Implications of Policy Interventions on Eliminating Gender Gaps*

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Abstract

This paper studies policy interventions intended to eliminate gender differences in labor market outcomes, principally wages. It studies these policies through an estimated model of statistical discrimination with dynamic choices of education and labor market participation. The estimated model succeeds in matching observed gender gaps in wages, college attainment rates, the college premium and labor market participation rates. Introducing the various interventions into the estimated model allows us to quantify both the intended and unintended consequences of the policies. In the short run the policy that requires gender free applications in the market for skilled labor eliminates wage gaps but once education choices respond, the effects are attenuated. A more comprehensive policy that enforces gender free compensation reverses the wage gap in skilled markets and eliminates it in unskilled labor markets. These interventions impact college rates, the college premium gap and participation rates as well. The effects are country specific reflecting underlying differences in estimated parameters by gender across countries.

1 Motivation

This paper studies the impact of interventions intended to eliminate gender differences in labor market outcomes, principally wages. These types of policies have been implemented among a broad range of economies in the past decades and fall broadly into two classes.[1] The first focuses on quantities like gender differences in participation rates and job assignment. The second one, focusing on wage gaps, intervenes directly on compensation. An extreme version of such an intervention would simply stipulate equal pay. A more subtle intervention would eliminate information about gender in the application process, so that neither job assignment nor compensation would (initially) be gender dependent.[2]

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[1]The OECD provides detailed information on gender issues, ranging from facts to policy interventions.

[2]As discussed, a similar experiment in a different model is explored in Lundberg and Startz (1983).

Characterizing the effects of these policies requires an equilibrium model: a counterfactual requires changes in the institutional structure relative to a baseline. A model serves two purposes. First, it allows us to evaluate not only the effects on the targeted gap but also on other dimensions. An intervention, say to reduce a wage gap, might impact other gender differences as changes in the labor market compensation can affect other individuals decisions like the education and the participation one. Second, a model facilitates the distinction between the short and long-run effects of the policy. Consider a policy intended to eliminate gender differences in compensation of skilled workers. Since education decisions were probably made before the intervention, we might be interested in understanding the impact on the wage gaps for the current population, given those education decisions. However, the intervention effects the return to college, thus changing incentives. Once agents choices respond to the new compensation structure, the effects on the wage gap can be mitigated or amplified, in part through changes in the distribution of agents choosing college. Ignoring the responses to these incentive effects would lead to an inaccurate assessment of the policy.

The analysis focuses simultaneously on four types of gender differences.[3] The first is the traditional wage gap, indicating that men are generally paid more than women, conditional on education. The second is the difference in the college attainment rate which is higher for women than men in a broad range of countries. The third is the difference across genders in the return to college, measured as the college premium. For all of the countries in our sample, the compensation to college workers exceeds that of non-college workers, i.e. the college premium is positive. In most of our countries, this premium is higher for women than men. This is termed a college premium gap. Finally, there are differences in labor force participation rates by gender, given educational attainment.[4] To be sure, these gaps have been documented in numerous studies. For policy intervention, it is important to study them simultaneously through an equilibrium model.

With these considerations in mind, our goal is to understand what are the equilibrium effects on gender gaps of policies intended to eliminate one of these gaps? The paper makes two contributions: (i) our estimated model is able to explain these four gaps simultaneously and (ii) we are able to analyze short- and long-run effects of anti-discrimination policies on the four gaps.

We pose and estimate an equilibrium model of statistical discrimination. The economic analysis of labor market discrimination has produced two general types of models: "taste" discrimination and informational or "statistical" discrimination. Taste discrimination models, such as Becker (2009), produce wage differentials based on the preferences of majority employers, employees, and customers. Statistical discrimination models, on the other hand,

[3]This comprehensive view is consistent with the OECD perspective of looking at the joint determination of many dimensions of gender inequality.

[4]In our model and data analysis, we do not distinguish between participation and employment rates : agents are either employed or not. There is no part-time employment nor distinction between being out of the labor force and unemployment.

demonstrate that treating two groups of workers differently may be the rational response of firms to uncertainty about an individual's productivity. In this case, persistent wage differentials may arise between workers with the same productivity who belong to different identifiable groups, even in competitive markets.

Our model entails a couple of key components. Individual agents make education and labor force participation decisions given expected labor market returns. These returns will depend on the beliefs of firms about workers productivity given their education and a signal of ability. The beliefs of firms are consistent with the choices of the agents: the analysis is about the equilibrium outcome of an economy with imperfect information. The equilibrium entails statistical discrimination in that workers who differ only in gender can be evaluated differently. Thus, the discrimination is not arising from "tastes" but is rather emerging from differences in conditional expectations of worker productivity given public signals and educational attainment. The model allows underlying parameters of tastes, ability, productivity in skilled and unskilled jobs, home production and the informativeness of the labor market signals to differ by gender and these differences generate the equilibrium statistical discrimination.

The quantitative analysis focuses on four main OECD countries: Germany, Italy, Japan and the US. From the findings reported in Cervantes and Cooper (2024), while these countries exhibit gender gaps, the source of these gaps seems to differ. For example, the college attainment rate for women exceeds that of men in all of these countries but the college premium is higher for women only in Japan and the US. Thus these gaps come from different sources in these countries and consequently policy interventions may operate very differently across them.

Moments from these four countries are used to estimate parameters. Both the moments and parameters are gender specific and the baseline estimation matches pretty well our four gaps. The various interventions are conducted as counterfactuals of the estimated model. As this is an equilibrium model, the full effects of the policy on choices and beliefs can be evaluated.

Among the experiments, there are a few results to highlight. First, with the exception of Italy, a policy that enforces gender free compensation and assignment of skilled workers can effectively reduce the wage gap among educated workers.[5] However, the magnitude of those effects varies from the short to the long run. That is, given education decisions, the policy will eliminate or even reverse the wage gap but once education decisions respond, the effects on the wage gap are smaller. The policy reduces the college premia for men and thus their education rates are lower in Germany, Japan and the US. A more comprehensive policy that eliminates the wage gap for both skilled and unskilled workers, succeeds in reversing the wage gap in skilled markets. Other responses are country specific. For example, under this policy, the gender gaps in the college premium, college rates and participation rates are reduced by more than 50% in the US. In contrast, for Germany the college rate gap more than doubles under the comprehensive policy and in Italy the policy leads to an increase in the wage

[5]As discussed, Italy is an interesting exception as the ordering of productivity gains from education are larger for women than men, in contrast to the other countries.

gap. A contribution of the paper is to understand these differential responses to the policy interventions.

1.1 Related Literature

This paper is related to two lines of inquiry: (i) the role of statistical discrimination in creating gender gaps and (ii) effects of policies to offset these gaps. Central contributions to those lines of inquiry are discussed here. Other papers that are related in terms of methods and findings are discussed in the text.

Gender Gaps On compensation gaps, Goldin (2014) argues that wage gaps reflect differences in willingness to accept job flexibility. 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. On college attainment, Goldin, Katz, and Kuziemko (2006) provides evidence on the evolution over time of the college education rate of women compared to men. Our paper adds to these studies by looking at the four gaps simultaneously through a model that allows to evaluate equilibrium effects of different policies.

Cervantes and Cooper (2024) provides an extensive discussion of the various contributions towards understanding the sources of gender gaps. Their main contribution is to study gender gaps in education, the college premium and wages for skilled workers jointly. The sources of these gaps are inferred from counterfactuals of an estimated model of college choice and labor market outcomes. This paper adds two elements to the companion paper. First, the model is enhanced to include a labor market participation choice that allows us to look at gender differences in this dimension. Second, the focus here is on the impact of labor market policies for the gender gaps rather than the source of those gaps. These two elements tie together since it is of interest to determine how, for example, policies that impact the gender way gap will effect labor market participation rates.

Gender Policies and Statistical Discrimination Lundberg and Startz (1983) is a leading paper on the study of gender policies. The paper starts by asking: "Do laws forbidding discrimination reduce allocative efficiency?" Their approach is to undertake a policy analysis in a model with statistical discrimination. They study the education choice of agents as dependent on labor market outcomes. In their model, agents fall into two groups. By assumption, signals of productivity are more informative for one group than the other. They impose a requirement that compensation be gender free though it is allowed to depend on the signal. They find that net output may rise due to the policy intervention as training costs are shifted from high to low marginal cost workers. In contrast, our model produces statistical discrimination based on gender differences that include the informativeness of a signal as well as other dimensions.

Further, in our setting education plays a distinct role from other sources of informative about a worker's productivity, as in the Lang and Manove (2011) study of racial disparities through statistical discrimination. Additionally, our model is estimated to match data moments which, among other things, allows us to infer the relative informativeness of gender specific signals.

Coate and Loury (1993) focuses on the effects of affirmative action in a model economy with two groups distinguished by race. Agents are *ex ante* homogenous but in an equilibrium with statistical discrimination, they are treated differently. This arises from the multiplicity of equilibria, as in Spence (1973), rather than differences in fundamentals across groups.. They too have imperfect information where firms receive a single signal about worker productivity. The equilibrium is characterized by a standard such that agents are assigned high skilled jobs iff their score exceeds the standard. The multiplicity simplifies to the existence of multiple self-fulfilling standards. The policy is a quantity intervention directed towards assignment of agents to skilled jobs insuring that the same fraction of agents are assigned to skilled jobs regardless of group identity. They provide conditions such that affirmative action eliminates differential treatment but also provide an example in which racial identity continues to matter. For their analysis, wages play a minor role: they are exogenous not allowed to adjust in response to the policy innovation.[6] In contrast, wage determination is key to our model. Further, we estimate differences across genders that underlie the different outcomes: the equilibrium given gender is unique in our model.

There are several empirical studies about the effects of anonymous job application on labor market outcomes. The vast majority estimate the effects of hiding applicants' characteristics such as name, race or sex during hiring processes to avoid group-based discrimination ((Goldin and Rouse (2000) and Aslund and Skans (2012), Ehaghel, Crépon, and Barbanchon (2015), Rinne (2018)). Their findings are consistent with positive effects on the labor market outcomes of workers from minority groups. Similar conclusions are drawn from Kuhn and Shen (2023) who studied the elimination of explicit gender requests from job adds in a Chinese job board. However, this effects usually come from an increase in call-backs and hiring rates, but not on final compensation or changes in human capital investment decisions.

Closer to the goal of this project, there is a second strand of the literature that focuses on the impact of non-discriminatory policies that enforce equal wages among comparable workers regardless of their gender, race and ethnicity. Altonji and Blank (1999) summarizes the findings about the effects of related civil right policies in the US (e.g. Equal Pay Act in 1963 and the Civil Rights Act of 1964) on race and gender differentials and conclude that there is reasonably strong evidence that they helped in closing gender and race gaps in terms of wages, employment and occupations during the 1960s and 1970s. More recently, Cruz and Rau (2022) analyze the effects on firm specific gender pay gap of Chile's 2009 Equal Pay for Equal Work Law. Through the estimation of a wage model with individual and firm fixed effects, the authors compute

[6]To what extent their results depend on these restrictions on wages is not clear.

firm-specific pay premium for males and females in connected firms before and after the law. Using a difference-in-differences analysis, they found that the law helped to reduce the gender pay gap explained by firms by 6.1%. Moreover, they show that those results correspond to the law effects on bargaining power (workers' ability to extract firm rents when negotiating wages) rather than on sorting (female workers sorting into low-pay firms). Specifically on the effect of gender pay transparency policy, Bennedsen, Simintzi, Tsoutsoura, and Wolfenzon (2019) uses a 2006 legislation change in Denmark to analyze the impact on gender pay gaps. The law requires firms to provide gender disaggregated wage statistics. They found that the law reduced the gender pay gap, primarily by slowing the wage growth for male employees.

