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Olle Hammar
Daniel Waldenström

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Olle Hammar
Uppsala University

Daniel Waldenström
*IFN and Paris School of Economics,
CEPR, IZA, UCFS and UCLS*

ABSTRACT

Global Earnings Inequality, 1970–2015[*]

We estimate trends in global earnings dispersion across occupational groups using a new database covering 66 developed and developing countries between 1970 and 2015. Our main finding is that global earnings inequality has declined, primarily during the 2000s, when the global Gini coefficient dropped nearly 10 points and the earnings share of the world's poorest half doubled. Decomposition analyses emphasize the role of income convergence between poor and rich countries and that earnings have become more similar within occupations in traded industries. Sensitivity checks show that the results are robust to varying real exchange rates, inequality measures and population definitions.

Corresponding author:
Daniel Waldenström
Paris School of Economics
48 Boulevard Jourdan
75014 Paris
France

E-mail: daniel.waldenstrom@psemail.eu

1. Introduction

The world economy has undergone tremendous change over the past few decades, and questions about its distributional impacts are commonly heard: Has everyone benefitted equally, or are there some groups who are winners while others have fallen behind? How can we explain these distributional outcomes, e.g., concerning the role of globalized labor markets? A small, but growing body of research literature has addressed these questions by pooling national household income surveys into one single global income distribution and analyzing its trends since the late 1980s (Anand and Segal, 2008, 2015, 2016; Atkinson and Brandolini, 2010; Bourguignon, 2015; Lakner and Milanovic, 2015; Milanovic, 2002, 2005, 2016b).[1] The findings so far suggest that global household income inequality has decreased, primarily since the late 1990s, and that substantial income gains in low- and middle-income countries, combined with a slower income growth in richer countries, is the main driver.

A still unaddressed issue is how the global *earnings* inequality has developed over the last decades. The previous literature has focused on the total income from all sources (labor, business and capital) and the global distribution across all households (including old-age pensioners and adjustments for children). While such focus is relevant when studying, e.g., the distribution of welfare, the majority of people in the world only have a single income source, labor earnings, which they earn as adults during their working life. Therefore, if one wants to understand the role of labor markets in shaping global inequality, examining the distribution of labor earnings among the world's working population is a natural starting point.

In this paper, we estimate the evolution of *global earnings inequality* over the past 45 years, from 1970 to 2015, and decompose it across its geographical, sectoral and occupational components. To the best of our knowledge, this is the first time such an analysis has been made. Our series emanate from a newly created database covering occupational earnings in 66 countries that represent 80 percent of the world's population and over 95 percent of the world's GDP, collected in a homogenous fashion for all countries and years covered. The database is constructed by combining two different and, in this literature, previously unutilized sources: earnings survey data in the Union Bank of Switzerland's (UBS) *Prices and Earnings* reports and labor market statistics from the International Labour Organization (ILO). The UBS earnings data comprise the central source, collected by the Swiss bank UBS in up to 85 cities

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[1] For a review of Bourguignon (2016) and Milanovic (2016b), see Ravallion (2017).

around the world every three years since 1970. This gives information about earnings, hours worked and the payment of taxes and social security contributions for up to 16 different occupations, collected in the same way for all countries and all years over the whole time period. The UBS data also include information about local prices, such that we can adjust our earnings data for local price level differences. Total and group-specific working populations are created using the occupational data available in the ILO statistics and country populations from the World Bank's *World Development Indicators* (WDI).

The desire for more-consistent and more-comparable survey data is highlighted in virtually all studies of global inequality. A key advantage of the UBS earnings data is that they are collected with the explicit purpose of being comparable both over time and across space, therefore lending them a uniquely high degree of consistency in the estimation of inequality levels and trends across countries, regions and at the global level. By contrast, the data used in most previous global inequality studies encompass combinations of outcomes based on incomes at the individual and household level and a mix of income and consumption (see further Anand and Segal, 2008; 2015).[2] In the sense of focusing on labor earnings, the project most similar to ours is probably the *University of Texas Inequality Project* (UTIP), which collects and analyzes data on pay inequality within and between different countries and regions around the world (see, e.g., Galbraith, 2007), although that project focuses primarily on industrial wages and international inequality, rather than estimating a global earnings distribution.

The UBS earnings data are not without problems. The most obvious is that the observational units are occupations, aggregated to be representative for the whole working population. Since this removes all individual earnings variation within country-occupations, our measured inequality is probably lower than it would have been had we used purely individual microdata.[3] Compared to other studies of global inequality, however, our baseline aggregation level of the underlying data is similar in the sense that most of them also use grouped data, albeit with the difference that our lowest level of observation is an occupation in a country instead of, e.g., a country-decile (Lakner and Milanovic, 2015). Another limitation is that the UBS data are

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[2] The data Lakner and Milanovic (2015) and Anand and Segal (2015) use are supposed to be based on individual or per capita household net income or consumption.
[3] To estimate the size of this bias, we apply Modalsli's (2015) correction method, adjusting for within-group inequality by applying assumptions on within-group dispersions based on observed within-country micro data, finding that such adjustments increase the level of estimated inequality with around one percent. As an alternative, we also add a within-group gender-gap adjustment, finding that this does not change our results.

collected in cities and therefore refer to urban earnings levels. We adjust for this by weighting in the share of the agricultural sector using ILO statistics and assigning the agricultural workers observed agricultural sector earnings from the *Occupational Wages around the World* (OWW) database (Freeman and Oostendorp, 2012), and by PPP-adjusting at the city level. The coverage of the very top and bottom of earnings is probably quite poor, as we have a limited number of occupations in our database, although these are supposed to be representative of the working population.[4] We adjust for this, at least to some extent, by adding the unemployed working age population in each country, assigning them zero labor earnings. Comparisons with top earnings data in the *World Wealth and Income Database* (WID, 2016) show that our data cover top earnings reasonably well up to the top ventile, and adding top earners from the WID in our robustness analysis does not change our overall results.

Our central finding is that global earnings inequality has decreased over the last decades. The main decline occurred in the 2000s, when the Gini coefficient fell by nearly ten points and the earnings share of the bottom half of the global distribution nearly doubled, from less than 8 percent to over 14 percent. Global earnings inequality was almost trendless between the 1970s and 1990s, with only a slight drop in the early 1970s and an increase in the first half of the 1990s. Since the mid-2000s, global earnings inequality has been stable at its lowest level during the past half-century. We show that these results are qualitatively robust to using different inequality measures, imputation methods, population weights, and PPP adjustments.

Our second main finding is that there is a combination of factors underlying the fall in global earnings inequality in the 2000s. Income convergence between poorer and richer countries is key, particularly China's growth, although it cannot account for the whole catch-up of the developing world. Within Europe, there is also a strong convergence, driven by fast-growing Eastern European economies. Looking at occupational and sectoral earnings dispersion, our data show that inequality within occupations and industry sectors contributes more to global inequality trends than earnings differences between them. This indicates that differences are greater between managers in different countries than between managers and workers in the same country, which corresponds with the geographical decomposition patterns. Furthermore, we find that inequality trends among industrial professions follow the global index closely, whereas services sector occupations exhibit a larger dispersion in within-occupation inequality

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[4] The data also correspond to full-time equivalents and do not include the informal sector.

levels and follow somewhat different trends. Such discrepancy between traded (industrial) and non-traded (services) sectors indicates that trade globalization matters for global inequality. Finally, our analysis of earnings ratios between workers of different skill, gender or tenure confirms the patterns described above, while adding some nuances. In short, the global gender gap decreases, while both experience and skill premia rise at the global level over the studied period.

Comparing our findings with the previous results on global income inequality, we find that global earnings inequality is lower than global income inequality. This result is expected for at least two reasons: first, since the labor earnings only reflects the working population and not the low-earning retirees, and second, because it excludes capital income, which is more unevenly distributed than labor earnings. Having said this, it is still interesting to note that both global income and earnings inequality fall during the 2000s, and for partly the same reasons: convergence between poorer and richer countries.

The rest of the paper is organized as follows. Section 2 describes the sources and section 3 the construction of our global earnings inequality database. Section 4 presents the main trends and section 5 its decomposition in geographical and sectoral dimensions. Section 6 presents sensitivity and heterogeneity analyses, and section 7 concludes.

2. Data

In previous attempts to estimate global inequality, researchers have constructed global income distributions using either country-level GDP per capita (or equivalent) to measure the average income of all citizens within a country (e.g., Deaton, 2010) or household income or expenditure surveys in different countries that are compiled into a unified world population (e.g., Anand and Segal, 2015; Lakner and Milanovic, 2015) or a combination of the two (e.g., Sala-i-Martin, 2006). In this study, we take a different approach and construct a global inequality database using two completely different kinds of sources: occupational earnings data from the occupation surveys by the UBS and population-wide labor market statistics from the ILO.

2.1 Earnings, hours, taxes, and prices: The UBS dataset
The *Prices and Earnings* (1970–2015) UBS reports present a standardized price and earnings survey conducted locally by independent observers in a large number of cities around the

world.[5] In the latest edition, more than 68,000 data points were collected and included in the survey evaluation. The UBS data have previously been used in research, e.g., by Braconier, Norbäck and Urban (2005), to construct measures of wage costs and skill premia, and as an example of selected wage gaps by Milanovic (2012). To our knowledge, however, our study is the first to use these data to construct broader measures of earnings inequality.

The UBS collection of data involves questions on salaries, income taxes and social security contributions as well as working hours for a number of different occupational profiles that are supposed to represent the structure of the working population in Europe (UBS, 2015). Underlying individual data items were collected from companies deemed to be representative, and the occupational profiles were delimited as far as possible in terms of age, family status, work experience and education (UBS, 2015). In total, the UBS survey provides an unbalanced panel of up to 85 cities in 66 countries (34 OECD members and 32 non-OECD countries)[6] from 16 specific years covering a period of 45 years (i.e., every third year between 1970 and 2015). The surveys cover four countries in Africa, 21 in Asia, 29 in Europe, eight in Latin America, two in Northern America and two in Oceania.[7] The data on gross and net yearly earnings in current USD as well as weekly working hours cover 16 occupations in total, five from the industrial sector and eleven from the services sector.[8] For a further description of the coverage of the UBS *Prices and Earnings* data, see Tables A1 and A2 in the appendix.[9]

Because we want to compare real earnings both within and across countries, we need to adjust these for any differences in local price levels, or *purchasing power parity* (PPP). Fortunately, the UBS has compiled a price level index (where prices in New York City = 100) based on a common reference basket of goods and services in all surveyed cities and years.[10] By dividing

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[5] The UBS has recently released their data as open data on https://www.ubs.com/. However, in the latest version (2015-10-06) that was available to us, these data were incomplete. Our analyses are thus based on the original data published in the printed versions of the *Prices and Earnings* reports (UBS, 1970–2015).
[6] Countries with full 1970–2015 coverage are Argentina, Australia, Austria, Belgium, Brazil, Canada, Colombia, Denmark, Finland, France, Germany, Greece, Hong Kong, Italy, Japan, Luxembourg, Mexico, Netherlands, Norway, South Africa, Spain, Sweden, Switzerland, the United Kingdom and the United States (see Table A1 in the appendix).
[7] Throughout this paper, we use the United Nations classification of macro geographical continental regions and geographical sub-regions (see Table A1 in the appendix).
[8] Two occupations were only available for a single year, i.e., financial analysts (2012) and hospital nurses (2015), and were therefore excluded from our analysis.
[9] For a graphical illustration, see Figure A1 in the appendix.
[10] The UBS (2015) uses a standardized basket of 122 goods and services based on the monthly consumption habits of a European three-person family. When products were not available or deviated too far, local representative substitutes were used. Changes in consumer habits stemming from technological developments were also

our earnings data by that index and then deflating all years for inflation in consumer prices for the United States using data from the WDI (World Bank, 2016), we obtain earnings in constant New York City PPP-adjusted 2015 USD for all available occupations, cities and years.[11] When there are observations from more than one city in a country and year,[12] we first PPP-adjust at the city level and then calculate population-weighted country-level averages for each occupational group using city population data from the United Nations (2017).[13]

2.2 Occupational statistics

To construct measures of earnings inequality, such as the Gini coefficient, we also need information about the relative proportions of the populations that are working within the different occupations. As such, we use data on employment by occupation from the ILO's (2010, 2011) databases *LABORSTA* and *ILOSTAT*, where the economically active population in each country is disaggregated by occupation according to the latest version of the *International Standard Classification of Occupations* (ISCO) available for that year. We thus categorize each of our 14 occupations into the most relevant of the nine (or ten, depending on year) ISCO categories and assign that category's population to the corresponding occupation (see appendix Table A2). If there is more than one occupation assigned to the same ISCO category, we weight them by their proportions using the second level of the ISCO data.[14]

Because the UBS data are built on surveys conducted in cities, our earnings data lack occupations assigned to the ISCO agricultural category. To adjust for this and to make our earnings data representative for the whole working population within each country, we also add the occupational category of agricultural workers, to which we assign the agricultural sector earnings available in the OWW database (Freeman and Oostendorp, 2012).[15] Thus, we have a

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accounted for. As our baseline, we use this UBS price level index excluding rent. For 1970 and 1973, the UBS does not report any composite index, so we instead use their index for food prices.

[11] In alternative specifications, we use price level data from the *Penn World Tables* (PWT) and the World Bank's WDI as alternative PPP sources, as well as the UBS price level index, including rent. For further robustness, we also alternatively compare prices across countries in one year (2015) and then let within-country prices follow domestic inflation.

[12] This is the case for ten countries: Brazil, Canada, China, France, Germany, India, Italy, Spain, Switzerland and the United States (see Table A1 in the appendix).

[13] Using urban agglomeration averages.

[14] When ISCO level 2 data are not available, we assign them equal proportions of the ISCO main category's population. If there is more than one ISCO categorization for the same year, we use their average. If there are missing values, we use linear interpolation or extrapolation using the earliest or latest available observation. For Kenya and Nigeria, which lack data, we use regional averages.

