Evergreen Background Methodological Paper to Valuing the Invaluable: The paid and unpaid contributions of women and men to health and care work (submitted to The Lancet September 2023) and the Report of the Lancet Commission on Women and Health (2015).

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Table of Content

This is a living document, also known as an evergreen document or dynamic document, that is continually edited and updated, evolving through successive updates to the original methodology for valuing paid and unpaid health contributions developed and published in the Lancet Commission on Women and Health (LCW&H) and will be expanded as needed. Revision may not reference all previous iterative changes but originates with the Supplement to: Langer A, Meleis A, Knaul FM, et al. Women and Health: the key for sustainable development. Lancet 2015; published online June 5.[1] Each version of this document that is linked to a specific publication will be marked as such and maintained as record. Data tables are available upon request from the authors.

1: Defining Paid and Unpaid Health Activities: Typologies of Paid and Unpaid Health and Care Contributions and What is Measurable

The contributions of women to health and the health sector are myriad and complex to categorize. We developed a framework that informed both a search methodology for data and a measurement framework. Activities are categorized first by sphere of work, where private refers to anything undertaken inside a person's own home. We then differentiate health-related activities by whether or not there is some remuneration in money. We thus arrive at four basic categories and then identify typical activities in each (Table 1).

Table 1: Health and health promoting activities by location and if remunerated.

	Public sphere	**Private sphere (Own home)**
Remunerated/valued yet often undervalued	• Health sector work • Health-related or promoting work non-health sectors (Education, etc.) • Health or health promotion work in other households	Health promoting work undertaken in one´s own home for payment as self employment (often for other households) e.g. washing clothes.
Not remunerated/not valued	• Volunteer work as direct or community service or help to directly support the health needs of friends and neighbors • Activities undertaken individuals as part of collective action in support of better health for the community, country or globally	Care of children, elderly and sick • Own household • Other household (family or friends)

Using the most detailed data sets available from Mexico (see below) that cover both labour force participation and time use overall (inside outside and outside of the home) we categorized all activities that can be considered primarily related to health in each of the four categories.

In the public sphere, we include all remunerated (cash or in kind) work in health. We consider all activities in the heath sector undertaken by anyone (e.g., health professional; a hospital administrator), and all activities that are undertaken in other productive sectors with the purpose of promoting health (e.g., school nurses). We also consider the health sector to include all work undertaken to produce goods for health regardless of whether production occurs in a setting where people are provided with health care (e.g., factories that produce medicines or devices for supporting the health of people).

In the private sphere, we also undertook a careful and detailed analysis of activities that can be considered primarily health producing. We based our analysis on the Mexico categorization of household activities in the Time Use Survey (see below for description). After reviewing all the categories and sub-categories, the following activities were categorized as strictly health producing:

1. Caregiving for family members (of all ages) that require support
   a. Feeding, bathing, cleaning, help with dressing, providing medications, and monitoring and caring for symptoms
   b. Accompanying a person to receive medical attention
   c. Providing special therapy and help with exercise
   d. Taking care or watching someone
2. Helping and caring for family members <15 years of age
   a. Bringing or accompany someone to receive medical attention
3. Helping and caring for family members >=60 years of age
   a. Bringing or accompany someone to receive medical attention
   b. Taking care of someone while they undertake other activities
4. Support for other households, the community and volunteering
   a. Helping other households by taking care of members voluntarily
   b. Childcare, elder care, care provided to temporarily or chronically ill people and persons with mental and physical disabilities

There are many activities that can be undertaken simultaneously, and this presents an additional measurement challenge. In the first place, if two health activities are undertaken at the same time, for example undertaking 1.a and 3.b for one hour, we count only one hour of health activity. Although in terms of time investment and for the calculation method used in this paper, one hour can only be counted as one hour, we acknowledge that people spending one hour taking on multiple health-producing or health-promoting activities are contributing more to health than those taking on a single activity, all else being equal, and thus should be valued accordingly. This is related to the concept of intensity and quality of time spent, and the value of the production of this labour, which is beyond the scope of this study but is an area that warrants further research. Further, if a non-health activity is listed as primary and a health activity as secondary, it is not clear what value to give the health activity. Similarly, a primary health activity if combined with another activity may reduce the efficacy or time spent on the health activity. One example of this is passive care giving – watching television while accompanying a person who is ill; having your own dinner with a person with a disability under your care. In the Mexico Time Use Survey, for a subset of the primarily health activities mentioned above, the person is asked if the health activity was combined with any other activity but not what the "other" activity is. In these cases, because of the difficulty of separating simultaneous and passive activities, we decided to use an arbitrary proportion and assigned only 20% of the time devoted to these activities as health producing.

A further issue that is not easily dealt with – conceptually or empirically – is the contributions to health of activities that are not purely or primarily dedicated to producing health.[2] Fetching water, washing clothes, cleaning floors, sourcing food, cooking and many other common daily activities have a health and a public health component. Similarly, activities such as providing a secure environment in the household or community – much of these activities require investing time in social capital – can contribute significantly to the production of health. Assigning an earnings value to these activities can be accomplished with the methodologies described below, yet it is difficult to assign a value in terms of time. In other words, of the many hours spent fetching water by many women in the poorest parts of the world, it is challenging to isolate the time that solely corresponds to producing health. Indeed, some would argue that all the time should be considered health-related even if other important items are produced in the short term as a result of having water (e.g., meal prepared). Further, how does one consider the value of clean water versus water that cannot be consumed for drinking or that if consumed produces illness? Indeed, one way of conceptualizing these core contributions, most of which are undertaken by women, is to consider what health would be lost if they were not done or not done 'well'. In the Mexico analysis we classified these additional activities as 'health promoting contributions' and provided some very initial estimates of the time value of these myriad activities in the household. These have not been updated in the current analysis but are the subject of a future paper.

Women contribute in many ways to economic growth and this in turn tends to be associated with greater investment in health care and improved health. We do not quantify this in the study, which focuses on the contribution of women to health, although these contributions are discussed in the report of the Lancet Commission on Women and Health. [3,4]

We only capture the work of women and men in this analysis as these data only disaggregate to this level for gender. Further, the Labour Force and Time Use surveys capture work performed by those who are over the age of 15 years. This is one limitation of the analysis as many girls and adolescents also undertake work that produces health, primarily but not only in their own homes, and this can often limit the amount of time that they devote to schooling. While this has been analyzed overall for girls' time use, to our knowledge it has not been studied in detail for the health sector.

2: Methods for Estimating the Value of Unpaid and Paid Care

For this update, we rely on the work previously developed by Knaul FM, Arreola-Ornelas H, et al., 2015.[1] The differences between the previous version and these new estimates are summarized in Table 2.

Table 2. Comparison of methods and definitions between the Lancet Commission on Women and Health 2015 analysis (LCR 2015) and the update paper.

	LCR 2015	Update
Gender	Women only	Men and women
Paid work	Volunteer health-related work (labour force survey) was included in paid contributions.	Volunteer health-related work (labour force survey) is included only in unpaid contributions.
	Base estimate for all workers, salaried or non-salaried – referred to as "net value" - excludes taxes and social benefits.	Base estimate for salaried workers includes taxes and social benefits. Base estimate for non-salaried workers excludes taxes and social benefits.
Unpaid work	Both opportunity cost method (Heckman model) and proxy good method (minimum wage and average health sector wage) were used in estimating the value of the unpaid work.	The average wage for all sectors from ILO database was used to value the unpaid hours instead of using the average health sector wage from microdata.
Discrimination	A discrimination factor based on gender was considered from the literature for the paid and unpaid contributions.	The discrimination was calculated based on the anchor country data by replacing the average wage from men to the women labour force.
Countries with micro data	Five countries: Canada, Mexico, Peru, Spain, Turkey.	Fifteen countries (including four previous ones and 11 new ones): Canada, Mexico, Peru, Spain, Brazil,

		Colombia, Chile, Germany, Ghana, Iceland, India, Japan, Mongolia, Pakistan, United States. Turkey: excluded due to data limitations.
Countries with aggregate unpaid labour force date	27 countries were added to the analysis (information based on official time use reports).	34 countries were added to the analysis (information based on official time use reports).
Sensitivity Analysis	Different assessments or wage levels for paid work were considered: Minimum wage, opportunity cost, wages reported in the survey, wages reported in the survey with gender discrimination, and wages reported in the survey with gender discrimination + cost of the social benefits package.	The average hours of paid and unpaid work were compared across countries and by income group using a simple mean, simple median, and the mean weighted by the population size of the anchor countries. Median was selected to best account for the spread of the estimates and to eliminate the effect of outliers. We also explored specific regions such us South Asia and Latin America to describe specific geographical and cultural differences.
Confidence Intervals	For the unpaid contribution, the confidence intervals were driven by the five anchor countries and 27 aggregated countries.	The confidence intervals were calculated based on the bootstrap distribution of 1000 repetitions computing the 2.5th and 97.5th percentiles. The 95% confidence intervals were calculated around the key outcome, GDP contribution (%), and by income group (low, lower-middle, upper-middle, and high).

For the updated analysis, we estimated the value of both paid and unpaid health and care separately in net and gross values. Our concern about gross values is related to estimating, across countries, the full value of remuneration. This can include social security and other benefits directly covered through payroll deductions, but also through taxes that are deducted at source and partially covered by employers. Extensive literature exists on methods to determine the wage value of these benefits, although it is especially difficult to compare across the salaried and non-salaried workforce in countries where much of the non-salaried workforce does not pay taxes. Again, a detailed analysis of these issues is considered to be beyond the scope of the study.

We also considered, to the extent possible, the issues of gender discrimination in the wages paid to women in the occupations they occupy, but we do not analyse for this study pre-labour market discrimination that is associated with access to quality education, health care before and after birth, early childhood stimulation and other key inputs that help define the extent to which any individual can achieve their full potential. Much of the discrimination faced by women occurs well before they begin to undertake activities that produce health in the labour market, home or community – an area for future research.

In order to undertake this type of analysis, different types of data are required, specifically a nationally representative labour market survey that includes detailed, coded information on sector and type of occupation as well as higher education; a time use survey that covers unpaid activities inside and outside the home with information on health-related activities; and, data on the tax regimes, social security and other labour market benefits and minimum wages.

We describe the data in greater detail below. For the cross-country comparative analysis, we use two-digit occupation coding based on the International Standard Classification of Occupations[5] and International Standard Industrial Classification, and focus on Codes 22 and 32 that correspond to the health sector (Table 3 and Table 4). For the country specific work, we use the full richness of the data at our disposal, often at four digits enabling us to identify not only broad sector of work, but also the exact nature of the work undertaken.

