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ABSTRACT

The extent to which women participate in the labor market varies greatly across the globe. If such differences reflect distortions that women face in accessing good jobs, they can reduce economic activity through a misallocation of talent. In this paper, we build on Hsieh et al. (2019) to provide a methodology to quantify these productivity consequences. The index we propose, the ”Global Gender Distortions Index (GGDI)”, measures the losses in aggregate productivity that gender-based misallocation imposes. Our index allows us to separately identify labor demand distortions (e.g., discrimination in hiring for formal jobs) from labor supply distortions (e.g., frictions that discourage women's labor force participation) and can be computed using data on labor income and job types. Our methodology also highlights an important distinction between welfare-relevant misallocation and the consequences on aggregate GDP if misallocation arises between market work and non-market activities. To showcase the versatility of our index, we analyze gender misallocation within countries over time, across countries over the development spectrum, and across local labor markets within countries. We find that misallocation is substantial and that demand distortions account for most of the productivity losses.

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1. INTRODUCTION

Labor market outcomes vary greatly along gender lines. Across most countries of the world, women have lower participation rates and earnings, are overrepresented in unpaid, informal jobs, and spend longer hours on home production and household chores. While lots of progress has been made among developed economies in the last decades, we are still far from equal representation along gender lines.

In this paper, we propose a methodology to measure the economic costs of such gender differences at the macroeconomic level. Building on the recent work by Hsieh et al. (2019), we show how labor income and job type data can be used to infer distortions that women face in the labor market and quantify their impact on aggregate productivity. We introduce the *"Global Gender Distortions Index (GGDI)"* a model-based, scalar measure of gender-based misallocation. The GGDI answers a simple question *"How much higher would economic activity be if women were to face the same playing field as men?"* Grounded in economic theory, the *GGDI* has a clear cardinal interpretation and allows for straightforward comparisons across countries and over time. This makes it a valuable tool for assessing the macroeconomic impact of policies promoting gender equality – or the lack thereof.

A key conceptual benefit of our approach is that it allows us to aggregate and meaningfully compare different dimensions of gender inequality. As highlighted above, gender differences are salient across a variety of measures such as labor force participation, income, and sorting across job types. Our index provides a natural way to combine these differences into a single scalar: the aggregate productivity consequences. Moreover, our methodology is suitable to both capture distortions on labor demand (e.g. firms discriminating against women and paying them less than their marginal product) and labor supply (e.g. the presence of institutions that discourage women to partake in full-time, market work). These distortions arguably coexist and interact in non-trivial ways, and our index captures both.

Another advantage of our index is its simplicity. Using data on labor income and job type choices for both men and women, the *GGDI* can be easily computed. Moreover, the definitions of job types can be flexibly adjusted to suit different contexts. In developed economies such as the US, Sweden, Canada or France, gender differences in access to high-skill occupations such as lawyers, doctors, and programmers might be particularly important. In developing economies, gender disparities are, for example, more pronounced in terms of job formality and payment. Our index is amenable to these contexts, providing researchers and policymakers with the flexibility to study whichever labor market dimension their application requires. As part of this paper, we also provide a full set of easy-to-use codes to compute the *GGDI*.

Finally, our analysis highlights an important distinction between welfare-relevant economic activity and measured GDP per capita. In the context of the study of gender gaps, home work plays an important role since large gender gaps in market work, are mirror images of large gender gaps in the provision of domestic services. While these activities generate economic output, they are not captured in measures of GDP according to existing national accounting rules.[1] The effect of distortions on aggregate GDP can therefore be larger than their effect on welfare-relevant economic activity if they prevent women to participate in market or unpaid work. Our methodology offers a straightforward-way to quantify such discrepancies and we do as part of our cross-country application. For the vast majority of countries we find that the effects of distortions on GDP *exceed* the one as implied by the GGDI. The reason is that the type of distortions we estimate, reduce female labor force participation and keep women in the home sector. Removing distortions therefore raises women's participation in market work and leads to a large increase in measured GDP.

These features of our index, of course, come with a cost. As mentioned above, the GGDI is a model-based measure and, as such, relies on our specific modeling assumptions and two structural parameters: the labor supply elasticity and the elasticity of occupational demand. We therefore view our index as a useful complement to existing, atheoretical measures of gender equality such as the World Bank "Women, Business and Law Index" (World Bank, 2024), that provides a de-jure measure of gender-based restrictions and regulations.

To showcase the applicability of our methodology in practice, we consider three applications. First, we compute the GGDI for selected countries over time. This exercise answers the question whether gender-based misallocation has shrunk over time and quantifies its productivity consequences. We find that misallocation indeed dropped markedly in the US between 1970 and 2020. At the same time, we also highlight that a fall in misallocation is by no means an automatic corollary of economic development. For example, despite its remarkable growth experience, we find no changes in gender-misallocation in India.

Second, we perform a cross-country exercise using microdata for 51 countries across the development spectrum from the Harmonized World Labor Force Survey (HWLFS). We find that gender-based misallocation is large and quantitatively important: in some countries productivity could be increased by 15%-20% if labor market distortions for women were abolished. We also find a systematic negative correlation between economic development (as measured by GDP per capita) and the *GGDI*, indicating that

[1] Some but only few countries report GDP figures based on the extended system of national accounts, which includes the valuation of unpaid domestic work. For instance, the Bureau of Economic Analysis provides data on Household Production Satellite Account, see Bridgman et al. (2022).

gender-based misallocation is more prevalent in developing countries. At the same time, there is substantial variation in the GGDI across countries at similar levels of development, indicating the importance of differences in culture and institutions as predictors of gender-misallocation. We also document that, reassuringly, the cross-country variation in the *GGDI* is highly correlated with the World Bank's "Women, Business and Law Index" (WBL) suggesting that our model-based measure of de-facto misallocation is broadly consistent with the de-jure measure of the WBL.

Finally, we conduct a within-country analysis by applying our methodology to the experience of Indian states in 2018. As with the cross-country data, we document large potential gains from reducing gender-based misallocation, which are negatively correlated with state-level GDP per capita. While the poorest states in India could increase GDP by up to 15%, we estimate that richer states only "lose" 5% of GDP through gender-based misallocation.

In terms of the relative importance between demand and supply distortions, our results suggest a larger role for distortions operating on the demand side. Interestingly, we find important complementarities: dismantling only demand distortions generates welfare gains that are quite close to the full gains when reducing both demand and supply distortions. The intuition for why this is the case is reminiscent of the "theory of the second best". Introducing a distortion in an efficient economy, does not have any welfare consequence to first order, because all marginal products are equalized in the initial allocation. Vice versa, starting from an allocation where supply distortions already generate a wedge between marginal products, a reallocation of resources induced by falling demand distortions can have large welfare consequences. We think that this result is important for policy-makers: to the extent that demand distortions are easier amenable through policies (e.g., because supply distortions reflect social norms), policies aimed at demand distortions might be able to capture a large share of the welfare benefits of reduced gender misallocation.

Related Literature Our paper builds on a large literature documenting the pervasiveness of gender gaps, in particular in developing countries (Jayachandran, 2015; Fletcher et al., 2019; Jayachandran, 2021; Duflo, 2012; Klasen, 2019; Agte et al., 2024; Gottlieb et al., 2024). A particular focus of that literature has been the participation gap and how female labor force participation varies with the course of economic development. Goldin (1994) uses cross-country data to highlight a U-shaped pattern in female labor force participation. Relatedly, Ngai et al. (2024) documents a U-shaped trend in women's hours worked in the US throughout the 20th century.

A recent literature highlights that such differences in labor market outcomes are the result of gender-specific frictions. Hsieh et al. (2019) document that such forms of misallocation are important and that improvements in allocative efficiency account for a sizable share of US economic growth in the post-war period. Chiplunkar and Kleineberg (2022) use cross-country data and show that frictions are important to explain gender gaps even when other determinants of gender-specific labor demand, such as structural change, are taken into account. For the case of India, Chiplunkar and Goldberg (2021) focus on female entrepreneurship and emphasize - consistent with the results of this paper - the importance of simultaneously addressing supply and demand-side distortions. An alternative measure of the aggregate implications of gender gaps is proposed in Pennings (2022). Relative to us, Pennings (2022) focuses on the gap between male and female employment as a share of total employment, as opposed to the (mis)allocation of talent across different activities.

The paper by Hsieh et al. (2019) is particularly related because we closely build on their methodology. In essence, our model is a simplified version of theirs in that we abstract from human capital accumulation. In doing so, our model is easier to implement and requires less data than they do. We hope that this increases the applicability of our method for researchers and policy-makers in the future.

A complementary literature highlights that gender gaps can also be the result of structural change (Ngai and Petrongolo, 2017; Rendall, 2018; Ngai et al., 2024), evolving social norms (Fernández, 2013; Fogli and Veldkamp, 2011; Jayachandran, 2015; Olivetti et al., 2024), technological change in household appliances (Greenwood et al., 2005), or the organization of production (Bandiera et al., 2022). Gottlieb et al. (2024) combine time-use data from 50 countries with a macroeconomic model of household time use and show that gender norms, more than home technology or income, drive the division of market and domestic work. For our analysis we take technologies and institutions as given when conducting our counterfactuals.

In our applications, we rely heavily on the cross-country data from the Harmonized World Labor Force Survey (HWLFS). This micro dataset has the benefit that it provides harmonized data on worker characteristics, employment and wages for a broad set of countries across the development spectrum. The latter information is particularly important for us because information on labor income is crucial to achieve identification in our model. These data, together with harmonized data on time-use, have also been used in Gottlieb et al. (2024), who document cross-country patterns of the gender division of market, domestic and care work.

Organization of the paper The remainder of the paper is organized as follows. Section 2 introduces our data. Section 3 empirically documents the pervasiveness of gender gaps around the world. Section 4 contains the theory and develops our index, the *GGDI*. There we also outline the distinction between welfare-relevant productivity and measured GDP. Section 5 discusses the identification of distortions, both on the supply and the demand side. Section 6 contains our quantitative results. In Section 7, we relate our results to the WBL Index. Section 8 considers the robustness of our results with respect to our parametric assumptions. Section 9 concludes. An appendix contains details of the data and technical results. There we also include a full replication package, including MATLAB codes for other researchers to use.

2. Data, Measurement and Evidence

For this paper, we construct two datasets: a country level dataset with 51 countries and a Indian States dataset in 2018. We use these data to compute the GGDI index for many countries, its evolution over time, and across Indian states.

2.1 Data sources

Our cross-country dataset draws from the Harmonized World Labor Force Survey (HWLFS), a large scale micro-dataset of labor force and household surveys, that harmonizes thousands of surveys from any countries across the globe.[2] For the purpose of this paper, we use surveys of the HWLFS that are (i) nationally representative, (ii) provide information on wages and hours worked, and (iii) on the industry of the main job for all workers.[3] See Appendix Section B-1.1 for more details.

For our application on Indian states, we rely on the publicly available data from Periodic Labour Force Survey (PLFS). The PLFS is a nationally representative household survey and covers about 100,000 households in India—see Appendix Section B-1.1 for more details.

Finally, to compute the GGDI along the development spectrum, we use data in GDP per capita at the country-level (measured in PPP) from the Penn World Tables (Feenstra et al., 2015).

2.2 Measurement

For all the data sources we mention, we use the micro data to measure a set of labor market and education outcomes for men and women. Also, we use the wage data to measure gender gaps in labor income. Throughout, we focus on individuals that are between 25 and 60 years old.

Job type. In our theory, individuals' labor market decisions are modeled as discrete choices: each individual chooses their preferred job type. Given our focus on developing countries, we focus on four mutually exclusive activities: wage jobs, unpaid work,

[2] It encompasses previously harmonized cross-country datasets such as EU-SILC (Survey Income and Living Conditions) dataset or the IPUMS amongst others.

[3] Some surveys provide industry and occupation codes for wage workers only.

self-employment and not employed.[4]

Following the International Conference for Labor Statisticians (ICLS), self-employment includes unpaid workers, own-account workers and employers. Unpaid workers work for the family farm or business and are unpaid because they don't derive income or profits from their activity.[5] They are employed since their work contributes to the production of goods and market services that fall within the production boundary as defined by the System of National Accounts (SNA).[6] We choose to make a distinction between self-employment and unpaid work, recognizing the significant gender implications of each. Therefore, when referring to self-employed workers, we specifically mean own-account workers and employers.

We use data on the main job to assign workers to these three job types. We refer to individuals who don't have a job as not-employed, and consider that they contribute to home production by providing (unpaid) care and domestic services.

Education. To measure educational attainment, we use data on years of schooling and highest completed degree. If information on years of schooling is not available, we impute years of education based on the completed degree using country level information on the education system. For example, if an individual in the US reports high-school degree as the highest completed degree, we consider that they have 12 years of schooling.

Labor income. To measure the return to different activities, we use data on labor earnings. We construct weekly income by combining information on hours worked and reported labor income. We prioritize data on actual hours worked; when unavailable, we use usual hours worked as a substitute. Reported earnings for wage workers are adjusted based on their reporting period and combined with hours data to compute weekly income.

While this measurement is conceptually straightforward for individuals with wage employment, we also need to assign economic returns to the other three activities. Ideally, we would directly measure the monetary value of providing labor as an unpaid family worker or in home-production. Because this information is, by construction, not observed, we impute the labor income for individuals that are not working for a wage based on their individual and job characteristics. In doing so, we follow the previous work of Young (1995); Gollin (2002) and Lagakos (2016), who uses similar imputation

[4]In principle, our theory is amenable to also allow for part-time work whereby individuals spend part of their time in wage work and part of their time in subsistence agriculture. If one could empirically measure the employment share and implied wage income in such activities, our theory would extend in a straight-forward way to this case.

[5]See paragraph 9b of the 13th ICLS (ILO, 1982) for the official definition of unpaid workers.

[6]The economic value of unpaid work is included in GDP through imputation methods, typically by using market equivalent prices or wages (see chapters 6 and 7 of United Nations (2008)).

methods to estimate labor earnings in economies with large self-employment shares.

More specifically, as we outline in more detail in Appendix Section B-1.2, we impute labor income for the self-employed, unpaid, and non-employed population, by running regressions of overall earnings of wage workers on their gender, age, marital status, education, and sector of employment.[7] We then use the estimated parameters to predict counterfactual earnings for non-wage workers.[8]

Having to rely on such imputed earnings is, of course, not particularly attractive. However, given the ubiquity of self-employment in developing countries, one cannot proceed without estimates of the economic returns to these activities. By associating earnings of self-employed or unpaid workers with the typical earnings an observationally equivalent individual receives in the market sector, we might understate the importance of misallocation, if frictions drive a wedge between market earnings and the opportunity costs of non-wage work. Improving the measurement of such opportunity costs is, in our opinion, an important avenue of future research.

2.3 Datasets

We measure the above mentioned outcomes for 581 surveys. We combine these data into three datasets, a cross-country dataset, a growth experience dataset and a state-level dataset for India in 2018. See Table B-I in the Appendix for a full list of surveys.

Cross-country dataset. The dataset provides data for 51 countries at all stages of development. For each country, we use data from the year 2015 or the nearest available year. The countries in our sample cover 69 percent of the World Population in 2015. The poorest country in our sample is Niger in 2005 with an GDP per capita level of USD 624 . The richest country in our sample is Luxembourg in 2005 with an GDP per capita level of USD 97973 .[9]

Growth experience dataset. In addition, we used our dataset to study the evolution of gender gaps in market work for a broad set of countries. This dataset is an unbalanced panel at the country level, and the country with the longest time series in our sample is the USA (1965-2022). For each country in this dataset, we have on average 12 years of data.

