Gender Gaps in Time Use and Entrepreneurship*

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Abstract

The prevalence of entrepreneurs, particularly low productivity non-employers, declines as economies develop. We show that this decline is more pronounced for women and that the gender gap in entrepreneurship *reverses* with development – from an over representation of women in entrepreneurship in less developed economies to an under representation in more developed economies. This paper explores whether gender asymmetries in time devoted to non-market responsibilities can explain this pattern across countries. Given the flexibility afforded to entrepreneurs, constraints on available market time can be an important factor impacting the selection into entrepreneurship. Such time constraints are tighter for women particularly those in less developed economies. To quantitatively assess the importance of time constraints, we develop a general equilibrium model of occupational choice where selection into entrepreneurship is driven by discretionary time and ability. Using a calibrated version of the model, we find that observed gender gaps in time use account for a significant share of cross-country differences in entrepreneurship, productivity and the firm size distribution. Our results highlight the importance of factors such as child-care policy or societal norms in not only influencing gender differences in labor market outcomes but also the quantity and quality of businesses in an economy.

JEL codes: J2, L2, O1
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1 Introduction

Economies undergo dramatic structural changes as they develop. Poor countries feature higher rates of low productivity entrepreneurship and striking gender differences in labor market outcomes and responsibilities compared to rich countries.[1] In this paper, we explore the interaction between these two phenomena and study how gender asymmetries in non-market responsibilities shape the quantity and quality of entrepreneurs across countries.

There is an intuitive relationship between gender gaps in non-market responsibilities and entrepreneurship. The ability of entrepreneurs to set their own hours implies that constraints on discretionary time, due to non-market responsibilities, can be an important factor influencing selection into entrepreneurship.[2] Since non-market responsibilities such as household work, and child and family care fall disproportionately on women – particularly so in developing economies – such constraints can be crucial for understanding rates of female entrepreneurship. Further, constraints on time use are likely unrelated to ability and therefore selection based on these constraints will impact the quality of entrepreneurs – lowering aggregate productivity and transforming gender gaps in time use into gender gaps in entrepreneur quality.

We begin by providing evidence supporting such a selection mechanism. Using data from the US, we show that around 30% of entrepreneurs report "flexibility of schedule" or "family obligations" as their primary reason for pursuing entrepreneurship. This share is even higher among those that do not hire others – non-employers. We also find that non-employers work much fewer average hours than either workers or employers, suggesting that non-employer entrepreneurship may be particularly attractive for those with constraints on their time.

[1]See for example Gollin (2008) and Poschke (2019) for evidence cross-country differences in the share of entrepreneurs and their productivity. Throughout this paper, we will use the term entrepreneur and self-employed interchangeably. See Antecol (2000) for cross-country differences in labor market outcomes by gender and Bridgman et al. (2018) for cross-country differences in household work by gender.

[2]Hurst and Pugsley (2011) show that non-pecuniary factors such as time are an important determinant of selection into entrepreneurship.

Consistent with women facing tighter constraints on time, we use the same US data to show that female entrepreneurs are much more likely to claim flexibility as a motive for entrepreneurship (around 40% vs 20% for males). Female entrepreneurs are also more likely to be non-employers, work fewer hours and earn less than their male counterparts.

Next, we use data across countries to study gender gaps in i) time use and ii) entrepreneurship. In line with existing work, we show that women in developing economies do indeed have more non-market responsibilities which limits their potential market time. We also find that the gender gap in (non-agricultural) entrepreneurship reverses with development – from an over representation of female entrepreneurs in developing economies to an under representation in developed economies. This reversal is driven almost entirely by changes in the gender gaps among non-employers – an occupation that we argue is particularly susceptible to selection based on time use.

These findings are consistent with selection based on time use. That is, since women in developing economies have tighter constraints on their time-use they may be self-selecting into non-employer/low productivity entrepreneurship. To formalize this idea, we develop a model of occupational choice where agents can select into one of three occupations; i) employment (employees) ii) entrepreneurship with employees (employers) and iii) entrepreneurship without employees (non-employers). Importantly, selection into these occupations is not only based on ability as in standard models but also available market time.

A key feature of the model is that entrepreneurs have production functions that are non-linear in their own hours. The return to hours is concave for non-employers and linear for workers and employers. This generates lower average hours worked for non-employers relative to workers or employers as observed in the data. The non-linearity in hours also induces selection into non-employer entrepreneurship for those that have less market time available.

We calibrate the model to US data and use it to quantitatively assess the role of gender gaps in time use in accounting for cross country gender gaps in entrepreneurship. To do this, we introduce gender-specific differences in time use as observed in the data and study the resulting selection into occupations implied by the model. We find that observed gender gaps in time use account for a significant share of the gender gaps in entrepreneurship and overall rates of entrepreneurship across countries. The model also allows us to quantify the role of unobserved (gender-specific) barriers to occupations, separately from constraints on time use, driving aggregate outcomes such as aggregate productivity and the firm size distribution.

Our preliminary results highlight that factors such as child-care policy or societal norms that put constraints on female time use are important not only in influencing gender differences in labor market outcomes but also the quantity and quality of businesses in an economy.

The two motivating facts of our paper, the evolution of gender gap in entrepreneurship and hours over the development process, have been independently studied in the literature. First, it is well known that the share of self-employment in the labor force is much higher in poor countries than rich countries (Poschke, 2019 and Jayachandran, 2020). Consequently, in most poor countries, small and non-employer businesses are the dominant form of businesses (Gollin, 2008, Feng and Ren (2021)). In this paper, we focus on another important and related difference of entrepreneurship across countries, namely, an over-representation of women in entrepreneurship in developing countries and an under-representation in developed countries. Related to our paper, Cuberes and Teignier (2018) document an under-representation of women in entrepreneurship in European countries and the US and attribute under-representation to gender-specific barriers of occupational choice.

The second motivating fact is that women in developing countries bore a significantly higher share of household work compared to men, but the gender inequality is much smaller, albeit still present, in developed countries (see also Bridgman et al., 2018). Although a fraction of the gender inequality in hours can be explained by the process of development, the gender gap/development relationship is robust even after controlling for sectoral composition and individual characteristics, that is, much is still left unexplained.

There exists an extensive literature studying the different forces shaping the outcome of the gender inequalities in labor market outcomes, including labor market participation rate, gender wage gap, and occupation shares. Among these papers, our work is motivated by Goldin (2014) and Erosa et al. (2017), which illustrate the consequence of gender inequality in housework responsibilities in the presence of a linear and a non-linear occupation. In a similar vein, our focus is on the occupation choice between entrepreneurship and salaried workers, thus allowing a direct link between hours and the availability of businesses. Besides hours, another important feature in our model is gender-specific distortions, which is related to recent researches exploring the distortions faced by female workers (Hsieh et al., 2019) and entrepreneurs (Bento, 2020) and its impacts on allocation and aggregate productivity.

2 Empirical Findings

In this section, we establish the empirical patterns that motivate and discipline our theory. First, we use data from the US to argue that entrepreneurship, particularly non-employer entrepreneurship is a relatively flexible occupation and is commonly pursued – especially by women – due to its flexibility. Second, we use data across countries to show that the gender gap in both non-market time use and entrepreneurship declines with development. That is, gender gaps in non-market time use are positively correlated with gender gaps in entrepreneurship.

2.1 Evidence from the US

Data from the US is from the Outgoing Rotation Group of the Current Population Survey (CPS). We pool monthly data from January 2014 to October 2019 and define the self-employed as entrepreneurs.[3] To be consistent with the cross-country samples in the following subsection, we restrict attention to individuals between the age of 15 and 65. In addition, we focus on those respondents that worked at least 10 hours and held only one job. Our analysis separates those working into three categories: i) employees – those that work for others, ii) non-employers – entrepreneurs that do not hire workers and iii) employer – entrepreneurs that hire workers.

Table 1 summarizes the hours worked, earnings and employment shares across these three occupation categories by gender. First, it is clear that there exists an under-representation of women in entrepreneurship (both employers and non-employers) in the US. Second, from the unconditional average of hours worked, we find that across all occupations, women work fewer hours than men. Further, for either gender, employers work the longest hours wile female non-employers work the shortest hours with male employees and non-employers working similar hours. Third, and consistent with existing work such as Yurdagul (2017), the standard deviation of hours worked is higher among entrepreneurs and highest among female non-employers.

We also uncover significant heterogeneity in the earnings across occupations. The unconditional average shows a clear gender wage gap across all occupations. Further, for either gender, employers and workers reports relatively similar earnings while non-employers report much lower average earnings.

While instructive, unconditional averages do not control for observable characteristics which could explain a significant share of the observed variation in hours worked. Next, we control for such characteristics and re-examine the occupational and gender differences

[3] Data is extracted from IPUMS as detailed in Flood et al. (2020). We start in 2014 as this is the first year in which the Outgoing Rotation Group has asked the self-employed if they hire others. The Contingent Worker Supplements conducted periodically since 1995, also contains this information although for a subset of the CPS sample.

Table 1: Summary Statistics by Occupation and Gender

	Male			
	All	Employers	Non-Employers	Employees
Share of Employment	1.000	0.030	0.081	0.890
Average Hours	41.37	48.41	42.23	41.09
S.D. of Hours	9.61	12.31	12.79	9.13
Mean Log Hourly Earnings	3.07	2.99	2.81	3.14
	Female			
	All	Employers	Non-Employers	Employees
Share of Employment	1.000	0.011	0.057	0.932
Mean Hours	37.39	42.53	35.50	37.43
S.D. of Hours	9.46	13.64	14.00	9.08
Mean Log Hourly Earnings	2.91	2.82	2.67	2.95

Notes: Mean and standard deviation of hours worked as well as the share of employment is is computed using the CPS ORG sample. Mean hourly earnings are reported in log 2010 USD and are computed using information from respondents in the Annual Social and Economic Supplement of the CPS (CPS ASEC) and the corresponding sample weights. The combined ORG-ASEC sample include those respondents that worked at least 40 weeks in the same occupation. Hourly earnings are computed as the ratio of annual earnings to the product of weeks worked and usual weekly hours. Earnings for entrepreneurs and employees are business income and wage income, respectively (variables `incbus` and `incwage` from IPUMS, respectively). Respondents that earn less than half the minimum wage are excluded. Top-coded earnings are multiplied by 1.5.

across occupations by estimating the coefficient β_o from the following OLS regression:

$$\log(h_i) = \alpha + \sum_o \beta_o D_i^o + X_i + \epsilon_i \tag{1}$$

where h_i is hours worked by individual i, D_i^o is a dummy variable indicating the occupation o of an individual. X_i is a vector of individual level controls comprised of a quadratic term in years of experience, race, marital status, number of children in household, 2-digit industry and 2-digit occupation fixed effects. We also include state and year fixed effects.

The coefficients of interest, β_o, are estimated separately for males and females and reported in table 2. For both men and women, non-employer entrepreneurs work the least hours while employer entrepreneurs work longest. Among men, the gap between non-employers and employees is around 3% while the analogous gap for women is much larger with non-employers working 10% less than employees. Female employers work around 9 to 12 % longer hours while male employers work 11 to 15% longer than comparable employees. Hours worked increase with firm size, particularly for men. Taken together, the results from table 2 ex-

Table 2: Hours Worked by Entrepreneurs, relative to Employees

	Non-Employers	Employers						N	R^2
		1 to 4	5 to 9	10 to 19	20 to 49	50 to 74	75+		
Male	-0.032***	0.093***	0.114***	0.130***	0.131***	0.132***	0.152***	460,596	0.153
	(0.002)	(0.003)	(0.006)	(0.007)	(0.009)	(0.020)	(0.015)		
Female	-0.108***	0.073***	0.099***	0.094***	0.087***	0.124***	0.103*	420,719	0.124
	(0.004)	(0.008)	(0.014)	(0.017)	(0.024)	(0.044)	(0.062)		

Notes: The table reports the coefficients on occupation from an OLS regression of log hours worked per week of respondents in the CPS sample. Controls include a quadratic term in years of experience, race, marital status, number of children in household, state, year, 2-digit industry and 2-digit occupation fixed effects. The first row and second row reports the results for the sample of males and females respectively. The columns report the estimated coefficient for non-employers and employers by the number of paid employees they hire. The excluded occupation is employees. Robust standard errors are reported in parentheses. *** and * indicate statistical significance at the 1% and 10% confidence level, respectively.

hibits a clear ranking of hours worked across occupations; employers work the longest while non-employers the shortest with employees working intermediate hours. [4]

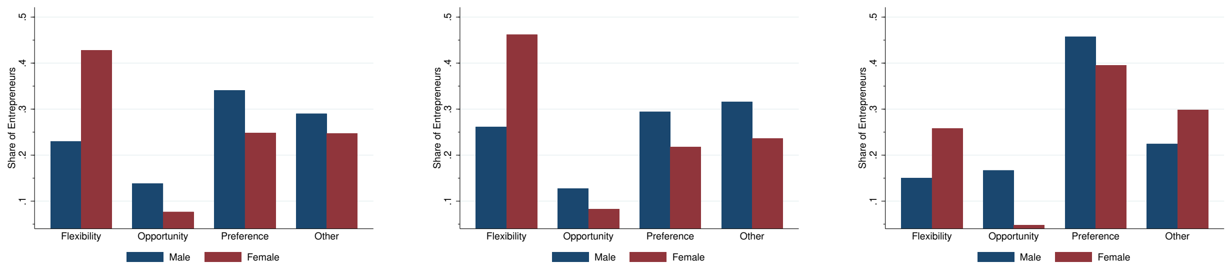
Short average hours suggest that selection into non-employer entrepreneurship might be attractive for those with constraints on their time. Non-pecuniary motives such as a desire for flexibility or preferences for being one's own boss have previously been emphasized by Hurst and Pugsley (2011) and Yurdagul (2017) among others. Since women are more likely to have constraints on their time - due to non-market responsibilities - it should follow that the flexibility motive is particularly strong for women especially non-employers. We show this to be the case using data from the 2017 Contingent Worker Supplement (CWS) of the CPS. This supplementary questionnaire asks respondents their primary motive for pursuing entrepreneurship.[5] We combine several possible motives into four exhaustive categories and figure 1 shows the share of entrepreneurs that report each motive.

Confirming the findings of existing work, the figure shows that, for both genders, flexibility and preferences are important reasons for pursuing entrepreneurship. We emphasize two additional findings. First, the flexibility motive is stronger for women - around 45% of female non-employers and 25% of female employers claim the need for a flexible schedule as

[4] The results from an analogous regression on log earnings are reported in table C.1 in the appendix. We find that after controlling for observable characteristics, employees and employers earn a similar wage while male and female non-employers earn 17 and 14 % lower earnings, respectively, than employees.