Table 3. Codes and categories to estimate the value of paid health work. [6]

Paid healthcare work

ISCO-88 Codes	Activity
22	Health Professionals
221	Medical Doctors
222	Nursing and Midwifery Professionals
223	Traditional and Complementary Medicine Professionals
224	Paramedical Practitioners
225	Veterinarians
226	Other Health Professionals
32	Health Associate Professionals
321	Medical and Pharmaceutical Technicians
322	Nursing and Midwifery Associate Professionals
323	Traditional and Complementary Medicine Associate Professionals
324	Veterinary Technicians and Assistants
325	Other Health Associate Professionals

Table 4. Codes and categories to estimate the value of unpaid health work [7]

Unpaid healthcare work

Activity
1.Caregiving for family members (of all ages) that require support
a. Feeding, bathing, cleaning, dressing, administering medications, and monitoring and caring for symptoms,
b. Accompanying a person to receive medical attention.
c. Providing special therapy and help with exercise.
d. Taking care of or watching someone.
2. Helping and caring for family members <15 years of age
a. Bringing or accompanying someone to receive medical

		attention.
3. Helping and caring for family members >=60 years of age		
	a.	Bringing or accompanying someone to receive medical attention.
	b.	Taking care of someone while they undertake other activities.
4. Support to other households, the community, and volunteering		
	a.	Helping other households by taking care of members voluntarily.
	b.	Childcare, elderly care, and care provided to temporarily or chronically ill people and people with mental and physical disabilities.

2.1 Estimating the Value of Unpaid Work

The value of unpaid work is calculated as the multiplication of three factors: 1) the percentage of full-time equivalent of work calculated from hours spent on health and care, 2) the annual wage, and 3) the total number of men or women population over 15.

For hours spent on health and care, we use micro data from the time use surveys in 15 anchor countries to calculate average, unpaid hours in health-specific care work for men and women. In addition, in the 35 countries with aggregate, reported data we harvested similar information and projected for the rest of the countries (see next section on data below to explain the projection methodology). Hours spent on care activities in a week are calculated by multiplying the weekday value by 5 and the weekend day value by 2. This time divided by 40 hours per week would generate the percentage of full-time equivalent as contributed by the unpaid work. Multiplying this estimated value by the predicted earnings of the individual gives us the yearly value of time spent on care by each individual in the dataset. Finally, determining and summing these numbers for all men or women over 15 in any country gives us the estimated economic value of time spent on care activities in a year for that country.

The estimation of wages was more complicated and we opt for using the average, nationwide earnings of men and women, collecting data on average wages from the International Labour Organization for 153 countries and imputing for missing values using gross domestic product per capita. We acknowledge that using the average wage in each country could bias (likely upward) the value of unpaid care, as sectors on the high-end of the salary spectrum are included and those who are out of the labour market may have lower productivity than many who are in the labour market. But, other options limited the number of countries with data as we have detailed micro data for only the 15 anchor countries. Hence, we considered and discarded as inferior several alternative approaches and then use these results for sensitivity analysis (see below).

2.2 Estimating the Value of Underpaid Work

In order to measure underpayment and compensate for gender wage differentials (sometimes referred to as discrimination), we used a simple approach of applying average, country-specific wages of men to women. We realize that this approach introduces bias – likely upward – and cannot be equated with discrimination. To bound our estimates, we also undertook a Oaxaca-Blinder decomposition (Oaxaca, 1973) exercise summarized below as part of the sensitivity analysis.

2.3 Estimating the Value of Paid Healthcare Work

We first estimated the yearly net earnings of the individuals working as life science and health professionals and associates (ISCO 88 code 22 and 32) in each country dataset. Next, we computed the total yearly value by summing up the earnings of all of the individuals in this group.

In order to compensate for the wage discrimination in the health sector, we again used Oaxaca decomposition method for average hourly earnings of life science and health professionals and associates. We repeat the same analysis using gross earnings.

2.4 Determining the total contribution of women (or men)

The total contribution (TC) of women (or men) to health and healthcare is obtained by summing the value of public-sphere paid, public-sphere unpaid, and private-sphere unpaid and paid work.

TC = Remunerated Public + Remunerated Private + NonRemerated Public +Nonremunerated Private...(1)

Remunerated = (Paid Public Sphere + Paid Private Sphere)=pub + priv...(2)

NonRemunerated Public Sphere = wiHec * hiNRPub ...(3)

NonRemunerated Private Sphere = wiSc * hiNRPriv ...(4)

where:

Remunerated: total value of paid work in the public or private sphere
i: if the individual is a woman, sums over entire population 15 and over; 1 to n wi: market wage for women.
hi: hours dedicated to activities in health production and or the health sector by women wiHec: market wage for women estimated using the Heckman model.
hiNRPub: number of unpaid hours dedicated to activities in health production and or the health sector by women.
wiSc: wage proxy for women that may be the minimum or average wage for performing health care activities in the home
hiNRPriv: number of hours dedicated to health care activities in the home by women.

3. Selection of and calculation for anchor countries

3.1 Selection of anchor countries

We conducted a systematic search strategy of global data repositories and government websites to identify countries with publicly available country-level Time Use Surveys and Labour Force Surveys carried out in the last 10 years (Table 5). We identified 15 countries with micro-data that met these criteria – called anchor countries - and sourced each data set either on-line or through national statistical agencies. We use these micro-data to generate country-specific estimates (paid and unpaid contribution) and to support the global projections as an input to the imputation strategy for countries in the same income group. We rely on data from lower-middle income countries to impute values for both low income and lower-middle income countries (see project section below).

Table 5. Data sources for anchor countries

		Paid contribution		Unpaid contribution	
Income group	Country	Survey	Date	Survey	Date
High	Iceland	Labour force survey	2018	European union statistics on income and living conditions (EU-SILC)	2018
	United States of America	Current Population Survey (CPS)	2018	American Time Use Survey	2018
	Germany	Germany Labour Force Survey, Eurostat	2015	German Time Use Survey	2012/ 2013
	Canada	Labour Force Survey	2017	General Social Survey on Time Use	2015
	Japan	Labour Force Survey	2019	Survey on Time Use and Leisure Activities	2016
	Spain	Encuesta de Poblacion Activa	2019	Encuesta de Empleo del Tiempo	2010
	Chile	Encuesta Nacional del Empleo	2015	Encuesta Nacional Sobre Uso del Tiempo	2015
Upper-middle	Mexico	Encuenta Nacional de Ocupación y Empleo	2014	Encuesta Nacional de Uso de Tiempo	2019
	Brazil	Pesquina nacional por amostra de domicilios continua – PNAD CONT NUA	2018	Pesquina nacional por amostra de domic lios contínua – PNAD CONT NUA	2018
	Peru	Encuesta Nacional de Hogares	2010	Encuesta Nacional de Hogares	2010
	Colombia	Gran Encuesta Integrada de Hogares	2016/ 2017	Encuesta Nacional de Uso del Tiempo	2016/ 2017
Lower-middle	Mongolia	Mongolia Labour Force Survey	2019	Time Use Survey	2015
	Ghana	Ghana Labour Force Survey	2015	Time Use Survey	2009
	India	Partial Labour Force Survey	2017/ 2018	Time Use Survey	2019
	Pakistan	Household Integrated Economic survey	2018/ 2019	Time Use Survey	2007

Data sets were available for a large group of high-income countries, and we took a deliberate sample based on geography, size of the population and gender policies. Our available resources were insufficient to cover all high-income countries. For low- and middle-income countries, our search was exhaustive, yet we identify no recent data for low-income countries. Our anchor countries represent 53% of the global population, and 48% of the high, 74% of the upper-middle, and 48% of the lower-middle-income population. Our data include several Latin America countries representing 75% of the population and this allows us to draw region-specific conclusions. The data for other regions is less representative. Our data set includes updated surveys for four (Canada, Mexico, Peru and Spain) of the five anchor countries that were in the LC report in 2015, but micro data for Turkey were not available.

Although the anchor countries all have the necessary data inputs and surveys to conduct the analysis, there are differences across countries and regions in data collection practices, job classification codes, jobs (e.g., traditional medicine in Latin America), construction of total remuneration (e.g. bonuses) and frequencies of payment. The research team was divided into two groups and cross-referenced work to standardize the information to make it as homogeneous as possible across all countries.

We identified an additional 34 countries with aggregate data reported from time use surveys and these data are used in the unpaid contribution calculations (Table 6). The aggregate data on unpaid hours represent 15% of the global population, and within it 32% of the high, 11% in the upper-middle, 8% of the lower-middle, and 31% of the low-income group population (Table 7). We selected only health-specific caregiving hours from the published data.

Table 6. Data sources for countries with aggregate date for the unpaid calculation

Income Group	**Country**	**Survey**	**Year**	**Source**
High	Czech Republic	Labour Force Survey	2010	http://www.oecd.org/social/soc/oecdfamilydatabase.htm#public_policy
	Estonia	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	France	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Greece	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Hungary	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Ireland	Irish National Time Use Survey	2005	https://www.ucd.ie/issda/data/irishnationaltimeusesurvey/
	Italy	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Netherlands	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Norway	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Panama	Encuesta Nacional de Uso del Tiempo	2011	https://www.inec.gob.pa/publicaciones/Default3.aspx?ID_PUBLICACION=515&ID_CATEGORIA=5&ID_SUBCATEGORIA=63

