Step
sdt_num	0.00117	0.140***	0.231*	0.0936**
	(0.189)	(0.0309)	(0.134)	(0.0382)
college	-0.0860	0.205***	0.0219	0.241***
	(0.388)	(0.0710)	(0.285)	(0.0607)
age	2.723**	-0.170	0.501	0.182
	(1.232)	(0.306)	(1.062)	(0.234)
agesq	-0.0442**	0.00301	-0.00879	-0.00245
	(0.0210)	(0.00502)	(0.0179)	(0.00403)
marriage	0.953***		0.512	
	(0.350)		(0.319)	
children	-0.0920		-1.277***	
	(0.383)		(0.287)	
inverse Mills ratio		-0.460*		-0.157
		(0.235)		(0.112)
Constant	-40.66**	4.954	-6.616	-0.717
	(17.97)	(4.673)	(15.61)	(3.384)
Observations	327	255	348	192
R-squared		0.280		0.272

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 23: Germany

VARIABLES	(1) Men Logit First Step	(2) Men Mincer Second Step	(3) Women Logit First Step	(4) Women Mincer Second Step
sdt_num	-0.0620	0.0609**	0.375**	0.109**
	(0.182)	(0.0285)	(0.183)	(0.0498)
college	-0.368	0.250***	-0.0983	0.231***
	(0.451)	(0.0756)	(0.337)	(0.0617)
age	2.437*	-0.228	0.438	0.123
	(1.388)	(0.226)	(1.296)	(0.253)
agesq	-0.0415*	0.00396	-0.00660	-0.00114
	(0.0233)	(0.00377)	(0.0219)	(0.00422)
marriage	0.949**		0.676*	
	(0.438)		(0.407)	
children	-0.316		-0.749*	
	(0.459)		(0.394)	
inverse Mills ratio		-0.112		0.105
		(0.137)		(0.145)
Constant	-34.87*	5.434	-7.504	-0.652
	(20.53)	(3.377)	(19.05)	(3.812)
Observations	227	166	237	111
R-squared		0.170		0.358

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Italy

VARIABLES	(1) Men Logit First Step	(2) Men Mincer Second Step	(3) Women Logit First Step	(4) Women Mincer Second Step
sdt_num	0.476***	0.168***	0.217	0.112***
	(0.172)	(0.0454)	(0.139)	(0.0219)
college	-0.229	-0.0160	0.361	0.199***
	(0.348)	(0.0448)	(0.288)	(0.0496)
age	1.042	0.0204	0.104	-0.212
	(1.451)	(0.223)	(1.053)	(0.163)
agesq	-0.0159	0.000581	-0.000295	0.00407
	(0.0246)	(0.00367)	(0.0177)	(0.00275)
marriage	0.129		-1.383***	
	(0.592)		(0.298)	
children	-0.123		-0.699**	
	(0.644)		(0.301)	
inverse Mills ratio		0.527		0.0650
		(0.389)		(0.0660)
Constant	-14.84	6.022*	-1.265	9.564***
	(21.20)	(3.386)	(15.51)	(2.385)
Observations	321	275	330	230
R-squared		0.231		0.240

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Japan

VARIABLES	(1) Men Logit First Step	(2) Men Mincer Second Step	(3) Women Logit First Step	(4) Women Mincer Second Step
sdt_num	0.133	0.164***	-0.0450	0.172***
	(0.204)	(0.0339)	(0.139)	(0.0270)
college	0.0226	0.177**	0.661**	0.359***
	(0.445)	(0.0728)	(0.275)	(0.0693)
age	-1.609	0.176	-1.271	0.447**
	(1.225)	(0.193)	(0.978)	(0.224)
agesq	0.0267	-0.00245	0.0240	-0.00689*
	(0.0207)	(0.00327)	(0.0165)	(0.00380)
marriage	1.301***		-0.259	
	(0.366)		(0.266)	
children	0.646*		-0.906***	
	(0.387)		(0.296)	
inverse Mills ratio		-0.342***		-0.0772
		(0.114)		(0.125)
Constant	24.23	-0.208	17.37	-4.507
	(17.95)	(2.825)	(14.41)	(3.232)
Observations	297	236	413	251
R-squared		0.345		0.453

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: US

These are the estimation results for the US using the revised Mincer regression coefficients.

