The Allocation of Talent and Income Differences Across Countries

Nan Li, Liang Zhang and Robert Zymek*

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Abstract

Barriers that selectively limit women's access to certain occupations constrain individual potential and undermine productivity–but how large are their macroeconomic effects? In this paper, we use a Roy model of occupation choice to derive a theoretically-founded, outcomes-based measure of female labor market barriers that can be compared across countries and time. This measure incorporates, but goes beyond, conventional gender wage gaps and is highly correlated with established gender indices. Applying the framework to harmonized income microdata for 43 diverse economies, we find that 2015 barriers for some major emerging markets were similar to 1960s barriers in the U.S. Lowering their barriers to 2015 U.S. levels would yield double-digit gains in per-capita market incomes and welfare, both by encouraging participation and by raising productivity via an improved allocation of talent. This suggests that policies aimed at reducing occupational barriers for women could be a powerful source of growth and international income convergence.

JEL: *E24, J16, J24, O11, O47*
Keywords: *talent allocation, occupational choice, barriers, productivity, income convergence*

*Li: IMF (NLi@imf.org); Zhang: Boston College (zhangpw@bc.edu); Zymek: IMF and CESifo (RZymek@imf.org).

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1 Introduction

Over the past half century, the U.S. labor market for women underwent a remarkable transformation. In 1965, U.S. women aged 25-34 were 6 times more likely than their male counterparts to be outside of formal employment, and employed women were virtually absent from many professional occupations. Moreover, the average full-time female worker providing clerical support−a common occupation for employed women at the time−earned about 66 cents against each dollar earned by her average male colleague. By 2015, the concentration of U.S. women in a small subset of occupations had declined by nearly half according to one measure, and the gender wage gap across all occupations had shrunk by 60 percent (see Figure 1).[1] A similar transformation took place concurrently across most advanced economies.

In this paper, we turn the spotlight towards emerging and developing economies (EMDEs). Using a consistent, theory-based framework, we compare the contemporary state of female labor-market integration in a diverse set of EMDEs with that of a number of advanced economies, and we assess the potential effects on incomes and productivity of "catching up" facilitated by a decline in female occupational barriers to advanced-economy levels.

Figure 1 compares 42 economies and the U.S. along two measures of the occupational parity of women and men. The vertical axis shows a measure of the relative concentration of women in a subset of occupations, with lower values indicating less concentration.[2] The horizontal axis shows a measure of the average gender wage gap in market occupations, with values closer to zero indicating a smaller gap. As shown in the figure, advanced economies tend to be located towards the South-East quadrant of the figure, indicating greater gender parity, and EMDEs towards the North-West quadrant, indicating less gender parity. However, there is a significant overlap between the two groups of economies. More strikingly still, the position of several large EMDEs looks comparable to the U.S. in 1965.

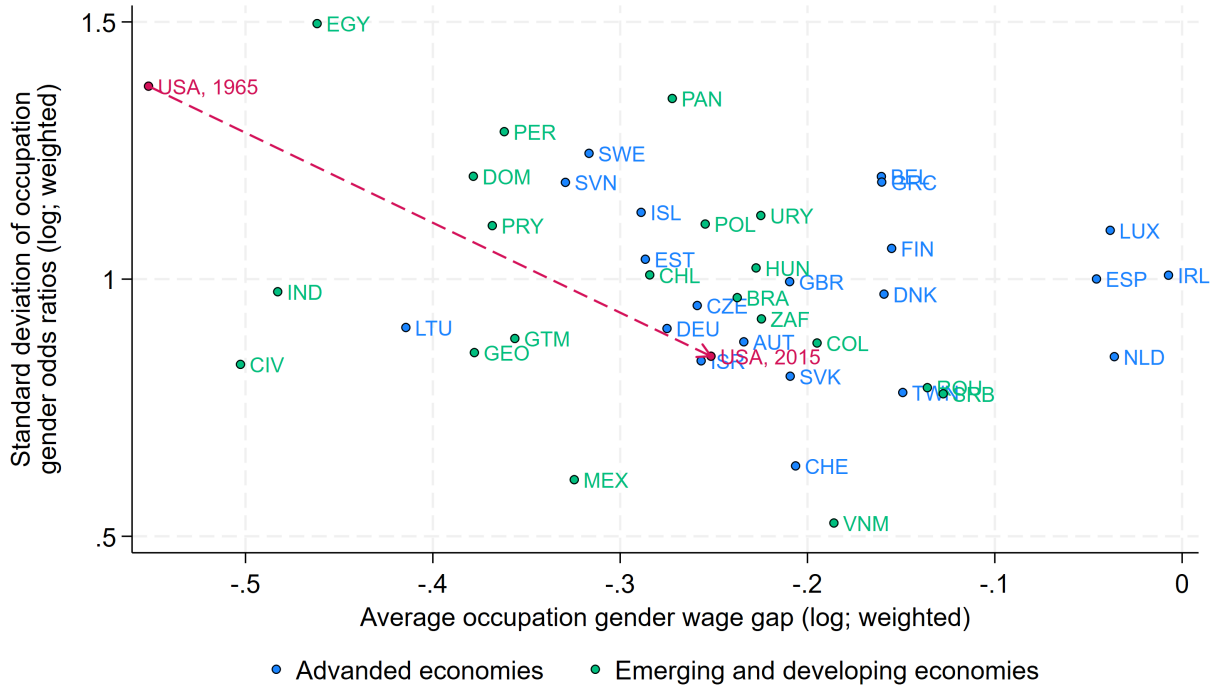
Hsieh et al. (2019) show that the decline in occupational barriers for women−alongside an accompanying decline for black workers−may have accounted for 20-40% of U.S. per capita income growth in the 1960-2010 period. Their work highlights that the decline in barriers affecting selected groups increases economic output by boosting both participation and productivity. The latter effect arises because workers are better able to exploit their individual comparative advantages, resulting in an improved allocation of talent. We extend this idea to a cross-country setting.

[1] To measure the relative concentration of women in a subset of occupations, we use the standard deviation across occupations of the log odds ratio of women choosing a given occupation relative to men. The smaller this standard deviation, the more similar the distribution of women and men across occupations. For details on data sources and construction, see the Figure 1 note and Section 3.

[2] For the purposes of this measure, non-employment is included in the set of occupations, defined as the "home" occupation.

It is well established that female occupational barriers remain high in many parts of the world, reinforcing employment segregation that persist across different stages of economic development (Das and Kotikula, 2019). Our paper provides novel evidence that the resulting constraints on the realization of individual potential can have sizable macroeconomic effects, and contribute to the large and persistent gaps in living standards between advanced economies and EMDEs.

Figure 1: Gender Concentration and Wage Gaps Across Countries, 2015



Notes: The vertical-axis variable is the earnings-weighted standard deviation across occupations of $\ln(P_{o,w}/P_{o,m})$, where $P_{o,w}$ and $P_{o,m}$ respectively represent the share of women and the share of men aged 25-34 in occupation o. Non-employment is included in the set of occupations, defined as the "home" occupation. The horizontal-axis variable is the earnings-weighted average across market occupations of $\ln(\overline{wage}_{o,w}/\overline{wage}_{o,m})$, where $\overline{wage}_{o,w}$ and $\overline{wage}_{o,m}$ respectively represent the geometric average earnings of full-time female and male workers aged 25-34 in occupation o. The source of all data is the Luxembourg Income Study (LIS) database. For details on the data source and variable construction, see Section 3.

Like Hsieh et al. (2019), we start from a model of occupational choice based on Roy (1951). Individuals born into different groups choose occupations to maximize their lifetime utility given their idiosyncratic and group-specific talents and preferences. They also make occupation-specific human capital investments. Their choices are potentially distorted by group-specific wedges ("barriers") that capture discriminatory policies, informal institutions, and social norms in a black-box fashion. These wedges reduce productivity and welfare by preventing individuals from pursuing their most productive activities or preferred occupational amenities. While the model can accom-

modate many distinct groups, our analysis focuses on women and men. Under the assumption that the innate comparative advantages of women and men−that is, their comparative advantages holding the economic and educational environment constant−are the same everywhere, the model provides sufficient structure to back out *differences* in relative occupational barriers and preferences for women across economies from observed labor market outcomes.

We apply this framework to harmonized microdata on occupational sorting and earnings from the Luxembourg Income Study (LIS), which allows us to compare the relative occupational barriers facing women across 43 diverse economies. This delivers three key findings. First, there is substantial cross-economy heterogeneity in female occupational barriers. Generally, these barriers are higher in EMDEs. However, some former communist economies have lower barriers than many advanced economies, pointing to political-cultural component of female labor market integration consistent with evidence by Campa and Serafinelli (2019). Second, the barriers we back out are highly correlated with both outcomes-based and institutions-based indicators of gender discrimination from a variety of sources. Third, while some of the differences in aggregated barriers across economies can be attributed to structural differences in economies at different stages of development−with different shares of female-friendly occupations in overall economic activity (Chiplunkar and Kleineberg, 2023)−a large part is contributed by higher barriers within the same occupations.

We then use our model to conduct counterfactual exercises that assess the potential income and productivity gains from reducing female occupational barriers. As a baseline exercise, we move barriers across all sample economies to make them no larger than 2015 U.S. barriers in a given occupation. In our adaptation of the framework of Hsieh et al. (2019), such exercises can be performed straightforwardly using a version of the "hat algebra" popular in the international trade literature (Dekle et al., 2007, 2008). Lowering barriers to close any gaps with the U.S. yields modest gains for most advanced economies, with the biggest winners seeing their steady-state per-capita incomes rise by around 5%. However, the gains are much larger for a number of EMDEs. The top quartile of sample EMDEs experience per-capita real GDP gains of 8-26%. Moreover, these gains stem primarily from productivity improvements due to a better allocation of talents, rather than simply from increases in labor force participation. Since these gains accrue disproportionally to economies with low per-capita incomes and productivity levels compared with the U.S., they contribute to shrinking international income differences.

We carry out several alternative counterfactuals to demonstrate that these findings are robust to reasonable variations in the value of crucial parameters, and to alternative assumptions about the nature of barriers. We also explore the role of cross-economy differences in female occupational

preferences, showing that among our sample economies about half of the deviation of women's occupational choices from a U.S. benchmark are due to differences in barriers and half to international differences in preferences. Overall, our findings confirm that policies aimed at reducing occupational barriers for women could be a powerful source of growth and international income convergence. This finding is particularly salient given slowing global growth amid aging and shrinking populations.