	Poland	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Portugal	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Romania	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Sweden	The Swedish Time Use Survey	2010	https://www.scb.se/publication/18561
	United Kingdom	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	Uruguay	Encuesta Continua de Hogares (ECH). Modulo de Encuesta de uso del tiempo (EUT).	2013	https://uruguay.unfpa.org/es/publications/uso-del-tiempo-y-trabajo-no-remunerado
Upper-Middle	Argentina	Encuesta sobre Uso del Tiempo en la Ciudad de Buenos Aires (UT-CABA)	2016	https://www.estadisticaciudad.gob.ar/eyc/?p=71834
	Armenia	Time Use Survey	2009	https://www.armstat.am/file/article/time_use_09e.pdf
	Bulgaria	Harmonised European Time Use Surveys (HETUS)	2010	https://ec.europa.eu/eurostat/web/time-use-surveys
	China	China Time Use Survey	2008	http://www.stats.gov.cn/ztjc/ztsj/2008sjly/
	Cuba	Encuesta sobre Igualdad de Género. Sección sobre uso del tiempo y cuidados	2016	http://www.onei.gob.cu/node/14271
	Dominican Republic	Módulo de uso del tiempo en la Encuesta Nacional de Hogares de Propósitos Múltiples	2016	https://web.one.gob.do/media/zsngmvuo/encuestanacionaldehogaresdepropósitosmútiplesinformegeneral2016.pdf
	Paraguay	Encuesta sobre Uso del Tiempo (EUT)	2016	https://www.ine.gov.py/publication-single.php?codec=Mjk=
	South Africa	Time Use Survey	2000	https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/116
	Thailand	Time Use Survey	2014	http://web.nso.go.th/eng/stat/timeuse/time_content.htm
	Turkey	Time Use Survey	2006	https://catalog.ihsn.or

				g/index.php/catalog/4765
Lower-Middle	Algeria	Enquête Nationale sur l'Emploi du Temps en Algérie ENET 2012	2012	https://www.ons.dz/IMG/pdf/RAPPORT_ENET_2012_FRAN_2_.pdf
	Bangladesh	Time Use Pilot Survey	2012	http://bbs.portal.gov.bd/sites/default/files/files/bbs.portal.gov.bd/page/96220c5a_5763_4628_9494_950862accd8c/TUSReport2012.pdf
	Benin	Enquête Modulaire Intégrée sur les Conditions de Vie des Ménages (EMICoV-2015). 2ème ÉDITION (EMICoV-2015). RAPPORT D'ANALYSE DU VOLET EMPLOI DU TEMPS	2015	https://instad.bj/images/docs/insae-publications/autres/Enquete-emploi-du-temps/EMICOV%202015%20VOLET%20EMPLOI%20DU%20TEMPS.pdf
	Nicaragua	Encuesta Nacional de Hogares sobre Medición de Nivel de Vida (EMNV'98)	1998	https://www.inide.gob.ni/docs/bibliovirtual/publicacion/usodeltiempo.pdf
Low	Mali	Enquête malienne sur l'utilisation du temps	2008	https://demostaf.web.ined.fr/index.php/catalog/389
	Ethiopia	Ethiopia Time Use Survey	2013	https://www.timeuse.org/sites/ctur/files/public/ctur_report/9414/ethiopian_time_use_survey_report_2014.pdf
	Madagascar	Enquête Permanente auprès des Ménages	2001	https://catalog.ihsn.org/index.php/catalog/3232
	Uganda	Uganda Time Use Survey	2017-2018	https://www.ubos.org/wp-content/uploads/publications/06_2020Final_Time_Use_report_published_June_2019.pdf

Table 7. Percentage of population covered by anchor countries and countries with aggregate data in 2023 updated paper

Income group	Micro data used/ Anchor country	Country	GDP per capita, 2019 (current US$)	Population 2019, (millions)	World population (%)	Cummulative world population (%)	Income region population (%)	Cummulative income region population (%)
High		Ireland	80886.62	4.93	0.06	0.06	0.41	0.41
		Norway	75826.08	5.35	0.07	0.13	0.44	0.85
	Yes	Iceland	68941.46	0.36	0.00	0.14	0.03	0.88
	Yes	United States	65279.53	328.33	4.27	4.41	27.12	28.00
		Netherlands	52476.27	17.34	0.23	4.64	1.43	29.43
		Sweden	51939.43	10.28	0.13	4.77	0.85	30.28
	Yes	Germany	46794.90	83.09	1.08	5.85	6.86	37.14
	Yes	Canada	46326.67	37.59	0.49	6.34	3.10	40.24
		United Kingdom	43070.50	66.84	0.87	7.21	5.52	45.76
	Yes	Japan	40777.61	126.26	1.64	8.86	10.43	56.19
		France	40578.64	67.25	0.88	9.73	5.55	61.75
		Italy	33641.63	59.73	0.78	10.51	4.93	66.68
	Yes	Spain	29555.32	47.13	0.61	11.12	3.89	70.57
		Czech Republic	23660.15	10.67	0.14	11.26	0.88	71.45
		Estonia	23397.12	1.33	0.02	11.28	0.11	71.56
		Portugal	23330.82	10.29	0.13	11.41	0.85	72.41
		Greece	19133.76	10.72	0.14	11.55	0.89	73.30
		Uruguay	17688.02	3.46	0.05	11.60	0.29	73.58
		Hungary	16735.66	9.77	0.13	11.72	0.81	74.39
		Panama	15774.25	4.25	0.06	11.78	0.35	74.74
		Poland	15732.20	37.97	0.49	12.27	3.14	77.88
	Yes	Chile	14741.71	18.95	0.25	12.52	1.57	79.44
		Romania	12899.35	19.37	0.25	12.77	1.60	81.04
Upper-middle		China	10143.84	1407.75	18.32	31.09	56.07	56.07
		Argentina	10056.64	44.94	0.58	31.68	1.79	57.86
	Yes	Mexico	9950.45	127.58	1.66	33.34	5.08	62.94
		Bulgaria	9879.27	6.98	0.09	33.43	0.28	63.22
		Cuba	9125.88	11.33	0.15	33.58	0.45	63.67
		Turkey	9121.52	83.43	1.09	34.66	3.32	66.99
	Yes	Brazil	8897.55	211.05	2.75	37.41	8.41	75.40
		Dominican	8282.12	10.74	0.14	37.55	0.43	75.82

		Republic						
		Thailand	7817.01	69.63	0.91	38.46	2.77	78.60
	Yes	Peru	7027.61	32.51	0.42	38.88	1.29	79.89
		South Africa	6624.76	58.56	0.76	39.64	2.33	82.22
	Yes	Colombia	6424.98	50.34	0.66	40.30	2.00	84.23
		Paraguay	5380.96	7.04	0.09	40.39	0.28	84.51
		Armenia	4604.65	2.96	0.04	40.43	0.12	84.63
Lower-middle	Yes	Mongolia	4404.85	3.23	0.04	40.47	0.10	0.10
		Algeria	3989.67	43.05	0.56	41.03	1.31	1.41
	Yes	Ghana	2246.63	30.42	0.40	41.42	0.93	2.33
	Yes	India	2100.75	1366.42	17.78	59.21	41.59	43.92
		Nicaragua	1926.70	6.55	0.09	59.29	0.20	44.12
		Bangladesh	1855.74	163.05	2.12	61.42	4.96	49.09
	Yes	Pakistan	1288.56	216.57	2.82	64.23	6.59	55.68
		Benin	1219.52	11.80	0.15	64.39	0.36	56.04
Low		Mali	879.04	19.66	0.26	64.64	3.03	3.03
		Ethiopia	855.76	112.08	1.46	66.10	17.30	20.33
		Uganda	798.59	44.27	0.58	66.68	6.83	27.17
		Madagascar	522.99	26.97	0.35	67.03	4.16	31.33

We used published data for 153 countries from the International Labour Organization[8] on national average wages and minimum wages disaggregated by sex. For the rest of the countries, average wages and minimum wages were imputed based on the average data from countries with available data within the same income group proportional to their GDP per capita (Table 7).

In addition, we sourced macro-economic and demographic data from the World Bank's global database[9] to be used as parameters in the global projection,[10] including GDP per capita, population over 15 years and total health expenditure for 203 countries covering 99.6% of the global population (Table 7).

3.2 Anchor country calculation and global Projection

3.2.1 Paid contribution:

Based on 15 anchor country microdata, we calculated the paid contribution stratified by sex for each anchor country as described in the main text and the data appendix.

In each anchor country, we calculated the paid contribution as the sum of the product between the average wage and the number of workers for each health occupation. In the Base paid contribution, the wage was the "take-home" remuneration plus taxes and social benefits for salaried workers, while for non-salaried (independent/informal) workers, the wage was based only on the "take-home" remuneration. For the base Plus contribution the wage was the "take-home" remuneration plus taxes and social benefits for all workers. The cost of the social benefit package in the different countries was approximated as the value of social contributions in direct income taxes, based on the information provided by UN-WIDER in the Government Revenue Dataset. In the Base Plus Discrimination contribution, we replaced the average wage for women with the average wage for men in all health-related occupations for all occupations where women earn less than men.

For the global projection, we group the anchor countries by income group and calculate the median of the following parameters: i) paid contribution by sex, ii) GDP, iii) total health expenditure, iv) female to male labour force ratio, and v) average salary by sex.

From the countries without microdata, the median of the anchor country estimates within each income group was calibrated using four, country-specific variables: the size of the health sector, measured as health spending as a proportion of GDP; GDP per capita; the ratio of female to male labour force participation; and, average, labour market-wide, sex-specific wages. We obtained ILO data[8] on the national average, sex-specific wage for 153 countries. For each income group, we generated a weighted mean average salary using GDP per capita as the weight, for countries that reported average wages. We then imputed the average wage for the countries with missing data within the same income group based on the ratio of their GDP per capita to the mean GDP per capita of countries with average wage data. For countries lacking sex-disaggregated population data, we use the simple, sex-specific mean from the rest of the countries of the same income group.

We applied the following formulas to calculate the country's contribution from the contribution of anchor countries in the same income group.

For women:

$$\widehat{Paid}_{c_f} = Paid_{g_f} * \left(\frac{THE_c}{THE_g}\right) * \left(\frac{GDP_c}{GDP_g}\right) * \left(\frac{RFMLFP_{cf}}{RFMLFP_{gf}}\right) * \left(\frac{FAW_{cf}}{FAW_{gf}}\right)$$

$Paid_{c_f}$ = Remunerated contributions of women (f) in country c
$Paid_{g_f}$ = Paid contributions of females in anchor countries representing income group g, to which country c belongs
THE_c = Size of the health sector in country c approximated as Total health expenditure as a percentage of GDP
THE_g = Size of the health sector in anchor countries representing income group g, to which country c belongs approximated as Total health expenditure for anchor countries as a percentage of GDP of anchor countries
$GDPc$ = Gross domestic product in country c
$GDPg$ = Gross domestic product in anchor countries representing income group g, to which country c belongs
$\left(\frac{RFMLFP_{cf}}{RFMLFP_{gf}}\right)$ = Adjustment factor with respect to Ratio female to male labour force participation in country c versus the same ratio for anchor countries representing income group g, to which country c belongs.
Note: Anchor countries representing lower-middle income region = low-income region

In the case of men's contributions, the same logic is applied as for women, only based on the values for men both in country X and in the region J to which it belongs. The only difference is that when adjusting using the ratio of female to male labour force participation, the inverse ratio was applied:

$$\widehat{Paid_{c_m}} = Paid_{g_m} * \left(\frac{THE_c}{THE_g}\right) * \left(\frac{GDP_c}{GDP_g}\right) * \left(\frac{RFMLFP_{gm}}{RFMLFP_{cm}}\right) * \left(\frac{MAW_{cm}}{MAW_{gm}}\right)$$

$Paid_{c_m}$ = Remunerated contributions of male (m) in country c
$Paid_m$ = Paid contributions of males in anchor countries representing income group g, to which country c belongs
THE_c = Size of the health sector in country c approximated as Total health expenditure as a percentage of GDP
THE_g = Size of the health sector in anchor countries representing income group g, to which country c belongs approximated as Total health expenditure for anchor countries as a percentage of GDP of anchor countries
$GDPc$ = Gross domestic product in country c
$GDPg$ = Gross domestic product in anchor countries representing income group g, to which country c belongs
$\left(\frac{RFMLFP_{gm}}{RFMLFP_{cm}}\right)$ = Adjustment factor with respect to Ratio female to male labour force participation in country c versus the same ratio in anchor countries representing income group g, to which country c belongs.