[5] We use the same sample restrictions as in the primary CPS sample and apply the appropriate supplement survey weights when reporting statistics.

Figure 1: Motives for Entrepreneurship



(a) All Entrepreneurs (b) Non-Employers (c) Employers

Notes: The figure shows the share of entrepreneurs by their primary reason for pursuing entrepreneurship. Data is from the 2017 Contingent Worker Supplement of the CPS. The "Flexibility" category includes those that stated their motive for entrepreneurship to be *Flexibility of schedule*, *family/personal obligations* or *Child care problems*. "Opportunity" groups the following responses; *Money is better*, *To obtain experience/training* and *For the money*. "Preference" includes those that report *Enjoys being own boss and independence*. The "Other" category groups all remaining responses. Table C.2 in the appendix reports the shares of entrepreneurs separately for each possible response.

their primary motive for pursuing entrepreneurship compared to only 25% and 15% of their male counterparts. Indeed, the gender gaps in motives are widest for the flexibility category. Second, for both genders, the flexibility motive is strongest for non-employers - the share of non-employers claiming flexibility as a motive is almost double that of employers.

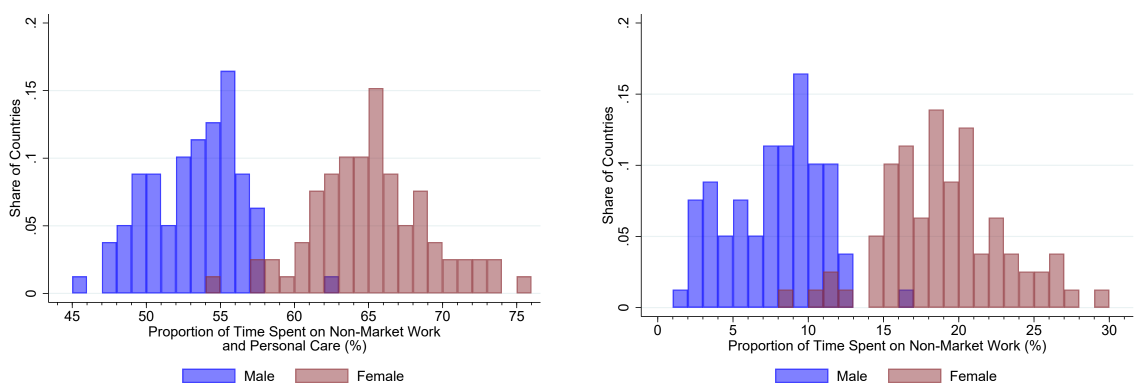
Combined with the findings of average hours by employment, these empirical patterns provide suggestive evidence that entrepreneurs - especially non-employers - select into entrepreneurship based on their time use. It follows then that differences in time use across genders will interact with this margin of selection and lead to gender differences in rates of entrepreneurship. We investigate this idea in the next section by comparing gender gaps in time use and entrepreneurship rates across countries.

2.2 Cross-Country Gender Gaps in Time Use

In this section, we document cross-country gender gaps in non-market time use. To analyse gender gaps in time use, we use aggregated statistics from time use surveys as compiled by i) the United Nations Statistics Division, ii) OECD Stat and iii) Bridgman et al. (2018). Each of these data report, by gender, the proportion of time spent doing domestic chores and caring for others. Such non-market work includes food preparation, cleaning, shopping, and caring for children, among other activities. In order to focus on gender gaps in non-discretionary time – that is time which cannot be used for either leisure or work – we consider activities related to personal care as non-discretionary. Personal care activities include sleeping (not naps), eating/drinking, and other personal services such as visits to the doctor, hairdresser, etc.

We focus on data from the most recent year available and restrict attention to countries with data derived from time use surveys rather than labour force of household surveys. Our final sample includes data from 79 countries which span the range of levels of development. Additional details on the construction of the data and results can be found in the appendix.

Figure 2: Distribution of Time Use by Gender



(a) Non-Market Work and Personal Care

(b) Non-Market Work Only

Notes: The figure reports distribution of the percentage of time spent in non-market work and personal care by male and females across countries.

Figure 2 reports the cross-country distribution of the percentage of time spent by males and females in non-market and personal care activities. Panel (a) shows that, across countries, around 50% of males' and 65% of females' time is spent in conducting non-market work or personal care activities. Focusing on only non-market work, panel (b) shows that across countries males spend around half the amount of time in non-market work than females (10% vs. 20%). Both panels show that there is very little overlap in the distributions of time use by gender suggesting, all over the world, women spend more time than men conducting non-market and personal care activities. This is onsistent with existing works such as Rubiano-Matulevich and Viollaz (2019) and Ferrant et al. (2014) that also document significant cross-country differences in the non-market responsibilities of men and women.

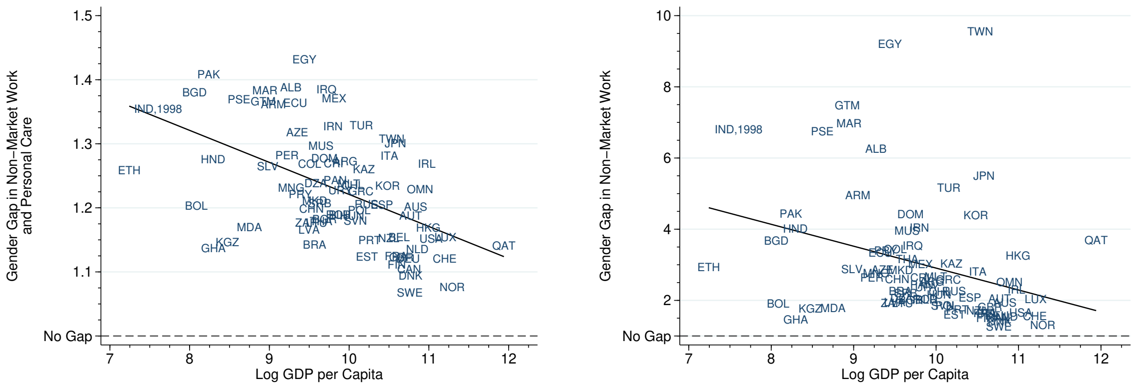
Comparing panels (a) and (b) also suggests that the difference in genders is driven by differences in time spent in non-market work rather than personal care activities. Indeed, in the data from the OECD, the average daily time spent in personal care is 667 minutes for women and 656 minutes for men. By contrast the average daily time spent in unpaid work is 264 minutes for women and 131 minutes for men.[6] Further, the majority (around 75%) of time in personal care is time spent sleeping with little difference across genders in time spent sleeping.

Figure 3 reports the gender gap in time use across countries. The gender gap is defined as the ratio of female and male time spent in non-market and personal care activities. Consistent with figure 2, there are significant gender gaps in time use across countries. For example, women in Pakistan spend 40% more time than men engaged in non-market and personal care activities while the analogous measure for women in Canada is around 10% more time. The figure also shows a strong negative relationship between gender gaps in time use and the level of development. That is, the gender gap shrinks with development although it does not close; even for high income economies the gap is positive and averages around 10%.

Panel (b) of figure 3 shows that there are much larger gender gaps in time use when focusing only on non-market work. For example, women in Pakistan spend around four times the amount of time on non-market work compared to men. In Egypt and Taiwan, this gap is even larger and approaches a ten-fold difference. In our quantitative analysis, we focus on gender gaps in time use for both non-market and personal care activities as we think of these activities as being non-discretionary and determined largely by biology (for example, time spent sleeping) and cultural norms (for example, the responsibility of domestic chores).

[6]For example, in Norway these analogous averages were 667 and 655 minutes for personal care, and 220 and 178 minutes in non-market work for women and men, respectively.

Figure 3: Gender Gaps in Time Use



(a) Non-Market Work and Personal Care

(b) Non-Market Work Only

Notes: The figure reports the ratio of female to male time spent in non-market work as reported from the World Bank and OECD and Bridgman et al. (2018).

2.3 Cross-Country Gender Gaps in Entrepreneurship

In this section, we document cross-country gender gaps in entrepreneurship. To measure rates of entrepreneurship by gender, we use both aggregated statistics from the International Labor Organization (ILO) and micro-level data from the International Integrated Public Use Surveys (IPUMS).[7] The ILO data reports the total number of individuals employed by their occupation, gender and industry. This allows us to construct the share of (non-agricultural) entrepreneurs among total (non-agricultural) employment for both males and females. Our final sample includes information from 83 countries.

The nationally representative surveys or censuses from IPUMS are used to confirm the findings from the ILO data. In addition, we use the IPUMS micro-data to construct disaggregated gender gaps in occupations by education, marital status and the number of children. We focus on those surveys which allow us to identify both employer and non-employer entrepreneurs and also report industry of employment. This restricts us to surveys

[7]International Labour Organization (2019) and Minnesota Population Center (2019) provide details on the construction of the ILO and IPUMS data, respectively. We also use data from the European Union Labor Force Surveys (EU-LFS). However, these data do not distinguish employers from non-employers so we only include it when discussing overall entrepreneurship.

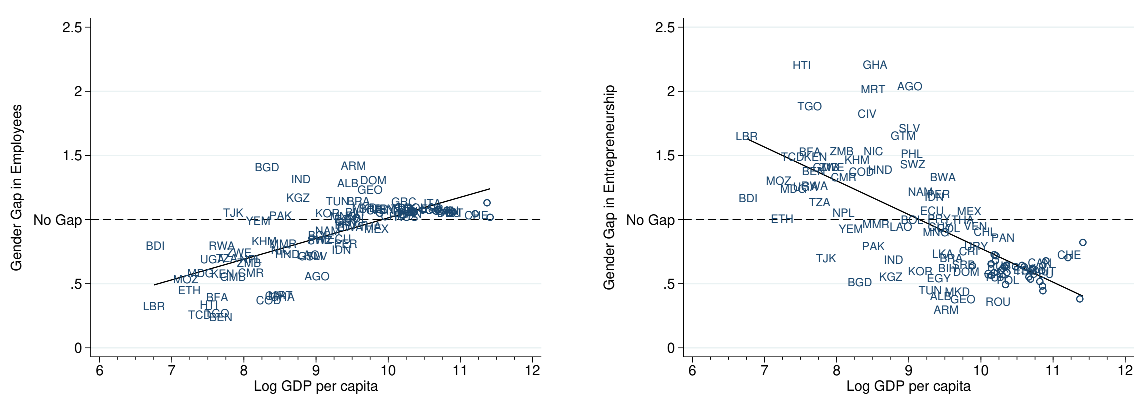
from 54 countries. Additional details on our treatment of the data can be found in the appendix.

We begin by documenting how gender gaps among employees and entrepreneurs (either employers or non-employers) change with development. We define the gender gap in an occupation, as the ratio of female to male share of those employed in an occupation among total employment. More specifically, for an occupation o the gender gap is defined as,

$$\text{Gender Gap}_o = \left(\frac{\text{Female}_o}{\text{Female Employment}}\right) \div \left(\frac{\text{Male}_o}{\text{Male Employment}}\right)$$

Figure 4 uses aggregated data from the ILO to plot the gender gaps for employees and entrepreneurs across countries. Panel (a) shows that the gender gap for workers closes as economies develop – from a relative over representation of male employees in poorer countries to a slight under representation in richer countries. Panel (b) shows that the gender gap in entrepreneurship reverses with development. In poor countries, women are over-represented in entrepreneurship compared to men while in rich countries they are under-represented. Taken together, the figure suggests that as economies develop, women – more so than men – switch away from entrepreneurship towards employment.

Figure 4: Gender Gaps for Employees and Entrepreneurs



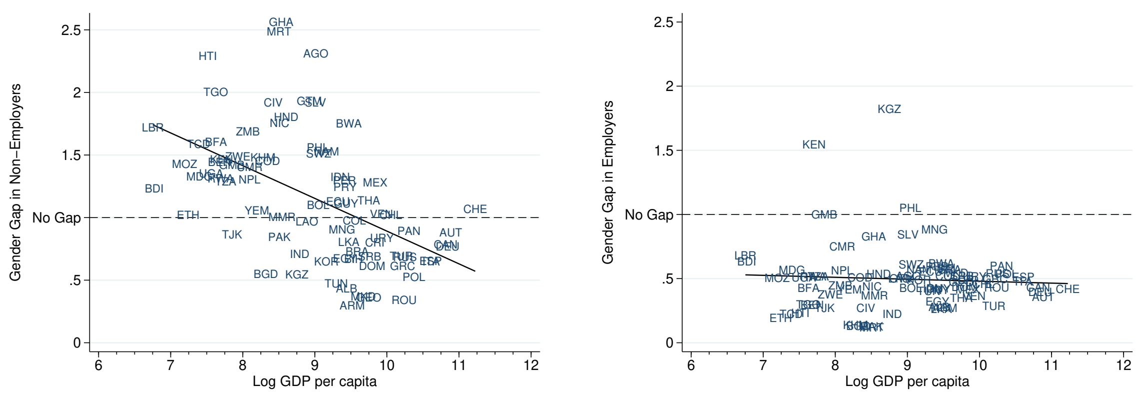
(a) Employees

(b) Entrepreneurs

Notes: The figure plots the ratio of female and male employees and entrepreneurs as a share of their respective total employment using data from the ILO. The unlabeled markers report data from the EU Labor Force Surveys.

Figure 5 dis-aggregates the gender gap for entrepreneurs by separately reporting the gender gap for non-employers and employers. Comparing panels (a) and (b), we observe that changes in the gender gap for entrepreneurs with development is driven almost exclusively due to changes in the gender gaps among non-employers. Indeed, the gender gap for non-employers almost exactly mirrors the gender gap for all entrepreneurs – the slope coefficient is -0.27 for the former and -0.26 for the latter. On the other hand, there is no statistically significant relationship between the gender gap for employers and the level of development – most economies feature relatively more male employers relative to female employers while this gaps declines only slightly with development.