	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**			
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
						Data						
U	0.422	-0.570	1.716	0.164	0.177	0.537	0.119	1.499	0.149	0.331	0.049	na
						Two-Step						
U	0.373	-0.560	1.716	0.121	0.158	0.489	0.129	1.500	0.137	0.331	0.047	0.007

Note: This table reports data and simulated moments for the estimated model for the US using the two-step procedure.

Table 27: Moments: Two-Step

8.5.2 Allowing $\bar{e}$ to Depend on Country and Gender

This sub-section shows the estimation results allowing $\bar{e}$ to depend on gender and country.

	Men					Women					
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$h^w(0)$
	Estimates										
U	5.025	0.171	0.253	0.658	0.911	6.123	0.355	0.108	0.931	1.000	0.818

Note: This table reports parameter estimates for the US using the two-step procedure. See Table 13 for other parameter definitions.

Table 28: Parameter Estimates : Two-Step

	Men							Women								
	Education			**Mincer Reg.**		**Participation**		**Education**			**Mincer Reg.**		**Participation**			
	ed	χ_0	χ_s	α_s	α_e	part no ed	part ed	ed	χ_0	χ_s	α_s	α_e	part no ed	part ed	wage gap	fit
	Data															
G	0.331	-0.994	1.395	0.111	0.239	0.756	0.786	0.430	-0.480	1.108	0.128	0.199	0.525	0.641	0.165	na
I	0.189	-2.130	1.734	0.061	0.210	0.705	0.623	0.303	-0.880	0.443	0.085	0.208	0.476	0.537	0.053	na
J	0.596	0.243	0.921	0.091	0.022	0.858	0.886	0.695	0.706	0.732	0.098	0.198	0.634	0.745	0.110	na
U	0.422	-0.570	1.716	0.155	0.162	0.762	0.795	0.537	0.119	1.499	0.149	0.331	0.555	0.726	0.049	na
	Baseline: Participation															
G	0.313	-0.989	1.393	0.098	0.199	0.692	0.826	0.397	-0.476	1.105	0.133	0.204	0.542	0.659	0.164	0.010
I	0.159	-2.128	1.727	0.081	0.177	0.592	0.689	0.297	-0.882	0.435	0.080	0.224	0.467	0.537	0.069	0.020
J	0.542	0.254	0.918	0.050	-0.007	0.863	0.877	0.652	0.707	0.722	0.197	0.226	0.621	0.737	0.157	0.021
U	0.382	-0.564	1.715	0.110	0.109	0.727	0.838	0.499	0.126	1.500	0.201	0.328	0.561	0.728	0.062	0.014
	Same $h^w(0)$															
G	0.313	-0.989	1.393	0.098	0.199	0.692	0.826	0.240	-1.498	1.450	0.114	0.112	0.540	0.656	0.048	1.219
I	0.159	-2.128	1.727	0.081	0.177	0.592	0.689	0.290	-0.916	0.435	0.079	0.206	0.467	0.532	0.068	0.021
J	0.542	0.254	0.918	0.050	-0.007	0.863	0.877	0.267	-1.219	1.194	0.125	-0.001	0.616	0.708	-0.148	4.216
U	0.382	-0.564	1.715	0.110	0.109	0.727	0.838	0.218	-1.731	2.275	0.151	0.112	0.562	0.710	-0.155	4.225
	Same $(\bar{\varepsilon}, \mu(\varepsilon))$															
G	0.313	-0.989	1.393	0.098	0.199	0.692	0.826	0.189	-1.993	1.637	0.107	0.359	0.540	0.731	-0.018	2.701
I	0.159	-2.128	1.727	0.081	0.177	0.592	0.689	0.089	-3.011	1.464	0.052	0.363	0.467	0.600	-0.135	5.713
J	0.542	0.254	0.918	0.050	-0.007	0.863	0.877	0.702	0.898	0.474	0.212	0.193	0.618	0.727	0.210	0.133
U	0.382	-0.564	1.715	0.110	0.109	0.727	0.838	0.484	0.154	2.307	0.190	0.350	0.563	0.737	0.028	0.668
	Same λ															
G	0.313	-0.989	1.393	0.098	0.199	0.692	0.826	0.450	-0.202	0.262	0.142	0.117	0.541	0.615	0.323	0.835
I	0.159	-2.128	1.727	0.081	0.177	0.592	0.689	0.400	-0.407	0.196	0.080	0.215	0.467	0.527	0.105	0.317
J	0.542	0.254	0.918	0.050	-0.007	0.863	0.877	0.523	0.092	0.214	0.195	0.215	0.617	0.727	0.222	0.703
U	0.382	-0.564	1.715	0.110	0.109	0.727	0.838	0.515	0.082	0.548	0.200	0.326	0.562	0.705	0.132	0.927