[7]For individuals that are not employed, we assign agriculture as their sector of employment. In doing so, we implicitly assume that agricultural work acts as the closest measure for the opportunity cost of being out of the labor force.

[8]We rely on this approach also for the self-employed, because self-employment earnings are recorded inconsistently across countries, making cross-country harmonization particularly challenging. Even when such data are available, additional measurement issues arise in both high- and low-income settings (Bhandari et al., 2024; Gollin, 2002). Given these limitations, we rely on wage data, which provide more comparable information across countries.

[9]We use the GDP per capita numbers provided by the Penn World Tables (Feenstra et al., 2015).

Indian states dataset. We apply the same approach to measure these outcomes for 27 states in India using the Periodic Labour Force Survey (PLFS) of 2018-19.

3. Global Gender Gaps

We use these datasets to document gender gaps in employment, labor income and educational attainment, both across countries at different income levels, as well as over time.

3.1 Gender Gaps across Countries

We first describe gender gaps across countries around the year 2015 using the "Cross-country dataset". We focus on differences in the type of jobs that men and women perform, differences in education, and differences in wage income.

Gender Work Gaps. We begin by documenting cross-country patterns in the nature of work conducted by men and women. To highlight differences across the development path, we aggregate the 51 countries in our dataset into three income groups: low (below \$10,000 of GDPpc), middle (between \$10,000 and \$30,000), and high (above \$30,000). Table B-IV in the Appendix contains a list of all countries in the respective groups. Table 1 contains the results.

The data reveals significant gender disparities in employment patterns, particularly in different types of work. Across all countries, wage work is the most common form of employment, but men have consistently higher participation rates in wage work than women. In low-income countries, only 16% of women work for a wage, compared to 37% of men. This gap is much narrower in high-income countries, where 61% of women and 69% of men work for a wage. This pattern suggests that high country income levels are associated with more opportunities for women to enter formal wage employment.

It is well known that in low-income countries, self-employment is the most prevalent form of work. Table 1 shows that this is particularly true for men, where 42% of them are self-employed in contrast to 28% of women. Comparing self-employment rates of men and women across country income groups reveals that the gender gap in self-employment rates is larger in high-income (2.2 = 0.13/0.06) than in low-income countries (1.5=0.42/0.28). Additionally, these data shows a large gender gap in unpaid work, with women being more likely to pursue this type of work across all country income groups. This is particularly true in low-income countries, where 15% of women do unpaid work, compared to only 5% of men. Arguably, this reflects barriers that limit women's access to income-generating opportunities, even when they are employed.

Table 1 further shows that the labor force participation varies greatly by gender and

Activity		Country Income Group Low	Middle	High	All
Wage work	Men	0.37	0.56	0.69	0.53
	Women	0.16	0.41	0.61	0.38
Self-employed	Men	0.42	0.23	0.13	0.27
	Women	0.28	0.12	0.06	0.16
Unpaid work	Men	0.05	0.03	0.00	0.03
	Women	0.15	0.06	0.01	0.08
Not employed	Men	0.16	0.19	0.18	0.17
	Women	0.41	0.41	0.32	0.38
Number of countries		18	19	14	51

TABLE 1: Activities of Men and Women by country income group.

Notes. This table reports the average share of men and women that are 25 to 60 and pursue either of the four activities. The income brackets we use to classify countries into income groups are [0, 10,000), [10,000, 30,000), [30,000, ∞), which we refer to as "Low income", "Middle income", and "High income". We assign to each country an income group based on the GDP per capita (PPP) reported by PWT (Feenstra et al., 2015) for that particular year.

income level. Across all countries, the share of women not working (38%) is twice higher than that of men (18%) (column 4). This gender gap varies strongly across country income levels. While in low-income countries, the share of women not working is 2.6 (= 0.41/0.16) times higher than for men, the gender gap is 1.9 (=0.32/0.17) in high-income countries. This suggests that while high-income countries are associated with a smaller gender gap in labor force participation, gender gaps persist in high-income countries.

Gender Education Gaps. A key determinant of both labor supply and demand is worker skill. The observed differences in the gender division of work and their allocation between work types may reflect gender gaps in educational attainment. A first-order measure to study the role of skills in explaining gender work gaps is the gender gap in years of schooling in each type of work.

We measure the gender education gap, the ratio of women's years of schooling relative to men, for individuals in each activity. We report the average of these ratios for each country income group in Table 2. The data suggest that the gender education gap across work types varies considerably in low-income countries. While women that work for a wage have similar education levels than men, women working in self-employment or as unpaid worker have a level of schooling that is 20 p.p. and 43 p.p lower than men, respectively. In middle-income countries, the gender education gaps are smaller. Men and women who are self-employment have on average the same level of education, while women working for a wage have 9 p.p. more years of schooling. In high-income countries, the gender education gap is larger than one and of similar magnitude across all activities, meaning that, across the board, women have higher levels of schooling than men. The fact that in high-income countries, fewer women work although they have higher levels of schooling is suggestive evidence for barriers to women's market work.

	Country Income Group			
Activity	Low	Middle	High	All
Wage work	1.00	1.09	1.02	1.04
Self-employed	0.80	1.00	1.04	0.94
Unpaid work	0.57	0.72		0.61
Not employed	0.73	0.96	1.01	0.89
Number of countries	18	19	14	51

TABLE 2: GENDER EDUCATION GAPS BY COUNTRY INCOME GROUP.

Notes. This table reports the average ratio of women and men's years of education for each country income group, and across all countries. Note that the in high-income countries, we don't report the gender education gap, since there are very few (if any) unpaid workers in those countries. The income brackets we use to classify countries into income groups are [0, 10,000), [10,000, 30,000), [30,000, ∞), which we refer to as "Low income", "Middle income", and "High income". We assign to each country an income group based on the GDP per capita (PPP) reported by PWT (Feenstra et al., 2015) for that particular year.

Gender Income Gaps. Finally, we use our micro data on wage income to measure gender income gaps in each activity. Recall that the gender income gap is the ratio of the weekly labor income of women to that of men working for a wage. Weekly income being the product of the hourly wage and weekly hours worked, a low gender income gap can be due to a gender wage gap or a gender gap in weekly hours worked. Figure B-1 in the Appendix displays gender income gaps for all countries in our sample. We find that the gender income gap does not vary much across countries. In low-income countries, women who work for a wage earn 35 p.p. less than men, while it amounts to 20 p.p. and 30 p.p. in middle- and high-income countries, respectively.

3.2 Gender Gaps over time

In Section 3.1 we analyzed the patterns of gender gaps across countries. We now examine gender gaps over time. To do so, we regress each gender gap on a time trend and country fixed effects. Specifically, let y_{ct} denote a particular gender gap, we consider a regression of the form

$$y_{ct} = \delta_c + \beta \times t + u_{ct}. \tag{1}$$

Note that we run (1) separately for each gender gap y. The coefficient β, reported in Table 3, therefore, reflects the average annual change in gender gaps within countries in our sample.

In the first column of Table 3, we focus gender differences in each activity. Our data suggests that over time, the share of women working for a wage or as self-employed has increased relative to men. On average, the gender gap in self-employment and wage work increased every year by 0.4 and 0.34 p.p relative to men. Since men are overrepresented in wage work and self-employment across countries, these increases for women imply a narrowing of gender gaps in these activities. Taken together these numbers suggest that over the course of a decade, the share of women worker for a wage or in self-employment increases by 3.5 and 4.1 p.p. relative to men, respectively. With regard to unpaid work and not working (row 3 and 4 in Table 3), the estimated coefficients are negative, suggesting that the share of women in these activities decreased relative to men. Since women are historically overrepresented in these activities, the gender gap in unpaid work and non-work have declined. The coefficient of the gender gap in not-employed is precisely estimated, and suggests that the ratio of non-working women relative to men has gone down by 3.1 percentage point per year relative to men. Note that since the gender gaps in non-employment and unpaid work are above one changes in the ratio cannot be directly interpreted as changes in relative group shares.

	Gender Gap		
	Activity	Education	Income
Wage work	0.0034 (0.0011)	0.0021 (0.0014)	0.0052 (0.0010)
Self-employed	0.0040 (0.0008)	0.0041 (0.0011)	
Unpaid work	-0.1898 (0.1070)	0.0029 (0.0013)	
Not employed	-0.0310 (0.0092)	0.0021 (0.0011)	

TABLE 3: GENDER GAPS OVER TIME.

Notes. This table presents coefficients from linear regressions of gender gaps on year and country fixed effects. Standard errors, reported in parentheses, are clustered at the country level. For example, the coefficient in the top-left cell indicates that, on average, the gender gap increased by 0.003 per year. A positive coefficient suggests women's increasing relative participation in that activity. However, it does not necessarily imply convergence toward gender parity, as this depends on whether women were initially underrepresented. Each regression is based on 530 observations, corresponding to an average of 10 observations per country.

Column 2 in Table 3 reports the estimated changes in the gender education gap by activity. Across all activities, the gender education gap has declined over time, as women's years of schooling have increased relative to men's. Since historically, women had fewer years of schooling, the gender gap in education narrowed over time. This is true for all women independently of their activity. Our findings suggest that the closure of the gender education gap has been particularly pronounced in the self-employed population, where on average women's years of schooling increased by 0.41 percentage point every year relative to men.

Finally, as seen in column 3 of Table 3, we find that the gender income gap has shrunk over time. The coefficient 0.0052 indicates that women's labor income has increased by 0.52 percentage points per year relative to men. Based on this trend, a country with an initial gender income gap of 0.79, the average gap we measure, would reach income parity in approximately 48 years.

4. Theory: The Global Gender Distortions Index

Motivated by these gendered differences in labor market outcomes, we now develop our methodology to quantify their consequences for aggregate productivity. The main result of this section is the "Global Gender Distortions Index (GGDI)", an easy-to-compute, scalar measure of the gender-based misallocation.

To construct the GGDI, we build heavily on the work by Hsieh et al. (2019). We consider a simplified version of their framework where we have two groups, men and women, and four types of jobs: wage work, self-employment, unpaid work and home production. Implicitly, we assume that not-employed individuals do home production. These choices, in particular the distinction between wage work on the one hand and unpaid work and self-employment on the other hand reflect that reality of most developing countries, where such informal work arrangements are the norm rather than the exception. An important implication, which is absent in Hsieh et al. (2019), is that our model features a distinction between market-based GDP and overall welfare-relevant economic activity; non-market home-production is not part of GDP, but generates economic output.

In our model, men and women differ in three dimensions. First, women might face a *demand distortion*, which we model as an exogenous tax wedge on their labor earnings. Second, women might face a *supply distortion*, whereby choosing a particular job reduces their utility. We refer to such gender-specific utility differences as "distortions", because our premise is that intrinsic preferences do not vary by gender, but that the utility derived from a specific employment choice may depend on existing norms and institutions that are beyond the control of individuals. Third, men and women can differ in their job-specific *human capital*, which we, for simplicity, take as exogenous. Hence, relative to Hsieh et al. (2019) we abstract from dynamic choices of human capital and only consider a static model of labor supply.

4.1 Labor Supply: Distortions vs Skills

We model the utility of an individual i of group $g = m, w$, i.e. man or woman, choosing a job j as

$$\ln U^i_{jg} = \ln C^i_{jg} + \ln z_{jg}. \tag{2}$$

Here C_{jg} denotes consumption of individual i and z_{jg} the utility of working in job j. Note that the utility consequences of working in a particular job are identical across individuals of a particular group. These utility consequences can be interpreted as job-specific amenities—that is, non-monetary attributes such as job-flexibility or the work environment. By contrast, consumption is individual-specific, because it is linked directly to total earnings, which in turn is given by individual's human capital, the equilibrium wage rate (per efficiency unit), and the prevailing demand distortion by the budget constraint

$$C^i_{jg} = (1 - \tau_{jg})\, w_j\, h_{jg}\, \epsilon^i_j. \tag{3}$$

Here w_j is the prevailing wage rate in job type j, h_{jg} denotes the job-specific human capital of an individual of group g, and τ_{jg} parametrizes the *demand distortion*. Finally, ϵ^i_j is an individual-specific, idiosyncratic productivity draw for job j that allows individuals to differ in their comparative and absolute advantage in different job types.

Substituting (3) into (2), an individual's utility is given by

$$U^i_{jg} = \overline{w}_{jg}\, \epsilon^i_j$$

where

$$\overline{w}_{jg} \equiv w_j(1 - \tau_{jg}) h_{jg} z_{jg}. \tag{4}$$

Hence, $\overline{w}_{jg}$ summarizes the systematic attractiveness of a job j for group g. It depends on skill prices w_j, labor demand distortions τ_{jg}, the average human capital endowment h_{jg}, and labor supply distortions z_{jg}. Note that skill prices w_j per efficiency unit of labor are common across groups g and determined in equilibrium.

Individuals choose a single job j to maximize U_{jg}. For tractability, we assume independent Fréchet-distributed ϵ^i_j :[10]

$$F(\epsilon^i_j) = e^{-(\epsilon^i_j)^{-\theta}}.$$

Standard arguments then allow us derive our first result:

Proposition 1. *Let p_{jg} denote the fraction of people from group g who choose job j and let*

[10]The fact that this distribution has the same mean for all groups g and jobs j is without loss of generality, because we allow for unrestricted heterogeneity in group-job specific human capital h_{jg}.

$\overline{wage}_{jg}$ denote the geometric average of earnings in job j by group g. Then

$$p_{jg} = \frac{\overline{w}_{jg}^{\theta}}{\sum_j \overline{w}_{jg}^{\theta}} \tag{5}$$

$$\overline{wage}_{jg} = \Gamma_\theta \left(\sum_j \overline{w}_{jg}^{\theta}\right)^{\frac{1}{\theta}} z_{jg}^{-1}. \tag{6}$$

where $\overline{w}_{jg}$ is given in (4) and $\Gamma_\theta \equiv \Gamma\left(1-\frac{1}{\theta}\right)$ is the gamma function.

Equations (5) and (6) are at the heart of our identification strategy. Equation (5) highlights that job-specific employment shares, p_{jg}, reflect a job's *relative attractiveness* $\overline{w}_{jg}$. This attractiveness in turn is fully determined by market prices and human capital endowments on the one hand and distortions (either from the supply or the demand side) on the other hand. In this environment, if a particular group g has a high employment share in job type j, it could be that (i) their human capital h_{jg} is large, (ii) skill prices w_j are high, (iii) distortions τ_{jg} are low, or (iv) the utility of working in this job, z_{jg}, is high. Using data on individuals' job choices alone is therefore not sufficient to disentangle these different objects.

Equation (6) highlights the information that is contained in group g's earnings and consumption. First of all, for a given group g, the *only* variation of average earnings across jobs is due to differences in supply distortions z_{jg}: The lower z_{jg}, the higher the average wage in job j, because earnings play the role of a *compensating differential*. By contrast, if z_{jg} was equalized across jobs, average earnings would also be equalized across jobs, i.e. neither differences in human capital, nor differences in skill prices or demand distortions, affect average earnings across jobs.

This stark result, which is due to the selection of individuals into different jobs, is a particular property of our assumptions of ϵ_j^i to be Fréchet distributed. However, the underlying intuition is more general: if there was a large demand distortion in job j for group g or if their systematic human capital h_{jg} was low, less people of group g would work in that job. As a consequence, the selection of individuals *into* that job would improve. This form of selection *increases* the average talent in job j and *decreases* the average talent in all other jobs. With the Fréchet distribution, these effects exactly cancel out, leaving overall earnings unaffected. The variation in earnings across different jobs alone is thus a poor measure of distortions that individuals face. It is only in conjunction with information on "quantities" (that is the job-specific employment shares by by group g) that the presence and the size of demand distortions can be identified.