Figure 5: Gender Gaps for Non-Employer and Employer Entrepreneurs



(a) Non-Employers

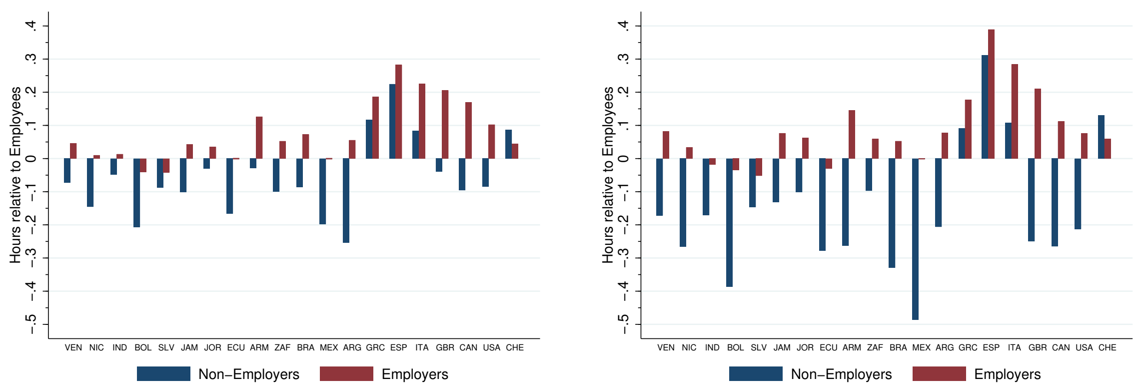
(b) Employers

Notes: The figure plots ratio of female and male non-employer and employer entrepreneurs as a share of their respective total employment using data from the ILO.

Dis-aggregating gender gaps in entrepreneurship as in figure 5 indicates that the decline in gender gaps in overall entrepreneurship in figure 4 is driven by women switching away from *non-employer* entrepreneurship into employment as economies develop. If, as in the US, non-employer entrepreneurship is susceptible to selection based on time constraints across countries, then changes in gender gaps in time use can be a potentially important factor in understanding these cross-country patterns.

To test the idea that non-employers select into their occupation based on time use, we repeat the regression in equation (1) using data from across countries.Figure 6 reports the coefficient β_o which captures the difference in hours worked for employers and non-employers relative to employees. With the exception of four developed economies, male and female non-employers work significantly fewer hours than employees.[8] The gap in hours worked is larger for female non-employers. For example, in Mexico male non-employers work around 20% shorter hours than male employees compared to a 50% gap between female non-employers and employees. The figure also shows that employers tend to work longer hours than employees particularly in relatively developed economies. Overall, these findings are qualitatively similar to the evidence we found for the US and is consistent with non-employers, particularly female non-employers, selecting into their occupation based on time use.

Figure 6: Hours Worked in Entrepreneurship relative to Employment



(a) Male Entrepreneurs

(b) Female Entrepreneurs

Notes: The figure plots the coefficient β_o estimated from the following regression, $\log(h_i) = \alpha + \sum_o \beta_o D_i^o + X_i + \epsilon_i$ where h_i is hours worked by individual i, D_i^o is a dummy variable indicating the occupation o of an individual. X_i is a vector of individual level controls comprised of a quadratic term in age, dummies for education, marital status and 2-digit industry fixed effects.The reference occupation category is employees. Data for Ecuador, El Salvador, Greece, Italy, Jamaica, Jordan, Nicaragua, Spain, Switzerland, Venezuela are from the IPUMS samples. Data for the remaining countries are collected from each country's labour force surveys. Details of the data are discussed in the appendix.

To provide further support for the link between gender gaps in both time use and entrepreneurship, we use data from IPUMS and show that the decreasing (increasing) gender

[8]The exceptions are Greece, Italy, Spain and Switzerland. In addition to being members of the European Union, these economies have legislation restrictions the maximum hours that employees can work. To our knowledge, there is no analogous legislation restricting on the hours that entrepreneurs can work.

gap for entrepreneurs (employees) is more salient when focusing on sub groups that are likely to have tighter constraints on their time use.

In particular, we estimate the slope coefficients from regressions of occupational gender gaps on log GDP per capita for difference sub groups of individuals. We focus on educational attainment, marital status and the number of children birthed as these characteristics have been identified by Rubiano-Matulevich and Viollaz (2019), among others, as influencing the gender gaps in non-market time use.

Table 3 reports these slope coefficients. The first and second row report, respectively, the coefficients on gender gaps derived from the ILO data and the coefficients derived from constructing (aggregated) gender gaps from the IPUMS samples. Qualitatively, the two data sets report similar findings; the gender gaps for workers increase with development while the gender gaps in entrepreneurship decrease with development driven primarily by decreasing gender gaps among non-employers. Quantitatively, the IPUMS data predicts a much less pronounced decrease (increase) among gender gaps for entrepreneurs (workers).[9]

The remaining rows of table 3 report the slope coefficient between log GDP per capita and gender gaps for sub groups of individuals derived from the IPUMS sample. First, we compare the gender gaps among those with high and low education respectively where an individual is said to have high education if they have completed secondary education. As gender gaps in non-market time use decline with educational attainment (see for example, Bank (2011) and Rubiano-Matulevich and Viollaz (2019)), constraints on time use are likely to be tighter for those with less education. Hence, we expect the relationship between development and gender gaps in entrepreneurship to be much more pronounced for the low education sub group as they may be selecting into entrepreneurship based on time constraints.

Comparing the high and low education groups in the third and fourth rows of table 3 show that this is indeed the case. The gender gaps for entrepreneurs (workers) declines (increases) much more strongly with development for those with lower education. Further, the gender

[9] Figure C.6 plot the gender gaps by occupation as derived from the IPUMS sample.

Table 3: Slope Coefficient of Gender Gaps on Log GDP per capita

	Employees	Entrepreneurs			N
		All	Non-Employers	Employers	
ILO	0.188***	-0.265***	-0.262***	-0.015	79
	(0.021)	(0.031)	(0.036)	(0.023)	
IPUMS	0.144***	-0.191***	-0.189***	-0.052	54
	(0.032)	(0.030)	(0.032)	(0.057)	
High Education	0.031**	-0.114***	-0.107***	-0.051**	51
	(0.012)	(0.029)	(0.032)	(0.023)	
Low Education	0.154***	-0.182***	-0.191***	0.023	51
	(0.026)	(0.038)	(0.040)	(0.026)	
Single	0.095***	-0.183***	-0.185***	-0.038	52
	(0.019)	(0.031)	(0.034)	(0.027)	
Married	0.179***	-0.212***	-0.210***	0.002	52
	(0.030)	(0.036)	(0.039)	(0.022)	
No Children	0.126***	-0.173***	-0.182***	-0.062**	40
	(0.040)	(0.036)	(0.037)	(0.030)	
$\geq$ 1 Child	0.195***	-0.223***	-0.236***	0.056*	40
	(0.036)	(0.050)	(0.055)	(0.031)	

Notes: The table reports the slope coefficients from regressions of occupational gender gaps on log GDP per capita and a constant term. The first and second rows report this coefficient from the ILO and IPUMS samples respectively. All remaining rows use gender gaps derived from IPUMS data. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Standard errors are reported in parentheses.

gap in overall entrepreneurship (for both either education level) is driven primarily by the gender gaps among non-employers. Having said this, many factors other than differences in time use are associated with educational attainment.[10] As such, we take this to provide only suggestive evidence supporting a link between gender gaps in time use and gender gaps in entrepreneurship.

Perhaps more convincing is the comparison of single and married individuals. Since married women have more non-market responsibilities due to, for example, the presence of children at home, they are more likely to select into entrepreneurship based on time use compared to single women. If constraint in time use are important in generating the relationship between gender gaps in entrepreneurship and development, we expect this relationship to be strong among married women. Comparing the fifth and sixth rows of table 3 shows that this is indeed the case; the gender gap in entrepreneurship (workers) declines (increases) much more so for married individuals relative to single individuals.

The last two rows of table 3 study the relationship between gender gaps and development separately for women who have not birthed a child and those that have.[11] Consistent with the results on marital status, we find that in entrepreneurship (workers) decline (increase) much more strongly for women who have had children relative to those that have not. We also find statistically significant relationship between the gender gaps for employer with this sub group although the relationship with development is much smaller in magnitude than that for non-employers.

We interpret the results in table 3 as providing suggestive evidence supporting the idea that the relationship between gender gaps in entrepreneurship is driven – in part – by gender gaps in time use. The table also serves to show that our results on the relationship of gender gaps in entrepreneurship and development are robust.

[10] For example, educational attainment is also associated with higher income and wealth which can impact individuals selection into entrepreneurship based on overcoming financing constraints.

[11] For this exercise, we define the occupational gender gap by taking the ratio of occupational shares among women who have and have not birthed a child to the occupational share among all men.

Table 4: Correlation between Gender Gaps in Time Use and Entrepreneurship

	All Entrepreneurs		Employees		Non-Employers		Employers	
Gender Gaps in Time Use	2.095***	1.070***	-0.475***	0.013	2.239***	1.253***	-0.045	-0.222
	(0.250)	(0.255)	(0.093)	(0.142)	(0.298)	(0.347)	(0.085)	(0.134)
Log GDP per capita	-	-0.213***	-	0.101***	-	-0.205***	-	-0.037
	-	(0.046)	-	(0.028)	-	(0.063)	-	(0.026)
N	118	118	118	118	118	118	118	118
R^2	0.393	0.535	0.148	0.384	0.309	0.399	0.002	0.056

Notes: The table reports the results from regressing gender gaps in entrepreneurship on gender gaps in time use. The underlying observations include all country-year observation for which data on both time use and entrepreneurship are available. ***, ** and * indicate statistical significance at the 1% level. Standard errors are reported in parentheses.

Finally, we consider the correlation between gender gaps in time use and entrepreneurship directly. To do this, we take all country-year observations of gender gaps in entrepreneurship and regress it against gender gaps in time use and log GDP per capita. Table 4 reports the results from these regression for each occupation and shows that even after controlling for development, gender gaps in time use are positively correlated with gender gaps in overall entrepreneurship. In line with the results above, this positive overall relation is driven by a strong positive relationship with gender gaps in non-employers. Indeed, there is no statistically significant relationship between gender gaps in time use and gender gaps in employers.

3 Model

Motivated by the empirical facts documented in the previous section, we build a simple occupation choice model where individuals differ from each other by their endowment in different discretionary hours and entrepreneurial talent.

Setup There is one good produced by entrepreneurs using only labor. The labor force consists of a measure one of individuals, a fraction ω of which are men, and the rest are women. We use $j \in \{\mathrm{f}, \mathrm{m}\}$ to denote the gender. Men and women are endowed with different discretionary hours $\bar{h}_j$, which they can allocate to market work and leisure. They also differ in their entrepreneurial ability z. Each individual is therefore characterized by two state variables: z and j and $\Phi(z, j)$ and $\phi(z, j)$ are the CDF and PDF of the distribution of the state variables.

Individuals consume and provide labor. An individual of gender j has a total of $\bar{h}_j$ discretionary hours that can be used for leisure or employment (h). Following Erosa et al. (2017), we specify their utility function as

$$U_j(c, h) = \log(c) + \nu_j \frac{(\bar{h}_j - h)^{1-\gamma}}{1-\gamma},$$

where $\log(c)$ is the utility from consumption and ν_j represents the gender-specific utility of leisure.

Production Technology All individuals are part of the labor force. They can choose to be a salaried worker (W) or an entrepreneur. Entrepreneurs can be non-employers (NE) who only use their own hours as inputs or employers (E) who employ workers in addition to their own labor.

As an employee/worker (W), individuals provide labor to the labor market and receive wage income wh. That is, workers can work as many hours as they choose given the equilibrium wage, a similar specification as in Bick et al. (2019).

Non-employers (NE) operate a decreasing returns to scale production technology

$$y = \chi A z h^{\lambda}, \tag{2}$$

where A is the aggregate productivity of the economy, z is the idiosyncratic productivity of the non-employer entrepreneurs, h is the hour of the non-employer individuals, $\lambda \in (0, 1)$ governs the decreasing returns to hours and χ represents the non-employer productivity relative to employers.

Employers (E) operate a Cobb-Douglas production technology that uses their own hours h and outside labor hour l to produce, such that

$$y = Azh^{\alpha}l^{1-\alpha}. \tag{3}$$

Given own hours h, the entrepreneurs choose optimal outside labor l to optimize their profit, such that $\pi_{\mathrm{E}}(z,h) = \max_l Azh^{\alpha}l^{1-\alpha} - wl$. It can be shown that the optimal earnings are $\pi_{\mathrm{E}}(z,h) = (Az)^{1/\alpha}(\frac{w}{1-\alpha})^{\frac{\alpha-1}{\alpha}}\alpha h$, which is linear in h.

The key takeaway from the discussions above is that earnings are linear in hours worked for the salaried workers and the employers; they are concave in hours for the non-employers. The difference in convexity across the three occupations leads to differences in occupation choice for individuals with different discretionary hours—we provide a more formal analysis of this in section 3.1.

One important assumption of the production technology is the decreasing returns to scale to non-employer hours. This assumption is motivated by findings in the literature that self-employment is a particularly flexible occupation (Hurst and Pugsley, 2011). The relative flexibility then maps into a less convex return to hours worked (see Goldin, 2014 for a micro-foundation of this theory). The declining marginal returns could also be an outcome of optimally allocating hours into projects with different productivity. Under the optimal allocation, the most productive projects are always carried out first. With an additional increment in hours, the marginal project is increasingly less productive—an idea dated back to Adam Smith and formalized by Eden (2017). In a recent study on Uber drivers by Cook et al. (forthcoming), the authors find the drivers' earnings are concave in hours worked because drivers who work fewer hours can pick the most high-pay hours but drivers of long hours have to work some of the less lucrative times too.

Distortions Individuals face gender- and occupation-specific distortions in the form of a tax or subsidy proportional to their earnings, represented by τ^j_{W}, τ^j_{E} and τ^j_{NE}. That is, for an individual (z, j) who provides hours h, their total earning in each occupation is

$$\begin{aligned}
\text{NE}: &\ (1-\tau^j_{\text{NE}})\pi_{\text{NE}}(z,h),\\
\text{W}: &\ (1-\tau^j_{\text{W}})\pi_w(z,h),\\
\text{E}: &\ (1-\tau^j_{\text{E}})\pi_{\text{E}}(z,h),
\end{aligned}$$

where $\pi_{\text{NE}}(z,h) = \chi A z h^{\lambda}$, $\pi_w(z,h) = wh$, and $\pi_{\text{E}}(z,h) = (Az)^{1/\alpha}(\frac{w}{1-\alpha})^{\frac{\alpha-1}{\alpha}}\alpha h$.

Government The government collects the gender-specific distortions and rebates the tax returns to all individuals equally. The government budget is balanced in each period, such that

$$\text{TR} = \iint \tau^j_o \pi_o(z, h(z,j))\mathbf{I}_{o(z,j)=o} d\Phi(z,j), \tag{4}$$

where TR is the government transfer, $o \in \{\text{NE,W,E}\}$ represents the occupation, $j \in \{\text{f}, \text{m}\}$ represents the gender and $o(z,j) \in \{\text{NE}, \text{W}, \text{E}\}$ is the occupation choice for an individual (z, j).