[15] This database contains normalized occupational wage data derived from the ILO (2010) from 1983 to 2008. For the agricultural workers, we use the average earnings within the agricultural production, plantation, forestry,

total of 15 occupational groups with earnings and population data for our broad panel of countries and years. Finally, we weight each country's occupational populations so that they sum to the country's total employed working age population (aged 15-64 years), and we add an unemployed category with zero earnings corresponding to the country's unemployed working age population, based on the World Bank's (2016) WDI.[16]

3. Estimation procedure

Our global earnings inequality database is constructed as follows. First, we use the data described above on yearly earnings, before (gross) and after (net) taxes and employee social security deductions,[17] as well as weekly working hours for our 15 different occupational profiles[18] and all countries and years available in the UBS *Prices and Earnings* reports.[19] All but two of the occupations are available from the 1970s, while call center agents and product managers are added during the 2000s.[20]

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logging, and deep-sea and coastal fishing industries. When there are missing observations, we use the same imputation methods as above, i.e., linear interpolation and extrapolation using the sub-regional or regional sector growth. For missing countries (France, Greece, Hong Kong, Israel, Lebanon, Luxembourg, Panama, Qatar, Saudi Arabia, South Africa, Spain, Switzerland, Taiwan, Thailand and the United Arab Emirates), we use GDP per capita weighted sub-regional or regional averages. For the years before 1982 and after 2009, we let the agricultural earnings follow the country-level growth of unskilled construction workers, i.e., the occupation that has the highest correlation with the agricultural sector earnings trend during the years when we observe both (the time-series correlation between the unweighted global average earnings of OWW agricultural workers and UBS construction workers is 96 percent for net yearly earnings; see Figure A2 in the appendix). In a robustness check, we instead let the agricultural earnings trend follow country GDP per capita growth during these years and find that this does not change the overall results. Finally, we also convert the monthly wage rates to yearly earnings, and the gross earnings to net earnings by using the elementary occupations (construction workers) tax rate.

[16] Except for Taiwan, which is not included in the WDI, where we instead use data from National Statistics Taiwan (2016).

[17] If a gross or net earnings observation is missing, we linearly interpolate the tax rate (calculated as the difference between gross and net earnings divided by gross earnings) and then use that to compute the missing earnings observation. For 2015, the UBS only reports taxes as country averages. We thus assume that the tax rate of each country-occupation was the same in 2015 as it was in 2012.

[18] These are bank credit clerks, bus drivers, call center agents, car mechanics, construction workers, cooks, department managers, engineers, female factory workers, female sales assistants, primary school teachers, product managers, secretaries, skilled industrial workers, and the added agricultural workers.

[19] First, we also check for potential errors in the original data by calculating the change in city-occupational earnings between all consecutive periods. Doing so, we identify three cases where the three-year change in earnings is tenfold or more and where the city-occupation trend and the overall country earnings trend suggest that there is a zero missing at the end of the earnings figure. The three earnings observations that we thus adjust accordingly are for car mechanics and construction workers in Hong Kong 1994 and skilled industrial workers in Jakarta 1991.

[20] Some of the occupations that have data from the 1970s lack data during the earliest years (see Table A2 in the appendix), which we then extrapolate with the corresponding change in average earnings for that occupation's sector in each country. If an occupation is missing completely for a country, we use sub-regional (or regional) averages for that country-occupation instead. In alternative specifications, we also exclude the "new" occupations that are added in the 2000s and, alternatively, extrapolate the "new" occupations to cover the full period. We find that this does not affect the overall results.

In the original UBS data, we have 737 country-year observations (Sample I). For a few countries, there are missing observations within the country's time trend, and we linearly interpolate them, increasing our sample size to 755 country-year observations. Because this is an unbalanced panel, we need to ensure that our findings about global earnings inequality are not driven by an increasing sample of countries over time.[21] Thus, to obtain a balanced panel, we extrapolate the missing country-occupation observations by the corresponding average sub-regional (or regional)[22] change for each occupation,[23] such that we obtain full sample coverage (Sample II) with observations from all 66 countries for all 16 time periods, i.e., every third year from 1970 to 2015, which gives us a total of 1,056 country-year observations for each of the 15 occupations (i.e., 15,840 observations for each of our earnings, taxes, hours, and population measures).

In Table 1, we present the database coverage separating the two data samples just described.[24] Sample II covers approximately 80 percent of the world's population and over 95 percent of its GDP. Note that despite being smaller, the original observed UBS sample (Sample I) covers almost 80 percent of the world's GDP in 1970 and more than 90 percent in 1985.

[Table 1 about here]

However, since our ultimate goal is to study global inequality, we also need to account for countries not in the original sample. We do this by imputing earnings for each occupation using the average earnings levels in the corresponding sub-region or region weighted by the GDP per capita of the excluded countries relative to that of the whole sub-region or region.[25] This sample (Sample III) yields a total of 20,400 country-year-occupation observations for each of our different statistics, or 21,760 observations, including the unemployed category, and it has 100

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[21] This kind of adjustment is not done by, e.g., Anand and Segal (2015) and Lakner and Milanovic (2015), who instead use their unbalanced country sample as the baseline and then include estimates based on a balanced, common sample over time as a robustness check.

[22] In all such imputations, we always use average data on the sub-regional level if they are available and regional level averages only when we do not have any observations at the sub-regional level (according to the United Nations' classification of geographical regions).

[23] In an alternative specification, we instead extrapolate these missing observations with country GDP per capita growth and an adjustment factor of 0.87 to reflect empirically observed differences between national accounts and survey growth following the World Bank (2015).

[24] For coverage in all years, see Table A3 in the appendix.

[25] A similar approach is used by, e.g., Modalsli (2016).

percent global coverage. Sensitivity analyses show that our general findings are not changed by excluding these latter imputations.

From these earnings and population data, we estimate the inequality of global, regional and country earnings over the entire period 1970–2015. Our main index of inequality is the Gini coefficient, but we have also assessed the inequality trends using other measures, such as generalized entropy indices and top earnings shares. In addition, we calculate a number of earnings ratios such as the gender gap (for male to female industry workers), skill premium (for skilled to unskilled workers) and the manager-worker gap. Finally, we also estimate our different inequality indices for gross and net, yearly and hourly earnings (where hourly earnings inequality corresponds to what we will refer to as wage inequality).[26]

3.1 Correlations with other datasets

When introducing a new source for cross-country inequality, it is important to check how well it reflects the levels and trends in other data sources. The first panel (Figure 1a) plots average country-level Gini coefficients for our net earnings against those for income or consumption in Milanovic's (2016a) *All the Ginis* (ALG) dataset.[27] There is a positive and significant correlation of 47 percent. The level of inequality is generally lower for earnings than for income (or consumption), which is expected, since earnings do not include income from capital (which is very skewed). When comparing the level of net earnings with the level of GDP per capita from the WDI (Figure 1b), we observe an even stronger positive correlation, 88 percent. Similarly, there is a strong correlation (84 percent) between the average country-level top 10 percent earnings in our dataset and the corresponding figures in the WID (Figure 1c). Comparing the country-average price levels based on the UBS data with prices based on the WDI or the PWT (Figure 1d), we also see a strong correlation of 87 percent. We can also check how well the UBS occupational earnings correspond to another international dataset of occupational wages, i.e., Freeman and Oostendorp's (2012) OWW database. In Figure 1e, we plot the occupational gross yearly earnings within the two datasets, where each observation represents the earnings of an occupation in a country and year.[28] The correlation between

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[26] Calculated as yearly earnings divided by weekly working hours times 52.
[27] For country-level averages of a number of different inequality measures, see Table A4 in the appendix. For country inequality trends, see Table A5. For pairwise correlations results, see Table A6 in the appendix.
[28] The occupations are matched as follows (in the UBS and OWW datasets, respectively): bank credit clerks with bank tellers; bus drivers with motor bus drivers; car mechanics with automobile mechanics in the repair of motor vehicles industry; construction workers with laborers in the construction industry; cooks with cooks; department

occupational earnings in the two datasets is high (86 percent), and for hourly wages even higher (88 percent).[29]

In panels f, g and h of Figure 1, we check the city data variation within countries. By comparing all within-country between-city pairs available in our data (i.e., the countries for which we have earnings data from more than one city in the same year), we see that after PPP-adjusting at the city level, average earnings within one city in a country seem to be strongly correlated with earnings in another city within the same country (Figure 1f). The same also seems to be the case for city earnings inequality (Figure 1g). While some earlier studies have argued for a potential relationship between inequality and city size (e.g., Glaeser, Resseger and Tobio, 2009, find this association to be negative, while Baum-Snow and Pavan, 2013, find it to be positive), we do not see such within-country correlation between city population and earnings inequality in our data (Figure 1h). Nevertheless, in one of our heterogeneity analyses, we focus our analysis exclusively on urban earnings inequality.

[Figure 1 about here]

Another consistency check is to compare our earnings Gini coefficients, their levels and trends at the country level with other sources. Figure 2 presents such comparison using three other data sources: 1) a special issue of the *Review of Economic Dynamics* (RED), which contains earnings and wage inequality series for nine countries (Krueger, Perri, Pistaferri and Violante, 2010); 2) microdata for nine countries over earned income and wages and salaries available from the Minnesota Population Center's (2015) *Integrated Public Use Microdata Series* (IPUMS) *International*; and 3) Milanovic's (2016a) ALG dataset with income or expenditure Gini coefficients from various sources. Figure 2 shows these comparisons for 15 countries from Europe, Asia and the Americas for which we found comparable series.[30] Overall, our estimated

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managers with supervising or general foremen in the manufacture of industrial chemicals industry; engineers with electronics engineering technicians; female factory workers with laborers in the spinning, weaving and finishing textiles industry; female sales assistants with salespersons in the retail trade (grocery) industry; primary school teachers with first-level education teachers; secretaries with office clerks in the printing, publishing and allied industries industry; and skilled industrial workers with mixing- and blending-machine operators in the manufacture of industrial chemicals industry.

[29] For earnings correlations per occupation, see Figure A3 in the appendix.

[30] Our earnings inequality here includes added top earnings from the WID (see Section 6.3 below) in order to offer better comparability with the other sources at the country level. Appendix Figure A4 shows non-adjusted comparisons with the ALG series for 60 of our 66 covered countries (the ALG lacks data for Bahrain, Lebanon, Qatar, Saudi Arabia and the United Arab Emirates; Pakistan is only included in the UBS for one year), i.e.,

earnings inequalities are reassuringly similar to those available for other countries in the other sources in both levels and trends. However, there are several examples of imperfect overlaps, not only for our series but also across the other estimates. Some discrepancy is expected given that the series differ in, e.g., the definitions of population (such as age cutoff differences) and income (the ALG shows mostly disposable income), and due to the omitted within-occupational-group dispersion in our data. In some cases, the deviations between our series and the others are more problematic for our estimates. For example, there are some instances of fairly large and swift changes in our inequality estimates that are not observed in the other sources. Our estimates also seem not to fully capture the rising trend in earnings inequality in the United Kingdom and in the United States seen in the RED and IPUMS sources.

[Figure 2 about here]

Summing up, the correspondence between our new earnings inequality database and previous evidence from other sources must be regarded as good. The correlation with national accounts and previous cross-country inequality data is generally quite high. The within-country comparisons of levels and trends are also acceptable, but show some cases of deviations.

4. Main results

4.1 Trends in global earnings inequality

The evolution of global earnings inequality between 1970 and 2015 is presented in Figure 3.[31] Gini coefficients for three different earnings concepts are shown: gross annual earnings, net annual earnings and net wage (or hourly earnings). The level of inequality in gross earnings is approximately three Gini points higher than the inequality in net earnings. Inequality in hourly wages is consistently higher than inequality in yearly earnings over this period, which suggests a negative correlation between earnings and hours worked at the global level.

Looking at the trends over the period, all three measures offer a similar picture. Global earnings inequality fell initially in the 1970s but was then virtually flat over the rest of the 1970s and 1980s, followed by a modest increase in the early 1990s. A large decline is recorded during the

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comparing Milanovic's (2016a) country-level estimations of income or consumption inequality with our measures of earnings inequality.

[31] For the exact number, see Table A7 in the appendix.

late 1990s and early 2000s, after which the decline halted, and global earnings inequality has been flat during the 2010s and at its lowest level over the entire period. The fall over the period is sizeable: the net earnings Gini dropped from 66 percent in 1997 to 57 percent in 2012, i.e., by almost ten points in only 15 years.

[Figure 3 about here]

Looking at other inequality metrics offers nuance and perspective to the evolution of global earnings inequality, and Figure 4 presents some of these. The first panel (Figure 4a) shows generalized entropy indices, GE(a), where a higher parameter a reflects a higher sensitivity to disparities in the top of the distribution. Figure 4b shows Atkinson indices, A(e), where e is society's aversion to inequality and makes the index more sensitive to earnings differences at the bottom of the distribution. Panels c and d of Figure 4, finally, show global earnings shares of the global top decile and the bottom 50 percent. As expected, the level of inequality varies across these measures, especially in the cases where specific parameter values differ. However, all series display a decline in global earnings inequality over the studied period. The GE measures and the top decile share move almost exactly in tandem with the Gini coefficient (except for the larger emphasis on the fall in the early 1970s), exhibiting a relatively flat level up until the late 1990s, after which inequality falls sharply. The Atkinson indices and the bottom 50 percent share portray a more gradual decline in inequality over the whole era, though with an acceleration in the 2000s. The share of the bottom half increases from just above seven percent of global earnings in 1970 to 14 percent today. Overall, we interpret the series in these four panels as reflecting a general sense of robustness of our main results.

[Figure 4 about here]

Figure 5 presents a completely different view of the evolution of inequality, depicting kernel densities of absolute earnings of occupations across countries every fifteenth year since 1970.[32] Comparing these densities over time shows that the distribution has drifted upwards, signaling an overall increase in real earnings across the world during the past half-century. The relatively thick left tail, i.e., sizeable mass of low-earners, is especially visible in 1970 and 1985 but then almost gone in subsequent decades, once again underlining the strong decline in global

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[32] Very similar results are also obtained if we use Epanechnikov instead of Gaussian kernel smoothing.

inequality, where earnings instead became more concentrated around the center, or lower middle, of the distribution. Other studies of the global income distribution over time have found that it was bimodal before 1970 and then became unimodal between 1980 and 2000 (Moatsos, Baten, Foldvari, van Leeuwen and van Zanden, 2014). We see a similar trend in the global earnings distribution, but in the very recent years, we also observe an indication of a potential return to a bimodal distribution, which could explain why global earnings inequality stopped falling during the 2010s. However, a difference is that it now has more density on the upper rather than the lower mode.