Our goal is also to estimate the effects of non-discriminatory policies on gender gaps. However, the approach is very different. The estimated model allows us to simulate the implementation of those policies by running counterfactual experiments and computing the resulting equilibrium to fetermine the implied changes in wage gaps and education rates by gender.

2 Facts

This section has two goals. First, we quantify the four gender gaps for the countries in our sample. Second, we construct the key moments that are subsequently used for model estimation and the conduct of the policy experiments.

We use the PIAAC data from the OECD Survey of Adult Skills.[7] The data was collected between 2011 and 2012. A key element of the data is the administration of a common set of tests used to assess proficiency. Our analysis uses the numeracy score as a signal of ability that impacts both education choices and labor market outcomes. We select a sample of relatively young agents, aged 25-34. These individuals are more likely to be subject to the information frictions that underlie the analysis. The education and labor market experiences of these agents reflects more current attitudes about gender roles.

As in Cervantes and Cooper (2024), the analysis focuses on four key countries: Germany, Italy, Japan and the US. These countries are of interest not just due to their prominence but also they exhibit different patterns of gender gaps and thus requiring different explanations for these data patterns. As we shall see, these countries will respond differently to the policy interventions. We divide our sample into two groups to define educational attainment: individuals without a college degree and those with college or a higher degree. To do so, we rely on the International Standard Classification of Education (ISCED).

2.1 Gender Gaps

Table 1 summarizes measured gender gaps in the data.[8] Explaining the source of the gaps in college attainment, the college premium and wages was the focus of Cervantes and Cooper

[7]The data is presented and described at `https://www.oecd.org/skills/piaac/data/`.

[8]These gaps are always presented as the value for men less that of women.

(2024). Here the gaps are used to motivate the policy interventions and as a measure of the effects of those interventions.

The negative college rate gap for the four countries indicates that the college attainment rate for women is larger than that of men in our countries. Here we focus on college attainment not admissions.[9]

The college premium gap is positive in Germany and Italy but negative in both Japan and the US. The college preium is measured as the difference between the mean log wage of college less that of non-college workers. The college premium gap is the difference between the college premium of men and that of women. This gap is important in understanding the relative incentives for attaining a college degree. In this regard, Germany and Italy exhibit higher college rates for women but a positive college premium gap, making clear that there are other forces determining education choice.

The wage gap is positive in all countries. This is measured as mean log wage of men minus the mean log wage of women. As discussed later, this summary statistic comes from the interaction of a wage function, describing compensation as a function of observables, and the gender specific distribution across those observables.

The final two gaps are related to labor force participation.[10] The participation rate of men exceeds that of women in all countries and for both the non-college and college groups.[11]

Taken together these gaps play two roles in our analysis. First, they motivate the policy interventions. Most frequently, these measures focus on narrowing the wage gap, which is positive for all of our countries. But clearly these are not the only gender differences. Second, the larger perspective allows us to consider the impact of interventions on other gaps, not just wages alone. Through the equilibrium of the model, interventions to reduce one gap will impact the others.

2.2 Moments

The estimated model parameters are determined to match the key moments shown in Table 2. These moments capture, by gender, three key elements of education and labor market experience: (i) college choice, (ii) wages and (iii) labor market participation.

There are three moments summarizing the education choice. The first is the college rate. The second two moments are the coefficients of a logistic regression that links the college choice to a test score. That regression is given by:

[9] College attainment is a dichotomous variable based on ISCED classification, with 5 and above indicating college. As discussed in Cooper and Liu (2019), this measure can include trade and technical school training.

[10] The participation rate gaps were not included in Cervantes and Cooper (2024).

[11] As pointed out to us by Anne Hannusch and Michele Tertilt, these are lower than standard reported participation rates. This is because we are equating employment (full time) with labor force participation rates.

	Germany	Italy	Japan	US
Gaps	Data			
College Rate	-0.099	-0.124	-0.099	-0.135
College Premium	0.095	0.053	-0.152	-0.132
Wage (non college)	0.070	0.007	0.262	0.181
Wage (college)	0.165	0.053	0.110	0.049
Participation (non college)	0.23	0.23	0.23	0.20
Participation (college)	0.14	0.08	0.14	0.07

This table reports the education, college premia, wage and participation rate gaps in the data. These gaps are measured as the value for men less that of women.

Table 1: Determinants of Education, College Premia, Wage and Participation Gaps

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

Here s is a (standardized) numeracy test score reported in the PIAAC data. We interpret it as a noisy measure of ability. As explained, there is a model counterpart interpreted as a signal of ability. The coefficient estimates are shown in Table 2. The college choice is increasing in the test score, indicating positive selection on the score.

The moments called "Mincer Reg" come from a regression of individual wages on education age and our proxy of ability. The regression is given by

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

The coefficients (α_e, α_s) are used as target moments in the estimation of the model to capture the response of wages to education and signals of ability. These coefficients are gender and country specific. The coefficients are all positive indicating a return to both education and the signal, though for Japanese males the education coefficient is quite small.[12] We do not directly interpret these coefficients, but use the estimated model to do so.

The moments include the participation rates, for both college and non-college workers. There are two patterns. First, participation rates are higher for college than non-college graduates. Second, the participation rates are higher for males in both education categories in the four countries. Finally, the wage gap conditional on college is also included in the model estimation.

It is useful to make clear the distinction between model moments and the gaps. Both summarize data patterns. The estimation is based upon the moments, in line with other papers the model generated gaps are created from simulated data given the estimated parameters. The counterfactuals are constructed from simulations under alternative policies at the baseline parameters.

[12]See Table 11 for the full estimation results.

	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
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
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
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
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

Note: This table reports data moments by gender and country.

Table 2: Data Moments

3 Model

We study a dynamic economy populated by workers and firms.[13] The model provides a structure for interpreting the moments and is used, through counterfactuals, to study the impact of policy interventions on gender specific education and labor market outcomes.

Workers are of two gender types. Given their ability, θ, and preferences over education they make a college decision: either to attend $e = 1$ or not $e = 0$. After finishing their education workers draw a signal of ability, s, and a home productivity shock, ζ_h. Only college educated workers can access skilled jobs where productivity depends on ability. Firms do not observe ability directly, but rather base their wage offers on the noisy signal, s, and educational attainment.[14] After their labor market signal and home productivity are revealed, workers decide whether to accept the offer or to not participate at all. Thus the model captures these two important worker choices: (i) education and (ii) participation.

Firms pay workers their expected marginal product given information, obtained by observing education and signals about worker's ability. Importantly, firms observe gender and condition expectations and hence compensation on gender. From this, compensation, job assignment and consequently education outcomes are driven by statistical discrimination in the labor market.

3.1 Firms

Firms have access to two technologies. One, termed high skilled, uses college educated workers to produce output. The technology is given by $h(1)\theta$, where $h(1)$ captures the productivity of college workers. Note that both education and ability determine output and they are complementary. The second job, a low skilled task, generates a level of output that is independent of ability, denoted $h(0)$. Both college and non-college workers are productive in low skill tasks while only college workers are productive in high skill tasks.[15] Both productivity parameters $h(0)$ and $h(1)$ are gender specific.

Firms do not observe workers' ability directly but instead infer ability from observing edu-

[13]This adds an *ex post* participation decision to Cervantes and Cooper (2024).
[14]Differ here from some papers as we have two not one signal.
[15]A non-college worker assigned to a high skill task would produce $h(0)$.

cation 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, $\bar{\theta}$. Though omitted from the notation, the informativeness of the signal, captured by λ is one of the potentially key gender differences.

Given the signal and the education level firms assign workers to either high or low skill tasks. As markets are competitive, firms offer workers their expected product given the signal:

$$w(e,s) = \begin{cases} \omega(s) = max(h(1)E(\theta|s), h(0)) & e = 1 \\ h(0) & e = 0. \end{cases} \tag{4}$$

The first component is for college workers, i.e. $e = 1$.[16] These agents receive a wage offer equal to the max of their productivity in skilled, $h(1)E(\theta|s)$, and unskilled jobs, $h(0)$. The expected productivity in skilled jobs has two components. The first is the productivity parameter for college workers at skilled jobs, $h(1)$. The second is the conditional expectation of ability, given the signal s and the college degree. Importantly, the level of education plays two roles: (i) it allows the access to the skilled job technology (ii) it provides information about ability. This latter effect is determined in equilibrium by the education choices of workers that, of course, will depend on how firms perceive the link between education and ability. For low enough values of the signals the worker is placed at an unskilled job. Both college workers assigned to unskilled jobs as well as non-college workers receive compensation of $h(0)$ independent of any signal. Thus, firms will assign a college educated worker to a skilled task iff $h(1)E(\theta|s) \geq h(0)$.

Though not explicitly indicated, the wages are dependent on gender. Firms observe gender and, in equilibrium, conditional expectations of productivity will be gender specific due to gender differences in the distribution of signals given education.

3.2 Worker Dynamic Choice

This section presents the choice problems of workers given the compensation function and assignment rule of firms. All of these choices are gender specific, though the gender identifier is suppressed in the notation.

Workers of each gender are active for two phases, shown in Figure 1. Individuals are born with innate ability θ and preferences over education. In the first 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

[16] Throughout, $E(\theta|s)$ is the expected value of ability given the signal for college educated workers only i.e $E(\theta|s) \equiv E(\theta|s, e = 1)$.

there is an opportunity cost of education (foregone earnings) 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 time cost of college. In addition, the individual education-specific taste shock, denoted $\varepsilon(e)$, is orthogonal to ability and impacts the education choice.

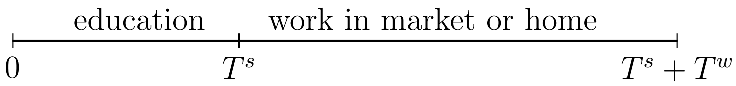


Figure 1: Phases of Household Life Cycle

Following the education phase, agents enter into the labor force and their labor market signal, s, is revealed. Their compensation and job assignment is given in (4). Upon entering the labor market, they draw also a shock that determines their home production. This shock is realized for the non-college agents during the schooling phase as they are not in school. For those going to college, the shock is realized at the start of the work phase. As with the signal, this shock is not known when the education choice is made, rather it is understood by agents as generating a future option. Thus, the college choice is made conditional on ability θ, the taste shock ε and gender. It is given by

$$W(\theta,\varepsilon) = max(W^{ed}(\theta,\varepsilon), W^{noed}) \tag{5}$$

where

$$\begin{aligned} W^{ed}(\theta,\varepsilon) = \tilde{\beta}^{T^s} \left(h(0)(1-\frac{\bar{e}}{\theta}) - p \right) + \\ \beta^{T^s}\tilde{\beta}^{T^w} E_{s,\zeta_h|\theta}\left(\underbrace{max(\omega(s), h(0)+\zeta_h)}_{\text{emp. decision}} \right) + \underbrace{\varepsilon}_{\text{ed. taste}} \end{aligned} \tag{6}$$

and

$$W^{noed} = \tilde{\beta}^{(T^s+T^w)} E_{\zeta_h}\left(max(h(0), h(0)+\zeta_h)\right). \tag{7}$$

The first term of (6) represents the income flow if college is chosen, discounted back to the start of the education phase. The direct cost of tuition is denoted p. The time spent working during college years is proportional to $(1 - C(\theta)) = (1 - \frac{\bar{e}}{\theta})$ so that the opportunity cost of education for a person with ability θ is the product of the time cost, $\frac{\bar{e}}{\theta}$, and the wage for workers without education, $h(0)$.