Related Literature This paper contributes to several strands of the literature. First, we build on a growing body of research on talent (mis)allocation and economic performance (Hsieh et al., 2019; Celik, 2023; Bandiera et al., 2024; Chiplunkar and Kleineberg, 2023). Our paper is most closely related to Hsieh et al. (2019) and Chiplunkar and Kleineberg (2023) who quantify the contribution of improved talent allocation to economic growth for the U.S. and a selected sample of six major economies, respectively. We extend this literature to the cross-sectional dimension, and consistently analyze the contribution of female occupational barriers to differences in the *levels* of per-capita incomes and productivity across 43 diverse economies.

Second, we add to a larger literature on the effects of gender inequality in the labor market on economic growth (Bertay et al., 2025; Agte et al., 2024; Ostry et al., 2018b; Gonzales et al., 2015; Schober and Winter-Ebmer, 2011). These studies typically rely on a reduced-form approach to relate economic performance to indicators of gender gaps such as labor force participation rates, wage disparities, educational attainment, and legal restrictions. By contrast, we rely on a structural framework to spell out explicitly assumptions required to identify the underlying barriers that drive observed gender gaps in outcomes, highlight and test crucial parameters, and engage in well-defined counterfactuals. In this way, we also speak to the empirical literature on cross-country gender gaps (Ostry et al., 2018a; Morazzoni and Sy, 2022; Bento, 2024), complementing existing index-based approaches to the international comparison of the economic status of women with a theoretically-founded measure of gender barriers that can be compared across economies and time.

Third, our work relates to the literature on the impact of gendered labor market distortions on productivity. For example, Lee (2024) provides empirical and theoretical insights into how gender-specific constraints influence labor market efficiency. Ashraf et al. (2024) investigates the effects of local labor market gender norms on employee performance by using personnel records from a multinational enterprise. Our paper adopts a more macroeconomic perspective: we assess the extent to which occupational barriers facing women may impact aggregate incomes and productivity across countries. This connects our work with a venerable literature that uses economic modeling and data to account for observed cross-country income and productivity differences (Hall and Jones,

1999; Caselli, 2005, 2017). While the impact of economic development on occupational gender segregation is well documented (Goldin, 1995; Ngai et al., 2024), our findings suggest that reduced gender segregation may also powerfully promote economic development.

Finally, our paper belongs to a broad methodological tradition−spanning papers such as Eaton and Kortum (2002) and Hsieh and Klenow (2009) −that builds on the foundational contributions of Roy (1951) and McFadden (1974) to choice theory, and uses structural frameworks to infer market distortions and analyze the potential effects of their removal.

The remainder of the paper proceeds as follows. Section 2 presents the theoretical framework and discusses key assumptions. Section 3 describes the data sources and construction. Section 4 reports our findings on the cross-economy variation in occupational barriers facing women. Section 5 performs our main quantitative exercises. Section 6 offers a brief summary and concluding remarks.

2 Theoretical Framework

2.1 Model Assumptions

In this section, we describe a model of occupation choice broadly along the lines of Hsieh et al. (2019). There are many atomistic individuals, born into a finite number of groups. These groups differ in their average aptitudes and preferences for the economy's given set of occupations and, in addition, individuals have idiosyncratic aptitudes and preferences for occupations. Individuals choose an occupation when young to maximize their lifetime utility, and invest in occupation-specific human capital. However, their choices may be distorted by group-occupation-specific "barriers", representing discriminatory practices or norms in a black-box fashion. Such distortions may reduce economic participation and give rise to a misallocation of talents, whereby individuals do not choose the occupation that best suits their comparative advantage.

We use the model to derive two key equations that link the labor market outcomes of all groups (relative to some reference group) to relative group-specific barriers and preferences. These equations can be used to identify variations in the barriers and preferences across economies, under the assumption that inherent group aptitudes−those not shaped by the economic or educational environments−are the same everywhere. We also show that the steady-state impact of counterfactual changes in barriers on macroeconomic outcomes can be obtained straightforwardly by means of the "hat algebra" approach pioneered by Dekle et al. (2007, 2008).

2.1.1 Workers

Time lasts forever, but individuals belong to overlapping cohorts with a certain lifespan of three periods ("young", "middle", "old"). Individuals are born into one of a given number of groups, $g \in \{1, ..., G\}$. They choose an occupation $o \in \{0, ..., O\}$ at the start of their "youth", and make occupation-specific human capital investments. Their occupation and human capital choices are then assumed to be fixed for the rest of their lives.

Lifetime utility of a worker from group g and cohort t' who chooses occupation o is:

$$\ln u_{og}\left(t'\right) = \beta \sum_{t=t'}^{t'+2} \ln c_{og}\left(t, t'\right) + \ln V_{og} + \ln v_{og}\left(t'\right), \tag{1}$$

where $c_{og}\left(t, t'\right)$ is period-t consumption of an individual from group g and cohort t' in occupation o; V_{og} is a common utility benefit to all members of group g from working in occupation o; and $v_{og}\left(t'\right)$ represents an idiosyncratic utility benefit to the individual from that occupation. V_{og} and $v_{og}\left(t'\right)$ represent the strength of non-consumption amenities offered by different occupations that have a distinct appeal to the group and the individual, respectively. The parameter $\beta > 0$ thus governs the trade-off between lifetime consumption and occupational amenities. Throughout we use large-cap letters to denote aggregate variables and small-cap letters to denote individual variables. We assume that the economy is in steady state, and omit time indices on aggregate variables for notational ease.

Consumption equals earnings net of human capital expenditures:

$$c_{og}\left(t, t'\right) = \left(1 - \tau_{og}^{w}\right) W_o h_{og}\left(t, t'\right) - \left(1 + \tau_{og}^{i}\right) i_{og}\left(t, t'\right), \tag{2}$$

where the consumption price level is normalized to 1; W_o is the common return per unit of human capital in occupation o; $h_{og}\left(t, t'\right)$ is the human capital supplied by the individual; $i_{og}\left(t, t'\right)$ represents individual human capital expenditures;[3] and $\tau_{og}^{w} \in [0, 1]$ and $\tau_{og}^{i} \geq 0$ respectively represent occupation-specific "barriers" that reduce the return to human capital or raise the cost of human capital for members of group g. These barriers are modeled in the form of black-box wedges, as elsewhere in the macroeconomics literature.[4]

Human capital is determined by the aptitude with which an individual is endowed as well as

[3] Hsieh et al. (2019) assume a more general human capital production function that requires not only physical resources but also a pre-period time investment as an input. Since this generalization is shown to have no bearing on all the key equations derived from the model, we omit it here to streamline the exposition.

[4] For example, see Chari et al. (2007) and Hsieh and Klenow (2009).

their human capital investments:

$$h_{og}\left(t,t'\right)=Z_{og}z_{og}\left(t'\right)\zeta\left(t-t'\right)i_{og}\left(t'\right)^{\eta},\qquad i_{og}\left(t'\right)=\sum_{t=t'}^{t'+2}i_{og}\left(t,t'\right), \tag{3}$$

where Z_{og} represents the innate group-specific aptitude for occupation o; $z_{og}\left(t'\right)$ represents the individual's idiosyncratic aptitude; $\zeta\left(t-t'\right)$ captures the returns to experience, with $\zeta\left(0\right)=1$ and $\zeta'\left(\cdot\right)>0$; and $\eta\in[0,1)$ is the elasticity of individual productivity with respect to human capital investments.

Finally, following Hsieh et al. (2019), we assume that a fraction $1-\delta$ of individuals in each cohort has $v_{og}=1$ for all o, and draws z_{og} from the multivariate Fréchet distribution:

$$F^{z}\left(z_{1},...,z_{O}\right)=\exp\left(-\sum_{o=1}^{O}z_{o}^{-\theta}\right). \tag{4}$$

The remaining fraction δ has $z_{og}=\Gamma\left(1-1/\theta\left(1-\eta\right)\right)^{1-\eta}\equiv\Gamma^{1-\eta}$ for all o, and draws v_{og} from the multivariate Fréchet distribution:

$$F^{v}\left(v_{1},...,v_{O}\right)=\exp\left(-\sum_{o=1}^{O}v_{o}^{-\theta\frac{1-\eta}{3\beta}}\right). \tag{5}$$

The parameter δ therefore represents the share of individuals who select into occupations based on factors *other than idiosyncratic ability* ("idiosyncratic preferences"): the smaller is δ, the greater the extent of selection based on idiosyncratic ability. The parameter $\theta>0$ is an inverse measure of idiosyncratic heterogeneity: the smaller is θ, the greater the dispersion of idiosyncratic abilities and preferences.[5]

Without loss of generality, we let occupation 1 denote non-market "home" production and normalize $V_{1g}=Z_{1g}=\tau_{1g}=1$ for all g.

2.1.2 Firms

The production technology for market output Y is given by

$$Y=\left[\sum_{o=2}^{O}\left(A_{o}H_{o}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

[5]The common ability of individuals selecting on preferences is normalized to equal the *average* ability of individuals selecting on ability. Furthermore, the shape parameter of the distribution $F^{v}\left(\cdot\right)$ is normalized to ensure to standardize the effect of ability and preference shocks on occupational utility, as can be seen from section 2.2.2.

where A_o is an exogenous occupation weight; H_o denotes the amount of occupation-o human capital used as an input in production; and $\sigma > 1$ is the elasticity of substitution between market occupations. In turn, total output Q combines home production and market output as follows:

$$Q = \left[(1-\mu) (A_1 H_1)^{\frac{\varepsilon-1}{\varepsilon}} + \mu Y^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}, \tag{7}$$

where $\varepsilon > 1$ is the elasticity of substitution between home and market output; and $\mu \in [0,1]$.[6]

There is a competitive representative firm that maximizes profits subject to (6) and (7), taking the returns required to compensate occupational human capital as given.

2.1.3 Market Clearing

Steady-state equilibrium is achieved for the unique set of occupational human capital returns $\{W_1, ..., W_O\}$ such that

$$H_o = \sum_{g=1}^{G} \sum_{t'=t-2}^{t} H_{og}(t'), \tag{8}$$

where $H_{og}(t')$ denotes the human capital supplied to occupation o by members of group g born in period t'.