Equilibrium We consider the competitive equilibrium where the three occupations coexist.[12] Let $V_{\text{NE}}(z,j)$, $V_{\text{W}}(z,j)$, and $V_{\text{E}}(z,j)$ be the value functions for the three occupation. The individual optimization problem can be written as

$$V_o(z,j) = \max\ \log(c) + \nu_j \frac{(\bar{h}_j - h)^{1-\gamma}}{1-\gamma},\ \ s.t.\ c = (1-\tau^j_o)\pi_o(z,h) + \text{TR}. \tag{5}$$

Individuals make an occupation choice $o(z,j) \in \{\text{NE}, \text{W}, \text{E}\}$ such that

$$V(z,j) = \max_{o(z,j)\in\{\text{NE,W,E}\}} \{V_{o(z,j)}(z,j)\}. \tag{6}$$

[12] If the non-employer relative productivity (χ) is very high, all individuals choose to be non-employers in equilibrium.

The competitive equilibrium of the economy consists of prices w, value functions $V(z, j)$, $V^{ne,w,e}(z, j)$, policy functions $c(z, j)$, $l(z, j)$, $h(z, j)$, and occupation choice $o(z, j) \in \{\text{NE}, \text{W}, \text{E}\}$, such that

(i) Given w, value functions and policy functions solve the individual's optimization problem 5 and 6.

(ii) Labor market clears,

$$\iint h(z, j)\mathbf{I}_{o(z,j)=w} d\Phi(z, j) = \iint l(z, j)\mathbf{I}_{o(z,j)=e} d\Phi(z, j).$$

(iii) Government budget is balanced in each period (equation 4).

3.1 Discretionary Time and Occupation Choice

Next we show how the difference in discretionary hours between men and women affect their occupation choice. Here, the analysis abstracts from the gender- and occupation-specific distortions.

3.1.1 Optimal Hours Worked

We first analyze how the choice of optimal hours changes with discretionary hours $\bar{h}$ conditional on the occupation. The optimization problem for the non-employers gives the following first-order-condition,

$$\lambda \frac{1}{h} = \nu \frac{1}{(\bar{h} - h)^{\gamma}}$$

Similarly, the optimal condition for salaried workers and employers is,

$$\frac{1}{h} = \nu \frac{1}{(\bar{h} - h)^{\gamma}}$$

.

The right hand side of these conditions, $\nu\frac{1}{(\bar{h}-h)^{\gamma}}$, is simply the marginal cost from working, given discretionary hours $\bar{h}$. The left hand side represents the marginal benefit of working an additional hour.

Two remarks are in order. First, the marginal benefit of one additional hour of working is lower for the non-employers compared with that for the workers and employers. Second, due to the assumption of log utility in consumption, neither productivity z or wage rate w affect individual's choice of hours.

How do optimal hours change with an increase in discretionary hours? The optimal hours worked for all three occupations increases with $\bar{h}$, but the increase is less significant in the concave occupation (NE) relative to the linear occupations (W and E). Intuitively, this is because one additional hour worked is less beneficial for the NE occupation as the marginal return diminished with hours worked.

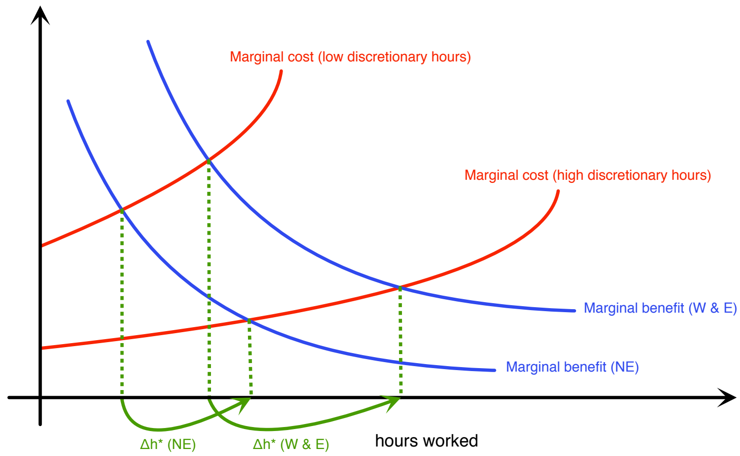
Figure 7 illustrates the intuition behind this result. In the figure, the red lines show the marginal cost curve for two levels of discretionary hours. The blue lines represent the marginal benefit curves for the three occupations. With an increase in discretionary hours, the marginal cost curve shifts downwards and flattens. Given that the marginal benefit curve for NE is lower that that for W and E, an increase in $\bar{h}$ results in a smaller increase in optimal hours for the NE occupation. More formally, it can be shown that $(\frac{dh^*}{d\bar{h}})^{\mathrm{W,E}} > (\frac{dh^*}{d\bar{h}})^{\mathrm{NE}}$ by applying the implicit function theorem to the two FOCs.[13]

3.1.2 Occupational Choice

The selection of individuals into different occupations is based on both the productivity z and the discretionary hours $\bar{h}$. Given $(z, \bar{h})$, we derive value functions for the three occupations by replacing the optimal consumption and hours in the utility function, such that

[13] See appendix section B.2.1 for details.

Figure 7: Comparative statistics of optimal hours when $\bar{h}$ increases



Notes: This figure shows the optimal hours choice by occupation. The red lines represent the marginal cost of working for two levels of discretionary hours, high and low. The blue lines represent the marginal benefit from working for the three occupations (W, E, and NE). The intersections of the marginal cost and marginal benefit curves are the optimal hours. The green arrows on the x axis represent the increase in optimal hours with an increase in discretionary hours for these three occupations.

$$
\begin{aligned}
W^{\mathrm{NE}}\left(z,\bar{h}\right) &= \log\left(\chi A z\left[h^{*\mathrm{NE}}\left(\bar{h}\right)\right]^{\lambda}\right)+\nu\frac{\left(\nu\left[h^{*\mathrm{NE}}\left(\bar{h}\right)\right]^{\lambda}\frac{1}{\lambda}\right)^{\frac{1-\gamma}{\gamma}}}{1-\gamma}, \\
W^{\mathrm{W}}\left(z,\bar{h}\right) &= \log\left(w\left[h^{*\mathrm{W}}\left(\bar{h}\right)\right]\right)+\nu\frac{\left(\nu\left[h^{*\mathrm{W}}\left(\bar{h}\right)\right]\right)^{\frac{1-\gamma}{\gamma}}}{1-\gamma}, \\
W^{\mathrm{E}}\left(z,\bar{h}\right) &= \log\left((Az)^{1/\alpha}\left(\frac{w}{1-\alpha}\right)^{\frac{\alpha-1}{\alpha}}\alpha\left[h^{*\mathrm{E}}\left(\bar{h}\right)\right]\right)+\nu\frac{\left(\nu\left[h^{*\mathrm{E}}\left(\bar{h}\right)\right]\right)^{\frac{1-\gamma}{\gamma}}}{1-\gamma}
\end{aligned}
$$

where $h^{*\mathrm{W}}(\bar{h}) = h^{*\mathrm{E}}(\bar{h}) > h^{*\mathrm{NE}}(\bar{h})$ are the optimal hours of workers (W), employers (E) and non-employers (NE), and $W^{\mathrm{W}}(z,\bar{h})$, $W^{\mathrm{E}}(z,\bar{h})$, and $W^{\mathrm{NE}}(z,\bar{h})$ are the value functions, respectively.

Conditional on Discretionary Time Consider the occupational choice of individuals for a given level of discretionary hours $\bar{h}$. First, given $\bar{h}$, the choice between the two occupations W and E is only determined by productivity z. As discussed in the previous section, the FOCs regarding hours worked are the same for W and E; hence, individuals choose the same hours worked in these two occupations. The occupation choice between W and E is determined by comparing hourly earnings in these two occupations—w and $(Az)^{1/\alpha}(\frac{w}{1-\alpha})^{\frac{\alpha-1}{\alpha}}\alpha$. Given $\bar{h}$, there is a threshold productivity, above which an individual prefers to be an employer over a worker.

Second, individuals with a high z are also more likely to choose NE over W. Given $\bar{h}$, the optimal hours of non-employers is lower than that of workers: $h^{*,ne}(\bar{h}) < h^{*\mathrm{W}}(\bar{h})$, but the difference is constant. However, the income of NE increases with z whereas the income of the workers stays constant. Therefore, as z increases, the occupation of non-employer becomes more desirable compared to workers (for a given level of $\bar{h}$).

Third, individuals with higher productivity z are more likely to choose E over NE. Similar to the previous point, given $\bar{h}$, the optimal hour of the non-employer entrepreneurs is lower than employers, but the difference is constant and independent of z. But since $\alpha < 1$, earnings of employers are convex in z whereas the earnings of non-employers is linear in z. As z increases, E is more desirable than NE.

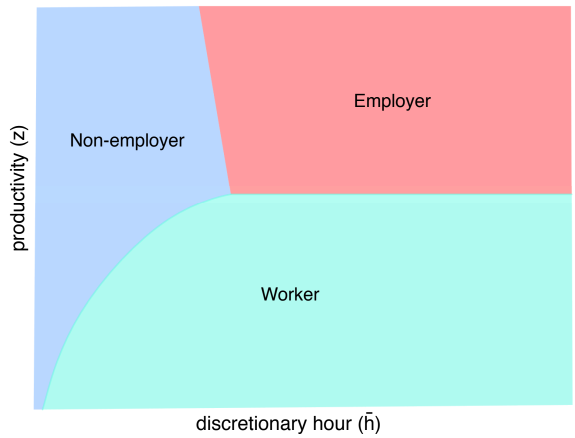
Conditional on Productivity Next we show that, given productivity z, individuals with higher discretionary hours are more likely to be employers and workers over non-employers. Consequently, the difference in value function between workers and non-employers, can be written as

$$\begin{aligned} W^{\mathrm{W}}(z,\bar{h}) - W^{\mathrm{NE}}(z,\bar{h}) = \;& \text{constant} + \log(h^{*\mathrm{W}}(\bar{h})) - \lambda \log(h^{*\mathrm{NE}}(\bar{h})) \\ & + \tfrac{\nu^{1/\gamma}}{1-\gamma} h^{*\mathrm{W}}(\bar{h})^{\frac{1-\gamma}{\gamma}} - \lambda^{\frac{\gamma-1}{\gamma}} \tfrac{\nu^{1/\gamma}}{1-\gamma} h^{*\mathrm{NE}}(\bar{h})^{\frac{1-\gamma}{\gamma}}, \end{aligned}$$

which increases with $\bar{h}$ if $\gamma > 1$. The same analysis can be applied to employers and non-employers. Therefore, as $\bar{h}$ increases, individuals are more likely to choose the linear occupations (W and E) over the concave occupation (NE).

Figure 8 provides a graphic illustration of the occupation choice by productivity z and discretionary hours $\bar{h}$.

Figure 8: Occupation map



Notes: The figures show the occupation choice conditional on productivity z and discretionary hour $\bar{h}$. Individuals with $(z, \bar{h})$ in the blue/red/green area choose to become a non-employer/employer/worker, respectively.

4 Quantative analysis

In this section, we perform several quantitative exercises. Section 4.1 calibrates the benchmark model to match the US data. Using the calibrated version of the model, section 4.2 shows the changes in occupation shares when we vary the gender gap in discretionary hours. In section 4.3.1, we ask how much of the empirical relationship between the gender gap in entrepreneurship and log GDP per capita can be accounted for by gender asymmetries in time use and distortions.

4.1 Calibration to the US data

We begin our calibration by directly setting or normalizing some parameters following the literature. We use the US economy as a benchmark for cross-country analysis. Hence following the literature, we assume that the US economy is undistorted, i.e., $\tau_o^j = 0$ and normalize TFP of US to $A = 1$. We follow Erosa et al. (2017) and set the curvature on leisure γ to 4. The gender gap in the endowment in discretionary hours is taken directly from the data. We normalize $\bar{h}_m$, the discretionary hours for men to 1 and set the discretionary hours for women $\bar{h}_f = 0.92$. In the data, men consist of 50 percent of the US's total labor force; therefore, we set $\omega = 0.5$. We assume that the productivity distribution z follows a Pareto distribution that can potentially differ across gender.[14]

We calibrate the remaining seven parameters to match seven data moments jointly. The parameters are: (i) ν_m, utility from leisure for men, (ii) ν_f, utility from leisure for women, (iii) η_m, Pareto tail of the productivity distribution for men, (iv), η_f, the Pareto tail of the productivity distribution for women, (v) λ, the span-of-control parameter in the non-employer production function, (vi) α, the span-of-control parameter in the employer production function, and (vii) χ, the relative productivity of the non-employers.

Table 5: Parameters

Parameter		value
	Predetermined	
A	Aggregate TFP	1.0
ω	Share of men in the labor force	0.5
γ	Frisch elasticity	4.0
$\bar{h}_m$	Discretionary hours for men	1.0
$\bar{h}_f$	Discretionary hours for women	0.92
	Calibrated	
ν_m	utility from leisure for men	0.62
ν_f	utility from leisure for women	0.54
η_m	Pareto tail of productivity distribution for men	3.8
η_f	Pareto tail of productivity distribution for women	4.7
λ	Non-employer span of control	0.8
α	Employer span of control	0.23
χ	Non-employer relative productivity	0.61

[14] In the quantitative exercises, we introduce a taste shock for the three occupations to convexify the occupation choice and improve the convergence of the code. The taste for each occupation is represented by an i.i.d. draw from a type-I extreme-value probability distribution (Gumbel distribution). Since the introduction of the taste shock only aims at improving the convergence property in the quantitative exercise, we picked a small scale parameter of 0.001. Details can be found in appendix section B.1.

The seven targeted moments are (i) the average hours worked for men (0.3), (ii) the average hours worked for women (0.27), (iii) the ratio of employer to non-employer revenue (46.2), (iv) the share of non-employers among women (7 percent). (v) the average hours worked of non-employer relative to workers (0.93), (vi) the share of non-employers among men (9 percent), and (vii) the share of workers among men (88 percent).