To see this more directly, use equation (6) to substitute $\overline{\text{wage}}_{jg}$ for the labor supply distortions z_{jg} in $\overline{w}_{jg}$ (see equation (4)). We can then express the share of women in job j *relative* to men as

$$\frac{p_{jw}}{p_{jm}} = \left(\frac{1-\tau_{jw}}{1-\tau_{jm}}\right)^{\theta} \times \left(\frac{h_{jw}}{h_{jm}}\right)^{\theta} \times \left(\frac{\overline{\text{wage}}_{jw}}{\overline{\text{wage}}_{jm}}\right)^{-\theta}. \tag{7}$$

Equation (7) highlights that relative employment shares in different jobs are driven by three considerations: women can be underrepresented in a particular activity j if (i) they face a higher labor demand distortion $(\tau_{jw} > \tau_{jm})$, (ii) they have a lower human capital endowment $(h_{jw} < h_{jm})$, and (iii) their average earnings are relatively *high* ($\overline{\text{wage}}_{jw} > \overline{\text{wage}}_{jm}$). This last effect of the wage operates through the labor supply distortion as high earnings reflect a compensating differential.

Under our assumptions on labor supply, we can also derive a closed form expression for the aggregate supply of efficiency units in activity j, H_j. In particular, H_j is given by

$$H_j = \sum_g L_g \, p_{jg}^{\frac{\theta-1}{\theta}} \, h_{jg} \Gamma_\theta, \tag{8}$$

where L_g denotes the aggregate population of group g. The term $p_{jg}^{\frac{\theta-1}{\theta}}$ accounts for selection: while overall human capital supply is *increasing* in p_{jg}, the elasticity is $\frac{\theta-1}{\theta} < 1$, reflecting the fact that average efficiency declines as more people sort into a particular job type. Finally, average human h_{jg} is, of course, a determinant of overall labor supply because it governs the average amount of efficiency units of members of group g in activity j.

Equation (8) fully determines the labor supply side. In particular, the expression for p_{jg} in (5) shows that H_j can be computed directly as a function of $\{\overline{w}_{jg}\}$. And given that everything in $\overline{w}_{jg}$ except for the skill prices w_j are exogenous, (8) determines labor supply as a function of $\{w_j\}$.

4.2 Labor Demand: Technology

To close the model in general equilibrium, we need to specify overall labor demand. To do so, we follow again Hsieh et al. (2019) and assume a representative "firm" that produces final output according to

$$Y = \left(\sum_j (A_j H_j)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{9}$$

Hence, overall economic output is a CES aggregator of the output produced in different activities and such activities differ by their total factor productivity, A_j.[11]

The reason we put "firm" in quotes is that the representation in (9) is, of course, an abstraction. As highlighted above, in our context individuals' labor supply takes place both in the market and in informal activities outside of formal market arrangements. This distinction becomes important when thinking about the relationship between welfare-relevant economic output Y in (9) and measured GDP, which only pertains to activities tied to the production of goods and services exchanged on the market. A richer model would explicitly model the distinction between goods and market services (produced according to (9)) and home services, such as care and domestic work, which enter utility directly and, by construction, are not exchanged on the market. For simplicity, in this paper, we assumed that overall labor demand for different activities stems from the representation in (9).

4.3 Equilibrium

A competitive equilibrium consists of a sequence of occupational choices, total efficiency units of labor in each group H_{jg}, final output Y, and a wage per efficiency unit w_j in each activity such that

1. Each individual's job choice maximizes utility taking as given skill prices w_j, job-specific human capital h_{jg}, demand distortions τ_{jg}, and supply distortions z_{jg},
2. The set of skill prices w_j clear each occupational labor market,
3. Total output is given by the production function in equation (9).

4.4 The Global Gender Distortion Index (GGDI)

Given this environment, we can now formally define the *Global Gender Distortion Index (GGDI)*. From above we can compute overall economic output as a function of supply and demand distortions (for all activities j) in each country c and year t:

$$Y_{ct}^{D} \equiv Y_{ct}\left(\left[\tau_{jgct}, z_{jgct}\right]_j\right),$$

where $Y_{ct}\left(\left[\tau_{jgct}, z_{jgct}\right]_j\right)$ denotes equilibrium output in the presence of *distortions*, hence the superscript D.

By contrast, economic output in the absence of distortions is given by

$$Y_{ct}^{E} \equiv Y_{ct}\left(\left[\tau_{jwct} = \tau_{jmct} = 0, z_{jwct} = z_{jmct} = 1\right]_j\right),$$

[11] Because the aggregator Y in (9) has constant returns to scale, differences in population size (across countries) or population growth (over time) do not affect any allocations and keep income per capita unchanged.

where we use the mnemonic E to indicate that it is the equilibrium output under *gender equality*. Hence, gender equality requires that women do not face any demand distortions relative to men $\left(\tau_{jwct} = \tau_{jmct} = 0\right)$ and that the utility of men and women to enter a particular activity is equalized $\left(z_{jwct} = z_{jmct} = 1\right)$.

The *Global Gender Distortion Index* is then given by

$$GGDI_{ct} \equiv \ln\left(Y_{ct}^{D} / Y_{ct}^{E}\right). \tag{10}$$

In words, our index is given by the *percentage loss in overall output due to gender-based distortions*: the higher the $GGDI$, the higher the extent of gender-based talent misallocation. Because our model is efficient in the absence of distortions, $Y_{ct}^{E} \geq Y_{ct}^{D}$, which implies that $GGDI_{ct} < 0$.

4.5 GDP versus Welfare-Relevant Output

The *GGDI* captures changes in total economic activity due to gender-based distortions, including home production. Since home production, i.e. the production of domestic services, such as household chores and care work for household members, falls outside the production boundary defined by the System of National Accounts (SNA 2008), the *GGDI* does *not* amount to changes in GDP. By incorporating home production, the GGDI also accounts for how supply and demand distortions influence the economy at large. In doing so, it provides a welfare-relevant measure of gender-based misallocation.

While total economic activity is, by construction, higher than measured GDP, the relationship between the GGDI and GDP changes due to gender-based distortions is unclear. It will depend on the relative magnitudes of supply and demand gender distortions across different activities. If, for example, women only faced demand distortions for wage jobs, a fall in distortions would both raise overall output (and hence the *GGDI*) and market GDP because more women would join the market sector. By contrast, if women were to only face distortions to provide home work, falling distortions would reduce misallocation, increase the *GGDI*, but market GDP could, in principle, contract if women leave the market sector and reallocation toward the home-sector.

To highlight the quantitative importance of the differences between the *GGDI* and induced changes in GDP, we will compute both in our model. Letting w_j denote the equilibrium skill price in activity j, GDP is given by the implicit total factor payments in all activities of employed workers. In the context of our model, wage work, self-employment, and unpaid work are labor inputs to measured GDP. Unpaid work, despite the fact that it does not entail a monetary compensation, should be part of the GDP, while home production should not. In practice, efforts are taken to adjust official GDP measurement for the existence of unpaid work.[12] By contrast, while home production, i.e. domestic services, generates economic value its output is not captured by GDP.

Given a system of distortions $\{\tau_{jgct}, z_{jgct}\}$, GDP can therefore be computed as

$$Y_{ct}^{GDP}(\{\tau_{jgct}, z_{jgct}\}) \equiv \sum_{j\in W,SE,U} \sum_{g\in w,m} w_j H_{jg} = Y_{ct}^{D} - \sum_{g\in w,m} w_h H_{hg}, \tag{11}$$

where the first summation sums over wage (W), self-employment (SE), and unpaid (U) activities, and the second equality highlights that measured GDP is equal to overall, economic output minus the aggregate output of the home sector.

Given this definition of GDP, in the same vain like we compute the *GGDI*, we compute the change in GDP if distortions were abolished as

$$\Delta_{ct}^{GDP} \equiv \ln\left(\frac{Y_{ct}^{GDP}(\{\tau_{jgct}, z_{jgct}\})}{Y_{ct}^{GDP}(\{\tau_{jgct}=0, z_{jgct}=1\})}\right). \tag{12}$$

In words, Δ_{ct}^{GDP} reflects the percentage change in aggregate GDP that would occur if all distortions, including the ones for the home sector, were to be eliminated.

5. Identification: Measuring Misallocation

To compute the *GGDI* in (10) and Δ^{GDP} in (12), we need to (i) measure the prevailing demand and supply distortions, (ii) compute Y_{ct}^{D} and Y_{ct}^{GDP}, and then (iii) compute counterfactual output Y_{ct}^{E} and GDP if these distortions were absent. To do so, one also needs to identify the job-specific demand shifters A_j in the aggregate production function (9) and the two structural parameters, the elasticity of substitution σ and the dispersion of idiosyncratic skills θ.

In this section, we describe these steps in detail. In Section 5.1 we focus on the estimation of demand distortions τ_{jg} and supply distortions z_{jg} taking as given the structural parameters σ and θ. In Section 5.2 we turn to estimation of A_j and the parameters σ and θ.

Because the estimation of distortions and demand-shifters is done at the country-year level, for notational convenience we suppress the subscripts for country (c) and year (t).

[12] Subsistence agriculture and unpaid family labor contributing to market output more broadly fall within the production boundary as defined by the System of National Accounts. The economic value of these activities is included in GDP through imputation methods, typically by using market equivalent prices or wages (see chapters 6 and 7 of United Nations (2008)).

5.1 Measuring Labor Market Distortions

To measure the extent of misallocation we utilize our empirical measures of job-specific employment shares p_{jg}, average earnings $\overline{\text{wage}}_{jg}$, and average human capital h_{jg}. For the latter we follow our approach in Section 2 and take human capital as reflecting educational attainment. To translate educational attainment to human capital, we follow the usual approach of Mincerian returns, where we assign an annual return to schooling of 8% - see Appendix Section B-2 for details. Furthermore, we assume that the parameters θ and σ are known. Given these objects, we can infer supply and demand distortions directly from the data.

Demand Distortions τ_{jg} To identify demand distortions, note first that all allocations only depend on the *relative* distortions between men and women. Hence, without loss of generality, we take men's labor market choices to not be affected by demand distortions, that is

$$\tau_{jm} \equiv 0 \quad \text{for all } j.$$

The demand distortions for women, τ_{jw} can then be directly recovered from equation (7):

$$\frac{1}{1-\tau_{jw}} = \left(\frac{p_{jw}}{p_{jm}}\right)^{-1/\theta} \times \left(\frac{h_{jw}}{h_{jm}}\right) \times \left(\frac{\overline{\text{wage}}_{jw}}{\overline{\text{wage}}_{jm}}\right)^{-1}. \tag{13}$$

Holding relative earnings and human capital fixed, a *lower* relative employment share of women in activity j is indicative of *higher* distortions. Intuitively, a low employment share means that the few women that choose job j are very favorably selected. To rationalize this positive selection with a constant level relative earnings requires a large demand distortion. A similar intuition holds true for relative human capital: holding employment shares and earnings constant, a higher relative human capital goes hand in hand with higher distortions.

Equation (13) is the first key equation for our measurement. As explained in detail in Section 2, our microdata from the HWLFS allows us to consistently measure employment shares p_{jg} and human capital attainment h_{jg}. Furthermore, our imputation procedure for hourly wages also allows to compute average earnings $\overline{\text{wage}}_{jg}$ for all activities j and groups g. Given an estimate of θ, these data directly imply a level of τ_{jw} from (13).

While, in principle, we could use (13) for all demand distortions τ_{jw}, we do *not* use it for the home sector. The reason is that we do not feel comfortable in leaning too heavily on the relative home-sectors earnings for men and women, as these are both imputed using the observed earnings in agriculture. We therefore assume that women also do not face demand distortions in the home-sector, that is

$$\tau_{hw} = 0.$$

To ensure that our data is consistent with this assumption, we thus do not rely on measured women's home-sector earnings but require it to be consistent with equation (13):

$$\overline{\text{wage}}_{hw} = \left(\frac{p_{hw}}{p_{hm}}\right)^{-1/\theta} \times \left(\frac{h_{hw}}{h_{hm}}\right) \times \overline{\text{wage}}_{hm}. \tag{14}$$

Given the imputed earnings for men in the home-sector and the observed employment shares and human capital, we compute $\overline{\text{wage}}_{hw}$ according to (14).

Supply Distortions z_{jg} To identify z_{jg}, we use the expression for relative earnings from equation (6). Note first that we can normalize the utility of one activity for each group because the expression for p_{jg} and $\overline{wage}_{jg}$ in Proposition 1 are homogeneous of degree zero: multiplying all z_{jg} by a constant for a given group g keeps p_{jg} and $\overline{wage}_{jg}$ unchanged. We therefore impose the normalization

$$z_{hw} = z_{hm} = 1.$$

Hence, for both groups, z_{jg} denotes group g's utility in activity j *relative* to working at home. Equation (6) therefore implies that

$$z_{jg} = \left(\frac{\overline{wage}_{jg}}{\overline{wage}_{hg}}\right)^{-1} \tag{15}$$

The *higher* average earnings in job *j relative to home production*, the *lower* the utility of choosing that activity has to be. This again highlights that earnings-premia play the role of compensating differentials for supply distortions. If, for example, traditional gender roles impose a high disutility for men to provide home-produced services, such as cooking, cleaning, or childcare, their utility in all other activities would be *high*. Equation (15) then implies that their earnings in non-home activities would be *relatively low*.

5.2 Other Parameters

The dispersion of the talent distribution θ Equations (13) and (15) are contingents on estimates of the parameter θ, which determines the degree of selection, or alternatively the labor supply elasticity across activities. Hsieh et al. (2019) estimate $\theta = 1.52$ after adjusting for the elasticity of human capital w.r.t. human capital expenditure. We follow their estimates and assume $\theta = 1.5$. Furthermore, we assume θ to be constant across countries and time. In Section 8 below we document that our results are robust to different choices of θ.

Job-specific demand shifters $\{A_j\}$ and the elasticity of substitution σ So far, we only exploited implications of the labor supply side. To compute counterfactual allocations, which are required to compute the *GGDI* and the impact of distortions on GDP, we need to specify the demand side of the economy, that is, we need to identify $\{A_j\}$ and σ in (9). For the elasticity of substitution σ we follow our strategy for θ and set it exogenously. We assume $\sigma = 3$ and show in Section 8 how our results change with σ.

To estimate A_j, we use the equilibrium restrictions of our model together with information on aggregate GDP. As we discuss in detail in see Section A-1 in the Appendix this is sufficient to fully calibrate A_j. Intuitively, there is a unique vector of *relative* demand shifters A_j, that ensures that the observed relative employment shares and average earnings are consistent with labor market clearing. To identify the *level* of A_j, we require our model to be consistent with the observed level of real GDP across countries and time.