2.2 Steady State Equilibrium

2.2.1 Human Capital Investment

It is straightforward to show that the optimal human capital investment is:

$$i^*_{og}(t') = \left[\frac{\eta \left(1-\tau^w_{og}\right) W_o Z_{og} z_{og}(t') \bar{\zeta}}{1+\tau^i_{og}} \right]^{\frac{1}{1-\eta}}, \tag{9}$$

where $\bar{\zeta} \equiv 1 + \zeta(1) + \zeta(2)$. Hence an individual's human capital conditional on choosing occupation o is described by:

$$h^*_{og}(t,t') = \left[Z_{og} z_{og}(t') \right]^{\frac{1}{1-\eta}} \zeta(t-t') \left[\frac{\eta \left(1-\tau^w_{og}\right) W_o \bar{\zeta}}{1+\tau^i_{og}} \right]^{\frac{\eta}{1-\eta}}. \tag{10}$$

[6] The production technology assumed in Hsieh et al. (2019) is a special case of the production technologies described here with $\varepsilon = \sigma$ and $\mu = 1/2$.

2.2.2 Occupation Choice

Substituting (2) and (9) into (1), lifetime utility for an individual from group g working in occupation o is:

$$u_{og}^{*}\left(t'\right)=\left[\bar{\zeta}W_{og}z_{og}\left(t'\right)\right]^{\frac{3\beta}{1-\eta}}v_{og}\left(t'\right), \tag{11}$$

where

$$W_{og}\equiv\frac{W_{o}Z_{og}V_{og}^{\frac{1-\eta}{3\beta}}}{\tau_{og}} \tag{12}$$

represents the group-specific return from selecting occupation o; and we define $\tau_{og}\equiv\left(1+\tau_{og}^{i}\right)^{\eta}/\left(1-\tau_{og}^{w}\right)$. For some group g, this return will be relatively high if its average aptitude or preference for that occupation is especially high, or its barrier−captured by τ_{og}−is low.

Use P_{og} to denote the share of individuals from group g that select occupation o at the start of their "youth". Given (4) and (5) the well-known properties of the Fréchet distribution imply that

$$P_{og}=\frac{W_{og}^{\theta}}{\sum_{o=1}^{O}W_{og}^{\theta}}. \tag{13}$$

2.2.3 Group-Occupation Human Capital Supply

Appendix A.1 shows that

$$H_{og}\equiv\sum_{t'=t-2}^{t}H_{og}\left(t'\right)=\Gamma\left(\frac{Z_{og}\bar{\zeta}}{\tau_{og}}\right)^{\frac{1}{1-\eta}}\left(\eta W_{o}\right)^{\frac{\eta}{1-\eta}}\left[\delta+\left(1-\delta\right)P_{og}^{-\frac{1}{\theta(1-\eta)}}\right]P_{og}N_{g}, \tag{14}$$

where N_g is the share of individuals from group g in the population.

2.2.4 Human Capital Demand and Equilibrium Returns

Human capital demand is given by:

$$H_{o}=\begin{cases}\frac{1-\mu}{\mu}\left(\frac{A_{1}^{\frac{\varepsilon-1}{\varepsilon}}}{W_{1}}\right)^{\varepsilon}\left[\sum_{o=2}^{O}\left(\frac{W_{o}}{A_{o}}\right)^{1-\sigma}\right]^{\frac{\varepsilon}{1-\sigma}} & \text{for } o=1\\ \left(\frac{A_{o}^{\frac{\sigma-1}{\sigma}}}{W_{o}}\right)^{\sigma}\left[\sum_{o=2}^{O}\left(\frac{W_{o}}{A_{o}}\right)^{1-\sigma}\right]^{\frac{\sigma}{1-\sigma}} & \text{for } o\in\{2,...,O\}\end{cases}. \tag{15}$$

The equilibrium human capital returns are then implicitly characterized by (8), (12), (13), (14) and (15).

2.3 Inferring Occupational Barriers and Preferences

2.3.1 Inferring Occupational Barriers

Let $\overline{wage}_{og}(t,t')$ denote the geometric average wage across all individuals from group g and cohort t' working in occupation o in period t. Appendix A.2 shows that:

$$\frac{\overline{wage}_{og}(t',t')}{\overline{wage}_{og'}(t',t')}\left(\frac{P_{og}}{P_{og'}}\right)^{\frac{1-\delta}{\theta(1-\eta)}}=\left(\frac{Z_{og}}{Z_{og'}}\right)^{\frac{1}{1-\eta}}\left(\frac{\tau_{og}}{\tau_{og'}}\right)^{-\frac{1}{1-\eta}}. \tag{16}$$

The left-hand side of equation (16) represents the "selection-adjusted" wage gap between the young from group g and a reference group g' in occupation o. The first term of this product is the directly observed wage gap. The second term of the product adjusts it to reflect that, to the extent that the relative propensity of g to select the occupation is low and there is selection on ability ($\delta<1$), the average productivity of individuals from group g will be high compared to group g'. Hence, if group g is less likely to select occupation o, the "selection-adjusted" relative wage of group g will be lower than the directly observed relative wage. For given parameter values δ, θ and η, the left-hand side of (16) can be computed based on observed wages and occupational choices for different groups.

The right-hand side of (16) shows that, through the lens of the model, observed wage gaps between groups in an occupation (after adjusting for selection) can be attributed to two unobserved drivers: relative difference in group-innate aptitudes; and relative differences in barriers. However, these two drivers cannot be disentangled without further assumptions. The assumption we impose throughout most of the rest of the paper is that relative group-innate aptitudes are the same across economies.

Define $\triangle$ as the difference operator with respect to a fixed reference economy. Then our identifying assumption implies:

$$\triangle\ln\left[\frac{\overline{wage}_{og}(t',t')}{\overline{wage}_{og'}(t',t')}\left(\frac{P_{og}}{P_{og'}}\right)^{\frac{1-\delta}{\theta(1-\eta)}}\right]=-\frac{1}{1-\eta}\triangle\ln\left(\frac{\tau_{og}}{\tau_{og'}}\right). \tag{17}$$

In words, if in some economy group g faces a low selection-adjusted relative wage in occupation o compared with the reference economy, it must imply a high relative barrier for that group compared with the reference economy. Throughout the applications in the rest of the paper, this reference economy will be the U.S.

2.3.2 Inferring Occupational Preferences

Appendix A.3 shows that:

$$\left(\frac{P_{og}}{P_{og'}}\Big/\frac{P_{1g}}{P_{1g'}}\right)^{\frac{1}{\theta(1-\eta)}}=\left(\frac{V_{og}}{V_{og'}}\right)^{\frac{1}{3\beta}}\left[\frac{\overline{wage}_{og}\left(t',t'\right)}{\overline{wage}_{og'}\left(t',t'\right)}\left(\frac{P_{og}}{P_{og'}}\right)^{\frac{1-\delta}{\theta(1-\eta)}}\right]. \tag{18}$$

The left-hand side of equation (18) represents differences in the propensity to choose occupation o (relative to the home occupation) of groups g and g'. For given parameter values θ and η, it can be computed based on groups' observed occupational choices. The right-hand side shows that the model attributes differences in these observed propensities to two drivers: the selection-adjusted relative wage, which can be computed from data; and relative group preferences, which are not directly observable. Hence, equation (18) can be inverted to obtain a measure of relative group occupational preferences. Intuitively, if group g is more likely than g' to choose occupation o for given relative wages, this group must have a relatively strong preference for that occupation.

Again taking log differences with respect to a reference economy,

$$\frac{1}{\theta\left(1-\eta\right)}\triangle\ln\left(\frac{P_{og}}{P_{og'}}\Big/\frac{P_{1g}}{P_{1g'}}\right)=\frac{1}{3\beta}\triangle\ln\left(\frac{V_{og}}{V_{og'}}\right)-\frac{1}{1-\eta}\triangle\ln\left(\frac{\tau_{og}}{\tau_{og'}}\right). \tag{19}$$

Under our assumptions, if in some economy group g is relatively more likely to choose occupation o compared with the reference economy, it must imply a high relative preference or low relative barrier for that group compared with the reference economy.

2.4 Hat Algebra

2.4.1 Main Equations

For any variable X, let $\hat{X}$ describe the ratio of its realization in a new steady state (after some parameter change) to its realization in the initial steady state (with the original set of parameters). Following an exogenous change in barriers given by $\{\hat{\tau}_{og}\}_{o,g}$ the change in key endogenous steady-state outcomes is fully characterized by the solution to the following set of equations:

1. Human capital demand:

$$\hat{H}_o^D=\begin{cases}\frac{\hat{Y}}{\hat{W}_1^{\varepsilon}}\left(\sum_{o=2}^{O}\hat{W}_o^{1-\sigma}\frac{S_o}{1-S_1}\right)^{\frac{\varepsilon}{1-\sigma}} & \text{for } o=1\\ \frac{\hat{Y}}{\hat{W}_1^{\sigma}}\left(\sum_{o=2}^{O}\hat{W}_o^{1-\sigma}\frac{S_o}{1-S_1}\right)^{\frac{\sigma}{1-\sigma}} & \text{for } o\in\{2,...,O\}\end{cases}; \tag{20}$$

2. Human capital supply:

$$\hat{H}_o^S = \begin{cases} \sum_{g\in G} \hat{P}_{og} \hat{W}_o^{\frac{\eta}{1-\eta}} \hat{\tau}_{og}^{-\frac{1}{1-\eta}} S_{og} & \text{if } \delta = 1 \\ \sum_{g\in G} \hat{P}_{og}^{\frac{\theta(1-\eta)-1}{\theta(1-\eta)}} \hat{W}_o^{\frac{\eta}{1-\eta}} \hat{\tau}_{og}^{-\frac{1}{1-\eta}} S_{og} & \text{for } \delta = 0 \end{cases}; \tag{21}$$

$$\hat{P}_{og} = \left(\frac{\hat{W}_o}{\hat{\tau}_{og}}\right) \Bigg/ \left[\sum_{o=1}^{O} \left(\frac{\hat{W}_o}{\hat{\tau}_{og}}\right) P_{og}\right]; \tag{22}$$

3. Market clearing:

$$\hat{H}_o^D = \hat{H}_o^S = \hat{H}_o; \tag{23}$$

$$\hat{Y} = \left[\sum_{o=2}^{O} \hat{H}_o^{\frac{\sigma-1}{\sigma}} \frac{S_o}{1-S_1}\right]^{\frac{\sigma}{\sigma-1}}; \tag{24}$$

where $S_o/(1-S_1)$ is the share of market occupation $o \in \{2, ..., O\}$ in initial market earnings; and S_{og} is the share of group g in initial occupation-o earnings.

