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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. This decline is more pronounced for women. Relative to men, women are more likely to be entrepreneurs in poor economies but less likely in rich economies. We investigate whether gender gaps in time dedicated to non-market activities, which narrow with development, can account for this pattern. We develop a quantitative framework in which selection into occupations depends on one's ability and time and features gender-specific distortions and social norms around market work. When we calibrate the model to match cross-country data, we find that differences in social norms are almost entirely responsible for the patterns of gender gaps in both time use and entrepreneurship. Through affecting time use and entrepreneurship, social norms account for a substantial part of cross-country differences in output per worker and firm size and have significant welfare implications for women.

Topics: Firm dynamics; Productivity
JEL codes: J2, L2, O1

Résumé

La proportion d'entrepreneurs, en particulier des leaders d'entreprises peu productives sans employés, diminue à mesure qu'une économie se développe. Ce phénomène est plus prononcé chez les femmes. En effet, comparativement aux hommes, elles sont plus susceptibles d'avoir leur propre entreprise dans les pays pauvres, mais le sont moins dans les pays riches. Nous cherchons à savoir si cette tendance peut s'expliquer par les écarts entre les sexes sur le plan du temps consacré à des activités non marchandes, ces écarts diminuant à mesure qu'une économie se développe. Nous élaborons un cadre quantitatif dans lequel le choix d'une profession dépend des capacités et du temps dont dispose une personne, et qui intègre des distorsions selon le sexe et les normes sociales liées au travail marchand. Lorsque nous étalonnons le modèle de sorte qu'il réplique les données portant sur plusieurs pays, nous constatons que les différences de normes sociales sont presque entièrement à l'origine des tendances relatives aux écarts entre les sexes sur les plans tant de la gestion du temps que de l'entrepreneuriat. Les normes sociales, en raison de leur effet sur la gestion du temps et l'entrepreneuriat, expliquent en grande partie les différences entre les pays en ce qui a trait à la production par personne et à la taille des entreprises, et elles ont une incidence importante sur le bien-être des femmes.

Sujets : Dynamique des entreprises; Productivité
Codes JEL : J2, L2, O1

1 Introduction

As economies develop, they undergo dramatic structural changes, including changes in outcome gaps between women and men. For instance, compared to richer economies, poor economies feature noticeable gender differences in time allocated for market vs. non-market (household) work and various other labor market outcomes.[1] In addition, poorer economies are characterized by a higher prevalence of entrepreneurs – particularly low-productivity entrepreneurs.[2] Recent studies argue that the allocation of time plays a pivotal role in shaping occupational choices and thus labor market outcomes. This paper explores the connection between time allocation and selection into entrepreneurship for women and men. Our objective is twofold: to document gender gaps in entrepreneurship across countries and to explore the role played by gender gaps in time use in these and other outcomes, including average firm size and aggregate output.

There is an intuitive relationship between entrepreneurship and factors impacting the allocation of time. The ability of entrepreneurs to set their hours implies that constraints on market hours can have significant influence on selection into entrepreneurship.[3] Women, especially those in developing countries, bear a disproportionate burden of non-market responsibilities such as household work and family care, suggesting they may have fewer hours for market activities, a factor potentially important for understanding the rate of female entrepreneurship. As a consequence, factors that influence gender gaps in time use, such as barriers to occupations and social norms around market work, can affect the quantity and quality of entrepreneurs and impact outcomes such as average productivity, firm size distribution, and aggregate output.

We start by documenting three empirical facts on the allocation of time across occupations and gender, and patterns of entrepreneurship across countries. Our empirical analysis distinguishes between three occupational categories within non-agricultural employment: i) employees, ii) non-employer entrepreneurs, and iii) employer entrepreneurs.

First, using microdata from 20 countries spanning the range of development stages, we

[1]See Antecol (2000) for cross-country differences in labor market outcomes by gender and Bridgman et al. (2018) for cross-country differences in market and household work by gender.

[2]Throughout this paper, we use the terms 'entrepreneur' and 'self-employed' interchangeably. See, for example, Gollin (2008) and Poschke (2019) for evidence of cross-country differences in the share of entrepreneurs and their productivity.

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

identify a clear ranking of hours worked across these occupational categories. We show that employees and employers work a similar number of hours on average, while non-employer entrepreneurs work the fewest hours. This ranking suggests that non-employer entrepreneurship may be particularly appealing to those with limited time for market activities. Second, we review the evidence on gender gaps in the time allocated to non-market activities across countries. Utilizing aggregated time use survey data, we show that, consistent with existing work such as Bridgman et al. (2018), women in less developed countries shoulder a more significant load of non-market responsibilities than men, and this gap narrows considerably with development. Finally, we show that the well-documented decline in entrepreneurship rates with development (Gollin, 2008; Poschke, 2019) is more pronounced for women. Using both aggregate and microdata sources across countries, we document that women are more likely than men to be entrepreneurs in poor economies but less likely in rich economies. We show this relationship is driven by gender gaps among non-employer entrepreneurs, an occupation we argue is particularly amenable to those with fewer available market hours.

The ranking of hours by occupation, the narrowing of the gender gap in time use with development, and the reversal of gender gaps in non-employer entrepreneurship are consistent with the idea that women in developing economies are choosing non-employer entrepreneurship based, in part, on time use. We quantitatively examine this idea by developing a model of occupational choice where women and men select into entrepreneurship or employment based not only on innate ability, as in standard models, but also on their time allocated to market work. Individuals allocate their time between market work (in their chosen occupation), non-market work (household production), and leisure. In addition to allowing for selection based on time use, we also allow for non-linear returns to non-employer entrepreneurs' hours. As highlighted in Erosa et al. (2022), non-linearities in the returns to hours across occupations have significant implications for labor supply and occupational choice, determining the relative ranking of hours worked across occupations. Calibrating our model to match key features of US data, we find the returns to non-employer entrepreneurship are concave in the own hours worked by these entrepreneurs. In contrast, returns to own hours are linear for employees and employer entrepreneurs. As a consequence, non-employers choose to work fewer hours compared to employees and employers, as in the data, which also encourages selection into non-employer entrepreneurship for those who devote more time to non-market activities.

The model includes two forces that can directly distort women's time allocation and occupational choices. First, we allow for the presence of social norms, modeled as affecting the disutility of market work for women. These norms capture societal attitudes towards women in the workforce (and women's internalization of these attitudes), which include a variety of documented phenomena like norms regarding whether and how women and men can work together (Miller et al., 2022), limits to female mobility outside the home (Aguilar et al., 2021) and beliefs about the acceptability of women in the workplace (Arielle et al., 2018).[4]

The second force directly affecting women's choices represents distortionary 'taxes' affecting actual or perceived returns to market work for women. We assume female employees face an effective tax rate on wage earnings to capture the gender wage gap in employment (Goldin, 2014; ILO, 2018). As in Hsieh et al. (2019), this tax compensates employers who dislike female workers, leaving them indifferent between hiring male and female workers. Similarly, female non-employers and employers face an effective tax on their output. These 'taxes' can capture consumer discrimination towards female entrepreneurs, which reduces demand for their output (Beede and Rubinovitz, 2015; Kricheli-Katz and Regev, 2016; Weikle, 2021), differences in access to inputs and finance (Coleman and Robb, 2009; Alesina et al., 2013; Morazzoni and Sy, 2022), and differential labor costs required to compensate employees that discriminate against female employers (Riffkin, 2014).

To quantify the contribution of gender-specific distortions and social norms to cross-country differences in gender gaps across countries, we first calibrate our model to match US data to obtain values for structural parameters. We then target cross-country data to obtain values for female-specific distortions and social norms across countries and for gender-neutral aggregate factors (such as productivity levels). We show that while differences in distortions and social norms can impact gender gaps in occupation choices, higher distortions tend to affect time use in the same direction for women and men. Cross-country differences in social norms are therefore necessary to account for the cross-country patterns in the time-use gender gaps we see in the data. Viewed through the lens of our calibrated model, the data imply significant cross-country variation in social norms and aggregate factors and moderate differences in gender-specific distortions. For example, the disutility from market work experienced by women in the lowest income countries is higher than in the US by a factor of 2.7 due to differing social norms and accounts for 97% of the observed difference in time-use gender gaps.

Differences in time-use gender gaps, driven primarily by differences in social norms across countries, also generate more pronounced gender gaps in entrepreneur shares in poorer

[4]See Dinkelman and Ngai (2022) and Jayachandran (2021) for more discussions of the factors that affect women's time allocation between market and non-market activities.

economies. Faced with a higher disutility from market work, women spend more time in non-market activities and less time active in the market. This motivates them to choose non-employer entrepreneurship where earnings are concave in hours worked and dissuades them from employment and employer entrepreneurship where returns to hours are linear. While the data suggest that social norms are more biased against female market work in poorer countries, the distortions implied by the data tend to be a more significant barrier to women in richer countries. While differences in distortions are not large, they are still strong enough to reduce the gender gap in non-employer shares across countries, relative to the US. Quantitatively, both social norms and distortions are necessary to explain the differences in gender gaps in occupational shares.

We use our calibrated model to quantify the influence of gender-specific distortions and social norms on cross-country differences in average firm size, firm productivity, aggregate output, and welfare. Although not directly targeted, the model captures the observed strong negative correlation between average firm size and development. Cross-country differences in aggregate factors account for most of the model-generated variation in average size for male employers and a considerable portion of the variation in female employer size. Nevertheless, social norms generate large differences in average firm size between female and male employers, especially in the poorest countries. And we find social norms still account for 6% of the difference in average employer size between the US and the poorest economies, along with 23% of the difference in the aggregate share of entrepreneurs (both non-employers and employers).

Cross-country differences in both average firm productivity and output per worker are also predominantly accounted for by differences in aggregate factors. However, social norms drive employer productivity higher in poorer countries, primarily by encouraging lower-productivity female entrepreneurs to be non-employers rather than employers so that the remaining female employers have a higher average productivity. Social norms, which are more biased against women in poorer countries, also play a significant role in accounting for cross-country differences in aggregate output. For example, social norms in middle-income countries are responsible for about one-sixth of the gap in non-agricultural output per worker between these countries and the US, while aggregate factors account for about one-third. In the poorest countries, social norms account for 4% of the gap in output per worker.

Finally, we use the model to infer the welfare implications of gender-specific distortions and social norms. The lower level of distortions in poorer countries tends to increase welfare for women with high entrepreneurial ability by increasing entrepreneurial earnings and encouraging more women to become entrepreneurs. But for all women, average welfare effects are moderate. For most countries, the lower level of distortions (relative to the US) are responsible for welfare gains equivalent to that from a 6% increase in consumption. Social norms, causing a higher disutility for market work for women, are much more impactful. Across countries, removing differences in social norms and setting them equal to the US level would significantly increase average welfare, equivalent to the gains from increasing consumption, by 34% to 87% for women. This change would impact the most entrepreneurial women most dramatically, but all women would see significant gains. We find cross-country differences in aggregate factors still play a very large role in generating welfare differences across countries for both men and women.

In summary, our quantitative analysis emphasizes the significant role of social norms in discouraging women from spending time in the market and, therefore, in affecting the occupation choices of both men and women. These norms impact not only gender gaps in labor market outcomes, but also the quantity and quality of businesses within an economy.

Related literature. This paper contributes to several strands of literature studying entrepreneurship and time use by gender both within and across countries.

The declining share of entrepreneurs with development, particularly smaller, low productivity non-employer entrepreneurs, is well-documented in the literature (Gollin, 2008; Poschke, 2018; Allub and Erosa, 2019; Bento and Restuccia, 2021). Existing empirical evidence on gender differences in entrepreneurship across countries is less comprehensive, with research typically focusing on developed economies. Klapper and Parker (2011) review evidence on gender differences in formal-sector entrepreneurship in industrialized countries. More recently, Cuberes et al. (2019) have documented an under-representation of female entrepreneurship in 40 European economies. We extend these findings by establishing a robust negative relationship between development and gender gaps in entrepreneurship across the entire range of development, particularly for non-employer entrepreneurship. Using detailed microdata across countries, we also show this pattern is stronger among subsets of people with tighter constraints on their market time, including those who are married, have children, or have low levels of education.

Our empirical work relates to the literature on the allocation of time across occupations and gender. Bridgman et al. (2018) and Gottlieb et al. (2023), among others, show that gender gaps in non-market activities narrow with development. We review this evidence and show that this pattern is evident across regions within countries and varies little by employment status. Wellschmied and Yurdagul (2021) explore the relative ranking of hours worked by employees, non-employer entrepreneurs, and employer entrepreneurs. We confirm their findings, which focus on the US, and extend their analysis using microdata for 20 countries to establish the ranking of hours across these occupations across the spectrum of development levels and to show this ranking holds broadly for both women and men.

A growing literature studying entrepreneurship across countries has incorporated selection into non-employer entrepreneurship into their models (Gollin, 2008; Allub and Erosa, 2019; Feng and Ren, 2023). We relate to this literature by highlighting the importance of non-employers in accounting for gender gaps in overall entrepreneurship across countries. As in Wellschmied and Yurdagul (2021), our model allows entrepreneurs' own hours to be an input to production. We extend their model by allowing for home production and gender-specific choices. Our theoretical framework is most closely related to Erosa et al. (2022), which quantifies the role of gender differences in time allocation for gender differences in labor market outcomes and emphasizes the importance of non-linearities in the returns to hours across occupations of workers. We extend their analysis to allow for a choice between entrepreneurship and employment, and to endogenize the allocation of time between non-market and market work. This allows us to quantify the impact of social norms and distortions on time use and entrepreneurship and, through these channels, to understand how they influence macroeconomic outcomes such as firm size distribution, firm productivity, and aggregate output.

The theoretical and quantitative body of literature on the decline in entrepreneurship with development has examined factors such as financial development (Buera et al., 2011; Feng and Ren, 2023), costs of formalization (Bruhn and McKenzie, 2014), and the extent of misallocation (Bento and Restuccia, 2021) across countries. Limited work studying gender gaps in the prevalence and performance of entrepreneurs has focused on gender disparities in these factors, including higher financing costs for females (Ranasinghe, 2023; Morazzoni and Sy, 2022) and distortions like discrimination against female entrepreneurs (Bento, 2020). Our quantitative framework incorporates these forces in the form of gender-neutral aggregate factors and gender-specific distortions. We contribute to this literature by studying how social norms, as well as the above factors, shape the relationship between entrepreneurship and development, and by studying gender gaps in entrepreneurship at all levels of development. Our quantitative analysis provides support for the narrative that time commitments in non-market work may be responsible for the entry decisions and performance outcomes of female entrepreneurs (Bruhn, 2009; Jayachandran, 2020). Furthermore, our results indicate that social norms biased against women working in the market are not only almost entirely responsible for the declining gender gap in entrepreneurship as economies develop, but also account for a significant portion of the link between development and overall entrepreneurship.

Though recent work emphasizes the role of social norms in acting as a barrier to women's market work (Dinkelman and Ngai, 2022; Jayachandran, 2021), there is relatively limited research quantifying the aggregate impact of norms. Existing work has focused on gender-specific distortions for entrepreneurs (Bento, 2020; Chiplunkar and Goldberg, 2021) and employees in different occupations (Hsieh et al., 2019), and found these to have important aggregate implications. We contribute to this literature by explicitly modeling social norms in addition to distortions and quantifying their impact. Importantly, when calibrating our model to match cross-country data on gender gaps in time use (neglected in this quantitative literature), the data suggest differences in social norms are much more important than occupation-specific distortions for generating observed differences in time use and aggregate outcomes.

The rest of the paper is organized as follows. Section 2 presents our main empirical findings, while Section 3 outlines our model. We calibrate the model to match US data in Section 4 and conduct the cross-country calibration in Section 5. Section 6 is dedicated to our main quantitative analysis, and we conclude in Section 7.

2 Empirical Findings

In this section, we establish the empirical patterns that motivate and discipline our theory. First, we use microdata to show that, across countries, non-employer entrepreneurs work fewer hours than either employer entrepreneurs or employees. We then use aggregated cross-country data to confirm findings in the literature that the gender gap in non-market time use declines as economies develop. Finally, using a combination of aggregated and microdata across countries, we show that gender gaps in entrepreneurship also decline with development and that this pattern is driven exclusively by gender gaps among non-employer entrepreneurs.

2.1 Entrepreneurship and Hours Worked

Data Description To compare the hours worked by entrepreneurs and employees, we utilize microdata from several countries that span the range of income levels. Specifically, we use nationally representative labor-force surveys or census samples from Argentina, Armenia, Bolivia, Brazil, Canada, Ecuador, El Salvador, Greece, India, Italy, Jamaica, Jordan, Mexico, Nicaragua, South Africa, Spain, Switzerland, United Kingdom, United States, and Venezuela. We utilize information on individuals' occupations, their usual weekly hours worked, and demographic information. Our analysis, which focuses on non-agricultural employment, classifies employed individuals into three categories: i) employees – those that work for others; ii) non-employers – entrepreneurs that do not hire employees; and iii) employers – entrepreneurs that hire employees.[5] To maintain consistency with the cross-country data in the following subsections, we include only individuals between the ages of 15 and 65. In addition, we focus on those respondents who worked at least 10 hours per week and held only one job. We provide more details on the data source of each country in Appendix B.1.

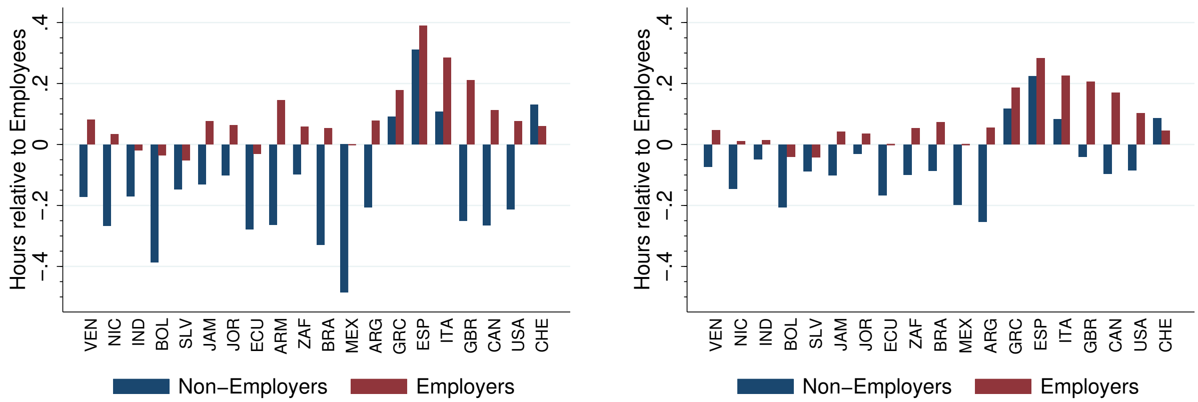
Ranking of Hours Worked, by Occupation We begin by investigating the ranking of hours worked across the three occupations we focus on. To do this, we estimate, separately for each country, the following regression:

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

where h_i is hours worked by individual i, D_i^o is a dummy variable indicating occupation o of an individual, and X_i is a vector of individual level controls consisting of a quadratic term in years of experience or age, dummies for education, marital status, and 2-digit industry fixed effects. These controls account for factors, such as industrial composition, that naturally generate differences in hours across occupations (Bick et al., 2022). Whenever available, we also control for race, the number of children in the household, 2-digit occupation, and state/province fixed effects. We estimate this equation separately for women and men and focus on the coefficient β_o, which captures the difference in hours worked across occupations.

[5] We include only non-agricultural employment to avoid the ambiguities in assigning contributing family workers, who tend to be females and concentrated in the agricultural sector, into one of our three occupational categories. Nevertheless, we confirm in Appendix B.3 that our empirical findings hold even if we include agricultural employment.

Figure 1: Hours Worked in Entrepreneurship Relative to Employment



(a) Female Entrepreneurs

(b) Male 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 occupation o of an individual, and X_i is a vector of individual level controls consisting 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, and Venezuela are from the IPUMS samples. Data for the remaining countries are collected from each country's labor-force surveys. Details of the data are discussed in Appendix B.1.

Figure 1 reports the coefficient, β_o, that captures the difference in hours worked by employers and non-employers relative to employees.[6] Except for four developed economies, female and male non-employers work significantly fewer hours than employees while employers tend to work either similar or longer hours than employees. For example, once we control for observable characteristics, in the US, female non-employers work 22% fewer hours than female employees while female employers work 8% more hours. The analogous numbers for men are 8% fewer hours for male non-employers and 10% more hours for employers.

This ranking of hours worked by occupation is consistent with Wellschmied and Yurdagul (2021), who study hours worked in the US. Figure 1 shows that this ranking of hours worked is largely evident across a sample of both developed and developing economies. Notably, there are four exceptions in our sample, Greece, Italy, Spain, and Switzerland, where both employers and non-employers work longer hours than workers. In addition to being members of the European Union, these economies differ from others in our sample in that they have legislation in place restricting the maximum hours employees can work. To our knowledge,

[6] The coefficient capturing the difference in non-employer hours relative to employees is statistically significant at the 5% level for all countries except Armenia in the sample of men, and for all countries in the sample of women. The coefficient capturing the difference in employer hours relative to employees is statistically significant at the 5% level for all countries except Argentina, Ecuador, India, Mexico, and Nicaragua for men, and Argentina, Bolivia, India, Mexico, and Nicaragua for women.

there is no analogous legislation restricting the hours of entrepreneurs.

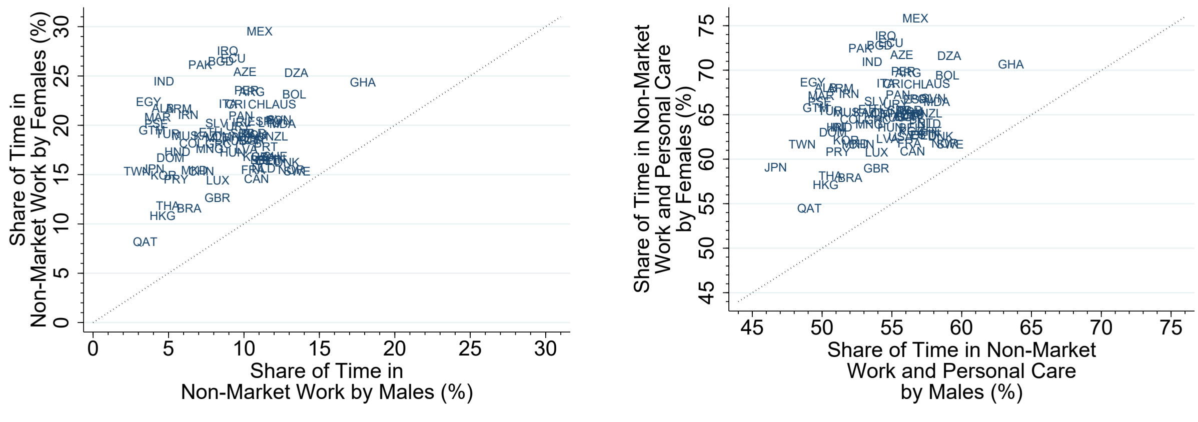
In addition to the broad ranking of hours across occupations, we also find that the relative difference in hours is larger for female non-employers. For example, in Brazil, male non-employers work around 20% shorter hours than male employees compared to a 35% gap between female non-employers and employees. Taken together, Figure 1 suggests that non-employers, particularly female non-employers, work much fewer hours than workers while employers tend to work similar or longer hours than workers. This suggests that non-employer entrepreneurship may be particularly amenable to those who have limited time available for market activity. In other words, given the low hours worked by non-employer entrepreneurs, this occupation may be more susceptible to selection based on time use.[7]

2.2 Cross-Country Gender Gaps in Time Use

Data Description To document cross-country gender gaps in non-market time use, we use aggregated statistics from time use surveys as compiled by i) the United Nations Statistics Division (UNSD), ii) OECD Stat and iii) Bridgman et al. (2018). Each of these datasets reports the proportion of time spent doing domestic chores and caring for others, by gender. Such non-market, or unpaid, work includes food preparation, cleaning, shopping, and caring for children, among other activities corresponding to categories 3 and 4 of the 2016 International Classification of Activities for Time Use Statistics (ICATUS 2016). The OECD data further reports time spent in personal care activities, which include sleeping (not naps), eating/drinking, and other personal services such as visits to the doctor, hairdresser, etc. We limit ourselves to the most recent year available to countries whose data are derived from time-use surveys rather than labor-force or household surveys. Our final sample includes data from 79 countries that span the range of levels of development. Further details regarding the data and additional results, including gender gaps in non-market time use by region and employment status, can be found in Appendix B.2.

[7]Hurst and Pugsley (2011) and Yurdagul (2017), among others, emphasize that the desire for flexibility or other non-pecuniary motives, such as preferences for being one's own boss, are an important driver of selection into entrepreneurship. In Appendix B.5 we use data from the Contingent Worker Supplement of the CPS to show that the flexibility motive for entrepreneurship is particularly salient for non-employers, particularly female non-employers.