We grouped all the countries by income group and sum the total contribution in USD, and the total income group GDP in USD, and divided them to calculate the contribution by income group. In a similar way we calculated the global contribution.

3.2.2 Unpaid contribution:

We calculated the average number of unpaid hours spent doing health and health-related work was calculated using micro data from anchor countries, summary data from 34 countries and imputed for all other countries.

We valued each hour of unpaid work at the average country wages. For anchor countries and countries with aggregate data, we calculated the Unpaid Base contribution per year as the product of the population over 15 years, the average unpaid hours per year, and the average yearly wage. The Unpaid Base Plus contribution includes country-specific, income-scaled taxes and social benefits, which were added to the base value for each hour expended on unpaid, health-related activities. For the Unpaid Base Plus discrimination contribution we imputed and applied a discrimination factor by replacing the country-specific, average wage for women with the country-specific, average wage for men. Each hour of unpaid health work undertaken by a woman is valued at for men, adding tax and social benefits.

In this analysis we value unpaid work using national average wages for workers. We argue that unpaid health-care work should be valued at this level, at a minimum, which tends to be below the average wage of paid health-care work (professional and non-professional roles). We undertook sensitivity analysis to value unpaid work under different scenarios: the minimum wage required by law; sex-specific average wages for all workers; and wages calculated from the Labour Force Survey for health-related jobs using the Heckman model.[11] We considered applying the wages of paid care providers (e.g. personal support workers), but the survey samples were too small to provide reliable estimates. We rejected the option of using the wages of all health-care workers as it biased the estimates upward by including higher-paid health professionals. For the countries with micro data, we undertook econometric estimation using Heckman methods, but were unable to identify appropriate instrumental variables.

For the global projection, we group the anchor countries by income group and calculate the mean of the unpaid hours by sex. For countries without micro or aggregate data on hours performing unpaid work, sex-specific mean hours spent on healthcare-specific activities for the anchor countries were applied to all countries in the same country income group. From the countries without microdata, we used the i) population over 15 years old, ii) average wage, iii) GDP and apply the following formulas to calculate the country contribution.

For women:

$$\widehat{Unpaid}_{c,w} = \frac{\left(\frac{WUH_{g,w}}{40} * WpplnOver15_{c,w} * MWW_{c,w} * 12\right)}{GDP_c}$$

$Unpaid_{c,w}$ = Unpaid contributions of women *w* in country *c*
$WUH_{g,w}$ = Median weekly unpaid hours of women *w* in anchor countries and countries with aggregate data in income group g, to which country c belongs
$WpplnOver15_{c,w}$ = Women *w* population over 15 years old in country *c*
$MWW_{c,w}$ = Monthly average wage of women *w* in country *c*
GDP_c = GDP in country c

For men:

$$\widehat{Unpaid}_{c,m} = \frac{\left(\frac{WUH_{g,m}}{40} * MpplnOver15_{c,m} * MWM_{c,m} * 12\right)}{GDP_c}$$

$Unpaid_{c,m}$ = Unpaid contributions of men *m* in country *c*
$WUH_{g,m}$ = Median weekly unpaid hours of men *m* in anchor countries and countries with aggregate data in income group g, to which country c belongs
$MpplnOver15_{c,m}$ = Men *w* population over 15 years old in country *c*
$MWM_{c,w}$ = Monthly average wage of men *m* in country *c*

GDP_c = GDP in country c

We have described above how we obtained the monthly average wage from International Labour Organization, and the data on GDP and population over 15 for men and women were obtained from the world bank database. We only included countries or territories with available total GDP data in the world bank database. For countries without the data on population over 15 for men and women, we first obtained the data on total population, and then applied the average proportion of population over 15 for men and women of the same income group. Average wage downloaded from the ILO were deflated to 2019 USD PPP.

3.3 The analysis for country México as an example:

3.3.1 Source of data:

Two datasets, official surveys undertaken by the Mexican government, were used in the analysis of both remunerated and unpaid work:

1) the third quarter, 2014 National Occupation and Employment Survey [(Encuesta Nacional de Ocupación y Empleo (ENOE)], carried out by the Mexican National Institute of Statistics and Geography [(Instituto Nacional de Estadística y Geografía (INEGI)]; and

2) the 2019 National Time Use Survey [(Encuesta Nacional de Uso de Tiempo (ENUT)] carried out by INEGI and the National Institute of Women [(Instituto Nacional de las Mujeres (INMUJERES)].

The ENOE is a quarterly survey designed to provide detailed information on socio-economic status, economic activity, occupation, employment status, working hours, and earnings of all individuals above the age of 12 (we use data for 15 and over). It is nationally representative, as well as representative of urban areas and cities of more than 100,000 inhabitants, middle urban areas (15,000 to 99,999 inhabitants), urban low areas (localities of 2,500 to 14,999 inhabitants), and rural areas (localities with less than 2,500 inhabitants). The 2009 ENOE has a quarterly sample size of approximately 103,902 households and/or 308,313 individuals. All of the information regarding remunerated, unpaid and voluntary work in the public sphere was extracted from this survey. The survey includes an embedded, rotating panel of five quarters and although we did not make use of these longitudinal data in this first stage of the project, we hope to do so in the future.

The ENUT is a nationally representative survey that was previously carried out in 1997 and 2003. The survey is designed to provide detailed information on time use of all family members and especially adult women in the household, including specifically in unpaid activities. This survey had a sample size of 17,000 households. Information regarding unpaid work was extracted from this survey, including health care activities within the household and caregiving in health outside the home.

3.3.2. Remunerated work

Using the ENOE Survey (2014 third quarter), we identified all individuals who in the last week reported working or taking leave from work with pay for illness, disability or vacation (in other words, all those considered employed). Subsequently, for the employed population, we identified if their primary activity corresponded to the health sector (see annex 1. NAICS codes). In the second step, we identified the occupation corresponding to their primary work activity (See annex 2. Mexican Classification of Occupations) within the 32 different activities in the sector. We then replicated this analysis for those individuals who reported having a second occupation that was health related. Finally, we identified all the individuals whose primary or secondary work activity was outside of the health sector but whose occupation corresponded to a health-related activity or occupation (See annex 3. for the list of occupations considered). Given the richness of the Mexico data we were able to go into detail and 4-digit occupation coding to identify a variety of contributions to health and the health sector.

Finally, we stratified by position at work according to four reported categories: a. Salaried worker, b. Unpaid family worker, c. Unpaid non-family worker/volunteer, and d. Self-employed worker. Note that b and d could occur in the private or public sphere as many people work from their homes. For the purposes of this analysis, the categories a and d correspond to paid work, while the categories b and c correspond unpaid work. In category c we were able to identify volunteer work.

To calculate the value of remunerated or paid work, we first identified the reported monthly salary in the ENOE survey for the primary occupation. However, because the survey only reports monthly salaries for the primary occupation, and because there are missing values on wages as well as reported non-monetary remunerations, we ran a Heckman selection bias model to predict the wage value of secondary work activities (Heckman, J.J., 1979)[12]. In the model, the dependent variable is the logarithm of monthly salaries. The independent variables in the income equation were: age, age squared, years of education, and if residence is in a rural zone. For the selection equation the variables used were: (i) if a person is married or has a partner in the household (ii) number of children under the age of five in the household, (iii) number of children between the ages of 6 and 14 in the household, and (iv) number of adults over the age of 65 in the household. (See Table 8 for a review of the results of the Heckman model).

Table 8. Heckman model results for Mexico

	Female						Male					
	(1)		(2)		(3)		(1)		(2)		(3)	
	log_earnings_net_monthly		select		mills		log_earnings_net_hourly		select		mills	
Age	0.0317	***	0.0231	***			0.0512	***	0.0108	***		
	(0.001)		(0.002)				(0.001)		(0.001)			
Age2	-0.0003	***	-0.0003	***			-0.0005	***	-0.0002	***		
	(0.000)		(0.000)				(0.000)		(0.000)			
Years of education	0.1084	***	-0.0349	***			0.0778	***	-0.0305	***		
	(0.001)		(0.001)				(0.001)		(0.001)			
Rural	-0.2004	***	-0.1311	***			-0.2501	***	-0.1974	***		
	(0.013)		(0.016)				(0.008)		(0.011)			
Married			-0.0503	***					0.2585	***		
			(0.009)						(0.010)			
Number of children aged 0-5			0.0124	**					0.0208	***		
			(0.005)						(0.005)			
Number of children aged 6-14			-0.0280	***					-0.0492	***		
			(0.004)						(0.004)			
Number of elderly*			-0.1022	***					-0.1031	***		
			(0.008)						(0.008)			
Constant	4.3796	***	0.5563	***			4.4041	***	0.7268	***		
	(0.030)		(0.037)				(0.020)		(0.029)			
lambda					-0.8386	***					-0.6684	***
					(0.004)						(0.005)	
Observations			64412						100856			

Once the values for monthly salaries and other remuneration were determined, we proceeded to estimate the annual, total value of remunerated work by multiplying by 12 and doing the sum for each worker. Finally, we disaggregated the information by gender to identify the total contributions of women and men.

Since unpaid family workers and unpaid non-family employees report working but do not receive any remuneration, it is necessary to assign a value to these types of work. We followed the strategy outlined above using the same Heckman selection model and inputted the value of wages.

In estimating the contribution of households to health-related activities, both of the two established methodologies were applied to determine the value of time: the opportunity cost method, and the best-proxy method (See Van Der Berg et al., 2004 [13] and description about). For this analysis, we consider average wage. The calculation of the total value is obtained by multiplying average wage by the annual total of hours spent by women and men undertaking these activities.

In order to strengthen our estimates, it was necessary to carry out additional adjustments in the wages used in the analysis due to, among other things, problems associated with the employment surveys used which fail to differentiate between net and gross wages. The estimates of wages were corrected by applying the cost of the social security benefits package to remove the issue of reported net salaries since the social cost does not correspond to the net value reported in the surveys, but the gross value that includes all of the benefits that workers receive.