2.4.2 Other Variables of Interest

We can further decompose the change in market output into the change in the share of the population choosing market occupations ("participation"), and the change in output per market participant ("productivity"):

$$\ln \hat{Y} = \underbrace{\ln\left(\sum_{o=2}^{O}\sum_{g\in G} \hat{P}_{og} \frac{P_{og}N_g}{\sum_g P_{og}N_g}\right)}_{Participation} + \underbrace{\ln\left(\frac{\hat{Y}}{\sum_{o=2}^{O}\sum_{g\in G} \hat{P}_{og}\frac{P_{og}N_g}{\sum_g P_{og}N_g}}\right)}_{Productivity}. \tag{25}$$

Finally, standard Fréchet results imply that the change in group welfare is:

$$\hat{U}_g = \left[\sum_{o=1}^{O} \left(\frac{\hat{W}_o}{\hat{\tau}_{og}}\right)^{\theta} P_{og}\right]^{\frac{3\beta}{\theta(1-\eta)}}; \tag{26}$$

and the change in the economy's average welfare is then simply $\hat{U} \equiv \sum_g \hat{U}_g N_g$.

3 Data and Measurement

3.1 Data Sources

3.1.1 Luxembourg Income Study Database

The main data source for our analysis is the Luxembourg Income Study (LIS) database. LIS offers the largest available database of harmonized microdata on individual and household labor market outcomes, based on official representative income surveys from 52 economies across Europe, North America, Latin America, Africa, Asia and Australasia, spanning up to five decades in some cases.

There are several desirable properties of LIS that make it particularly suitable for our purposes. First, LIS provides coverage of a diverse set of economies, including both advanced economies and EMDEs, thereby facilitating a rich set of international comparisons. Second, LIS employs a rigorous data collection and curation process to ensure data quality. The primary data are mainly sourced from established official income surveys and, to be included in LIS, these national surveys must meet a range of quality standards with respect to collection, reporting and survey representativeness. Third, and most importantly, the harmonization of income and labor market variables across economies ensures comparability and consistency, which is crucial for the comparative measurement of occupational barriers at the heart of our analysis.

To perform our analysis, we require three types of variables: measures of individual market income, if employed; indicators of individual's main occupation, including non-market activity; and information on individual characteristics, including gender but also part-time/full-time status and recent employment history. Below is a list of the key variables we draw from LIS, alongside brief descriptions. A comprehensive list of variables can be found in Appendix Table B1.

- `pi11`: wage income in national currency.
- `pi12`: self-employment income in national currency.
- `occb1`: occupation category (ISCO-88: major groups).
- `sex`: gender.
- `age`: age in years.
- `emp`: =1 if employment is the main current activity, 0 otherwise.
- `hourstot`: total weekly hours worked.
- `weeks`: number of weeks worked during the reference year.

Whenever one of these variables is not consistently reported for an economy in LIS, and the information cannot be inferred from other available variables, we have to drop that economy from our sample. Given that constraint, the year 2015 maximizes cross-economy coverage, allowing us to include 43 of the full set of 53 economies covered by LIS.[7] Following Hsieh et al. (2019), we use earnings data reported in gross terms for all economies where such data is reported, and net earnings otherwise.[8] We restrict our attention to individuals aged 25-54 who are not in the military. As in Hsieh et al. (2019), individuals who are neither full-time nor part-time employed are classified as working in the home sector. Among market occupations, our baseline analysis relies on harmonized ISCO-88 occupation codes, which delivers 10 major occupation categories including the home occupation, as shown in Appendix Table B2.[9]

3.1.2 Supplementary Data Sources

We cross-check our measure of female occupational barriers against a few outcomes-based and institutions-based gender indices that have been used widely for international comparisons. Specifically, we draw on the Gender Development Index (GDI, United Nations Development Programme, 2015) and the Gender Inequality Index (GII, United Nations Development Programme, 2015), both developed by the United Nations Development Programme (UNDP); the Global Gender Gap Index (GGGI, World Economic Forum, 2015) from the World Economic Forum; and the Women, Business and the Law 1.0 Index developed by the World Bank (World Bank, 2016).

3.2 Measurement of Barriers

To construct our baseline measure of the difference in relative occupational barriers for women across economies, we utilize the variables listed in Section 3.1.1 to construct the two empirical objects on the left-hand side of equation (16) for each occupation category o.

- Observed wage gap among the "young", $\overline{wage}_{og}(t',t')/\overline{wage}_{og'}(t',t')$:

  We take the geometric average earnings (from both employment and self-employment) across all female and male individuals working in occupation o that are aged 25-34 in 2015. The wage gap is computed as the ratio of the female geometric average earnings to the male geometric average earnings. When calculating earnings, we restrict the sample to individuals who were

[7] In some cases, we use data from adjacent years, when such data is available and 2015 data is not.

[8] A subset of our sample economies report *both* individuals' gross and net earnings. We use these for a robustness check, and find that this distinction makes little difference to our measure of their female occupational barriers.

[9] We use ISCO-08 for some economies if ISCO-88 is not available. The longitudinal dimension of LIS enables us to replicate the barrier measures reported in Hsieh et al. (2019) using U.S. data from 1965-2015 with our 10 baseline occupational categories, which delivers qualitatively and quantitatively similar results as in their paper.

working full-time at the time of the survey and had been working for the full reference year.[10] We exclude individuals that report positive earnings below the 0.2 percentile of the earnings distribution.[11]

- Occupation-group odds ratios, $P_{og}/P_{og'}$:

  For each occupation o, we compute the share of all women aged 25-34 working in this occupation, and divide it by the share of all men aged 25-34 working in the occupation. Here, a full-time worker counts as 1 worker, while a part-time worker counts as 0.5 workers. Part-time workers are defined as employed individuals who work 15-30 hours per week.[12]

To compute cross-economy differences in barriers using equation (17), we need to impose values for the parameters δ, θ and η. Our baseline calibration follows Hsieh et al. (2019) exactly. The parameter values are listed in Table 1 and discussed in Section 5.1.1.

4 Relative Occupational Barriers for Women Across Economies

Figure 2 illustrates the differences in the composite occupational barrier for women relative to men across economies in 2015. The composite barrier for each economy is computed by using equation (17) at the occupation level with the U.S. in 2015 as the reference economy, then aggregating across market occupations with their shares in the economy's total earnings as weights. By way of illustration, we also add the composite barrier for the U.S. as of 1965 (relative to the U.S. in 2015).

As can be seen from the figure, many EMDEs face relatively high female occupational barriers, while advanced-economy barriers tend to be lower and more similar to U.S. The 10 countries with the highest barriers are all EMDEs, led by Egypt. At the high end of the spectrum, contemporary barriers are comparable to those of the U.S. in 1965. By contrast, the contemporary U.S. is in the bottom third of barriers in our overall sample, and about "average" for an advanced economy. This suggests that the U.S. is a reasonable advanced-economy benchmark against which to evaluate gender parity in the labor market for other economies.

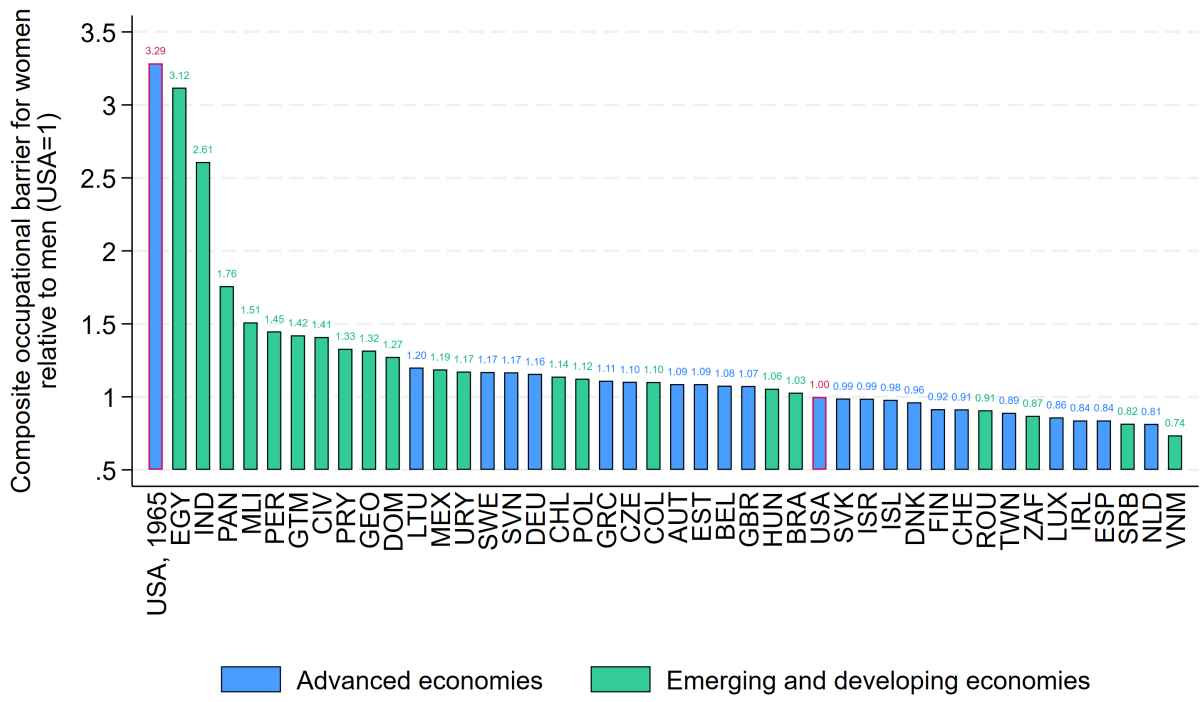
Strikingly, some of the economies with the lowest relative barriers for women in our sample are also EMDEs. Vietnam has the lowest barriers among all sample economies, and barriers are also

[10] Full-year full-time workers are defined as individuals who worked at least 48 weeks in the survey year and more than 30 hours per week. For some sample economies, for which either weekly hours or weeks worked are not reported in the LIS database, we use additional variables to identify full-time full-year workers. For the full set of LIS variables used, see Appendix Table B1.

[11] For the U.S. in 2010, this corresponds to annual earnings of below $1000, the minimum-earnings cut-off imposed by Hsieh et al. (2019).

[12] In cases where hours worked per week are unavailable, we rely on the indicator of part-time status provided in the LIS database.