The second term represents earnings during the work phase. Because the job market signal and the value of home production are realized after the college decisions, these are expected earnings. Notice that ability has two roles in the education decision: it impacts the opportunity cost of college and it gives information about the future signal and thus labor market returns. The ex-post realization of the signal generates options for the college educated worker to either be assigned to a high skill job or a low skill job by the firm contained in $\omega(s)$. Further, they have an option to stay at home, effectively earning $h(0) + \zeta_h$ rather than working at either task.[17]

The final term is a taste shock that impacts the value of education, ε. As with other discrete choice models, this is a choice specific shock independently drawn for each agent. 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.

For individuals not going to college, they retain an option of home production rather than working as an unskilled worker. Workers without a college degree do not have an opportunity to work in a skilled job.

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 for college educated workers as that determines market compensation.[18] All else the same, this selection will increase the average compensation of college educated workers and thus 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 gap.

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.[19]

3.3 Equilibrium

A key component of the model is the compensation function for college educated workers, defined as $\omega(s)$. 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 part of the estimation routine as a consistency requirement between the beliefs of firms about ability of

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

[18]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.

[19]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.

college education workers given the signal, $E(\theta|s)$, and the education choices of the individuals, $Z(\theta, \boldsymbol{\varepsilon}) \in \{0, 1\}$, taking those beliefs as given.

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 generating gender-specific compensation functions. So, as a leading example, the informativeness of the signal, λ, could be gender specific. In that case, $E(\theta|s)$, 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 parameter $h(1)$ 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.[20]

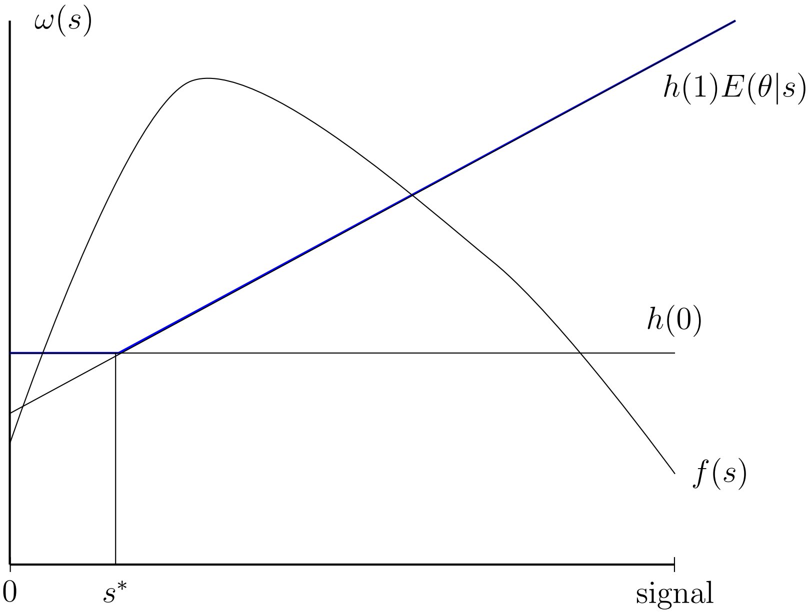
It is important to make clear why gender differences emerge in wages, as well as education rates and job assignments. First, as already mentioned, the parameters throughout are gender specific. These differences in parameters will lead to differences in conditional expectations that underlie the gender specific outcomes. Second, firms observe gender and are able to respond to gender differences, say, in productivity and in the informativeness of the job signal. This is important as one of our policy experiments eliminates the ability of the firm to condition compensation and assignment on gender.

An interesting aspect of the equilibrium outcome is the assignment of college workers to skilled versus unskilled jobs. Agents may go to college and yet work in unskilled jobs either due to an unexpectedly low signal of productivity despite of the agent's relatively high ability or selection induced by a high realization of a taste shock for college despite the agent's relatively low ability.

Figure 2 shows compensation and job assignment for a college educated individual of a given gender. The wage received is the maximum of the expected productivity in the skilled job and the productivity in the unskilled job. The critical test score, s^*, comes from equating these two productivities, $h(0) = E(\theta|s^*)$ and, in this illustration, serves as a cutoff value for the firms job assignment. Only agents with a score above this critical level are assigned to skilled jobs. The vertical axis is the compensation received for a given signal. The distribution across the signals for college educated is indicated by the pdf, $f(s)$. The outcome depends on the schedules as well as the distribution of signals. Since this is the distribution of signals for college workers, the distribution itself is endogenous, reflecting college choice.

Clearly the fact that the elements in this figure are gender specific implies that the critical

[20] 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.



This figure illustrates compensation and the job assignment for a given gender country pair. The wage received is the bold, blue maximum of the compensation from the two jobs. The critical test score level for the assignment is s^*: i.e. the agent is assigned a skilled job iff $s \geq s^*$.

Figure 2: Compensation and Job Assignment : Baseline

value of the signal will generally also be gender specific. Among other things, this allows for an outcome in which the fraction of college educated women in unskilled jobs exceeds that of men.

3.4 Gender Gaps and Policy Implications

The model serves as a basis for generating gender gaps in compensation, education and participation rates. Here we explain the mapping from the model to the gaps. We then discuss through the model the policies.

Gender Gaps In a model without a participation choice, Cervantes and Cooper (2024) argue that a combination of gender specific productivity for non-college workers and social attitudes are the main factors generating gender gaps. Moreover, it is important to keep in mind the role of statistical discrimination: a key to generating these gaps in labor market returns and education decisions is the inability of firms to observe workers productivity and thus the role of inference based upon (gender-specific) education and signals.

Building on these gaps, the main point of our analysis is to study the effects of policy interventions. As noted, these interventions are stylized, highlighting the key channels of various intervention. Further, our focus is on the implications of these interventions rather than their welfare effects. That is, we take these interventions as given rather than motivate them through an inefficiency.

Policy I : Gender Free Applications (GFA) The first policy intervention imposes gender free applications so that firms are unable to condition assignment and compensation on gender in the skilled labor market. Firms do not observe the gender but do observe a signal and the college choice and use all information to compute expected productivity of an applicant for a high skilled job. Although the firm is unable to condition on gender directly, to the extent that the signals are drawn from gender specific distributions, the firm will try to infer gender from the signal.

Specifically, in the market for college educated workers, this policy implies that compensation of an individual with a signal s, denoted $\bar{\omega}(s)$ is given by:

$$\bar{\omega}(s) = max\{E_{j,\theta}[h^j(1)\theta|s], E_j[h^j(0)]\}. \tag{8}$$

where now the expectation is taken not only over θ but over the gender $j \in \{m, w\}$ as well. In that expression,

$$E_{j,\theta}[h^j(1)\theta|s] = p(s)h^w(1)E_\theta[\theta|s, j = w] + (1 - p(s))h^m(1)E_\theta[\theta|s, j = m] \tag{9}$$

and

$$E_j[h^j(0)] = p(s)h^w(0) + (1 - p(s))h^m(0) \tag{10}$$

where p(s) indicates the probability of being a women given the signal s and a college degree. This expression derives from the compensation to a college worker in (4). But, under the policy, compensation is not conditional on gender and hence there is an expectation over gender conditional on the signal, denoted $E_j(\cdot)$. The distribution across signals conditional on education is endogenous and will, in the long run, respond to the policy.

The job assignment under the policy is also embedded in the compensation function. For signals in which the expected productivity of the college education worker in the skilled job exceeds that of the unskilled job, i.e. $E_{j,\theta}[h^j(1)\theta|s] > E_j[h^j(0)]$, then the worker will be assigned the skilled job. The assignment, like compensation, is gender free.

The introduction of the policy can potentially impact job assignment. Under the policy there is a single cut-off score, $\bar{s}^*$, such that the assignment is to a skilled job iff this critical value is exceeded. As noted, in the baseline s^* is gender specific so that the policy has gender specific effects on job assignment relative to the baseline.

In thinking through the implications of this intervention, it is useful first consider the effects with fixed education and then to allow adjustment of the college choice. With fixed education, i.e. in the short run, the compensation function is just a weighted average of the two compensation functions from the baseline. The weights are the conditional probability of gender given the signal. Suppose, as an example, that the expected productivity of college educated males given a signal is higher compared to women. Then pooling through gender free applications will raise the wages of women relative to men. All else the same, this will :

(i) reduce the gender wage gap of college workers, (ii) increase the college premium of women relative to men, and (iii) increase the labor force participation rate of women.

Once education adjusts, then the distributions over the signals and thus the beliefs given the signals will change in the new equilibrium. The initially higher college premium for women will lead to a higher college education rate while the pooling will have the opposite effect for men. There will be selection effects on wages through the revised education choices. With a higher college rate for women, there will be more weight on lower levels of the signal and this will reduce mean wages (increase the wage gap) relative to the results with fixed education. Accordingly, the college premium of women will fall relative to that of men.

Policy II: Wage Equality for All Workers The analysis from Cervantes and Cooper (2024) that uncovers the sources of gender gaps in education and labor market outcomes highlights the importance of gender differences in the productivity of non-college workers. Given this, a natural policy exercise is to explore the implications of imposing wage equality in this market as well. To do so, we set the wage of unskilled women equal to that of men. This policy will have implications for education choices of women since the college premium, all else the same, would be lower since, as indicated in Table 1, the noncollege wage of men exceeds that of women.[21] Of course, in equilibrium, as the selection of women into college changes, so will the inferences about ability and thus the wages of college education women. Further, holding fixed the return to productivity at home, this policy ought to close the participation gap.

4 Quantitative Analysis

The model confronts the data through a simulated method of moments approach. The moments, presented in Table 2, include those that summarize: (i) college rates, (ii) selection into college, (iii) wages and (iv) participation rates.

4.1 Approach and Functional Forms

The estimation finds the parameter vector Θ that solves:

$$\pounds \equiv min_{\Theta}(M^d - M^s(\Theta))W(M^d - M^s(\Theta))'. \tag{11}$$

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 an identity matrix.

The model plays a prominent role in the analysis since it provides the mapping from the parameters Θ to the moments. This mapping comes from: (i) the policy functions at the individual level characterizing education and participation decisions given Θ, (ii) solving for a

[21]The ordering of the noncollege wage holds in the estimated model as well.

(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 (11) is obtained by comparing the model generated moments with the data moments. Again, these moments are gender and country specific. The simulated sample contains $100,000$ individuals to eliminate simulation error.