[Figure 5 about here]

How do our global earnings inequality series relate to other estimates of global inequality? Figure 6 contrasts our gross and net earnings and wage Gini coefficients with the Gini coefficients of global income, as presented by Lakner and Milanovic (2015), Bourguignon (2015), and Anand and Segal (2016).[33] Interesting patterns emerge from this comparison. First, the inequality we find in earnings is markedly lower than in surveyed income, with Gini coefficients being approximately eight percentage points lower. One important explanation of this gap is that our focus on the working age population implies that we exclude many low- or zero-earners such as children, students and retirees. Another reason is that our earnings data do not include incomes from capital, which are more unevenly distributed. Second, the trends in inequality point in the same direction. They all indicate that global inequality has decreased in recent decades, from a high level in the late 1980s and early 1990s to a lower level in the late 2000s and early 2010s. Looking at the magnitude of this inequality decline, the decrease is larger in our earnings data than in the income and consumption data.

[Figure 6 about here]

4.2 Growth incidence curves

Another way of depicting and understanding the evolution of inequality is to examine the rate of earnings growth across the distribution. Figure 7 depicts *growth incidence curves* (GICs) for percentiles in the global earnings distribution, measured as the average annual percentage

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[33] We use their inequality indices based on household surveys without imputed top income shares in order to increase the comparability across sources.

growth of each percentile's mean earnings between the 1970s and 2010s.[34] During this long period, the average compounded global real earnings grew by approximately 0.8 percent annually. However, seen over the entire earnings distribution in the 1970s, the growth rates differ considerably. The lower half of the distribution records above-average earnings growth, and we see a peak for the lower-middle quintile, the "global middle class", with an average real earnings growth of 3 percent per year. By contrast, in the two highest quintiles, earnings growth was considerably below average and, quite notably, in the top of our earnings data, earnings growth was essentially zero. While perhaps surprising, a recent study by Sacerdote (2017) similarly found that the growth of US real wages since the 1970s was zero (with some variation due to the choice of price index). In the very top percentile, in which the largest group is US managers, real earnings growth was even negative, and although this may be too low, our sensitivity analysis below shows that the relatively low growth of the top persists even after adding top earnings amounts from other sources.

[Figure 7 about here]

By varying the time frame over which GICs are computed, we can study how robust the income growth pattern is over different periods. Figure 8a shows such an exercise, varying the GICs over six different periods since the 1970s. The main message is that the pattern does not change much. The hump in income growth appears in the global lower-middle part in almost all cases, is largest in the 1990s-2010s case and is smallest in the 1970s-1990s case, indicating that the 1990s were indeed a decade of relatively low earnings in the lower half of the global earnings distribution. It is notable that in none of these cases do we observe a marked income growth in the top of the distribution; in fact, the top experiences the lowest earnings growth in the entire distribution, regardless of starting period.

How do these GICs compare with the so-called "elephant curve" in the global household income growth found by Lakner and Milanovic (2015)? In Figure 8b, we compare our global growth incidence for earnings for the period between 1988 and 2009 with the corresponding annual decile growth for income or consumption, as estimated for 1988–2008 by Lakner and

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[34] GICs were first formulated by Ravallion and Chen (2003). Note also that this is a so-called *anonymous* GIC in the sense that we do not take any account of which groups are associated with each earnings percentile, and it is therefore likely that the recorded earnings growth rates refer to earners from different countries and occupations in the two different periods. For a *non-anonymous* GIC, with some marked country-occupations, see Figure A5 in the appendix.

Milanovic (2015) and for 1988–2012 by Anand and Segal (2016). Compared with Lakner and Milanovic's (2015) findings, we find a similar overall pattern, with higher growth rates in the bottom and middle than in the top of the global distribution. However, the earnings growth deviates in two respects: it is more concentrated in the lower middle part of the distribution, and we do not see any evidence of a peak in the top of the distribution.

One possible explanation of the difference in income growth among the very top group is that Lakner and Milanovic (2015) cover top capital accumulation, which our labor earnings do not take into account. However, in the sensitivity analysis below, we add top earnings data from the WID (see Figure 13 and appendix Figure A6), and even if this adjustment, for some years, more than doubles our recorded earnings growth of the top percentile, it is still much below those of Lakner and Milanovic (2015). It should also be noted that Anand and Segal (2016) find much lower income growth for the top percentile than Lakner and Milanovic (2015), despite also using surveyed incomes (rather than earnings) and additions of top incomes of various forms. As Anand and Segal (2015) highlight in their survey of this literature, the top income adjustments made by Lakner and Milanovic (2015), especially adding the residual between national account totals and surveyed totals to the observed top decile's income, could potentially explain their very high rates of income growth in the global top. Moreover, in one of our robustness checks (see Figure A6), we find similar top 1 percent growth as Anand and Segal (2016), but our overall results indicate that this finding is quite exclusive to that particular choice of PPP adjustment, top imputation and time period.

[Figure 8 about here]

5. Decomposing global inequality trends

Accounting for the drivers of the evolution of global earnings inequality is an important part of our analysis. The approach we choose is to study how different sub-components contribute to this evolution. We begin by statistically estimating the relative contributions from inequality within and between countries and, for the first time in this literature, occupational groups and industrial sectors. Thereafter, we present some more-fine-grained decompositions, depicting the evolution of earnings inequality within world regions. Finally, we illustrate how earnings ratios with respect to sex, skills, education and experience have evolved during this period.

5.1 Country and regional decompositions

Figure 9 presents four panels of decomposition results with respect to countries and regions. Since the Gini coefficient is not additively decomposable into within and between components, we use the Theil index, as is commonplace in this kind of exercise. However, to maintain consistency in the rest of the analysis, we scale the Theil within and between contributions with their corresponding total Gini coefficients.[35] Looking first at the country-based decomposition in Figure 9a, the major part (between three- and four-fifths) of the inequality can be attributed to earnings differences between countries, i.e., their differences in average earnings level. Over time, however, this between-inequality component becomes less important, while the relative importance of the within-country component increases. In the 2000s, the fall in the between component exceeded that in the overall inequality because the within component increased in this period. Also, the small increase in the overall global inequality trend during the early 1990s seems to be driven by increased within-country inequality. If we instead perform this country decomposition on yearly earnings versus hourly wages and pre- versus post-tax, we see that the negative relationship between earnings and hours worked reflects between-country differences, while gross inequality is higher than net inequality both within and between countries (see Figure A7 in the appendix). Analyzing the decomposition trends within and between our different geographical regions (see Figure 9b), we can also see that the between-region component seems to be driving most of the falling global earnings inequality trend, although it has a lower level than the within-region counterpart.

An alternative decomposition is to differentiate between countries' level of development. In Figure 9c, we separate countries into OECD members and non-OECD members, and this decomposition shows that the global inequality decrease during the 2000s is linked to a fall in the between component, i.e., reduced earnings differences across these two country groups. When we look within these two groups, we can also see that wage inequality (not shown in this figure) has fallen relative to earnings inequality in the OECD, while there has been an opposite trend among non-OECD members, i.e., the negative correlation between earnings and working hours has increased outside the OECD, while it has fallen within the OECD. This latter finding is in line with findings by Checchi, García-Peñalosa and Vivian (2016). If we decompose inequality within and between countries for the OECD and non-OECD members separately, we

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[35] The corresponding Theil decomposition figures look essentially the same and are available from the authors upon request. For an alternative decomposition method, see, e.g., Modalsli (2016).

also see similar trends as the global pattern, with an initially much larger, but over time falling, relative importance of the between-country component of earnings inequality.[36]

In Figure 9d, we decompose global earnings inequality within and between the two most populous countries on earth, China and India, versus the rest of the world. The result shows that while the global inequality decline is associated with an earnings convergence between these two "groups", inequality within them is still more important for explaining the total level of global inequality. In fact, the 2010s brought a shift where the inclusion of China now actually lowers our estimate of global earnings inequality in contrast to the beginning of the period, when it increased the global Gini coefficient by approximately seven percentage points (see Figure A8 in the appendix). When we only exclude China, the trend is nearly flat over the investigated period. Thus, the four panels in Figure 9 suggest that the level of development, cross-country convergence and economic growth of especially China, play a central role when one accounts for the drivers of global earnings inequality and, in particular, the downward trend since the late 1990s.

[Figure 9 about here]

Figure 10 displays regional earnings inequality trends in Africa, Asia, Europe, Latin America, Northern America and Oceania.[37] There is a large heterogeneity in both levels and trends across continents. Asia and Europe experienced lowered inequality, with the latter experiencing basically a level shift in the 2000s. Regional decomposition[38] shows that both of these inequality decreases were due to falls in between-country inequality, which might, e.g., be explained by exceptionally high earnings growth rates among the low-income Asian countries and earnings convergence among European countries with the expansion of the European Union and the introduction of the euro. Africa and Latin America also have high levels of regional earnings inequality, but more-volatile trends, where the earnings inequality in Latin America and the increasing trend in Africa are more dominated by the within- than between-country

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[36] Results available upon request.
[37] See Table A1 in the appendix for country coverage for each of the regions. Regional earnings inequality trends for gross yearly earnings and net hourly wages are shown in Figure A9 and regional GICs in Figure A10 in the appendix. For a similar regional inequality analysis, see Ravallion (2014), which focuses on the developing world.
[38] As above, our figures show the Theil index within and between contributions scaled by total regional Gini coefficients. The corresponding Theil decompositions are available upon request.

inequality. The smaller regions, Northern America and Oceania, have lower levels of initial regional earnings inequality and exhibit essentially flat and increasing trends, respectively.

[Figure 10 about here]

5.2 Occupations, sectors, gender and skills

A unique aspect of our global database is its labor market variables. We exploit this to decompose global inequality by occupations and sectors. We then examine the specific earnings relations due to gender, skill and seniority. Figure 11a shows a decomposition by occupation. It shows that the within-occupation inequality is the dominant component and that it is primarily its decrease that accounts for the fall in global earnings inequality.[39] This result goes well with the country-based analysis, since the large within-occupation inequality reflects the large earnings differences across countries. The sectoral decomposition in Figure 11b, in which we divide the world's earners into the agricultural, industrial and services sectors, shows that the within-sector component dominates the between-sector inequality. This is once again in line with our previous findings, since the dispersion across earners in different countries within these sectors dominates the average earnings gaps between sectors. We can also see that during the late 1990s and early 2000s, inequality falls both within and between these sectors.

In Figures 11c and 11d, we examine the earnings inequality within different occupations in the industrial and services sectors, respectively. We document a large variation in the level of earnings inequality across occupations. For example, there is a larger earnings dispersion among the world's construction workers than among the department managers of the world, and secretaries in the world are more homogenously paid than primary school teachers. Looking at trends, almost all occupations (except for bank credit clerks) have experienced decreased global occupational inequality over this period, which matches the overall global trend. However, the decrease is more pronounced in the industrial sector, and the industrial occupations are clearly more closely gathered in terms of this trend than the services professions are. A possible explanation of this is trade globalization. Since the industrial sector is more exposed to international competition, industrial earnings become compressed, and thus equalized globally, by globalization. By contrast, services sector earnings are to a larger extent

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[39] Same decomposition method as above. Corresponding Theil index decomposition figures available upon request.

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determined by national conditions, and therefore, they respond much less to rising globalization.

[Figure 11 about here]

Finally, we examine a number of earnings ratios across occupational and gender categories. Recall that the earnings reflect UBS' methodology of surveying people whose background characteristics (e.g., gender, age, skills, education, experience, and family status) are comparable across occupations and constant over time and space. Figure 12a displays the global earnings ratios of different industrial occupational groups, all represented by male earners, relative to the mean global earnings of female unskilled workers. Most of these trends are relatively flat, possibly with a small increase during the 2000s, which might explain the essentially non-trending, or slightly increasing, within-country inequality we saw in our previous decomposition analysis. As illustrated by the bottom line, the global gender gap fell during this period. In Figure 12b, we instead analyze the trends net of the gender effect by relating the same occupational groups to the mean global earnings of male unskilled workers. This time, we observe increasing pay ratios for all the three occupations. In other words, there seems to be opposing effects by a decreasing global gender gap and, at the same time, increasing experience, education and skill premia at the global level. This is further illustrated in Figures 12c and 12d, where we explicitly show these different earnings ratios.

The global skill premium, measured as the global population-weighted average earnings ratio between skilled male industrial workers and unskilled male construction workers, is shown in Figure 12c. The global skill premium increases at a constant rate from approximately 1.5 to almost 2. The global gender gap, computed as the mean population-weighted earnings of male unskilled construction workers to female unskilled factory workers,[40] instead decreases from nearly 1.5 in 1970 to approximately 1 in 2015, which is a large decline. In other words, the effect of rising skill biases on global inequality is being opposed by declining gender differences. Figure 12d captures aspects of workplace hierarchies in the manager premium, measured as the ratio of global population-weighted mean earnings of male skilled department managers to the mean earnings of male skilled engineers. Over the period, this ratio has

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[40] These earners are similar in the sense of being around 25 years old, single, without children, and working in the industrial sector.

decreased, while we can see an opposing increasing trend for the global education premium (i.e., measured as the engineer-skilled worker gap).[41]

[Figure 12 about here]

6. Sensitivity and heterogeneity analysis

Even though we have presented the main results using variants in certain outcomes (net or gross of taxes, different time periods and geographical units), there are still some important dimensions to explore. In this section, we examine how global earnings inequality responds to the following robustness checks and alterations: using different PPP-adjustments, restricting the analysis to the urban and employed populations, adding top earnings from other sources, and simulating earnings dispersion within occupations within countries. Some further robustness checks, using alternative imputations when generating the database, are presented in appendix Figure A11.[42]

6.1 Using different PPP-adjustments

Adjusting incomes for PPP has been found to be of particular relevance when assessing global inequality (see, e.g., Almås, 2012; Deaton, 2010; Deaton and Aten, 2015; Deaton and Heston, 2010). In Figure 13a, we therefore re-estimate the global earnings Gini coefficients using several different price indices. The results show that it does not make a huge difference whether we include or exclude rents and whether we compare prices across cities and countries in each year or only in one year, i.e., 2015, and then let prices in each country follow national inflation. Furthermore, we find that our preferred adjustment, based on local prices collected homogenously by the UBS for all cities and years in direct correspondence with the earnings information, delivers a long-run pattern that is relatively close to, although generally higher than, what we obtain when using PPPs from the WDI (World Bank, 2016) or the PWT

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[41] All of these earners are aged around 35-40, married, with two children, and employed within the industrial sector.