6. The Economic Losses of Gender Misallocation

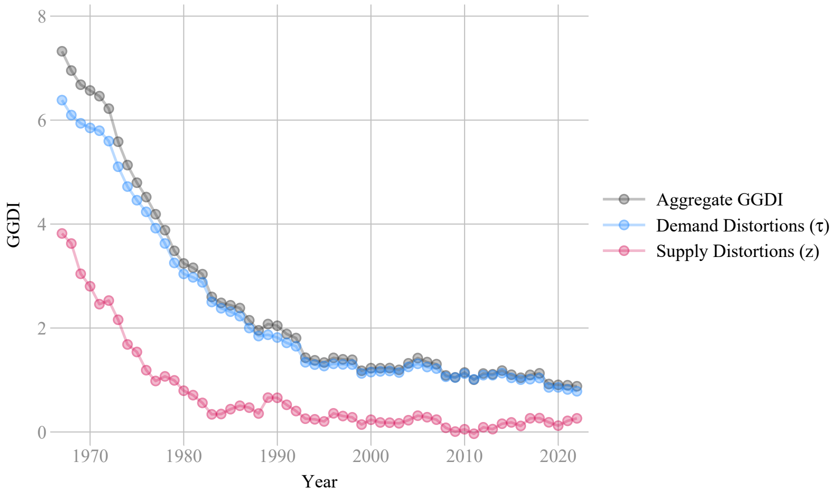
We now turn to our quantitative results. Given the estimated distortions, $[\tau_{jgct}, z_{jgct}]$, job-specific demand shifters $[A_{jct}]$, and the two parameters σ and θ we can compute equilibrium output, Y^D_{ct}, counterfactual output, Y^E_{ct}, and the $GGID_{ct}$ according to (10). Similarly, we can use equation (11) to compute GDP in both the distorted and undistorted economy and equation (12) to compute the implied change in GDP. In Section A-2 in the Appendix we outline the exact algorithm, including a sample code, to compute these objects.

A key benefit of our methodology is its versatility. Given the necessary data on earnings and employment shares, the *GGDI* can be computed over time for a given country, across countries at a given point in time, or even across local labor markets within a country. In Section 6.1 we focus on time-variation of the *GGDI* within countries. This exercise highlights whether gender misallocation changes over time and quantifies the aggregate consequences of such changes. In Section 6.2 we turn to the cross-country variation and compare estimates of the *GGDI* across countries at different stages of development. Finally, in Section 6.3 we turn to a within-country exercise and compute the *GGDI* across Indian states.

6.1 The *GGDI* Within Countries

We start by documenting changes in the *GGDI* over time within countries. As a starting point, we focus on the US. In Figure 1 we plot the *GGDI* for the US between

FIGURE 1: THE GGDI IN THE US: 1970-2020



Notes: The figure shows the GGDI for the US for the period 1967-2022. Grey points show increase in output when both labor demand and labor supply distortions are removed. Red points show the increase in output when only labor supply distortions are removed. Blue points show increase in output when only labor demand distortions are removed.

1970 and 2020 as the dark solid line. The extent to which economic growth in the US was associated with reductions in gender-based misallocation is vividly apparent. In 1970, differences in distortions between men and women reduced overall GDP by about 7%. Since then, misallocation has continuously declined. Today, we estimate that misallocation losses in the US are below 2% of annual GDP.

In the other two lines in Figure 1 we highlight the relative role of demand distortions (in blue) and supply distortions (in red). More specifically, we compute the $GGDI$ in (10) when we either *only* set demand distortions to zero (keeping supply distortions at their estimated level) or only reduce supply distortions (keeping demand distortions fixed). Figure 1 shows that reductions in misallocation at both margins contributed economic growth. Quantitatively, we find demand distortions to be more important.

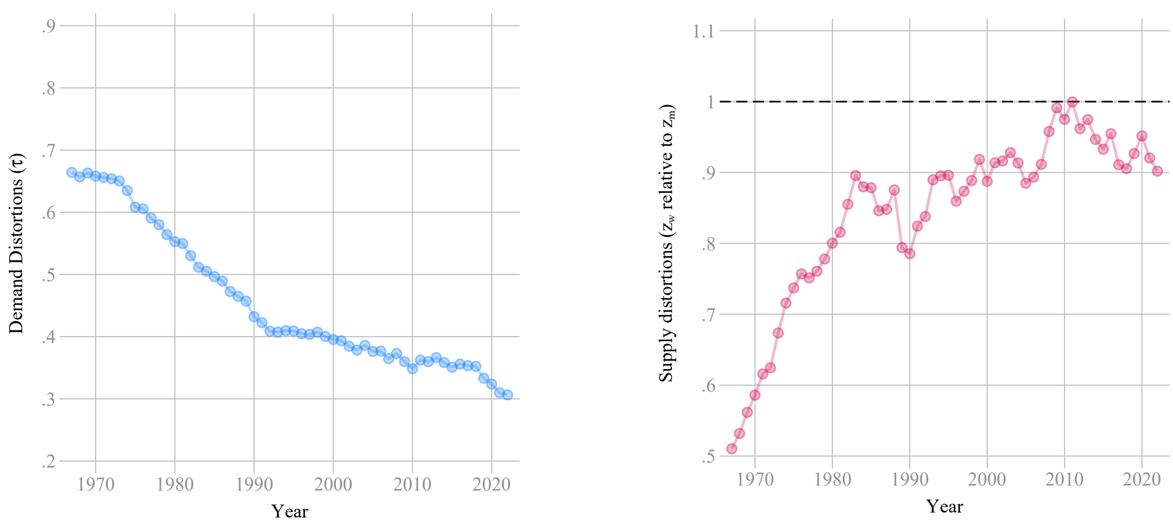
Interestingly, note that the $GGDI$ is not "additive" in these two components: the overall gains from reducing *both* demand and supply distortions is smaller then the sum of the individual part. This reflects the fact that both margins are complementary. Intuitively, if the labor market is subject to demand distortions which raise the marginal product of labor of women relative to men, supply distortions that keep women out of the labor force have a first order impact on overall GDP. This complementarity is important when thinking about policies. If, for example, demand distortions are amenable to particular policies such as anti-discrimination laws or other regulations, these policies have large effects on allocative efficiency in an environment where supply distortions are also present.

In Figure 2 we display the evolution of our estimated demand and supply distortions. For parsimony, we focus on the distortions for wage work.[13] In the left panel, we plot the time paths for τ_{wt}. Recall that τ measures the implicit tax a women has to pay relative to a men when working for a wage or in self-employment. In 1970, we estimate a tax of almost 70%, indicating that women only kept 30 cents of a dollar. This observations reflect the fact that few women worked but that the wage premium of these very positively selected women was not particularly large. Over time, this implicit tax declined substantively. Today, we estimate a tax of about 30%.

In the right panel we plot the path of relative supply distortions in the wage sector, that is z_{ww}/z_{wm}. Recall that we normalized the utility of home work to unity for both men and women. Hence, z_{ww}/z_{wm} measures the utility loss of women, relative to home production, when working, *relative* to men. A number of 0.7 means that the typical woman has to be paid 30% more than a man to compensate her for the higher utility in home production. Figure 2 shows this relative disutility of market work declined sharply. In 1970, women faced a utility loss of 50%. 50 years later, we estimate that overall supply distortions are very small, below 10%. This pattern reflects the well-known fact of rising female labor force participation, especially between 1970 and 2000.

FIGURE 2: DEMAND AND SUPPLY DISTORTIONS IN THE US

(A) Demand Distortions (B) Supply Distortions

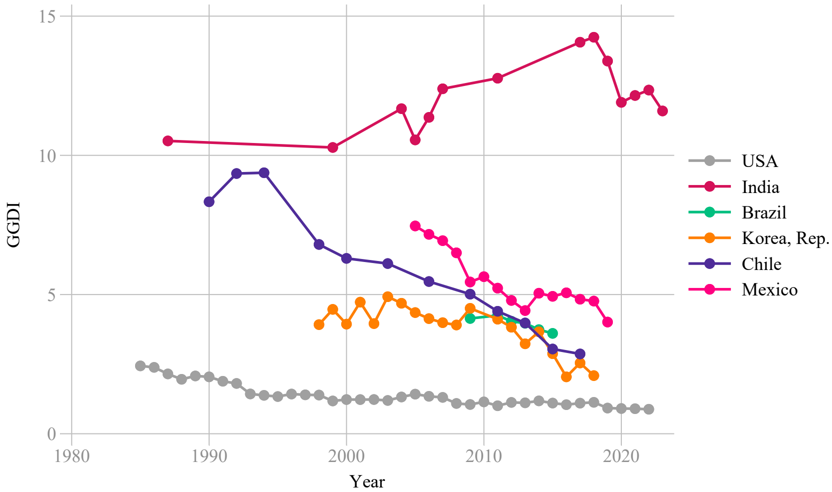


Notes: Panel A plots demand distortions for market sector (τ) for USA for the period 1967-2022. Panel B plots relative disutility of working in market sector ($\frac{z_w}{z_m}$) for USA for the period 1967.

Figures 1 and 2 paint an optimistic picture in that they suggest that rising gender equality might be a natural corollary of economic growth. This view, however, is only

[13]The patterns for self-employment are quite similar. And unpaid work does not play a large quantitative role in the US economy.

FIGURE 3: THE GGDI IN DIFFERENT COUNTRIES



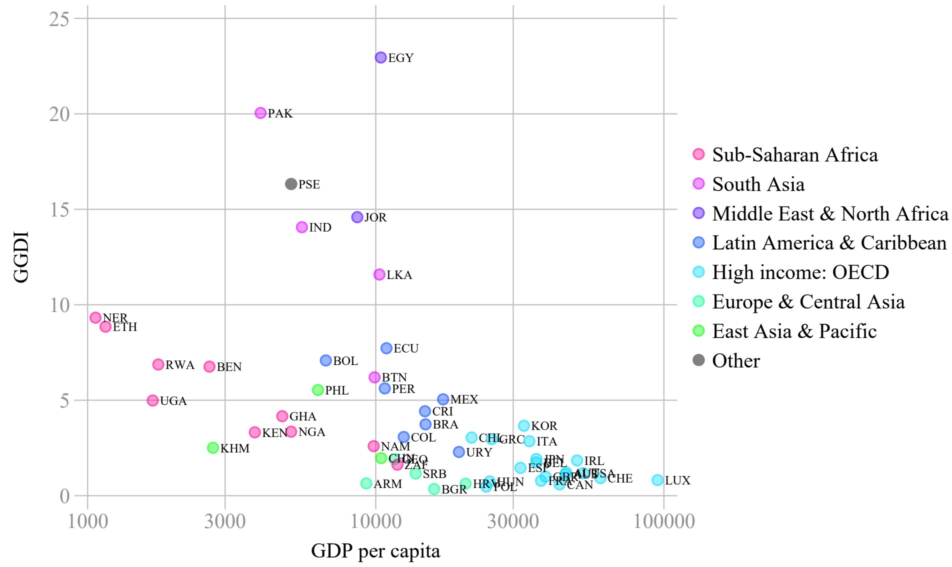
partly borne out in the data.

To analyze the relationship between the $GGDI$ and economic development more systematically, we now compute the $GGDI$ for four countries along the whole development spectrum: Brazil, India, South Korea, and Chile. For comparison, we also include the US experience that we already depicted in Figure 1. To see that the systematic decline of gender-based misallocation along the development path observed in the US is *not* a natural law, consider Figure 3, where we depict the evolution of the GGDI in different countries. Two patterns are apparent. First of all, relative to the US, gender-based misallocation in much higher in India, Chile, Brazil, and South Korea. While these level differences might reflect differences in economic development (i.e. among the countries depicted in Figure 3, the US is the richest), the $GGDI$ is not declining in all countries, despite the fact that these countries grew substantially. While allocative efficiency in Chile declined from about 8% in the early 1990s to around 3% in 2018, misallocation along gender lines, if anything, increased in India.

6.2 The $GGDI$ Across Countries

We now move beyond the "case-studies" shown in Figure 3 and study the relationship between gender misallocation and economic development more systematically. Figure 4 plots the GGDI for all countries against log GDP per capita. While there is a systematic negative relationship, the cross-country variation holding economic development constant (that is for a given GDP pc) is also very large. While GDP per capita in Egypt could be increased by 24% if gender-distortions were abolished, this number falls to 5% in Peru, even though Peru is only slightly richer. This highlights the importance of country-specific characteristics in shaping gender-based misallocation and the potential

FIGURE 4: THE GGDI AND ECONOMIC DEVELOPMENT



Notes: The figure plots GGDI for all country observations near the year 2014 against their GDP per capita. The points are colored according to the continent they belong to. GGDI measure the increase in output from removal of labor demand and labor supply distortions.

productivity gains of leveling the playing field.

To see this underlying heterogeneity more directly, in Figure 4 we also indicate the broad geographical regions of the different economies. The pattern is stark. Countries in the Middle East and North Africa experience annual productivity losses of about 20% through gender-based misallocation in the labor market. Countries in Sub-Saharan Africa or Latin America have substantially smaller losses given their low GDP per capita. Interestingly, the relationship between gender-based misallocation and GDP pc capita is systematically negative within region but much smaller than the unconditional relationship.

Despite these differences for the overall $GGDI$, the *relative* importance between demand and supply distortions is in fact rather similar to the case of the US. As we have shown in Figure 1 above, demand distortions played a much more important role for the over $GGDI$ in the US as opposed to supply distortions. In Figure B-3 in the Appendix, we show that the same is true along the development spectrum: independent of countries' GDP pc, we find that demand distortions have a bigger on aggregate productivity than supply distortions.

The economic gains of falling misallocation are achieved through reallocation whereby men and women resort in the labor market. To illustrate one margin of such reallocation, in Figure 5 we plot the changes in female labor force participation that were to ensue if demand distortions (blue markers) and supply distortions (red markers) were dismantled. Figure 5 shows distortions are major drags on female labor force participation. Demand distortions reduce the private benefits of working and therefore contribute to keep women out of the labor force. If women were not disadvantaged by the implicit taxes that we estimate, labor force participation would increase by 40% in India, by 20% in Brazil, and by 10% in the US. Hence, a key reason why demand distortions lower overall productivity is that they keep talented women out of the labor force altogether.

For comparison, Figure 5 also displays the change in female labor force participation (FLFP) in the absence of supply distortions. Again, we see that the presence of supply distortions is an important aspect of low participation. However, their overall impact of smaller than for demand distortions, especially in rich countries. For the US, for example, supply distortions only account for a small share of female participation.[14]

The reason why falling supply distortions have a smaller impact on overall productivity as measured by the *GGDI* despite the fact that they trigger large changes in labor market participation is again the complementarity between supply and demand distortions. In the presence of demand distortions on the labor market, changes in the relative utility of market work might trigger large changes in participation, but only smaller changes in overall productivity, precisely because women are still subject to distortionary taxes that affects their relative marginal product across different activities.

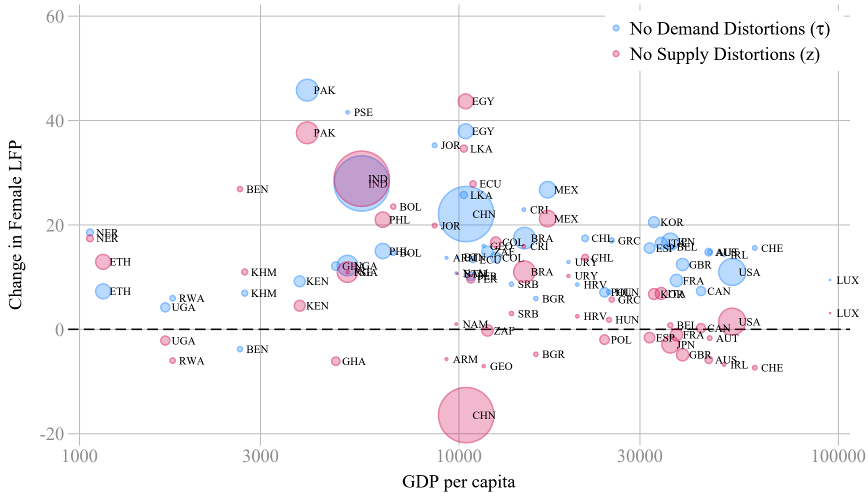
GGDI versus GDP

The fact that distortions affect women's labor supply between market activities and home production highlights that they reduce both overall, welfare-relevant productivity and measured GDP. However, as discussed in Section 4.5, the economic gains in total economic activity captured by the *GGDI* are distinct from those measured by GDP.