Parameters There are some functional form assumptions, as in Cooper and Liu (2019) and Cervantes and Cooper (2024), that underlie Θ. First, ability has a Pareto distribution, with a shape parameter denoted ϕ.[22] So the CDF of ability, θ, is given by $1-\theta^{-\phi}$ with a mean of $\frac{\phi}{\phi-1}$, decreasing in ϕ.[23] Second, taste for college and home production shocks are assumed to be uniformly distributed between $[\mu(\varepsilon)-\bar{\varepsilon},\mu(\varepsilon)+\bar{\varepsilon}]$ and $[\mu(h)-\bar{h},\mu(h)+\bar{h}]$ with mean $\mu(\varepsilon)$ and $\mu(h)$, 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.[24] The noise in these test scores are assumed to be uncorrelated with ability.

The out of pocket cost is country specific.[25] 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 $\bar{e}=0.75$.[26]

Given these functional forms, for the baseline estimation, the parameter vector is $\Theta \equiv (\phi,\bar{\varepsilon},\mu(\varepsilon),\lambda,h^w(0),h(1),\mu(h),\bar{h})$. Though not explicit in the notation, the parameters are estimated by gender and country. The productivity and thus compensation of men assigned to unskilled jobs, $h^m(0)$, is normalized to 1.

Moments The moments were presented in Section 2.2. They are informative about underlying structural parameters in Θ. It is a nonlinear equilibrium model so that there is no simple mapping from moments to parameters as a basis for discussing identification. We show that

[22] The scale parameter is set to 1. Identifying this from the productivity gain from college, $h(1)$, is difficult. Thus we set the scale to 1 and interpret $h(1)$ as the composite of the human capital accumulated and the mean ability.

[23] 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.

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

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

[26] From `https://www.oecd.org/education/skills-beyond-school/EDIF_23` the time to completion is roughly the same across countries.

locally these moments are informative about parameters.

4.2 Imposing Equilibrium Beliefs

The estimation involves both the solution of an individual choice problem over education and participation as well as an equilibrium condition for the determination of the wage function. Through competition, wages will equal the expected productivity of the worker conditional on a signal and the education. The inference from the signal and education choice, reflected by $E(\theta|s, e = 1)$, is determined in equilibrium through the selection of workers into education, as in Spence (1973).

We impose structure of beliefs and thus in the determination of wages. We stipulate a wage function for college workers that is quadratic in the signal:

$$\tilde{\omega}(s) = h(1)E(\theta|s) = h(1)[\tilde{\omega}_{con} + \tilde{\omega}_s \times s + \tilde{\omega}_{sq} \times s^2] \tag{12}$$

where $\tilde{\omega} \equiv (\tilde{\omega}_{con}, \tilde{\omega}_s, \tilde{\omega}_{sq})$ are determined in equilibrium.

Specifically, given parameterized beliefs, agents jointly make education decisions which generates a relationship between ability and the signal for college educated workers. From simulated data based upon these choices, we regress ability on the test score conditional on college to obtain estimated coefficients $\hat{\omega} \equiv (\hat{\omega}_{con}, \hat{\omega}_s, \hat{\omega}_{sq})$. When these regression coefficients and beliefs match, i.e $\hat{\omega}$ is close enough to $\tilde{\omega}$, then an (approximate) equilibrium obtains.

An important component is the dependence of these beliefs on gender. That is, coefficients $\tilde{\omega}_{con}, \tilde{\omega}_s, \tilde{\omega}_{sq}$ are gender specific. This is natural given potential gender differences in parameters, and thus choices, along with the fact that in the baseline employers observed gender. Further, the policy interventions will act on these beliefs, either directly say through gender free applications or indirectly by affecting education choices.

There are a couple of points about this approach to make clear. First, this is a quadratic approximation to beliefs so that this is only an approximate rational expectations equilibrium. The closeness of the approximation is captured by the model of the belief function. Second, there is no guarantee that an equilibrium exists nor that it is unique. As seen in the quantitative exercise, we do find approximate equilibria. From experimentation, they are unique.

Finally, the coefficients in these conditional wage functions are affected by two forces. First, they depend on selection into college. The higher the mean ability of college educated workers, for example, the higher the constant $\tilde{\omega}$. This selection into college is of course affected by all parameters of the model. Second, they depend on the informativeness of the labor market signal, λ. If $\lambda = 1$ then s is a perfect signal of ability and $(\tilde{\omega}_{con}, \tilde{\omega}_s, \tilde{\omega}_{sq}) = (0, 1, 0)$. However, if $\lambda = 0$ then the signal of just noise and the constant should be equal to the mean ability of college educated workers conditional con college. Put differently, the noisier the signal, the higher the dependence of compensation on the mean ability of college educated workers, giving relatively low ability agents the incentive to attend. Similarly, the more accurate the signal is, the higher the dependence of compensation on individual signals as it relates with true ability.

4.3 Baseline Estimation

	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								
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	0.547	0.254	0.921	0.080	0.009	0.853	0.897	0.653	0.714	0.728	0.131	0.211	0.659	0.738	0.117	0.007
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

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

Table 3: Moments: Data and Model

Tables 3 and 4 present moments and parameter estimate for the baseline estimation. The fit is 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 gaps in college rates and education coefficients on the Mincer regression are well-matched. Further, the simulated model successes in generating wage gaps that are in accord with the data. Matching the participation rates for men is more difficult: the model moments for noncollege men are below the rates in the data for all countries while the opposite is the case for educated men.

From the parameter estimates in Table 4, a main finding is that the productivity of non-college women is less than that of men in all countries. The difference is particularly large in both Japan and the US and almost nonexistent in Italy. This parameter difference is key for the wage gap and college premium as it has a direct effect on determining gender differences in wage functions. Note too that the informativeness of the job signal, λ is estimated to be lower for women than men in all countries except Japan. This accords with some discussion, such as Lang and Manove (2011), of statistic discrimination based upon noisier signals for women supporting a higher college attainment rate. Finally, notice that in all countries except for Italy the productivity parameter for college educated workers at skilled job, $h(1)$, is higher for men. This difference will be quite important for the analysis of gender free applications.

Looking specifically at the home production option, the mean values of the home productivity shocks, $\mu(h)$, 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.

	Men							Women							
	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$\mu(h)$	$\bar{h}$	ϕ	$\bar{\varepsilon}$	$\mu(\varepsilon)$	λ	$h(1)$	$\mu(h)$	$\bar{h}$	$h^w(0)$
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	6.788	0.091	0.494	0.653	0.848	-1.504	2.129	6.158	0.209	0.497	0.677	0.794	-0.747	2.332	0.704
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

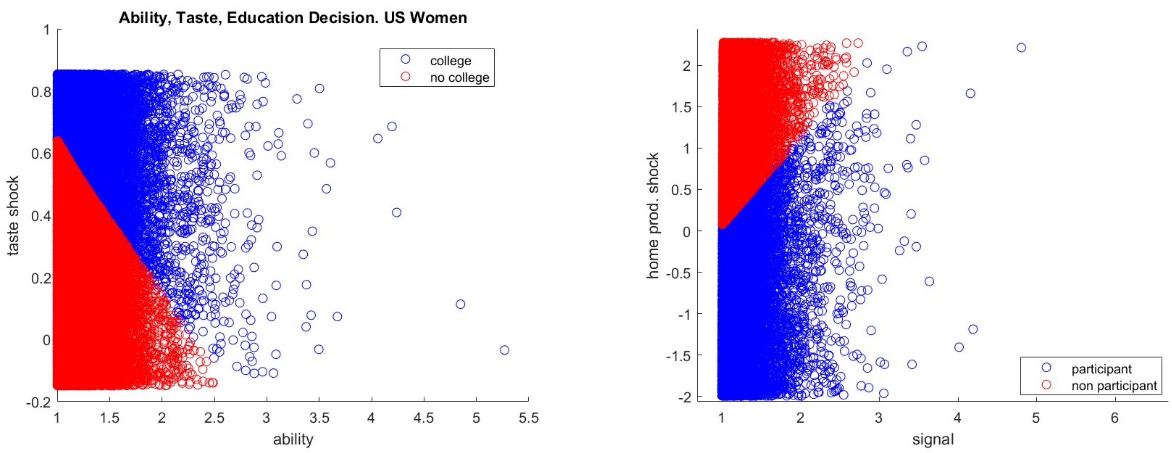
Note: This table reports parameter estimates for the baseline model.

Table 4: Parameter Estimates

4.4 Equilibrium Outcomes: Beliefs and Choices

We use the estimated model to study the equilibrium wage functions and workers' education and participation choices in our baseline specification where firms observe workers' labor market signals, educational attainment and gender.

The way firms form their expectations about workers' productivity has an important impact on gender gaps since it determines compensation at skilled jobs and thus the incentive for attending college. The response of these beliefs to interventions are an important component of the the policy analysis.



(a) Education Decision

(b) Participation Decision

These figures shows the simulated education and participation choices of Italian women.

Figure 3: Education and Participation Choices

Choices Figure 3 shows the education and participation decisions of women in Italy for pairs of ability and tastes. The figures are comparable for other country and gender pairs. The participation decision, on the right, pertains to college educated agents.

For the education decision, on the left, the axes show ability and the taste shock, which are known to agents at the time of the education decision. 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).

The right side of the figure shows the participation choice given the labor market signal and the realized home production shock for college workers. The non participants are in the upper left of the graph: Italian women with high productivity at home and low job market signals are more likely not to participate. The graph illustrates the decision rule which creates two distinct regions in this space.[27]

	Men				Women			
	constant	s	s^2	R^2	constant	s	s^2	R^2
	Baseline							
G	1.310	-0.573	0.512	0.675	1.182	-0.411	0.465	0.647
I	-0.002	1.002	-0.000	1.000	-0.015	1.012	0.000	1.000
J	1.113	-0.616	0.583	0.705	0.672	-0.014	0.380	0.772
U	0.847	-0.093	0.377	0.754	-0.182	1.069	0.071	0.866

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

Beliefs Table 5 reports the equilibrium beliefs, i.e. as given in (12), for the estimated model. The fit of the quadratic model is very good. The R^2 measure is 100% for Italian men and women Note that for Italy the coefficient on the score is 1 and other coefficients are zero. This is in accord with the estimated value of λ near 1. The fit falls to 64.7% for German women.

Figure 4 shows the mapping from signals to beliefs about ability by gender and country for college educated workers, i.e. those with a college degree who choose to participate in the labor market.[28] The distributions across the signals for this group are shown as well. These distributions are gender specific, reflecting differences in choices and in parameters.

Figure 4 is evidence of statistical discrimination. By statistical discrimination, expected ability depends on gender, not just education and the signal. For the estimated model, there is essentially no differences in expected ability across genders given a signal in Germany and Italy. That is, the two curves essentially coincide.[29] In both Japan and the US, there are

[27]The regions are distinct as there are no additional shocks that impact this choice.

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

[29]Here the findings differ from those reported in Cervantes and Cooper (2024) where there were differences in beliefs in both Germany and Italy. This is due to the inclusion of the participation margin in this model.