Figure 2: Time Use by Gender Across Countries



(a) Non-market Work Only

(b) Non-market Work and Personal Care

Notes: The figure plots the share of time spent in non-market work and personal care by women and men across countries. Panel (a) plots only time in non-market work while Panel (b) combines non-market work and personal care time. Data are from UNSD, OECD, and Bridgman et al. (2018), with additional details provided in Appendix B.2.

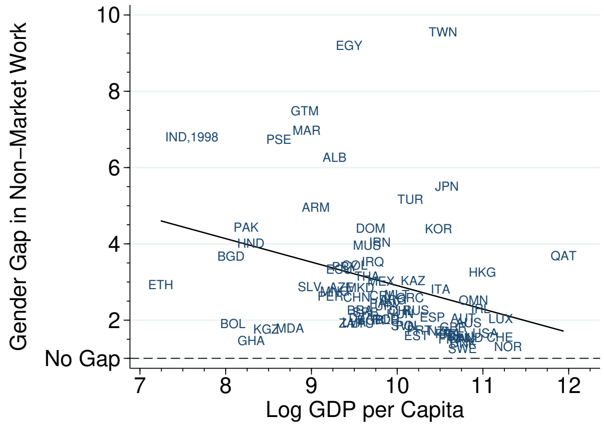
Gender Gaps in Time Use We begin by comparing the (average) time women and men spend in non-market and personal care activities across countries. Panel (a) of Figure 2 shows that across all countries, women spend twice as much time in non-market work as men (20% vs. 10%). Panel (b) includes time spent in personal care (in addition to non-market work) and displays similar gender asymmetries, showing that around 50% of mens' time and 65% of womens' is spent in non-market activity. This confirms findings in work such as Rubiano-Matulevich and Viollaz (2019) and Ferrant et al. (2014), which show that across all countries, women spend more time than men engaging in non-market activity.

Comparing Panels (a) and (b) also suggests that the gender gap in time use is driven by differences in non-market work rather than personal care activities. Indeed, using the OECD data, we find that the average daily time spent in personal care is 667 minutes for women and 656 minutes for men, across countries. In contrast, the average daily time spent on non-market (unpaid) work is 264 minutes for women and 131 minutes for men.[8] Further, the majority (around 75%) of time in personal care is spent sleeping, with little difference between genders in sleep times. Given this, our quantitative analysis will allow for both types of non-market activity – non-market work (home production) and personal care (leisure).

Figure 3 illustrates gender gaps in non-market time use, plotting the ratio of female to

[8]For example, in Norway these analogous averages are 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



Notes: The figure reports the ratio of female to male time spent in non-market work, computed using data from UNSD, OECD, and Bridgman et al. (2018).

male time spent in non-market work in each country against GDP per capita. Consistent with Figure 2, significant gender gaps in time use exist across countries. For example, women in Honduras spend around four times the amount of time on non-market work compared to men. This gap is even larger in Egypt and Taiwan, approaching a ten-fold difference. Further, a negative relationship between gender gaps in time use and the level of development exists. Gender gaps in time use shrink with development, but do not disappear – even in high-income economies, the gap is positive and averages around 60%.[9]

2.3 Cross-Country Gender Gaps in Entrepreneurship

Data Description To measure entrepreneurship by gender, we use aggregated data on occupation shares from the International Labor Organization (ILO). We supplement this aggregate data and compute analogous occupation shares using microdata from the International Integrated Public Use Surveys (IPUMS).[10]

Occupation shares reported in the ILO are either computed directly from an underlying

[9]Gender gaps in non-market work and personal care activities also exhibit a negative relationship with income per capita, although the gap is smaller. Figure A.1 in Appendix A reports gender gaps in time use in both non-market work and personal care activities. In Appendix B.2, we confirm that the relationship between development and gender gaps in time use is not driven by differences in the size of the agricultural sector or by differences in employment rates across countries.

[10]Details on the construction of the ILO and IPUMS datasets are outlined in ILO (2019) and Minnesota Population Center (2019).

survey or ILO modeled estimates. The ILO data reports the number of individuals by their status in employment, by gender and industry, according to the International Classification of Status in Employment (ICSE-93). This classification permits six possible employment statuses: employees, employers, own-account workers, members of producers' cooperatives, contributing family workers, and workers not classifiable by status. We define employees, employers, and non-employers to correspond to the first three ICSE-93 categories, respectively. We consider members of producers' cooperatives and contributing family workers as representing some mixture of the first three categories – perhaps being most closely related to non-employers. This is made clear in the ICSE-93 definitions, which classify 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.

Given the ambiguity involved in classifying members of producers' cooperatives and contributing family workers as either employees or entrepreneurs, we restrict attention to employment in non-agricultural sectors – sectors that feature a low share of either members of producers' cooperatives or contributing family workers. Indeed, the employment share of these two employment types for 90% of all countries is under 6% when excluding agricultural employment but over 15% when the agricultural employment sector is included. Having said this, including agricultural sector employment has little impact on our empirical findings. We discuss this further and provide additional results, including a consideration of alternative classifications of non-employers, in Appendix B.3. Our final sample from the ILO includes information from 111 countries with a minimum and maximum GDP per capita of around \$770 and \$83,000 (in 2017 USD at PPP), respectively.[11]

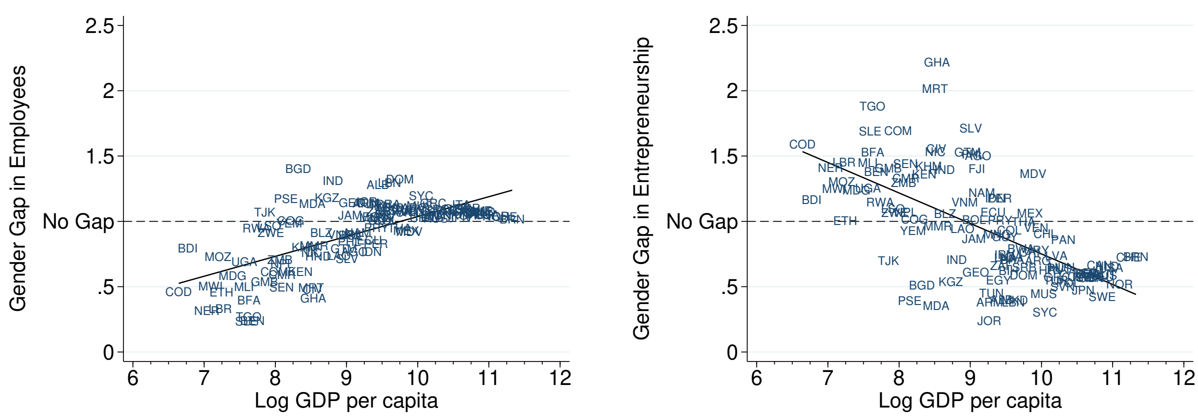
Gender Gaps in Entrepreneurship We begin by using data from the ILO to document how gender gaps among employees and entrepreneurs (either employers or non-employers) change with development. We define the gender gap in an occupation as the ratio of females among total employment employed in an occupation to the analogous male employment share. Specifically, the gender gap for an occupation o is defined as:

$$\text{Gender Gap}_o = \frac{\text{Female}_o/\text{Female Employment}}{\text{Male}_o/\text{Male Employment}}.$$

[11] Data from the US is constructed using microdata from the CPS, bringing the total number of countries for which we have occupation-share data to 112.

Figure 4 plots gender gaps for employee and entrepreneur (both non-employer and employer) shares across countries. Panel (a) shows that the gender gap for employees closes as economies develop – from an under-representation of female employees in poorer countries to a slight over-representation in richer countries. Panel (b) shows that the gender gap in entrepreneurship is negatively related and reverses with development. In poor countries, women are over-represented in entrepreneurship compared to men, while in rich countries they are under-represented. Taken as a whole, the figure suggests that as economies develop, women – even more so than men – shift away from entrepreneurship into employment.

Figure 4: Gender Gaps for Employees and Entrepreneurs



(a) Employees

(b) Entrepreneurs

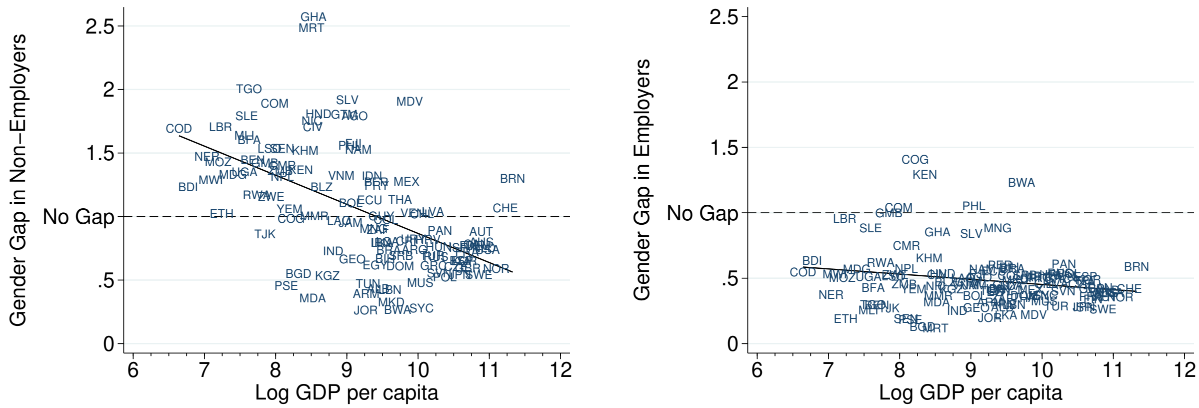
Notes: This figure plots the share of employed women who are employees or entrepreneurs, relative to the share of employed men, using data from the ILO.

We now disaggregate the gender gap for entrepreneurs by separately reporting the gender gap for non-employers and employers, in Figure 5. The gender gap for non-employers, shown in Panel (a), closely mirrors the gender gap in overall entrepreneurship – the slope coefficient is around -0.23 for both. On the other hand, the gender gap for employers (Panel b) features only a modest relationship with development. Most economies feature more male employers relative to female employers, and this gap changes only slightly with development. Comparing Panels (a) and (b) suggests that the relationship between gender gaps in entrepreneurship and development is driven almost exclusively by the gender gaps among non-employers.[12] Combined with the rankings of hours worked by occupation and gender gaps in time use,

[12]We confirm this by conducting a simple counterfactual exercise in Appendix B.3, which suggests that 75% of the cross-country relationship between development and gender gaps in entrepreneurship is accounted for by gender gaps in non-employer entrepreneurship.

the pattern of gender gaps among non-employers that we uncover is consistent with women selecting into non-employer entrepreneurship based on time use.[13]

Figure 5: Gender Gaps for Non-employers and Employers



(a) Non-employers (b) Employers

Notes: This figure plots the share of employed women who are non-employers or employer entrepreneurs, relative to the share of men, using data from the ILO.

In Appendix B.4, we use data from IPUMS International to confirm our findings from the ILO by conducting subgroup analysis of gender gaps. Specifically, we find that the negative (positive) relationship between development and gender gaps in entrepreneurship (employees) is stronger when focusing on subgroups that are likely to have tighter constraints on their time use (those with low education, who are married, or with have children). This provides further support for the idea that the relationship between development and gender gaps in entrepreneurship may be driven, at least in part, by gender gaps in time use.

3 Model

Environment We model a static non-agricultural economy populated by a unit continuum of agents who differ in their gender, indexed by $j \in \{f, m\}$. All agents feature the same labor productivity but are heterogeneous with respect to their productivity in entrepreneurship z. For both genders, z follows the distribution $\Phi(z)$. Each agent is endowed with a unit

[13]Figure A.2 in Appendix A reports the share of people who are female in a given occupation. We find a qualitatively similar relationship between development and the female share in employment and entrepreneurship.

of time and chooses how to allocate it across home production (h_n), market work (h), and leisure. Agents derive utility from leisure and a composite good C, which is a bundle of consumption goods produced at home (b) and perceived consumption of goods produced in the market (c), where c is purchased with income that depends on market occupation o and productivity z. We use 'perceived' to take into account particular preferences with respect to sources of income and the gender of employees, which we discuss below in more detail.

There are L_f women and $1-L_f$ men in the economy.[14] All agents are employed and choose between one of three occupations; employee/worker (W), non-employer (NE), or employer (E). We assume that the utility cost of working depends on the gender and chosen occupation of agents. This captures the idea that women and men in the same occupation may not derive the same level of utility from their work and that individuals may derive different utility from different occupations. We discuss these and other gender-specific variables below. Utility for an agent of gender j with productivity z who is employed in occupation o with chosen time allocation $\mathbf{h} = (h_n, h)$, is given by

$$\ln\left(C\left(z, o\right)\right) + f_j\left(\mathbf{h}, o\right),$$

where, following Parente et al. (2000), $C\left(z, o\right)$ is a CES consumption aggregate of home and market goods given by

$$C\left(z, o\right) = \left[\phi c\left(z, o\right)^{\rho} + (1-\phi) b^{\rho}\right]^{1/\rho}.$$

The value of leisure is captured by $f_j\left(\mathbf{h}, o\right)$ and is assumed to have the following functional form:

$$f_f\left(\mathbf{h}, o\right) = \nu_f \frac{(1-\zeta_f^o h - h_n)^{1-\gamma}}{1-\gamma}, \qquad f_m\left(\mathbf{h}, o\right) = \nu_m \frac{(1-h-h_n)^{1-\gamma}}{1-\gamma}.$$

This specification builds on Erosa et al. (2016) but features two distinctions. First, we allow men and women to differ in their value of leisure, as captured by ν_j. Second, we introduce an occupation-specific parameter, ζ_f^o, for women, which acts to scale the disutility from market work in occupation o. For instance, ζ_f^o may capture social norms or stigma associated with female market work compared to male market work. ζ_f^o can also capture differences in occupational preferences between women and men that are assumed constant across countries. We elaborate on the interpretation of this parameter below and will allow

[14] We take gender composition of the population as given. To remain consistent with our empirical analysis, which focuses on those engaged in the labor market, we set the gender composition in the model economy to match the observed gender composition of the labor force. As we discuss below, the gender composition in the model economy has little impact on our quantitative analysis.

it to vary in our quantitative analysis to capture cross-country differences in social norms associated with female market work.

Production Home (non-market) production is linear in non-market hours h_n and aggregate home productivity B, described as

$$b = Bh_n.$$

All income is spent on consumption of the market good, $c\left(z,o\right)$, with income coming from employment in one of three occupations, $o \in \{\mathrm{W}, \mathrm{NE}, \mathrm{E}\}$. As employees (W), agents provide their market hours h and earn an hourly wage w, so total earnings for a male employee are wh. To capture the gender wage gap in employment (Goldin, 2014; ILO, 2018), we assume female employees face an effective tax rate on wage earnings τ_f^{W}. This 'tax' exactly compensates employers who dislike female workers, leaving them indifferent between female and male workers. Earnings for female workers are therefore $\left(1-\tau_f^{\mathrm{W}}\right)wh$, while employers perceive their corresponding costs to be wh.

Non-employer entrepreneurs (NE) operate a decreasing returns-to-scale production technology that depends on their productivity z and own market hours h. All non-employers have access to the same technology, but female non-employers face an effective tax rate on output τ_f^{NE}. This gender-specific distortion reduces the returns to entrepreneurship for female non-employers relative to those of males. τ_f^{NE} could capture phenomena like consumer discrimination, which lowers demand for goods from female entrepreneurs, or less access to financial markets. Perceived market consumption for non-employers is described by

$$c_f\left(z,\mathrm{NE}\right) = \left(1-\tau_f^{\mathrm{NE}}\right)A_{\mathrm{NE}}zh^{\lambda}, \quad c_m\left(z,\mathrm{NE}\right) = A_{\mathrm{NE}}zh^{\lambda},$$

where A_{NE} is the aggregate productivity of the non-employer sector and λ governs the degree of decreasing returns to hours. Including the possibility of decreasing returns to hours for non-employers allows the model to match the ranking on hours worked by occupation. In particular, if the return to market hours is relatively concave for non-employers compared to workers or employers, the optimal level of hours worked for non-employers will be lower, which is consistent with our findings. A similar specification has been used by Erosa et al. (2022) to generate empirically consistent rankings of hours worked between occupations (of workers). Intuitively, the declining marginal returns to own hours for non-employers could be thought of as an optimal outcome of allocating hours into projects with different productivity.[15]

Employer entrepreneurs (E) operate a constant returns-to-scale production technology that uses their own productivity z, own hours h, and outside labor hours l to produce output y:

$$y(z) = A_{\mathrm{E}} z h^{\alpha} l^{1-\alpha},$$

where A_{E} is the aggregate productivity of the employer sector. As with non-employers, female employers face an effective tax rate on output τ_f^{E}. This 'tax' captures similar forces reducing the returns to entrepreneurship. We allow for consumer discrimination, financial constraints, etc. to differentially affect the returns to female non-employer and employer entrepreneurship, so $\tau_f^{\mathrm{NE}} \neq \tau_f^{\mathrm{E}}$. Given own market hours h, employers demand labor l to optimize their perceived profits by solving the following:

$$\max_{l} \left(1 - \tau_f^{\mathrm{E}}\right) A_{\mathrm{E}} z h^{\alpha} l^{1-\alpha} - wl \equiv \left(\frac{\alpha}{1-\alpha}\right) \left[\frac{(1-\alpha)\left(1-\tau_f^{\mathrm{E}}\right) A_{\mathrm{E}} z}{w^{1-\alpha}}\right]^{1/\alpha} h,$$

implying the following optimal labor demand and optimal output:

$$l(z) = \left[\frac{(1-\alpha)\left(1-\tau_f^{\mathrm{E}}\right) A_{\mathrm{E}} z}{w}\right]^{1/\alpha} h,$$

$$y(z) = (A_{\mathrm{E}} z)^{1/\alpha} \left[\frac{(1-\alpha)\left(1-\tau_f^{\mathrm{E}}\right)}{w}\right]^{\frac{1-\alpha}{\alpha}} h,$$

where τ_f^{E} should be understood to apply only to female employers. Notice the returns to employer entrepreneurship feature complementarity between hours worked h and productivity z. As a result of this complementarity, the ability to work longer hours is especially beneficial to higher productivity employers. Limiting the market time of agents is therefore particularly costly for higher productivity (would-be) employers. Finally, note that the returns to being a worker or an employer are linear in hours while the returns to being a non-employer entrepreneur are potentially concave, governed by the parameter λ.

Perceived consumption of the market good for an agent with productivity z in occupation o, conditional on market hours worked h, is then given by

[15] For example, in an alternative setup, Eden (2017) and Cook et al. (2021) argue that optimal allocation of production factors requires the most productive projects to be carried out first, with increasingly less productive projects pursued using additional units of inputs.

$$c(z,o)=\begin{cases}\left(1-\tau_f^{\mathrm{W}}\right)wh & \text{if } o=\mathrm{W}\\ \left(1-\tau_f^{\mathrm{NE}}\right)A_{\mathrm{NE}}zh^{\lambda} & \text{if } o=\mathrm{NE}\\ \left(\frac{\alpha}{1-\alpha}\right)\left[\frac{(1-\alpha)\left(1-\tau_f^{\mathrm{E}}\right)A_{\mathrm{E}}z}{w^{1-\alpha}}\right]^{1/\alpha}h & \text{if } o=\mathrm{E}\end{cases}, \tag{2}$$

where each τ_f^o applies only to women.

Occupational Choice Given the nature of production and consumption, agents choose their occupation in the market o and allocate their hours $\mathbf{h}=(h_n,h)$ between leisure, non-market (home) work, and market work. Specifically, an agent of gender j with productivity z solves the following maximization problem:

$$V_j(z)=\max_{o\in\{\mathrm{W},\mathrm{NE},\mathrm{E}\}}\{U_j(z,o)\}, \tag{3}$$

where $U_j(o,z)$ is the utility of an agent with gender j and productivity z is conditional on choosing occupation o. This utility is the solution to the following problem, which involves choosing a time allocation $\mathbf{h}=(h_n,h)$:

$$U_j(z,o)=\max_{\mathbf{h}}\ln\left(\left[\phi c_j(z,o)^{\rho}+(1-\phi)b^{\rho}\right]^{1/\rho}\right)+\nu_j\frac{\left(1-\zeta_j^o h-h_n\right)^{1-\gamma}}{1-\gamma}, \tag{4}$$

where $c_j(z,o)$ is given by (2) and $b=Bh_n$.[16]

Equilibrium The equilibrium of the economy consists of a market clearing wage w, aggregate output Y, value functions $V_j(z)$ and $U_j(z,o)$ for each gender j and occupation o, and policy functions $\{c_j(z,o),\ b_j(z,o),\ \mathbf{h}_j(z,o),\ o_j(z)\}$, with occupational choice $o_j(z)\in\{\mathrm{W},\mathrm{NE},\mathrm{E}\}$, such that the following conditions hold:

(i) Given the wage w, value functions and policy functions solve the individual's optimization problem (3);

[16] In the quantitative exercise, we introduce a taste shock for these three occupations, which is represented by an i.i.d. draw from a type-I extreme-value probability distribution (Gumbel distribution). The introduction of such a taste shock aims at convexifying the occupation choice by introducing randomness and improving the convergence property of the model. We provide further details in Appendix D.1.

(ii) The labor market clears:

$$\Sigma_j L_j \int h_j \mathbf{I}_{o_j(z)=\mathrm{W}} d\Phi(z) = \Sigma_j L_j \int l_j(z) \mathbf{I}_{o_j(z)=\mathrm{E}} d\Phi(z);$$

(iii) The goods market clears:

$$Y = \Sigma_j L_j \left(\int A_{\mathrm{NE}} z h_j^{\lambda}(z) \mathbf{I}_{o_j(z)=\mathrm{NE}} d\Phi(z) + \int y_j(z) \mathbf{I}_{o_j(z)=\mathrm{E}} d\Phi(z) \right)$$

$$= \Sigma_{o\in\{\mathrm{W,NE,E}\}} \left(L_f \int \frac{c_f(z,o)}{(1-\tau_f^o)} \mathbf{I}_{o_f(z)=\mathrm{o}} d\Phi(z) + L_m \int c_m(z,o) \mathbf{I}_{o_m(z)=\mathrm{o}} d\Phi(z) \right).$$

Before discussing our quantitative analysis, a few remarks on the model assumptions are in order. In the model, we introduce two forces that result in women choosing to spend more time in home production. First, we use ζ_f^o to allow for women's preferences to differ from men's with respect to time spent working in each occupation. $\zeta_f^o \neq 1$ directly impacts hours worked in any particular occupation (relative to non-market hours), as well as the choice of occupation. This is meant to capture differences in occupational preferences between women and men that could exist both because of inherent differences and because of the impact of societal attitudes towards women in the workforce, to the extent these attitudes are internalized by women. More generally, women may not derive the same utility from working as men (Kaplan and Schulhofer-Wohl, 2018) and may derive different utility from different occupations (Hurst and Pugsley, 2011). Cross-country differences in the parameter governing the disutility of market work for women captures a range of documented phenomena. This includes differences in perceptions of whether and how women and men can work together (Miller et al., 2022), constraints on female mobility outside the home (Aguilar et al., 2021), and prevailing beliefs regarding the appropriateness of women in the workplace (Arielle et al., 2018). Both Dinkelman and Ngai (2022) and Jayachandran (2021) provide thorough discussions on the societal norms that hinder women's participation in market work in developing economies.

Second, we model distortionary 'taxes' affecting the perceived or actual returns to market work for women, relative to men. Following Hsieh et al. (2019) and others, τ_f^{W} captures a preference for male employees by employers. τ_f^{W} exactly compensates employers such that they are indifferent between female and male employees in equilibrium. As such, employers perceive the wage to be the same for all employees. τ_f^{NE} and τ_f^{E} are indirectly driven by societal and cultural attitudes towards female entrepreneurs. Consumer discrimination towards female entrepreneurs can reduce demand for a woman's output, lowering its price relative to that of other output (Beede and Rubinovitz, 2015; Kricheli-Katz and Regev, 2016; Weikle, 2021). These 'taxes' also capture the extent to which female entrepreneurs face higher input costs for a given level of output. For example, female entrepreneurs may face higher financing costs and less access to finance (Coleman and Robb, 2009; Alesina et al., 2013; Morazzoni and Sy, 2022). And to the extent employees may have preferences with respect to the gender of their boss, female entrepreneurs may need to compensate with higher wages or more at-work amenities (Riffkin, 2014).

4 Calibration to the US

The remaining sections of this paper are dedicated to quantitatively analyzing the determinants of gender gaps in entrepreneurship across countries, focusing on the role of gender gaps in time use. To do this, we calibrate the model's parameters so that the model exactly matches salient features of the data across countries, including gender gaps in occupations and time use. By comparing the outcomes of this benchmark calibration to counterfactual parameterizations that remove distortions or gender gaps in time use, we can then quantify the role of such factors in generating gender gaps in entrepreneurship across countries. This section details the calibration of parameters to match US data.