Given the comments received in two external advisory meetings, we devised an approach, included in the 2015 LCR to account for hours dedicated to health in the home using a much more open and inclusive definition that included activities not exclusive to health. These included:

a) collection, preparation or storage of firewood
b) sourcing of fruits and vegetables
c) carrying or collecting water
d) preparing, cooking and grinding corn or flour for making tortillas
e) lighting or tending a stove for cooking with firewood or charcoal
f) cooking or preparing food or drink for breakfast, lunch, dinner, or between meals
g) warming food or drink for breakfast, lunch, dinner or between meals
h) washing, drying or putting away dishes
i) cleaning the inside of the house
j) cleaning the exterior of the house
k) separating, discarding, or burning trash
l) washing and drying clothes
m) home repairs or installation of household items
n) shopping for household goods
o) waiting for gas, water, trash collection or other utility service

As described in the Report of the Lancet Commission on Women and Health,[4] using open definition for the analysis generated a much higher number of hours dedicated to health producing activities. We then undertook some basic sensitivity analysis and assigned a value to these hours of work in health. As described in the Report of the Lancet Commission on Women and Health, it is very challenging to assign a proportion of wages to these hours dedicated to health. In some senses the value is much higher than the wage, because these activities often prevent diseases that could cost both society and families large sums (health care costs and lost income; the spread of disease). At the same time, only a proportion of the hours dedicated to these activities are actually health related. For example, preparing a meal often involves both setting a table nicely (little health value) and combining healthy ingredients in ways that preserve the quality of the food (cleaning foodstuffs, using clean utensils). This is an issue that deserves further analysis and will be taken up in forthcoming work.

3.4 Analysis in four sample countries to determine the contribution of a secondary job as a proportion in the total contribution:

In many counties, and especially in low- and middle-income settings, men and women take on two or even more jobs to support their living. For people working in the health care sector, the secondary job could very well be in the health care sector as well. For example, a physician working in a public hospital might have a part-time contract at a private hospital. To examine the effect of the secondary job in the total contribution, we selected three countries in our database with detailed data on secondary jobs: Peru, Mexico, and India. See the table below for details.

Table 9. Population % with principal and secondary occupation in the health sector

	Principal occupation in the health sector	Secondary occupation in the health sector
	% Population	% Population
Peru	2.500%	0.150%
Mexico	2.260%	0.030%
India	0.700%	0.001%

In those three countries, we examined the occupational and industry code for the secondary job using the same criteria and added up the reported salary value of those deemed related to health care. and our results show that, in those three countries, including the total value of all secondary job in the health sector would only add about 0.01% to the total value of the primary job in the health sector. And considering the fact that for many anchor countries, we do not have access to the data on the detailed nature as well as the reported value of the secondary job, we decided not to include the value of the secondary job in our final analysis. See below for the table on the proportion of the value brought by the secondary job in the three countries we had data for.

Table 10. Paid GDP% contribution comparing primary occupation and primary plus secondary occupation.

	Paid contribution, GDP%				
	Base		Base + Tax and SB		Sex discrimination
	Men	Women	Men	Women	Women
Anchor Country	Primary occupation only				
Mexico	0.500	0.595	0.510	0.600	0.709
Peru	0.623	1.065	0.629	1.074	1.286
India	1.281	0.495	1.301	0.498	0.683
	Including secondary occupation				
Mexico	0.502	0.595	0.512	0.600	0.709
Peru	0.643	1.095	0.650	1.105	1.328

India	1.285	0.511	1.305	0.513	0.687
			Difference		
Mexico	0.002	0.000	0.002	0.000	0.000
Peru	0.020	0.029	0.021	0.031	0.042
India	0.004	0.015	0.003	0.015	0.004
Average difference	0.008	0.015	0.009	0.015	0.015

4. Sensitivity Analysis

4.1 Representative parameters for anchor countries

As described above, when calculating the paid contribution for non-anchor countries, each country was compared to the "average situation" of anchor countries within their income group based on a list of parameters. We thus experimented with a few different scenarios for the average situation, including simple mean, median, weighted mean by population, and weighted mean by GDP per capita. While we acknowledge that mean or weighted mean would ensure all data we have collected were taken into account, median numbers were chosen to remove the effect of out-lying performers among the anchor countries.

Table 11. Results using means versus median for female-to-male labour force participation.

	Paid contribution, GDP%				
	Base		Base + Tax and SB		Sex discrimination
	Mean female-to-male labour force participation				
Income group	Men	Women	Men	Women	Women
Global	1.384	2.925	1.407	2.939	3.460
High	1.631	3.999	1.647	4.003	4.658
Upper-middle	0.775	1.188	0.811	1.228	1.540
Lower-middle	1.470	0.955	1.492	0.957	1.207
Low	0.259	0.169	0.253	0.170	0.209
	Median female-to-male labour force participation				
Global	1.389	2.911	1.413	2.925	3.453
High	1.638	3.983	1.656	3.987	4.639
Upper-middle	0.787	1.169	0.825	1.208	1.515
Lower-middle	1.440	0.981	1.462	0.983	1.240
Low	0.211	0.175	0.255	0.176	0.217

Table 12. Results using means versus median for wages.

	Paid contribution, GDP%				
	Base		Base + Tax and SB		Sex discrimination
	Mean wages				
Income group	Men	Women	Men	Women	Women
Global	1.384	2.925	1.407	2.939	3.460
High	1.631	3.999	1.647	4.003	4.658
Upper-middle	0.775	1.188	0.811	1.228	1.540
Lower-middle	1.470	0.955	1.492	0.957	1.207
Low	0.259	0.169	0.253	0.170	0.209
	Median wages				
Global	1.454	3.063	1.479	3.078	3.623
High	1.748	4.174	1.767	4.178	4.859
Upper-middle	0.818	1.255	0.856	1.297	1.627
Lower-middle	1.597	1.062	1.621	1.064	1.341
Low	0.253	0.195	0.257	0.195	0.241

In both analyses from Table 11 and Table 12, we have observed slight differences between using means or medians for these parameters. We have determined that these differences do not have a significant impact on our estimates. As such, we have decided to use the median to represent our findings. By using the median, we are selecting the middle value in a sorted list of data, which makes it less sensitive to extreme values or outliers. This can provide a more robust and stable estimate of the central tendency of the data.

4.2 Separating South Asia from other lower-middle income countries

Much lower ratios of female-to-male labour force participation were observed in a few countries, and specifically in two of the four anchor countries used for all low and lower-middle income regions – Pakistan and India. Their calculation thus skewed the results for the whole region. After internal discussion, we decided to separate South Asia from other countries in each of the income groups they belonged to: low income, lower-middle income and upper-middle income.

Table 13. Comparison of female-to-male labour force participation ratio in South Asia and other countries

Income group	Anchor Country	Ratio female-to-male labour force participation
High	Iceland	89.42
	United States of America	82.31
	Germany	83.04
	Canada	87.63

	Japan	73.99	
	Spain	81.75	
	Chile	70.02	
Upper-middle	Mexico	56.32	
	Brazil	73.15	
	Peru	82.54	
	Colombia	70.89	
Lower-middle	Mongolia	80.3	
	Ghana	88.51	
	India	26.98	South Asia
	Pakistan	26.81	

The table 13 provides data on the ratio of female-to-male labour force participation across various income groups and anchor countries. In the high-income group, Iceland has the highest ratio at 89.42%, followed by Canada at 87.63% and Germany at 83.04%. The United States of America and Spain also have relatively high ratios at 82.31% and 81.75%, respectively. In contrast, Japan has a lower ratio at 73.99%, while Chile has the lowest at 70.02%. In the upper-middle income group, Peru has the highest ratio at 82.54%, followed by Brazil at 73.15% and Colombia at 70.89%. Mexico has a relatively lower ratio at 56.32%. Among the lower-middle income countries, Ghana has the highest ratio at 88.51%, followed by Mongolia at 80.3%. In contrast, India and Pakistan have the lowest ratios among all countries at 26.98% and 26.81%, respectively, reflecting the significant gender gap in labour force participation in South Asia. These findings highlight the substantial differences in female-to-male labour force participation across income groups and anchor countries, which have important implications for gender equality and economic development.

As a result, the value for the paid sector of South Asian countries – most are lower-middle income countries - were calculated based on the results from India and Pakistan, while the value for the rest of the lower-middle income countries were calculated based on the results from Mongolia and Ghana.

Table 14. Results with the separation of South Asian countries

	Paid contribution, GDP%				
	Base		Base + Tax and SB		Sex discrimination
Income group	Men	Women	Men	Women	Women
Global	1.384	2.925	1.407	2.939	3.460
High	1.631	3.999	1.647	4.003	4.658
Upper-middle	0.774	1.187	0.810	1.227	1.540
South Asia	1.278	0.589	1.298	0.589	0.788
Lower-middle	0.684	0.869	0.693	0.874	1.051
Low	0.076	0.092	0.077	0.093	0.112

The analysis of paid contribution in South Asia reveals some differences compared to the main analysis, particularly in the lower and low-income groups, driven by the female-to-male labour force ratio in South Asian countries. However, due to data limitations, we were unable to accurately assess the regional effect in the low and lower-middle groups, and only had data for two countries in South Asia. As a result, we decided to group South Asian countries in the main analysis according to their corresponding income group. Nonetheless, in future studies, we aim to better understand these differences and provide a more detailed analysis. Despite these limitations, our findings emphasize the importance of addressing gender inequality in the labour market, especially in regions with significant disparities, to promote economic growth and achieve sustainable development goals.

4.3 Global projection for the unpaid sector directly from anchor countries

We were able to calculate the value of contribution for health care in the unpaid sector for countries without micro-data on time use survey, because the equation to calculate the unpaid contribution is more straightforward and can be decomposed on the macro-level into total amount of time multiplied by population size and then value per time unit of each country. This allowed us to have a more precise estimate of the value for each country from those components.

However, we also applied another way of calculating the value of the unpaid sector: calculating the income group average of time spent on health care from anchor countries and multiply that by the population size and value per time unit of each income group. See below for the results table.

This exercise yielded similar results, but we opted for the country specific calculation as it allowed us to make use of more granular data on population size, wages, and GDP, as well as to analyze and compare results from key countries individually.

Table 15. Male and Female contribution to health in the unpaid sector as % of GDP under different scenarios using income group average data.