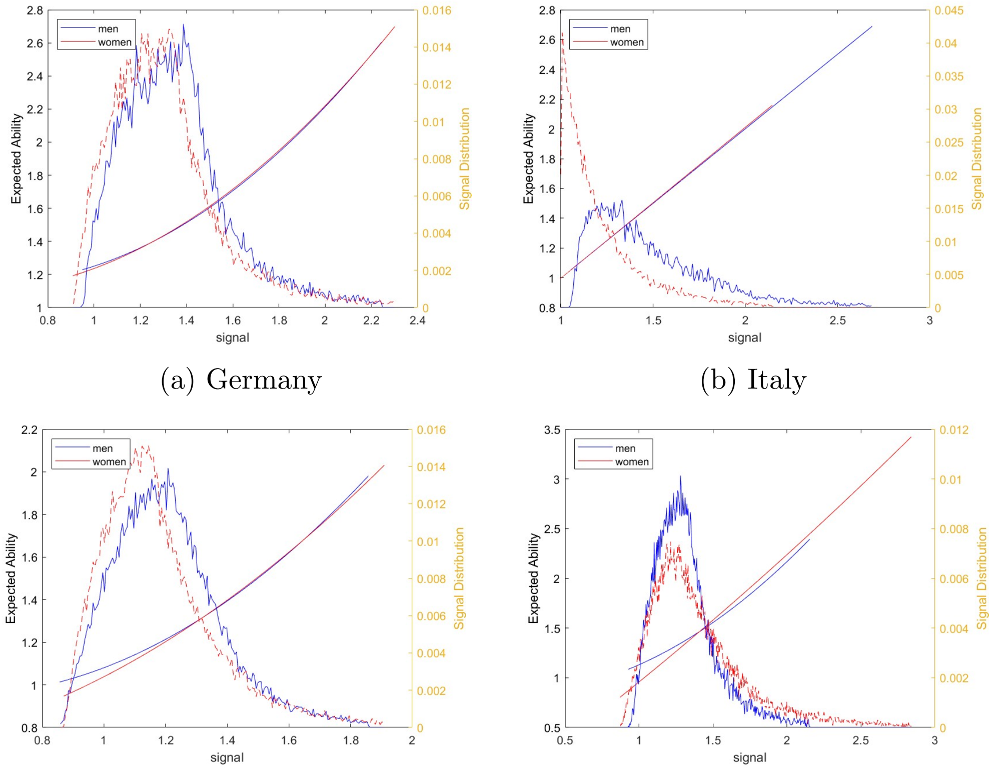
gender differences in beliefs given the signal. For the US, the curves cross so that expected ability of men with a college degree exceeds that of women for low but not for high signals.

There are also differences across genders in the distributions of the signal conditional on education and employment. In all countries, the distributions of the signal put more weight on low signals for college women. Except for the US, there is also more weight on high signals for men. There are a number of factors that can contribute to these differences in distributions. First, there is selection into education based upon ability. All else the same, a higher college rate for women implies that relatively lower ability women select into college. If signals are not too noisy, so that their distribution is close to that of true ability, then there will be a larger fraction of women with college degrees and low ability and thus labor market signals . Second there is the selection based on the participation choice. The lower participation rates of women imply that those with low signals are more likely to work at home rather than accept a low wage in a skilled job or be assigned to an unskilled job. Third, in our model, tastes also impact the education decision. From Table 4 there is significantly more dispersion in taste for women compare to men which increases the probability of women with relatively low ability/signal and relatively high taste selecting into college. Finally, note that the domain of the signal is also gender specific due to differences in ϕ and λ.

To be clear, these beliefs and the consequent statistical discrimination are endogenous objects so that variations in parameters influence selection into college and thus 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.

Compensation The choices of agents, the conditional beliefs of firms about ability and the productivity parameter for skilled jobs combine to create the distributions of compensation across educated workers. As in (12), compensation is the product of the conditional expectation of ability explained above and the gender specific productivity parameter for skilled jobs, $h(1)$. These differences in the productivity parameter drive an additional wedge between expected ability and compensation. Recall from the estimation that for all countries except Italy, college was more productive for men than women: $h^m(1) > h^w(1)$.

From Figure 5 there are differences across genders within countries both in terms of the dependence of wages on signals and, again, in the distributions across signals conditional on college and labor market participation. For Italy, college educated women receive higher wages than men for all values of the signal. But, in Italy there is a wage gap: educated men on average are paid more than educated women. This is due to the differences in the distributions with more weight placed on low signals for women with college than men. This is a clear example where the selection into education and labor market participation decisions jointly come into



(a) Germany (b) Italy

(c) Japan (d) US

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

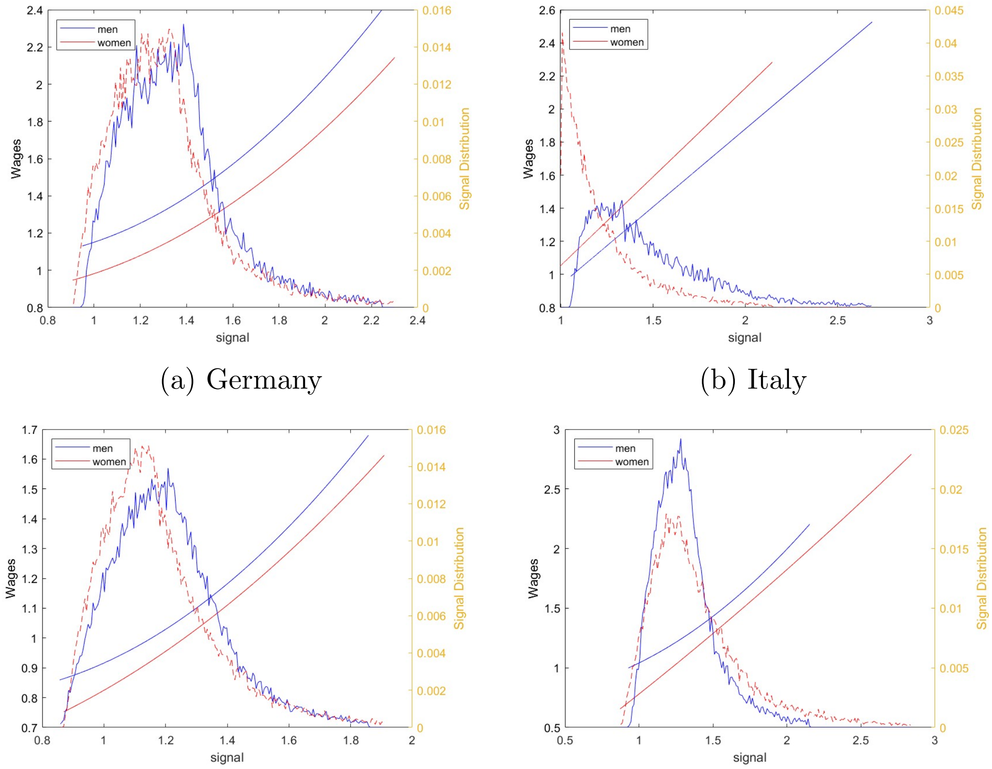
Figure 4: Dependence of Expected Ability on the Signal

play. For Germany, Japan and the US, differences in distributions are less marked but the higher estimated values of $h(1)$ for men combined with firms' beliefs produce higher wages for college educated men given a signal. That is, conditional on a labor market signal and a college degree, men are offered higher wages than women. On balance, the model matches the data and generates a wage gap in favour of men. The policy experiments that we analyze later will impact those wage functions directly through restrictions in the compensation structure and indirectly through changes in selection into college and labor market participation.

4.5 Gender Differences

A key point of the paper is to evaluate the effects of policy interventions on education and labor market outcomes by gender. To motivate and understand these interventions, we demonstrate that the estimated model generates gender gaps in these dimensions that are consistent with the data.

From Table 3, in both the data and the model the college rate of women exceed that of men in all countries. Further, from the targeted moments, the model produces a wage gap in all countries: men with college education assigned to skilled jobs earn more than women. This



(a) Germany (b) Italy

(c) Japan (d) US

These figures show the equilibrium dependence of wage on the signal and the distribution of the signal by country and gender for college educated participants.

Figure 5: Dependence of Wages on the Signal

wage gap is not inconsistent with the higher college attainment rate of women. The incentive to go to college is heavily influenced by productivity and hence compensation in unskilled jobs. For all countries, this is lower for women than for men. The gender difference in college rates is also a consequence of taste differences. Consistent with the findings in Cervantes and Cooper (2024), differences in $h(0)$ are most important for explaining the college rate gap in Japan and the US while taste differences play a larger role in Germany and the US.[30]

From Figure 5, it should be clear that these measured wage gaps summarize rich gender differences in compensation. First, the difference in wages as a function of the signal themselves depend on the magnitude and informativeness of the signal. Second, the distributions over the signals matter as well for the summary statistics. This distinction will be relevant for the policy analysis which looks separately at the short run (i.e. given education decisions and thus these distributions) and long run when education choices adjust.

Looking at participation rates, in both the data and the model, college educated individuals are more likely to participate in the labor market. This is true for both genders in all countries. The estimated model also reproduces the data pattern that the participation rate is lower for women than men, regardless of education. This includes the very low participation rates in

[30]This is made clear through model simulations reported in Appendix section 7.2.

Italy. Within the estimation, a key factor influencing the participation rates is the distribution of shocks to home production. The mean value of these shocks is higher for women in all countries as is the dispersion, with the exception of Germany.

5 Policy Interventions

This section analyses the impact of policy interventions using the estimated model. The main result is that the policies, with the exception of Italy, effectively reduce wage gaps, particularly in the short-run when education choices are taken as given. Once these choices adjust, the policies lead to changes in the level and composition of the college educated. As we demonstrate, these responses can attenuate the direct effects of the intervention. This is particularly clear when the policy intervention is directed at skilled labor markets alone.

We consider a number of interventions intended at eliminating both the college and non-college wage gaps, distinguished by the market in which the wage equality is imposed. The first exercise looks at the impact of wage equality in the market for skilled workers by imposing gender free applications. That is, employers are not allowed to observe the gender of the applicant. As a result, wage functions are gender-free such that a male and a female worker with a college degree and same labor market signal are offered the same wage. Thus, with this policy, statistical discrimination disappears. The second exercise focuses also on the unskilled market wage gap which is key to generating a range of gender gaps. For this exercise we impose wage equality in both labor markets.

For each policy, there are two different analysis. The first has exogenous education: all education decisions are fixed at their baseline values. This implies that the coefficients governing conditional beliefs for a given gender remain at their baseline values. This is due to the fact that the distribution of signals for each gender conditional on education, the ingredient in computing expected ability, is fixed by the baseline as well. However, effective wages offers do change differently for both genders compared to the baseline from the imposition of (10). The second analysis allows education choices to adapt to the wage policy.

The fixed education exercise illustrates the effects of the policy given a group of workers with predetermined education. These would be short term policy effects on agents, i.e. those in the work phase of our model, who are unable to modify education choices. The exogenous education case provides a comparison to the results once education choices respond to the policy. As we shall see, these are very different outcomes. Their difference highlights the power of selection.