Our calibration proceeds in two steps. First, we calibrate all the parameters of the model to match moments of the US economy.[17] Next, keeping fundamental utility and production parameters as being fixed across countries (and equal to those calibrated to the US), we (re)calibrate a subset of parameters to exactly match averaged data targets across the range of development levels. This cross-country calibration, which we describe in the next section, results in a unique parameterization for each level of development (and the US) with which the model exactly matches observed levels of output per worker, gender gaps in time use, and gender-specific occupation shares. In Section 6, we conduct several quantitative exercises that utilize these calibrated parameters.

[17] Our choice of the US economy as a benchmark is motivated by data availability, particularly the availability of detailed information on time use, which is not readily available across all countries. Further, the US is a relatively high-income economy and relatively undistorted, making it a natural candidate to serve as a benchmark for lower-income economies.

4.1 Calibration Strategy and Model Fit

We choose a subset of parameter values following the literature (or as a normalization). These parameters are reported in Panel A of Table 1. The parameter ρ, which governs the elasticity of substitution between home and market goods, is fixed at 0.60, following Parente et al. (2000).[18] The parameter γ, which governs the curvature in the return to leisure, is set to 3, following Erosa et al. (2016). Productivity in home production, B, is normalized, without loss of generality, to be 1. We set the value of ϕ, the weight of market goods in the consumption bundle, to 0.48, following Gomme and Rupert (2007).

We assume that men do not face any occupation-specific distortions. Thus, the distortions experienced by women, $\left\{\tau_f^o\right\}_{o\in(\mathrm{W,NE,E})}$, should be interpreted as distortions relative to men in the same occupation. We set the distortion parameter faced by female workers, τ_f^{W}, to be 0.19 – the level of the gender wage gap in the US as reported by the ILO in 2015.[19] Related to this, we assume that males do not feature any (additional) disutility from market work. The parameters $\left\{\zeta_f^o\right\}_{o\in(\mathrm{W,NE,E})}$ represent the disutility experienced by women relative to men in each occupation that may arise from differences in preferences or social norms and stigma associated with market work by women.

All other parameters are jointly calibrated by solving the model to match salient moments of the US economy. Although changes in a single parameter will affect all model-implied moments, for each parameter, we assign targets that are most likely to be determined by that parameter. The calibrated parameter values, along with the model fit to the data, are reported in Panel B of Table 1, and we discuss each of the 13 jointly calibrated parameters below.

We assume that the exogenous productivity distribution $\Phi(z)$ is a Pareto distribution with a lower bound of 1 and tail parameter η, which we calibrate to match the employment share of the top 5% of employer establishments in the US.

The aggregate productivity parameter in employer production, denoted as A_{E}, holds

[18] Fang and Zhu (2017) estimate the elasticity of substitution between home and market goods using a combination of time use, labor force, and consumption expenditure surveys and estimate an elasticity parameter ρ of 0.56.

[19] For our measure of the gender wage gap, we use the ILO's Indicator 8.5.1 from the UN Sustainable Development Goals database, which reports the average hourly earnings for female and male employees. $1-\tau_f^{\mathrm{W}}$ maps to the log difference in average hourly earnings by gender. We use this measure of the gender wage gap since it is available for a large group of countries and allows us to use a consistent measure of the wage gap when conducting our cross-country analysis.

Table 1: Parameters

Panel A: Fixed

Parameter	Value	Basis
ρ	0.60	Parente et al. (2000)
γ	3	Erosa et al. (2016)
B	1	Normalization
$\{\tau_m^o\}_{o\in(\mathrm{W,NE,E})}$	0	Normalization
$\{\zeta_m^o\}_{o\in(\mathrm{W,NE,E})}$	1	Normalization
τ_f^{W}	0.19	Gender Wage Gap
ϕ	0.48	Gomme and Rupert (2007)

Panel B: Jointly Calibrated

Parameter	Value	Basis	Model	Data
η	3.50	Top 5% Firm Employment Share	0.48	0.51
α	0.25	Share of Employers	0.025	0.025
A_{E}	1.69	Avg. Home Production Hours	0.084	0.084
A_{NE}	1.01	Share of Non-employers	0.081	0.081
λ	0.84	Avg. Market Hours of Non-Employers	0.81	0.81
(ν_m, ν_f)	(1.05,1.15)	Avg. Non-leisure Hours, by Gender	(0.31,0.30)	(0.31,0.30)
$\left(\tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}\right)$	(0.18,0.20)	Occupation Shares, Female	(0.067,0.013)	(0.068,0.013)
$\left(\zeta_f^{\mathrm{W}}, \zeta_f^{\mathrm{NE}}, \zeta_f^{\mathrm{E}}\right)$	(0.98,1.18,1.23)	Avg. Female Market Hours	(0.91,0.68,0.97)	(0.91,0.68,0.97)

Notes: Panel A reports parameter values that are normalized or chosen following the literature. Panel B reports parameters that are jointly calibrated to match specific features of the data. The last two columns in Panel B compare data targets to model-implied values. Data targets for overall and female occupation shares are from the 2014–2019 Current Population Survey (CPS). All measures of average market hours are relative to male employees. Home production (non-leisure) hours are from the 2014–2019 American Time Use Survey (ATUS). The top 5% employment share of (employer) establishments is from the 2015 Business Dynamics Statistics (BDS).

significant influence over the time allocation between home production and market work. We set A_{E} to match the average home production hours, resulting in a calibrated value of 1.69. Conversely, the productivity in non-employer production, or A_{NE}, is chosen to match the share of non-employers in the economy, with its calibrated value found to be 1.01. This calibration suggests that otherwise identical employers are more productive than non-employers.

The parameter α in the employer's production function determines the distribution of revenue between employers and workers. We calibrated $\alpha = 0.25$ to match the share of employer entrepreneurs in the economy. This value is within the range of values used in the macroeconomic development literature featuring employer entrepreneurs. For instance, Restuccia and Rogerson (2008) set this parameter to be 0.15 while Buera and Fattal Jaef (2018) set it to 0.29, and Hopenhayn and Rogerson (1993) to 0.36.

The parameter λ governs the concavity in the return to own hours for non-employers and, thus, directly influences their hours worked. As such, we choose λ to match the average market hours of (all) non-employers, which implies $\lambda = 0.84 < 1$ so that the returns to hours are strictly concave for non-employers while linear for employees and employers.

The gender-specific scalar parameters (ν_m, ν_f) shift the overall utility of leisure and are chosen to match the average (gender-specific) non-leisure hours (i.e., time spent in market and home production). Our joint calibration implies that the return to leisure is slightly higher for women than for men ($\nu_f > \nu_m$).

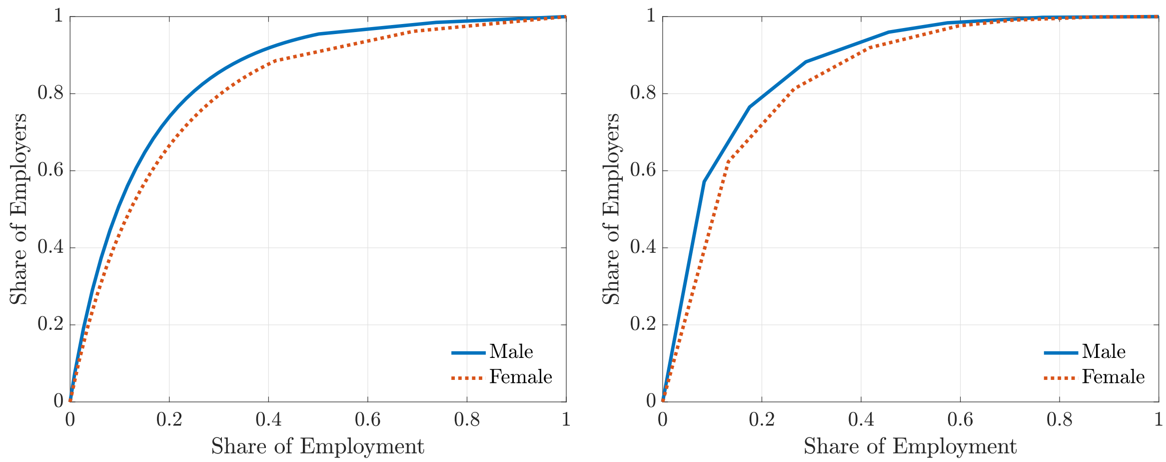
The occupation-specific distortions faced by female entrepreneurs $\left(\tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}\right)$ are chosen to exactly match female occupation shares across the three market occupations: workers, non-employers and employers. The calibrated values imply a relatively low level of distortion for female non-employers with $\tau_f^{\mathrm{NE}} = 0.18$, with slightly higher levels for employers with $\tau_f^{\mathrm{E}} = 0.20$.

The parameter determining the disutility of market work for females $\left(\zeta_f^{\mathrm{W}}, \zeta_f^{\mathrm{NE}}, \zeta_f^{\mathrm{E}}\right)$ governs female market hours in each occupation. Accordingly, these parameters are calibrated to match female market hours worked (relative to male workers' hours worked) in each occupation. In order to match the data moments, the calibration finds $\left(\zeta_f^{\mathrm{W}}, \zeta_f^{\mathrm{NE}}, \zeta_f^{\mathrm{E}}\right) = (0.98, 1.18, 1.23)$. Recall that the analogous values for males are normalized to one, so the calibration suggests that female workers face a slightly smaller disutility from working (0.98 vs. 1). In contrast, female non-employers and employers experience a higher utility cost of working compared to their male counterparts.

The last two columns of Table 1 show that the calibrated model performs well in matching targeted data moments. We also compare, in Figure 6, the model's fit to the observed (untargeted) *gender-specific* employer firm size distribution. The firms of male employers tend to be larger than those of female employers, with the firm size distribution for males first-order stochastically dominating that of females. For instance, in the data, the bottom 80% of firms account for around 21% of total employment in male-owned employer firms, while the analogous measure for female-owned firms is around 26%. The model matches this difference in distributions across genders relatively well – the bottom 80% of male employers in the model account for 24% of employment (in firms operated by men), and the bottom 80% of female employers account for around 30% of employment.

Taken together, outcomes in our benchmark parametrization closely resemble salient targeted and untargeted moments of the data.

Figure 6: Firm Size Distribution, Model and Data



(a) Model (b) Data

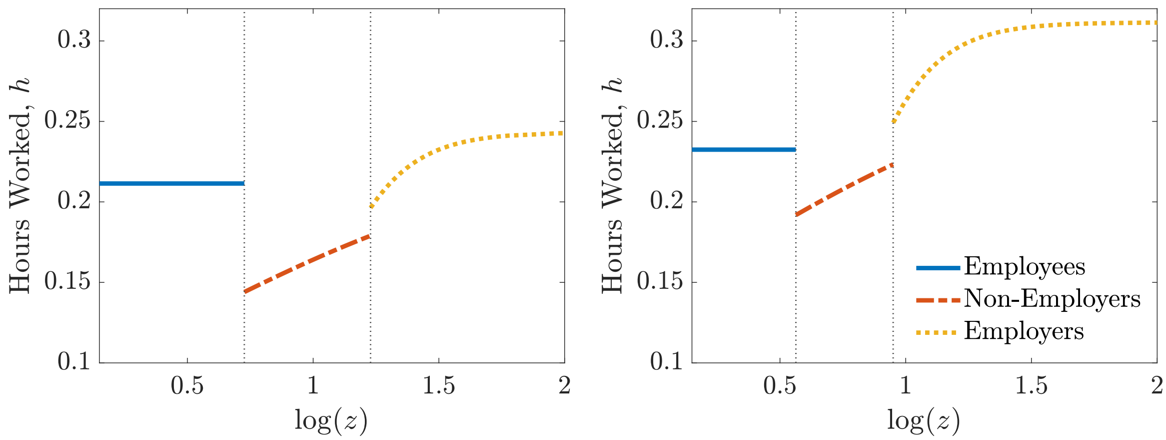
Notes: Panel (a) plots the cumulative distribution of model-implied firm size for employer firms operated by women (dashed line) and men (solid line). Panel (b) plots analogous measures from the data. Data is from the 2012 Survey of Business Ownership (SBO), which reports the share of employers across size categories by the gender of business owner.

4.2 Model Implications

Before describing the cross-country calibration, we will briefly describe the equilibrium implications of the model calibrated to the US economy. We focus on the mechanisms affecting selection into occupations and choices of market hours.

Figure 7 summarizes the occupational choices of women and men in the model and their market hours worked. It reports market hours h and also highlights the occupations chosen by agents for a given level of productivity. For either gender, the most productive agents (high z) pursue employer entrepreneurship, while the least productive (low z) pursue wage employment. Those with intermediate levels of productivity choose to be non-employers. Compared with men (Panel b), fewer women (Panel a) pursue employer entrepreneurship, and the average productivity of those who do is higher than their male counterparts. The difference across genders in the employer entrepreneurship rate is because female employers face significant distortions affecting returns to market activity, as well as social norms biased against their work as entrepreneurs (Table 1). Social norms, in particular, make entrepreneurship more costly for women (relative to working as employees). Those who choose to pursue entrepreneurship in spite of these higher relative costs are therefore highly productive. This selection mechanism is akin to that highlighted by Hsieh et al. (2019), who examine barriers faced by female employees.

Figure 7: Occupation Choice and Market Hours in Equilibrium, by Gender



(a) Female (b) Male

Notes: This figure reports market hours h for women and men by productivity z, while also indicating their occupations in equilibrium.

For both genders, there is a clear ranking of occupations based on hours worked. Employer entrepreneurs tend to work the longest hours, while non-employers work the least. Employee hours lie somewhere in between the two entrepreneurial occupations. This ranking of hours worked across occupations in the model is consistent with what we document in Section 2.

In the model, two forces determine the ranking of hours among the three occupations. First, non-employer entrepreneurs face a more concave return to own hours than workers and employer entrepreneurs. In equilibrium, time-constrained individuals are more likely to become non-employers and work shorter hours than those in the other two occupations, leading to shorter average hours for non-employers. Second, for entrepreneurs, hours worked increase with their productivity, consistent with empirical findings in the literature.[20] The positive relationship between hours and productivity is generated by the complementarity between entrepreneurial productivity z and own hours h in their production functions, which incentivizes high-productivity entrepreneurs to allocate more time to market production. Therefore, employers whose productivity falls in the right tail of the distribution are those working the longest hours among all individuals. Together, these two forces generate the ranking of average working hours across occupations.

[20]The positive relationship between employer hours and employer productivity is consistent with Wellschmied and Yurdagul (2021), who show that more productive employers (as proxied by number of employees) work longer hours.

5 Cross-Country Calibration

5.1 Calibration Strategy

Starting from the calibration to the US data, we jointly recalibrate a subset of parameters to exactly match data across countries while keeping all others fixed at their US values. Specifically, we assume that three sets of parameters differ across the development spectrum. These are i) aggregate parameters $(A_{\mathrm{E}}, A_{\mathrm{NE}}, B, \alpha)$; ii) female distortions in market occupations $\left(\tau_f^{\mathrm{W}}, \tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}\right)$; and iii) the relative disutility of market work for females $\left(\zeta_f^{\mathrm{NE}}, \zeta_f^{\mathrm{W}}, \zeta_f^{\mathrm{E}}\right)$. We use aggregate parameters to match cross-country differences in aggregate (non-gender-specific) outcomes, while differences in distortions and relative disutilities generate the cross-country differences most relevant for our analysis – differences in time use and occupation shares between women and men.

To replicate cross-country differences in non-agricultural output per worker, we adjust the aggregate productivity in the employer sector, A_{E}. This parameter directly influences overall labor demand and thus wages and output per worker in the model economy. The share of non-employers tends to decrease with development (see, for example, Gollin 2008 and Poschke 2019), so we use the aggregate productivity in the non-employer sector, A_{NE}, to match the non-employer share. We adjust productivity B in home production to match (gender-neutral) differences in non-market work across countries. Specifically, we target time in market relative to non-market work among *men* when adjusting B. α directly affects the fractions of both women and men choosing to be employers, given relative productivities. We, therefore, choose α across countries to match the employer share of men. Broadly, we treat cross-country differences in α and productivities as capturing differences in the overall landscape of economic activity, creating a benchmark from which to analyze the impact of gender-specific differences.

As with the US calibration, we target the share of female non-employers and employers to pin down τ_f^{NE} and τ_f^{E}, respectively, while feeding in the observed gender wage gap for τ_f^{W}. Conditional on aggregate parameters, distortions are chosen to exactly match the female occupation shares and gender gaps in occupations.

Finally, we adjust the relative disutility of market work for females $\left(\zeta_f^{\mathrm{W}}, \zeta_f^{\mathrm{NE}}, \zeta_f^{\mathrm{E}}\right)$, which captures cross-country differences in gender-specific social norms. Since only aggregated information, rather than occupation-specific information on market (and non-market) hours, is readily available by gender across countries, we assume that $\{\zeta_f^o\}$ for all occupations o differ from their corresponding US levels by a common shifter $\bar{\zeta}$. In particular, the disutility faced by women from working in occupation o in country c is given by $\zeta_f^{o,c} = \bar{\zeta} \cdot \zeta_f^{o,\mathrm{US}}$. We calibrate $\bar{\zeta}$ to match gender gaps in time use in non-market work, and this parameter stands in for differences in social norms or stigma relating to female market work across countries. Note an important identifying assumption here: cross-country differences in relative preferences for market work between women and men are due to differences in social norms.

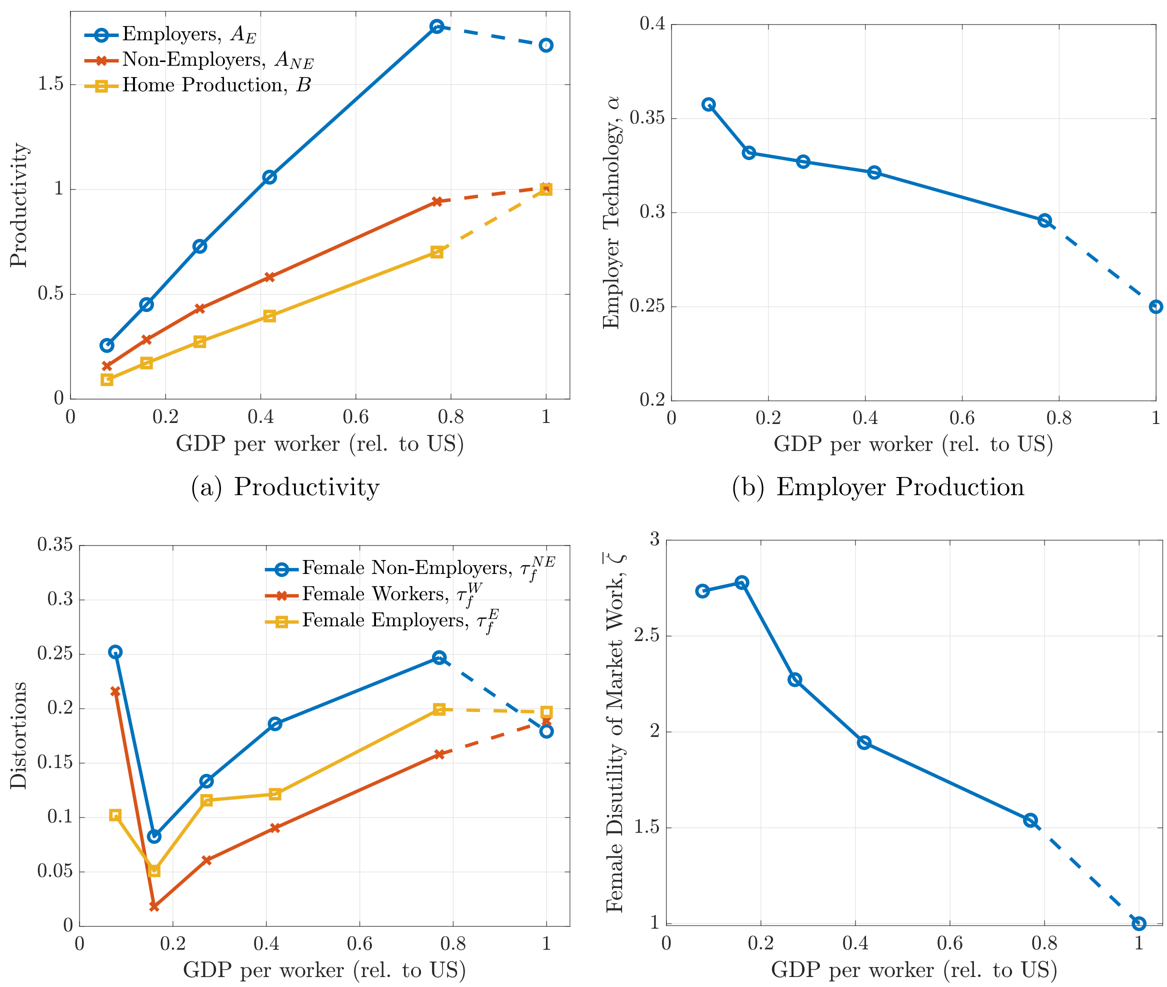
In addition to these parameters, we also account for differences in female labor-force participation rates across countries by exogenously adjusting the share of females in the model to exactly match the share of females in the labor force.

To operationalize the cross-country calibration, we begin by grouping all countries for which we have information on occupation shares into quintiles based of total GDP per worker. Next, we take averages of data moments for all countries within each group and use these averages as targets for the cross-country calibration. This results in five sets of data moments for five country groups that span the range of the development spectrum. Details on the cross-country calibration, including the data moments, are reported in Appendix C.1.

5.2 Calibrated Country-Specific Parameters

Figure 8 reports the results of the cross-country calibration. Focusing first on aggregate factors, Panels (a) and (b) illustrate how these factors must differ across countries to match differences in aggregate occupation shares, time spent in market versus non-market activity, and output per worker. Panel (a) shows that all three productivity terms increase monotonically with development. Consistent with Gollin (2008), relative productivity in the non-employer sector $\frac{A_{\mathrm{NE}}}{A_{\mathrm{E}}}$ tends to decline with development, resulting in a higher share of non-employers in poorer economies. Panel (b) shows how α decreases monotonically with development. While higher productivity drives up wages and employer profits relative to non-employer earnings, a lower α is required in richer countries to further increase the share of employers in order to match the data. A lower α implies a higher labor-elasticity of employer output, effectively raising the return to productivity z for employers, relative to non-employers. As an aggregate (non-gender-specific) factor, we interpret cross-country differences in α as capturing gender-neutral differences across economies in characteristics like levels of financial development or the ease of operating an employer firm relative to a non-employer business.[21]

Figure 8: Cross-Country Parameterization



(a) Productivity (b) Employer Production

(c) Distortions (d) Disutility of Market Work

Notes: This figure reports parameter values resulting from the cross-country calibration for five country quintiles as well as the US. Panel (a) reports measures of productivity, Panel (b) reports the parameter α, Panel (c) reports gender-specific distortions, and Panel (d) reports the disutility of market work for females, $\bar{\zeta}$.

Panel (c) reports the calibrated levels of gender-specific distortions across countries. The distortions faced by female non-employers and female workers evolve similarly to each other across development levels. Both tend to be high for countries in the lowest income quintile and low for the second quintile while monotonically increasing with further development. By design, τ_f^{W} is equal to the observed gender wage gap. Its similarity with τ_f^{NE} suggests that many of the same factors generating the gender wage gap also impact female non-employers.

[21] In Appendix C.2 we show that these inferred differences in α generate cross-country differences in labor's share of aggregate income that closely resemble those reported in Gollin (2002).

The distortion faced by female employers (relative to their male counterparts), τ_f^{E}, tends to increase with development. Note that a higher level of τ_f^{E} in developed economies does not imply that female employers in developed economies face greater distortions compared to female employers in developing economies. Rather, it reflects the fact that female employers face more pronounced distortions relative to male employers *within* a country. To compare female employers across countries, we must consider the combination of the gender-specific distortion, τ_f^{E}, and gender-neutral aggregate productivity A_{E}. For instance, aggregate productivity A_{E} might capture the economy-wide (gender-neutral) extent of financial frictions while the gender-specific τ_f^{E} captures gender-specific financial frictions.

Finally, Panel (d) reports the calibrated values of $\bar{\zeta}$, which captures the relative disutility of market work for females. Our calibration implies that females in poorer economies face significant disutility to employment in the market compared to men and to women in richer economies. Indeed, $\bar{\zeta}$ almost doubles between the highest and lowest income quartiles (a 2.7-fold increase relative to the US level). This decreasing relationship is consistent with evidence of cross-country differences in social norms and stigma faced by females engaged in market work (for example, Jayachandran 2021).