Note: This table reports data and simulated moments for the model with participation. See Table 14 for a full list of other variables.

Table 29: Moments: Participation

8.6 Discrimination

	Men							Women							
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	μ_h	$\bar{h}$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	μ_h	$\bar{h}$	$h^w(0)$
	Baseline: Participation														
G	5.201	0.006	0.356	0.527	0.921	-0.804	2.098	4.524	0.008	0.477	0.465	0.795	-0.170	2.089	0.823
I	6.589	0.254	0.332	0.998	0.940	-0.323	1.789	7.310	0.501	0.353	0.986	1.058	0.142	2.135	0.980
J	7.084	0.194	0.510	0.879	0.715	-0.895	1.230	3.431	0.003	0.455	0.355	0.588	-0.453	1.963	0.584
U	5.748	0.043	0.414	0.632	0.920	-0.875	1.930	4.069	0.153	0.407	0.620	0.815	-0.248	2.032	0.677
	Baseline														
G	3.774	0.270	0.096	0.522	0.853	na	na	5.131	0.443	0.141	0.764	0.942	na	na	0.953
I	6.550	0.321	0.114	0.800	0.944	na	na	5.826	1.154	-0.208	0.940	1.021	na	na	1.000
J	6.972	0.218	0.458	0.757	0.864	na	na	6.274	0.030	0.302	0.531	0.775	na	na	0.766
U	5.057	0.169	0.258	0.659	0.908	na	na	6.248	0.352	0.108	0.946	1.002	na	na	0.814

Note: This table reports parameter estimates for the model with participation. See Table 13 for other parameter definitions.

Table 30: Parameter Estimates : Participation

	Education		Mincer Reg.			Education		Mincer Reg.				
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
	Data											
G	0.331	-0.994	1.395	0.111	0.239	0.430	-0.480	1.108	0.128	0.199	0.165	na
I	0.189	-2.130	1.734	0.061	0.210	0.303	-0.880	0.443	0.085	0.208	0.053	na
J	0.596	0.243	0.921	0.091	0.022	0.695	0.706	0.732	0.098	0.198	0.110	na
U	0.422	-0.570	1.716	0.155	0.162	0.537	0.119	1.499	0.149	0.331	0.049	na
	Baseline											
G	0.299	-0.992	1.395	0.137	0.251	0.382	-0.472	1.107	0.136	0.192	0.151	0.005
I	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
J	0.545	0.254	0.919	0.086	0.028	0.654	0.716	0.730	0.078	0.196	0.108	0.005
U	0.373	-0.564	1.716	0.120	0.154	0.489	0.131	1.496	0.135	0.332	0.048	0.006
	Country and Gender Specific $\bar{e}$											
G	0.299	-0.989	1.401	0.135	0.239	0.387	-0.472	1.108	0.123	0.198	0.162	0.004
I	0.164	-2.127	1.734	0.067	0.207	0.298	-0.879	0.444	0.089	0.211	0.057	0.001
J	0.544	0.255	0.920	0.098	0.028	0.653	0.715	0.729	0.097	0.192	0.104	0.005
U	0.371	-0.560	1.716	0.133	0.165	0.491	0.130	1.495	0.143	0.325	0.048	0.006

Note: This table reports data and simulated moments for the estimated models in which $\bar{e}$ is dependent on gender and country.