Focusing first in the short-run, we find that by eliminating statistical discrimination with gender free applications in the skill labor market alone, the wage gap for college educated workers disappears and even reverses. The mechanism is that by being pooled with men, women received higher wages for a given signal and education. However, once education choices respond to the implied changes is the college premium, this effects is mitigated although the wage gap is still lower compared to the baseline. Once education adjusts, the policy has a substantial negative impact of college rates of men in Germany, Japan and the US. For this exercise, the results for Italy stand in contrast to the other countries: the wage gap actually increases in Italy in response to the gender free application policy. We trace this to the fact that the return to education was higher for women than men, i.e. $h^w(1) > h^m(1)$, which was not the case in the other countries.

For the intervention that equalizes wages in all markets, the wage gap is eliminated both in the short and long runs, except, again, in Italy. For all countries, except Germany, this policy eliminates the college rate gap as well, in contrast to the policy intervention in skilled markets only.

For these exercises, it is important to keep Figure 5 in mind. The direct effect of an intervention, such as the gender free application, implies that wages, given a signal, must be gender independent. But the underlying distributions across the signals are endogenous, responding in the long run to the policies. Thus, even though the wage function is stipulated to be gender independent under a policy, the resulting summary statistics of average wages will not be.

5.1 Gender Free Applications for Skilled Workers

Here we focus on a labor market policy in which gender is eliminated from the job application of an individual. In our context, the gender free application means that a firm looks at the observable characteristics of an individual, but gender is not included. Put differently, we eliminate the statistical discrimination.

Our analysis focuses on the effects of the intervention on the gender gaps. The model generated gaps arise from statistical discrimination and thus does not represent a market failure. As in Lundberg and Startz (1983), one motivation for the analysis is simply that the outcome may appear to be discrimination in the eyes of outsiders, creating a basis for policy action.

The evaluation of the policy intervention takes as given the baseline parameters. It introduces the policy restriction through restricting wages. Specifically, in the case of quadratic beliefs, expected productivity in the skilled job for a given signal is:

$$\begin{aligned} E_{j,\theta}[h(1)^j\theta|s] = \quad & p(s)h^w(1)(\omega_0^w + \omega_1^w \times s + \omega_2^w \times s^2) + && (13) \\ & +(1-p(s))h^m(1)(\omega_0^m + \omega_1^m \times s + \omega_2^m \times s^2) && (14) \end{aligned}$$

and expected productivity in the unskilled job given college education is:

$$E_j[h(0)^j] = p(s)h^w(0) + (1-p(s))h^m(0). \tag{15}$$

The assignment is based upon a comparison of these expected productivities. The interpretation of (15) is that a college educated individual with a low signal can be assigned to an unskilled job but that assignment and compensation do not depend on the agents gender. In contrast, all non-college workers are assigned to unskilled jobs and, under this policy, their compensation is gender specific since no restriction is placed for the unskilled market.

In finding an equilibrium, there is an added element. Beyond the gender specific parameters of beliefs about ability given a signal, $(\omega_0^j, \omega_1^j, \omega_2^j)$, computing wages from (13) also requires an expectation over gender given a signal. As shown in both (13) and (15), compensation is a weighted average of the expected productivity given that worker is a women and the expected productivity if the worker was male. This weight is indicated by $p(s)$ which is the conditional probability the applicant is a women given the signal s and a college degree. This probability must be consistent with individual choices in equilibrium. So, relative to the baseline model, there is an additional component in computing a rational expectations equilibrium.

The findings from this intervention, both in the short and the long run, are reported in two ways. First, Table 6 reports the data moments under these two scenarios with gender free applications. Second, Table 7 looks at the effects of the policy on gender gaps.

	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
	Baseline															
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	0.547	0.254	0.921	0.080	0.009	0.853	0.897	0.653	0.714	0.728	0.131	0.211	0.659	0.738	0.117	0.0068
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
	Gender Free Applications: Education Fixed															
G	0.313	-0.989	1.393	0.096	0.121	0.692	0.796	0.397	-0.476	1.105	0.131	0.275	0.542	0.685	-0.040	0.070
I	0.159	-2.128	1.727	0.073	0.255	0.592	0.715	0.297	-0.882	0.435	0.070	0.193	0.467	0.525	0.184	0.042
J	0.547	0.254	0.921	0.102	-0.076	0.853	0.887	0.653	0.714	0.728	0.127	0.254	0.659	0.745	-0.015	0.034
U	0.382	-0.564	1.715	0.115	0.019	0.727	0.812	0.499	0.126	1.500	0.179	0.428	0.561	0.745	-0.106	0.061
	Gender Free Applications: Education Endogenous															
G	0.133	-2.919	2.134	0.076	0.172	0.692	0.833	0.462	-0.150	1.018	0.150	0.215	0.543	0.671	0.081	4.428
I	0.222	-1.468	1.539	0.087	0.201	0.591	0.696	0.276	-0.989	0.404	0.067	0.184	0.467	0.522	0.140	0.519
J	0.257	-1.440	1.728	0.078	-0.022	0.853	0.913	0.700	0.948	0.736	0.137	0.237	0.659	0.745	0.073	3.662
U	0.161	-2.800	2.665	0.084	0.099	0.727	0.851	0.586	0.523	1.331	0.208	0.356	0.562	0.731	0.039	6.154

Note: This table reports data and simulated moments for the model with gender free applications.

Table 6: Moments: Gender Free Applications

5.1.1 Fixed Education

Our initial experiment fixes the individual education policy functions at their baseline. That is, they are predetermined and consistent with the previous (baseline) wage functions. However, because firms are not allowed anymore to observe the gender of the applicant, workers expected productivity and thus compensation in skilled jobs is determined from (13). To be clear, wages are independent of gender for a given signal but the distributions across signals for educated workers remain gender specific.

The middle panel of Table 6 shows the moments for this experiment. The moments associated with education decisions are the same as in the baseline. Compensation though changes and this is reflected in the coefficients of the Mincer regressions, wage gap and the participation decisions of the educated workers.[31]

From Table 7, there are a couple of key implications of the policy for the gaps. First, in Germany, Japan and the US this policy reverses the wage gap so that average wages of women are higher than those of men. Compensation under the policy amounts to averaging across the gender specific wage functions in Figure 5, where the weights are signal specific as shown in equation (13). From that figure, compensation is higher for men compared to women in Germany, Japan and the US. As a consequence, women's wages are higher than in the baseline and men's are lower, eliminating the wage gap. This leads to a small reduction in labor force participation rates of college men and an increase in those of college women in these three countries.

The effects of the policy are the opposite in Italy. In that country, the estimated productivity parameter for skilled jobs was lower for men than women. Accordingly, the gender blind application process reduces the expected wage given a signal for college educated women compared to men so that the wage gap increases. Labor force participation is thus higher for men and lower for women as a consequence of the policy.

Figure 9 shows the comparison between wage functions for the baseline and under the policy with fixed education. The blue and the red lines represent the compensation functions for males and females respectively for our baseline equilibrium. The black line corresponds to expected productivity and thus compensation under the policy which is by construction gender independent. As already explained, with fixed education, this function is a weighted average of the gender specific compensation functions from the baseline. The weights come from the probability the worker is female given the observed signal and selection into college. Appendix section 7.3.1 shows those probability functions. In Italy, for example, the distribution of scores for men puts much more weight on high values compared to women. This is consistent with the lower college rate of Italian men and produces the large wage gap. For the US, the signal distributions are much closer but there is more of a right tail for women. This creates the reported wage gap in favor of women for this experiment. Compared to Figure 4, these distributions are essentially the same as the education decisions are identical.

Thus, for given education decisions, a policy that eliminates statistical discrimination by banning employers from observing the gender of the worker would reverse the wage gap in Germany, Japan and the US, and amplify it in Italy.

[31] With exogenous education, the participation decisions of the non-college workers do not change.

	Germany	Italy	Japan	US
	Baseline			
College Rate	-0.084	-0.138	-0.105	-0.117
College Premium	-0.031	0.049	-0.234	-0.329
Wage Coll.	0.164	0.069	0.117	0.062
Participation (noncoll)	0.150	0.125	0.194	0.166
Participation (coll)	0.167	0.152	0.160	0.110
Participation (uncond.)	0.146	0.120	0.167	0.125
	Short-run : Exog. Ed.			
College Rate	-0.084	-0.138	-0.105	-0.117
College Premium	-0.235	0.164	-0.366	-0.497
Wage Coll.	-0.040	0.184	-0.015	-0.106
Participation No-Coll.	0.150	0.125	0.194	0.166
Participation Coll.	0.111	0.189	0.142	0.068
Participation Uncond.	0.126	0.127	0.156	0.107
	Long-run : Endog. Ed.			
College Rate	-0.329	-0.054	-0.443	-0.425
College Premium	-0.114	0.120	-0.278	-0.351
Wage Coll.	0.081	0.140	0.073	0.039
Participation No-Coll.	0.149	0.125	0.194	0.165
Participation Coll.	0.162	0.173	0.168	0.121
Participation Uncond.	0.109	0.132	0.150	0.086

This table reports the education, college premia, wage and participation gaps for the baseline and policy experiments.

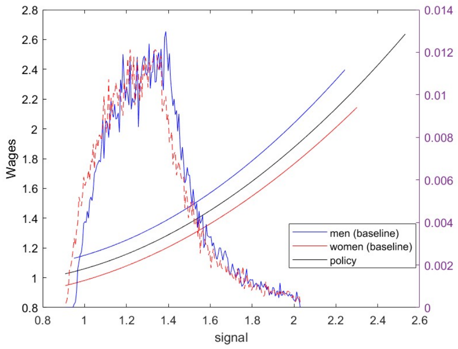
Table 7: Gaps: Gender Free Applications

5.1.2 Endogenous Education

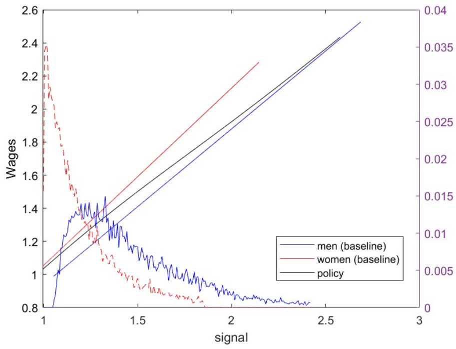
In the endogenous education version we allow both men and women to alter their education decision in respond to a labor market in which applications are gender blind. From the results with fixed education, the policy eliminated the wage gap in favor of men in three of the four countries. But given that college women are now paid higher wages and college men paid less, this will lead to alternative education decisions by all agents. Since education choices take time to respond, we call this long-run effects.

Importantly, the assessment of these effects requires the computation of a new labor market equilibrium. As agents change their choices, the expected productivity function conditional on gender changes as well. Therefore we need to find the equilibrium under the new labor market structure so that the choices of the agents and expected productivity given those choices are consistent. As a consequence, the compensation function is not a weighted average of the baseline functions anymore.