Together with the US calibration, these cross-country parameters comprise our benchmark calibration, which will be utilized in the quantitative analysis below.

5.3 Identification

To better understand identification in our cross-country calibration above, we show how equilibrium outcomes are affected when we change each cross-country parameter in isolation relative to its US level, keeping all other parameters at their US levels. Specifically, we increase, in turn, each of $\left(A_{\mathrm{E}}, A_{\mathrm{NE}}, B, \alpha, \tau_f^{\mathrm{W}}, \tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}, \bar{\zeta}\right)$ by 5% and report the corresponding percentage change in output, wages, occupation shares, and time allocation.

Increases in aggregate factors $(A_{\mathrm{E}}, A_{\mathrm{NE}}, B, \alpha)$ generally result in significant changes to all outcomes. Note that these factors can generate quantitatively different impacts by gender because of their interaction with gender-specific differences in distortions and social norms present in the US economy. Unlike other aggregate factors, home-production productivity B has little impact on occupational choice or aggregate output. Instead, it serves to increase the time spent in non-market work. As highlighted in Fang and Zhu (2017), the relative productivity in market and home production are a key determinant in the allocation of time

Table 2: Percentage Change in Outcomes in Response to Parameter Changes

	Aggregate Factors				Distortions			Social Norms
	A_{E}	A_{NE}	B	α	τ_f^{W}	τ_f^{NE}	τ_f^{E}	$\overline{\zeta}$
GDP per Worker	6.16	0.25	-1.51	-6.71	-0.18	0.00	-0.20	-2.68
Wage	4.26	0.16	0.33	-5.40	0.07	-0.02	-0.17	0.39
Share of Employees								
Women	1.32	-1.61	-0.02	-2.03	-0.38	0.30	-0.05	-0.24
Men	2.09	-2.60	0.01	-3.30	0.04	-0.01	-0.10	0.23
All	1.72	-2.12	-0.01	-2.69	-0.16	0.14	-0.08	0.00
Share of Non-employers								
Women	-22.15	19.52	0.28	21.34	**4.95**	**-4.20**	0.76	3.16
Men	**-24.43**	**25.57**	1.57	**25.19**	-0.13	0.05	0.40	-0.54
All	-23.53	23.24	1.07	23.70	1.89	-1.60	0.54	0.93
Share of Employers								
Women	9.93	-0.30	-0.06	15.62	-0.01	0.13	-0.21	-0.08
Men	4.81	-14.38	-4.50	4.92	-0.69	0.21	1.38	-4.41
All	6.12	-10.66	-3.36	7.72	-0.52	0.19	0.98	-3.30
Avg. Market Hours								
Women	-0.56	-0.02	-0.61	-1.26	-0.02	-0.01	-0.44	-5.51
Men	0.22	1.47	-0.12	0.20	0.05	-0.01	-0.08	0.33
All	-0.18	0.48	-0.42	-0.61	0.00	-0.01	-0.09	-1.09
Avg. Non-market Hours								
Women	7.07	0.23	**7.71**	15.23	0.26	0.13	**5.65**	**7.92**
Men	-2.99	-22.11	1.61	-2.70	-0.63	0.19	1.11	-4.52
All	-0.33	-15.53	3.19	2.38	-0.41	0.17	2.25	-1.21

Notes: The table reports the percentage change of each outcome in response to a 5% increase in each parameter, starting from calibrated US levels. The largest value in each column is boldfaced.

between market and non-market work. And again, the presence of gender-specific differences in distortions and social norms results in a greater impact from changes in B on women. For example, a 5% increase in B causes women to increase average non-market hours by 7.7%, while the corresponding male increase is only 1.6%.

Focusing next on distortions, increases in $\left(\tau_f^{\mathrm{W}}, \tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}\right)$ have a relatively modest impact on time allocation, primarily affecting the occupation shares of men and women. For instance, an increase in τ_f^{NE} lowers the female non-employer share while slightly increasing the female employer share and each of the male entrepreneur shares. At the same time, a higher τ_f^{NE} slightly reduces market hours for men and women. A larger wage gap, τ_f^{W}, significantly increases the share of women choosing to be non-employers rather than workers, while slightly reducing female market hours. Increasing the distortion on female employers encourages both female workers and employers to shift into non-employer entrepreneurship, while increasing non-market hours significantly for women and moderately for men.

More restrictive social norms around female market work, represented by an increase in $\overline{\zeta}$, have the greatest impact on the time allocation of both men and women, significantly reducing non-market hours for men while significantly increasing non-market hours for women. Occupation shares are also affected, with higher $\overline{\zeta}$ pushing female workers and employers into non-employer entrepreneurship and encouraging male entrepreneurs to become workers.

Overall, Table 2 shows that distortions faced by female entrepreneurs have the potential to cause gender gaps in occupation shares by pushing female and male shares in opposite directions. At the same time, these distortions result in less time spent in market work for everyone. Social norms, in contrast, can significantly widen the gap in market hours between women and men. This all suggests that variation in the level of distortions alone is not enough to generate the cross-country differences in time-use gender gaps documented in Section 2 and that variation in social norms are necessary to account for these differences. In Appendix C.3 we confirm this by performing an alternative cross-country calibration by fixing $\overline{\zeta} = 1$ as in the US, ignoring separate occupation share targets for female non-employers and employers and adding a combined target of female entrepreneur share. We then choose values for the same parameters as in our benchmark calibration, minus $\overline{\zeta}$, to minimize the distance between the remaining data targets and model moments. While the rest of our data targets are matched almost exactly, we show our model without cross-country differences in social norms is entirely unable to generate the documented differences in gender gaps in time use.

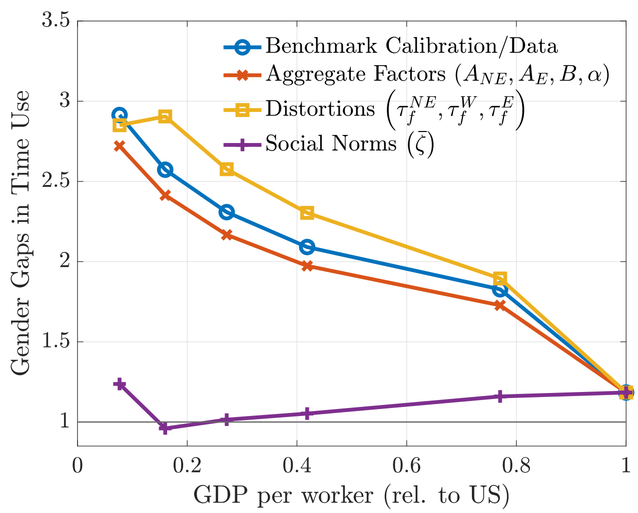
6 Quantitative Analysis

In this section, we use the calibrated US and cross-country parameter values to quantitatively assess the impact of gender gaps in time use on gender gaps across occupations and aggregate outcomes, including employer size, productivity, and output. To do this, we compare the benchmark calibration of the model, which delivers outcomes that exactly match the data, to three counterfactual parameterizations. These comparisons are designed to quantify the contributions of differences in i) aggregate factors $(\alpha, A_{\mathrm{NE}}, A_{\mathrm{E}}, B)$, ii) gender-specific distortions $\left(\tau_f^{\mathrm{W}}, \tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{E}}\right)$, and iii) gender-specific social norms, $\bar{\zeta}$, for cross-country differences in salient outcomes such as gender gaps in occupations or output. For example, to quantify the role of distortions, we substitute the US values for each occupational distortion while keeping all other model parameters equal to their calibrated levels for each country quintile.[22]

6.1 Gender Gaps in Time Use

Figure 9 compares gender gaps in time spent in non-market work (home production) in the benchmark and counterfactual calibrations.[23] Recall that, by construction, outcomes in the benchmark calibration (indicated by ∘ markers) match the data. Focusing first on the counterfactual removing differences in aggregate factors (× markers), we find almost no impact on gender gaps in time use across income quintiles relative to the benchmark. Intuitively, while aggregate factors vary significantly across countries, they impact both genders in much the same way.

Figure 9: Counterfactual Gender Gaps: Time Use in Non-Market Work



Notes: Gender gaps in time use are defined as the fraction of time spent in home production by women, relative to that for men. This figure shows gender gaps in non-market time use implied by the model in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

The impact of removing differences in distortions $\left(\tau_f^{\mathrm{NE}}, \tau_f^{\mathrm{W}}, \tau_f^{\mathrm{E}}\right)$ is represented by □ markers. Unlike aggregate factors, distortions directly impact only women and so result in differ-

[22]For each of these counterfactual exercises, we continue to adjust the gender composition of the model economy to exactly match the data, as in the benchmark. In Appendix D.2 we show that cross-country differences in labor-force composition alone have minimal impact on model outcomes.

[23]We focus here on non-market work, rather than total non-market activity (including leisure) since gender gaps in leisure (personal care) do not vary significantly with development, as discussed in Section 2.

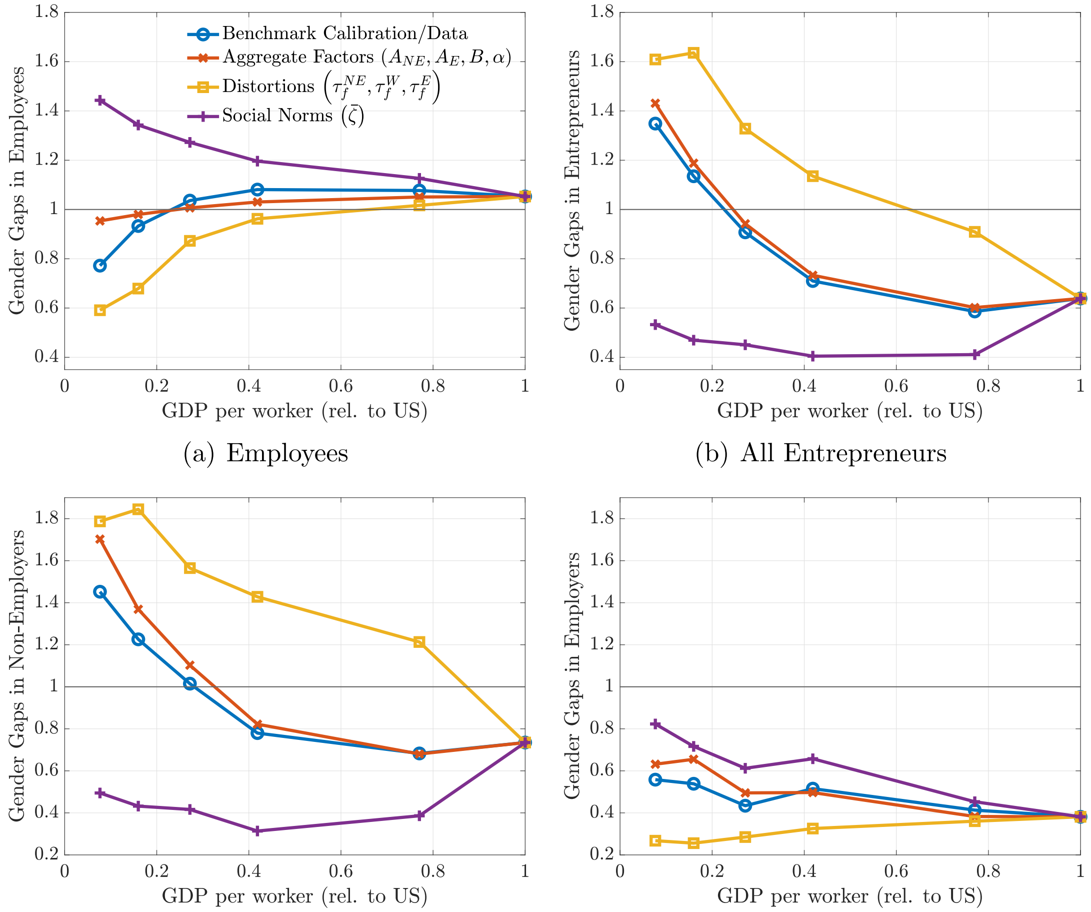
ential impacts by gender. Higher levels of τ_f^o lead women to shift away from market work (in occupation o) and towards home production, thereby expanding gender gaps in time use. Given the relatively small cross-country differences in inferred distortion levels, illustrated in Figure 8, it is unsurprising that inferred distortions generate correspondingly small quantitative differences in time use across countries. Further, our benchmark calibration implies that τ_f^{W}, τ_f^{NE}, and τ_f^{E} tend to increase with development, leading to a *widening* of the gender gap in time use with development across most income groups.

The discussion above suggests cross-country differences in aggregate factors and gender-occupation-specific distortions play essentially no role in generating observed differences in time use gender gaps across countries. This implies differences in social norms, represented by $\bar{\zeta}$, must be quantitatively important. Figure 9 makes clear that cross-country differences in gender gaps in time use are driven almost exclusively by differences in social norms. When we set $\bar{\zeta}$ to US levels in every quintile, gender gaps in time use come very close to those observed in the US. We emphasize that cross-country differences in all of our parameters are obtained simultaneously in our cross-country benchmark calibration. Thus, *a priori*, it is not necessary that gender gaps in time use be driven primarily by $\bar{\zeta}$. Intuitively, higher values of $\bar{\zeta}$ discourage women from spending time in market work, leading them to allocate more time to non-market work. When $\bar{\zeta}$ decreases to its US level, it can account for around 97% of the observed difference in time-use gender gaps between the US and the countries in the lowest income quintile. The remainder is explained by differences in aggregate factors, distortions, and the interaction of these with social norms.

6.2 Gender Gaps in Occupation Shares

We now explore the role of aggregate factors, distortions, and social norms in generating gender gaps in occupation shares across countries. Panels (a) and (b) of Figure 10 illustrate how gender gaps amongst employees and entrepreneurs (non-employers and employers combined) behave in our benchmark and in each counterfactual calibration. With the exception of the economies in the lowest quintile, cross-country differences in aggregate factors cannot account for the observed gender gaps among employees. Indeed, for all but the first quintile economies, eliminating differences in aggregate factors leads to relatively similar levels of gender gaps among employees as in the benchmark calibration. The impact of aggregate factors on gender gaps amongst entrepreneurs is even smaller. Differences in gender-specific distortions, on the other hand, lead to more pronounced gender gaps in both employee and

Figure 10: Counterfactual Gender Gaps: Employee and Entrepreneur Shares



(a) Employees

(b) All Entrepreneurs

(c) Non-employers

(d) Employers

Notes: The gender gap in the occupation-o share is defined as the fraction of employed women in occupation o, relative to that of men. This figure shows gender gaps in the employee (Panel a), entrepreneur (Panel b), non-employer (Panel c), and employer (Panel d) shares implied by the model in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

entrepreneur shares. This suggests that distortions serve to generate a positive (negative) relationship between development and gender gaps in entrepreneur (employee) shares, in contrast to the observed relationships in the data.

An implication of the relatively modest impact of aggregate factors and the opposing impact of distortions is that differences in social norms, $\bar{\zeta}$, are responsible for generating the observed relationships between development and gender gaps in employee and entrepreneur occupation shares. Panel (a) shows that as we decrease $\bar{\zeta}$ from almost 3 in the poorest quintile countries to 1 (the US level), the female employee share rises relative to the male employee share, which raises the gender gap for employees well above the US level. At the same time, Panel (b) shows that lower values of $\bar{\zeta}$ decrease the female entrepreneur share relative to the male share, resulting in lower gender gaps among entrepreneurs. We note that equalizing social norms across countries results in significantly lower (higher) gender gaps among entrepreneurs (employees) compared to the data, which suggests distortions and aggregate factors (and their interaction with norms) play an important role in partially offsetting the impact of social norms.

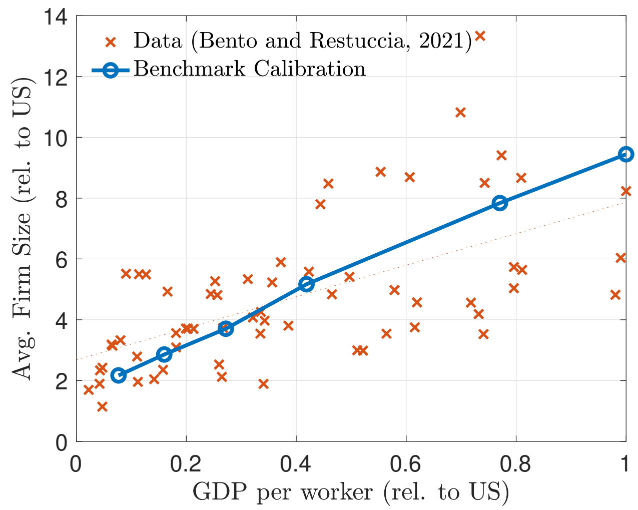
Focusing more closely on entrepreneur shares, Panels (c) and (d) of Figure 10 consider gender gaps in non-employer and employer shares separately. These panels show that aggregate factors play only a minor role in accounting for gender gaps among either non-employers or employers. Removing differences in distortions across country quintiles significantly increases gender gaps in non-employer shares, while lowering gaps in employer shares. The above findings imply that cross-country differences in social norms ($\bar{\zeta}$) generate a strong negative relationship between development and non-employer shares, strong enough to more than compensate for the effects of distortions, while generating a counter-factual positive relationship between development and gender gaps in employer shares, offsetting the impact of distortions. Thus, social norms are crucially important for generating the negative relationship between development and gender gaps in non-employer shares. At the same time, distortions are crucial for the observed pattern of gender gaps in employer shares.

Intuitively, the higher $\bar{\zeta}$ in poorer economies encourages women to spend more time in non-market activity and less time active in the market. This lowers total labor supply in the market, which raises wages. For both men and women, the higher wage discourages employer entrepreneurship, while encouraging other employment. Further, the higher disutility of market work from social norms encourages women to shift their remaining time in the market away from employment and employer entrepreneurship, where the return to hours is linear, and towards non-employer entrepreneurship, where earnings are concave in hours.

While aggregate factors play essentially no role in accounting for gender gaps in occupation shares, they are important in accounting for cross-country differences in overall occupation shares. In Appendix D.3 we show this by examining occupation shares separately for women and men.

Overall, while differences in social norms effectively account for all cross-country differences in gender gaps in time use, distortions and social norms both play a significant role in accounting for gender gaps in occupational shares, while aggregate factors are crucial for matching levels of occupation shares by gender.

Figure 11: Average Firm Size, Model and Data



Notes: The figure plots average size of employer firms in the model relative to the US calibration (○ markers) and observed average establishment size in service and manufacturing sectors, as reported in Bento and Restuccia (2021) (× markers). The dashed line reports the line of best fit for the data. Consistent with the measure of size in the data, we compute average size in the model as the ratio of all those engaged in employment (both employees and entrepreneurs) relative to the total number of entrepreneurs. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

6.3 Aggregate Implications

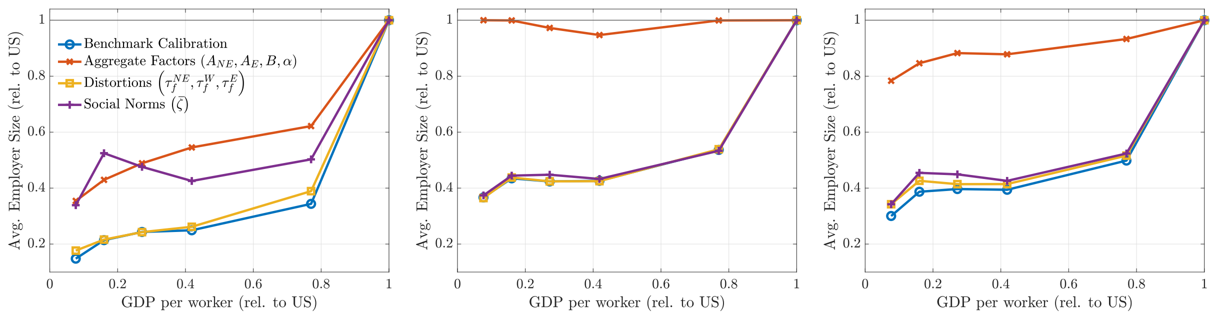
We now consider the contributions of aggregate factors, distortions, and social norms to cross-country differences in other aggregate outcomes. While cross-country differences in output per worker are targeted in our benchmark calibration, we also consider an untargeted aggregate outcome for which data is available – average firm size – and another that helps to provide intuition for our other results – average firm productivity. We begin by discussing average firm size.

Firm Size In Figure 11 we plot average firm size from Bento and Restuccia (2021) against average size in our benchmark calibration, both measured as total persons engaged (employees and entrepreneurs) divided by the number of firms (employers and non-employers).[24] Although our model equates an entrepreneur with a firm, while Bento and Restuccia (2021) count the number of firms directly, Figure 11 suggests our data capture the variation in average firm size very well. In Appendix D.3 we quantify the contributions of aggregate factors, distortions, and social norms to differences in the aggregate entrepreneur share (the inverse of average firm size in the model) and find differences in social norms account for

[24]The measure we take from Bento and Restuccia (2021) is average size across all service- and manufacturing-sector firms.

23% of the difference in entrepreneurship between the US and the poorest quintile countries.

Figure 12: Counterfactual Employer Size



(a) Female Employers (b) Male Employers (c) All Employers

Notes: Average employer size is measured as average hours worked by employees in employer firms. Panels show average size for female (a), male (b), and all employers (c) implied by the model in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

In Figure 12 we turn to a measure of average firm size more closely related to productivity – total employee hours per employer firm. We illustrate this measure (relative to the US) across income quintiles for female, male, and all employers in our benchmark calibration and in each of our three counterfactuals. Figure 12 shows aggregate factors explain much of the average size differences across countries for male and all employers and a significant portion of the differences for female employers. Distortions play only a small role in impacting average size, while social norms ($\bar{\zeta}$) play an essential role in generating differences in average size between female and male employers. For example, the figure suggests gender gaps in time use driven by social norms account for 22% (6%) of the difference in average size between female (all) employers in the poorest quintile and the US.

Note that increases in $\bar{\zeta}$ lead to reduced market time for women, who adapt by shifting out of employee and employer occupations and into non-employer occupations. Moreover, the large drop in female employer hours shrinks the optimal size of female employers (similar to a drop in productivity), relative to male employers. As a result, employees as a whole shift from female to male employers.

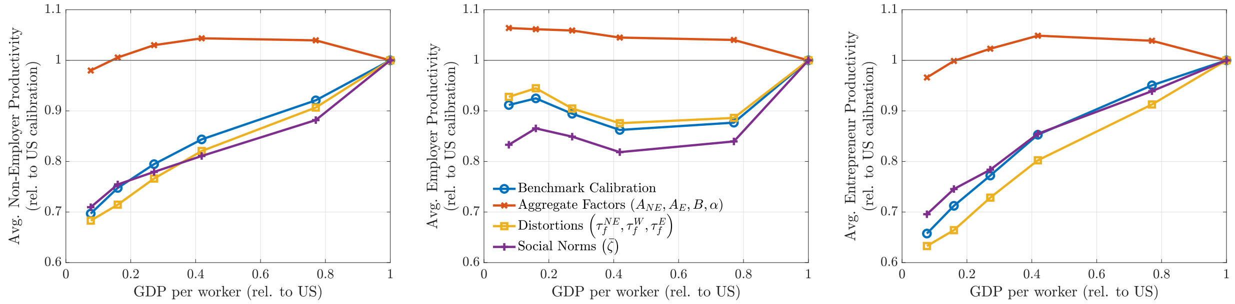
Productivity Average entrepreneurial productivity is an important contributor to aggregate outcomes, including output per worker. Figure 13 shows how average z across non-employers, employers, and all entrepreneurs differs across countries in the benchmark and counterfactual calibrations. In the benchmark, average productivity across all entrepreneurs tends to increase with development. The lower productivity of entrepreneurs in poorer countries is due to a combination of two (somewhat competing) factors. The first is selection, as more entrepreneurship tends to imply people with lower entrepreneurial ability start firms. Second, poorer countries have a much higher female-male ratio of entrepreneurs relative to richer countries. As this ratio goes to one (from a low ratio in rich countries), average productivity is pushed higher as low-productivity men are replaced by higher-productivity women. As this ratio increases past one, average productivity is pushed back down.

Panels (a) and (b) of Figure 13 show that differences in average productivity for both non-employers and employers are generally over-explained by differences in aggregate factors, with small impacts from distortions and social norms generally offsetting each other. Panel (a) shows that social norms have a relatively modest impact on average non-employer productivity. This modest impact results from opposing effects of social norms on male and female non-employer productivity. As women choose less market time under stricter social norms, they select into non-employer entrepreneurship rather than employment or employer entrepreneurship. The increase in the share of female non-employers, particularly from otherwise would-be employees, results in a decline in average non-employer productivity z. At the same time, as $\bar{\zeta}$ increases, female, and therefore, aggregate labor supply, declines, which raises wages. Higher wages encourage lower productivity non-employers to become employees, thus raising the average productivity z of male non-employers. The net effect is that social norms have a modest impact on the average productivity of all non-employers.