Table 31: Moments: $\bar{e}$

	Men					Women					
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$\bar{e}^w$
	Estimates										
G	3.828	0.266	0.109	0.529	0.848	5.411	0.308	0.152	0.702	0.926	0.707
I	6.562	0.321	0.115	0.801	0.944	5.857	1.157	-0.209	0.981	1.017	0.754
J	6.329	0.287	0.450	0.777	0.848	6.434	0.088	0.171	0.607	0.798	0.545
U	4.671	0.201	0.230	0.651	0.902	5.799	0.365	0.155	0.867	1.005	0.829

Note: This table reports parameter estimates for the model matching wage gaps. Here $\bar{e}^w$ is the time to complete college for women. See Table 13 for other parameter definitions.

Table 32: Parameter Estimates : $\bar{e}$

	Men					Women						
	Education			**Mincer Reg.**		**Education**			**Mincer Reg.**			
	ed	χ_0	χ_s	α_s	α_e	ed	χ_0	χ_s	α_s	α_e	wage gap	fit
	Data											
G	0.331	-0.994	1.395	0.111	0.239	0.430	-0.480	1.108	0.128	0.199	0.165	na
I	0.189	-2.130	1.734	0.061	0.210	0.303	-0.880	0.443	0.085	0.208	0.053	na
J	0.596	0.243	0.921	0.091	0.022	0.695	0.706	0.732	0.098	0.198	0.110	na
U	0.422	-0.570	1.716	0.155	0.162	0.537	0.119	1.499	0.149	0.331	0.049	na
	Baseline: Gap											
G	0.299	-0.992	1.395	0.137	0.251	0.382	-0.472	1.107	0.136	0.192	0.151	0.005
I	0.164	-2.127	1.735	0.067	0.207	0.298	-0.879	0.443	0.089	0.207	0.052	0.001
J	0.545	0.254	0.919	0.086	0.028	0.654	0.716	0.730	0.078	0.196	0.108	0.005
U	0.373	-0.564	1.716	0.120	0.154	0.489	0.131	1.496	0.135	0.332	0.048	0.006
	Discrimination											
. G	0.320	-0.730	1.202	0.203	0.201	0.325	-0.704	1.269	0.214	0.219	0.068	0.221
I	0.204	-1.417	1.173	0.182	0.206	0.193	-1.483	1.054	0.158	0.173	-0.146	1.631
J	0.598	0.467	0.800	0.195	0.057	0.602	0.491	0.841	0.208	0.061	0.093	0.175
U	0.428	-0.228	1.600	0.206	0.241	0.430	-0.221	1.620	0.209	0.247	0.022	0.292

Note: This table reports data and simulated moments for the model with discrimination. See Table 14 for a full list of other variables. Full time employees

Table 33: Moments: Discrimination

	Men					**Women**					
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	z
	Baseline: Discrimination										
G	1.987	1.654	-0.462	0.998	0.533	1.987	1.654	-0.462	0.998	0.533	-0.110
I	2.365	1.320	-0.592	0.992	0.603	2.365	1.320	-0.592	0.992	0.603	0.269
J	2.809	1.152	0.504	0.823	0.603	2.809	1.152	0.504	0.823	0.603	-0.107
U	1.731	1.866	-0.207	0.875	0.512	1.731	1.866	-0.207	0.875	0.512	-0.039

Note: This table reports parameter estimates for the model with discrimination. See Table 13 for other parameter definitions.

Table 34: Parameter Estimates : Discrimination