[42] As shown in Figure A11 in the appendix, whether or not we include our proxies for the countries that are not in our original data does not seem to have an important effect on the results, nor does excluding or extrapolating the two "new" occupation that are added during the 2000s, nor using total instead of working age country population weights. Extrapolating missing observations with changes in the country's GDP per capita instead of sub-regional changes yields a more constant development of the global earnings inequality during the first year of our data but then yields a very similar trend from the mid-1970s onwards. Most of the trend also seems to be driven by earnings and country populations rather than occupational group populations, although changes in the latter have dampened the fall in global inequality somewhat.

(Feenstra, Inklaar and Timmer, 2015).[43] The main trend differences when using these alternative PPP sources is that the fall in global earnings inequality becomes steeper and more concentrated from the mid-1980s to the late-1980s and that the flattening out of inequality begins already in the late 1990s. Third, as expected, our PPP-adjusted measures of global earnings inequality are generally lower than the global earnings inequality in current market prices (i.e., using market exchange rates and no adjustments for local price differences), but they follow somewhat similar trends.

In Figure 13a, we also show our global earnings GIC between the 1970s and 2010s using these different PPP sources. While the use of these alternative PPP-adjustments has some impact on the shape of the GIC, especially among the lower deciles, the overall conclusion of relatively high earnings growth among the lower half of the global earnings distribution and earnings stagnation among the top deciles remains. We can also note that the GIC using our preferred PPP-adjustment (i.e., using local price levels from the UBS) lies between the corresponding curves when using PPPs from the WDI and the PWT, respectively.

[Figure 13 about here]

6.2 Restricting the analysis to global urban and employed populations

A heterogeneity analysis with respect to populations, where we focus only on the global urban and global employed earnings inequalities, is presented in Figure 13b. Weighting each country by its urban, instead of total, working age population and excluding our added agricultural workers yields lower levels of inequality. Moreover, the global urban population has experienced a somewhat flatter earnings inequality trend during this period. When instead excluding the unemployed populations, we obtain a lower level, but similar trend, of the global earnings inequality. The difference between including and excluding the unemployed has increased over this period, suggesting that global unemployed has increased. The GIC looks quite different when we only use the urban populations, particularly through the absence of the strong income growth of the middle-income agricultural earners in China and India. However, earnings grow essentially at the same pace in the bottom and top of the earnings distributions.

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[43] Based on the 2011 *International Comparison Program* (ICP). If there are missing values, we use the same imputation methods as above, i.e., linear interpolation and sub-regional means extrapolation.

6.3 Adding top earnings

One concern with our earnings data is their insufficient coverage of earners at the very top of the distribution. Correlations between our data and the WID top earnings data are positive and significant (see Figure A12 in the appendix), but we know that by construction, we miss all the very highest-paid professions and their incomes in our estimations. The correlations in appendix Figure A12 indicate that the highest-earning occupations in the UBS data (i.e., managers) have earnings around the 95-99th income percentile, which means that, e.g., CEO salaries and bonus programs, stock options pay and other high-end remuneration are not well covered by our database.

To account for earnings in the very top, we thus add national top earnings using data from the WID.[44] Because our analysis focuses on earnings, we only include the top incomes in the WID that come from wages, salaries and pensions, or corresponding estimates.[45] We add the national top 5 percent (or, alternatively, the top 1 or top 10 percent), treat them as their own occupational group and reduce the other employed working age population by the corresponding percentage.[46] When missing, we impute these data using the same methods as described above, i.e., by linear interpolation and sub-regional or regional extrapolation.[47] Because the original data in the WID cover relatively few countries, we also use an alternative imputation method following the approach used by Anand and Segal (2015, 2016), but where we estimate the missing top earnings as a function of the country's GDP per capita in order to alternatively make it more exogenous from our other data.[48] Finally, we also try adding all income, i.e., the

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[44] Countries with data both in our sample and top earnings data in the WID are Argentina, Australia, Canada, China, Colombia, Denmark, France, Germany, India, Ireland, Italy, Japan, Malaysia, Netherlands, New Zealand, Norway, Portugal, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, Taiwan, the United Kingdom and the United States.

[45] That is, we adjust the recorded national top total incomes into earnings by using evidence on earnings shares in the WID. Since this calculation relies on even fewer data observations, we also show results without this adjustment, using the national top total income data available in the WID.

[46] Alternatively, we have also added the national top 1, 5 and 10 percent simultaneously as well as added all of these data on top of the other populations, finding very similar results.

[47] If the countries included in the WID have some missing observations, we first use linear interpolation, second use changes in another similar measure for that country and year, and third use sub-regional or regional changes. For countries that are not included in the WID, we use sub-regional or regional means, weighted by the country-to-region relative mean earnings of the ISCO categories 1-3 occupations (i.e., managers, professionals, technicians and associate professionals; see Table A2 in the appendix). Similarly, we use the mean taxes and working hours of these occupations to calculate net and hourly earnings.

[48] Here, we assign to the country-years with missing information on the wage share of top incomes the global average share, which we find to be that wages make up 68 percent of top 5 incomes. Missing years for countries included in the WID are extrapolated using the country's GDP per capita growth. Countries not included in the WID are imputed by the estimated OLS regression, which gives $Top5earnings = 2864 + 2.53 \cdot$

national top 5 percent average total income, including capital income and without adjusting for the earnings share of total income, available in the WID.[49]

The results from the top earnings addition are shown in Figure 13c. The Gini coefficient increases somewhat, from 58 to 59 in 2015, and this effect appears to be roughly the same regardless of how we impute the top incomes. Similarly, the GIC does not change much from adding top earnings. The average annual growth of the top percentile rises by nearly one percentage point, which is a notable increase but still at a level far below the growth rates in the bottom half of the global distribution.

6.4 Within-group dispersion adjustment

Another sensitivity check is made to examine the role of within-country-occupation earnings dispersion. Because our data emanate from occupational groups, they do not capture any earnings differences among workers within the same occupation in the same country. This problem is not unique to our dataset; all the other previous studies of global inequality are based on grouped data, mainly in the form of deciles or ventiles (e.g., Anand and Segal, 2015; Bourguignon and Morrisson, 2002; Lakner and Milanovic, 2015), and they therefore also face this problem of underestimating the within-country-group dispersion. Consequently, the estimates presented elsewhere and in our study can probably be thought of as lower bounds.

While we cannot know exactly how large the bias from the omitted within-group dispersion is, Modalsli (2015) suggests a correction method to adjust for this, applied to historical social tables. While his method imposes a number of distributional assumptions, it is interesting enough to implement it on our global earnings inequality measures. As far as we know, this is the first time such adjustments of within-group dispersion have been made when estimating global inequality.

The method begins by assuming a log-normal distribution within each group. It then assigns a within-group dispersion in terms of the *coefficient of variation* (CV), given by the standard deviation divided by the mean. Modalsli (2015) finds that most modern-day social groups have

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GDPpercapita. The overall R^2 is 72 percent, which is higher than what Anand and Segal (2016) find for their model.

[49] Here, missing data are also imputed by regression estimation, which gives $Top5income = 4431 + 3.71 \cdot GDPpercapita$, with an overall R^2 value of 73 percent.

coefficients of income variations between 0.5 and 1 (corresponding to within-group Gini coefficients of 26 and 44 percent, respectively). However, since earnings are generally less dispersed than income, and since occupational groups might have lower dispersions than other social groups, it is plausible that the within-group dispersion in our data would rather be somewhere between the lower coefficient of variation of 0.1 (corresponding to a within-group Gini coefficient of 6 percent) and 0.5. Thus, in order to gain a better sense of the size of this within-group dispersion, we will use the micro-data available from IPUMS International and from Krueger, Perri, Pistaferri and Violante (2010). Comparing the levels of micro-data-estimated inequality with our estimations based on occupational groups, we find that the former is, on average, 10 Gini points higher for earnings and 4 Gini points higher for wages for the 15 countries available in the IPUMS and RED sources.[50] If we assume that this difference corresponds to the mean within-country-occupation inequality,[51] the corresponding within-group coefficients of variation would be approximately 0.2 for earnings and 0.1 for wages. As such, this also indicates a positive relationship between earnings and hours worked within country-occupations.

The new global earnings inequality adjusted for within-country-occupations dispersion is presented in Figure 14 below.[52] As is immediately visible, assuming a within-group coefficient of variation of 0.1 does not change the global Gini coefficients at all, while coefficients of variation of 0.2 and 0.5 increase the global earnings inequality by approximately 1 and 4 Gini points, respectively. Even if this suggests that total earnings inequality is probably somewhat higher than our baseline estimates show, it does not change the overall picture that global earnings inequality has decreased over time.

[Figure 14 about here]

6.5 Gender composition

Finally, another way of adjusting for the within-group earnings dispersion is to expand the gender analysis by adding a within-country-occupation between-sex dimension. That is, instead

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[50] See Figure 2.

[51] That is, we assume that our data capture the inequality between occupations within countries and that the micro data estimations capture the total within-country inequality (both within and between occupations), while the overlap category is assumed to be negligible.

[52] We first compute the adjustments excluding the unemployed and then weight total inequality including the unemployed with the ratio between the adjusted estimates and our unadjusted measures of inequality excluding the unemployed.

of having male earnings for some occupations and female earnings for other occupations, we separate each country-occupational group into a male and a female group of workers. In contrast to studies using income data on the household level, this also adds a between-gender inequality analysis that we believe has not been done on the global level before.

We make this adjustment by using the gender composition in ILO's (2010, 2011) data on employment by sex and occupation[53] and by using the sectoral gender earnings gap in the UBS data.[54] Because the UBS male-female earnings gap is only available on the sectoral level, as an alternative, we also use ILO's (2011) data on earnings by sex and occupation to estimate occupational-level gender earnings gaps.[55]

Figure 15a shows the global earnings inequality trend adjusted for this within-group between-sex earnings dispersion, using the UBS and the ILO sources of the gender earnings gaps, while Figure 15b shows the corresponding GICs. As we can see, this adjustment has virtually no effect on the global inequality trend (if anything, the level of inequality is slightly lower with this adjustment). Similarly, the GIC is largely unaffected, except for some higher growth rates in the lowest quintile when taking the between-gender dispersion into account. A gender decomposition of the global earnings inequality trend is illustrated in Figure 15c, which shows that the between gender inequality is very small in comparison to the within gender inequality. In other words, inequality between countries and occupations seems to explain more of the overall global earnings inequality trend than inequality between sexes. Nevertheless, we can also see that global between-gender inequality has fallen since the 1970s. Finally, global earnings inequality among males and females, respectively, is shown in Figure 15d. During most of this period, female earnings inequality was slightly higher than male earnings

[53] That is, after separating each occupational group into its male and female components, we weight the population of each group by the male/female employment share of that particular country-year-occupation. For missing observations, we use the same approach as for the other ILO occupational population data (i.e., linear interpolation and extrapolation using the earliest or latest available observation). For missing countries (Kenya and Taiwan), we use sub-regional or regional occupational averages.

[54] These UBS gender earnings gaps are estimated by using the earnings ratio of occupational groups that are similar in terms of skills, experience, education, age and family status but differ in terms of gender. The industrial (and agricultural) sector gender earnings gap is calculated as the mean earnings of male construction workers divided by the mean earnings of female factory workers, and the services sector gender earnings gap as the mean earnings of male secretaries and car mechanics divided by the mean earnings of female sales assistants. We then weight the earnings of each male and female country-year-occupational group by the corresponding earnings ratio.

[55] Same imputation approach as above. For missing occupations, we use country-sectoral averages, and for missing countries (Bahrain, Chile, China, Iran, Japan, Kenya, Lebanon, Mexico, New Zealand, Nigeria, Singapore, Taiwan, Ukraine and the United States), we use sub-regional or regional occupational averages. These ILO occupational earnings data, however, are only available for the years 2002-2015. For the years before that, we assume the gender earnings gap to be constant on the country-occupational level.

inequality, but over time, this difference has decreased, and today, global inequality is basically the same across both genders.

[Figure 15 about here]

7. Conclusions

The purpose of this study was to contribute to our understanding of global inequality by studying the distribution of labor market outcomes in a large panel of countries around the world over almost half a century. Admittedly, focusing on labor earnings in the global working population is narrower than what previous studies have done, namely, focusing on the distribution of total household income among all households in the economy. However, how people fare in the labor market and why they do so are important dimensions in most people's life. Because this particular aspect of global inequality has not been studied before, our study appears to be a unique contribution to the literature. Also, instead of using a mix of household surveys from many different sources, we use one consistent, and previously unutilized, source for our earnings data.

We find that global earnings inequality was stable between the 1970s and mid-1990s, dropped sharply until the mid-2000s, and then stabilized again, but at a lower level. The main driver behind the fall was the global income convergence between developed and developing countries. However, we also document a rise in the within-country earnings dispersion beginning in the 1990s that somewhat dampened the overall decrease in global inequality.

There is more to learn about the links among national, regional and global labor markets and their role in global distributional outcomes. We hope that this study, and the new database, which we make publicly available, will spur continued analysis on this important topic.