Panel (b) shows that social norms play a larger role in offsetting the impact of aggregate factors on average employer productivity, working to drive it higher. This is the result of less market time, leading female entrepreneurs to shift from being employers to non-employers in poorer countries. The few females that remain in employer entrepreneurship have much higher levels of productivity z. As wages rise in response to a higher $\bar{\zeta}$ (as described above), male employers become less profitable and so the least productive pursue non-employer entrepreneurship instead. This raises the average productivity z of remaining male employers. Due to these selection effects for both women and men, removing cross-country differences in social norms ($\bar{\zeta}$) *lowers* average productivity across all employers.

Panel (c) shows that removing cross-country differences in social norms generally has a negligible effect on average productivity across all entrepreneurs, as the effects described above do not change the overall entrepreneurship rate much. This suggests any impact of social norms on aggregate output will come predominantly from the misallocation of talent through distorted occupational choices (i.e., a change in the composition of non-employers

Figure 13: Counterfactual Average Productivity



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

Notes: Average productivity is measured as the average level of productivity z across entrepreneurs. Panels show average productivity across non-employers (a), employers (b), and all entrepreneurs (c) implied by the model in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

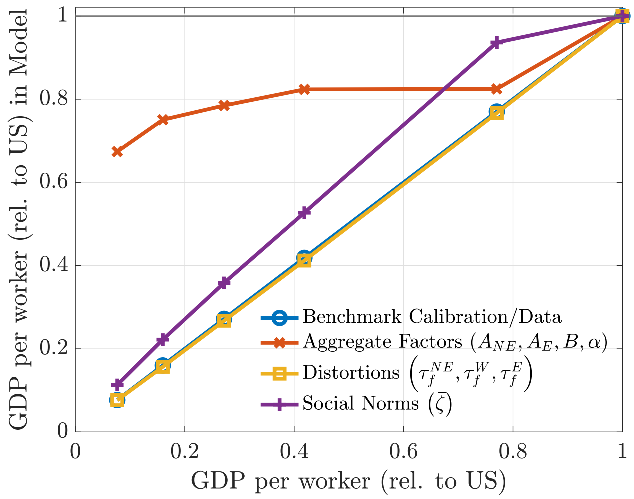
and employers) and from changes in market hours.

Aggregate Output Figure 14 shows how aggregate factors, distortions, and social norms impact aggregate output per worker in the model. Aggregate factors by themselves clearly generate much of the cross-country differences in non-agricultural output observed in the data, especially between the US and the poorest quintiles. For example, when differences in aggregate factors are eliminated, output per worker in the poorest quintile economies increases from 8% of US levels, as observed, to 67%.

Setting gender-specific distortions for all economies to the US level has very little impact on output in most economies but results in slightly lower output in the richest economies. This is because inferred distortions in our benchmark are generally lower in the richest economies but similar to the US in other economies.

Eliminating social norms that are biased against market activity by women raises output per worker across all countries, with output in the poorest quintile rising from 8% to 11% of the US level. This is significant and suggests that social norms (and the resulting gender gaps in time use) account for around 4% of the observed differences in output per worker between the US and the poorest economies in our sample. Removing differences in $\bar{\zeta}$ explains a larger share of differences in output between the US and richer economies – accounting for 19% and 72% of output differences between the US and the fourth and fifth quintile economies. The larger role of social norms in richer economies is due to these economies being relatively similar to the US in other dimensions, particularly aggregate factors, with

Figure 14: Counterfactual Output



Notes: This figure shows aggregate non-agricultural output implied by the model in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

more pronounced differences in inferred social norms.

Social norms impact output per worker through three channels. The first is a direct labor supply effect as women supply fewer hours to the market. The second is selection. By encouraging fewer market hours, biased social norms encourage both female employees and (lower-productivity) employers to choose non-employer entrepreneurship instead. Third, a lower labor supply increases wages in general equilibrium, leading men to shift from employers to non-employers and non-employers to employees. And of course higher wages feed back into the hours decisions of all men and women. As argued above, the selection effect is essential for understanding how gender gaps in time use, driven by $\bar{\zeta}$, influence gender gaps in occupations. In Appendix D.4 we decompose the impact of social norms on aggregate output into that due to selection and that due to other channels. Overall, we find selection is responsible for 10–12% of the impact. Looking separately at output produced by female and male entrepreneurs, we find that selection does not contribute to the lower output from female entrepreneurs but contributes 26–50% of the lower output from men. Although social norms only directly affect women, they cause a misallocation of talent among employed males who select into less productive occupations.

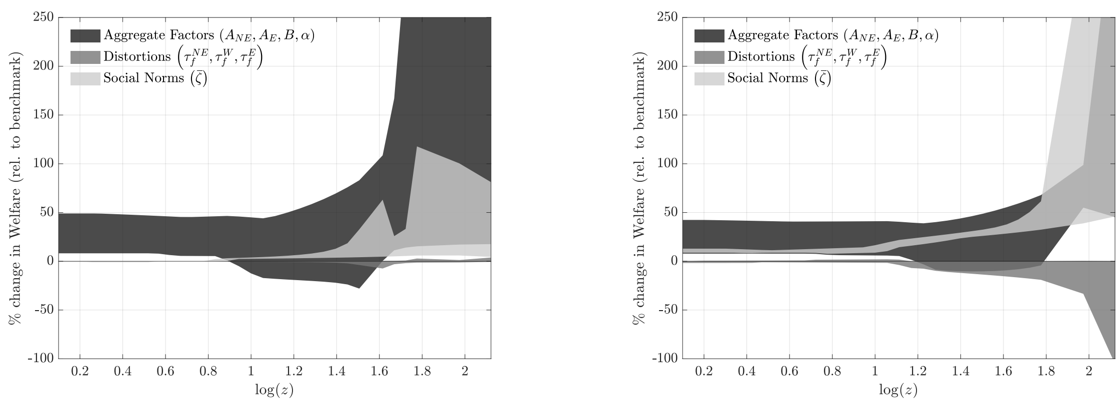
In summary, our results show that social norms biased against female market work, the factor primarily responsible for generating gender gaps in time use, are important for accounting for cross-country differences in gender gaps in entrepreneurship, employer size, average productivity, and aggregate output, with changes in occupational choices playing a significant role in these aggregate outcomes.

6.4 Welfare

We now explore how cross-country differences in aggregate factors, distortions faced by women, and social norms affecting the female disutility of market work impact the welfare of women and men. To do this, we compare implied welfare in the benchmark calibration to that implied by counterfactuals in which cross-country differences in each of these three sets of parameters are removed and set to US levels. We measure welfare gains as the percentage change in utility under each counterfactual relative to the benchmark calibration.

Figure 15 and Table 3 summarize the results of this exercise. Figure 15 reports the range of welfare gains across country income quintiles from removing differences in each set of factors for each level of entrepreneurial ability z and gender.[25] Table 3 reports average percentage gains across all women and all men, separately for each quintile.

Figure 15: Welfare Gains from Removing Cross-Country Differences



(a) Men (b) Women

Notes: The figure plots, by entrepreneurial ability, the range of welfare gains across country income quintiles obtained when removing cross-country differences in aggregate factors (dark shaded area), female-specific distortions (medium shaded area), and social norms affecting the disutility from market work for women (light shaded area). Welfare gains are computed as percentage differences in utility relative to the utility in the benchmark calibration, and range is the maximum and minimum gains obtained across all quintiles.

Focusing first on the welfare implications of removing cross-country differences in aggre-

[25] Each shaded area represents the maximum and minimum percentage change in utility for a person with a given z across all country quintiles. Figure A.3 in Appendix A reports level differences in utility separately for each quintile.

gate factors, Figure 15 shows that there are significant gains from removing differences in (gender-neutral) aggregate factors related to production for both genders and across most of the productivity distribution. Welfare gains for low-productivity agents, who tend to be employees, stem from a significant increase in wages driven by higher labor demand from more productive employers. Non-employers, those in the middle of the productivity distribution, gain from higher levels of A_{NE}. Higher A_{E} and lower α more than offset the negative impact of wage increases on profits for employers, resulting in large gains for those at the top end of the productivity distribution. Since women face higher disutility from market work, their labor supply and occupational choices are relatively constrained, resulting in lower gains in utility for women compared to men when differences in aggregate factors are removed. Note that exogenous employer productivity A_{E} is higher in the richest quintile of countries than in the US, so removing aggregate factor differences in the richest quintile results in modest welfare losses for agents with intermediate productivity levels who switch from being employers to non-employers. On average, welfare gains from eliminating differences in aggregate factors are positive and large as can be seen in the first rows of Panels A and B of Table 3, which report the average welfare gains for males and females. They suggest that men in the lowest (highest) income quintiles experience an increase in utility of around 49% (7%) from eliminating differences in aggregate factors, while the analogous welfare gain for females is 42% (8%).

Table 3: Average Welfare Gains (%) from Removing Cross-Country Differences

	Panel A: Men					**Panel B**: Women				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Aggregate Factors	49.1	41.9	34.3	25.5	6.9	42.1	35.2	28.5	22.1	7.5
Distortions	0.0	0.0	0.0	0.0	0.0	0.4	-1.6	-1.6	-1.6	-0.4
Social Norms	-0.4	-0.4	-0.4	-0.4	-0.3	9.8	13.2	12.3	11.7	9.4
All Factors	48.2	41.2	33.7	24.9	6.6	51.4	44.3	37.4	30.5	15.6

Notes: Panels A (Men) and B (Women) report, by country income quintile, the average percentage change in welfare obtained when removing cross-country differences in aggregate factors (first row), female-specific distortions (second row), and social norms affecting the disutility from market work for women (third row), and all of the above (last row). Welfare gains are computed as percentage differences in utility relative to the utility in the benchmark calibration when parameter values corresponding to each row are set equal to their US levels.

Removing differences in the distortions faced by women has minimal impact on welfare for men and generally results in modest welfare *losses* for females. Across much of the productivity distribution, Figure 15 shows that setting distortion levels to US levels has a modest negative impact on the welfare of most men, with modest welfare gains for those with the highest productivity. The net effect, reported in Panel A of Table 3, is that men on average experience neither welfare gains nor losses when gender-specific distortions are set to their US level. Intuitively, changes in female-specific distortions only impact men via general equilibrium effects, namely wage changes. However, the market clearing wage changes very little when setting distortions to their US levels.

Women, on the other hand, are directly impacted by changes in relative distortions. In all but the lowest income quintile countries (where distortions are similar to the US), when differences in distortions are removed, women experience modest welfare losses and these losses are increasing in entrepreneurial ability. These losses stem from the distortions tending to be higher in the US relative to other quintile groups (Figure 8). Setting these distortions to US levels, therefore, tends to *raise* the level of gender-specific distortions. As a result, women experience average welfare losses ranging from -0.4% in the fifth quintile to -1.6% in the second quintile economies. The average welfare change for women in the lowest quintile economies is a positive 0.4%.

Removing differences in social norms, that is, setting $\bar{\zeta}$ equal to 1 as in the US, generates small average welfare losses for men and significant average welfare gains for women. For men, removing the relative disutility of market work results in small welfare losses for all but the highest productivity agents, a small share of the population. For the majority of men, welfare losses arise from the lower wages resulting from the increase in the supply of female employees. For male employers, welfare tends to increase with lower wages. While these same forces also impact women, the resulting higher hours worked by female employees (as well as the direct positive impact of lower disutility of market hours) more than offsets the decline in wages, leading to higher welfare for all women and even larger gains for those with higher productivity. As shown in Panel B of Table 3, removing differences in social norms, the factor responsible for the bulk of cross-country gender gaps in time use, raises the average welfare of women by 10–13% across countries.[26] In consumption equivalent terms, these welfare gains are equivalent to the gains from increasing the consumption of women (relative to the benchmark calibration) by 71% in the lowest quintile economies, 87% in the second, 68% in the third, 56% in the fourth, and 34% in the fifth quintile economies, while keeping time use constant at benchmark levels.[27]

[26]Table A.1 in Appendix A decomposes the welfare gains into those stemming from changes in consumption and from changes in the value of leisure. We find that consumption gains account for almost all of the welfare gains for females when eliminating differences in social norms. Changes in the value of leisure act to modestly decrease welfare since the reduction in $\bar{\zeta}$ is more than offset by the increase in market hours. For example, of the 9.8% welfare gains for females in the first quintile economies, around 9.9 percentage points are due to increases in consumption and the remainder (around -0.1 percentage points) is due to changes in the value of leisure.

[27]The analogous welfare gains in consumption equivalence terms for women when eliminating gender-

In summary, there are significant potential welfare gains for women when gender gaps in time use are eliminated through changes in social norms. To put the above magnitudes into perspective, the average gains to women from eliminating differences in social norms around female market work are between one-fifth to one-half of the potential gains from eliminating differences in aggregate factors. These results and our quantitative analysis of the impact on firm size, productivity, and aggregate output show that removing barriers to female market work is a promising avenue for developing economies to achieve growth.

7 Conclusion

This paper explores the relationship between gender gaps in time use and entrepreneurship. We provide evidence supporting the idea that gender asymmetries in time allocated to non-market (household) work, which tend to narrow with development, may in part be driving gender asymmetries in rates of entrepreneurship across countries. Specifically, we show gender gaps in entrepreneurship reverse with development such that women are more likely than men to be entrepreneurs in poor economies, but less likely in rich economies. Further, we show that this pattern is largely due to gender gaps among non-employer entrepreneurs. This is significant to note since we find, across all levels of development, non-employers work the least amount of hours, making it an occupation that may be particularly amenable to those with limits on their time.

To quantitatively assess the relationship between gender gaps in time use and gender gaps in entrepreneurship, we build a general equilibrium model of occupational choice where women and men select into occupations based not only on their innate ability, as is standard, but also on their own time allocated to market work. The model features two types of barriers that distort women's occupational and time-use choices: (i) 'social norms' affecting women's preferences for market work relative to men's and (ii) distortionary 'taxes' affecting the actual and perceived returns to market work for women relative to men. When calibrated to match salient features of the data including the relative ranking of market hours worked by occupation, the model implies that gender gaps in time use are driven almost exclusively by cross-country differences in social norms. Social norms are also crucial for generating the pattern of gender gaps in occupation shares that we document.

specific distortions are a consumption increase of 2% in the lowest quintile economies and decreases of 7% in the second, 7% in the third, 6% in the fourth and 1% in the fifth quintile economies.

We find that gender gaps in time use driven by social norms – both through their direct impact on time use and indirect impact on occupational selection – have important aggregate implications. In particular, we show that differences in social norms can account for 6% of the observed differences in average employer firm size and 4% of differences in output per worker between the US and the least developed economies. Importantly, we also find that social norms biased against market work result in significant welfare losses for women, particularly those with high entrepreneurial ability. Removing differences in social norms across countries would result in welfare gains equivalent to a 71% (34%) increase in consumption in the poorest (richest) economies.

Overall, we highlight the significant role of social norms, especially in less developed countries, in dissuading women from participating in market work. Differences in these social norms across countries not only generate a strong negative relationship between economic development and gender gaps in entrepreneurship, but also significantly impact the quantity and quality of businesses in an economy and the welfare of women active in the market economy.

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For Online Publication

Appendix for:

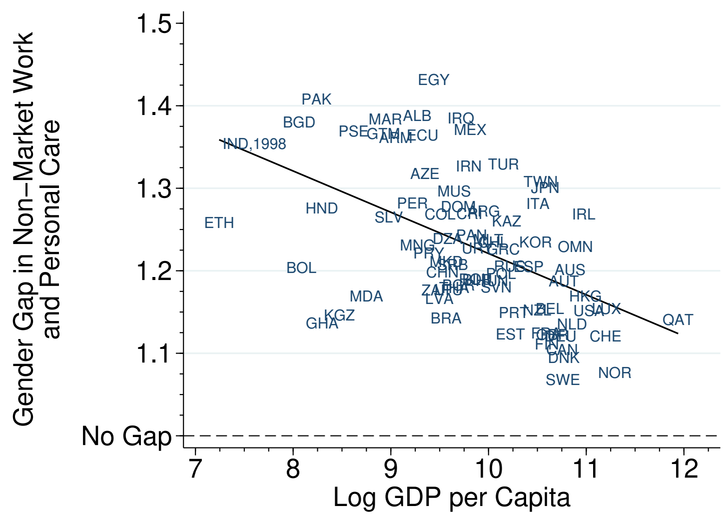
Gender Gaps in Time Use and Entrepreneurship

Pedro Bento Lin Shao Faisal Sohail

A Additional Tables and Figures

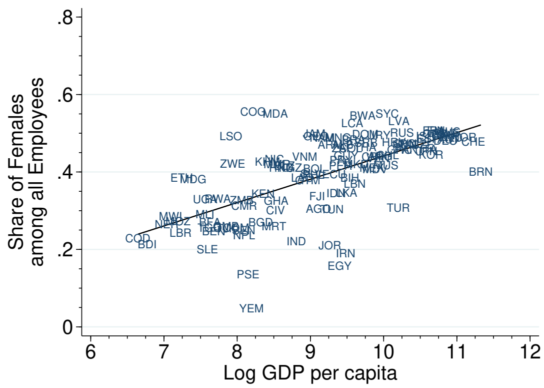
This appendix includes additional tables and figures complementing discussions in Sections 2 and 6.

Figure A.1: Gender Gaps in Non-Market Work and Personal Care

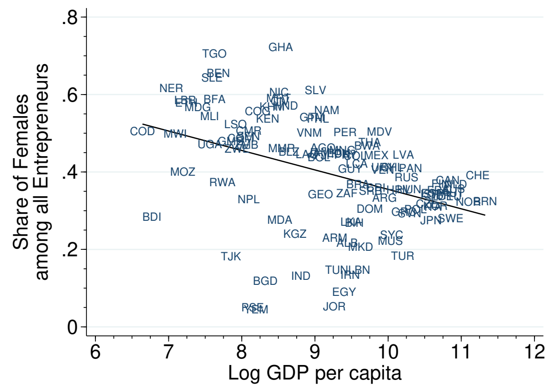


Notes: This figure reports the ratio of female to male time spent in non-market work and personal care activities (combined), computed using data from UNSD, OECD and Bridgman et al. (2018).

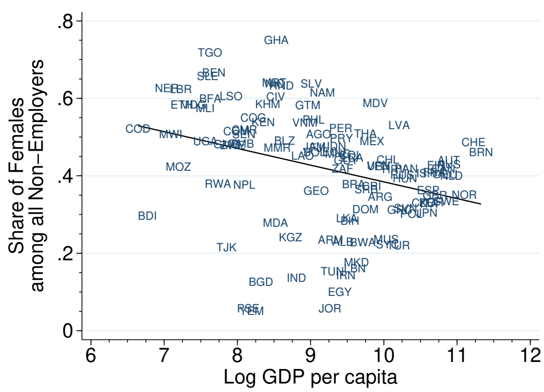
Figure A.2: Share of Women by Occupation



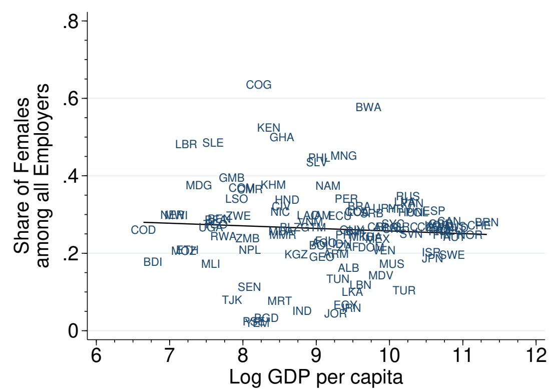
(a) Employees



(b) All Entrepreneurs



(c) Non-employers



(d) Employers

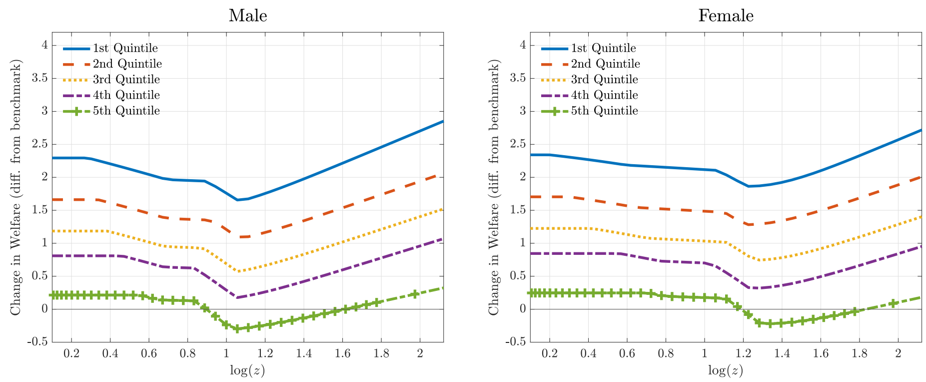
Notes: This figure plots female employees, entrepreneurs, non-employers, and employers as a share of all people (women and men) in each occupation.

Table A.1: Average Welfare Gains (%) from Removing Cross-Country Differences, by Contribution of Consumption and Leisure

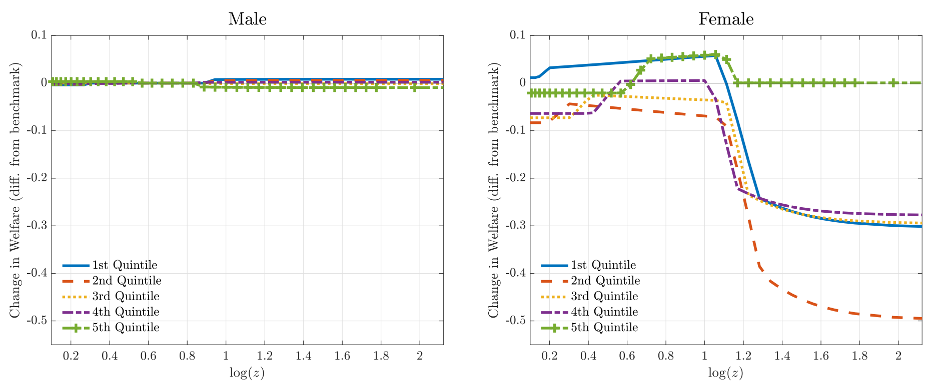
	Male					Female				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
Aggregate Factors										
Consumption	49.4	42.2	34.5	25.6	6.9	42.3	35.4	28.6	22.1	7.5
Leisure	-0.3	-0.3	-0.2	-0.1	0.0	-0.2	-0.2	-0.1	-0.1	0.0
Total	49.1	41.9	34.3	25.5	6.9	42.1	35.2	28.5	22.1	7.5
Distortions										
Consumption	0.0	0.0	0.0	0.0	0.0	0.3	-1.8	-1.7	-1.7	-0.5
Leisure	0.0	0.0	0.0	0.0	0.0	0.1	0.1	0.1	0.1	0.1
Total	0.0	0.0	0.0	0.0	0.0	0.4	-1.7	-1.6	-1.6	-0.4
Social Norms										
Consumption	-0.5	-0.5	-0.5	-0.4	-0.3	9.9	13.3	12.4	11.8	9.5
Leisure	0.1	0.1	0.1	0.0	0.0	-0.1	-0.1	-0.1	-0.1	-0.1
Total	-0.4	-0.4	-0.4	-0.4	-0.3	9.8	13.2	12.3	11.7	9.4

Notes: This table reports, by country income quintile, the total average percentage change in welfare, the change in utility from consumption and the change in utility from leisure that is obtained when removing cross-country differences in aggregate factors (first three rows), female-specific distortions (next three rows), and social norms affecting the disutility from market work for women (last three rows). Total welfare gains are computed as percentage differences in total utility relative to the utility in the benchmark calibration when parameter values corresponding to each row are set equal to their US levels. Welfare changes due to consumption are measured as the change in the utility from consumption relative to the total utility in the benchmark economy. Welfare changes due to leisure are similarly measured as the change in the utility from leisure relative to the total utility in the benchmark economy.

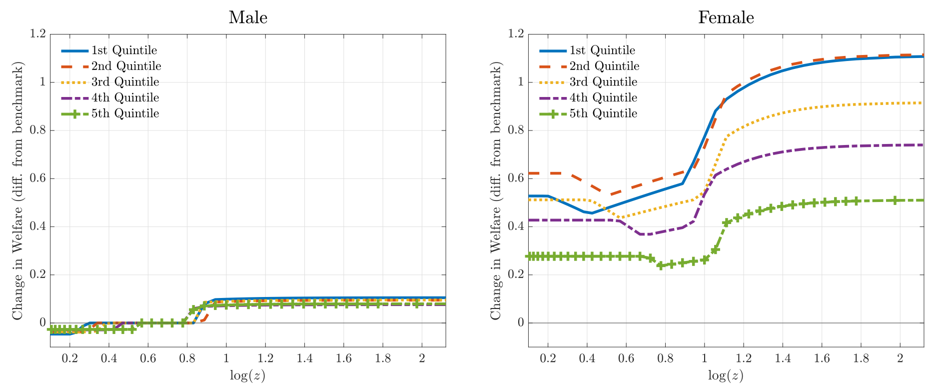
Figure A.3: Differences in Utility under Counterfactual Parameterizations



(a) Removing Differences in Aggregate Factors



(b) Removing Differences in Distortions



(c) Removing Differences in Social Norms

Notes: This figure plots percentage welfare gains when cross-country differences in aggregate factors, gender-specific distortions, and social norms are removed, separately by country income group. Welfare differences are computed as the difference in utility relative to the utility in the benchmark calibration.