	Male				Female			
	Minimum	Medium	Adjusted by sex differences	Adjusted by social benefits package and sex differences	Minimum	Medium	Adjusted by sex differences	Adjusted by social benefits package and sex differences
Low income	0.5	1.1	1.1	1.3	1.7	2.8	4.0	4.8
Lower middle income	0.5	1.0	1.0	1.2	0.9	1.5	2.0	2.3
Upper-middle-income	0.4	0.9	0.9	1.0	0.9	1.4	1.8	2.2
High-income	0.5	1.8	1.8	2.0	1.1	3.2	3.8	4.3
Global	0.5	1.5	1.5	1.7	1.0	2.6	3.1	3.5

4.4 Wages and value for paid and unpaid contributions

For unpaid work the sensitivity analysis involved the following and the results are summarized in the first block of rows of Tables 16 and 17:

1) A proxy good method that involved estimating the value of unpaid care work based on the market value of similar paid work activities. Specifically, the method assumes that the value of care provided by an unpaid worker, such as a family member, is equivalent to the value of a professional caregiver or an average worker who is hired to perform caregiver tasks. For the anchor countries, we separated out wage data for nurses, midwives and others undertaking specific health-related care duties or caring for those who are ill. ISCO codes: 322: Nursing and Midwifery Associate Professionals (Taking care of someone while they undertake other activities); and 325 - Other Health Associate Professionals (Childcare, elderly care, care provided to temporarily or chronically ill people and persons with mental and physical disabilities). Unfortunately, sample sizes in the surveys are very small making the estimates of wages unreliable, especially differentiating between men and women.
2) The minimum net hourly wage in each country and, as expected, found that this is often above average wages as many people earn less than the minimum wage, especially in non-salaried work such as caregiving.
3) The average wage in the health sector, but also found, as expected, that this was much higher than the average wage for care workers. (Exclusively ISCO-88 codes presented in table 3).
4) An opportunity cost method to estimate potential market wages for those out of the labour force. To build an equation capable of predicting earnings for everyone (both for the individuals who are working and non-working) taking into consideration selection into the labour market, we use the Heckman selection method (Heckman, 1979). The Heckman selection model is a two-equation model whereby the first equation is a probit regression in which the dependent variable is probability of working and the second equation is the earnings equation, including the correction term for selection bias calculated using the probit regression. The model is used here to predict earnings for all women, because using a regular OLS regression would overestimate the predicted earnings of individuals, since it would not take into account selection into the labour market. While this approach helps correct for overestimation, there are serious limitations because of the difficulty of identifying appropriate variables to predict labour force participation that do not also predict wages (exclusion criteria or instrumental variables). Thus, the model specification relies on limited information for identification and hence prediction of the wage for unpaid workers (Heckman et al., 2000[11]; Schultz, T. P., & Tansel, A. 1997[14]; Madden, D. 2008[15]; Wooldridge, J. 2012[10]). We ran a health-sector specific model to compare to the previous approaches and another using all labour market data, individually for men and women. Lacking sufficient micro-data for more precise identification, and given that it is not an ideal approach for sector-specific analysis, we use these results only to bound our reported estimate that uses sex-specific average wages.

To better bound our estimates of underpaid work we use the Oaxaca-Blinder decomposition, which explains the gap in the means of an outcome variable between two groups (in this case men and women in the labour force). The following three equations illustrate the Oaxaca-Blinder decomposition. Estimate separate linear wage regressions for individuals *i* in groups *A* and *B*:

$$lnwage_{A_i} = X_{A_i}\beta_{A_i} + \mu_{A_i} \qquad \text{...(Eq. 3)}$$

$$lnwage_{B_i} = X_{B_i}\beta_{B_i} + \mu_{B_i} \qquad \text{...(Eq. 4)}$$

where X is a vector of explanatory variables such as education, experience, industry, and occupation, β_A and β_B are vectors of coefficients and μ is an error term.

Let b_A and b_B be respectively the regression estimates of β_A and β_B. Then, since the average value of residuals in a linear regression is zero, we have:

$$\begin{aligned} mean(lnwage_A) - mean(lnwage_B) &= b_A mean(X_A) - b_B mean(X_B) \\ &= b_A\left(mean(X_A) - mean(X_B)\right) + mean(X_B)(b_A - b_B) \qquad \text{...(Eq. 5)} \end{aligned}$$

The first part of the Eq. 5 is the impact of between-group differences in the explanatory variables X, evaluated using the coefficients for group A. The second part is the differential not explained by these differences in observed characteristics X.

The gap is decomposed into the part that is due to group differences in the magnitudes of the determinants of the outcome in question on the one hand, and into the part due to group differences in the effects of these determinants on the other. For example, women may have lower earnings not only because they have less education, but also because their returns to education are lower than men. Explanatory variables used in the decomposition are years of education, age groups and location (urban/rural). This approach is more conservative but yields only the market differentials, not pre-market differences. We analyzed labour-market wide results rather than health sector specific results, the latter being difficult to interpret using the Oaxaca-Blinder model (right columns table 16 & second block of rows of Table 17).

In terms of the global figures, we find our estimates to be biased up by no more than 4-5% (less than .5% of global GDP). Regarding unpaid work, as expected, our global estimate using average country-specific wages is higher than either the Heckman or proxy wage model, but lower that the sector-specific models. The differences are small, ranging from 2-3% for women and no more than 7% for men. Correcting for underpaid using the Oaxaca-Blinder compared to the estimate presented in the manuscript - 7.73% versus 7.22% of GDP – yields a 7% overestimate. Considering both unpaid and underpaid (comparing the Heckman full labour force model and the Oaxaca-Blinder) the maximum difference shows a 9% overestimate in our figures (7.73% versus 7.05%) such that our maximum estimate with wage differentials would be 10.54% of global GDP as opposed to 11% of global GDP. Without considering underpaid components, our global estimate would be 9.3% of global GDP compared to the reported 9.7% (a difference of 4%).

We do find important differences across the models for the upper middle income country group, and this is function of our sample that relies on countries in Latin America. Using the Heckman correction or the proxy method, requires that we fully project the Latin America figures onto countries from other regions that likely have different wage differentials. Similar issues are likely for lower middle and especially low-income regions. While this does put in doubt our income-region-specific findings for lower- and middle-income groups, it also suggests that using the average country specific wages provides additional and useful information that we have incorporated into the global projections.

Table 16: Sensitivity Analysis for Estimation of Value of Unpaid and Underpaid Health and Care Contributions, disaggregated by tax and social benefit scenarios and by type of discrimination factor

Gender wage differentials

Model	Income Group	Paid contribution: SB+ Tax Salaried GDP % men	Paid contribution: SB+ Tax Salaried GDP % Women	Paid contribution: SB+ Tax All GDP % men	Paid contribution: SB+ Tax All GDP % Women	Paid contribution: SB+ Tax All Sex disc. GDP % women	Unpaid Contribution: Base GDP % men Unpaid	Unpaid Contribution: Base GDP % Women Unpaid	Unpaid Contribution: SB+ Tax All GDP % men Unpaid	Unpaid Contribution: SB+ Tax All GDP % Women Unpaid	Unpaid Contribution: SB+ Tax All Sex disc. GDP % women Unpaid	Total contribution: Men	Total contribution: Women	Total contribution: Men + Tax and SB	Total contribution: Women + Tax and SB	Total contribution: Women + Tax and SB + Sex discrimination
Heckman correction model using full labour force	Global	1.36	2.96	1.38	2.96	3.51	1.31	2.60	1.67	3.30	4.03	2.67	5.56	3.05	6.26	7.54
	H	1.63	4.04	1.64	4.04	4.74	1.65	3.12	2.14	4.04	4.91	3.28	7.16	3.78	8.08	9.65
	UM	0.77	1.23	0.81	1.23	1.54	0.70	1.34	0.87	1.66	2.04	1.47	2.57	1.68	2.89	3.58
	LM+L	1.39	0.91	1.41	0.91	1.14	0.95	3.37	1.11	4.00	4.85	2.34	4.27	2.52	4.91	6.00
Heckman correction model: Health sector-specific	Global	1.36	2.96	1.38	2.96	3.51	1.52	2.77	1.93	3.52	4.30	2.88	5.73	3.31	6.48	7.81
	H	1.63	4.04	1.64	4.04	4.74	1.92	3.30	2.48	4.28	5.20	3.55	7.34	4.12	8.32	9.94
	UM	0.77	1.23	0.81	1.23	1.54	0.78	1.42	0.97	1.76	2.17	1.55	2.65	1.78	2.99	3.71
	LM+L	1.39	0.91	1.41	0.91	1.14	1.18	3.79	1.39	4.51	5.46	2.57	4.70	2.80	5.41	6.61
Average Country-specific wages (*__Estimates and model shared in the manuscript__*)	Global	1.36	2.96	1.38	2.96	3.51	1.49	2.72	1.90	3.46	4.22	2.85	5.68	3.28	6.42	7.73
	H	1.63	4.04	1.64	4.04	4.74	1.73	2.97	2.24	3.86	4.69	3.36	7.02	3.88	7.90	9.43
	UM	0.77	1.23	0.81	1.23	1.54	1.11	2.04	1.37	2.53	3.12	1.88	3.27	2.18	3.76	4.66
	LM+L	1.39	0.91	1.41	0.91	1.14	1.05	3.18	1.23	3.79	4.59	2.45	4.17	2.64	4.69	5.74
Proxy wages (paid care workers using survey data from 15 countries)	Global	1.36	2.96	1.38	2.96	3.51	1.62	2.57	2.06	3.27	3.99	2.98	5.53	3.44	6.23	7.50
	H	1.63	4.04	1.64	4.04	4.74	2.00	2.88	2.58	3.73	4.54	3.63	6.92	4.22	7.77	9.28
	UM	0.77	1.23	0.81	1.23	1.54	1.04	2.01	1.28	2.49	3.08	1.81	3.24	2.09	3.72	4.62
	LM+L	1.39	0.91	1.41	0.91	1.14	0.86	2.35	1.01	2.80	3.39	2.25	3.26	2.42	3.70	4.54
Average health-sector specific wages	Global	1.36	2.96	1.38	2.96	3.51	1.54	2.88	1.96	3.66	4.46	2.90	5.84	3.34	6.62	7.97
	H	1.63	4.04	1.64	4.04	4.74	1.88	3.32	2.43	4.31	5.24	3.51	7.36	4.07	8.35	9.98
	UM	0.77	1.23	0.81	1.23	1.54	0.97	1.89	1.20	2.34	2.89	1.74	3.12	2.01	3.57	4.43
	LM+L	1.39	0.91	1.41	0.91	1.14	1.05	3.19	1.23	3.79	4.60	2.44	4.10	2.65	4.70	5.74