Figure 2: Composite Occupational Barriers Across Economies in 2015



Notes: Composite occupational barriers for women relative to men are computed (relative to U.S. barriers) at the occupation level, using the formula in equation (17) with $\delta = 0$, $\theta = 2$, $\eta = 0.103$. They are then aggregated using occupation shares in whole-economy earnings as weights. The source of all data is the Luxembourg Income Study (LIS) database. For details on the data source and variable construction, see Section 3. For a discussion of parameter choices, see Section 5.1.1.

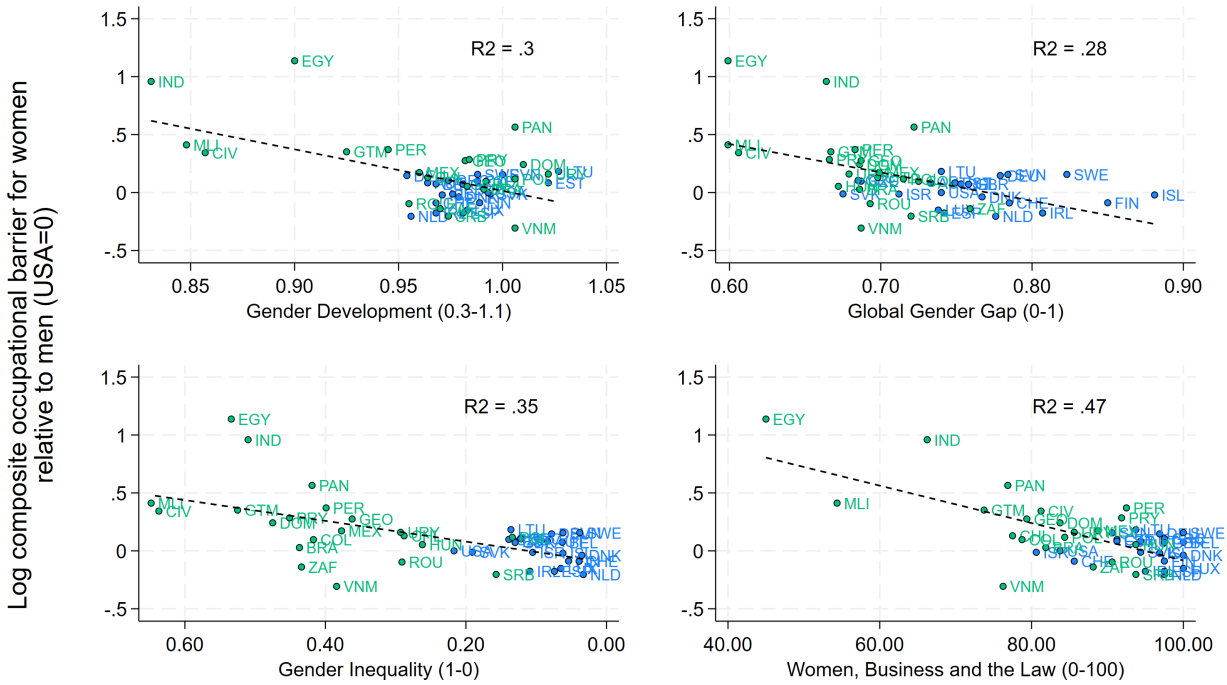
very low in two other sample EMDEs with a recent history of communist economic management (Romania and Serbia). This suggests that there is a political-cultural component to international differences in female labor market barriers.[13]

Figure 3 presents correlations between our measure of relative occupational barriers for women and four popular established gender indices. This serves as a cross-check, to ascertain whether the ranking of economies implied by our measure is backed up by other sources. As the figure shows, our composite barriers are strongly correlated with all four gender indices presented. All of the correlations are statistically significant, with the R^2 ranging from 0.28-0.47. Notably, our measure of barriers correlates both with outcomes-based measures of gender parity, like the GDI, GGGI and the GII, and an institutions-based measure like the Women, Business and Law index.

In principle, an economy's composite occupational barrier could be high relative to the U.S.

[13] In a recent paper, Huynh and Ku (2024) use Vietnam as a case study to document empirically that such cultural factors are at play even *within* economies by exploiting differences between Vietnam's always-socialist North and former-capitalist South.

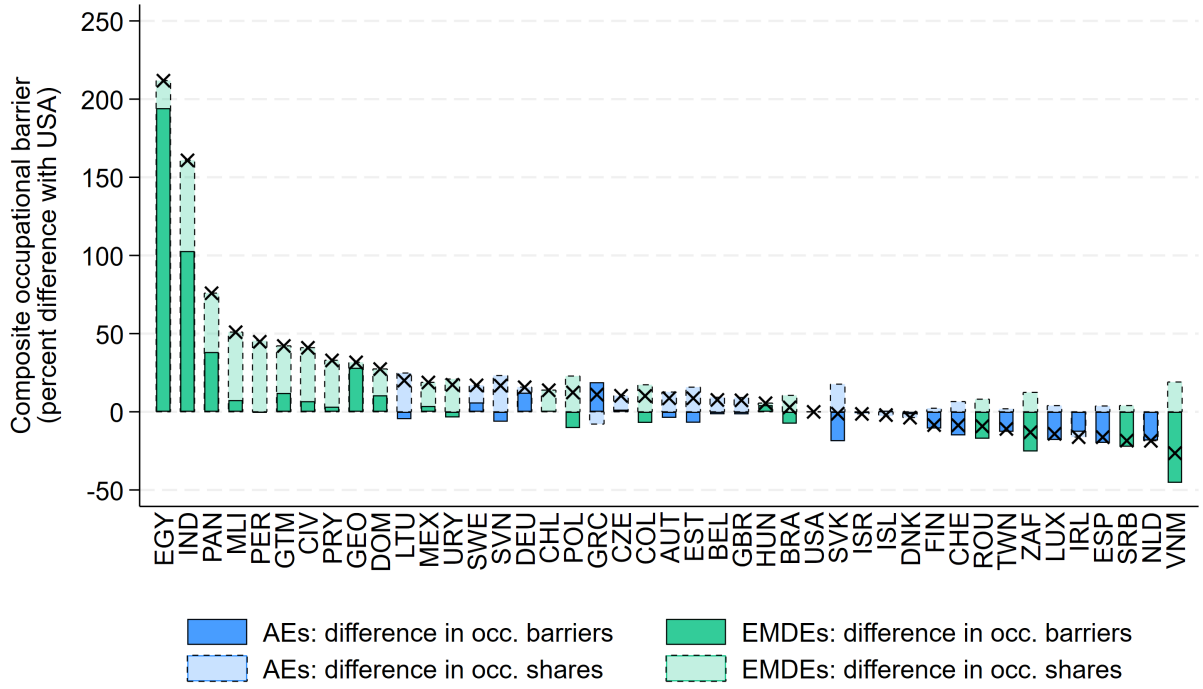
Figure 3: Composite Occupational Barriers and Gender Indicators



Notes: Composite occupational barriers for women relative to men are computed (relative to U.S. barriers) at the occupation level, using the formula in equation (17) with $\delta = 0$, $\theta = 2$, $\eta = 0.103$. They are then aggregated using occupation shares in whole-economy earnings as weights. The source of all data for the computation of barriers is the Luxembourg Income Study (LIS) database. The Gender Development index ranges from 0.3 to 1.1 and is taken from United Nations Development Programme (2015). The Global Gender Gap index ranges from 0 to 1 and is taken from World Economic Forum (2015). The Gender Inequality index ranges from 1 to 0 and is taken from United Nations Development Programme (2015). The Women, Business and the Law index ranges from 0 to 100 and is taken from World Bank (2016). For details on the data source and variable construction, see Section 3. For a discussion of parameter choices, see Section 5.1.1.

either because its barriers at occupation level are high, or because occupations that have relatively high barrier account for a larger share of the value of its overall economic activities. Figure 4 separates these two components of our measure of female occupational barriers by means of a shift-share decomposition. In the figure, "x" marks the percent difference of an economy's composite occupational barrier facing women from the U.S., and the shaded bars represent its two components: the contribution of differences in barriers at the occupation level (dark-shaded bar segments), and the contribution of differences in the composition of economic activity (light-shaded bar segments).

Figure 4: Decomposition of Composite Occupational Barriers



Notes: Composite occupational barriers for women relative to men are computed (relative to U.S. barriers) at the occupation level, using the formula in equation (17) with $\delta = 0$, $\theta = 2$, $\eta = 0.103$. They are then aggregated using occupation shares in whole-economy earnings as weights. The source of all data is the Luxembourg Income Study (LIS) database. For details on the data source and variable construction, see Section 3. For a discussion of parameter choices, see Section 5.1.1. The decomposition uses the formula $\triangle \sum_o S_o \ln(\tau_{og}/\tau_{og'}) = \sum_o S_o \triangle \ln(\tau_{og}/\tau_{og'}) + \sum_o \ln(\tau_{og}/\tau_{og'}) \triangle S_o$, where S_o denotes the share of occupation o in whole-economy earnings.

The left-hand side of Figure 4 shows the first third of economies with the highest barriers, which primarily consists of EMDEs. The economies in this group generally exhibit both higher occupation-level barriers and higher shares of high-barrier occupations. The middle third of economies in the figure mainly consists of advanced economies with composite barriers higher than that of the U.S. For this group, the main factor behind the overall barrier difference is the variation in occupational shares. The final third of economies with the lowest overall barriers comprises a mix of advanced economies and EMDEs. Their lower overall barriers are mainly attributable to lower occupation-level barriers. While this dissection of cross-economy differences in our measure of composite barriers is informative, it represents a pure accounting decomposition that cannot speak to possible links between the level of female barriers in an occupation and its share of overall activity. Doing so requires a formal counterfactual, to which we turn in the next section.[14]

[14]In our model, lowering barriers for women in an occupation increases the supply of human capital to that

5 Quantitative Exercises

5.1 Baseline Counterfactuals

In this section, we perform our main quantitative exercises, using the model from Section 2. We first outline our baseline calibration strategy, then describe the macroeconomic effects under this parametrization of moving all sample economies' female occupational barriers so as to make them no higher than U.S. barriers. Section 5.2 discusses several alternative parameter choices and barrier experiments. Finally, Section 5.3 explores the role of cross-economy differences in occupational preferences.