B Data Appendix

In this section, we provide more detail on our data sources as well as additional empirical analysis.

B.1 Labor-Force Surveys

Data Sources Data for Ecuador, El Salvador, Greece, Italy, Jamaica, Jordan, Nicaragua, Spain, Switzerland, and Venezuela are from IPUMS International. These are the only countries in the IPUMS sample for which information on working hours, together with information on employer and non-employer entrepreneurs is included. We extract data for 10 additional countries directly from labour force surveys. These include 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 (CPS). CPS 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 asked the self-employed if they hired others.

B.2 Time-Use Data

Data Description We measure gender gaps in time use using three different sources: i) the United Nations Statistics Division (UNSD), 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 and gender. In our primary empirical analysis, we only include data from the most recent year for each country. Figure B.1 plots the gender gaps in time use for all country-year observations included in these three data sources. Table B.1 reports the source of time-use data for each country in Figures 2 and 3.

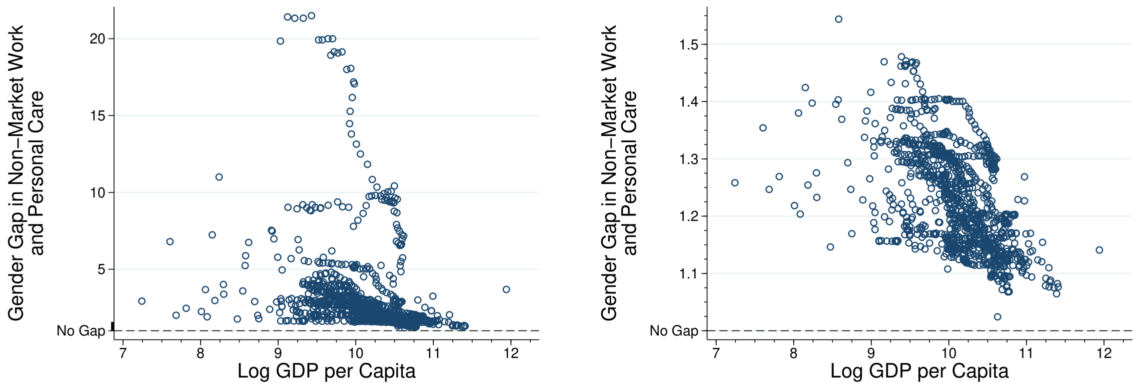
The UNSD data, which comprises the majority of our sample, report time spent on unpaid domestic and care work. More specifically, these include any activities that are listed in the International Classification of Activities for Time Use Statistics 2016 (ICATUS 2016) categories 3 and 4. These include 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 B.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 that shrink as economies develop.

Table B.1: Source of Time-Use Data

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

Notes: UNSD indicates that data are 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 are from Bridgman et al. (2018).

Figure B.1: Gender Gaps in Time Use, All Available Data

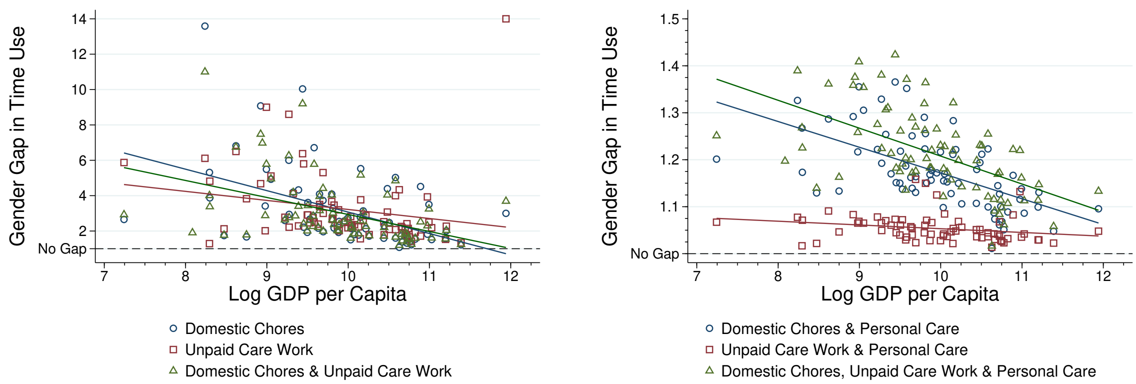


(a) Non-market Work

(b) Non-market Work and Personal Care

Notes: This 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 UNSD, OECD Stat, and Bridgman et al. (2018).

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



(a) Excluding Personal Care Activities

(b) Including Personal Care Activities

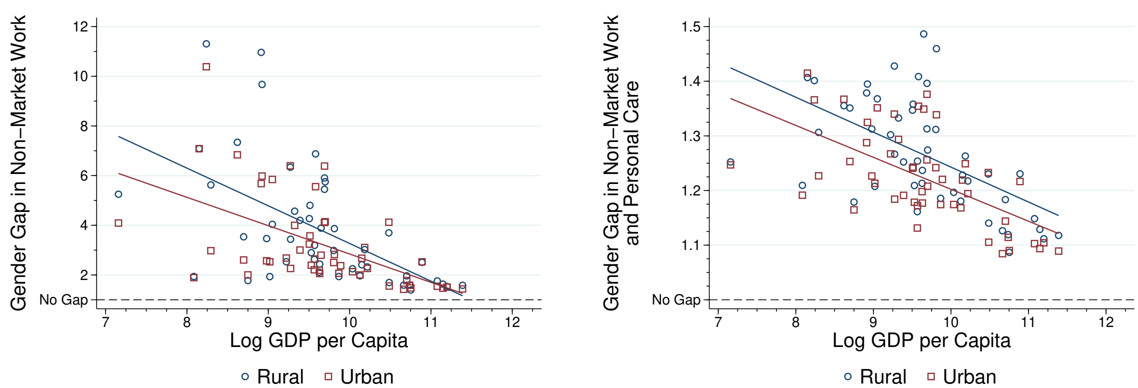
Notes: This figure reports the ratio of female to male time spent in domestic chores, unpaid care, and personal care activities by urban/rural status, using UNSD data.

While the UNSD 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 on time spent in non-market work, the OECD Stat data also report time spent in additional categories including personal care activities. These activities correspond 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 UNSD 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 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 UNSD and Bridgman et al. (2018).

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

Gender Gaps by Region and Employment Status The aggregated data used to measure gender gaps in time are based on information for the entire population (above a certain age, usually 15 years) regardless of the sector or status of employment. However, our quantitative analysis focuses on non-agricultural employment abstracting from the agricultural sector, unemployment and the extensive margin of labor-force participation. With this in mind, it is important to establish that the patterns of gender gaps in time use are not driven entirely by changes in the sectoral composition or labor-force participation rates by gender across countries.

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



(a) Non-market Work

(b) Non-market Work and Personal Care

Notes: This figure reports the ratio of female to male time spent in non-market work and personal care activities by urban/rural status using information for all country-year observations in the UNSD data.

To address the concern of sectoral composition, we explore gender gaps in time use separately for rural and urban regions. Regional information is included in the UNSD data for a subset of countries and is informative for gender gaps amongst those in the agricultural sector, which tends to be in rural regions. Figure B.3 compares the gender gaps in time use for rural and urban regions. The figure shows that for both rural and urban regions, the gender gap in time use declines with development. However, gender gaps in time use are larger (in levels) in rural areas. To explore whether the relationship between gender gaps in time use and the level of development is stronger in the agricultural sector, we estimate the following regression:

$$g_{i,c,t} = \alpha + \beta \mathbb{I}_{i,c,t} + \gamma Y_{c,t} + \theta (Y_{c,t} \times \mathbb{I}_{i,c,t}) + \mathbf{A}_t + \epsilon, \tag{B.1}$$

where $g_{i,c,t}$ is the gender gap in time use in region i, in country c in year t. The dummy variable $\mathbb{I}_{i,c,t}$ indicates whether the region is rural or urban, $Y_{c,t}$ is the log GDP per capita in country c, in year t, and the variable $\mathbf{A}_t$ captures year fixed effects. The coefficient θ on the interaction between the log GDP per capita and the region indicator captures the extent to which the relationship between gender gaps in time use and development varies across rural and urban regions.

Table B.2 reports the results from estimating equation (B.1) and shows that there is no statistically significant difference in the relationship between development and gender gaps in time use across regions. This provides some confidence that the cross-country patterns of gender gaps in time use we focus on are not driven by agricultural employment.

Table B.2: Slope Coefficient of Gender Gaps in Time Use by Region

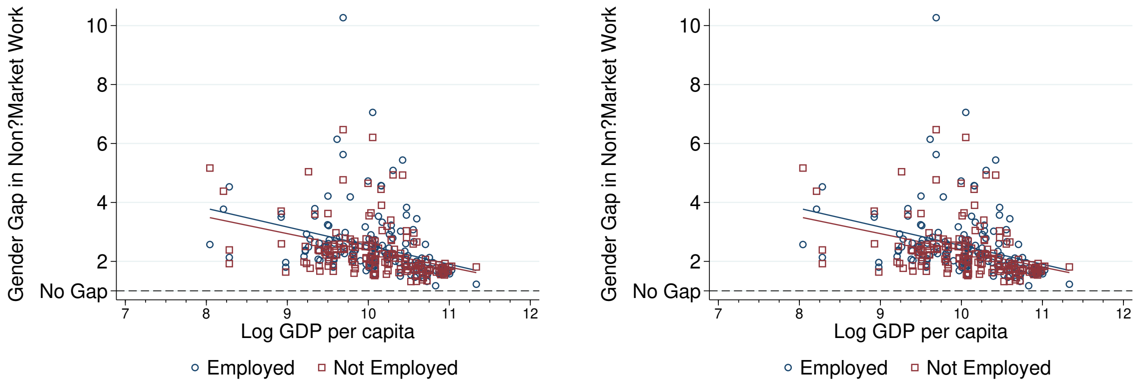
	Non-market Work and Personal Care		Non-market Work	
Log GDP per Capita	-0.064***	-0.087***	-1.517***	-1.799***
	(0.012)	(0.012)	(0.290)	(0.266)
Urban Region = 1	-0.095	-0.095	-4.181	-4.172
	(0.171)	(0.143)	(3.964)	(3.164)
Urban Region = 1 × Log GDP per Capita	0.005	0.005	0.376	0.374
	(0.018)	(0.015)	(0.409)	(0.327)
Year FE	N	Y	N	Y
N	99	99	99	99
R^2	0.369	0.623	0.323	0.632

Notes: This table reports the results from estimating equation (B.1) using data on regional gender gaps in time use from the UNSD. Standard errors are reported in parentheses, and *** indicates statistical significance at the 1% confidence level.

Related to the concern about sectoral composition, we are also concerned that gender gaps in time use are larger among the non-employed, and when combined with the pattern of female labor-force participation across countries, could be driving the cross-country patterns of gender gaps in time use for the entire population that we focus on. To evaluate this concern, we separately document gender gaps in time use by employment status for a subset of countries. Unfortunately, the aggregated data source we use does not allow us to document gender gaps by employment type. Instead, using a combination of time-use reports, data reported by statistical agencies and harmonized databases, we compile a dataset of gender gaps in time use for individuals that are either employed or non-employed (that is, either out of the labor force or unemployed).

In particular, we take data from time-use reports or statistical agencies for Albania, Algeria, Argentina, Australia, Bangladesh, Chile, South Africa and Turkey. Data for Brazil, Chile, Colombia, Costa Rica, Ecuador, El Salvador, Guatemala, Honduras, Mexico, Panama, Paraguay, Peru and Uruguay are taken from the United Nations Economic Commission

Figure B.4: Gender Gaps in Time Use for Employed and Non-employed



(a) Non-market Work

(b) Non-market Work and Personal Care

Notes: This figure reports the ratio of female to male time spent in non-market work and personal care activities by employment status.

for Latin America and the Caribbean (CEPAL in Spanish). Finally, data from Austria, Lithuania, Finland, Germany, Estonia, Romania, France, Serbia, Netherlands, Hungary, Italy, Spain, Poland, Norway, Latvia, Greece, Belgium, Hungary, Bulgaria, South Korea, Israel, Serbia, United States, Canada, Spain, France, Denmark, Czech Republic, Slovenia and the United Kingdom come from either the Harmonised European Time Use Surveys (HETUS) or the Multinational Time Use Study (MTUS) time-use databases. Figure B.4 compares gender gaps in time use by employment status across levels of development for these countries.

The figure shows that the cross-country relationship between GDP per capita and gender gaps in time use for both employed and non-employed individuals is remarkably similar. To test differences by employment status more rigorously, we estimate a version of (B.1) where the dependent variable is gender gaps in time use by employment status and the indicator variable $\mathbb{I}_{i,c,t}$ denotes employment status. Table B.3 reports the results from this estimation and shows that there is no statistically significant difference in the cross-country relationship between gender gaps and the level of development by employment status. As with regions, these findings are reassuring and support the idea that cross-country gender gaps in time use are driven by differences in employment rates across countries.

B.3 Entrepreneurship Data

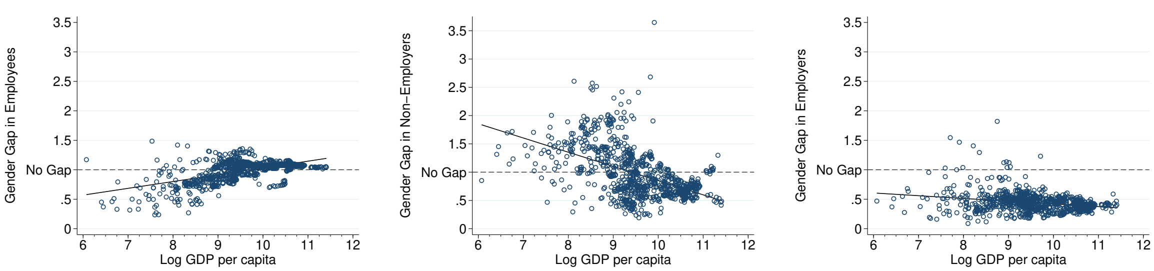
ILO data In the main text, we restrict attention to the most recent country-year observation from the ILO. Panel A of Table B.4 reports the country-year observations from the ILO used in the main text. Including all country-year observations delivers very similar relationships between occupational gender gaps and development. This can be seen in Figure B.5, which plots gender gaps across development for all country-year observations.

Table B.3: Slope Coefficient of Gender Gaps in Time Use by Employment Status

	Non-market Work and Personal Care		Non-market Work	
Log GDP per Capita	-0.568***	-0.526***	-0.0602***	-0.0575***
	(0.127)	(0.111)	(0.00854)	(0.00873)
Not Employed = 1	0.804	0.970	-0.0166	-0.00784
	(1.790)	(1.430)	(0.121)	(0.112)
Not Employed = 1 × Log GDP per Capita	-0.064	-0.0796	-0.00149	-0.00227
	(0.177)	(0.141)	(0.0119)	(0.0111)
Year FE	N	Y	N	Y
N	323	323	323	323
R^2	0.132	0.525	0.279	0.465

Notes: This table reports the results from estimating equation (B.1), where the dependent variable is gender gaps in time use by employment status and the indicator variable reflects employment status. Standard errors are reported in parentheses, and *** indicates statistical significance at the 1% confidence level.

Figure B.5: Gender Gaps for Employees, Non-employers and Employers, All Country-Year Observations



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

Notes: This figure plots the ratio of female and male employees and entrepreneurs as a share of their respective total employment, using all country-year observations from the ILO.

Table B.4: Sources of Measures of Occupation Shares

Panel A: ILO

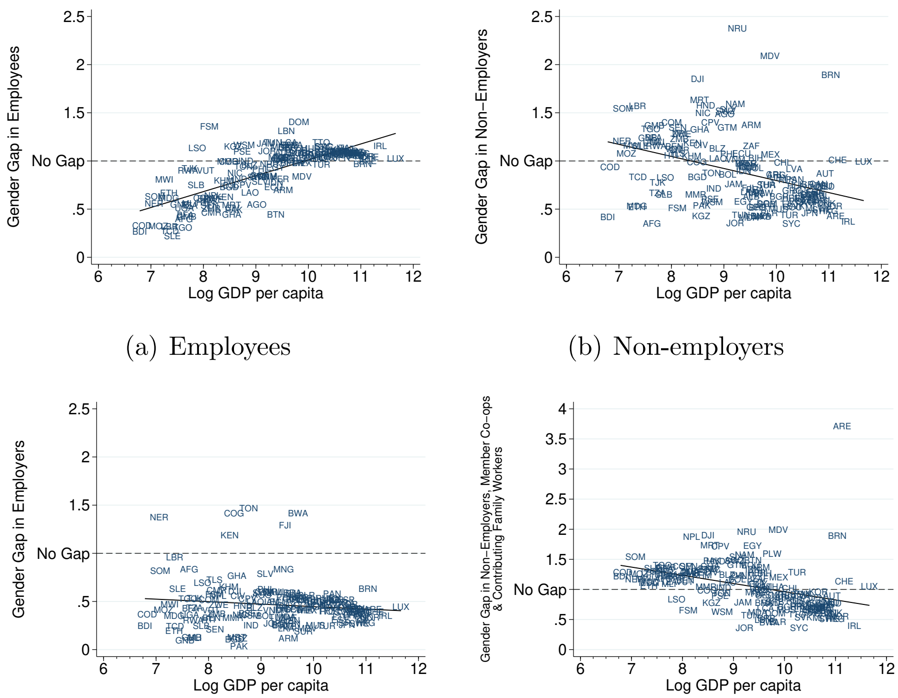
Country	Year	Country	Year	Country	Year
Angola	2014	Ghana	2017	Malawi	2013
Albania	2019	Gambia	2012	Namibia	2018
Argentina	2013	Greece	2019	Niger	2011
Armenia	2014	Guatemala	2019	Nicaragua	2014
Australia	2019	Guyana	2019	Netherlands	2019
Austria	2019	Honduras	2019	Norway	2016
Burundi	2014	Croatia	2017	Nepal	2017
Benin	2011	Hungary	2019	Panama	2019
Burkina Faso	2018	Indonesia	2019	Peru	2019
Bangladesh	2017	India	2019	Philippines	2019
Bosnia and Herzegovina	2019	Iran	2019	Poland	2019
Belize	2019	Israel	2017	Paraguay	2019
Bolivia	2019	Italy	2019	Occupied Palestinian Territory	2000
Brazil	2019	Jamaica	2019	Russian Federation	2019
Brunei Darussalam	2014	Jordan	2017	Rwanda	2019
Botswana	2019	Japan	2019	Senegal	2019
Canada	2019	Kenya	2019	Sierra Leone	2018
Switzerland	2019	Kyrgyzstan	2019	South Korea	2019
Chile	2019	Cambodia	2019	El Salvador	2019
Côte d'Ivoire	2019	Lao Peoples' DR	2017	Serbia	2019
Cameroon	2014	Lebanon	2019	Slovenia	2015
Congo, DR	2012	Liberia	2017	Sweden	2018
Congo	2009	Saint Lucia	2019	Seychelles	2015
Colombia	2019	Sri Lanka	2019	Togo	2017
Comoros	2004	Lesotho	2019	Thailand	2019
Costa Rica	2019	Latvia	2017	Tajikistan	2009
Czechia	2019	Moldova, Republic of	2010	Tunisia	2017
Germany	2019	Madagascar	2015	Turkey	2019
Dominican Republic	2018	Maldives	2019	Uganda	2017
Ecuador	2019	Mexico	2019	United Kingdom	2019
Egypt	2019	North Macedonia	2016	Uruguay	2019
Spain	2019	Mali	2013	Venezuela	2012
Ethiopia	2013	Myanmar	2019	Viet Nam	2019
Finland	2019	Mongolia	2019	Yemen	2014
Fiji	2011	Mozambique	2015	South Africa	2019
France	2019	Mauritania	2017	Zambia	2019
Georgia	2010	Mauritius	2018	Zimbabwe	2019

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

A point of concern with the ILO data is that their modeled estimates may lead to occupational shares being non-comparable across countries. Feng et al. (Forthcoming) highlight this point when studying unemployment across development. 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 is similar suggests that this is the case.

Figure B.6: Gender Gaps in Employees and Entrepreneurs, Including the Agricultural Sector



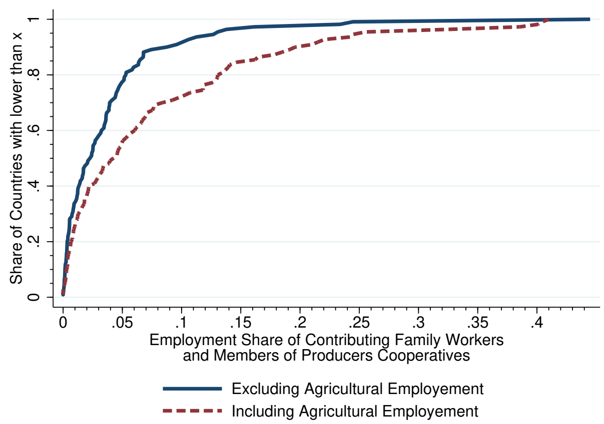
(a) Employees (b) Non-employers

(c) Employers (d) Non-employers+

Notes: This figure plots the ratio of female and male occupations as a share of their respective total employment using data from the ILO, including the agricultural sector. Panel (d) reports the gender gaps when members of producers' cooperatives and contributing family workers are also considered to be non-employers.

Including Agricultural Employment While our primary empirical analysis focuses on non-agricultural employment, we find that the patterns of gender gaps in occupations do not change when we also include the agricultural sector. This is shown in Figure B.6, which replicates the gender gap figures in the main text while including agricultural employment. Panels (a) to (c) show that the gender gaps in employees and non-employers continue to move in opposite directions while the gender gap for employers changes little with development. Panel (d) shows that the negative relationship between income and gender gap does not change when members of producers' cooperatives and contributing family workers are also considered to be non-employers.

Figure B.7: Cumulative Distribution of Share of Members of Producers' Cooperatives and Contributing Family Workers Across Countries



Notes: This figure plots the cumulative distribution of the total employment share of members of producers' cooperatives and contributing family workers across countries, when including or excluding the agricultural sector.

Our focus on non-agricultural employment is motivated by the fact that the agricultural sector has a large share of individuals engaged as either members of producers' cooperatives or contributing family workers, and it is unclear whether individuals in these two occupations are unambiguously workers or entrepreneurs. Instead, the non-agricultural sector features a much smaller share of these occupations and avoids this classification concern. Figure B.7 illustrates this by plotting the CDF of employment share in either members of producers' cooperatives or contributing family workers across countries in the ILO sample.

Alternative Definitions of Entrepreneurs In our main analysis, we do not classify members of producers' cooperatives and contributing family workers as non-employers in our main sample of non-agricultural employment. However, we find similar results for gender gaps among entrepreneurs and non-employers if we instead consider them to be non-employers (see also Panel (d) of Figure B.6). Indeed, the slope coefficient with development of the gender gap among non-employers does not change when including these two additional employment categories along with non-employers. Focusing on employment in non-agricultural sectors allows us to classify employees and entrepreneurs in an unambiguous and consistent manner across countries while having little impact on the patterns of occupational gender gaps that are our focus.

Counterfactual Gender Gaps in Entrepreneurship To illustrate the relative importance of gender gaps among non-employers for the gender gap in overall entrepreneurship, we conduct a simple counterfactual exercise. This decomposition is based on the definition of gender gaps in occupations. In particular, directly following our definition of gender gaps, the gender gap in occupation i in each country can be denoted as

$$g_i = \frac{N_i^f}{N_i^m} \frac{T^m}{T^f},$$

where N_i^f and N_i^m indicate the number of females and males employed in occupation i and T^f and T^m are the total employment for females and males, respectively. Letting $i = 1$ indicate employers and $i = 0$ indicate non-employers, the gender gap in overall entrepreneurship e can be written as

$$g_e = \frac{N_0^f + N_1^f}{N_0^m + N_1^m} \frac{T^m}{T^f}.$$

With some rearrangement, this can be rewritten as

$$g_e = \lambda g_0 + (1 - \lambda) g_1, \tag{B.2}$$

where g_0 and g_1 are the gender gaps among non-employers and employers, respectively, and $\lambda = N_0^m / (N_0^m + N_1^m)$ is the share of male non-employers among all male entrepreneurs.