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Figures

Figure 1: Correlations: inequality, earnings, prices and populations.
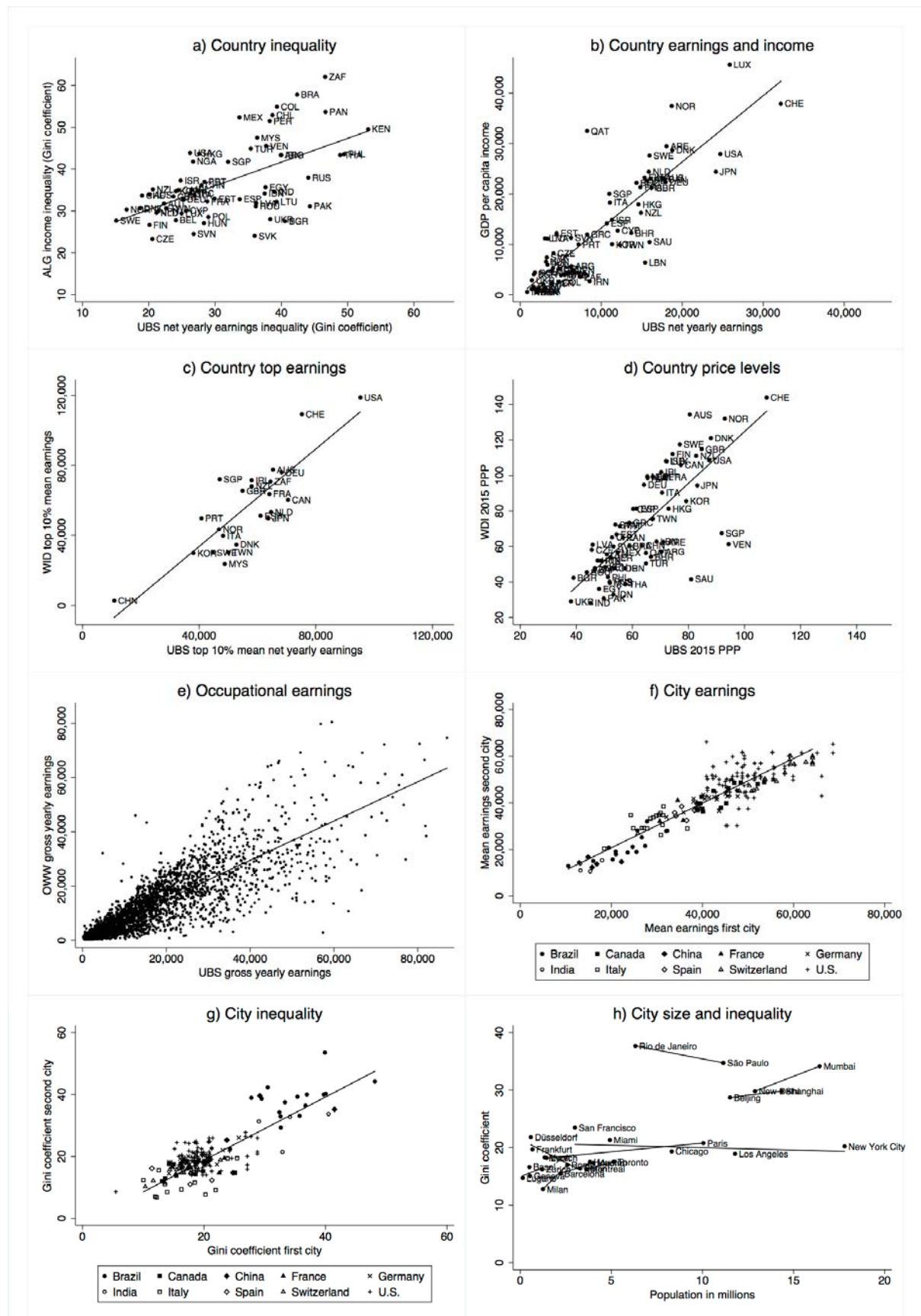
Notes: a) Country-level inequality averages for 1970-2015. UBS net yearly earnings inequality refers to this study with calculations based on net yearly earnings weighted by occupational group populations. ALG income inequality refers to interpolated values of Milanovic (2016a) All the Ginis Dataset. b) Country-level earnings and income per capita averages for 1970-2015 in current USD. UBS net yearly earnings weighted by occupational group populations. c) Country-level top 10 percent net yearly earnings averages for 1970-2015 in PPP-adjusted (using UBS price levels) 2015 USD. UBS top 10% mean net yearly earnings refers to this study with calculations based on net yearly earnings weighted by occupational group populations. WID top 10% mean earnings refers to the World Wealth and Income Database (2016). d) Country-level price levels in 2015. For UBS 2015 PPP, prices in New York City 2015 = 100. For WDI 2015 PPP, prices in the United States 2011 = 100. e) Country-occupation gross yearly earnings in current USD in the UBS and the Occupational Wages around the World (OWW) datasets. Each point corresponds to an occupation in a country in a specific year. f) Average net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) correlations for each within-country between-city pairs in our data. g) Average net yearly earnings inequality correlations for each within-country between-city pairs in our data. h) Within-country correlations between city population and average earnings inequality for all countries with more than one city in our data.

Sources: Authors' calculations based on data described in the text; Freeman and Oostendorp (2012); Milanovic (2016a); UN (2017); WID (2016); World Bank (2016).

Figure 2: Some country-specific earnings inequality trends and comparisons.
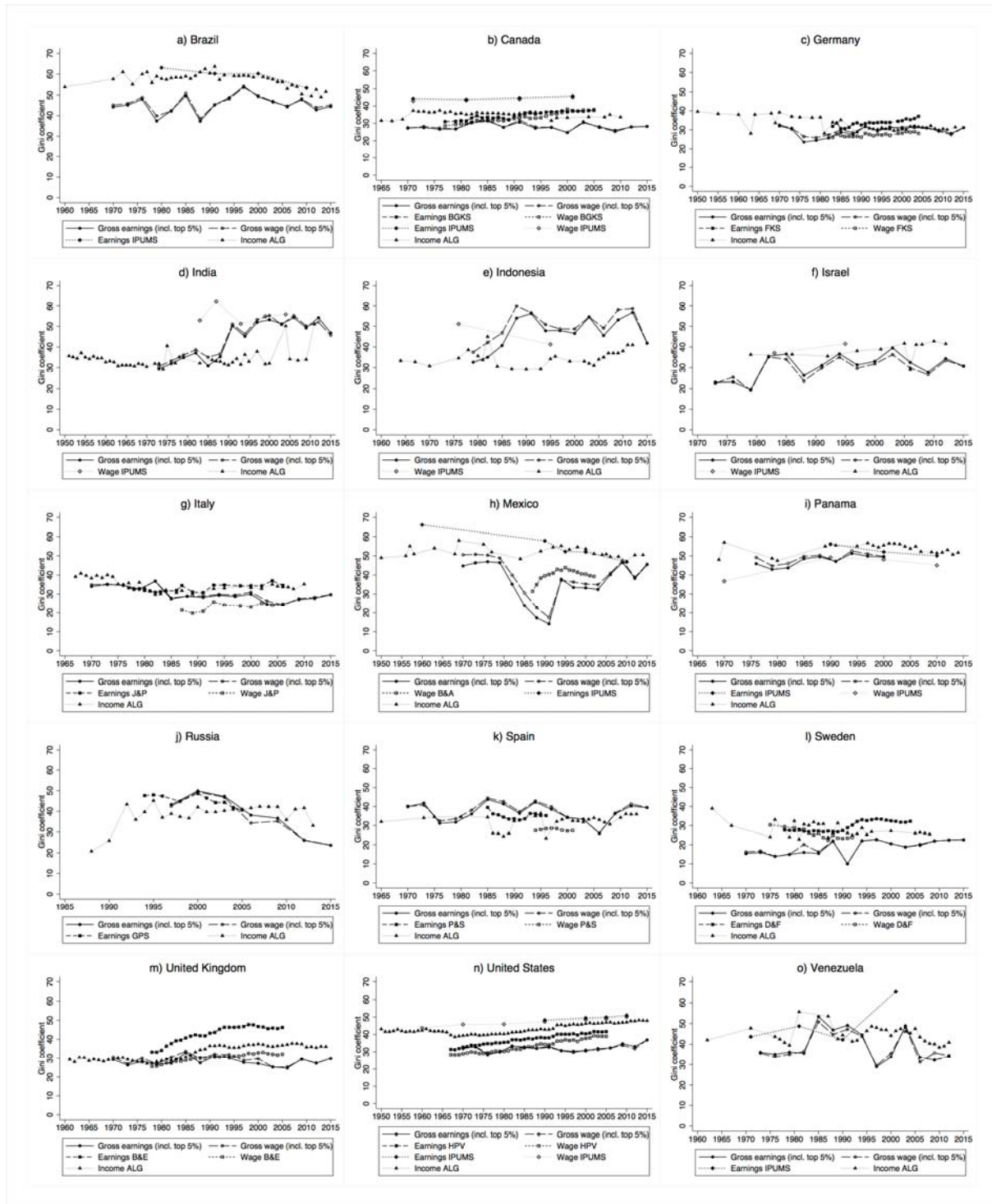
Notes: Gross earnings and gross wage refer to this study and are country-level Gini coefficients based on gross yearly and hourly earnings, respectively, weighted by occupational group populations including the unemployed and the top 5 percent earnings added from the WID. Extrapolated years are excluded. Earnings and wage refer to the country-level micro data studies available in the *Review of Economic Dynamics'* special issue "Cross-sectional facts for macroeconomists" (Krueger, Perri, Pistaferri and Violante, 2010), where BGKS refers to Brzozowski, Gervais, Klein and Suzuki (2010), FKS to Fuchs-Schündeln, Krueger and Sommer (2010), J&P to Jappelli and Pistaferri (2010), B&A to Binelli and Attanasio (2010), GPS to Gorodnichenko, Peter and Stolyarov (2010), P&S to Pijoan-Mas and Sánchez-Marcos (2010), D&F to Domeij and Flodén (2010), B&E to Blundell and Etheridge (2010), and HPV to Heathcote, Perri and Violante (2010), and the authors' own calculations based on micro data

available in the IPUMS International database. All the Ginis (ALG) refers to Milanovic's (2016a) estimations of country-level income and/or consumption inequality.

Sources: Authors' calculations based on data described in the text; Binelli and Attanasio (2010); Blundell and Etheridge (2010); Brzozowski, Gervais, Klein and Suzuki (2010); Domeij and Flodén (2010); Fuchs-Schündeln, Heathcote, Perri and Violante (2010); Gorodnichenko, Peter and Stolyarov (2010); Krueger and Sommer (2010); Jappelli and Pistaferri (2010); Milanovic (2016a); Minnesota Population Center (2015); Pijoan-Mas and Sánchez-Marcos (2010); WID (2016). Source data for IPUMS International are provided by the following national statistical offices: Institute of Geography and Statistics for Brazil, Statistics Canada, Ministry of Statistics and Programme Implementation for India, BPS Statistics Indonesia, Central Bureau of Statistics for Israel, National Institute of Statistics, Geography, and Informatics for Mexico, Census and Statistics Directorate for Panama, Bureau of the Census for United States, and National Institute of Statistics for Venezuela.

Figure 3: Global earnings inequality, 1970–2015.
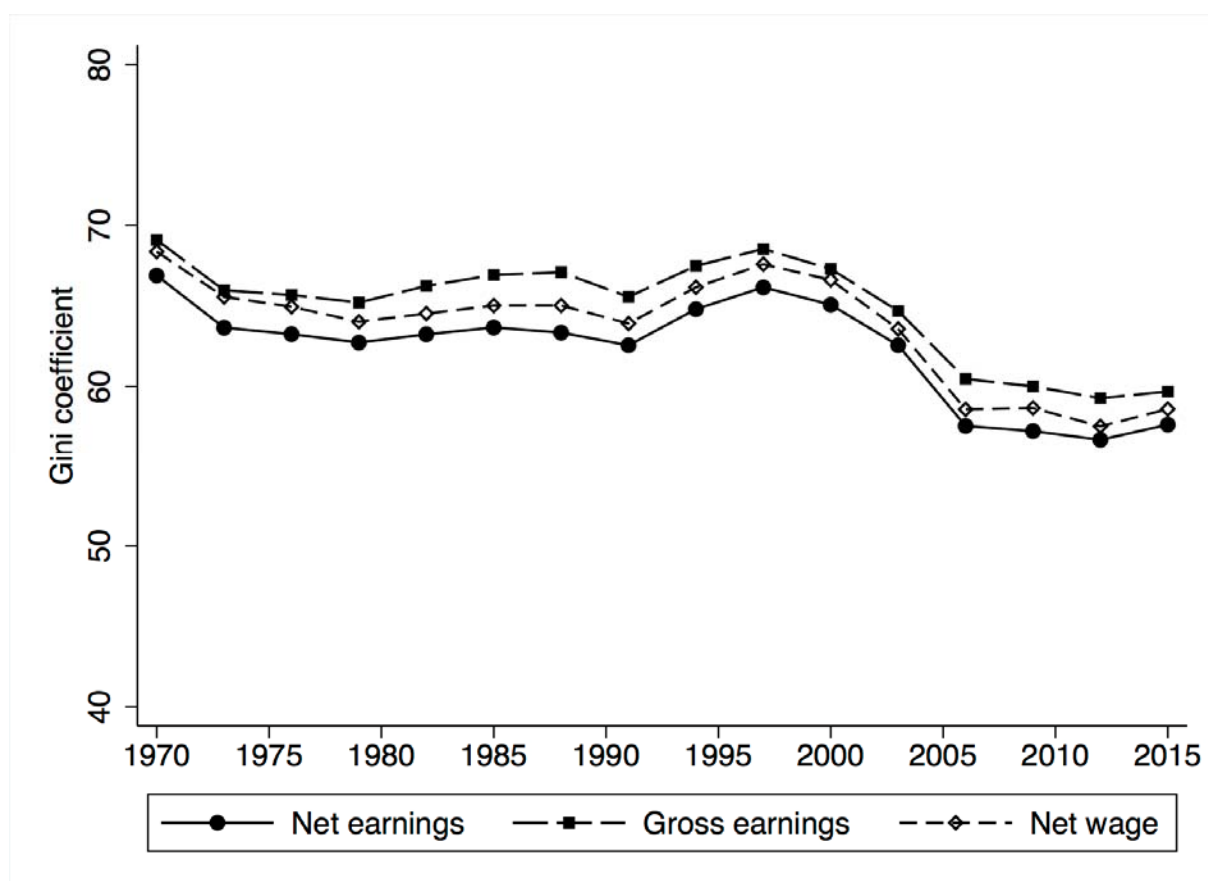
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD, weighted by working age populations and including the unemployed. Earnings refer to yearly earnings and wages to hourly earnings.
Source: Authors' calculations based on data described in the text.