Whether the *GGDI* exceeds the impact on GDP, Δ^{GDP}, is theoretically ambiguous. If distortions keep a large number women in home activities and dismantling distortions encourages more market participation, the impact on GDP tends to be higher because the opportunity cost of market work, the forgone output of home production, is not counted. At the same time, in equilibrium, an increase in female labor supply crowds out male employment and male participation in home production increases. This form of reallocation will reduce GDP substantially but have smaller effects on the *GGDI*.

[14] Note that, for a small number of countries, labor supply distortions *increase* FLFP. Recall that we infer the labor supply distortions for a given group using the wage in job type *j relative* to wage in the home sector, which we proxy as agricultural earnings, adjusted for individual characteristics. For some countries, this "earnings premium" is *higher* for men compared to women, leading us to infer higher higher labor supply distortions in the home sector for men. And because our counterfactual equalizes distortions across groups, the home sector becomes *relatively* more attractive for women.

FIGURE 5: Distortions and Female Labor Force Participation



Notes: The figure shows the change in female labor force participation (FLFP) by removing all demand and supply distortions, respectively, for all countries, plotted against their GDP per capita. The size of points are proportional to the country's population. The sample for the plot is all country observations near the year 2014.

Hence, the effect on distortions on both the GGDI and overall GDP is, in the end, a quantitative question.

In Figure 6, we report the GGDI and the change in measured in GDP in response to a dismantling of both demand and supply distortions. We find that the GGDI (shown in green) and the change in GDP (shown in yellow) are highly correlated and that the change in GDP is *higher* than the change in the GGDI for all countries in our sample. This pattern stems from the fact that distortions keep many women in home activities. If such distortions were abolished, overall efficiency would increase but measured GDP would increase even more.[15]

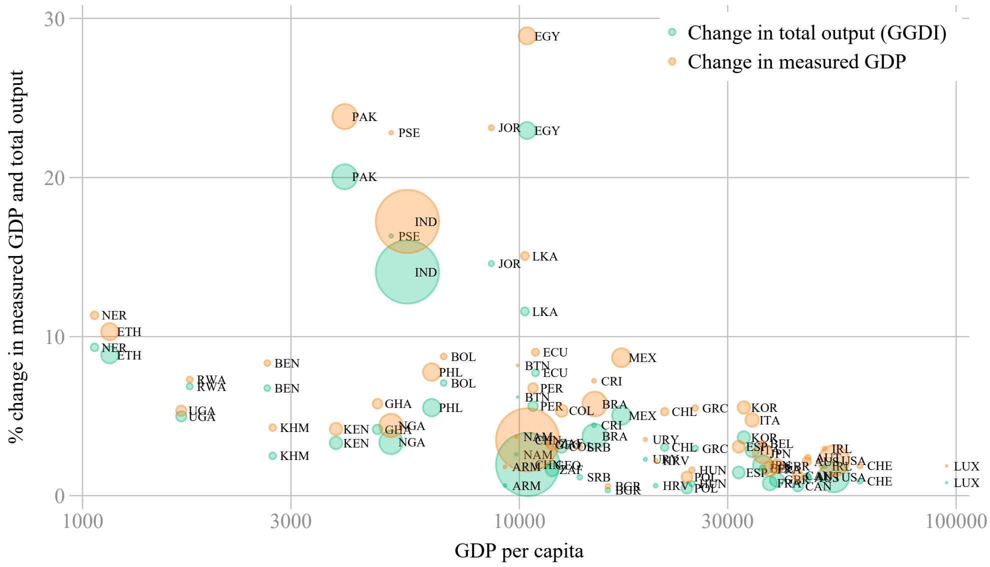
6.3 The $GGDI$ Across Indian States

We now turn to our last application: quantifying the losses of gender-based misallocation across local labor markets *within* a country. This perspective might be particularly interesting because it potentially highlights the importance of specific institutions, laws, and regulations to the extent that other determinants of gender-specific differences such as social norms, cultural traditions, or the general functioning of the labor market are common across labor markets within the country.

As a proof of concept of this exercise, we focus on the case of India and estimate the $GGDI$ at the state-level. In Figure 7 we plot the $GGDI$ among Indian States. In the left

[15] In Appendix Figure B-5 we show a version of Figure 6 where we individually shut down demand and supply distortions. We find that the effect of GDP exceeds the GGDI for both sources of misallocation.

FIGURE 6: THE *GGDI* AND THE CHANGE IN GDP

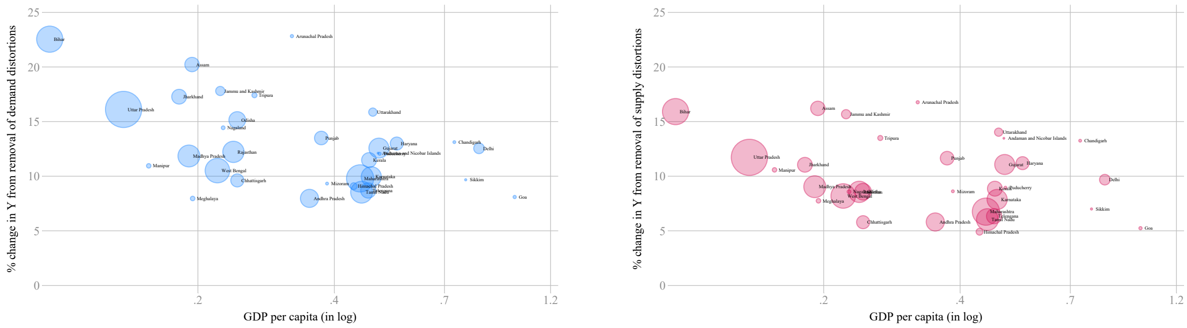


Notes: The figure plots *GGDI* and the change in measured GDP for all country x year observations in the sample against their GDP per capita. GGDI measure the increase in total economic activity (including home production) due to the removal of labor demand and labor supply gender distortions. Measured GDP is the increase in GDP following the removal of labor demand and labor supply gender distortions.

panel we focus on the case of demand distortions, in the right panel we focus on the case of supply distortions. The results are interesting in three aspects. First, the productivity losses from gender-based misallocation are sizable; they range from 5% to 15%. Second, like in the cross-country data shown in Figure 4, there is a systematic correlation with state-level GDP: the richer the state, the lower gender-based misallocation. Third, Figure 7 shows that the productivity losses from supply distortions are if anything slightly lower than the ones from demand distortions.

FIGURE 7: THE *GGDI* ACROSS INDIAN STATES

(A) Demand Distortions (B) Supply Distortions



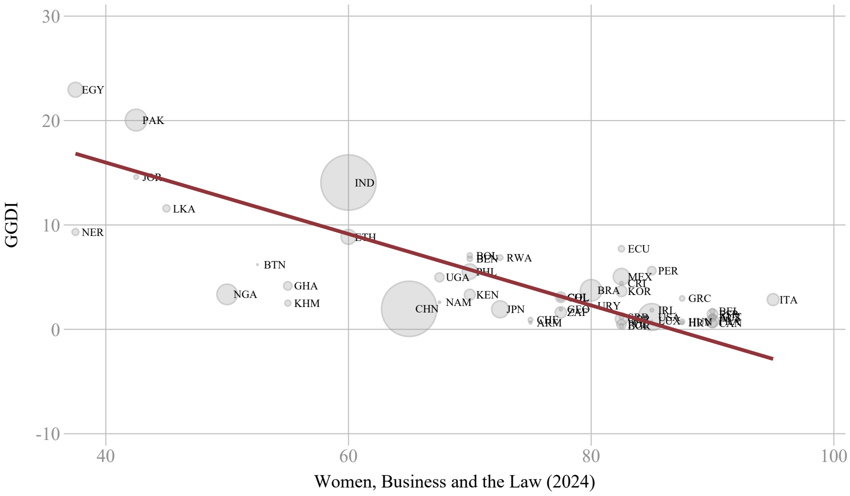
Notes: The figure plots the GGDI against the log of GDP per capita across India states. In panel A, we set $\tau_{jw} = 0$. In panel B, we set $z_{jw} = z_{jm} = 1$. The x-axis measure GDP per capita of each state relative to that of Haryana.

7. VALIDATION: DIRECT MEASURES OF GENDER EQUALITY

The *GGDI* is a model-based measure of gender equality. This has the benefit that it has a clear cardinal interpretation and that it aggregates different aspects of women's labor market outcomes such as participation gaps, wage gaps, and differences in occupational employment patterns into a scalar, that can be compared across countries, local labor markets, and time. In addition, it directly relates empirical gender gaps to aggregate productivity. The productivity consequences of gender-based misallocation might be of particular importance for policy makers. The disadvantage is that is is model-based and therefore relies on a particular theoretical structure and the assumptions on functional forms that we impose.

In this section, we relate the demand and supply distortions and the GGDI to *de-jure* measures of gender discrimination. To do so, we use the Women, Business, and Law dataset (World Bank, 2024) (henceforth WBL) that provides measures of equality of economic opportunity under the law between men and women in 190 economies, for 50 years, from 1970 until today. The WBL Index is a summary statistic of specific restrictions women face to participate in the labor market and society at large. Figure 8 is a scatter plot of our *GGDI* and the WBL Index across countries. Reassuringly there is a strong negative relationship, indicating that countries with a higher index (a sign of more gender equality) are indeed inferred to suffer from less misallocation according to our index. The bivariate correlation between the two variables is 0.74. We find this strong relationship between the *de-jure* equality measures of the WBL and our *de-facto* measure according to the *GGDI* reassuring that the *GGDI* indeed captures gendered differences in labor market outcomes.

FIGURE 8: THE GGDI AND THE WOMEN, BUSINESS, AND LAW INDEX



Notes: The figure plots the GGDI that we measure for each country in our sample against the Women, Business and Law Index (World Bank, 2024) for that same year.

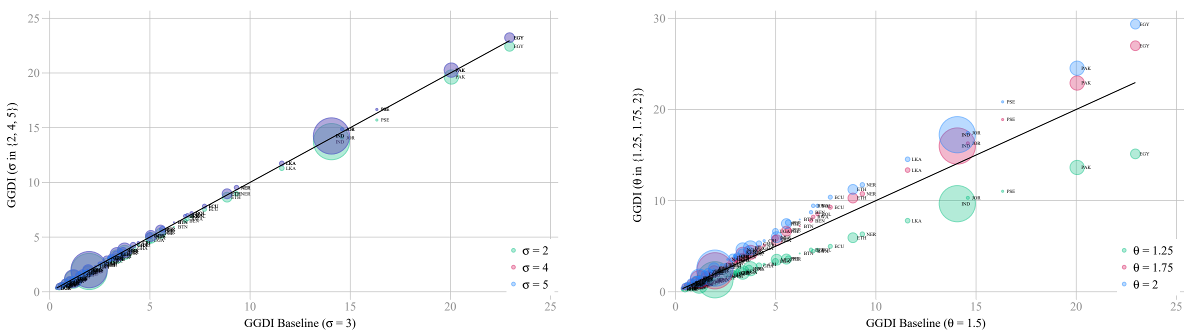
8. ROBUSTNESS

In the section, we explore the sensitivity of our estimates to the values of the structural parameters σ and θ. For our baseline analysis we chose σ, the elasticity of substitution between the different activities for aggregate output, to be equal to three. In the left panel of Figure 9 we plot the GGDI for different values of σ from 2 to 5. Our results are robust to the values of σ. The estimates remain within 1% range of the baseline estimates.

The second structural parameter, scale parameter of Fréchet distribution of idiosyncratic talent θ, is more consequential. Our baseline choice of $\theta = 1.5$ is close to the estimate of 1.52 used in Hsieh et al. (2019). In the right panel of Figure 9, we plot the GGDI for

FIGURE 9: ROBUSTNESS: THE EFFECTS OF σ AND θ

(A) Elasticity of Substitution σ (B) Talent Disperions θ



Notes: The left (right) panel of the figure plots the GGDI for different values of σ (θ). For all parameters we full re-calibrate the model.

different values of θ between 1.25 to 2. We note that the GGDI is similar to our baseline results as long as $\theta > 1.5$. However, for smaller values of θ, the aggregate implications of gender-based misallocation are sensitive to the particular choice of θ. Future research should aim to estimate θ directly from the microdata and to allow it to vary across countries.

9. CONCLUSION

In this paper we proposed a methodology to estimate the macroeconomic productivity losses of gender misallocation. Building on the work of Hsieh et al. (2019) we show that using data on employment shares across different activities, earnings, and human capital one can compute the overall productivity gains that an economy could reap if distortions could be abolished.

This statistic, which we refer to as the *Global Gender Distortion Index (GGDI)*, captures the productivity losses of the observed allocation relative to a situation of gender equality. As such, the *GGDI* is comparable across countries and time, is grounded in economic theory, has a straightforward cardinal interpretation, and captures both distortions on the labor demand side (such as wage discrimination or flatter career ladders for women) and on the labor supply side (such as institutions that discourage women to partake in full-time, market work).

While the GGDI captures the correct welfare-relevant notion of aggregate productivity, it is distinct from measured GDP. The reason is that the GGDI captures all economic activity, that is, market work, home production, and unpaid activities. By contrast, GDP is confined to activities that fall within the production boundary as defined by the system of national accounts. This distinction is conceptually important in the context of developing countries where informal, non-market transactions play an outsized role. Nevertheless, the implications of gender-based misallocation on aggregate GDP can also be readily computed. In our applications, we find that the change in GDP exceeds the GGDI, highlighting that distortions are a key reason that keep too many women in home activities.

Because our methodology is easy to implement, we view the *GGDI* as a complementary tool to other measures of gender equality and we hope that future research will make use of it. As part of this paper, we also distribute the MATLAB codes to compute the *GGDI* for other datasets that contain the required information on employment shares, earnings, and human capital.

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APPENDIX A: THEORETICAL RESULTS

This section contains additional details on the theoretical analysis. In Section A-1 we describe how we calibrate the job-specific demand shifts A_{jct} in (9). In Section A-2 we describe how we compute the equilibrium allocations for given parameters and distortions.

A-1. Calibrating A_{jct}

Let w_j denote the equilibrium skill prices of activity j. The optimality condition for labor demand in job j from (9) is given by

$$w_j = \left(\sum_j (A_j H_j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{1}{\sigma-1}} A_j^{\frac{\sigma-1}{\sigma}} H_j^{\frac{-1}{\sigma}} = A_j^{\frac{\sigma-1}{\sigma}} \left(\frac{Y}{H_j} \right)^{1/\sigma}. \tag{A-1}$$

Total labor supply, H_j is given in equation (8) as $H_j = \sum_g L_g \, p_{jg}^{\frac{\theta-1}{\theta}} \, h_{jg} \Gamma_\theta$. The equilibrium skill prices w_j can be inferred from equations (4), (6), and (5). In particular, the employment share of men in activity j is given by

$$p_{jm} = \frac{\overline{w}_{jm}^{\theta}}{\sum_j \overline{w}_{jm}^{\theta}} = \frac{(w_j h_{jm} z_{jm})^{\theta}}{\sum_j \overline{w}_{jm}^{\theta}} = \left(\frac{w_j h_{jm} z_{jm} \Gamma_\theta}{\overline{\text{wage}}_{jg} z_{jm}} \right)^{\theta} = \left(\frac{w_j h_{jm} \Gamma_\theta}{\overline{\text{wage}}_{jg}} \right)^{\theta} \tag{A-2}$$

Hence,

$$w_j = p_{jm}^{1/\theta} \frac{\overline{\text{wage}}_{jg}}{h_{jm} \Gamma_\theta}, \tag{A-3}$$

which expresses w_j in terms of observables.