Equation (B.2) shows that the gender gap in overall entrepreneurship is driven by three components: i) gender gaps among non-employers, ii) gender gaps among employers and iii) the relative prevalence of non-employer entrepreneurs as captured by the share of male non-employers among entrepreneurs. To illustrate the role of each of these three components in driving the cross-country relationship between gender gaps in entrepreneurship, g_e, and the (log) GDP per capita, we construct counterfactual gender gaps, $\hat{g}_e$, by holding each of these three components fixed to their cross-country average. Then, we compute the resulting slope coefficient between $\hat{g}_e$ and income per capita. Comparing the observed and counterfactual relationships between gender gaps and the (log) GDP per capita allows us to illustrate the relative importance of gender gaps among non-employers.

Table B.5 reports the results of this exercise. It shows that keeping gender gaps among non-employers fixed (equal to the cross-country average) results in counterfactual gender gaps in entrepreneurship that are weakly related to income: a slope coefficient of -0.06 compared to the observed -0.23 in the data. This suggests that gender gaps among non-employers account for around 75% of the relationship between gender gaps in entrepreneurship and income. On the other hand, keeping gender gaps among employers fixed only modestly impacts the negative slope with gender gaps in entrepreneurship (-0.23 vs. -0.22). So, gender gaps among non-employers and the changing composition of (male) entrepreneurs across countries account for around 96% (-0.22/-0.23) of the observed negative relationship between gender gaps in entrepreneurship and development. Finally, holding the composition of male entrepreneurs, λ, fixed shows that the negative relationship between development and gender gaps in entrepreneurship is even stronger (-0.29 vs. -0.23). Taken together, this exercise confirms that the majority of the gender gaps in entrepreneurship are driven by

Table B.5: Slope Coefficient of Gender Gaps in Entrepreneurship on Log GDP Per Capita, Counterfactual Analysis

	Data	Counterfactual		
		Fixed g_0	Fixed g_1	Fixed λ
Slope Coefficient	-0.233***	-0.055***	-0.224***	-0.289***
	(0.020)	(0.006)	(0.020)	(0.022)
N	112	112	112	112
R^2	0.405	0.393	0.398	0.466

Notes: This table reports slope coefficients from OLS regressions of alternative measures of gender gaps in entrepreneurship on the (log) GDP per capita. The first column uses observed gender gaps. The remaining columns construct counterfactual gender gaps in entrepreneurship using equation (B.2) and holding gender gaps among non-employers fixed to their cross-country average (second column), holding gender gaps among employers fixed to their cross-country average (third column), and holding the composition of male entrepreneurs fixed to their cross-country average (fourth column).

gender gaps among non-employers.

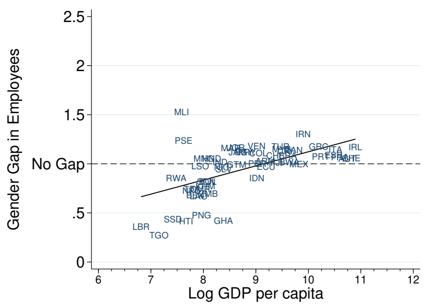
B.4 Subgroup Analysis of Gender Gaps using IPUMS International Data

In this section, we use data from IPUMS International to conduct subgroup analysis and confirm the findings from the ILO on gender gaps in occupation shares. The IPUMS data are nationally representative surveys and censuses that include information on industry, gender, and employment status, among other variables.[1] Importantly, they allow us to construct dis-aggregated gender gaps in occupations by education, marital status, and number of children. To be consistent with the ILO sample, we exclude all 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 as employers, and all other self-employed as non-employers. We then construct occupation shares using the provided sample weights and use these shares to construct occupational gender gaps. The final sample includes microdata from 54 countries.

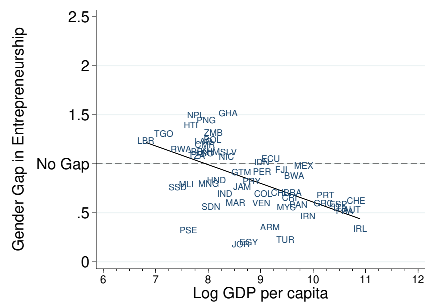
We find that the negative (positive) relationship between development and gender gaps among entrepreneurs (employees) is stronger when focusing on subgroups that are likely to have tighter constraints on their time use. To do this, we estimate the slope coefficients from regressions of occupational gender gaps on the (log) GDP per capita for difference subgroups 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 gender gaps in non-market time use through their impact on women's time allocation.

[1]Table B.4 in Appendix B.3 reports the countries included in the IPUMS sample.

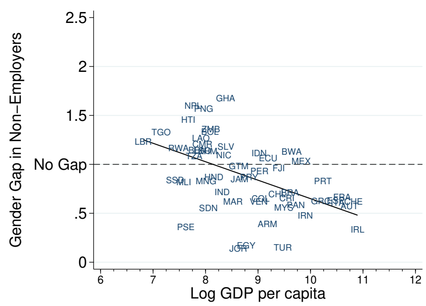
Figure B.8: Gender Gaps by Occupation – IPUMS International Data



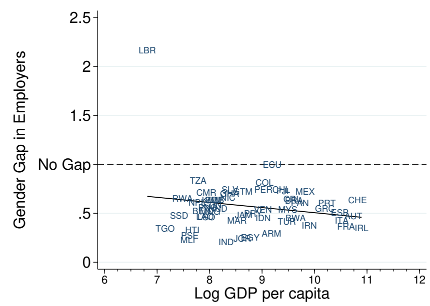
(a) Employees



(b) All Entrepreneurs



(c) Non-employers



(d) Employers

Notes: This figure plots the ratio of female and male employees and entrepreneurs as a share of their respective total employment, computed from the IPUMS International microdata. 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.

Table B.6 reports these slope coefficients. The first row reports the coefficients on gender gaps derived from the ILO data, while the second row reports the same when we construct aggregated gender gaps from the IPUMS samples. Qualitatively, the two data sets report similar findings: gender gaps for employees increase with development, while gender gaps for entrepreneurship decrease with development, driven primarily by decreasing gender gaps among non-employers. Quantitatively, the IPUMS data predicts a less pronounced decrease (increase) of gender gaps for entrepreneurs (employees). Figure B.8 plots the gender gaps by occupation as derived from the IPUMS sample.

The remaining rows of Table B.6 report the slope coefficient between the (log) GDP per capita and gender gaps for subgroups of individuals derived from the IPUMS sample. First, we compare gender gaps among those with high and low education, 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, World Bank Group, 2011; 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

Table B.6: Slope Coefficient of Gender Gaps on (Log) GDP per Capita

	Employees	Entrepreneurs			N
		All	Non-employers	Employers	
ILO	0.152***	-0.233***	-0.229***	-0.040**	112
	(0.016)	(0.020)	(0.026)	(0.017)	
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)	
$\geq$ 1 Child	0.195***	-0.223***	-0.236***	0.056*	40
	(0.036)	(0.050)	(0.055)	(0.031)	
No Children	0.126***	-0.173***	-0.182***	-0.062**	40
	(0.040)	(0.036)	(0.037)	(0.030)	

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

and gender gaps in entrepreneurship to be much more pronounced for the low education subgroup, 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 B.6 shows 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 relationships for entrepreneurship (for both education levels) are driven primarily by gender gaps among non-employers. Having said this, many factors other than differences in time use are associated with educational attainment. For example, educational attainment is also associated with higher income and wealth, which can affect selection into entrepreneurship in the presence of financing constraints. As such, we view these results as 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 time constraints 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 B.6 shows that this is indeed the case; the gender gap in entrepreneurship (workers) declines (increases) much more for married individuals relative to single individuals.

The last two rows of Table B.6 examine the relationship between gender gaps and development separately for women who have birthed a child and women who have not.[2] Consistent with the results on marital status, we find that gender gaps in entrepreneurship (workers) decline (increase) much more strongly for women who have had children than for those who do not have children.

We interpret the results in Table B.6 as providing suggestive evidence supporting the idea that the relationship between gender gaps in entrepreneurship may be driven, in part, by gender gaps in time use. These findings also serve to show that the relationship between gender gaps in entrepreneurship and development are robust to using alternative (micro)data and across various characteristics of individuals.

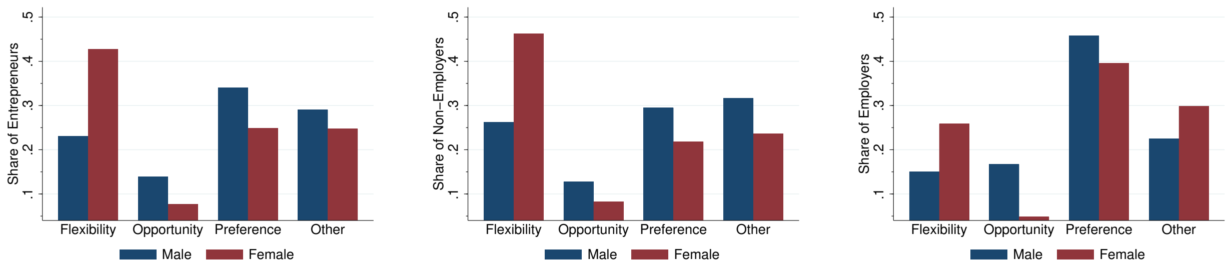
B.5 Flexibility and Non-employer Entrepreneurship

The idea that selection into entrepreneurship might be based on considerations related to time use, such as a desire for flexibility, or other non-pecuniary motives, such as preferences for being one's own boss, has previously been emphasized by Hurst and Pugsley (2011) and Yurdagul (2017), among others. Given the relative ranking of hours documented in Section 2.1, it is natural to imagine that the flexibility motive for entrepreneurship may be particularly salient for non-employers and for those who have limited availability of time.

To explore this idea, we use data from the 2017 Contingent Worker Supplement (CWS) of the CPS in the US. This supplementary questionnaire asks respondents their primary motive for pursuing entrepreneurship. We use the same sample restrictions as in the primary CPS sample and apply the appropriate supplement survey weights when reporting statistics. By combining several possible motives into four exhaustive categories, Figure B.9 reports the share of non-employer and employer 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 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.

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

Figure B.9: Motives for Entrepreneurship



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

Notes: This 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 who 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.

Combined with the findings of average hours by employment, these empirical patterns provide suggestive evidence that non-employer entrepreneurs may select into entrepreneurship based on their time use. It follows then that differences in time use across genders could interact with this margin of selection and shape gender differences in rates of entrepreneurship. We explore this idea in the following subsections by analyzing gender gaps in time use and entrepreneurship rates across countries.

C Cross-Country Calibration Details

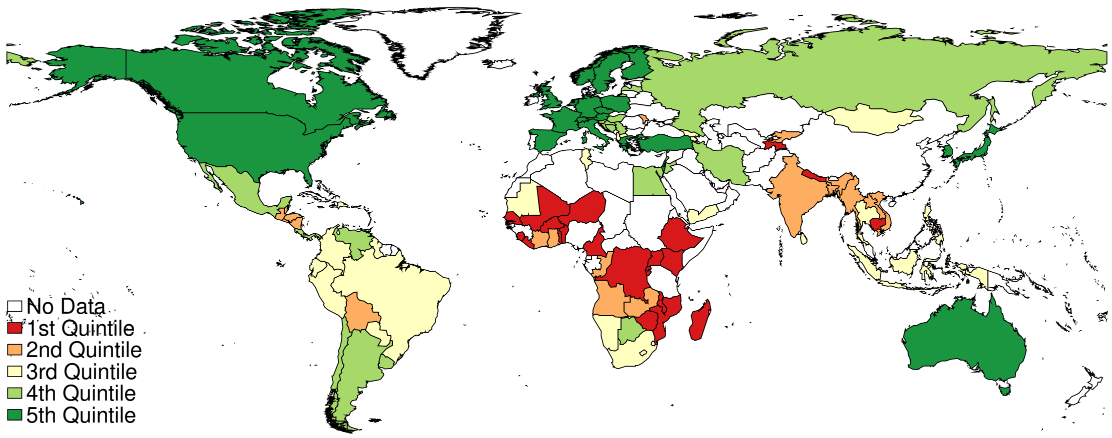
Here we provide details on the implementation of our cross-country calibration, starting with a description of the data targets that are used to discipline parameters across countries. Next, we conduct a comparative statics exercise in order to illustrate how each of the model's parameters influence the model-implied moments. This exercise also serves to identify the parameters that are most relevant for matching specific data moments.

C.1 Data Targets

For clarity of exposition, we group countries into quintiles of (log) GDP per worker and target averages of data moments within each quintile group. To determine the five groups of countries, we use the sample of 112 economies for which we have information on occupation shares and split these countries into quintiles based on (log) GDP per worker. Figure C.1 shows a map of the 112 countries that comprise our sample and the income quintile to which they belong.

Noticethat although we calibrate the model to match non-agricultural GDP per worker, we do not use this measure to group economies into incomes quintiles. We instead use total

Figure C.1: Country Groups for Cross-Country Calibration



Notes: This figure highlights the 112 countries in our sample, color-coded by income quintile rank using (log) GDP per worker.

GDP per worker since it is measured more precisely than non-agricultural output. In order to measure non-agricultural output, we adjust total GDP by one minus the value-added share of agriculture. Non-agricultural employment is measured similarly by adjusting total employment by the share of agricultural employment. We take measures of value-added and employment shares from the World Bank's World Development Indicators database. Then, non-agricultural output per worker is the ratio of non-agricultural output and non-agricultural employment. We experimented with calibrating the model using only non-agricultural GDP per worker, and our quantitative implications changed minimally.

The first six rows of Table C.1 report the average measures of output per worker (relative to the US) along with gender-specific occupation shares of employers and non-employers, which serve as targeted moments in our calibration.

Given the grouping of countries, we merge data on occupation shares to data on time use. To be consistent with our model, which only features employed individuals, we only use time-use statistics for employed individuals. As we described above and show in Figure B.4, the relationship (slope) between gender gaps in non-market time use and development are almost identical for both employed and non-employed individuals, with a lower level for employed individuals. However, the sample of countries for which we have time-use data by employment status is smaller than the sample for which we have averages across the entire population with missing data from relatively poorer economies. To account for this, we interpolate data for missing countries by assuming a linear relationship between time use in market and non-market activities and the level of development measured by GDP per worker. We then average, across income quartiles, the two data moments that relate to time use. These are gender gaps in non-market work and the ratio of hours spent in market work to non-market work for males. Rows 7 and 8 of Table C.1 report these data moments.

We proceed in a similar manner for the two remaining data targets; the gender wage gap and the share of females in the labor force. Specifically, we interpolate data for any missing

Table C.1: Data Targets for Cross-Country Calibration

	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
GDP per Worker (rel. to US)	0.04	0.11	0.23	0.40	0.76
Non-Agric. GDP per Worker (rel. to US)	0.08	0.16	0.27	0.42	0.77
Female Non-employers	0.508	0.353	0.232	0.125	0.069
Female Employers	0.026	0.024	0.023	0.030	0.023
Male Non-employers	0.350	0.288	0.228	0.160	0.101
Male Employers	0.046	0.044	0.052	0.058	0.056
Gender Gaps in Non-mkt Time	2.91	2.57	2.31	2.09	1.83
Ratio of Mkt to Non-mkt Work, Males	3.92	4.00	4.07	4.12	4.19
Gender Wage Gap	0.22	0.02	0.06	0.09	0.16
Share of Females in Labor Force	0.48	0.40	0.40	0.38	0.45

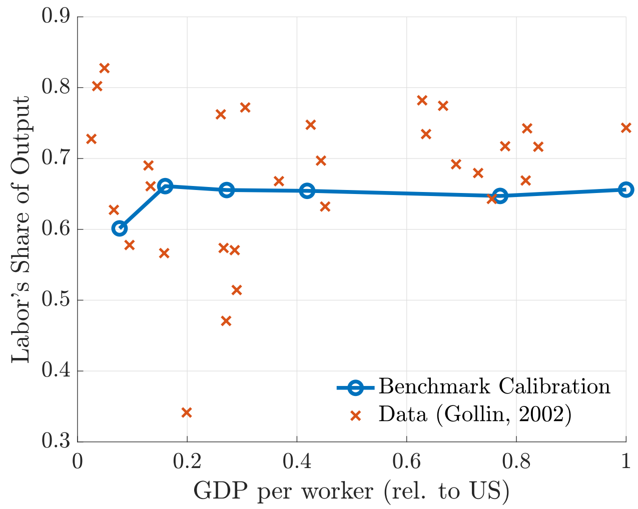
Notes: This table reports the data targets used for the cross-country calibration. Data on GDP per worker comes from the PWT 10.0. Data on occupation shares is described in Appendix B.3. Information on time use of employed individuals comes from a variety of time-use surveys and reports, as described in Appendix B.2. Information on the gender wage gap is computed using Indicator 8.5.1 from the UN Sustainable Development Goals, as reported by the ILO. The share of women in the labor force is also retrieved from the ILO.

countries assuming a linear relationship between (log) GDP per worker and the moment of interest and then take averages of countries over income quintiles. The last two rows of Table C.1 report these measures.

C.2 Labor's Share of Output

The cross-country calibration implies a negative relationship between development and α, the parameter governing labor-elasticity of output produced by employers. Consistent with Akcigit et al. (2021), the inferred values of α imply a weaker span of control of employers in poorer economies. However, changes in α also have implications for labor's share of output. Figure C.2 compares the labor share of output implied by our benchmark calibration and the data. Specifically, we compare the 'Adjustment 2' estimates of labor share reported in Gollin (2002) to the analogous shares implied by the model. This measure of the labor share adjusts for the incomes of entrepreneurs by explicitly including non-employer earnings and assuming that the profits of employers are split between their own earnings and earnings from capital in the same proportion as the output share paid to (hired) employees. The figure shows that the model outcomes and the data line up closely, suggesting that our inferred values of α are consistent with observed measures of the labor share observed across countries.

Figure C.2: Labor's Share of Output, Data and Model



Notes: Labor's share of output is calculated as the aggregate wage and (partial) entrepreneurial earnings, relative to GDP. This figure shows labor's share across countries from Gollin (2002) and that are implied by the model.

C.3 Alternative Calibration with $\bar{\zeta} = 1$

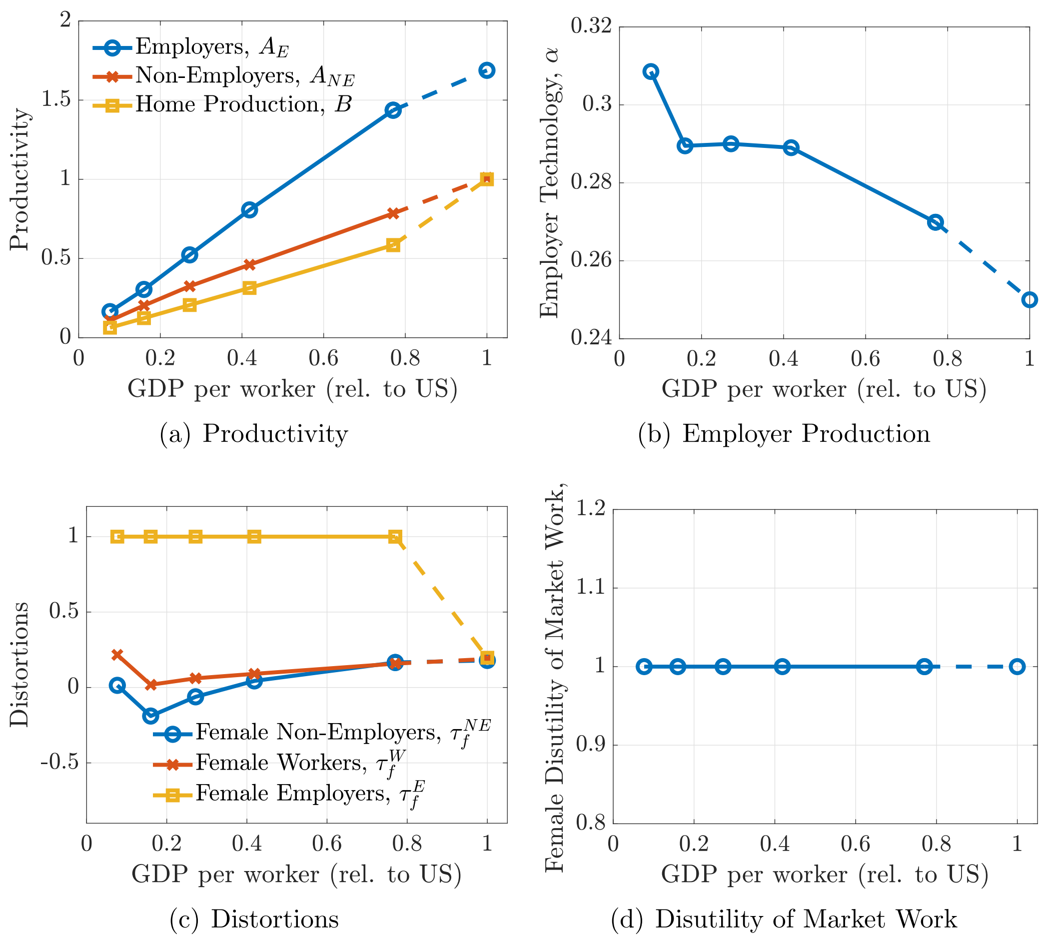
In this section, we examine the identification of our social norm parameter, $\bar{\zeta}$, in the cross-country calibration. We employ an alternative calibration strategy where social norms are fixed at the US level ($\bar{\zeta} = 1$). The aim is to examine if the model is able to match the data well without adjusting $\bar{\zeta}$.

We are left with seven parameters $(A_E, A_{NE}, B, \alpha, \tau_f^{NE}, \tau_f^{W}, \tau_f^{E})$ to match seven targets: (i) output per worker, (ii) share of male non-employer, (iii) male home-to-market time, (iv) share of male employer, (v) gender wage gap, (vi) share of female entrepreneurs (employer+non-employer) and (vii) gender time-use gap.

Figure C.3 displays the parameters calibrated to minimize the distance between data and model moments. While most parameters mirror the cross-country pattern seen in the benchmark calibration, the calibrated values of τ_f^E stand out as an exception. Specifically, given the absence of separate targets for female employers and non-employers, and the inability of the model to match time-use gender gap targets, our calibration results in values for τ_f^E that are as close as possible to 1 in order to get closer to the time-use targets (in the calibration we set an upper bound of 0.999).

Figure C.4 compares the data with the model moments. Note that Figure C.4 includes only six model moments since the gender wage gap is directly taken from the data, making the data and model moments inherently identical. Although this calibration can match most data moments, including GDP per worker, occupational shares, and the ratio of market to non-market hours for men, it fails to generate gender gaps in time use that align with the data. Particularly, the model moments show that the ratio of female to male non-market

Figure C.3: Calibrated Parameters, Alternative Calibration Strategy with $\bar{\zeta} = 1$



(a) Productivity (b) Employer Production

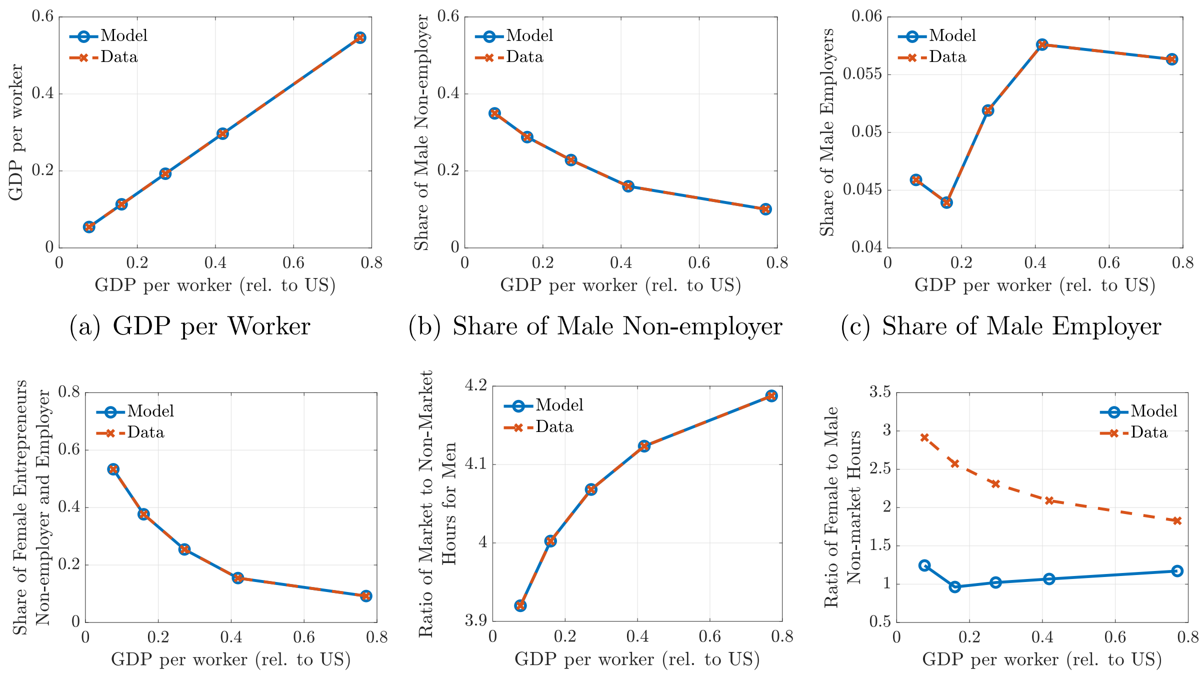
(c) Distortions (d) Disutility of Market Work

Notes: These figures report parameter values resulting from an alternative cross-country calibration, where social norm parameters are set to the US level ($\bar{\zeta} = 1$).

hours remains relatively constant across countries, with only a slight uptick for the lowest income group.