Figure 4: Other measures of global earnings inequality trends.
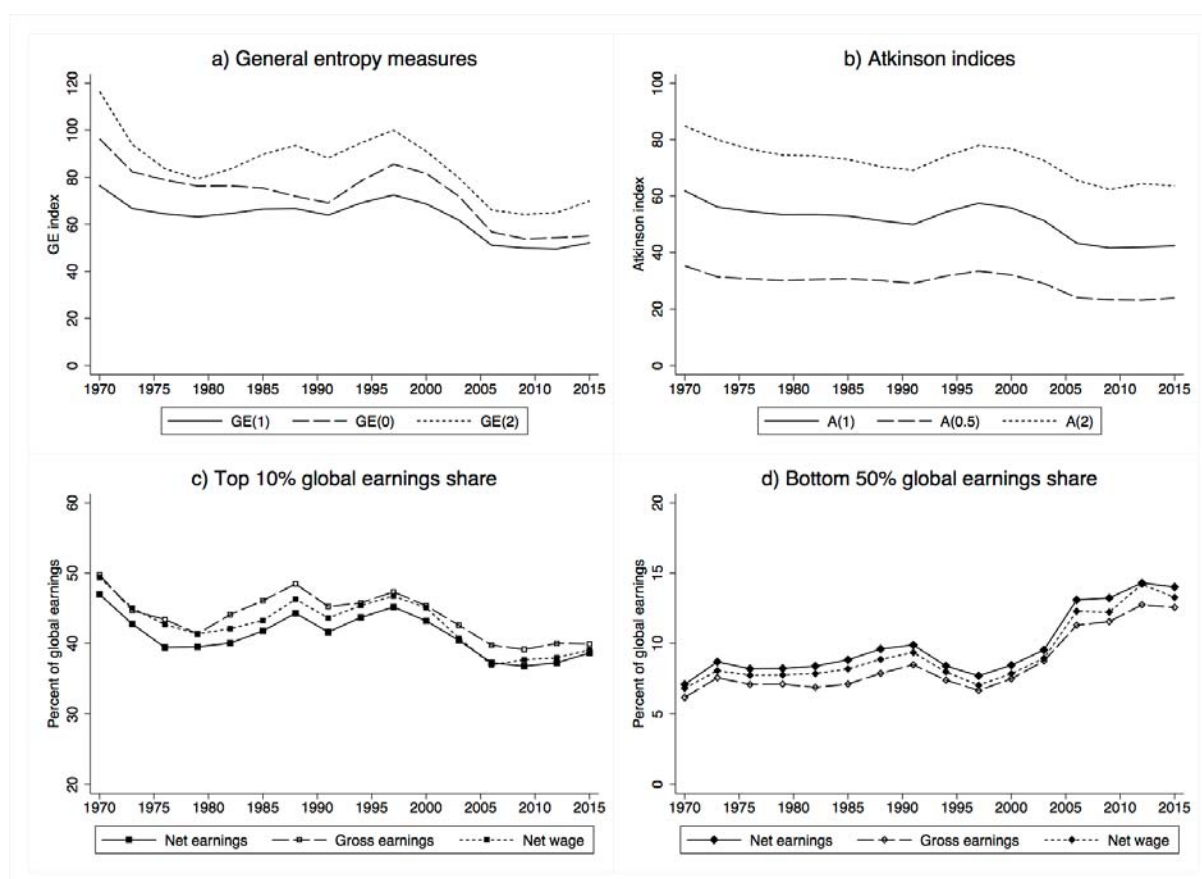
Notes: Calculations based on net yearly earnings (if nothing else specified), PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations, excluding the unemployed. Earnings refer to yearly earnings and wages to hourly earnings.
Source: Authors' calculations based on data described in the text.

Figure 5: Kernel densities over time.

Notes: Density of log net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations, excluding the unemployed. Horizontal axis in log scale. Gaussian smoothing.
Source: Authors' calculations based on data described in the text.

Figure 6: Earnings versus income inequality comparisons.
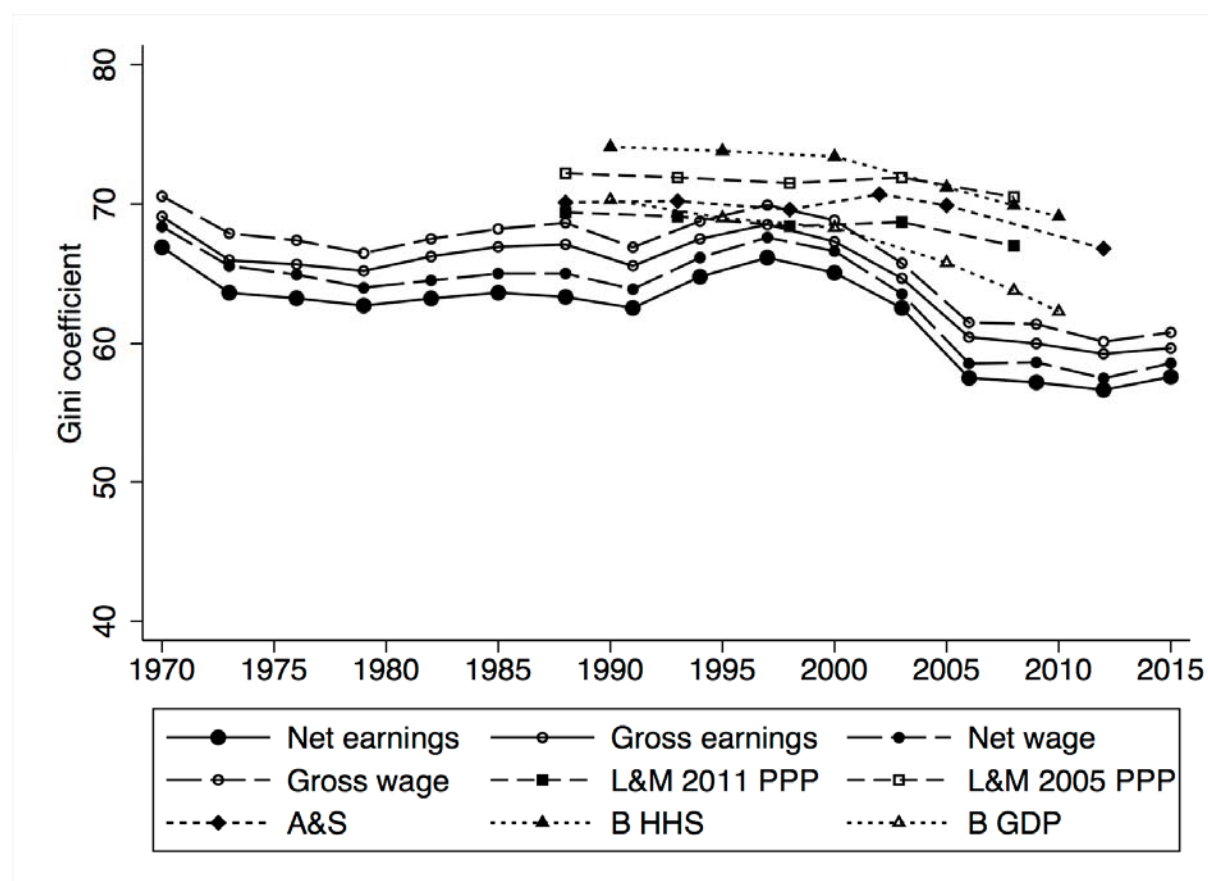
Notes: Net and gross earnings and wage inequality refer to this study and are based on yearly and hourly earnings, respectively, which are PPP-adjusted using UBS price levels in 2015 USD and weighted by working age populations including the unemployed. L&M refers to Lakner and Milanovic (2015). A&S refers to Anand and Segal's (2016) estimations without top incomes. B refers to Bourguignon's (2015) estimations based on household surveys and data rescaled by GDP per capita, respectively.
Sources: Authors' calculations based on data described in the text; Anand and Segal (2016); Bourguignon (2015); Lakner and Milanovic (2015).

Figure 7: Global growth incidence curve (anonymous), 1970s–2010s.
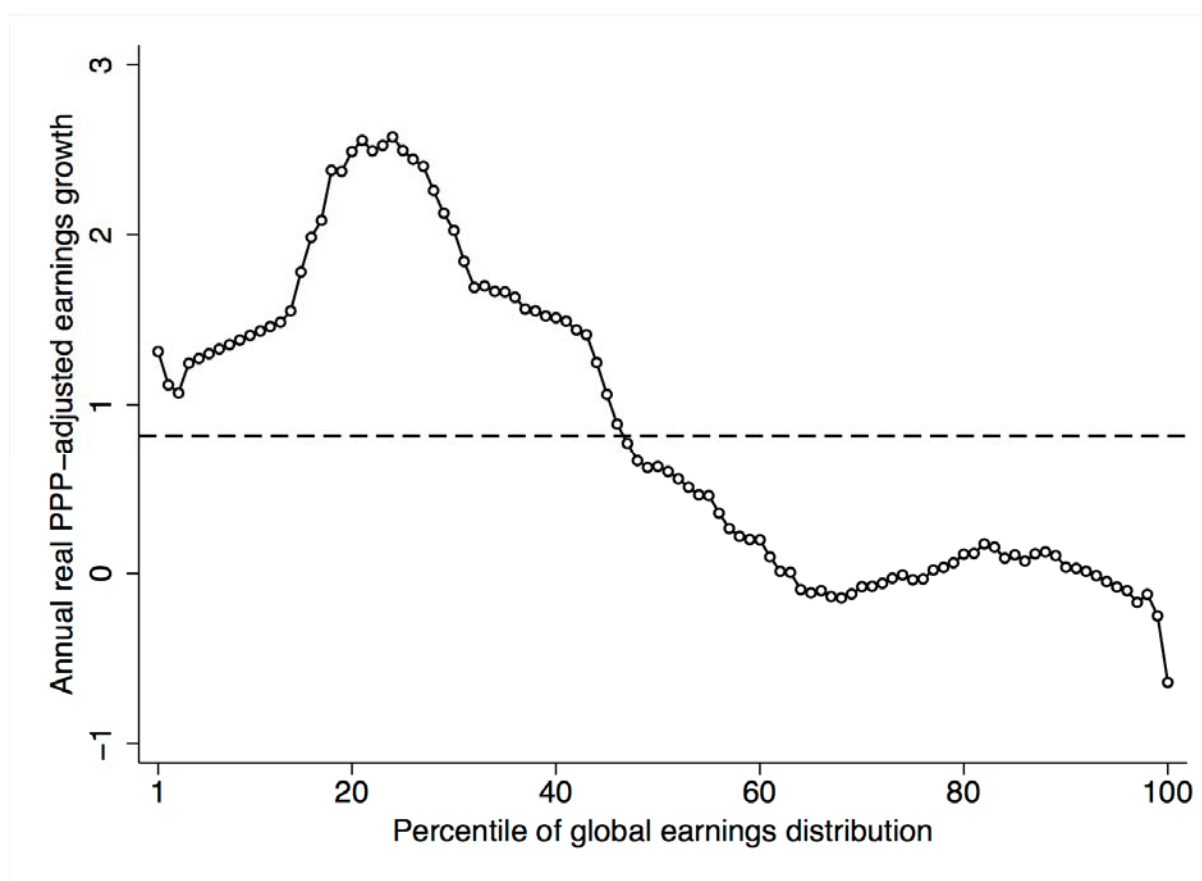
Notes: Average annual percentile growth rate 1970s-2010s in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and excluding the unemployed. Dashed line shows average annual earnings growth rate 1970s-2015s for all percentiles. Horizontal axis ranked according to earnings percentiles in 1970s. Decade averages for 1970s and 2010s correspond to the years 1970-1979 and 2006-2015, respectively.
Source: Authors' calculations based on data described in the text.

Figure 8: Global growth incidence curves, over time and comparing with other studies.
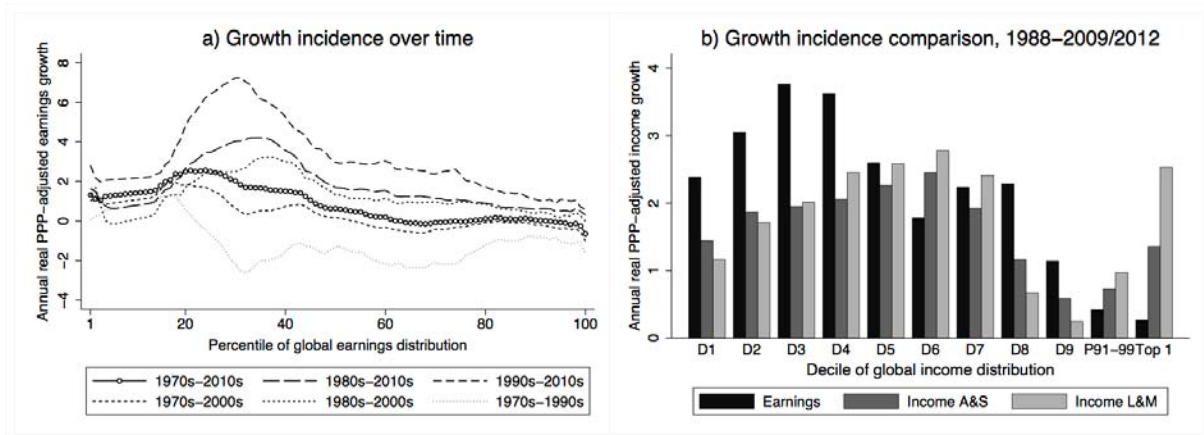
Notes: a) Average annual percentile growth rate in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) weighted by working age populations, excluding the unemployed. Horizontal axis ranked according to earnings percentiles in initial decade. Decade averages correspond to the years 1970-1979, 1982-1988, 1991-1997, 2000-2009 and 2006-2015, respectively. b) Earnings refer to average annual decile growth rate between 1988 and 2009 in net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations excluding the unemployed. "Income A&S" and "Income L&M" are annual decile growth recalculations approximated from figures in Anand and Segal (2016), for 1988–2012, and Lakner and Milanovic (2015), for 1988–2008, respectively. Horizontal axis ranked according to income quantiles in 1988, where D1-D9 are deciles, while P91-P99 and Top 1 are percentiles.
Sourcse: Authors' calculations based on data described in the text; Anand and Segal (2016); Lakner and Milanovic (2015).