5.1.1 Calibration

Table 1 gives an overview of our baseline parameter choices. As the table shows, we import a number of key parameter settings directly from Hsieh et al. (2019). We set the elasticity of substitution between market occupations to $\sigma = 3$; the dispersion of idiosyncratic abilities/preferences to $\theta = 2$, reflecting the unexplained dispersion in U.S. occupational earnings; the human capital elasticity to $\eta = .103$, reflecting the share of education spending in U.S. labor income; and the consumption weight to $\beta = .231$, reflecting the Mincerian return to education in the U.S.

Table 1: Baseline Calibration

Parameter	Value	Justification
δ	0	Only selection on ability
ε	1	Cobb-Douglas over home/market consumption
μ	0.8	Arbitrary
σ	3	Hsieh et al. (2019)
θ	2	Hsieh et al. (2019)
η	0.103	Hsieh et al. (2019)
β	0.231	Hsieh et al. (2019)

Notes: For a discussion of baseline calibration choices, see Section 5.1.1.

Unlike Hsieh et al. (2019) we impose a unitary elasticity of substitution between home production and market occupations; and in our baseline we set the utility share of home output to $\mu = .2$.[15] Finally, like Hsieh et al. (2019), our baseline assumption is that *all* individuals select into occupations on the basis of idiosyncratic ability ($\delta = 0$). In Section 5.2.1, we discuss the

occupation, reducing the price of its output. Since occupations are assumed to be gross substitutes for the aggregate economy, this generally increases the share of that occupation in overall activity.

[15] Reasonable variation in this parameter choice have no material effect on the results presented below.

implications of relaxing this assumption.

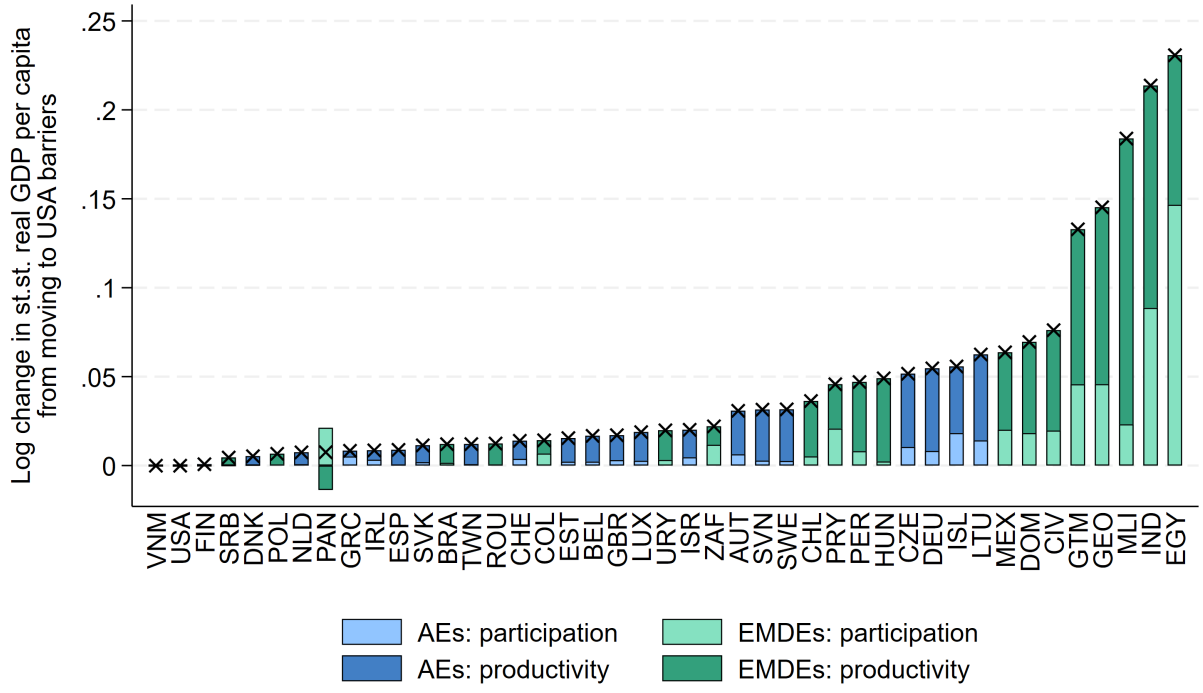
5.1.2 Results

Our baseline experiment assumes that the relative occupational barriers facing women in all sample economies fall to U.S. levels, wherever they are not already lower. In terms of the hat notation introduced in Section 2.4.1:

$$\hat{\tau}_{og} = \begin{cases} \min\left\{\exp\left[-\triangle \ln\left(\frac{\tau_{o,w}}{\tau_{o,m}}\right)\right], 1\right\} & \text{if } g = w \\ 1 & \text{if } g = m \end{cases}. \tag{27}$$

Figure 5 presents the impact on the steady-state per-capita real GDP of each sample economy.

Figure 5: Baseline Real Per-Capita Income Gains from Lowering Occupational Barriers



Notes: Real income changes from setting economies' occupational barriers to be no greater than U.S. levels are computed using the hat algebra described in Section 2.4.1, calibrating parameters in accordance with Table (1). The changes are decomposed using the formula provided in equation (25). For a more detailed discussion of the counterfactual experiment and calibration choices, see Section 5.1.

Almost all sample economies experience some positive income gains in this scenario, closely correlated with the size of their barriers (relative to the U.S.) identified in Figure 2. However, for the bulk of advanced economies, these gains are fairly small. The advanced economies with

the largest gains – Czech Republic, Germany, Iceland and Lithuania – see their steady-state per-capita GDP rise by around 5 percent. By contrast, the picture for EMDEs is more mixed. While some reap no or modest gains, a significant number of sample EMDEs benefit from income gains of around or above 10 percent. This includes the large emerging markets of Egypt and India, whose real per-capita GDP increases by $\exp(.23) \approx 26$ percent and $\exp(.22) \approx 24$ percent, respectively.

The figure also decomposes these income gains into the contributions of the change in the share of the population choosing market occupations ("participation"; light-shaded bar segments), and the change in output per market participant ("productivity"; dark-shaded bar segments). This illustrates that for most sample economies, the productivity gains from improved talent allocation across market occupations make up the largest portion of the hypothetical GDP increase. For the median sample economy, about 2/3 of income gains are derived from improved productivity, and only 1/3 from increased participation.[16]

Although the potential increases in market incomes from addressing female labor market barriers are interesting from a macroeconomic perspective, they present an incomplete picture of the overall effects on welfare. This is because the model assumes that agents derive welfare from both market and non-market output. The first columns of Table 2(b) and 2(c) contrast the income and welfare effects in our baseline scenario. They show that the average welfare impacts, while highly correlated with the per-capita GDP impacts, are only about half has large. This reflects the fact that the reduction in female barriers in market occupations reduces non-market output in most of our sample economies, offsetting some of the welfare gains from increased market incomes. Nevertheless, even in welfare terms, our our exercise suggests broad-based gains from lowering female occupation barriers, with sizable double-digit gains for a number of EMDEs.

5.2 Alternative Counterfactuals

5.2.1 Selection Only on Preferences

The baseline assumption we have imposed so far is that all individual selection is based on ability ($\delta = 0$). While the exact extent of selection on ability is difficult to pin down in practice, column 2 in Table 2 explores the quantitative importance of this assumption by describing the polar opposite case: individual selection purely based on unobserved individual preferences ($\delta = 1$).

As column 2 of Table 2(a) shows, selection on preferences implies numbers for economies' composite occupational barriers that differ from those shown in Figures 2 and 3. Specifically, these

[16] Panama is a notable exception to this overall pattern, where the overall income gains derive from a large increase in participation that more than offsets a productivity *loss*. This reflects underlying data patterns that suggest little misallocation of talents *between* market occupations in Panama, but a sizable female barrier to market participation which – when removed – reduces market productivity as a result of the selection effect.

Table 2: Overview of Counterfactuals Output

Panel (a)

Composite occ. barrier for women relative to men (USA=1)	Baseline	Selection only on preferences (δ=1)	No education (η=0)	Z_{og}=$Z_{og'}$ for o≠7,8,9; τ_{og}=$\tau_{og'}$ for o=7/8/9
Median	**1.09**	**1.00**	**1.09**	**0.96**
75th pctl.	1.19	1.08	1.22	1.02
Max.	3.12	1.56	3.18	2.17
St. dev.	0.43	0.15	0.45	0.25
Correlation with Baseline	1.00	0.65	1.00	0.91

Panel (b)

Log change in real per-capita GDP	Baseline	Selection only on preferences (δ=1)	No education (η=0)	Set τ_{og}=$\tau_{og'}$ for o≠7,8,9
Median	**0.02**	**0.01**	**0.02**	**0.08**
75th pctl.	0.05	0.04	0.05	0.11
Max.	0.23	0.22	0.23	0.30
St. dev.	0.06	0.04	0.06	0.07
Correlation with Baseline	1.00	0.72	1.00	0.95

Panel (c)

Log change in average welfare	Baseline	Selection only on preferences (δ=1)	No education (η=0)	Set τ_{og}=$\tau_{og'}$ for o≠7,8,9
Median	**0.02**	**0.01**	**0.01**	**0.05**
75th pctl.	0.03	0.03	0.03	0.08
Max.	0.14	0.18	0.14	0.19
St. dev.	0.03	0.04	0.03	0.04
Correlation with Baseline	1.00	0.69	1.00	0.94

Notes: Composite occupational barriers for women relative to men are computed at the occupation level, using equations (16) and (17). They are then aggregated using occupation shares in whole-economy earnings as weights. Real income and welfare impacts from changes in economies' occupational barriers are computed using the hat algebra described in Section 2.4.1. The source of all data is the Luxembourg Income Study (LIS) database. All parameters are calibrated in accordance with Table 1 unless otherwise specified. For a more detailed discussion of the counterfactual experiments and calibration choices, see Sections 5.1 and 5.2.

barriers are now somewhat lower in magnitude. Full selection on preferences eliminates the need to adjust observed wage gaps for the selection effect on average ability, as highlighted in equation (16). This generally implies smaller wage gaps and, hence, smaller barriers—but the implied barriers remain highly correlated with their baseline counterparts. Correspondingly, the income effects from reducing barriers to the U.S. level in Table 2(b) are also somewhat reduced, primarily by weakening the productivity channel (partially offset by stronger participation effects).