Although the set of parameters is calibrated jointly to match the data moments, each of these parameters is intuitively linked to a particular moment. The utility from leisure, ν_m and ν_f, are closely linked to the average hours worked by men and women. The Pareto tails, η_m and η_f, govern the ratio of employer revenue to non-employer revenue. The difference between η_m and η_f, i.e. the different productivity distribution across gender, also affects the differences in entrepreneurship across gender. Our calibration delivers a value of $\eta_m = 3.8$ and $\eta_f = 4.7$.[15] Following Bick et al. (2019), we calibrate $\lambda = 0.8$ to match the average non-employer hours relative to employees. Intuitively speaking, the span of control λ in the non-employer production function determines the concavity of return to hours for the non-employers and is closely related to hours worked of the non-employers. In the employers' production function, α determines the divide between the labor income and entrepreneurial returns. It is therefore calibrated to match the share of workers for men in equilibrium. Our calibration yields $\alpha = 0.23$. This means that the employer span-of-control parameter is $1 - \alpha = 0.77$, which is well within the range of estimates in the literature. Lastly, we calibrate $\chi = 0.61$, the relative productivity of non-employers to match the share of non-employer entrepreneurs for men. Table 5 displays the calibrated parameter values and table 6 shows how well the calibration matches the data moments.

In addition to these seven targeted data moments, the model also performs well in matching several untargeted data moments. As shown in the lower panel of table 6, the calibrated model can match the gender-specific occupation shares exactly. The top 5 percent earnings

[15] This finding is consistent with the findings in the empirical literature that gender gap in earnings is even higher among entrepreneurs than workers (see Hundley, 2001, Lawter et al., 2016, and Lechmann and Schnabel, 2012).

Table 6: Model performance

Moment	Data	Model
Targeted		
Average hours for men	0.3	0.3
Average hours for women	0.27	0.27
Ratio of employer to non-employer revenue	46.2	46.2
Average hours worked non-employer relative to worker	0.93	0.93
Share of employer for men	0.03	0.03
Share of worker for men	0.88	0.88
Share of non-employer for women	0.07	0.07
Non-targeted		
Share of employer for men	0.03	0.03
Share of worker for women	0.92	0.92
Share of employer for women	0.01	0.01
Top 5 percent earnings share	0.3	0.24
Top 10 percent employment share	0.69	0.67

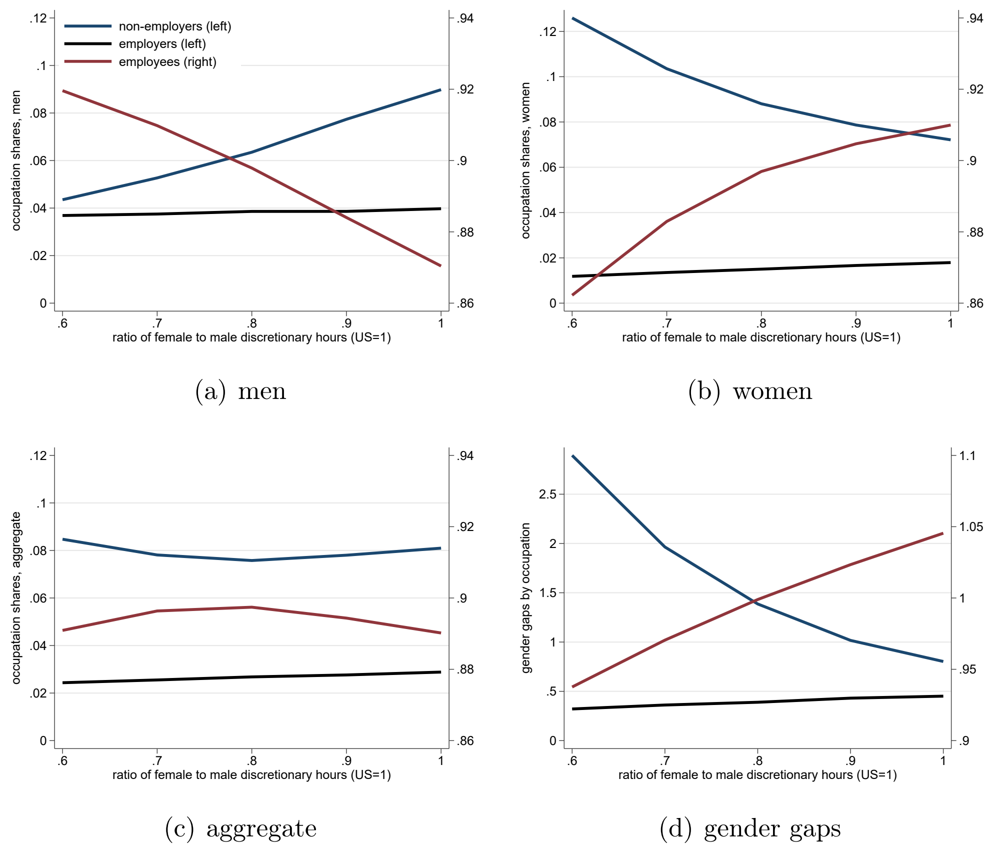
share in the model is 24 percent, somehow lower than the 30 percent in the data. It also generates a top 10 percent employment share of 67 percent, closely matching the 69 percent in the data.

4.2 Varying gender gap in time use

Before moving to the cross-country analysis, we perform a simple exercise to provide some intuition on how the gender gap in time use affects the gender occupational gaps. Recall that, in the calibrated model, the ratio of female-to-male discretionary hours is set to 0.92 at the US level. In this exercise, we take this calibrated model and increase the gender gap in time use while keeping the aggregate discretionary hours constant. Figure 9 shows the changes in occupation shares in equilibrium.

As the gender gap in discretionary hours widens, men, who have more available time, move out of the non-employer occupation into the employee occupation (panel a). The opposite trend shows up for women, with more women self-selecting into being non-employers (panel b). These changes largely reflect the changes in the selection of men and women into

Figure 9: Occupation shares when varying gender gap in time use



(a) men

(b) women

(c) aggregate

(d) gender gaps

Notes: This figure is produced using the calibrated model by decreasing female-to-male discretionary hours while keeping aggregate discretionary hours constant. The x-axis shows the f-to-m ratio relative to the US level. Panel (a) and (b) plot the occupation shares among men and women, respectively. Panel (c) plots the occupation shares in the population. Panel (c) shows the gender occupational gaps, defined as female occupation shares divided by male shares. The y-axis on the left shows the values for non-employers and employers and the right y-axis shows the value for employees.

occupations with different convexity by time use. Quantitatively, if the ratio of female-to-male discretionary hours decreases by 40%—from 0.92 to 0.55—the share of male non-employers would drop from 9 percent to around 4.5 percent, while the share of female non-employers would increase from 7 percent to more than 12 percent. These changes lead to a significant increase in the non-employer gender gap from slightly below one to more than 2.5 (panel d).

On the other hand, as the gender gap in time use widens, fewer men and women choose to be employers (panels a and b), although relative to women, more men become employers (panel d). While the increasing gender gap in time use is responsible for decreasing female employer share relative to men, the decline in the aggregate employer share comes from the general equilibrium effect.

Lastly, as shown in panel (c), the model predicts a non-monotonic relationship between aggregate occupation shares and the gender gap in time use. The non-monotonicity depends on the calibrated distribution of productivity z.[16] Also, it is worth noting that the magnitude of the changes in aggregate shares is tiny—for example, with a range of gender gap in time use between 0.6 and 1, the aggregate employee share variation is within one percentage point.

4.3 Cross-country analysis

The previous exercise has shown that the gender gap in discretionary hours can generate significant changes in the gender occupational gaps. Given the observation that the gender gap in time use is higher in developing countries than developed countries, a natural question is how much of the empirical relationship between gender occupational gaps and GDP per capita can be accounted for by time use and gender-specific distortions. Besides occupational composition, we are also interested in examining the impacts of gender asymmetries on aggregate productivity, output, and ultimately the welfare of individuals. The cross-country exercises we perform in this section aim at answering these questions.

In these exercises, we recalibrate some of the parameters to match data moments in each country. The first set of parameters is common across gender and the second set is gender-specific. The common parameters are the structural parameters that, without the gender asymmetries, would affect the occupation choice in a gender-neutral way. In particular, we are interested in $\{\chi^c, \alpha^c\}$, which are calibrated to match the share of non-employers and employees among men, respectively. To put it differently, underlying this

[16]The non-monotonicity seems to stem from the fact that the productivity distribution differs across gender in our calibration. We find that when the productivity distribution is identical across gender, the non-monotonicity disappear.

strategy is the assumption that men do not face distortions. Hence, their occupation choice reflects the fundamental changes in economic structure over the development process. In the absence of gender asymmetries, changes in $\{\chi^c, \alpha^c\}$ do not lead to any changes in the gender occupational gaps because they always equal 1.[17]

The second set of parameters, including $\{\omega^c, \bar{h}^{m,c}, \bar{h}^{f,c}, \tau_{ne}^{f,c}, \tau_w^{f,c}\}$, is gender-specific. Changes in these parameters directly impact the gender occupational gaps, either through affecting individuals' occupation choice or the equilibrium wage. Among these parameters, the gender composition of the labor force ω^c and the discretionary hours $\bar{h}^{j,c}$ are taken directly from the data. The gender-specific distortions, $\tau_{ne}^{f,c}, \tau_w^{f,c}$, are calibrated to match the female non-employer and employee shares, respectively. We restrict our sample to 35 countries with data available for labor force composition, discretionary hours, and occupation shares by gender.

4.3.1 Accounting for the gender occupational gaps across countries

We begin by studying the empirical correlation between the gender occupational gaps and GDP per capita across countries. The question we seek answers to is how much of the empirical correlation can be accounted for by the two types of gender asymmetries in time use and distortions.

In the first exercise, we focus on examining the role of gender gap in discretionary hours and abstract from the gender-specific distortions. To do so, we set $\tau_{ne}^{f,c} = \tau_w^{f,c} = 0$ while recalibrating the rest of the parameters. This recalibration matches the male occupation shares perfectly while leaves the female occupation shares untargeted. We then compare the model-generated correlation between gender occupational gaps to the data correlation to see how much of the empirical correlation can be accounted for by the model.

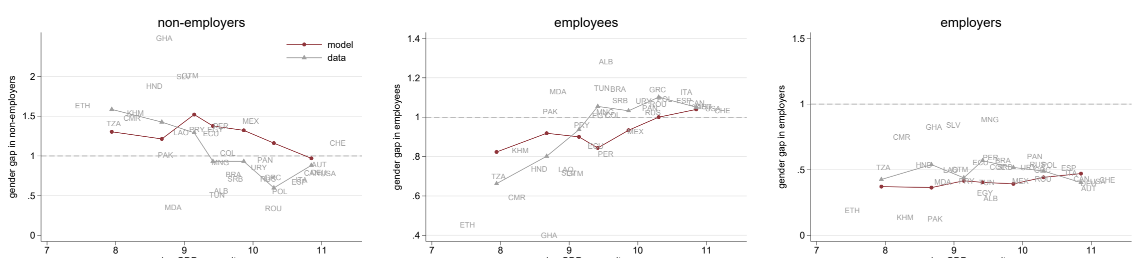
In the second exercise, we calibrate all the parameters to match the occupation shares for both men and women exactly. The calibrated $\tau_{ne}^{f,c}$ and $\tau_w^{f,c}$ measures the distortions faced

[17] However, in the presence of gender asymmetries, a change in these common parameters might affect men and women differently and result in changes in the gender occupational gaps. We provide a more detailed discussion later in this section.

by female non-employers and workers relative to their male counterparts. They can also be viewed as the residuals that are unexplained by the gender gap in time use. This calibration allows us to perform a simple decomposition to see the relative importance of the two types of gender asymmetries.

The role of gender asymmetry in time use Results from the first exercise are presented in figure 10, where the grey scatter plots are the gender gaps by occupation in the data. We divide the 35 countries into seven groups of equal size by GDP per capita. The points on the grey line represent the group averages in the data, and the red line is the model counterpart. Similar to the data, the model generates a reversal of the gender gap in non-employers, from an over-representation of female non-employers in poor countries to an under-representation in rich countries. The reverse of the gender gap is also present in the employee occupation, with an under-representation of female workers in poor countries and an over-representation in rich countries. Across the different income groups, the prediction of the model is closest to the data for the richest countries. For the poorest group of countries, the model generates smaller gender gaps in non-employers and employees than the data. Overall, the predicted correlation between gender gaps in occupations and GDP per capita is flatter than the empirical correlation found in the data.

Figure 10: Model with only gender asymmetry in time use



Notes: These figures are produced by recalibrating the model to match the male occupation shares in each country while feeding in the labor force composition and discretionary hours by gender, directly taken from the data. We divide the 35 countries into seven income groups and plot each group's average in the model (red) and data (grey). The gray scatter plots are the gender occupational gaps in the data.

How much does the model explain the empirical correlation? Table 7 reports the slope coefficients from regression of gender gaps in occupations on log GDP per capita and a constant term in the data and the model. The model predicts a non-employer gender gap elasticity of -0.09, compared to -0.31 in the data. That is, in terms of the gender gap in non-employers, approximately 30 percent of the correlation in the data can be accounted for by the model. Moving on to the gender gap in employees, the estimated elasticity in the data is 0.15, while the model generates an elasticity of 0.07, which indicates that slightly less than 50% of the correlation in the data can be accounted for by the model. Lastly, the data shows no significant correlation between the gender gap in employers and a country's income level with an estimated elasticity of essentially 0. The model, on the other hand, predicts a small, albeit positive, elasticity between the gender gap in employers and GDP per capita.

Table 7: Slope coefficients: data and model

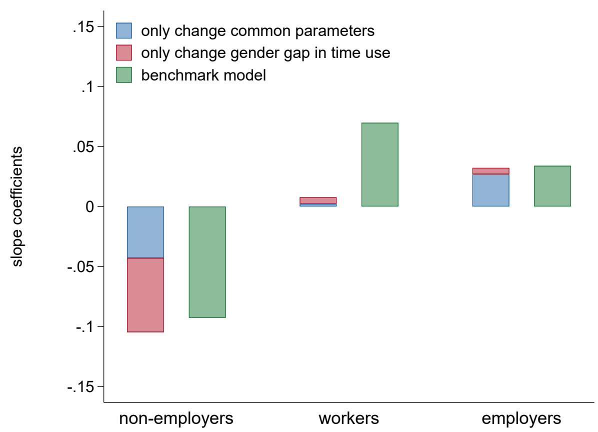
	non-employers	employees	employers
data	-0.31	0.15	0.00
	(-4.02)	(5.41)	(0.01)
model	-0.09	0.07	0.03
	(-1.72)	(3.97)	(3.66)

Notes: This table reports the slope coefficients from regression of gender gaps in occupations on log GDP per capita and a constant term in the data (and the benchmark model) and two counterfactual models. The model used in this table matches the occupation shares for men in each country while feeding in labor force composition and the discretionary hours by gender. In the counterfactual models, we remove one set of gender asymmetries while keeping the other one at the benchmark level. The t-statistics are in the parentheses.