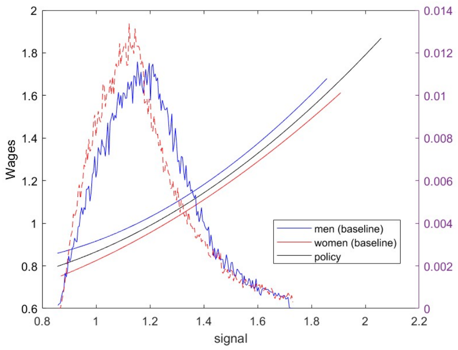
From the simulated moments reported in the bottom panel of Table 6 the responses are present and substantial. In Germany, Japan and the US, the college rate of men falls and that of women rises relative to the baseline and thus the policy experiment with fixed education.



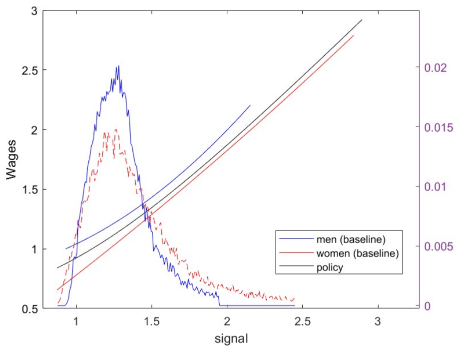
(a) Germany



(b) Italy



(c) Japan



(d) US

These figures shows the comparison between expected compensation for the baseline and that under the gender free application experiment with exogenous education. Distributions over the signal among college educated workers are shown as well.

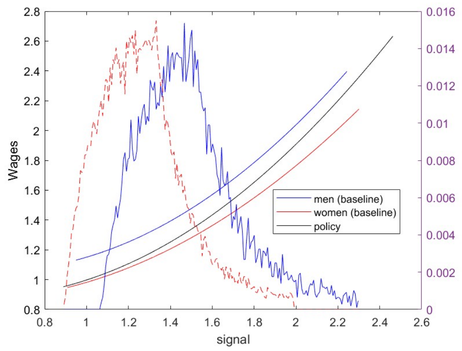
Figure 6: Expected Compensation Under Baseline and Policy with Fixed Education

For these three countries, the reduction in the college rate of men is more than 50% increasing the college rate gap. For Italy, the education response is present as well but in the opposite direction due to the gender differences in $h(1)$.

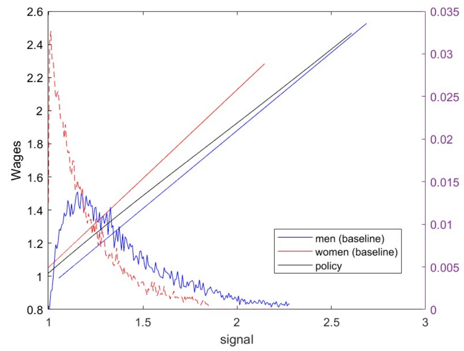
The selection of fewer men into college in Germany, Japan and the US leads to much higher participation rates for college men compared to the fixed education rates. Essentially with the reduced compensation for men, selection favor higher ability men and thus, on average, higher compensation so that participation rates conditional on college are higher. The same argument applies to women with their higher college rate leading to lower participation. As a result, the particpation gap widens.

Importantly, for Germany, Japan and the US the wage gaps that had disappeared with the exogenous education experiment reappear once agents reoptimize over their education. But the wage gaps are much smaller than in the absence of the policy. That is, the intervention effectively reduces the wage gaps although long-run effects are more moderate. For Italy, the gap is smaller than with education fixed but larger than in the baseline.

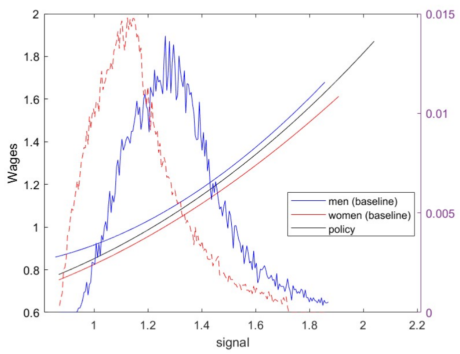
These effects of the policy on wages and participation rates are largely driven by selection into college. Figure 7 illustrates the new labor market equilibrium for our four countries.[32] Comparing the exogenous and endogenous cases, for Germany, Japan and the US a key observation is the rightward shift in the distribution of signals by college men. This reflects the lower college rate and hence the selection of higher ability males into college. This leads to the wage gap reappearing. For Italy, the selection effects appear to be much smaller insofar as the distributions over the signals are very similar. Appendix 7.3.2 shown the probability function of the worker being female under this policy in the new equilibrium. An interesting observation is that the rightward shift in the distribution for college educated males changes the monotonicity of the probability function: the probability of being women is decreasing in the magnitude of the signal.



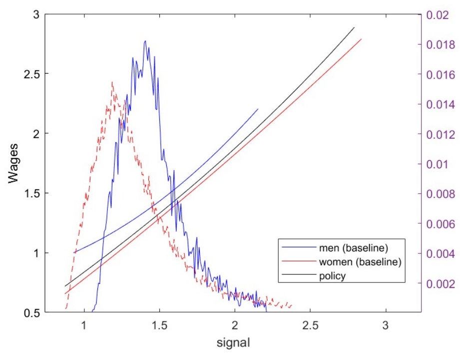
(a) Germany



(b) Italy



(c) Japan



(d) US

These figures shows the comparison between expected compensation for the baseline and that under the gender free application experiment with endogenous education. Distributions over the signal among college educated workers are shown as well.

Figure 7: Expected Compensation Under Baseline and Policy with Endogenous Education

5.1.3 Effects on other Gender Gaps

Table 7 summarizes the effects of the policy intervention on the gender gaps. The point here is to see how a policy intended to reduce the gender wage gap impacts other gaps. First, in

[32] Additional material is presented in Appendix 7.3.2.

the long run, there is a widening of the college rate gaps in all countries except Italy. This reflects the fact that in these countries women benefit from pooling with men who have the higher productivity gain from college. A consequence of this is that the distribution of signals for those going to college changes as well and this feeds into the wage gap. Italy is different as it is the only country with $h^m(1) > h^w(1)$ so that the effects of pooling are reversed.

The college premium gap is also impacted by the policy. In the short-run, with education fixed, the premium rises considerably in the three countries where average wages of college women rose: Germany, Japan and the US. In the long-run, with the education response, the college premium decreases but remains slightly higher than the pre-policy levels.

As for the participation rates, the gap is lower with fixed education as more women work due to the higher wages. But once education choices respond and lower signal women select into college, the reduction in conditional wage functions recreates the participation gaps. In fact, the levels are quite close to the baseline.

5.1.4 Effects on Assignment

Section 3.3 discussed discussed job assignment. Having estimated the model, we can study assignment both in the baseline and under the policy. The focus in on the outcome of college educated workers: are they assigned to skilled or unskilled jobs?

The job assignments in the baseline and under the policy in the long-run are shown in Table 8. Specifically, this is the fraction of working college educated workers assigned to skilled jobs, thus excluding the non-participants. For the estimated baseline model, the fraction of college workers going to skilled jobs is almost one, except for Japanese males. For this reason, introducing policies that aim to equalize job assignment by gender, as in Coate and Loury (1993), would have essentially no impact on education and labor market outcomes except for in Japan.

We re-estimated Japan because of this right? still afraid this will raise that question! In the baseline estimates for Japanese males, the average value of home production is low, the average taste shock for education is high and the signal is noisy. Together, this induces the typical Japanese male to attend college and take a chance at a high job market signal. If that does not occur, they work in the unskilled sector rather than not participating in the labor market. This is consistent with their very high labor force participation rates and the fact that nearly 42% of college educated Japanese males are in unskilled jobs. As seen in Figure 5, a large fraction expected productivity less than the wage in the unskilled job and hence do not work in skilled jobs. Given the estimated low productivity at home, these agents work in unskilled jobs.

Under the policy, there are both short and long run effects for Japanese men and short run effects on women. For other country, gender pairs, the policy has no impact on assignment.

For Japan, the compensation in a skilled job falls since the Japanese men are pooled with

Japanese women who have a lower estimate of $h(1)$. Second, the compensation in the unskilled job, given that the agent is assigned to that job, is also lower due to the pooling with Japanese women. This would lead Japanese men to be assigned (and accept) jobs in the skilled sector, albeit at a low wage. From Table 8 this second effect dominates so that, in the short run, the policy reduces the rate of college educated Japanese men in unskilled jobs. For Japanese women, the policy leads to about 5.5% of college women in unskilled jobs. In this case, the pooling with men increases the compensation in unskilled jobs so that some college educated women take those jobs rather than work at skilled jobs. From the moments, there is no change in the labor market participation rate of Japanese women.

In the long run, like other countries, all college educated individuals in Japan work in skilled jobs. For Japanese men, relative to the baseline the adjustment is in terms of education as the college rate is cut by more than 50%.

	Germany		Italy		Japan		US	
	Men	Women	Men	Women	Men	Women	Men	Women
Baseline	1	1	1	1	0.583	1	1	1
Policy (SR)	1	1	1	1	0.956	0.944	1	1
Policy (LR)	1	1	1	1	1	1	1	1

This table reports the fraction of college workers assigned to skilled jobs relative to all college workers.

Table 8: Job Assignment

5.2 Equal Compensation for All Workers

For skilled workers, gender free applications implied that compensation was the same across genders. One interpretation of this policy was that it eliminated statistical discrimination by reducing the information set available to firms. This policy did not impact compensation for unskilled workers since, in our model, there is perfect information about productivity given gender: i.e. there is no statistical discrimination in the market for unskilled workers. Yet, due to $h^m(0) \neq h^w(0)$ there are gender wage differences for unskilled workers. From our analysis of the estimated model, these differences are key to generating gender gaps.

This section combines the policies, imposing wage equality for unskilled workers along with the imposition of gender free applications. Here though the intervention for non-college workers is direct in that we impose equality in compensation for unskilled workers. In equilibrium, firms will pay workers the average of $h^m(0)$ and $h^w(0)$ using the equilibrium gender specific education rates.

There is also the assignment part of the labor market outcome. If firms condition assignment on gender, then clearly the policy of equaliziing compensation will imply, given our estimates, that women will not be assigned unskilled jobs since their productivity is less than the common wage. This is surely an anticipated effect of the policy on employment and once that would be circumvented by requiring gender free assignment along with compensation. This is what we explore.[33]

	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
								Baseline								
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	0.547	0.254	0.921	0.080	0.009	0.853	0.897	0.653	0.714	0.728	0.131	0.211	0.659	0.738	0.117	0.0068
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
								Gender Free Compensation: Education Fixed								
G	0.313	-0.989	1.393	0.108	0.153	0.672	0.786	0.397	-0.476	1.105	0.142	0.121	0.565	0.674	-0.045	0.069
I	0.159	-2.128	1.727	0.075	0.252	0.589	0.711	0.297	-0.882	0.435	0.071	0.169	0.469	0.522	0.188	0.044
J	0.547	0.254	0.921	0.094	0.068	0.823	0.885	0.653	0.714	0.728	0.114	0.059	0.696	0.744	-0.014	0.047
U	0.382	-0.564	1.715	0.133	0.110	0.689	0.806	0.499	0.126	1.500	0.199	0.149	0.606	0.738	-0.123	0.080
								Gender Free Compensation: Education Endogenous								
G	0.232	-1.623	1.621	0.093	0.210	0.672	0.810	0.418	-0.369	1.076	0.135	0.152	0.566	0.682	-0.005	0.513
I	0.227	-1.419	1.518	0.089	0.207	0.589	0.694	0.274	-1.001	0.407	0.067	0.173	0.469	0.522	0.137	0.598
J	1.000	NaN	NaN	NaN	NaN	NaN	0.867	1.000	NaN	NaN	NaN	NaN	NaN	0.731	-0.030	
U	0.439	-0.230	1.586	0.122	0.166	0.688	0.805	0.498	0.109	1.440	0.176	0.213	0.603	0.743	-0.121	0.191

Note: This table reports data and simulated moments for the gender free wage experiments.