Oaxaca-Blinder decomposition

Model	Income Group	Paid contribution: SB+Tax Salaried GDP% men	Paid contribution: SB+ Tax Salaried GDP % Women	Paid contribution: SB+ Tax All GDP % men	Paid contribution: SB+ Tax All GDP % Women	Paid contribution: SB+ Tax All Sex disc. GDP % women	Unpaid Contribution: Base GDP % men Unpaid	Unpaid Contribution: Base GDP % Women Unpaid	Unpaid Contribution: SB+ Tax All GDP % men Unpaid	Unpaid Contribution: SB+ Tax All GDP % Women Unpaid	Unpaid Contribution: SB+ Tax All Sex disc. GDP % women Unpaid	Total contribution: Men	Total contribution: Women	Total contribution: Men + Tax and SB	Total contribution: Women + Tax and SB	Total contribution: Women + Tax and SB + Sex discrimination
Heckman correction model using full labour force	Global	1.36	2.96	1.38	2.96	3.33	1.31	2.60	1.67	3.30	3.72	2.67	5.56	3.05	6.26	7.05
	H	1.63	4.04	1.64	4.04	4.52	1.65	3.12	2.14	4.04	4.52	3.28	7.16	3.78	8.08	9.04
	UM	0.77	1.23	0.81	1.23	1.45	0.70	1.34	0.87	1.66	1.95	1.47	2.57	1.68	2.89	3.40
	LM+L	1.39	0.91	1.41	0.91	0.99	0.95	3.37	1.11	4.00	4.38	2.34	4.27	2.52	4.91	5.38
Heckman correction model: Health sector-specific	Global	1.36	2.96	1.38	2.96	3.33	1.52	2.77	1.93	3.52	3.96	2.88	5.73	3.31	6.48	7.29
	H	1.63	4.04	1.64	4.04	4.52	1.92	3.30	2.48	4.28	4.78	3.55	7.34	4.12	8.32	9.30
	UM	0.77	1.23	0.81	1.23	1.45	0.78	1.42	0.97	1.76	2.08	1.55	2.65	1.78	2.99	3.53
	LM+L	1.39	0.91	1.41	0.91	0.99	1.18	3.79	1.39	4.51	4.93	2.57	4.70	2.80	5.41	5.93
Average Country-specific wages (*__Estimates and model shared in the manuscript__*)	Global	1.36	2.96	1.38	2.96	3.33	1.49	2.72	1.90	3.46	3.89	2.85	5.68	3.28	6.42	7.22
	H	1.63	4.04	1.64	4.04	4.52	1.73	2.97	2.24	3.86	4.31	3.36	7.01	3.88	7.90	8.83
	UM	0.77	1.23	0.81	1.23	1.45	1.11	2.04	1.37	2.53	2.98	1.88	3.27	2.18	3.76	4.43
	LM+L	1.39	0.91	1.41	0.91	0.99	1.05	3.18	1.23	3.79	4.15	2.44	4.09	2.64	4.69	5.14
Proxy wages (paid care workers using survey data from 15 countries)	Global	1.36	2.96	1.38	2.96	3.33	1.62	2.57	2.06	3.27	3.68	2.98	5.53	3.44	6.23	7.00
	H	1.63	4.04	1.64	4.04	4.52	2.00	2.88	2.58	3.73	4.17	3.63	6.92	4.22	7.77	8.69
	UM	0.77	1.23	0.81	1.23	1.45	1.04	2.01	1.28	2.49	2.94	1.81	3.24	2.09	3.72	4.39
	LM+L	1.39	0.91	1.41	0.91	0.99	0.86	2.35	1.01	2.80	3.06	2.25	3.26	2.42	3.70	4.06
Average health-sector specific wages	Global	1.36	2.96	1.38	2.96	3.33	1.54	2.88	1.96	3.66	4.11	2.90	5.84	3.34	6.62	7.44
	H	1.63	4.04	1.64	4.04	4.52	1.88	3.32	2.43	4.31	4.82	3.51	7.36	4.07	8.35	9.34
	UM	0.77	1.23	0.81	1.23	1.45	0.97	1.89	1.20	2.34	2.76	1.74	3.12	2.01	3.57	4.21
	LM+L	1.39	0.91	1.41	0.91	0.99	1.05	3.19	1.23	3.79	4.15	2.44	4.10	2.65	4.70	5.15

Table 17: Sensitivity Analysis for Estimation of Value of Unpaid and Underpaid Health and Care Contributions

		Proxy wages (paid care workers using survey from 15 countries)		**Heckman correction model using full labour force**		**Average Country-specific wages (*Estimates and model shared in the manuscript*)**		**Heckman correction model: Health sector-specific**		**Average health-sector specific wages**	
		Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
UNPAID: Using average country-specific wages differentials	**Global**	**3.44**	**7.50**	**3.05**	**7.54**	***3.28***	***7.73***	**3.31**	**7.81**	**3.34**	**7.97**
	High	4.22	9.28	3.78	9.65	*3.88*	*9.43*	4.12	9.94	4.07	9.98
	Upper Middle	2.09	4.62	1.68	3.58	*2.18*	*4.66*	1.78	3.71	2.01	4.43
	Lower middle and low	2.42	4.54	2.52	6	*2.64*	*5.74*	2.8	6.61	2.65	5.74
UNDERPAID: Using Oaxaca-Blinder decomposition	**Global**	**3.44**	**7.00**	**3.05**	**7.05**	**3.28**	***7.22***	**3.31**	**7.29**	**3.34**	**7.44**
	High	4.22	8.69	3.78	9.04	3.88	*8.83*	4.12	9.3	4.07	9.34
	Upper Middle	2.09	4.39	1.68	3.4	2.18	*4.43*	1.78	3.53	2.01	4.21
	Lower middle and low	2.42	4.06	2.52	5.38	2.64	*5.14*	2.8	5.93	2.65	5.15

Our results are presented by country income group; however, we identified important differences within and across specific regions. Specifically, we identified much lower ratios of female-to-male labor force participation in Pakistan and India that skewed the analysis by country income group. A review of aggregate data showed similarly low rates for some countries in South Asia and the MENA region. We analyzed our country-income-specific and global results with and without Pakistan and India and undertook a sub-group analysis for the Southeast Asia region.

Additionally, we explored different summary measures for our continuous variables. For the paid contribution, we explored mean versus median in our imputation method for total health expenditure and female to male labor force participation ratio. We used mean and median values to impute missing wages and health-specific unpaid hours by income group and compared the results. We also calculated the global projection based only on the anchor countries by summing individual anchor country estimates, grouping them by income group, calculating the income group's average parameters, and imputing the total value for each income group using those parameters.

The Oaxaca-Blinder [16,17]decomposition [18,19] explains the gap in the means of an outcome variable between two groups (in this case men and women in the labour force). The gap is decomposed into the part that is due to group differences in the magnitudes of the determinants of the outcome in question on the one hand, and into the part due to group differences in the effects of these determinants on the other. Explanatory variables used in the decomposition are years of education, age groups and location (urban/rural). For example, women may have lower earnings not only because they have less education, but also because their returns to education are lower than men. Note that in this instance of the application of the Oaxaca-Blinder decomposition, we cannot use education level as one of the independent variables in the model, as we already control for education level in the calculation of each group's earnings. The Oaxaca- Blinder decomposition in this scenario takes on as independent variables only urban/rural location and age categories. Table 18 shows the codes used in state for the estimation of cost opportunity model with the Heckman selection model and decomposition by gender using Oaxaca-Blinder.

Table 18 Do file in state for Heckman Selection Model and Oaxaca-Blinder Model

```
* Generating a dummy for those who work--ie, have positive wages:
generate d = 1
replace  d = 0 if wage == .

** Wages depend on (X vars) education and age...
** But there is a prior decision to get a job
** So the labor force participation decision affects the wage observed sample

** We need to estimate a "selection equation":
** Work-decision (a dummy) depends on (Z vars): being Married, Number of children aged 0-5, Number of children aged
6-14,  Number of elderly
** plus education age age2 and rural
** Note that X is a subset of Z--otherwise the system is not identified

** 1. Using Heckman (1979)  "two-step consistent" procedure:
heckman wage educ age age2 rural, select (married children1 childen2 elderly educ age age2 rural) twostep

* Note that stata automatically assumes missing wage cases as unobserved
* And reports the estimated results of both the structural and the selection equations

** 2. Using a maximum-likelihood procedure (pretty much the same thing--but
** ML is a little biased):
heckman wage educ age age2 rural, select (married children1 childen2 elderly educ age age2 rural) nolog

** 3. To avoid ambiguity, you also can specify the selection equation:
heckman wage educ age age2 rural, select (married children1 childen2 elderly educ age age2 rural) twostep nolog
```

```
* Same result as in model 1

* Recall that the selection equation is just a probit (because Heckman assumes
* a normal distribution for "d")
probit d  married children1 children2 elderly educ age age2 rural, nolog

* It's the same result as the "selection" model in 3

** Exploring Model 3
heckman wage educ age age2 rural, select (married children1 childen2 elderly educ age age2 rural) twostep nolog

predict cndwage, ycond
* ycond calculates the expected value of the dependent variable conditional on the
* dependent variable being observed/selected; E(y | y was observed).

predict expwage, yexpected
* yexpected calculates the expected value of the dependent variable (y*), where that
* value is taken to be 0 when it is expected to be unobserved;
* y* = P(y observed) * E(y | y was observed).

* Create an artifact variable (actually, a left-censored variable)
gen wage0 = wage
replace wage0 = 0 if wage >= .
* wage0 contains positives wages or zeros when wage was missing

summarize wage cndwage if wage < .
* The mean predicted wage (conditional on being observed) is the same
* as the mean observed wages!

summarize wage0 expwage
* The mean predicted wage (for the full sample) is the same
* as the mean of the wage0 artifact!
```

To better assess the robustness of our global projections, we decided to separate the scenarios of estimated wages apart from the microdata of the employment surveys in the 15 anchor countries (Table 19). It was observed that the dispersion between the data for the lowest scenario of the Heckman correction model using the full labour force versus the estimation considering average country-specific wages in these anchor countries was on average less, by 11.5% for men and 9.7% for women. Meanwhile, the difference between the upper scenario of average health-sector specific wages was on average 9.0% for men and 9.7% for women in the same 15 anchor countries. Furthermore, similar to the global population, applying the gender discrimination factor of the Oaxaca-Blinder method showed an average lower difference among this group of countries by 3.3%.