Interaction between changes in times use and productivity of non-employers In this exercise, both the changes in the common and the gender-specific parameters can lead to the cross-country patterns in gender-occupation shares in the model. In figure 11, we perform a decomposition exercise to examine the interaction between these changes as well as their relative importance. The green bars represent the slope coefficients between gender occupational gaps and the log GDP per capita in the benchmark model in table 7. Red bars are the model correlation when the common parameters are kept that the same level as the US calibration; blue bars are where the gender-specific distortions are kept at the US level. In other words, the blue bars represent the effects of changes in the common parameters, the red bars represent the effects of gender gap in discretionary hours and the green bars are the effects from changing both simultaneously.

In terms of the relative importance of these changes, the figure shows that it varies across occupations. While the effects from changes in gender gap in time use are relatively more prominent for non-employers and employees, they are less important for the employers. Interestingly, a comparison between the size of these coefficients suggests that there might be an interaction effect between these changes. This interaction effect is most significant for employees, where the slope coefficients are less than 0.01 when we only change one set of the parameters whereas it is approximately 0.07 when we change both. That is, the mechanism through which gender gap in time use operates is significantly amplified by the changes in the common parameters over the development process. What can explain this amplification effect?

Figure 11: Interaction effects between time use and non-employer productivity



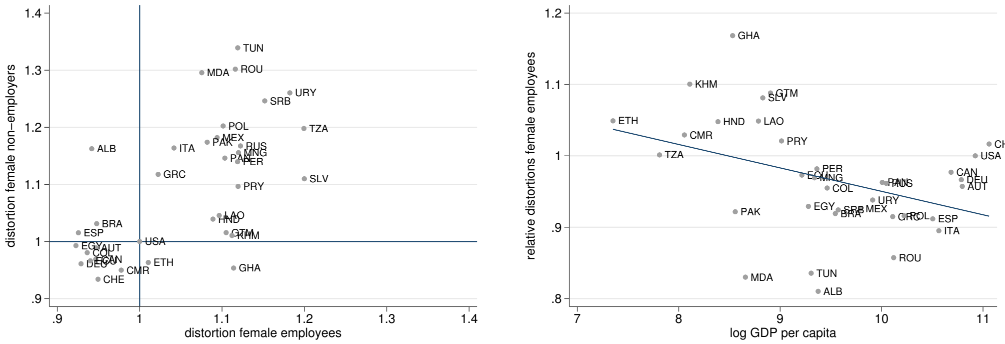
Notes: These figures are produced by recalibrating the model to match the male occupation shares in each country while feeding in the labor force composition and discretionary hours by gender, directly taken from the data. We divide the 35 countries into seven income groups and plot each group's average in the model (red) and data (grey). The gray scatter plots are the gender occupational gaps in the data.

To answer this question, we first examine how the calibrated common parameters vary over the development process. We find that, although the calibrated α^c varies across countries, it does not have a significant correlation with a country's income level. In contrast, the calibrated χ^c decreases significantly with GDP per capita with an estimated semi-elasticity of -0.12. This is because the share of non-employers decreases over the development process in the data (see Gollin, 2008 and Poschke, 2019). To match this trend, the productivity of non-employers relative to employers needs to decline so that individuals move out of the non-employer sector as a country develops (Bick et al., 2020). This means that, as a country develops, employers become more productive than non-employers, thus making workers relatively more productive too. Therefore, more men and women self-select into being employees. At the same time, there is also an increase in time available for women, which according to our analysis in figure 7, means a larger increase in hours worked for female workers than female non-employers. The interaction between the increases in productivity and hours for female workers relative to female non-employers thus makes it even more desirable for women to become employees, resulting in a faster narrowing of the gender gap in employees over the development process.

The role of gender asymmetry in time use and distortions: A decomposition In the second exercise, the calibration jointly recalibrates all the country-specific parameters and aims at matching the occupation shares perfectly by gender; therefore, they also match the occupational gender gap. Clearly, both types of gender asymmetries in time use and distortions play a role in generating the empirical patterns, but how important are they quantitatively? To decompose the effects of these two types of asymmetries, we perform counterfactual exercises by removing one type of gender asymmetry while keeping the other one constant at the calibrated value.

Before discussing the results, we first take a look at the calibrated distortions faced by women across countries. We define the gender-specific frictions faced by women in occupation o as $\tilde{\tau}_o^c = \frac{1}{1-\tau_o^{f,c}}$. Note that although we have three occupations, we are only able to identify two distortions ($\tilde{\tau}_{ne}^c$ and $\tilde{\tau}_w^c$) due to Walras's law. They should be interpreted as distortions relative to that faced by female employers.

Figure 12: Calibrated gender-specific distortions faced by women



(a) Employees and non-employers (b) Relative distortion of female employees

Notes: This table is produced by recalibrating the model to match the male occupation shares in each country while feeding in the labor force composition and discretionary hours by gender taken from the data. It reports the slope coefficients from regression of gender gaps in occupations on log GDP per capita and a constant term in the data and the model. The t-statistics are in the parentheses.

Panel (a) of figure 12 shows that for most countries in our sample, female employees and non-employers faced even higher barriers than female employers with the value of $\tilde{\tau}^c_{ne}$ and $\tilde{\tau}^c_w$ being higher than 1. While the absolute values of these implied barriers are not very informative, the relative value between them acts to distort the allocation of talents between the occupations of employees and non-employers. As shown in panel (b) of the same figure, the relative distortion of female employees to non-employers is above 1 for the poorest countries and declines with GDP per capita. This means that, the changes in implied distortions over the development process makes the occupation of employees more attractive to women relative to non-employers. Qualitatively, they play a similar role as the gender asymmetry in time use in narrowing the gender gaps in non-employers and workers.

Table 8 reports the slope coefficients from regression of gender gaps in occupations on log GDP per capita and a constant term in the data and the two counterfactual models. The counterfactual model with the gender gap in time use only (remove gender-specific distortions) predicts very similar slope elasticities to the exercise in the previous section (Table 7). The results in these two exercises suggest that the gender gap in time use consistently accounts for about 30 percent of the gender gap in non-employers and slightly less than

Table 8: Slope coefficients: data and counterfactual models

	non-employers	employees	employers
data / model	-0.31	0.15	0.00
	(-4.02)	(5.41)	(0.01)
counterfactual: remove gender-specific distortions	-0.09	0.07	0.03
	(-1.72)	(4.31)	(3.54)
counterfactual: close gender gap in time use	-0.23	0.09	-0.01
	(-3.69)	(2.58)	(-0.36)

Notes: This table reports the slope coefficients from regression of gender gaps in occupations on log GDP per capita and a constant term in the data (and the benchmark model) and two counterfactual models. The benchmark model used in this table matches the occupation shares for men and women in each country using gender asymmetries in time use and distortions. In the counterfactual models, we remove one set of gender asymmetries while keeping the other one at the benchmark level. The t-statistics are in the parentheses.

50 percent of the gender gap in employees. The counterfactual model with gender-specific distortions only (close gender gap in time use) predicts a slope coefficient of -0.23 for non-employers and 0.09 for workers, which account for slightly more than 70 percent and 50 percent of the empirical correlations, respectively. A comparison between the size of the slope coefficients in the data and the models suggests little interaction effect between these two types of gender asymmetries in affecting occupation choices.

5 Final Remarks

In this paper, we show that the gender gap in non-agricultural entrepreneurship reverses with development; female entrepreneurs are over-represented in poor countries and under-represented in richer countries. We theorize that observed gender gaps in non-market responsibilities can account for this pattern across countries. In particular, as the market time available to women declines with development, more women in poorer economies select into occupations based on their time constraints. This leads them to select into entrepreneurship, particularly non-employer entrepreneurship, as it provides allows them to work relatively lower hours.

We build a simple theoretical framework to formalize this theory. Our model features selection into entrepreneurship based not only on ability but also available time. Our key innovation is to apply non-linear returns to hours across occupations such that the model matches patterns of hours worked for employees and both non-employer and employer entrepreneurs. A quantitative version of the model allows us to assess the role of gender gaps in time use in shaping gender gaps in entrepreneurship across countries. Our preliminary results highlight that factors such as child-care policy or societal norms that put constraints on female time use are important not only in influencing gender differences in labor market outcomes but also the quantity and quality of businesses in an economy.

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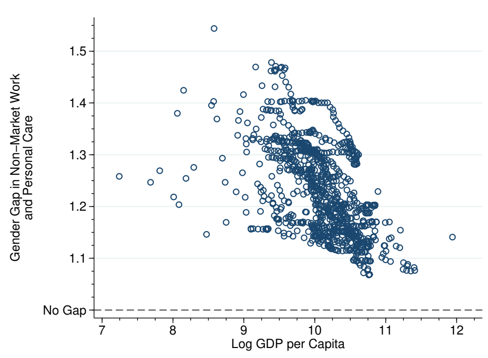
Appendix

A Data Appendix

A.1 Measuring Time Use

Our measures of time use come from three different sources i) the United Nations Global Sustainable Development Goals (UNSDG) Indicators Database, ii) OECD Stat and iii) Bridgman et al. (2018). Each of these data sources compile the results of time use surveys from national statistical agencies and report aggregated measures of time use by type of activity. For each country, we only include data from the most recent year. Figure A.1 plots the gender gaps in time use for all country year observations included in these three data sources. Table C.3 reports the source of time use data for each country in figures 3 and 2.

Figure A.1: Gender Gaps in Time Use, all available data

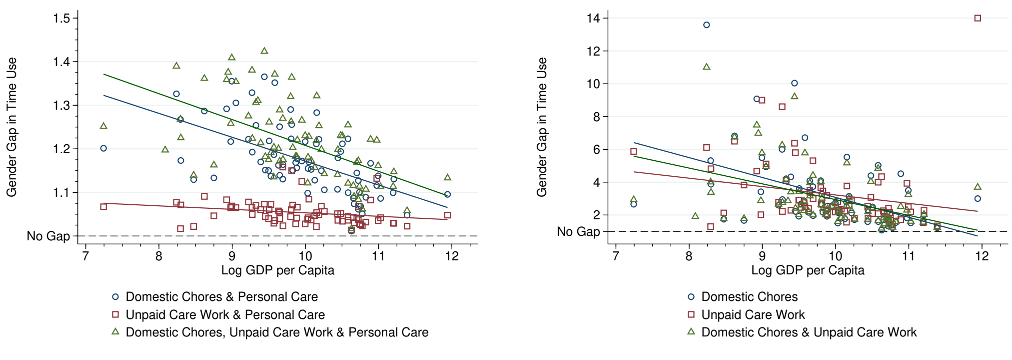


Notes: The figure reports the ratio of female to male time spent in non-market work and personal care activities for all country-year observations reported in the UNSDG, OECD Stat and Bridgman et al. (2018).

The UNSDG data, which comprises the majority of our sample, reports time spent on unpaid domestic and care work. More specifically these include any activities which are listed in the International Classification of Activities for Time Use Statistics 2016 (ICATUS 2016) category 3 and 4. These include, food preparation, dishwashing, cleaning and upkeep of the dwelling, laundry, childcare, and care of family members, among others. We refer to these activities as non-market work. Figure A.2 plots the gender gaps in time use separately for domestic chores and unpaid care work. The figure shows that both types of activities feature significant gender gaps which shrink as economies develop.

For a subset of countries, the UNSDG data also reports time use separately for rural and urban regions. Figure A.3 plots the gender gaps in time by region for these countries. The figure shows that for both rural and urban regions, the gender gap in time use declines with development and that the gender gap is larger n rural areas.

Figure A.2: Gender Gaps in Time Use by Type of Activity

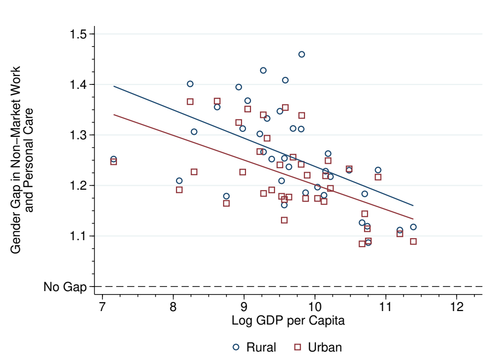


(a) Including Personal Care Activities (b) Excluding Personal Care Activities

Notes: The figure reports the ratio of female to male time spent in domestic chores, unpaid care and personal care activities by urban/rural status using the UNSDG data.

While the UNSDG data covers the entire spectrum of development levels, OECD Stat reports time use for relatively developed economies including 30 OECD member countries as well as 3 non-members; China, India (in 1998) and South Africa. In addition to including information of time spent in non-market work, OECD stat also reports time spent in additional categories including personal care activities. These activities corresponds to category 9 of ICATUS 2016 which are activities related to biological needs, such as sleeping, eating and time related to receiving health/medical services. Neither the UNSDG or Bridgman et al. (2018) include information of these activities. We find almost no gender gap in time spent in personal care activities. Indeed, the average daily time spent in personal care is 667 minutes for women and 656 minutes for men. Further, the the majority (around 75%) of time in personal care is time spent sleeping with little difference across genders in time spent sleeping. Given this, we apply the gender specific OECD average time spent in personal care activities to countries with data from UNSDG and Bridgman et al. (2018).

Figure A.3: Gender Gaps in Time Use in Rural and Urban Regions



Notes: The figure reports the ratio of female to male time spent in non-market work and personal care activities by urban/rural status using the UNSDG data.

Finally, the dataset constructed in Bridgman et al. (2018) reports time spent doing household work by gender.[18] This closely corresponds to non-market work (that is, domestic chores and caring for others). Indeed, the correlation of time use in household work between and the UNSDG measure of non-market work is around 0.93 for those country-year observations which are observed in both samples.

A.2 Measuring Entrepreneurship

ILO Our primary measures of occupation shares by gender are from the International Labour Organisation (ILO). Theses shares are either computed directly from an underlying survey or ILO modeled estimates. This data reports, by gender and industry, the number of individuals by their status in employment according to the International Classification of Status in Employment (ICSE-93). This classification permits six possible employment status; Employees, Employers, Own-account workers, Members of producers' cooperatives, Contributing family workers, and Workers not classifiable by status. We drop all country-year observations for which there is missing information on the first four ICSE categories and consider only those employed in non-agricultural sectors.