Figure 9: Decomposing inequality within and between countries and regions.
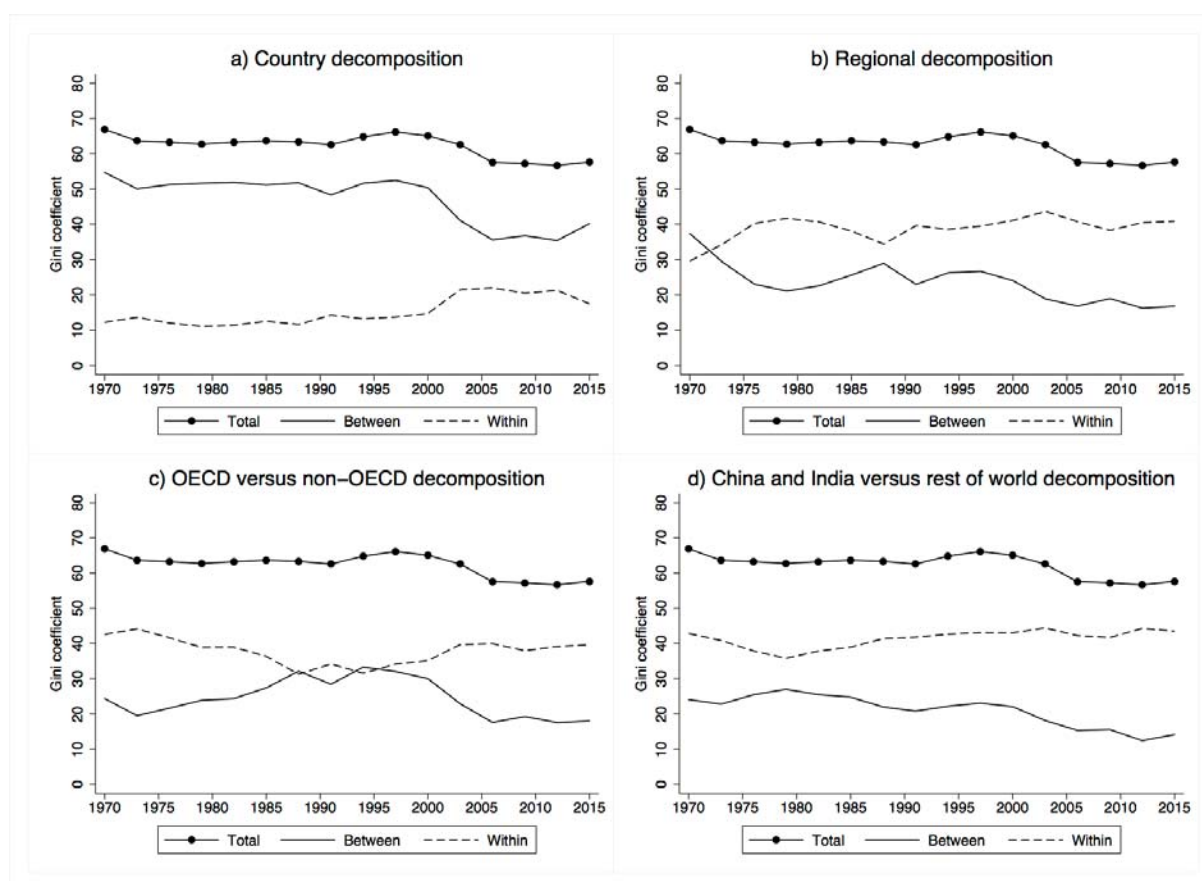
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations including the unemployed. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient. b) Regional decomposition refers to Africa, Asia, Europe, Latin America, Northern America and Oceania.
Source: Authors' calculations based on data described in the text.

Figure 10: Earnings inequality in world regions and its country decomposition.
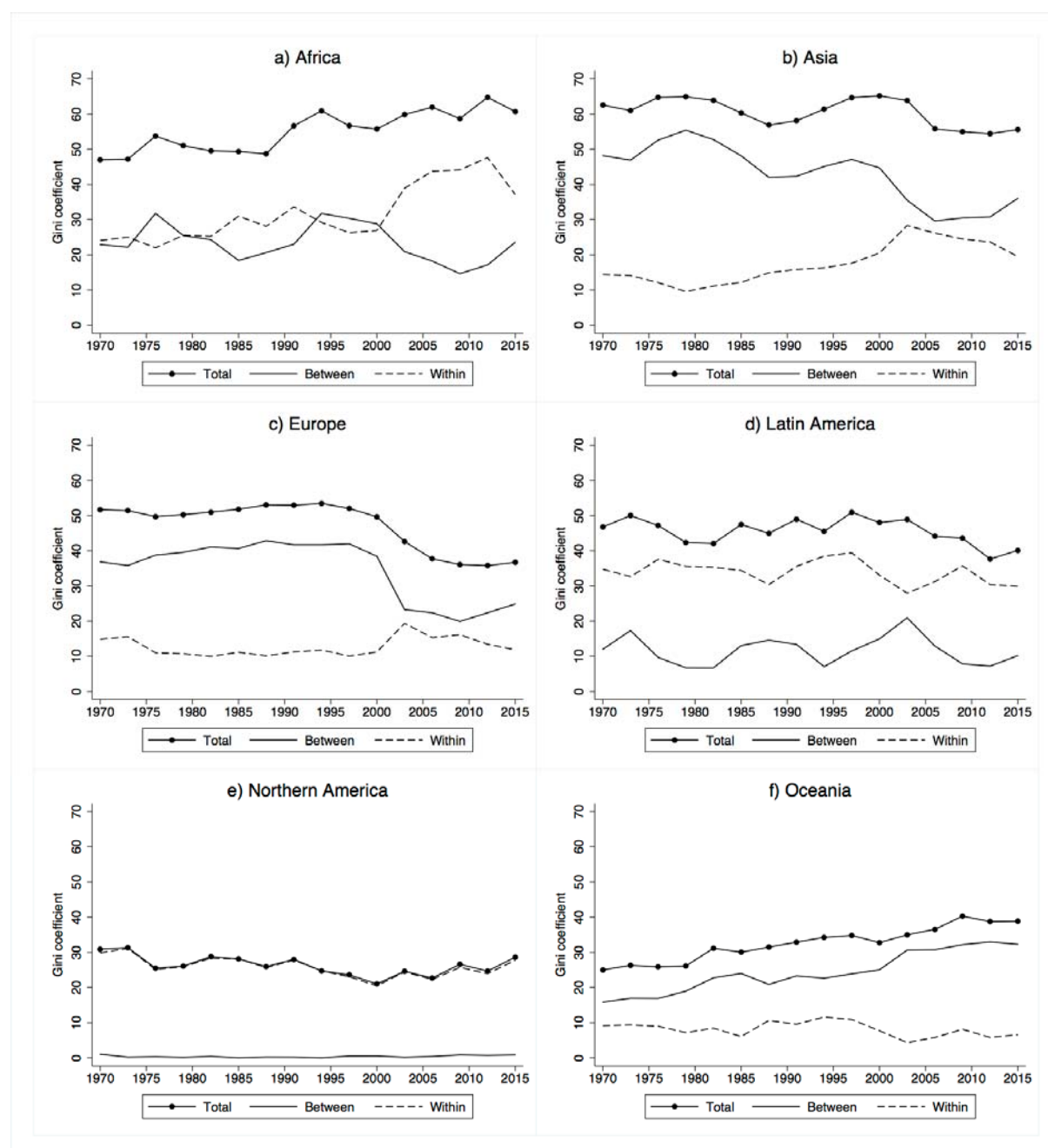
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations including the unemployed. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total regional Gini coefficient.
Source: Authors' calculations based on data described in the text.

Figure 11: Occupational and sectoral decompositions of global earnings inequality.
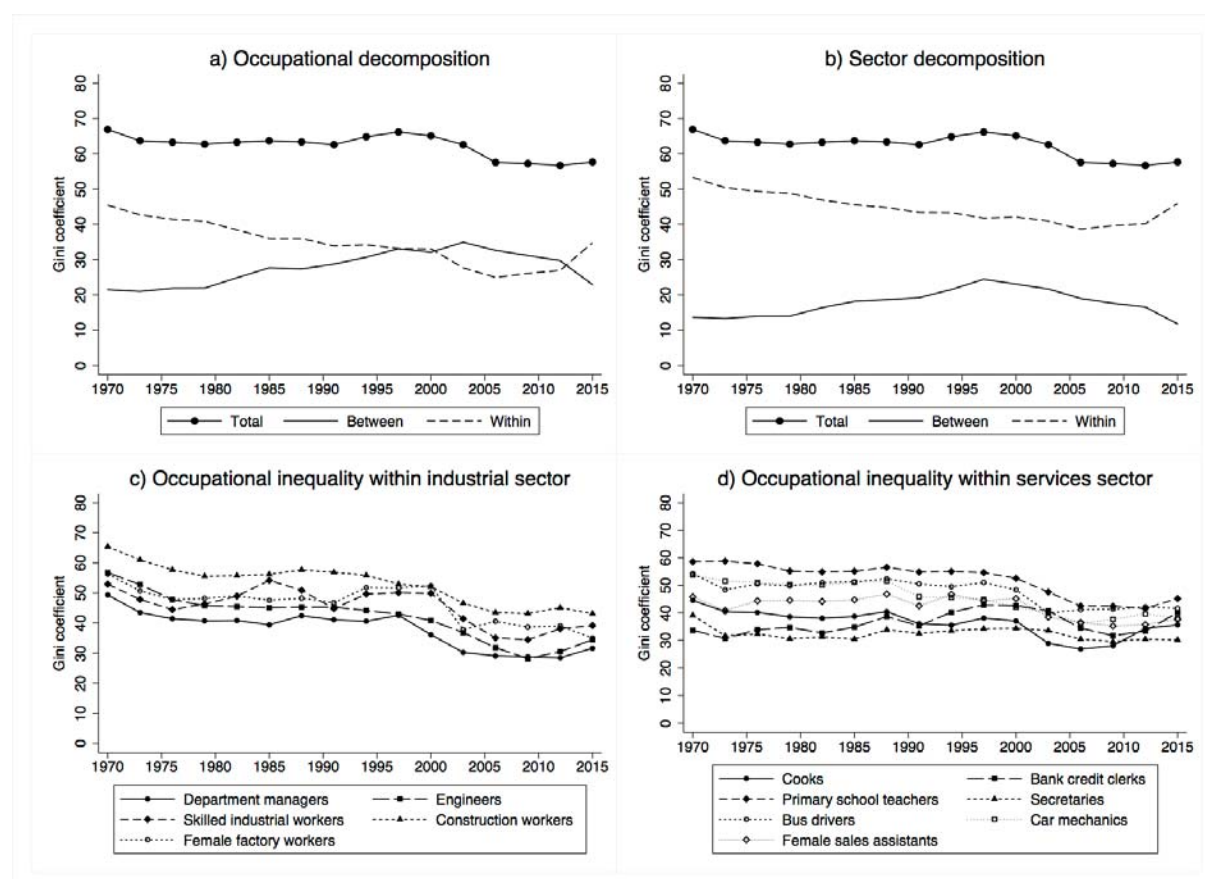
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations. a) and b) Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient including the unemployed. Sector decomposition refers to agricultural, industrial and services sectors. c) and d) Excluding the unemployed.
Source: Authors' calculations based on data described in the text.
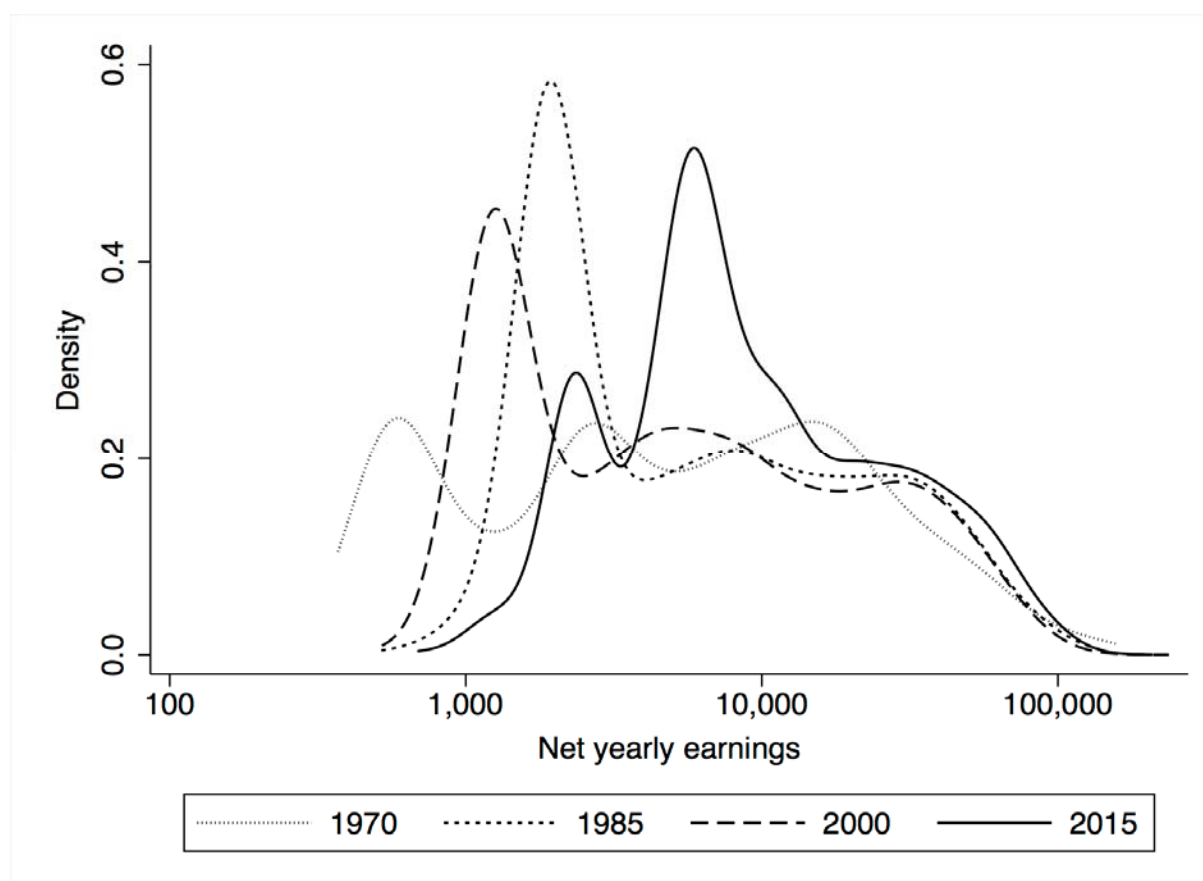
Figure 12: Global earnings ratios.
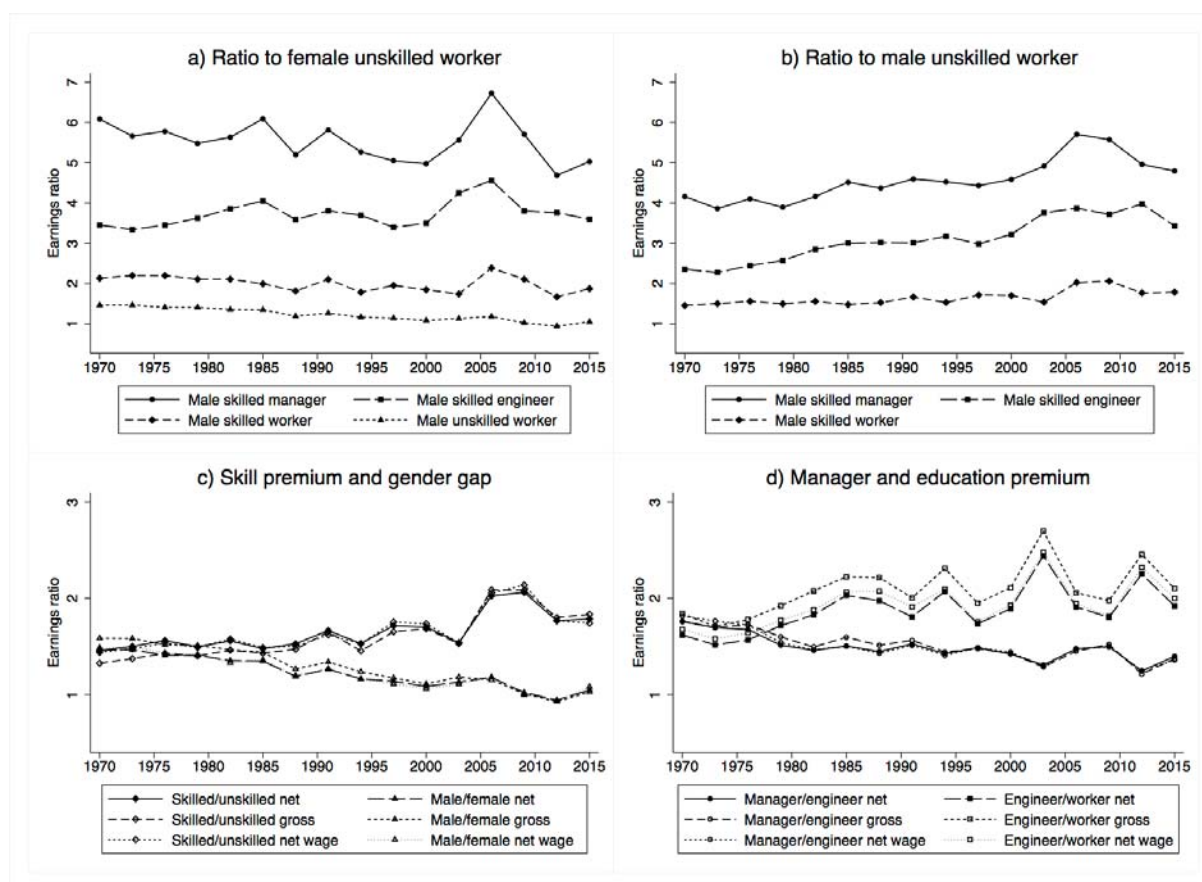
Notes: Calculations based on net yearly earnings (if nothing else specified), PPP-adjusted using UBS price levels in 2015 USD and weighted by working age populations excluding the unemployed. Net and gross refer to yearly earnings and net wage to hourly earnings. Manager represented by department managers, skilled worker by skilled industrial workers, male unskilled worker by construction workers, and female unskilled worker by female factory workers.
Source: Authors' calculations based on data described in the text.