Using (A-1) for activity j and the market sector w, yields

$$\left(\frac{A_j}{A_w} \right) = \left(\frac{w_j}{w_w} \right)^{\frac{\sigma}{\sigma-1}} \left(\frac{H_j}{H_j} \right)^{\frac{1}{\sigma-1}}, \tag{A-4}$$

which determines A_j relative to A_w. To determine A_w we use that total output is given in (9) as

$$Y = \left(\sum_j (A_j H_j)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} = \left(\sum_j \left(\frac{A_j}{A_w} H_j \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \times A_w, \tag{A-5}$$

and we chose A_w to match a given level for real GDP per capita.[1]

[1]Strictly speaking, Y is not equal to GDP, because it also includes home production and unpaid work. However, because we only use this moment to calibrate the level of A_j across countries and years, this discrepancy is not important and we equalize the model-based measure Y with the empirically measured level of GDP per capita.

A-2. Solving for the Equilibrium

Given the parameters and distortions, we can solve the model in an iterative way. To do so guess total labor demand in each activity H_j. Then use (A-5) to compute Y and (A-1) to compute w_j. Given w_j and the relative distortions, we can compute labor supply by men and women and compute aggregate labor supply. We then iterate on this guess for H_j until labor supply is equal to labor demand.

APPENDIX B: EMPIRICAL RESULTS

B-1. Details for Empirical Analysis

Our empirical analysis uses the Harmonized World Labor Force Survey (HWLFS), a large scale micro dataset that harmonizes over 2'500 surveys and contains individual level data on individual characteristics, education, employment and jobs from 120 countries. From this dataset, we select specific surveys to build two datasets, a cross-country and an Indian state dataset.

B-1.1 Construction of variables

Cross-country dataset For our cross-country dataset, we use nationally representative surveys that contain data on hours worked, wages, and industry codes for all workers. Overall, our analysis currently draws from 51 countries and our sample cover 69 percent of the World Population in 2015. The poorest country in our sample is Niger in 2005 with an GDP per capita level of USD 624 while the richest country is Luxembourg in 2005 with an GDP per capita level of USD 97973 .[1] In Table B-I we list all country surveys and their year coverage.

For each survey, we focus on individuals aged 25 to 60. For these, we record information on their marital status and their educational attainment. When available, we use reported years of schooling; otherwise, we impute years of schooling based on the highest completed degree.

We use the main job section of the surveys to classify workers by their job type: wage worker, self-employed (either employer or own-account worker), or unpaid worker. An unpaid worker is an individual engaged in a job without receiving a formal wage or salary, typically contributing to a family business, farm, or household enterprise. Unlike own-account workers and employers, unpaid workers have no claim to the profits of the activity. They contribute economically but are not compensated in wage nor in profits. Alongside their job type, we also record information on their sector of employment and weekly hours worked.

For wage workers, we measure labor income. To do so, we use data on their most recent payment, payment frequency and hours worked, to compute their hourly wage. Individuals with no main job are classified as not working, a category we also refer to as working in the home sector.

Indian States data For our cross-state exercise, we use Periodic Labour Force Survey (PLFS) of 2018-19. It contains detailed data on labor force participation of a representative sample of (approx.) 100,000 households. We restrict the sample to working age population: age 25-60 years. This leaves us with 202,696 individual level observations.

PLFS classifies the employment status of an individual into following categories: wage workers (code 31, 41, 42, 51, 71, 72), Self employed (code 11, 12, 61, 62), unpaid workers (code 21). As shown in table B-II, roughly 75% of women are not in labor force, where as this number is less than 10% for men. The majority of people are self-employed, followed by regular wage and casual labor.[2]

[1]The GDP per capita numbers Are taken from the Penn World Tables (Feenstra et al., 2015).

[2]Maybe surprisingly, Table B-II shows that educational attainment of the few men doing unpaid work

TABLE B-I: LIST OF SURVEYS

heightCountry	Survey Name	Year coverage
Armenia	Labour Force Survey	2014-2019
Australia	Household, Income and Labour Dynamics in Australia	2001-2017
Austria	European Union Statistics on Income and Living Conditions	2004-2020
Belgium	European Union Statistics on Income and Living Conditions	2004-2005
Benin	Enquête Modulaire Intégrée sur les Conditions de Vie des ménages	2010-2015
Bhutan	Labor Force Survey	2018-2020
Bolivia	Encuesta de Hogares	2005-2020
Brazil	Pesquisa Nacional por Amostra de Domicílios	2009-2015
Bulgaria	European Union Statistics on Income and Living Conditions	2008-2020
Cambodia	Cambodia Labor Force and Child Labor Survey	2012-2019
Canada	Labour Force Survey	1997-2020
Chile	Encuesta de Caracterización Socioeconómica Nacional	1990-2017
China	Family Panel Studies	2012-2016
Colombia	Gran Encuesta Integrada de Hogares	2006-2019
Costa Rica	Encuesta Continua de Empleo	2010-2023
Croatia	European Union Statistics on Income and Living Conditions	2010-2020
Ecuador	Encuesta Nacional de Empleo, Desempleo y Subempleo	2007-2018
Egypt	Harmonized Labor Force Survey	2007-2017
Ethiopia	National Labour Force Survey	2005-2013
France	Enquête emploi annuelle	2003-2019
Georgia	Labour Force Survey	2017-2021
Ghana	Ghana Living Standard Survey	1987-2017
Greece	European Union Statistics on Income and Living Conditions	2004-2020
Hungary	European Union Statistics on Income and Living Conditions	2006-2020
India	Indian National Sample Survey	1987-2011
India	Periodic Labor Force Survey	2017-2023
Ireland	European Union Statistics on Income and Living Conditions	2004-2019
Italy	European Union Statistics on Income and Living Conditions	2004-2020
Japan	Employment Status Survey	1997-2017
Jordan	Harmonized Labor Force Survey	2005-2016
Kenya	Kenya Continuous Household Survey Programme	2019-2021
Luxembourg	European Union Statistics on Income and Living Conditions	2012-2015
Mexico	Encuesta Nacional de Ocupación y Empleo	2005-2019
Namibia	Labor Force Survey	2012-2018
Niger	National Survey on Household Living Conditions and Agriculture	2011-2014
Nigeria	Living Standards Measurement Survey	2010-2018
Pakistan	Labor Force Survey	2010-2018
Palestinian Territories	Harmonized Labor Force Survey	2000-2016
Peru	Encuesta Nacional de Hogares	2007-2019
Philippines	Labor Force Survey	2005-2019
Poland	European Union Statistics on Income and Living Conditions	2005-2019
Rwanda	Enquête Intégrale sur les Conditions de Vie des Ménages	2000-2016
Serbia	European Union Statistics on Income and Living Conditions	2013-2020
South Africa	Labor Market Dynamics	2010-2019
South Korea	Korean Labor and Income Panel Study	1998-2018
Spain	European Union Statistics on Income and Living Conditions	2004-2012
Sri Lanka	Labor Force Survey	1996-2022
Switzerland	European Union Statistics on Income and Living Conditions	2007-2020
Uganda	Uganda National Panel Survey	2009-2019
United Kingdom	European Union Statistics on Income and Living Conditions	2005-2018
United States	Current Population Survey	1967-2022
Uruguay	Encuesta Continua de Hogares	2006-2017

is very high. This subpopulation tends to be young and work in family firms, potentially in managerial positions (see Bloom et al. (2013)).

TABLE B-II: Descriptive Statistics

	Men	Women	Total
Shares	49.46%	50.54%	100.00%
Employment Proportions			
Wage work	45.68%	12.14%	28.73%
Self employed	40.14%	5.82%	22.80%
Unpaid work	4.14%	17.74%	11.02%
Home sector	10.03%	64.29%	37.46%
Total	100.00%	100.00%	100.00%
Average Monthly Earnings (in rupees)			
Wage work	2851	1974	2408
Self employed	2530	1458	1988
Unpaid work	2292	1212	1747
Home sector	1809	-	-
Education (Years of Schooling)			
Wage work	8.92	7.85	8.38
Self employed	7.93	5.35	6.63
Unpaid work	9.88	4.64	7.23
Home sector	9.09	6.55	7.56

Notes: Descriptive statistics are calculated from Periodic Labor Force Survey of 2018-19.

B-1.2 Measurement of labor income

We use data on weekly hours worked (h) and hourly wages (w) to impute weekly labor income ($y = wh$) for all individuals in the dataset. In particular, for each country-year survey and for each gender, we run a Mincerian wage regression

$$\ln y_i = \delta_{\mathcal{I}(i)} + \gamma \, \text{yrs}_i + x_i'\beta + \varepsilon_i, \tag{B-1}$$

where $\delta_{\mathcal{I}}$ is a set of sector fixed effects, yrs_i denotes years of schooling for individual i, and x is a set of individual characteristics such as marital status and age. For each country-year survey, we estimate the coefficients $(\hat{\delta}, \hat{\gamma}, \hat{\beta})$ for both men and women separately. We thus allow for the return to human capital, the marriage premium, and sectoral premia to differ by gender. We consider three sectors—agriculture, industry, and services—as defined by the International Standard Industrial Classification (ISIC): agriculture corresponds to ISIC Section A; industry includes Sections B to F (e.g., mining, manufacturing, and construction); and services comprise Sections G to U, including trade, transport, finance, education, health, and other service activities.

We then use these coefficients to predict weekly labor income for all individuals in the dataset. Specifically, for self-employed and unpaid individuals we compute (log) earnings by

$$\widehat{\ln y_i} = \widehat{\delta_{\mathcal{I}(i)}} + \widehat{\gamma} \, \text{yrs}_i + x_i'\widehat{\beta}, \tag{B-2}$$

that is we use both the individual characteristics, i.e. marital status, age, and education as well as the sector of employment to predict overall earnings. For individuals that are not working we impute earnings assuming that they work in the agricultural sector, exploiting the idea that agricultural work might be the closest comparison for the appropriate opportunity cost of home production.

To get a sense of the magnitude of the returns to experience, marital, and sectoral premia, we estimate regression B-1 pooling all the data and incorporating survey-year-country fixed effects. In table B-III, we reported the estimated coefficients. On average, women earn 36.3% less than men, and married individual earn 9.2% more than singles. The estimated returns to schooling amount to 8% which is in line with estimates in the literature, and our assumed return of human capital for our structural analysis (see equation B-3). We estimate sectoral income gaps of 50% and 42.6% for workers in industry and services relative to agricultural wage workers.

	Weekly Income
Women	-0.364
	(0.021)
Married	0.092
	(0.015)
Years of Education	0.080
	(0.004)
Age	0.008
	(0.001)
Industry	0.491
	(0.076)
Services	0.417
	(0.078)
Adj. R-squared	0.908
Within R-squared	0.211
Observations	22'782'947

TABLE B-III: Mincer Regression.

Notes. This table shows the estimated coefficients of regression B-1. The left hand side variable is weekly income of wage workers, i.e. hourly wage times weekly hours worked. We pool all country year surveys and incorporate survey, county and years fixed effects. Standard errors, clustered at the country, year and survey level, are reported in parentheses.

B-1.3 Cross-country data: Income groups

In Tables 1 and 2 we reported gender differences in educational attainment and the type of work for countries of different income. Table B-IV reports the individual countries by income group.

B-1.4 Gender Earnings Gaps over Time

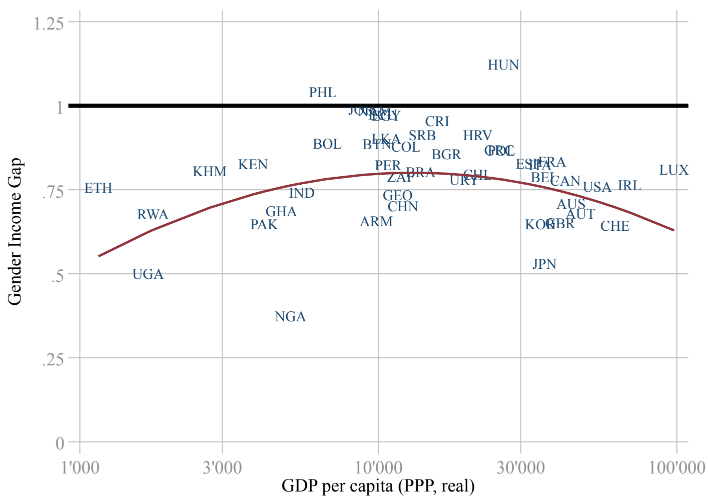
In Figure B-1 below we plot the gender income gap, that is average earnings in the wage sector of women relative to men, against GDP per capita in 2014.[3]. For the vast majority of countries the gender income gap is below one, that is women earn less than men. The cross-country pattern is suggestive of a U-shape relationship between income per capita and the gender income gap.

[3] In case a country does not report data in 2014, we take the closest year

TABLE B-IV: INCOME GROUPS

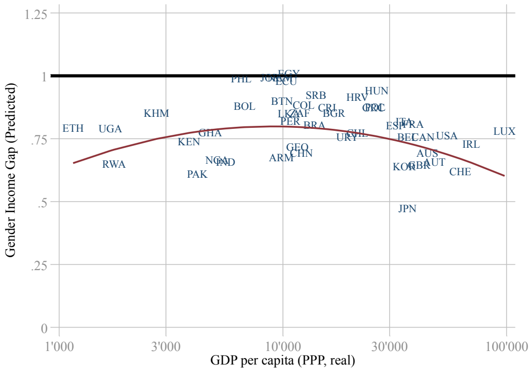
Income Group	Countries
High income	Australia, Austria, Belgium, Canada, Chile, Croatia, France, Greece, Hungary, Ireland, Italy, Japan, Korea, Rep., Luxembourg, Poland, Spain, Switzerland, United Kingdom, United States, Uruguay
Middle income	Armenia, Benin, Bhutan, Bolivia, Brazil, Bulgaria, Cambodia,China, Colombia, Costa Rica, Ecuador, Egypt, Arab Rep., Georgia, Ghana, India, Jordan, Kenya, Namibia, Nigeria, Palestine, Pakistan,Peru, Philippines, Serbia, South Africa, Sri Lanka
Low income	Ethiopia,Niger, Rwanda, Uganda

FIGURE B-1: RAW GENDER INCOME GAP ACROSS COUNTRIES

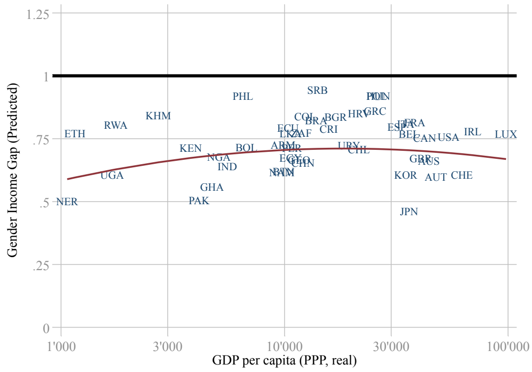


Notes: This figure plots the gender income gap for all countries in our cross-country dataset against the log of GDP per capita as provided by Feenstra et al. (2015). Gender income gap is the ratio of weekly income of women relative to men. Weekly income is the product of hourly wage and weekly hours worked.