Employees, employers and non-employers correspond to the first three ICSE categories, respectively. We consider members of producers' cooperatives or contributing family workers as representing some mixture of the first three categories being most closely related to non-employers. This is made clear in the documentation of the ICSE-93 definitions which classifies both contributing family workers and members of producers' cooperatives as holding self-employment jobs with varying levels of commitment and equity in the operation of a business. As we focus on non-agricultural employment, we find that the employment share of these two categories is under 10% for almost all of the countries. Hence, the gender gap in members of producers' cooperatives, contributing family workers and non-employers evolves with development in almost the same manner as the gender gap in non-employers alone. Indeed, the slope coefficient with development of the gender gaps in non-employers is -0.26 compared to -0.27 when including these additional employment categories.

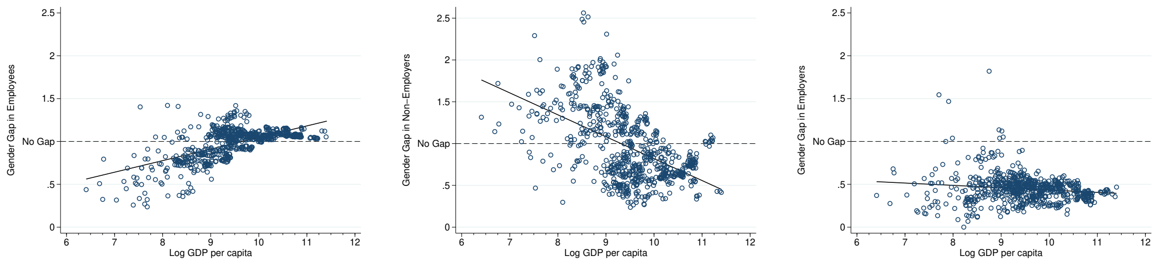
Having defined our three broad occupational categories, we restrict our attention to the most recent country-year observation from the ILO. Including all country-year observation delivers very similar relationships between occupational gender gaps and development. This can be seen in figure A.4 which plots gender gaps across development for for all country-year observations.

A point of concern with the ILO data is that their modeled estimates may lead to occupational shares being non-comparable across countries.[19] However, if the ILO modeled estimates are comparable across genders within countries, then the *gender gaps* in occupations can be compared across countries. Our finding that the relationship between gender gaps and development in both the aggregated ILO and micro level IPUMS samples are similar suggests that this is the case.

[18]The data construction is described in detail in section 8 of their data supplement.

[19]Feng et al. (2018) highlight this point when studying unemployment across development.

Figure A.4: Occupational Gender Gaps in the Full ILO Sample



(a) Employees (b) Non-Employers (c) Employers

IPUMS International To conduct our subgroup analysis and confirm the findings of the ILO, we utilize micro-data from IPUMS International. These are nationally representative surveys or censuses which include information on industry, gender and employment status among other variables. Panel B of table C.4 reports the country-year samples that we use. To be consistent with the ILO sample, we exclude all non-agricultural employment and define employees, employers and non-employers using the harmonized variables `classwk` and `classwkd`. In particular, we consider all wage/salaried workers as employees, all self-employed employers and employers and all other self-employed as non-employers. We then construct occupation shares using the provided sample weights and then use these share to construct occupational gender gaps. We also use the IPUMS data to compare working hours across occupations. Information on working hours is available for only 10 countries in our IPUMS sample: Ecuador, El Salvador, Greece, Italy, Jamaica, Jordan, Nicaragua, Spain, Switzerland, Venezuela.

Additional Labour Force Surveys In order to construct figure 6, we use data from labour force survey for 10 additional countries: Argentina, Armenia, Bolivia, Brazil, Canada, India, Mexico, South Africa, United Kingdom and the United States. Data from Argentina is from the 2016 *Encuesta de Hogares y Empleo*,Armenia: 2014-2016 Labour Force Survey, Bolivia: 2018 *Encuesta Continua de Empleo*, Brazil: 2016 National Household Sample Survey - PNAD, Canada: 2014-2016 Labour Force Survey, India: Periodic Labour Force Survey, Mexico: 2016 Encuesta Nacional de Ocupación y Empleo, South Africa: 2017 Quarterly Labour Force Survey, United Kingdom: 2016 Labour Force Survey and United States: 2014-2019 Current Population Survey.

Combined with the 10 countries from IPUMS that included information on hours (as well as employer/non-employer status), we are able to run the following regression,

$$\log(h_i) = \alpha + \sum_o \beta_o D_i^o + X_i + \epsilon_i$$

where h_i is hours worked by individual i, D_i^o is a dummy variable indicating the occupation o of an individual. X_i is a vector of individual level controls comprised of a quadratic term in age, dummies for education, marital status and 2-digit industry fixed effects. We restrict attention to these controls as they are consistently available in the surveys for each country.

B Model Appendix

B.1 Taste shocks

In the quantitative exercise, we introduce a taste shock for these three occupations in order to convexify the occupation choice and improve the convergence of the algorithms. The taste for each occupation is represented by an i.i.d. draw from a type-I extreme-value probability distribution shock (Gumbel distribution). Since the introduction of the taste shock only aims at improving the convergence property in the quantitative exercise, we picked a small scale parameter of 0.001.

Consider a value function of the following form,

$$V(\boldsymbol{\theta}) = \max_{i \in \{\text{NE,W,E}\}} \{V_i(\boldsymbol{\theta}) + \epsilon_i\}$$

where $\boldsymbol{\theta} = (z, \nu, j)$ is the vector of state variables and ϵ_i is an independent and identically distributed random variable following a Gumbel distribution with shape parameter λ_i and scale parameter ζ_i. The cdf of a Gumbel distribution with parameters ζ_i and λ_i is

$$F(x) = \Pr(\epsilon_i < x) = \exp\left(-e^{-\left(\frac{x-\zeta_i}{\lambda_i}\right)}\right).$$

Then, the probability of picking occupation j is $\Pr\left(\max_{i \neq j}\{V_i(\boldsymbol{\theta}) + \epsilon_i\} < V_j(\boldsymbol{\theta}) + \epsilon_j\right)$. The CDF of $\max_{i \neq j}\{V_i(\boldsymbol{\theta}) + \epsilon_i\}$ can be written as

$$\Pr\left(\max_i \{V_i(\boldsymbol{\theta}) + \epsilon_i\} < x\right) = \prod_i \Pr\left(V_i(\boldsymbol{\theta}) + \epsilon_i < x\right) = \exp\left(-\sum_i e^{-\left(\frac{x - V_i(\boldsymbol{\theta}) - \zeta_i}{\lambda_i}\right)}\right).$$

Define $\varsigma = V_j(\boldsymbol{\theta}) + \epsilon_j$, then ς is distributed Gumbel with shape parameter λ and scale parameter $\zeta_j - V_j(\theta)$. We can show that

$$\Pr\left(\max_{i \neq j}\{V_i(\boldsymbol{\theta}) + \epsilon_i\} < \varsigma\right) = \int_{-\infty}^{\infty} \exp\left(-\sum_{i \neq j} e^{-\left(\frac{\varsigma - V_i(\boldsymbol{\theta}) - \zeta_i}{\lambda}\right)}\right) dF(\varsigma) = \frac{1}{\sum_{i \neq j} e^{-\left(\frac{V_j(\boldsymbol{\theta}) - V_i(\boldsymbol{\theta}) + \zeta_j - \zeta_i}{\lambda_i}\right)}}.$$

Suppose that $\zeta_i = \zeta$ and $\lambda_i = \lambda$, the probability of choosing occupation j over the other occupations is $\frac{1}{\sum_{i \neq j} e^{-\left(\frac{V_j(\boldsymbol{\theta}) - V_i(\boldsymbol{\theta})}{\lambda}\right)}}$.

B.2 Proof of the claims

B.2.1 Optimal hours

We first show that given $\bar{h}$,$\bar{h}^{*,ne} < \bar{h}^{*,w}$. To see this, recall that the FOCs for NE and W are

$$\lambda \frac{1}{h^{*,ne}} = \nu \frac{1}{(\bar{h} - h^{*,ne})^{\gamma}}, \tag{7}$$

and

$$\frac{1}{h^{*,w}} = \nu \frac{1}{(\bar{h} - h^{*,})^{\gamma}}, \tag{8}$$

respectively. It is therefore sufficient to show that $\frac{dh^*}{d\lambda} > 0$ in equation 7. Applying the implicit function theorem to equation 7, we get

$$\frac{dh^*}{d\lambda} = \frac{(\bar{h} - h^*)^{\gamma}}{\nu + \lambda\gamma(\bar{h} - h^*)^{\gamma-1}} > 0.$$

Next, we aim to show that $\frac{dh^{*,w}}{d\bar{h}} > \frac{dh^{*,ne}}{d\bar{h}}$. Again we apply the implicit function theorem to equation 7 and 8. We get

$$\frac{dh^{*,ne}}{d\bar{h}} = 1 - \frac{\nu}{\nu + \lambda^{1/\gamma}\gamma\nu^{\frac{\gamma-1}{\gamma}} h^{*,ne\frac{\gamma-1}{\gamma}}},$$

$$\frac{dh^{*,w}}{d\bar{h}} = 1 - \frac{\nu}{\nu + \gamma\nu^{\frac{\gamma-1}{\gamma}} h^{*,w\frac{\gamma-1}{\gamma}}}.$$

Because $h^{*\mathrm{NE}} < h^{*\mathrm{W}}$ and $\lambda < 1$, it is clear that $\frac{dh^{*,ne}}{d\bar{h}} < \frac{dh^{*,w}}{d\bar{h}}$ if $\gamma < 1$.

C Additional Tables and Figures

Table C.1: Hourly Income of Entrepreneurs, relative to Employees

	Non-Employers	Employers	N	R^2
Male	-0.169***	-0.065	9,170	0.218
	(0.035)	(0.066)		
Female	-0.137***	-0.055	10,642	0.219
	(0.038)	(0.095)		

Notes: The table reports the coefficients on occupation from an OLS regression of log hourly income of respondents in the CPS sample. Controls include a quadratic term in years of experience, race, marital status, number of children in household, state, year, 2-digit industry and 2-digit occupation fixed effects. The first row and second row reports the results for the sample of males and females respectively. The columns report the estimated coefficient for non-employers and employers. Robust standard errors are reported in parentheses. *** indicates statistical significance at the 1% confidence level.

Table C.2: Detailed Reasons for Entrepreneurship

	All Entrepreneurs		Non-Employers		Employers	
	Male	Female	Male	Female	Male	Female
Laid off and hired back as temporary worker	0.01	0.00	0.01	0.00	0.01	0.00
Only type or work could find	0.07	0.06	0.09	0.06	0.01	0.02
Hope job leads to permanent employment	0.01	0.01	0.01	0.01	0.00	0.01
Other economic	0.05	0.04	0.05	0.03	0.06	0.06
Flexibility of schedule	0.20	0.33	0.23	0.35	0.14	0.22
Other family/personal obligations	0.02	0.08	0.03	0.09	0.01	0.03
Child care problems	0.00	0.02	0.00	0.02	0.00	0.01
In school/training	0.01	0.00	0.01	0.00	0.00	0.00
Money is better	0.10	0.05	0.10	0.05	0.13	0.05
To obtain experience/training	0.01	0.00	0.01	0.00	0.00	0.00
For the money	0.03	0.02	0.03	0.03	0.04	0.00
Other personal	0.07	0.07	0.06	0.06	0.10	0.14
Health limitations	0.01	0.01	0.01	0.01	0.00	0.00
Retired/Social Security earnings limit	0.00	0.00	0.00	0.00	0.00	0.01
Nature of work/seasonal	0.02	0.02	0.02	0.02	0.01	0.03
Enjoys being own boss and independence	0.34	0.25	0.29	0.22	0.46	0.40
Refused	0.01	0.01	0.01	0.01	0.01	0.01
Don't know	0.02	0.01	0.02	0.01	0.01	0.00
No Response	0.01	0.02	0.02	0.02	0.01	0.02
N	2,198	1,343	1,565	1,111	633	232

Notes: The table reports the share of entrepreneurs by their reported reason for entrepreneurship in the 2017 Contingent Work Supplement of the CPS.

Table C.3: Source of Time Use Data

Country	Year	Source	Country	Year	Source
Albania	2011	UNSDG	Italy	2014	BDH
Argentina	2013	UNSDG	Japan	2016	OECD
Armenia	2008	UNSDG	Kazakhstan	2018	UNSDG
Australia	2014	BDH	Kyrgyzstan	2015	UNSDG
Austria	2014	BDH	Republic of Korea	2014	OECD
Azerbaijan	2008	UNSDG	Lithuania	2003	OECD
Belgium	2013	OECD	Luxembourg	2014	UNSDG
Bangladesh	2012	BDH	Latvia	2003	OECD
Bulgaria	2010	UNSDG	Morocco	2012	UNSDG
Belarus	2015	UNSDG	Republic of Moldova	2012	UNSDG
Bolivia	2001	UNSDG	Mexico	2014	UNSDG
Brazil	2017	UNSDG	North Macedonia	2015	UNSDG
Canada	2016	UNSDG	Malta	2002	UNSDG
Switzerland	2016	UNSDG	Mongolia	2015	UNSDG
Chile	2015	UNSDG	Mauritius	2003	UNSDG
China	2018	UNSDG	Netherlands	2016	OECD
Colombia	2017	UNSDG	Norway	2014	BDH
Costa Rica	2017	UNSDG	New Zealand	2014	BDH
Germany	2013	UNSDG	Oman	2008	UNSDG
Denmark	2012	BDH	Pakistan	2007	BDH
Dominican Republic	2016	UNSDG	Panama	2011	BDH
Algeria	2012	BDH	Peru	2010	UNSDG
Ecuador	2012	BDH	Poland	2013	OECD
Egypt	2015	UNSDG	Portugal	2015	UNSDG
Spain	2014	BDH	Paraguay	2016	UNSDG
Estonia	2014	BDH	State of Palestine	2013	UNSDG
Ethiopia	2013	UNSDG	Qatar	2013	UNSDG
Finland	2014	BDH	Romania	2012	UNSDG
France	2014	BDH	Russian Federation	2014	UNSDG
United Kingdom	2015	UNSDG	El Salvador	2017	UNSDG
Ghana	2009	BDH	Serbia	2015	UNSDG
Greece	2014	UNSDG	Slovenia	2001	UNSDG
Guatemala	2017	UNSDG	Sweden	2014	BDH
Hong Kong	2013	UNSDG	Thailand	2015	UNSDG
Honduras	2009	UNSDG	Turkey	2015	UNSDG
Hungary	2010	UNSDG	Taiwan	2004	BDH
India	1998	OECD	Uruguay	2013	UNSDG
Ireland	2005	OECD	United States	2018	OECD
Iran	2009	UNSDG	South Africa	2014	BDH
Iraq	2012	BDH			

Notes: UNSDG indicates that data is retrieved from the United Nations Global Sustainable Development Goals Indicators Database. This database is available at unstats.un.org/sdgs/indicators/database. OECD indicates data retrieved from OECD Stat. BDH indicates that data is from Bridgman et al. (2018).