However, crucially, this does *not* correspond to reduced welfare effects from lowering barriers, as can be seen in column 2 of Table 2(c). The intuition is as follows: while barriers now no longer reduce welfare by preventing individuals from exploiting their idiosyncratic comparative

advantages, making the distortions less "visible" in productivity and income, they instead reduce welfare by preventing individuals from pursuing their preferred amenities. This leaves the welfare case for addressing barriers broadly unchanged relative to our baseline.

5.2.2 Role of Human Capital Investment

In the model of Section 2, human capital investments amplify the effect of occupational barriers on productivity and income differences across groups. Our baseline calibration assumes that such investments are subject to the same human capital production function for all sample economies, with a parametrization based on U.S. data. Yet it seems reasonable to suppose that the human capital production technology accessible to different economies may vary in its effectiveness.

To assuage the concern that this may be an important assumption underpinning our quantitative findings, in column 3 of Table 2 we switch off human capital investment all together ($\eta = 0$). This turns out to have virtually no discernible effect on implied barriers, GDP changes and welfare changes, and strongly suggests that reasonable variation in the human capital parameter would do little to alter our main conclusions.

5.2.3 "Brawn"-Intensive Occupations

So far, we have maintained our main identifying assumption that there exists an unobserved set of group-inherent comparative advantages (represented by $Z_{og}/Z_{og'}$ in the model) that vary across occupations but are common across economies. In this subsection, we proceed from an alternative identifying assumption:

$$\frac{\overline{wage}_{o,w}(t',t')}{\overline{wage}_{o,m}(t',t')}\left(\frac{P_{o,w}}{P_{o,m}}\right)^{\frac{1-\delta}{\theta(1-\eta)}} = \begin{cases} \left(\frac{Z_{o,w}}{Z_{o,m}}\right)^{\frac{1}{1-\eta}} & \text{if } o \in \{7,8,9\} \\ \left(\frac{\tau_{o,w}}{\tau_{o,m}}\right)^{-\frac{1}{1-\eta}} & \text{otherwise} \end{cases}. \tag{28}$$

In words, in occupations 7 ("skilled agriculture"), 8 ("craft and related trades") and 9 ("machine operators") any selection-adjusted wage gaps in favor of men reflect a male comparative advantage. In all other occupations, selection adjusted wage gaps reflect occupational barriers for women in excess of those faced by men. As discussed more extensively in Appendix B.X, we set aside occupations 7, 8 and 9 because they display much larger wage gaps than other occupations across *all* our sample economies−and are arguably more intensive in their use of physical strength ("brawn"-intensive, in the terminology of Hsieh et al. 2019).

The new identifying assumption in (28) implies a different distribution of composite occupational barriers across sample economies, as shown in column 4 of Table 2(a). We continue to express

barriers relative to the U.S., although they are pinned down in absolute terms by (28). The variation in barriers across economies is now somewhat smaller than under our baseline assumptions, but the ranking of economies by the size of their barriers remains virtually unchanged.

Proceeding from (28), we explore the GDP and welfare impacts of eliminating *all* relative barriers in the occupations where they are present:

$$\hat{\tau}_{og} = \begin{cases} \frac{\tau_{o,m}}{\tau_{o,w}} & \text{if } g = w; o \notin \{7,8,9\} \\ 1 & \text{otherwise} \end{cases}. \tag{29}$$

Unsurprisingly, this leads to somewhat larger effects on incomes and welfare in column 4 of Table 2(b) and 2(c) than in our baseline experiment, which sets a weaker plausible benchmark for the lowering of barriers. However, the size of the effects is in a similar ballpark, and their incidence across economies is almost perfectly correlated with what we find in our baseline scenario.

Unlike our baseline experiment, the exercise performed in this subsection also delivers income and welfare effects for the U.S. These can be interpreted as the gains, as of 2015, which could still be achieved by removing all residual U.S. occupational barriers for women, under the assumption in (28). Our computations put the per-capita real-GDP boost at 9.3 percent−very similar comparable numbers produced by Hsieh et al. (2019).[17] This reinforces their message that most of the productivity gains that can be achieved from occupational convergence across groups have already been achieved in the U.S., and that the removal of residual barriers is unlikely to provide a major boost to economic growth going forward.

5.3 Group Preferences versus Group Barriers

5.3.1 Variance Decomposition

We have so far focused on the role of barriers in shaping individuals' occupational choices and, through these, macroeconomic outcomes−leaving aside the potential role of cross-economy differences in preferences. The main justification for this focus is that selective occupational barriers are more amendable to being addressed directly by labor market or education policies. Nevertheless, it is interesting to explore how important preferences are for explaining observed differences in occupational sorting, and to what extent differences in preferences and differences in occupational barriers interact.

[17] Using a comparable parameter configuration, Hsieh et al. (2019) calculate a potential 9.9 percent GDP gain from removing residual U.S. occupational barriers facing black men, black women and white women as implied by 2010 labor market data.

To do so, note that equation (19) implies the following variance decomposition:

$$\frac{1}{\theta^2\left(1-\eta\right)^2}\text{Var}_o\left[\triangle \ln\left(\frac{P_{og}}{P_{og'}}\Big/\frac{P_{1g}}{P_{1g'}}\right)\right]=\frac{1}{9\beta^2}\text{Var}_o\left[\triangle \ln\left(\frac{V_{og}}{V_{og'}}\right)\right]+$$

$$+\frac{1}{\left(1-\eta\right)^2}\text{Var}_o\left[\triangle \ln\left(\frac{\tau_{og}}{\tau_{og'}}\right)\right]+\frac{2}{3\beta(1-\eta)}\text{Cov}_o\left[\triangle \ln\left(\frac{V_{og}}{V_{og'}}\right),\triangle \ln\left(\frac{\tau_{og'}}{\tau_{og}}\right)\right]. \tag{30}$$

Intuitively, deviations in relative occupational choices of an economy's group from what is observed in some reference economy can be attributed to deviations in relative group preferences from that reference economy, deviations in relative barriers, and the correlation between preference and barrier differences. Below we apply this formula to our sample economies, once again using the U.S. economy as the reference case.

5.3.2 Results

Table 3 reports the results from the variance decomposition in (30) for different economies and economy groups from our sample. Throughout, we compute weighted variances, using occupations' share in whole-economy earnings as weights.

Table 3: Decomposition of Occupational Choice Variance with Respect to U.S.

		VAR(choices)	VAR(prefs.)/ VAR(choices)	VAR(barrs.)/ VAR(choices)	2COV(barrs.,prefs.)/ VAR(choices)
All economies	(Avg.)	0.330	0.40	0.43	0.17
AEs	(Avg.)	0.176	0.40	0.50	0.09
EMDEs	(Avg.)	0.484	0.39	0.37	0.24
Egypt		0.551	0.28	0.38	0.34
India		1.807	0.47	0.14	0.39
Peru		1.040	0.30	0.23	0.47

Notes: The table provides an overview of the results from the variance decomposition described in equation (30), performed at the economy level. VAR(choices) refers to the left-hand-side of equation (30). VAR(prefs.), VAR(barrs.) and 2COV(barrs.,prefs.) respectively refer to the first, second and third right-hand-side terms of equation (30). The different objects in equation (30) are computed as described in Section 2.3, with all parameters calibrated in accordance with Table 1. The source of all data is the Luxembourg Income Study (LIS) database.

As would be expected, column 1 of Table 3 shows that the deviation of women's occupational choices from what is observed in the U.S. is larger for EMDEs than for the average advanced economy−and it is especially large for some larger EMDEs, including Egypt, India and Peru. Less obviously, columns 2 and 3 document that across all economies, differences in barriers and preferences contribute about equally to differences in women's occupational choices from U.S. patterns (with some individual exceptions).

The most intriguing finding emerges in column 4. For advanced economies deviations in preferences and barriers from the U.S. reference appear to be almost completely uncorrelated, suggesting that these two data-implied drivers of occupational choices are largely orthogonal in this group. Meanwhile, among EMDEs−especially those with high barriers compared with the U.S.−there is a strong positive correlation, whereby occupations that appear to be less preferred by women also appear to characterized by relatively high female occupational barriers. This may suggest that some of the higher occupational barriers detected for these economies reflect the prevalence of social norms that prescribe certain occupations as undesirable for women and, in so doing, also lower their return to female human capital. While a full exploration of this issue is beyond the scope of the present paper, this finding suggests potential avenues for future research on the cross-country drivers of female occupational barriers.

6 Conclusion

This paper examines the macroeconomic implications for different economies of occupational barriers that penalize women relative to men. Using a Roy model of occupation choice, we construct a theoretically grounded measure that can be used to compare the magnitude of these barrier across countries and time. We find substantial heterogeneity in female occupational barriers, with many EMDEs exhibiting barriers comparable to those observed in the U.S. during the 1960s. We show that reducing these barriers could lead to double-digit gains in incomes and welfare for some major emerging markets. These gains arise primarily from an improved talent allocation, rather than mere increases in labor force participation.

From a policy perspective, our findings suggest that policy interventions to reduce occupational segregation by gender could be a powerful catalyst of economic growth and international income convergence. This is salient at a time in which global economic growth has slowed, and there are widespread concerns that societal aging and population decline will reduce the size of workforces and stall the growth of labor productivity. Policies that address female occupational barriers may include expansions of educational and training opportunities for women in non-traditional fields, legal reforms to address workplace discrimination, and public support for families and childcare.

Future research should further explore the long-term dynamics of group-specific occupational barriers, their interaction with other labor market frictions, and the impact of specific policy interventions on reducing these distortions. Our paper contributes to a growing body of evidence that such interventions could pay sizable macroeconomic dividends.

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A Model Derivations

A.1 Human Capital Supply

By construction, for individuals selecting into occupations on preferences equation (10) implies:

$$E\left[h_{og}^{*}\left(t,t'\right)\right]=\Gamma Z_{og}^{\frac{1}{1-\eta}}\zeta\left(t-t'\right)\left[\frac{\eta\left(1-\tau_{og}^{w}\right)W_{o}\bar{\zeta}}{1+\tau_{og}^{i}}\right]^{\frac{\eta}{1-\eta}}. \tag{31}$$

For individuals selecting into occupations on abilities, equation (10) and standard Fréchet results instead imply:

$$E\left[h_{og}^{*}\left(t,t'\right)\right]=\Gamma Z_{og}^{\frac{1}{1-\eta}}\zeta\left(t-t'\right)\left[\frac{\eta\left(1-\tau_{og}^{w}\right)W_{o}\bar{\zeta}}{1+\tau_{og}^{i}}\right]^{\frac{\eta}{1-\eta}}P_{og}^{-\frac{1}{\theta(1-\eta)}}, \tag{32}$$

where the last term of the product on the right-hand side captures the diminishing average productivity as more members of group g join occupation o. Then, across all individuals:

$$H_{og}\equiv\sum_{t'=t-2}^{t}\left(1-\tau_{og}^{w}\right)E\left[h_{og}^{*}\left(t,t'\right)\right]P_{og}N_{g}=$$

$$=\sum_{t'=t-2}^{t}\Gamma\left(\frac{Z_{og}\bar{\zeta}}{\tau_{og}}\right)^{\frac{1}{1-\eta}}\frac{\zeta\left(t-t'\right)}{\bar{\zeta}}\left(\eta W_{o}\right)^{\frac{\eta}{1-\eta}}\left[\delta+\left(1-\delta\right)P_{og}^{-\frac{1}{\theta(1-\eta)}}\right]P_{og}N_{g}, \tag{33}$$

where N_g is the share of group g in the population. This yields equation (14).