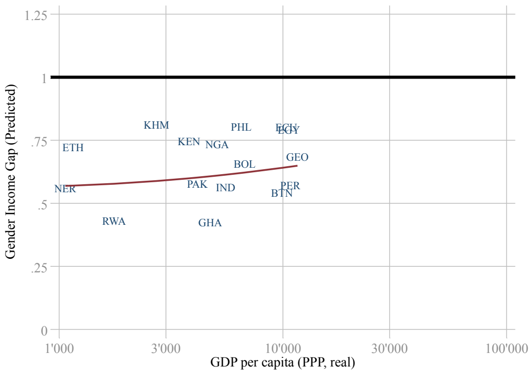
FIGURE B-2: PREDICTED GENDER INCOME GAP ACROSS COUNTRIES BY ACTIVITY



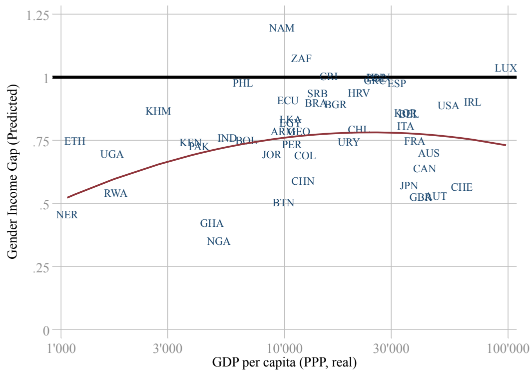
(A) Wage work



(B) Self employment



(C) Unpaid work



(D) Home work

Notes: Each panel plots the predicted gender income gap against log GDP per capita (PPP, real) for a specific work activity as outlined in B-1.2. The gender income gap is the ratio of predicted weekly income for women relative to men. GDP data is from Feenstra et al. (2015).

B-2. Measurement for Structural Analysis

To calibrate our model, we require three objects from the HLWFS microdata: (i) the job-specific employment shares for each group g, p_{jg}; (ii) average earnings of group g in activity j, $\overline{\text{wage}}_{jg}$; (iii) group g's average human capital for activity j, h_{jg}.

The employment shares p_{jg} are directly observed in the HLWFS data. To measure the stocks of human capita, h_{jg}, we rely on Mincerian wage regressions to project observed schooling into unobserved human capital. Specifically, we assume an annual return of human capital of 8% and hence compute h_{jg} according to

$$h_{jg} = \exp\left(0.08 \times \text{yrs of schooling}_{jg}\right), \tag{B-3}$$

where yrs of schooling$_{jg}$ denotes average years of schooling of individuals of group g in activity j. Finally, we compute $\overline{\text{wage}}_{jg}$ directly from observed earnings. Note that $\overline{\text{wage}}_{jg}$ is the *geometric* average of earnings. Empirically, we observe the arithmetic average of earnings, $\bar{e}_{jg}$. Given the Frèchet distribution, we can convert the arithmetic average of earnings $\bar{e}_{jg}$ to the geometric average $\overline{\text{wage}}_{jg}$ using the relationship

$$\overline{\text{wage}}_{jg} = \bar{e}_{jg} \frac{\tilde{\Gamma}}{\Gamma(1 - \frac{1}{\theta})}$$

where $\tilde{\Gamma} = e^{\frac{\gamma_{em}}{\theta}}$. γ_{em} is Euler–Mascheroni constant (≈ 0.5772).

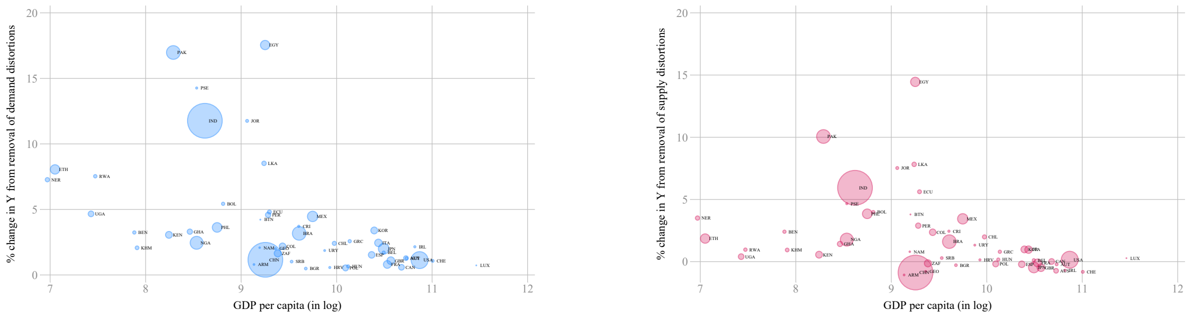
B-3. Demand and Supply Distortions Across the World

In Figure 4 in the main text, we reported the GGDI in the cross-section of countries. The GGDI measures the productivity increase induced by eliminating *both* supply and demand distortions. In Figure B-3 below we report the results separately: In the left panel we report the productivity consequences of eliminating demand distortions (keeping supply distortions in place), in the right panel we eliminate supply distortions but keep demand distortions untouched. Figure B-3 shows that, on average, demand distortions are economically more costly for aggregate productivity and that the gains from dismantling either distortions are higher in poor countries.

FIGURE B-3: DEMAND VS. SUPPLY DISTORTIONS

(A) Demand Distortions

(B) Supply Distortions

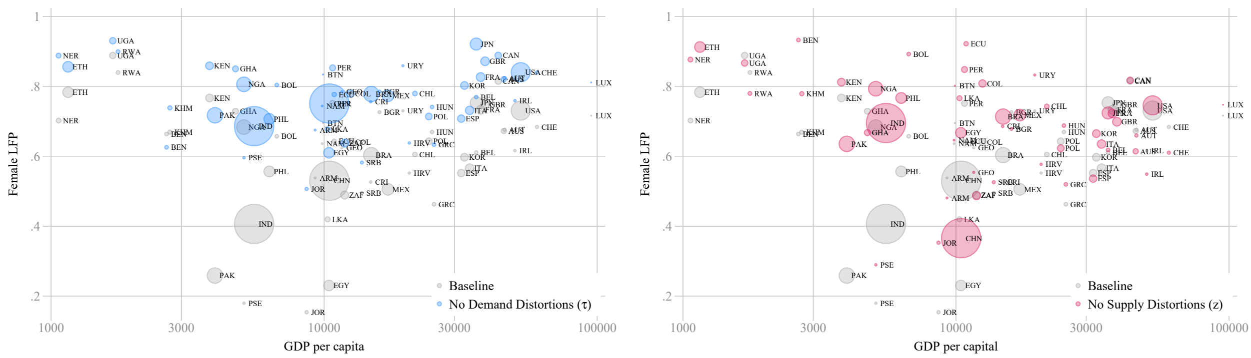


Notes: Panel A plots the increase in GDP from removal of labor demand distortions and Panel B plots the same for the case of removal of labor supply distortions. The sample consists of all country observations near the year 2014.

FIGURE B-4: DISTORTIONS AND FEMALE LABOR FORCE PARTICIPATION

(A) Demand Distortions

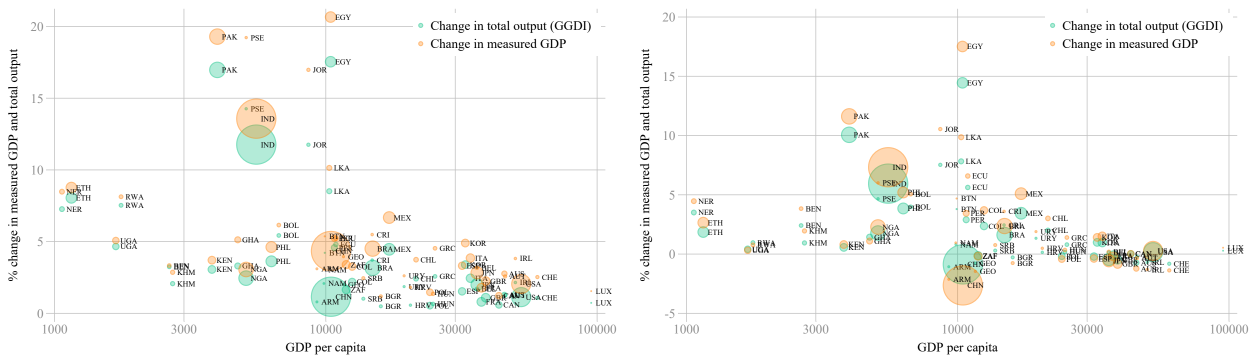
(B) Supply Distortions



Notes: Panel A (Panel B) shows female labor force participation (FLFP) in the baseline calibration and in an economy with no demand (no supply) distortions for all countries, plotted against their GDP per capita. The size of points are proportional to the country's population. The sample for the plot is all country observations near the year 2014.

FIGURE B-5: THE *GGDI* AND THE CHANGE IN GDP

(A) Demand Distortions　　　　(B) Supply Distortions



Notes: The figure plots *GGDI* and the change in measured GDP for all country observations near the year 2014 against their GDP per capita. GGDI measure the increase in total economic activity (including home production) due to the removal of labor demand (panel A) and labor supply (panel B) gender distortions. Measured GDP is the increase in GDP following the removal of labor demand (panel A) and labor supply (panel B) gender distortions.

APPENDIX C: REPLICATION PACKAGE

C-1. REPLICATION PACKAGE

The GGDI replication code is written in MATLAB. It consists of two main functions `distortions()` and `equilibrium()`. For a given data set, `distortions()` provide the magnitudes of the distortions of labor demand and labor supply implied by the model. For a given set of distortion parameters, `equilibrium()` provides the level of output and sectoral labor allocations implied by the model. This can be used to estimate the counterfactual output and labor allocations. We describe both functions, along with the format of input and output vectors in detail below.

C-1.1 `distortions()`

```
[tau,z,parameters] = distortions(data,theta,sigma)
```

The function `distortions()` takes 3 inputs.
`data` is a 'table' object with observations at the level of country x year. It should have the following variables: Country name, year, sectoral participation rates (p_{jg}), sectoral earnings ($wage_{jg}$), sectoral human capital (h_{jg}), and gender proportions in the economy (q_g) where $j \in \{h,u,s,w\}$ (home, unpaid, self-emplyed, wage work) and $g \in \{w,m\}$ (women, men). These variables should have the following column titles in the table:
`country,year,p_hm,p_um,p_sm,p_wm,p_hw,p_uw,p_sw,p_ww,wage_hm,wage_um,`
`wage_sm,wage_wm,wage_uw,wage_sw,wage_ww,h_hm,h_um,h_sm,h_wm,h_hw,h_uw,`
`h_sw,h_ww,q_m,q_w`
A recommended approach is to have a dataset with the above variable names in .csv file and import it in 'table' format in MATLAB using `readtable()` function.
As mentioned in the paper, we use `theta=1.5` and `sigma = 3` throughout our analysis.

The function `distortions()` gives 3 outputs.
`tau` and `z` are arrays of dimension s x 2 x 4 which represent country-year x group x

occupation observations in the order country-year x $\{w,m\}$ x $\{h,u,s,w\}$. For example, distortions related to women in the white collar sector are given by `\tau (:,1,4)` and `z(:,1,4)`
`parameters()` is a 'structure' object which contains the values of other parameters estimated by the model. These include $A_j, w_j, Y(\text{Baseline}), p, h, q, \theta, \gamma, \sigma, country, year$. These objects are defined in the paper. p and h are the arrays representing p_{jg} and h_{jg} with the same dimension of s x 2 x 4 representing country-year x group x job-type observations. q represents q_g and is of dimension s x 2.

C-1.2 `equilibrium()`

`output = equilibrium(tau,z,parameters)`

The function equilibrium takes 3 inputs.
`tau` and `z` are of same dimensions as above: s x 4 x 2. Including the same arrays as the one given by the output of the function `distortion()` gives the implied model values for the baseline economy. Alternatively, entering different values of `tau` and `z` will provide counterfactual estimates of the output and sectoral labor allocations implied by the model.
`parameters` is the one which is given as output of the `distortions()` function.

`output` is a 'structure' object whose elements are `Y_model`, `w_model` and `p_model`. `p_model` represents p_{og} whose dimensions are s x 4 x 2 as described above.

C-1.3 Example

The following code highlights how to calculate counterfactual GDP and labor allocations for the case when labor demand distortions are set to 0.

LISTING 1: MATLAB example

```
clear
clc
close all

% Set Parameters
theta = 1.5;
sigma = 3;

% Read Data
data = readtable("data.csv");

% Estimating Distortions
[tau,z,parameters] = distortions(data,theta,sigma);

% Setting counterfactual labor demand distortions
tau_cf = tau;
tau_cf(:,1,:) = 0;

% Estimating counterfactual output
output = equilibrium(tau_cf,z,parameters);
```

APPENDIX D

D-1. GGDI Estimates

Tables D-I to D-VIII contain GGDI estimates and implied GDP change for all country-year observations.