Table C.4: Sources of Measures of Entrepreneurship

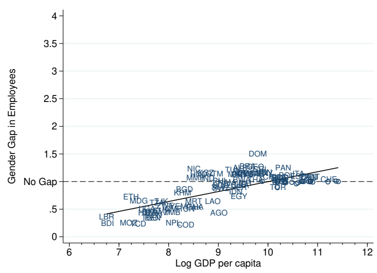
Panel A: ILO

Country	Year	Country	Year	Country	Year
Albania	2019	Gambia	2012	Panama	2019
Angola	2011	Georgia	2019	Paraguay	2019
Armenia	2018	Germany	2019	Peru	2019
Austria	2019	Ghana	2017	Philippines	2019
Bangladesh	2017	Greece	2019	Poland	2019
Benin	2011	Guatemala	2017	Republic of Moldova	2019
Bolivia	2018	Guyana	2018	Romania	2019
Bosnia and Herzegovina	2019	Haiti	2012	Russian Federation	2019
Botswana	2009	Honduras	2019	Rwanda	2018
Brazil	2019	India	2018	Serbia	2019
Burkina Faso	2018	Indonesia	2019	Spain	2019
Burundi	2014	Italy	2019	Sri Lanka	2018
Cambodia	2017	Kenya	1999	Switzerland	2019
Cameroon	2014	Kyrgyzstan	2018	Tajikistan	2009
Canada	2019	Lao People's DR	2017	Thailand	2019
Chad	2018	Liberia	2010	Togo	2017
Chile	2019	Madagascar	2015	Tunisia	2017
Colombia	2019	Mauritania	2017	Turkey	2019
Congo	2005	Mexico	2019	Tanzania	2014
Costa Rica	2019	Mongolia	2019	Uganda	2017
Côte d'Ivoire	2017	Mozambique	2015	Uruguay	2019
Dominican Republic	2019	Myanmar	2019	Venezuela	2012
Ecuador	2019	Namibia	2018	Yemen	2014
Egypt	2018	Nepal	2017	Zambia	2018
El Salvador	2019	Nicaragua	2014	Zimbabwe	2014
Eswatini (Swaziland)	2016	North Macedonia	2019		
Ethiopia	2013	Pakistan	2018		

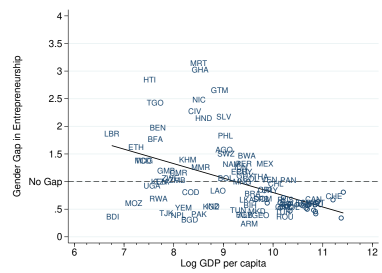
Panel B: IPUMS

Country	Year	Country	Year	Country	Year
Armenia	2011	Guatemala	2002	Nepal	2011
Austria	2011	Haiti	2003	Nicaragua	2005
Benin	2013	Honduras	2001	Palestine	2007
Bolivia	2001	India	2009	Panama	2010
Botswana	2011	Indonesia	2010	Papua New Guinea	2000
Brazil	2010	Iran	2011	Paraguay	2002
Cambodia	2013	Ireland	2011	Peru	2007
Cameroon	2005	Italy	2015	Portugal	2011
Chile	2002	Jamaica	2001	Rwanda	2012
Colombia	2005	Jordan	2004	South Sudan	2008
Costa Rica	2011	Lao People's DR	2005	Spain	2015
Ecuador	2010	Lesotho	2006	Sudan	2008
Egypt	2006	Liberia	2008	Switzerland	2000
El Salvador	2007	Malaysia	2000	Togo	2010
Fiji	2014	Mali	2009	Turkey	2000
France	2011	Mexico	2015	Tanzania	2012
Ghana	2010	Mongolia	2000	Venezuela	2001
Greece	2011	Morocco	2004	Zambia	2010

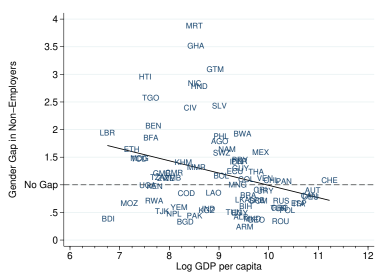
Figure C.5: Gender Gap by Occupation, as share of Labor Force



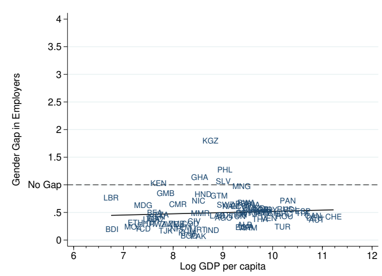
(a) Employees



(b) All Entrepreneurs



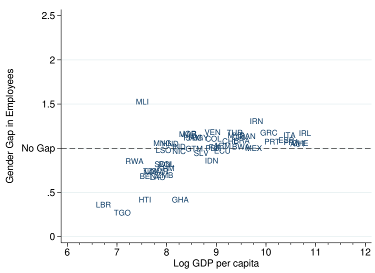
(c) Non-Employers



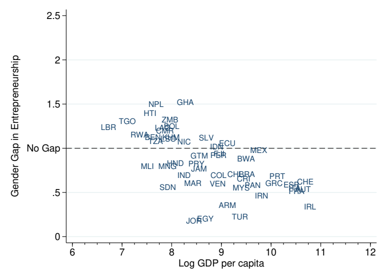
(d) Employers

Notes: The figure plots ratio of female and male employees and entrepreneurs as a share of their respective labor force. Panel (a) plots the ratio of $\left(\frac{\text{Female Employees}}{\text{Female Labor Force}}\right)$ and $\left(\frac{\text{Male Employees}}{\text{Male Labor Force}}\right)$. Panel (b) plots the ratio of $\left(\frac{\text{Female Entrepreneurs}}{\text{Female Labor Force}}\right)$ and $\left(\frac{\text{Male Entrepreneurs}}{\text{Male Labor Force}}\right)$. Panels (c) and (d) report separately the gender gaps for non-employers and employers respectively.

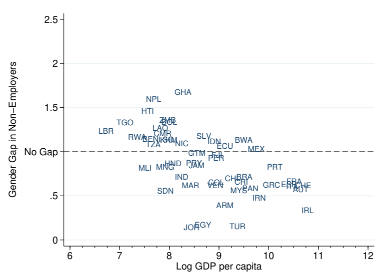
Figure C.6: Gender Gaps by Occupation - IPUMS International Data



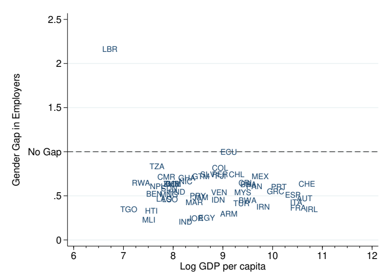
(a) Employees



(b) All Entrepreneurs



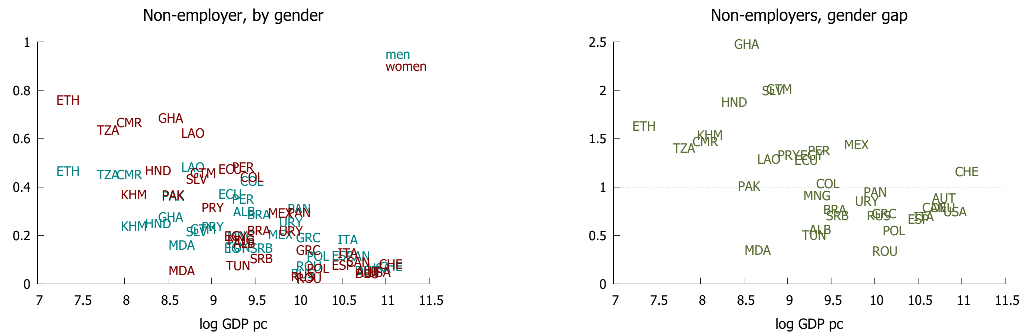
(c) Non-Employers



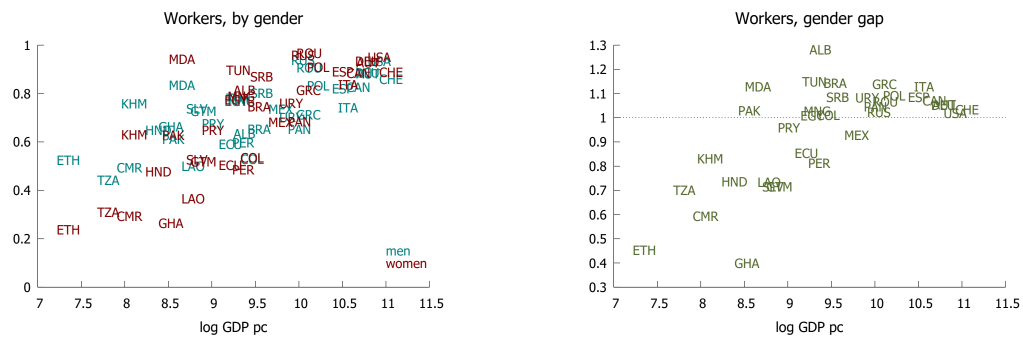
(d) Employers

Notes: The figure plots ratio of female and male employees and entrepreneurs as a share of their respective total employment as computed from the IPUMS International micro-data. Panel (a) plots the ratio of $\left(\frac{\text{Female Employees}}{\text{Female Employment}}\right)$ and $\left(\frac{\text{Male Employees}}{\text{Male Employment}}\right)$. Panel (b) plots the ratio of $\left(\frac{\text{Female Entrepreneurs}}{\text{Female Employment}}\right)$ and $\left(\frac{\text{Male Entrepreneurs}}{\text{Male Employment}}\right)$. Panels (c) and (d) report separately the gender gaps for non-employers and employers respectively. The red markers indicate data from the EU Labor Force Surveys.

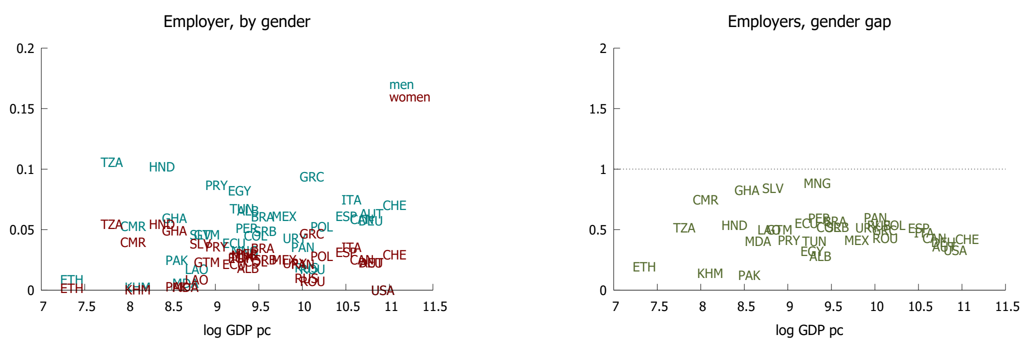
Figure C.7: Occupation shares by gender across countries, restricted sample



(a)



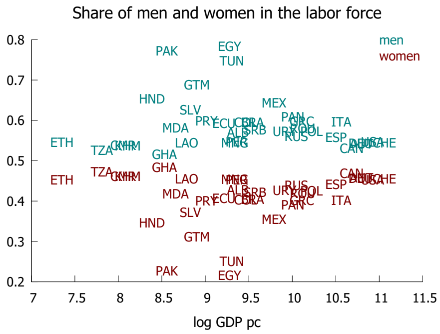
(b)



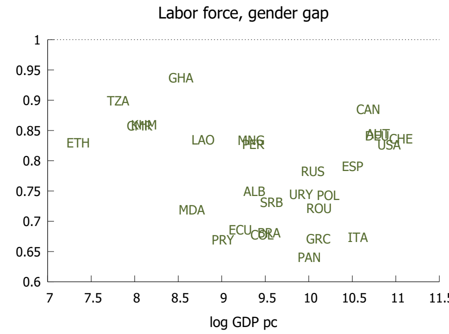
(c)

Notes: These figures plots the occupation shares by gender and the gender gaps for NE (panel a), W (panel b) and E (panel c) in the data for the restricted sample of firms used in the quantitative exercise (see section **??**).

Figure C.8: Labor force across countries

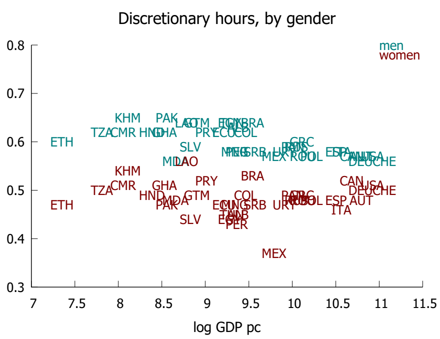


(a)

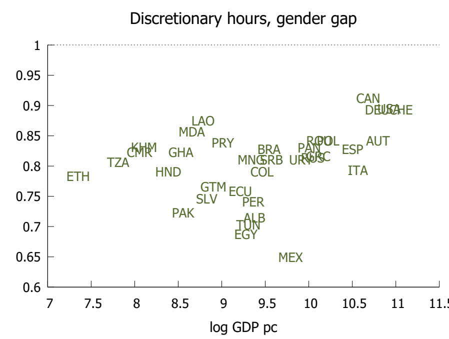


(b)

Figure C.9: Discretionary hours across countries

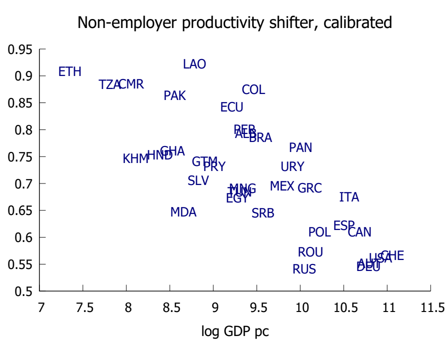


(a)

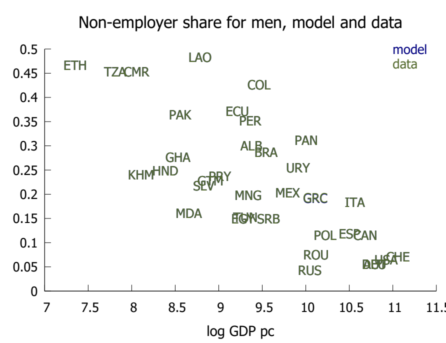


(b)

Figure C.10: Calibrated χ and share of non-employers for men



(a)



(b)