Table 9: Moments: Gender Free Compensation

The moments for both the short and long run outcomes are shown in Table 9. The policies together reverse the wage gap in all countries except Italy, where it increases. In contrast to the first policy, the education response matters much less for the impact of the policy on the wage gap.

For the US, the wage gap is about the same regardless of whether education responds or not. For both Italy and the US, the education rate of men is higher and that of women slightly lower once it is allowed to adjust. For Germany, once education responds, the education rate of men falls.

The results of this exercise for the gaps are shown in Table 10. There are two versions reported, one with education fixed and the other allowing the education choices to change. As before, participation responds to the policy.

Looking at the resulting gaps in Table 10, in the short run the policy eliminates the wage gaps in all countries except Italy, where the gap emerges after the intervention. Once education adjusts, the wage gaps are still eliminated in Germany, Japan and the US. This is because now the college premium is not significantly larger because the wages of non college workers increase as well. In fact, for the US there is little difference in the short and long run results. The long run effect in these countries is much stronger than the policy applied to skilled labor alone. For Italy, the results are essentially the same as in the experiment with only gender free applications since the non-college productivity for women is so close to that of men.

With the non-college wage set at a common level, the college wage premium gap will be the same as the wage gap in the skilled labor market. For both Germany and the US, the college premium gap remains negative, as in the baseline, but it is considerably smaller. For

[33] This is one way to link our experiments with the affirmative action type policies, that work on quantities rather than prices, explored in Coate and Loury (1993).

the US the college gap is smaller as the college premium gap is reduced by the intervention. For Germany, the college rate gap is much larger than in the baseline as the college rate for men is much smaller. This is a reflection of the reduction in the wage gap.

	Germany	Italy	Japan	US
	Baseline			
College Rate	-0.084	-0.138	-0.105	-0.117
College Premium	-0.031	0.049	-0.234	-0.329
Wage Coll.	0.164	0.069	0.117	0.062
Participation (noncoll)	0.150	0.125	0.194	0.166
Participation (coll)	0.167	0.152	0.160	0.110
Participation (uncond.)	0.146	0.120	0.167	0.125
	Short Run : Exog. Ed.			
College Rate	-0.084	-0.138	-0.105	-0.117
College Premium	-0.040	0.184	-0.015	-0.106
Wage Coll.	-0.040	0.184	-0.015	-0.106
Participation non-college.	0.107	0.120	0.127	0.084
Participation college.	0.111	0.189	0.142	0.068
Participation all	0.098	0.123	0.130	0.061
	Long Run : Endog. Ed.			
College Rate	-0.186	-0.046	0.000	-0.058
College Premium	-0.005	0.137	na	-0.121
Wage Coll.	-0.005	0.137	-0.030	-0.121
Participation non-college	0.106	0.120	na	0.085
Participation college.	0.128	0.171	0.136	0.062
Participation all.	0.090	0.129	0.136	0.066

This table reports the education, college premia, wage and participation gaps for the gender free wage experiments.

Table 10: Gaps : Gender Free Wages

6 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.

A policy experiment in which applications were assumed to be gender blind was studied using the baseline model. Interestingly, the pooling across genders leads to an increase in the wage gap and a reduction in the education gap in Germany, Italy and the US. This reflects the finding that college is more productive for women than men in these countries. By pooling applications, this advantage for women is lost.

There are a couple of interesting model extensions to consider.[34] 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.

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7 Appendix

7.1 Mincer Regressions

	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 11: Mincer Regressions by Country.

7.2 Counterfactual Effects on Gaps

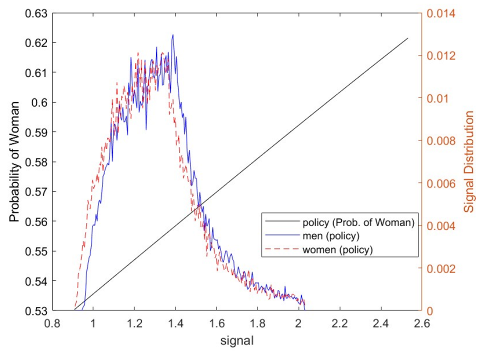
	Germany	Italy	Japan	US	Germany	Italy	Japan	US
	Data				Baseline			
Ed. Rate Gap	-0.099	-0.124	-0.099	-0.135	-0.084	-0.138	-0.105	-0.117
College Premium Gap	0.095	0.053	-0.152	-0.132	-0.031	0.049	-0.234	-0.329
Wage Gap	0.165	0.053	0.110	0.049	0.164	0.069	0.117	0.062
Part. Gap No Coll	0.23	0.23	0.23	0.20	0.150	0.125	0.194	0.166
Part. Gap Coll	0.14	0.08	0.14	0.07	0.167	0.152	0.160	0.110
	Same $h(0)$				Same $(\bar{\varepsilon}, \mu(\varepsilon))$			
Ed. Rate Gap	0.073	-0.132	0.176	0.165	0.124	0.070	0.185	0.101
College Premium Gap	0.048	0.068	0.005	-0.155	-0.213	-0.155	-0.231	-0.362
Wage Gap	-0.048	-0.068	-0.005	0.155	-0.018	-0.135	0.120	0.028
Part. Gap No Coll	0.151	0.125	0.193	0.165	0.152	0.125	0.194	0.165
Part. Gap Coll	0.170	0.156	0.211	0.128	0.095	0.089	0.162	0.101
	Same λ				Same $(\bar{h}, \mu(h))$			
Ed. Rate Gap	-0.040	-0.139	-0.107	-0.115	-0.453	-0.246	-0.396	-0.497
College Premium Gap	-0.064	0.047	-0.231	-0.333	0.098	0.056	-0.222	-0.225
Wage Gap	0.131	0.067	0.120	0.058	0.293	0.076	0.129	0.165
Part. Gap No Coll	0.150	0.125	0.194	0.166	-0.004	0.000	-0.002	-0.000
Part. Gap Coll	0.156	0.152	0.160	0.111	0.046	0.012	-0.040	-0.041

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

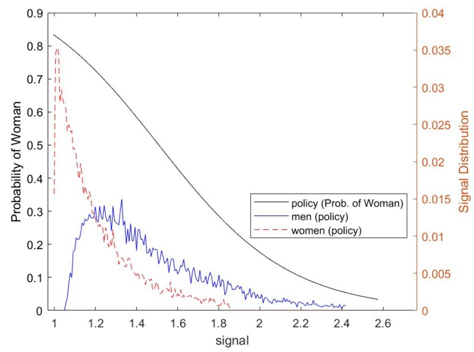
Table 12: Determinants of Education, Compensation and Participation Gaps

7.3 Gender Free Applications

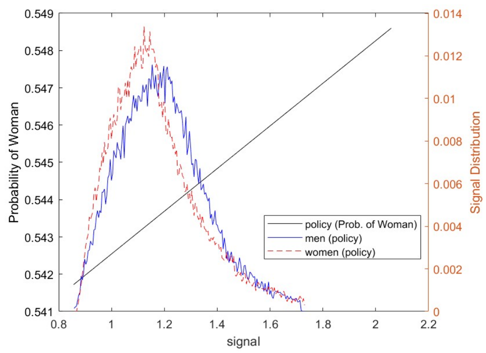
7.3.1 Education Fixed



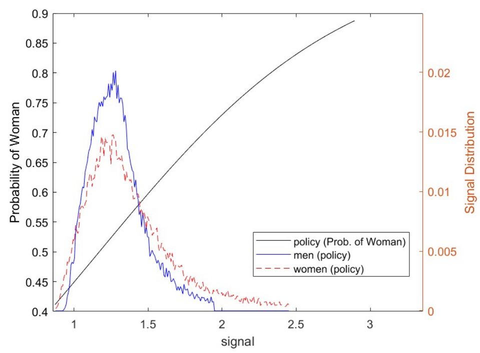
(a) Germany



(b) Italy



(c) Japan

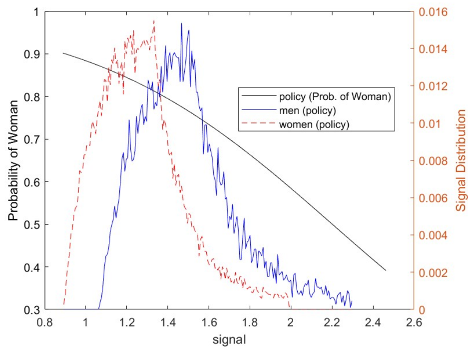


(d) US

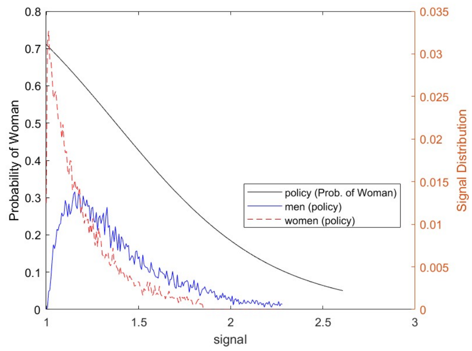
These figures shows the probability function of a worker being female given a labor market signal and a college degree. Distributions over the signal among college educated workers, which are the basis of that probability function, are shown as well.

Figure 8: Probability the Worker is Female Given a Signal and Education

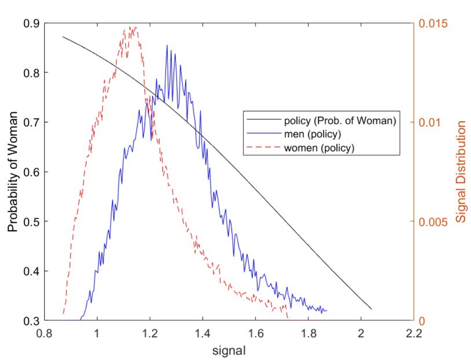
7.3.2 Education Endogenous



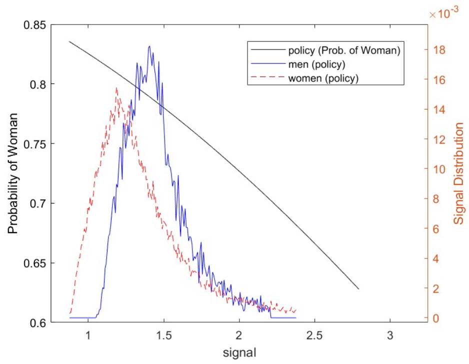
(a) Germany



(b) Italy



(c) Japan



(d) US

These figures shows the probability function of a worker being female given a labor market signal and a college degree. Distributions over the signal among college educated workers, which are the basis of that probability function, are shown as well.

Figure 9: Probability the Worker is Female Given a Signal and Education