TABLE D-I: GGDI Estimates – Part 1 of 9

Armenia

Year	2014	2015	2016	2017	2018	2019
GGDI	0.64%	0.64%	0.66%	0.61%	0.71%	1.14%
GDP change	1.82%	1.99%	1.74%	1.93%	2.97%	3.10%

Australia

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
GGDI	1.09%	1.04%	1.12%	1.00%	1.09%	1.10%	1.01%	0.83%	1.04%	1.04%	1.36%	1.08%	1.23%	1.12%	1.05%	0.87%	0.79%
GDP change	2.15%	2.08%	2.32%	2.19%	2.04%	1.88%	1.82%	1.59%	1.89%	1.92%	2.37%	1.92%	2.21%	2.15%	1.98%	1.73%	1.72%

Austria

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	1.93%	2.05%	1.91%	1.79%	1.96%	1.24%	1.78%	1.55%	1.72%	1.60%	1.22%	1.08%	1.35%	1.04%	1.07%	1.06%	0.98%
GDP change	3.48%	3.64%	3.46%	3.35%	3.23%	2.53%	2.78%	2.69%	2.80%	2.64%	2.41%	2.52%	2.53%	2.16%	1.96%	1.90%	1.71%

Belgium

Year	2004	2005
GGDI	1.30%	1.74%
GDP change	3.40%	3.28%

Benin

Year	2010	2015
GGDI	4.79%	6.76%
GDP change	5.47%	8.33%

Bhutan

Year	2018	2019	2020
GGDI	6.20%	8.33%	7.00%
GDP change	8.19%	10.53%	8.88%

Bolivia

Year	2005	2006	2007	2008	2009	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	9.61%	8.38%	9.63%	7.51%	7.66%	7.07%	6.80%	6.45%	7.08%	6.80%	5.75%	6.09%	5.99%	5.23%	5.79%
GDP change	11.77%	10.90%	11.86%	9.41%	9.42%	8.96%	8.57%	8.36%	8.75%	8.86%	7.82%	8.03%	8.15%	7.14%	8.19%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-II: GGDI Estimates – Part 2 of 9

Brazil

Year	2009	2011	2012	2013	2014	2015
GGDI	4.14%	4.25%	4.04%	3.97%	3.74%	3.60%
GDP change	6.22%	6.37%	6.04%	6.01%	5.76%	5.74%

Bulgaria

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	0.91%	0.80%	0.72%	0.50%	0.33%	0.34%	0.35%	0.54%	0.61%	0.48%	0.55%	0.55%	0.52%
GDP change	1.77%	1.52%	1.39%	1.04%	0.83%	0.71%	0.59%	1.08%	1.22%	0.92%	1.10%	1.08%	1.22%

Cambodia

Year	2012	2019
GGDI	2.51%	2.55%
GDP change	4.28%	3.80%

Canada

Year	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
GGDI	1.13%	1.09%	0.98%	0.99%	0.96%	0.88%	0.76%	0.78%	0.84%	0.82%	0.72%	0.75%	0.68%	0.65%	0.63%	0.55%	0.57%
GDP change	2.24%	2.14%	1.99%	1.97%	1.91%	1.73%	1.58%	1.57%	1.64%	1.57%	1.40%	1.39%	1.30%	1.26%	1.28%	1.19%	1.17%

Canada

Year	2014	2015	2017	2018	2019	2020
GGDI	0.59%	0.57%	0.54%	0.43%	0.56%	0.51%
GDP change	1.25%	1.30%	1.18%	1.07%	1.18%	1.10%

Chile

Year	1990	1992	1994	1998	2000	2003	2006	2009	2011	2013	2015	2017
GGDI	8.33%	9.35%	9.38%	6.80%	6.30%	6.11%	5.47%	5.01%	4.40%	3.98%	3.04%	2.87%
GDP change	12.12%	12.69%	12.25%	9.98%	9.36%	9.01%	7.99%	7.78%	6.80%	6.22%	5.28%	4.92%

China

Year	2012
GGDI	1.97%
GDP change	3.51%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-III: GGDI Estimates – Part 3 of 9

Colombia

Year	2006	2007	2008	2009	2010	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	5.19%	4.45%	5.11%	4.54%	3.62%	3.43%	3.19%	3.08%	3.08%	2.82%	2.90%	2.76%	2.80%
GDP change	7.51%	7.07%	7.68%	6.81%	6.24%	5.83%	5.63%	5.33%	5.33%	5.17%	5.35%	5.22%	5.35%

Costa Rica

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
GGDI	5.95%	5.36%	3.44%	4.04%	4.42%	4.26%	4.44%	4.30%	3.88%	4.34%	3.55%	3.75%	4.14%	3.62%
GDP change	8.52%	8.00%	5.94%	6.69%	7.22%	7.17%	7.54%	7.04%	6.67%	6.90%	7.32%	7.02%	6.89%	6.70%

Croatia

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	0.56%	0.69%	0.77%	0.61%	0.63%	0.47%	0.58%	0.74%	0.78%	0.74%	0.83%
GDP change	1.98%	1.97%	2.26%	2.03%	2.20%	1.74%	1.83%	2.06%	1.98%	1.80%	2.00%

Ecuador

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GGDI	7.14%	7.19%	6.63%	7.35%	7.53%	7.41%	7.73%	7.72%	7.15%	6.33%	5.78%	6.23%
GDP change	8.23%	8.40%	7.89%	8.81%	9.02%	8.90%	9.26%	9.01%	8.34%	7.42%	6.86%	7.40%

Egypt, Arab Rep.

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
GGDI	23.06%	24.04%	23.79%	22.08%	22.38%	19.53%	22.79%	22.95%	21.36%	19.06%	18.37%
GDP change	28.06%	29.32%	29.19%	26.94%	27.54%	26.37%	28.48%	28.90%	27.41%	25.42%	25.29%

Ethiopia

Year	2005	2013
GGDI	11.09%	8.85%
GDP change	12.49%	10.31%

France

Year	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	1.29%	1.24%	1.22%	1.07%	0.96%	1.02%	0.96%	1.04%	1.03%	1.00%	0.88%	0.78%	0.78%	0.74%	0.78%	0.83%	0.80%
GDP change	2.51%	2.39%	2.42%	2.20%	2.09%	2.05%	1.96%	1.97%	1.94%	1.91%	1.73%	1.68%	1.63%	1.66%	1.73%	1.73%	1.64%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-IV: GGDI Estimates – Part 4 of 9

Georgia

Year	2017	2018	2019	2020	2021
GGDI	1.91%	1.56%	1.62%	2.36%	2.14%
GDP change	3.22%	3.45%	3.52%	4.47%	4.52%

Ghana

Year	1987	1988	1991	1998	2005	2008	2017
GGDI	4.15%	6.70%	8.21%	6.46%	7.34%	5.00%	4.16%
GDP change	6.01%	8.97%	8.82%	7.09%	8.47%	6.06%	5.78%

Greece

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	5.51%	5.00%	4.71%	4.30%	3.93%	3.36%	2.53%	2.55%	2.72%	2.29%	2.96%	2.33%	2.47%	2.36%	2.72%	2.67%	2.80%
GDP change	7.49%	7.13%	7.20%	6.69%	6.06%	5.25%	4.21%	4.90%	4.99%	4.71%	5.51%	4.64%	4.78%	4.73%	5.08%	4.90%	5.14%

Hungary

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	1.44%	1.17%	1.11%	1.15%	0.91%	0.90%	0.83%	0.99%	0.75%	0.82%	0.66%	0.84%	0.40%	0.51%	0.75%
GDP change	2.85%	2.39%	2.42%	2.45%	2.07%	1.99%	2.03%	2.14%	1.62%	1.71%	1.38%	1.56%	0.83%	1.26%	1.44%

India

Year	1987	1999	2004	2005	2006	2007	2011	2017	2018	2019	2020	2021	2022
GGDI	10.52%	10.28%	11.68%	10.55%	11.37%	12.39%	12.77%	14.06%	14.24%	13.39%	11.90%	12.15%	12.35%
GDP change	12.31%	11.77%	13.46%	11.96%	13.09%	14.18%	14.73%	17.24%	17.61%	16.40%	15.40%	15.33%	15.04%

Ireland

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	3.31%	3.37%	3.85%	3.24%	3.23%	3.16%	2.67%	1.92%	1.64%	1.73%	1.85%	2.09%	2.15%	1.95%	1.76%	1.55%
GDP change	5.22%	4.94%	5.13%	4.36%	4.46%	4.47%	3.79%	3.40%	2.70%	2.71%	2.96%	3.35%	3.49%	3.23%	2.85%	2.73%

Italy

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	3.61%	3.56%	3.69%	3.82%	3.62%	3.29%	3.18%	3.04%	3.08%	2.67%	2.85%	2.61%	2.75%	2.69%	3.17%	2.91%	2.43%
GDP change	6.16%	6.01%	6.05%	6.12%	5.86%	5.74%	5.57%	5.21%	5.10%	4.76%	4.76%	4.76%	4.83%	4.81%	5.07%	4.66%	4.42%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-V: GGDI Estimates – Part 5 of 9

Japan				
Year	1997	2002	2007	2017
GGDI	4.15%	3.30%	2.98%	1.92%
GDP change	5.28%	4.61%	4.00%	2.66%

Jordan											
Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2016
GGDI	18.65%	18.74%	15.78%	16.16%	16.38%	15.46%	14.88%	14.51%	14.79%	14.59%	9.55%
GDP change	27.93%	27.80%	23.68%	23.92%	23.47%	22.58%	21.76%	21.49%	22.48%	23.13%	17.26%

Kenya			
Year	2019	2020	2021
GGDI	3.32%	4.54%	4.10%
GDP change	4.19%	5.69%	5.10%

Korea, Rep.																	
Year	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2011	2012	2013	2014	2015
GGDI	3.92%	4.47%	3.94%	4.73%	3.96%	4.92%	4.69%	4.35%	4.14%	3.99%	3.91%	4.50%	4.11%	3.83%	3.23%	3.66%	2.88%
GDP change	7.98%	7.88%	8.17%	7.86%	7.12%	7.53%	7.52%	7.35%	6.82%	6.48%	6.32%	6.56%	5.84%	5.63%	4.97%	5.54%	4.84%

Korea, Rep.			
Year	2016	2017	2018
GGDI	2.04%	2.54%	2.09%
GDP change	4.10%	4.24%	3.72%

Luxembourg			
Year	2012	2014	2015
GGDI	1.06%	0.82%	0.63%
GDP change	2.12%	1.87%	1.61%

Namibia					
Year	2012	2013	2014	2016	2018
GGDI	2.88%	2.94%	2.60%	2.18%	1.89%
GDP change	3.98%	3.84%	3.71%	3.25%	2.78%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-VI: GGDI Estimates – Part 6 of 9

Niger

Year	2011	2014
GGDI	5.62%	9.32%
GDP change	6.15%	11.34%

Nigeria

Year	2010	2012	2015	2018
GGDI	5.43%	5.27%	3.35%	3.54%
GDP change	6.89%	7.25%	4.41%	4.36%

Pakistan

Year	2010	2011	2013	2014	2015	2018
GGDI	23.16%	22.05%	21.71%	20.05%	19.57%	21.11%
GDP change	27.28%	26.06%	25.89%	23.83%	23.20%	25.12%

Palestine

Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GGDI	18.19%	16.09%	14.73%	15.03%	15.66%	17.44%	16.69%	16.94%	15.55%	16.18%	17.79%	19.16%	18.04%	18.44%	16.33%	16.72%	18.00%
GDP change	26.79%	25.18%	23.97%	23.64%	23.43%	24.74%	23.21%	23.18%	22.46%	22.87%	24.16%	24.83%	24.33%	24.36%	22.81%	23.44%	24.50%

Peru

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	6.92%	6.22%	6.75%	5.88%	5.62%	5.64%	5.85%	5.62%	5.84%	5.37%	5.45%	4.88%	5.09%
GDP change	8.15%	7.56%	7.94%	6.99%	6.81%	6.76%	7.05%	6.77%	7.02%	6.52%	6.51%	5.82%	6.03%

Philippines

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	6.04%	5.83%	5.78%	5.87%	5.61%	5.43%	5.32%	5.67%	5.59%	5.53%	5.38%	6.61%	6.61%	6.01%	5.58%
GDP change	8.39%	8.15%	8.06%	8.22%	7.96%	7.73%	7.60%	8.02%	7.88%	7.77%	7.65%	8.87%	9.22%	8.44%	7.75%

Poland

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	0.85%	0.84%	0.93%	1.07%	0.81%	0.66%	0.71%	0.77%	0.64%	0.48%	0.44%	0.42%	0.44%	0.33%	0.16%
GDP change	2.30%	2.37%	2.40%	2.40%	2.02%	1.79%	1.69%	1.81%	1.54%	1.17%	1.26%	1.20%	1.12%	0.83%	0.23%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

TABLE D-VII: GGDI Estimates – Part 7 of 9

Rwanda

Year	2000	2005	2013	2016
GGDI	9.30%	11.00%	8.42%	6.87%
GDP change	9.32%	11.16%	9.05%	7.30%

Serbia

Year	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	1.36%	1.16%	1.00%	0.68%	0.83%	0.95%	1.19%	1.13%
GDP change	3.37%	3.06%	2.85%	2.48%	2.49%	2.73%	2.86%	2.81%

South Africa

Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	2.41%	2.23%	2.16%	1.72%	1.63%	1.59%	1.66%	1.38%	1.23%	1.35%
GDP change	4.14%	3.91%	3.73%	3.32%	3.32%	3.31%	3.42%	3.02%	2.95%	3.03%

Spain

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
GGDI	2.56%	3.53%	2.92%	2.74%	1.92%	1.37%	1.29%	1.43%	1.46%
GDP change	5.16%	5.89%	5.02%	4.65%	3.42%	2.80%	2.76%	3.05%	3.08%

Sri Lanka

Year	1996	1997	1998	1999	2001	2002	2003	2004	2011	2012	2013	2014	2015	2016	2017	2018	2019
GGDI	8.60%	9.50%	9.48%	10.03%	10.50%	11.29%	10.84%	11.09%	12.03%	11.49%	11.10%	11.58%	11.45%	11.66%	10.66%	12.32%	11.75%
GDP change	12.56%	13.43%	12.89%	13.55%	14.34%	14.70%	14.34%	14.77%	15.29%	15.18%	14.30%	15.07%	14.73%	14.52%	13.43%	14.70%	14.32%

Sri Lanka

Year	2020	2021	2022
GGDI	12.67%	11.85%	12.32%
GDP change	15.22%	14.34%	14.62%

Switzerland

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
GGDI	1.81%	2.25%	0.93%	0.89%	1.03%	1.08%	1.11%	0.92%	0.98%	0.81%	0.52%	0.45%	0.59%	0.58%
GDP change	3.23%	3.80%	1.94%	1.77%	2.02%	1.92%	2.12%	1.88%	1.94%	1.77%	1.21%	1.00%	0.92%	0.90%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.

Table D-VIII: GGDI Estimates – Part 8 of 9

Uganda

Year	2009	2010	2011	2013	2016	2018	2019
GGDI	7.34%	6.49%	6.32%	4.99%	4.81%	4.60%	5.49%
GDP change	7.85%	7.45%	6.76%	5.34%	5.36%	5.37%	5.98%

United Kingdom

Year	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GGDI	0.65%	0.65%	0.43%	0.47%	1.20%	1.43%	1.30%	0.94%	1.19%	1.00%	1.02%	1.13%	1.23%	0.73%
GDP change	1.32%	1.30%	1.19%	0.77%	1.98%	2.18%	2.06%	1.85%	2.01%	1.85%	1.96%	2.02%	1.73%	1.52%

United States

Year	1967	1968	1969	1970	1971	1972	1973	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983
GGDI	7.32%	6.95%	6.68%	6.57%	6.46%	6.22%	5.58%	5.13%	4.80%	4.52%	4.19%	3.88%	3.49%	3.24%	3.16%	3.04%	2.60%
GDP change	8.69%	8.35%	8.10%	7.97%	7.92%	7.72%	7.04%	6.62%	6.48%	6.14%	5.76%	5.31%	4.80%	4.56%	4.43%	4.27%	3.80%

United States

Year	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
GGDI	2.48%	2.44%	2.38%	2.15%	1.96%	2.08%	2.04%	1.88%	1.81%	1.43%	1.38%	1.34%	1.43%	1.40%	1.39%	1.18%	1.23%
GDP change	3.63%	3.47%	3.36%	3.07%	2.81%	2.94%	2.90%	2.74%	2.67%	2.29%	2.18%	2.20%	2.25%	2.20%	2.15%	1.92%	2.03%

United States

Year	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
GGDI	1.23%	1.23%	1.20%	1.32%	1.42%	1.34%	1.31%	1.09%	1.05%	1.14%	1.01%	1.13%	1.11%	1.18%	1.10%	1.04%	1.10%
GDP change	2.03%	2.11%	2.08%	2.25%	2.28%	2.23%	2.12%	1.96%	1.98%	2.06%	1.98%	2.07%	2.07%	2.20%	2.06%	1.97%	2.06%

United States

Year	2018	2019	2020	2021	2022
GGDI	1.13%	0.92%	0.91%	0.90%	0.88%
GDP change	2.03%	1.71%	1.67%	1.71%	1.67%

Uruguay

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
GGDI	3.86%	3.62%	3.22%	3.15%	2.87%	2.52%	2.38%	2.49%	2.29%	1.91%	1.95%	1.76%
GDP change	5.48%	5.17%	4.61%	4.54%	4.18%	3.75%	3.63%	3.76%	3.53%	3.17%	3.17%	2.95%

Notes: GGDI shows the % change in total output from removal of gendered labor market distortions. GDP changes shows the associated change in measured GDP, which exclude home sector.