This exercise demonstrates that, when social norms are held constant across countries, the model is unable to match the cross-country variations in the gender time-use gap. However, it effectively matches other data moments, including gender-specific occupation shares. These findings underscore the importance of the social norm parameter, $\bar{\zeta}$, in matching time-use values, and the identification of this parameter is through the gender gap in time use.

Figure C.4: Data and Model Moments, Alternative Strategy with $\bar{\zeta} = 1$



(a) GDP per Worker

(b) Share of Male Non-employer

(c) Share of Male Employer

(d) Share of Female Entrepreneurs

(e) Market-to-Non-market Hours Ratio, Men

(f) Female-to-Male Non-market Hours Ratio

Notes: These figures present the six data moments targeted by the alternative calibration strategy, alongside their model-generated counterparts.

D Quantitative Analysis Appendix

In this section, we provide additional quantitative results and more details about our quantitative analysis.

D.1 Taste shocks

In the quantitative exercise, we introduce a taste shock to the three occupations: NE, W, and E. The taste for each occupation is represented by an i.i.d. draw from a Type-I extreme-value probability distribution, specifically the Gumbel distribution. The existing literature has employed similar taste shocks in various discrete choice models, as seen in McFadden (1978), Wolpin (1984), and Caliendo et al. (2019). In our paper, the introduction of this taste shock specifically aims to convexify the occupation choice and enhance algorithm convergence.

Consider the following value function of an occupation choice model:

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

Here, $\boldsymbol{\theta}$ represents the state variables vector, $U_i(\boldsymbol{\theta})$ is the deterministic value an agent obtains when selecting occupation i, and ϵ_i is an i.i.d. random variable that adheres to a Gumbel distribution with shape parameter λ and scale parameter ζ. Its CDF is given by $F(x) = \exp\left(-e^{-\left(\frac{x-\zeta}{\lambda}\right)}\right)$.

The probability of choosing occupation j can be expressed as

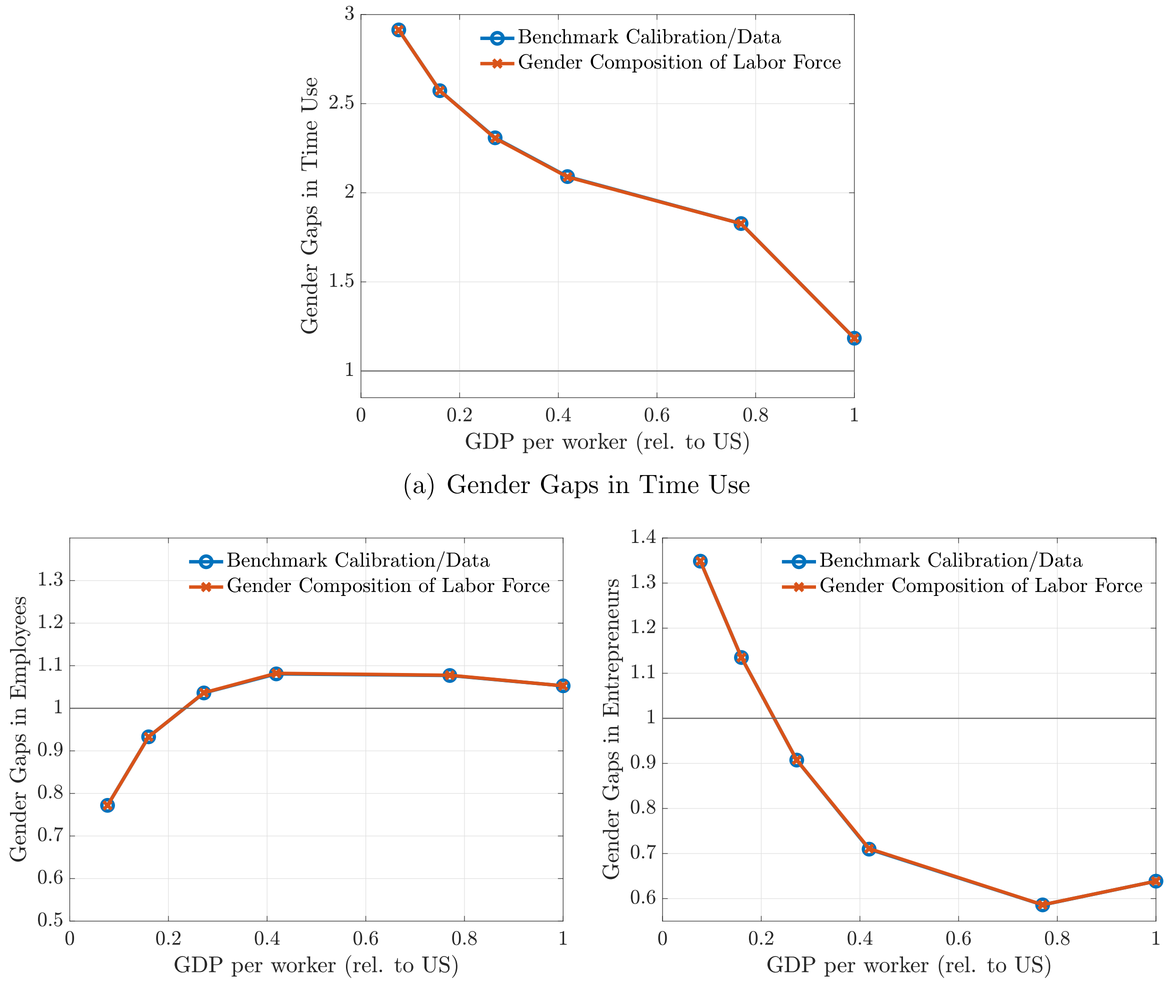
$$\mathbf{P}_j = \frac{e^{\frac{U_j(\boldsymbol{\theta})}{\lambda}}}{\sum_i e^{\frac{U_i(\boldsymbol{\theta})}{\lambda}}}.$$

This equation shows that the taste shock transitions the policy function of workers' occupation choices from a binary outcome (0 or 1) to a probability ranging from 0 to 1, aiding algorithm convergence. In our model, a very small λ is sufficient to significantly improve convergence, and we adopt a value $\lambda = 0.01$ throughout our quantitative analysis. A smaller λ implies a lower randomness of the utility, thereby allowing the deterministic component of the utility to play a more dominant role in choice probabilities.

D.2 The Role of Labor-Force Composition

In this section, we explore the impact of differences in the gender composition of the labor force across countries. This gender composition depends on gender-specific labor force participation rates that have been found to vary across countries. For instance, there is a well-documented u-shaped relationship between the level of development and female labor-force participation rates. Our groupings of countries by income quintile replicates the u-shaped pattern with around 48% of the labor force in economies in the first income quintile being female, 40% in the second and third, 38% in the fourth and 45% in the fifth quintile. The analogous share in the US is 43%.

Figure D.1: Gender Gaps and the Role of the Gender Composition of the Labor Force



(a) Gender Gaps in Time Use

(b) Gender Gaps in Employees

(c) Gender Gaps in Entrepreneurs

Notes: This figure compares gender gaps in non-market time (Panel a), the share of employees (Panel b), and the share of entrepreneurs (Panel c) in the benchmark calibration (∘ markers) and in an alternative parameterization that sets, for all countries, the share of female agents amongst total employment to the level observed in the US (× markers). The gender gap in time use is defined as the fraction of time spent in leisure and home production by women, relative to that by men. Gender gap in occupation shares is defined as the fraction of employed women in each occupation, relative to the share of men. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

As in our baseline quantitative exercise, to evaluate the impact of differences in the gender composition of the labor force, we compare outcomes in the benchmark calibration to an alternative parameterization that removes differences in gender composition and sets the share of females among total employment to be that observed in the US (43%).

Figure D.1 reports the results of this exercise for gender gaps in time use (Panel a) and gender gaps among employees and entrepreneurs (Panels b and c). The figure shows that removing differences in the share of females in the labor force has almost no impact on measures of gender gaps in time use and gender gaps in occupations, with the benchmark and counterfactual measures closely lining up to each other. This suggests that the difference in female labor-force participation accounts for very little of the gender gaps in time use and occupations that we explore in this paper.

We also consider the impact of the gender composition of the labor force on aggregate output per worker. Table D.1 reports the overall impact of removing cross-country differences in labor-force participation by gender on output per worker (first row), output produced by females (second row), and output produced by males (third row). As with gender gaps, the gender composition of the labor force has very little impact on these measures of output and accounts for a very small share of differences in output relative to the US. For instance, for economies in the third quintile, the gender composition of the labor force only accounts for 0.28% of the observed differences in output per worker relative to the US. The explanatory power of the gender composition is larger for economies in the fifth quintile as it explains 2.29% of differences in output per worker and as much as 3% of differences in the output produced by males. Having said this, gender composition has no impact on output produced in the poorest economies, which feature the largest differences in output relative to the US.

Table D.1: The Impact of Gender Composition of the Labor Force on Measures of Output

	Q1	Q2	Q3	Q4	Q5
Output per worker	0.00%	0.00%	0.30%	1.20%	2.40%
Output produced by females	0.00%	0.00%	0.20%	0.50%	0.90%
Output produced by males	0.00%	0.00%	0.40%	1.20%	3.20%

Notes: This table reports the overall impact of the gender composition of the labor force on non-agricultural output per worker (first row), output produced by females (second row), and output produced by males (third row). The overall impact is measured as the share of the benchmark level of differences between output in the US and in each quintile that can be accounted for by removing differences in the gender composition of the labor force. For instance, the first row shows that eliminating these differences shrinks the differences in output per worker between the US and the first (fifth) quintile economies by 0.00% (4.50%).

Taken together, these results suggest that cross-country differences in labor-force participation rates, which we take as given, have very little impact on gender gaps or aggregate outcomes, namely output.

D.3 Contributing Factors to Occupation Shares by Gender

Figure 10 in Section 6.2 reports *relative* levels of occupation shares (gender gaps), so does not illustrate which factors are quantitatively important for shaping the gender-specific levels of occupation shares. We do this in Figure D.2, which reports occupation shares separately for women and men. The figure shows that while aggregate factors have little impact on employee gender gaps, they are crucially important for quantitatively matching the observed levels of all occupation shares for each gender. Importantly, removing differences in aggregate factors moves occupation shares for women and men in a similar manner and thus have little impact on gender difference in occupation shares (as highlighted in Figure 10).

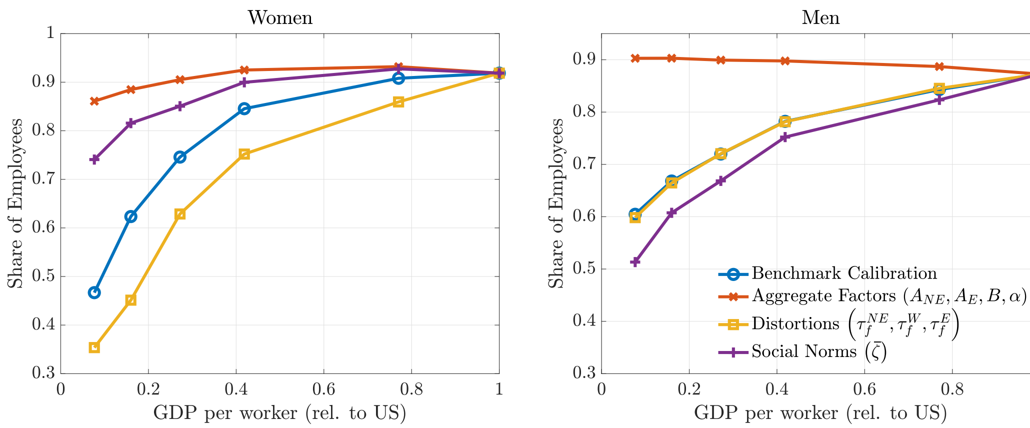
Removing cross-country differences in distortions faced by women has very little impact on the occupational choices of men (Panels b, d, and f). Relative to the benchmark, the share of employees declines only slightly in poorer quintiles, accompanying a modest increase in the shares of both non-employers and employers. Naturally, distortions have a much stronger impact on the occupation shares of women. Setting distortions in all quintiles to their US levels results in a decline in female employees and employers and a rise in non-employers, compared to the benchmark shares. Recall that the inferred distortions for female employers and employees are higher in the US for all but the first quintile economies, so it is intuitive that the shares of female employers and employees decline in this counterfactual. Similarly, for most quintiles, the inferred level of τ_f^{NE} is lower in the US, which, combined with the decline in employees and employers, leads to an increase in female non-employers relative to the benchmark. The stronger response from women drives the significant impact on gender gaps in occupation shares from eliminating distortions, in Section 6.2.

Eliminating differences in social norms impacts the occupational choices of both men and women. Relative to the benchmark, setting $\bar{\zeta}$ to 1 (the US level) across all country groups lowers the male employee share while raising the male non-employer and employer shares. On the other hand, the female employee and employer shares increase, while the female non-employer share significantly declines. Importantly, the share of employees and non-employers move in opposite directions for women and men and, therefore, have a large impact on the associated gender gaps in these occupations, while the employer shares move in the same direction, suggesting social norms cannot account for gender gaps in employer shares.

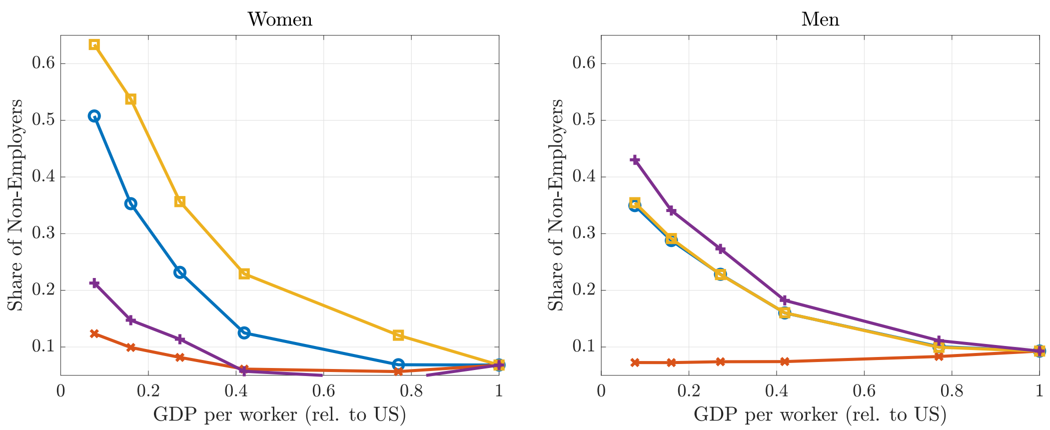
Intuitively, the higher $\bar{\zeta}$ in poorer economies encourages women to spend more time in non-market activity and less time active in the market. This lowers total labor supply in the market, which raises wages. For both men and women, the higher wage discourages employer entrepreneurship, while encouraging other employment. Further, the higher disutility of market work from social norms encourages women to shift their remaining time in the market away from employment and employer entrepreneurship, where the return to hours is linear, and towards non-employer entrepreneurship, where earnings are concave in hours. Figure D.2 shows that when $\bar{\zeta}$ is set to 1 across all countries, the share of female non-employers declines significantly while the share of female employees and employers increases. While differences in social norms effectively account for all cross-country differences in gender gaps in time use, distortions and social norms both play a significant role in accounting for gender gaps for occupational shares, and aggregate factors are crucial for matching levels of occupation shares by gender.

Figure D.3 summarizes the impact of aggregate factors, distortions, and social norms on overall entrepreneurship by plotting the share of entrepreneurs (employers and non-employers) in total employment in the benchmark and counterfactual calibrations. Consistent with Figure D.2, aggregate factors account for the bulk of the well-documented decline

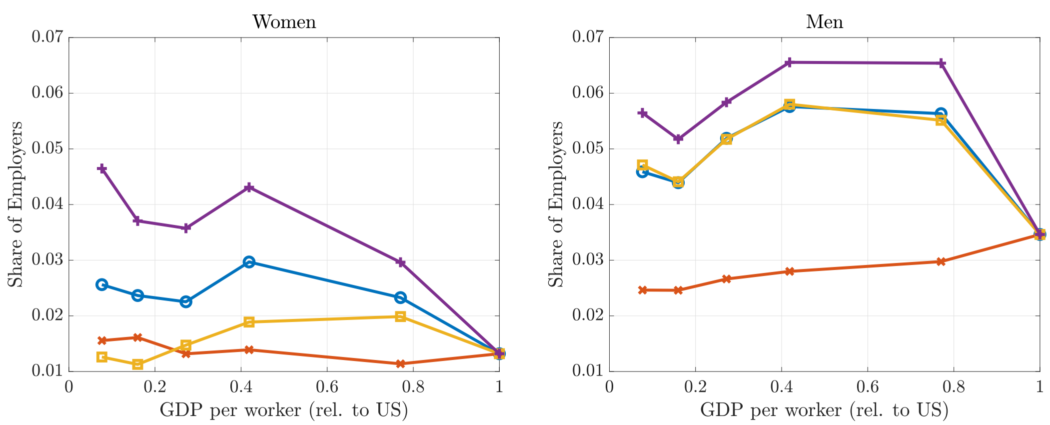
Figure D.2: Counterfactual Occupation Shares, by Gender



(a) Employees



(b) Non-employers

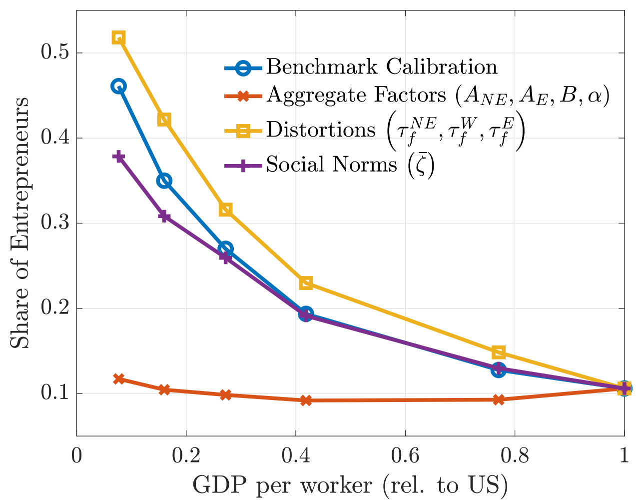


(c) Employers

Notes: This figure reports the employee, non-employer, and employer shares separately for women and men in the benchmark calibration and three counterfactual parameterizations. For each sex, the occupation-o share is defined as the share of people employed in occupation o. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

in entrepreneurship with development. Gender-specific distortions and social norms tend to have an offsetting impact on the share of entrepreneurs. Indeed, distortions decrease rates of entrepreneurship such that eliminating distortions across countries raises the share of entrepreneurs by 6 percentage points, from 0.46 to 0.52, for economies in the lowest income quintile. Social norms have the opposite impact, increasing overall rates of entrepreneurship. Our counterfactual suggests differences in social norms account for 23% of the observed difference in the share of entrepreneurs between the US and economies in the poorest income quintile.

Figure D.3: Counterfactual Shares of Entrepreneurs



Notes: This figure reports the share of entrepreneurs (non-employers and employers) in aggregate employment in the benchmark calibration and three counterfactual parameterizations. Each counterfactual substitutes US values for the identified set of parameters, while keeping all other parameters at benchmark values. The horizontal axis reports non-agricultural GDP per worker for each quintile group, relative to the US.

D.4 Decomposing the Impact of Social Norms on Output

Here we complement our discussion of the impact of social norms on aggregate output in Section 6.3 by isolating the contribution of selection. To do this, we decompose the overall impact of eliminating differences in social norms into a component that is due to changes in agents' occupational choices (the selection effect) and a residual component that captures all other policy functions such as hours worked (labor supply) and labor demand. The selection effect is measured as the difference between the benchmark (observed) level of output per worker and a measure of output per worker computed using policy functions from the benchmark economy but occupational choices from the counterfactual parameterization (where $\bar{\zeta} = 1$). The remaining impact on output per worker is due to changes in policy functions between the benchmark and counterfactual economies, which we attribute to a combination of the labor supply and demand effects.

Table D.2 reports the results of this decomposition exercise, with Panel A reporting the impact of eliminating differences in social norms on total output per worker. Panels B and

C repeat this exercise but focus instead on the impact on output produced by female and male entrepreneurs.

Table D.2: Decomposition of the Impact of Social Norms on Aggregate Output

Panel A: Aggregate Output per Worker

	Q1	Q2	Q3	Q4	Q5
Overall	0.039	0.074	0.119	0.187	0.723
Selection Effect	11%	10%	11%	12%	12%
Labor Supply and Demand Effects	89%	90%	89%	88%	88%

Panel B: Output Produced by Female Entrepreneurs

	Q1	Q2	Q3	Q4	Q5
Overall	0.110	0.228	0.325	0.490	0.929
Selection Effect	-6%	-4%	-3%	-1%	1%
Labor Supply and Demand Effects	106%	104%	103%	101%	99%

Panel C: Output Produced by Male Entrepreneurs

	Q1	Q2	Q3	Q4	Q5
Overall	0.016	0.027	0.051	0.077	0.501
Selection Effect	50%	42%	35%	33%	26%
Labor Supply and Demand Effects	50%	58%	65%	67%	74%

Notes: The table decomposes the impact of social norms, $\bar{\zeta}$, on non-agricultural output per worker, output produced by male entrepreneurs, and output produced by female entrepreneurs. The first row in each panel reports the fraction of output differences between the US and a country quintile accounted for by differences in social norms ($\bar{\zeta}$). Percentage values indicate the percentage of this fraction due to a particular effect.

Focusing first on Panel A, the first row reports the overall impact of social norms on aggregate output per worker, reported as the fraction of the difference in output between the US and a given quintile accounted for by differences in social norms, $\bar{\zeta}$. For instance, setting $\bar{\zeta} = 1$ shrinks the differences in output per worker between the US and the first (fifth) quintile economies by 3.9% (72%). Decomposing the impact of $\bar{\zeta}$ reveals that the more direct labor-supply and demand effects (third row) account for most (88–90%) of the overall impact of social norms across all income quintiles. However, there is still a significant role for changes in occupational choices, with the selection effect accounting for between 10 and 12% of the overall impact of $\bar{\zeta}$ on output per worker.

To understand the impact of $\bar{\zeta}$ on output per worker, it is useful to consider how the output produced by female and male entrepreneurs changes when removing differences in social norms. Panel C of Table D.2 shows that 1.6% (50%) of the difference in output produced by male entrepreneurs between the US and the first (fifth) quintile economies can be accounted for by differences in social norms. The selection effect lowers output produced by male entrepreneurs, accounting for between 26% and 50% of the overall impact of $\bar{\zeta}$. Though changes in $\bar{\zeta}$ do not directly impact male labor supply, higher wages push marginal male employers to become non-employers and marginal non-employers to become employees. Remaining employers hire fewer workers, further decreasing output. Overall, social norms discouraging female market work lead to a misallocation of *male* talent as men select into less productive occupations.

Panel B of Table D.2 shows that while the overall impact of $\bar{\zeta}$ on output produced by female entrepreneurs is larger than that for men, the selection effect for women contributes little to this. To understand this, recall that higher values of $\bar{\zeta}$ encourage both female employees and low-productivity employers to become non-employers, as the concave return to hours for non-employers becomes more important. But the decrease in employer output from fewer employers is offset by the increase in output from the higher number of non-employers, As a result, the selection effect only slightly raises the output of female entrepreneurs. Overall, the direct labor supply and demand effects, which lower market hours across all occupations, account for the entire impact of $\bar{\zeta}$ on the output of female entrepreneurs.

In summary, our results show that while social norms lower aggregate output primarily by lowering time spent in market work by women, their impact through selection still plays a significant role. Further, the contribution of selection works mostly through the misallocation of male talent as men select into less productive occupations.