Table 19. Sensitivity Analysis for Estimation of Value of Unpaid and Underpaid Health and Care Contributions for 15 anchor countries

		Proxy wages (paid care workers using survey data from 15 countries)		**Heckman correction model using full labour force**		**Average Country-specific wages *Estimates and model shared in the manuscript***		**Heckman correction model: Health sector-specific**		**Average health-sector specific wages**	
		Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
UNPAID: Using average country-specific wages differentials	Iceland	4.48	9.70	3.58	8.38	***4.69***	***10.04***	3.77	8.68	4.98	10.61
	United States of America	4.74	10.08	4.41	11.25	***5.04***	***12.27***	4.92	11.55	5.74	13.47
	Germany	4.19	11.33	3.63	9.97	***3.68***	***10.10***	4.31	11.39	4.07	11.08
	Canada	4.98	12.15	4.07	10.59	***4.11***	***10.59***	4.27	11.57	4.51	11.60
	Japan	6.51	10.50	4.76	8.50	***4.81***	***8.60***	5.05	9.17	5.15	9.08
	Spain	2.84	6.57	2.93	7.10	***2.98***	***7.16***	3.64	8.23	3.21	7.77
	Chile	3.10	4.83	3.12	6.45	***3.31***	***6.62***	3.44	6.75	3.57	7.30
	Mexico	3.17	4.96	2.44	4.44	***2.84***	***4.70***	2.86	4.95	3.17	5.18
	Brazil	3.20	7.77	1.91	4.20	***3.00***	***6.80***	2.09	4.26	3.52	8.09
	Peru	0.95	2.05	1.01	2.32	***1.04***	***2.37***	1.31	3.18	1.12	2.54
	Colombia	1.90	3.61	1.87	3.52	***2.28***	***4.06***	2.03	3.58	2.45	4.37
	Mongolia	0.92	3.82	0.67	2.51	***0.93***	***3.09***	0.89	2.86	1.03	3.29
	Ghana	0.79	2.86	0.76	1.67	***0.79***	***1.70***	1.22	2.56	0.83	1.85
	India	2.23	4.36	2.40	5.46	***2.41***	***5.72***	2.60	6.99	2.59	6.38
	Pakistan	2.33	5.32	2.21	5.18	***2.82***	***7.5***	2.35	5.43	3	8.64
UNDERPAID: Using Oaxaca-Blinder decomposition	Iceland	4.48	8.79	3.58	7.60	***4.69***	***9.11***	3.77	7.87	4.98	9.62
	United States of America	4.74	9.57	4.41	10.69	***5.04***	***11.65***	4.92	10.97	5.74	12.80
	Germany	4.19	11.44	3.63	10.07	***3.68***	***10.21***	4.31	11.50	4.07	11.18
	Canada	4.98	12.08	4.07	10.53	***4.11***	***10.54***	4.27	11.50	4.51	11.54
	Japan	6.51	11.38	4.76	9.37	***4.81***	***9.47***	5.05	10.04	5.15	9.95
	Spain	2.84	6.13	2.93	6.65	***2.98***	***6.71***	3.64	7.76	3.21	7.31
	Chile	3.10	4.40	3.12	5.94	***3.31***	***6.10***	3.44	6.22	3.57	6.74
	Mexico	3.17	4.44	2.44	3.98	***2.84***	***4.21***	2.86	4.43	3.17	4.63
	Brazil	3.20	7.61	1.91	4.11	***3.00***	***6.66***	2.09	4.17	3.52	7.92
	Peru	0.95	2.06	1.01	2.32	***1.04***	***2.37***	1.31	3.16	1.12	2.53
	Colombia	1.90	3.16	1.87	3.07	***2.28***	***3.57***	2.03	3.12	2.45	3.84
	Mongolia	0.92	3.77	0.67	2.46	***0.93***	***3.04***	0.89	2.81	1.03	3.24
	Ghana	0.79	3.08	0.76	1.94	***0.79***	***1.97***	1.22	2.79	0.83	2.12
	India	2.23	4.47	2.40	5.61	***2.41***	***5.89***	2.60	7.21	2.59	6.57
	Pakistan	2.33	4.68	2.21	4.56	***2.82***	***6.60***	2.35	4.78	3.00	7.60

5. Results with confidence intervals

We present the paid and unpaid contributions to GDP, as well as the total contribution, based on income group, sex, and the inclusion of taxes and social benefits (SB) (Appendix Table 9 & 10). The values are presented both as a percentage of GDP and using equivalent Purchasing Power Parity in US dollars. Notably, the table reveals that women's unpaid contributions to GDP are consistently higher than men's in all income groups and scenarios. For instance, in the global scenario, women's unpaid contribution to GDP is 3.5% compared to men's 1.9%. Additionally, in all scenarios, the inclusion of taxes and social benefits increases women's contributions to GDP, indicating the importance of policies that support caregivers and promote gender equity. The table also includes a category for "sex discrimination" to illustrate the gender gap in paid and unpaid contributions to GDP. Notably, in all income groups and scenarios, women's contributions to GDP are consistently undervalued when compared to men. For example, in the high-income scenario, women's paid contribution to GDP is 4.0% compared to women's contribution accounting for sex discrimination at 4.7%, indicating significant gender-based wage disparities. Similarly, in the global scenario, women's unpaid contribution to GDP is 3.5% compared to 4.3% accounting for sex discrimination.

We provide a comprehensive overview of the 95% confidence intervals for paid and unpaid contributions to GDP, along with the total contribution, across different income groups and genders (Appendix Table 9 & 10). The confidence intervals were obtained through a bootstrapping process, which involved calculating the 2.5 and 97.5 percentiles. These wider intervals reflect variability within surveys in how health and care contributions are defined and measured in the anchor countries as well as the variability in the parameters within each income group, such as the average wage between countries.

Table 20. Unpaid and paid contributions to GDP %

	Paid contribution, GDP% (95% CI)					Unpaid contribution, GDP% (95% CI)					Total contribution, GDP% (95% CI)				
	Base		Base + Tax and SB		Sex discrimination	Base		Base + Tax and SB		Sex discrimination	Base		Base + Tax and SB		Sex discrimination
Income group	Men	Women	Men	Women	Women	Men	Women	Men	Women	Women	Men	Women	Men	Women	Women
Global	1.36	2.96	1.38	2.96	3.51	1.49	2.72	1.9	3.46	4.22	2.85	5.68	3.28	6.42	7.73
	(0.58-2.47)	(1.08-5.59)	(0.62-2.51)	(1.18-5.85)	(1.32-6.85)	(0.55-3.11)	(1.12-5.55)	(0.69-3.92)	(1.4-6.97)	(1.75-8.60)	(1.19-5.55)	(2.34-11.04)	(1.32-6.46)	(2.59-12.56)	(3.3-14.90)
High	1.63	4.04	1.64	4.04	4.74	1.73	2.97	2.24	3.86	4.69	3.36	7.02	3.88	7.90	9.43
	(0.57-3.31)	(1.32-8.33)	(0.54-3.38)	(1.33-8.57)	(1.48-9.90)	(0.47-4.33)	(0.78-6.76)	(0.58-5.48)	(1.02-8.58)	(1.3-11.14)	(0.97-7.43)	(2.29-14.95)	(1.23-8.78)	(2.46-17.15)	(2.82-19.97)
Upper-middle	0.77	1.23	0.81	1.23	1.54	1.11	2.04	1.37	2.53	3.12	1.88	3.27	2.18	3.76	4.66
	(0.20-1.72)	(0.24-2.99)	(0.24-1.84)	(0.24-2.97)	(0.30-3.81)	(0.29-2.42)	(0.58-4.4)	(0.34-2.92)	(0.77-5.21)	(0.96-7.06)	(0.52-4.21)	(0.88-7.02)	(0.59-4.89)	(0.98-8.64)	(1.23-10.46)
Lower-middle	1.47	0.96	1.49	0.96	1.21	1.05	3.18	1.22	3.71	4.47	2.52	4.14	2.71	4.67	5.68
	(0.52-3.00)	(0.45-1.62)	(0.51-3.02)	(0.49-1.62)	(0.58-2.08)	(0.47-1.98)	(1.17-6.54)	(0.52-2.3)	(1.3-7.89)	(1.52-9.54)	(0.96-4.87)	(1.74-8.27)	(1.06-5.55)	(1.76-9.39)	(2.23-12.29)
Low	0.26	0.16	0.26	0.16	0.20	1.19	4.38	1.33	4.89	6.35	1.45	4.54	1.59	5.05	6.55
	(0.08-0.51)	(0.11-0.21)	(0.08-0.52)	(0.11-0.22)	(0.14-0.26)	(0.74-1.71)	(3.09-5.85)	(0.84-1.92)	(3.35-6.49)	(4.38-8.54)	(0.91-2.09)	(3.12-5.97)	(1.00-2.25)	(3.57-6.77)	(4.53-9.06)

Table 20 provides the results with 95% confidence intervals for paid and unpaid health contributions to GDP, as well as the total contribution, by income groups and sexes. The table shows that the unpaid contribution to GDP is consistently higher than the paid contribution for both men and women in all income groups, indicating the significant role of unpaid work in economic production. Additionally, the table demonstrates the impact of tax and social benefits on both paid and unpaid contributions to GDP. Sex discrimination is also taken into account, showing that women's unpaid contributions to GDP are consistently higher than men's, further highlighting the gendered nature of unpaid work. The confidence intervals reflect the variability within income groups and globally.

Table 21. Paid and Unpaid contribution by sex and type of contribution (PPP)

	Paid contribution, billion PPP$					Unpaid contribution, billion PPP$					Total contribution, billion PPP$				
	Base		Base + Tax and SB		Sex discrimination	Base		Base + Tax and SB		Sex discrimination	Base		Base + Tax and SB		Sex discrimination
Income group	Men	Women	Men	Women	Women	Men	Women	Men	Women	Women	Men	Women	Men	Women	Women
Global	1,760	3,830	1,785	3,830	4,541	1,928	3,519	2,458	4,476	5,460	3,687	7,349	4,244	8,306	10,001
High	993	2,460	999	2,460	2,887	1,054	1,809	1,364	2,351	2856	2,046	4,275	2,363	4,811	5,743
Upper-middle	336	536	353	536	672	484	890	598	1,103	1,361	820	1,426	951	1,640	2,032
Lower-middle	343	224	348	224	283	245	743	285	866	1,044	588	967	633	1,090	1,326
Low	4	2	4	2	3	18	66	20	74	96	22	69	24	77	99

Table 21 displays the estimated paid and unpaid health contributions, measured in billion PPP$, by income groups and genders. The table presents the original estimates as well as the ones adjusted for taxes and social benefits, and those that consider sex discrimination. It also shows the total contribution, which accounts for both paid and unpaid health work. The data highlights that women globally contribute more to both paid and unpaid health work compared to men, with a larger gap when considering sex discrimination. The table also indicates considerable variations in health contributions across income groups, with higher-income groups exhibiting higher total contributions.

6. Miscellaneous

6.1 Data Checks

All data were reviewed independently by at least two researchers. Multiple indicators were set up to standardize the process and for quality control, for example, the contribution level should go up from “Base” to “Base Plus”, and women’s contribution usually goes up after adjusting for sexual discriminations. We also compared the results using different wage data, and the value calculated using the average wage or the Heckman’ed wage should be higher than that calculated using the minimum wage data. We then compared the results across countries and see if any countries have particularly high or low contribution that cannot be explained by any possible scenarios, which will trigger a full review of the data from the beginning. For example, we noticed some unusual results in the paid sector calculation for south Asian countries and identified that it is sue to the unusually low female to male labour force participation ratio brought by Pakistan and India, which leads to the adjustment of separating South Asian countries in our calculation as described in earlier sections.

In addition, for a few specific parameters, data from multiple sources were obtained to verify each other. For example, we identified a few countries whose wage data from ILO were extremely low and later identified that it is because hourly wage was used instead of monthly wages for those countries. Corrections were made on a case-by-case basis after consensus reached among all team members.

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