A.2 Geometric Average Wages

For individuals selecting into occupations on preferences equation (10) implies:

$$\exp\left\{E\left[\ln h_{og}^{*}\left(t,t'\right)\right]\right\}=\Gamma Z_{og}^{\frac{1}{1-\eta}}\zeta\left(t-t'\right)\left[\frac{\eta\left(1-\tau_{og}^{w}\right)W_{o}\bar{\zeta}}{1+\tau_{og}^{i}}\right]^{\frac{\eta}{1-\eta}}. \tag{34}$$

For individuals selecting into occupations on abilities, equation (10) and standard Fréchet results instead imply:

$$\exp\left\{E\left[\ln h_{og}^{*}\left(t,t'\right)\right]\right\}=\tilde{\Gamma}Z_{og}^{\frac{1}{1-\eta}}\zeta\left(t-t'\right)\left[\frac{\eta\left(1-\tau_{og}^{w}\right)W_{o}\bar{\zeta}}{1+\tau_{og}^{i}}\right]^{\frac{\eta}{1-\eta}}P_{og}^{-\frac{1}{\theta(1-\eta)}}, \tag{35}$$

where $\tilde{\Gamma}\equiv\exp\left[\gamma/\theta\left(1-\eta\right)\right]$ and $\gamma\approx0.5772$ is the Euler-Mascheroni constant.

Let $\overline{wage}_{og}\left(t,t'\right)$ denote the geometric average wage across all individuals from group g and

cohort t' working in occupation o in period t. Then, using (34) and (35),

$$\overline{wage}_{og}\left(t,t'\right)=\frac{\exp\left\{E\left[\ln h_{og}^{*}\left(t,t'\right)\right]\right\}W_{o}}{1-\tau_{og}^{w}}=$$

$$=\eta^{\frac{\eta}{1-\eta}}\Gamma^{\delta}\tilde{\Gamma}^{1-\delta}\frac{\zeta\left(t-t'\right)}{\bar{\zeta}}\left(\frac{Z_{og}\bar{\zeta}W_{o}}{\tau_{og}}\right)^{\frac{1}{1-\eta}}P_{og}^{-\frac{1-\delta}{\theta(1-\eta)}}. \tag{36}$$

This immediately yields equation (16).

A.3 Occupation Choice

Given the normalizations imposed on occupation 1 ("Home"):

$$\frac{P_{1g}}{P_{1g'}}=\left(\frac{\sum_{o=1}^{O}W_{og}^{\theta}}{\sum_{o=1}^{O}W_{og'}^{\theta}}\right)^{-1}. \tag{37}$$

It follows from (12) and (13) that:

$$\left(\frac{P_{og}}{P_{og'}}\Big/\frac{P_{1g}}{P_{1g'}}\right)^{\frac{1}{\theta(1-\eta)}}=\left(\frac{V_{og}}{V_{og'}}\right)^{\frac{1}{3\beta}}\left(\frac{Z_{og}}{Z_{og}}\right)^{\frac{1}{1-\eta}}\left(\frac{\tau_{og}}{\tau_{og'}}\right)^{-\frac{1}{1-\eta}}. \tag{38}$$

Substituting in from (16) yields (18).

B Data

B.1 Variables from LIS Database

Table B1: Key Variables from LIS

	Definition
General	
cname	Full name of country
year	Year
grossnet	Information on whether the current incomes reported in the dataset are gross of taxes and social security contributions (i.e. taxes and contributions fully captured), net (i.e. taxes and contributions not captured) or any inbetween situation (i.e. taxes and contributions insufficiently captured)
ppopwgt	Population individual cross-sectional weight: this weight inflates the result to reflect the total individual population covered by the dataset.
Demographics	
age	Age
sex	Gender
Labor Market	
emp	Indicator of employment as the respondent's main current activity status.
lfs	Main current activity status as self-reported by the respondent, categorizing individuals into employed, unemployed, and not in the labour force.
hourstot	Regular hours worked at all jobs currently held (including family work and overtime, whether paid or unpaid).
weeks	Number of weeks worked during the year (ideally the same year as the income reference period) in any job.
pxitsc	Income taxes and social security contributions paid.
fyft	Indicator of whether a person has worked full-time for the entire reference year.
occb1	Occupational classification of the main job based on the 10 major groups of the International Standard Classification of Occupations (ISCO-88).
ptime1	Indication of part-time employment in the main job. Part-time employment refers to a work arrangement where an individual works fewer hours than the standard full-time schedule in main job.
indb1	Classification of the economic activity in the main job into nine categories.
Income	
pi11	Monetary payments received from regular and irregular dependent employment. This includes cash wage and salary income (gross of social security contributions and income taxes) and monetary supplements to the basic wage, such as overtime pay, employer bonuses, 13th month bonus, profit-share, tips.
pi12	Total income from self-employment, defined as profits/losses from self-employment activities, including farm and non-farm businesses.

B.2 Major Occupation Categories

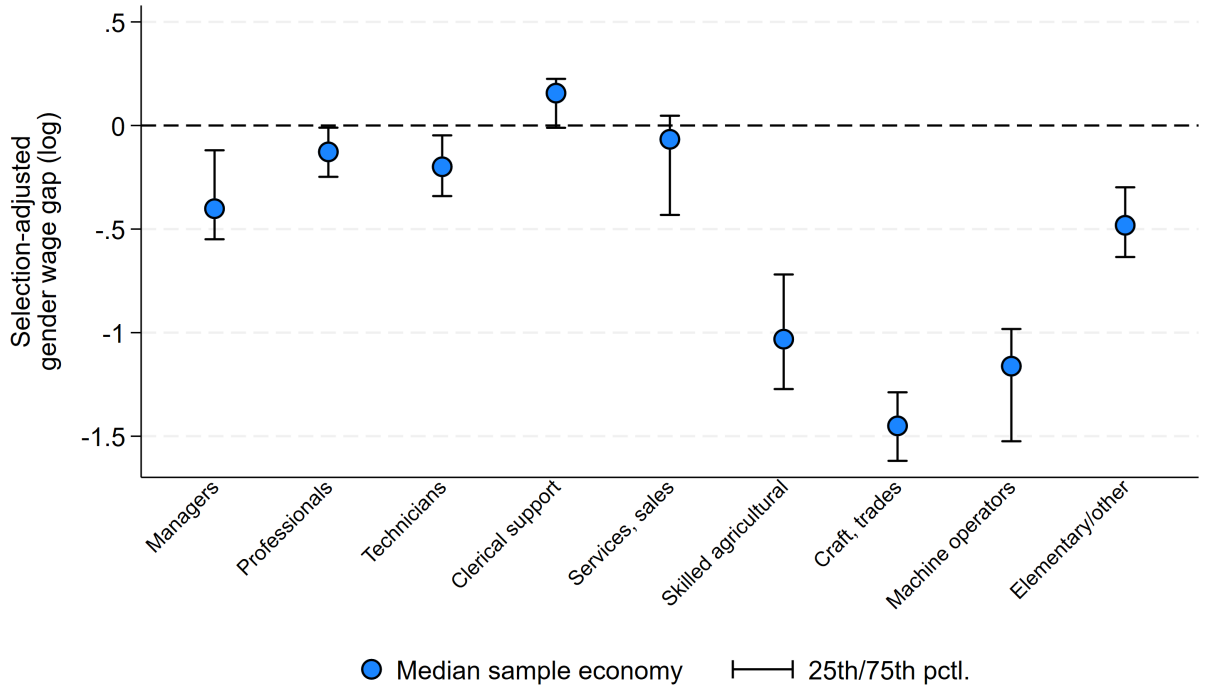
Table B2: ISCO-88 Major Occupation Categories

o	Description	Example
1	"Home"	Not full-time or part-time employed
2	Managers	Corporate managers, public officials
3	Professionals	Scientists, teachers, doctors
4	Technicians	Nurses, legal assistants
5	Clerical support workers	Clerks, receptionists
6	Service, sales workers	Salespeople, waitstaff
7	Skilled agricultural workers	Farmers, forestry and fishery workers
8	Craft, related trades workers	Electricians, carpenters, tailors
9	Plant/machine operators	Drivers, assembly workers
10	Elementary occupations/Other	Cleaners, laborers, street vendors

B.3 Selection-Adjusted Wage Gaps By Occupation

Figure B1 provides an overview of the cross-economy distribution of the selection-adjusted gender wage gap, as defined in equation (16), broken down by occupational category. The figure documents that these wage gaps are an order of magnitude larger for occupation categories 7 ("skilled agriculture"), 8 ("craft and related trades") and 9 ("machine operators") than for all other occupations. Indeed, for all other occupations, there is a significant share of sample economies that display no wage penalty for women, or even a modest wage advantage. By contrast, this is not the case for *any* sample economy in categories 7, 8 and 9.

Figure B1: Cross-Economy Distribution of Selection-Adjusted Wage Gaps



Notes: Selection adjusted wage gaps are computed at the occupation level as defined on the left-hand-side of equation equation (16) with $\delta = 0$, $\theta = 2$, $\eta = 0.103$. The source of all data is the Luxembourg Income Study (LIS) database.

One possible interpretation of this evidence is that women do not have an inherent productivity disadvantage relative to men in *most* occupations−with categories 7, 8 and 9 as the main exception, given the strong wage penalty consistently observed across a diverse set of economies. In subsection 5.2.3, we explore the implications of this interpretation of the data, both for our measure of differences in composite occupational barriers across economies and for the potential income and welfare gains from removing said barriers.