Figure 13: Alternative price indices, populations and adding top earnings.
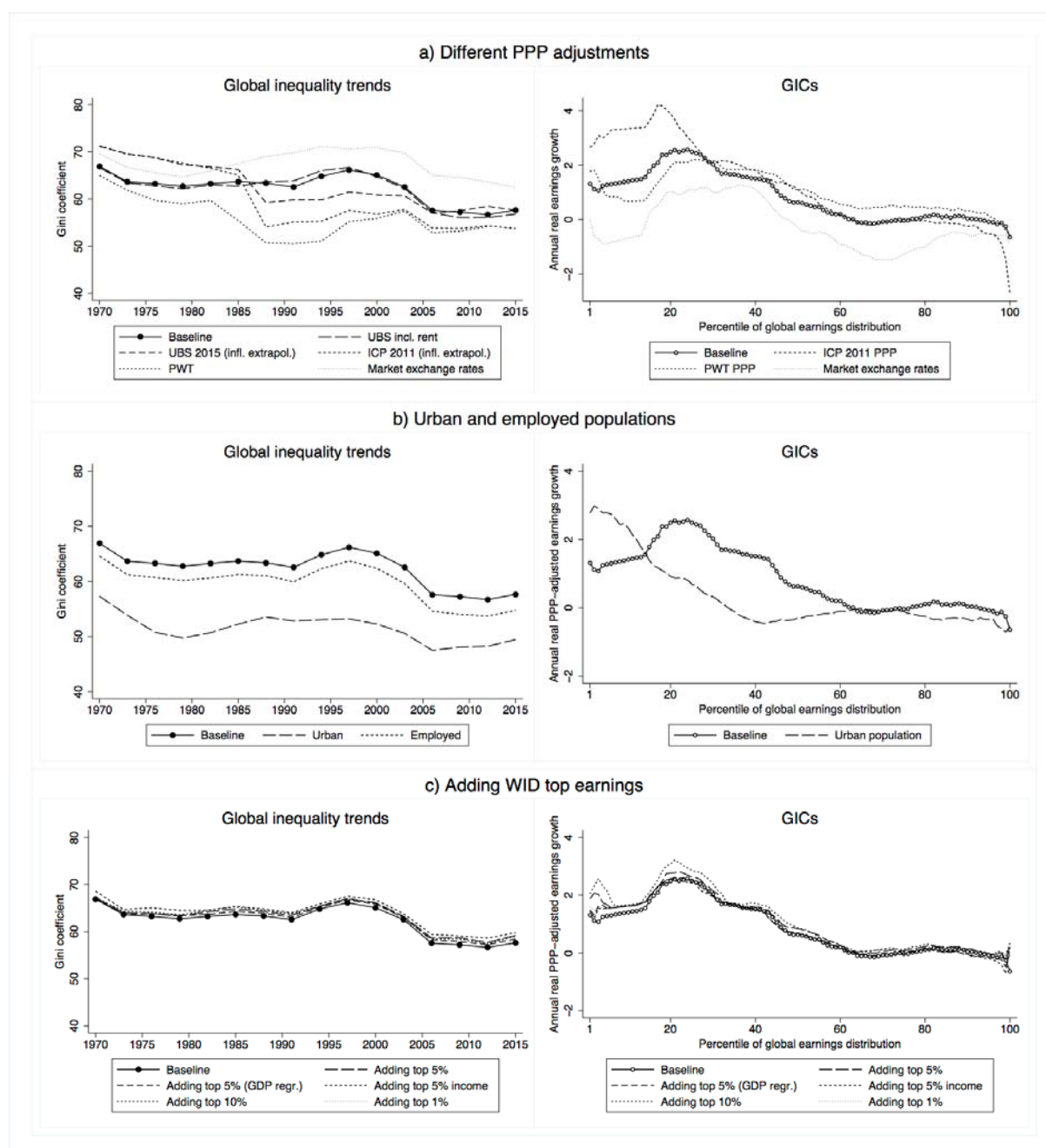
Notes: Calculations based on net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD (if nothing else specified), and weighted by working age populations. Left column: Including the unemployed (if nothing else specified). Right column: Average annual percentile growth rate 1970s–2010s, excluding the unemployed; horizontal axis ranked according to earnings percentiles in 1970s; decade averages for 1970s and 2010s corresponding to the years 1970–1979 and 2006–2015 (or 2006–2012 for PWT PPP), respectively. a) Baseline implies UBS PPP excluding rent. For UBS 2015 and ICP 2011, prices are compared across countries in 2015 (for ICP 2011 using the 2011 ICP round from the WDI) and extrapolated using national inflation. For UBS and PWT, prices are compared across countries each year. Market exchange rates imply no PPP adjustments. b) Baseline implies total rural and urban working age population. Urban means that urban working age populations are used as country population weights instead of total working age populations and that the agricultural sector is not included. Employed means that the unemployed are excluded. c) Top national earnings or income added from the WID (not added in baseline). GDP regression imputation means that missing country-year top earnings data are imputed using an estimated regression equation of GDP per capita ($Top5earnings = 2864 + 2.53 \cdot GDPpercapita$). Top income implies that total income is added for the top (i.e., not adjusted for the wage share

of top income), where missing country-year top income data are imputed using an estimated regression equation of GDP per capita ($Top5income = 4431 + 3.71 \cdot GDPpercapita$).

Sources: Authors' calculations based on data described in the text; Feenstra, Inklaar and Timmer (2015); WID (2016); World Bank (2016).

Figure 14: Within-group dispersion adjustments.
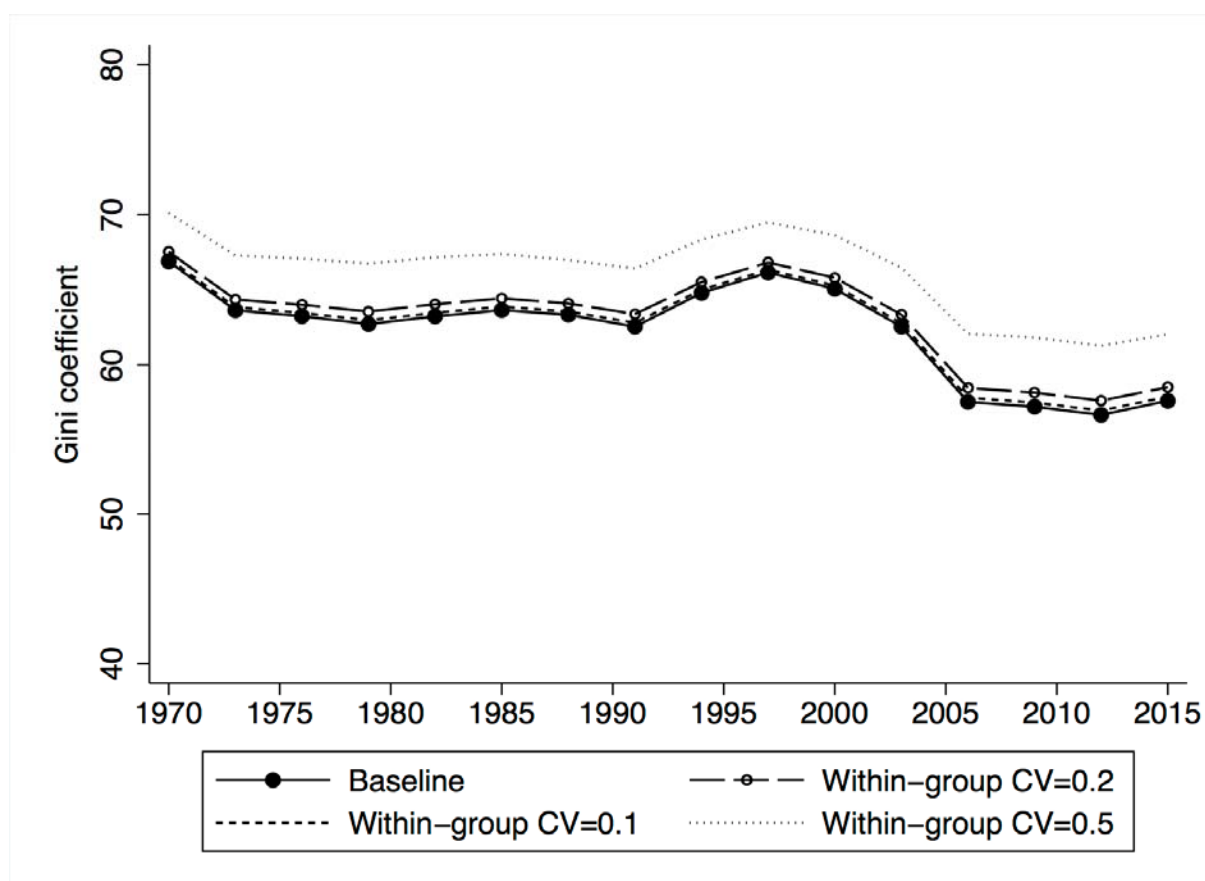
Notes: Calculations based on net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations including the unemployed. Within-group CV implies that country-occupations are assigned within-group earnings distributions with coefficients of variation of 0.1, 0.2 and 0.5, respectively. For the adjustment method applied, see Modalsli (2015).
Sources: Authors' calculations based on data described in the text and using Modalsli's (2015) correction method.

Figure 15: Gender composition.
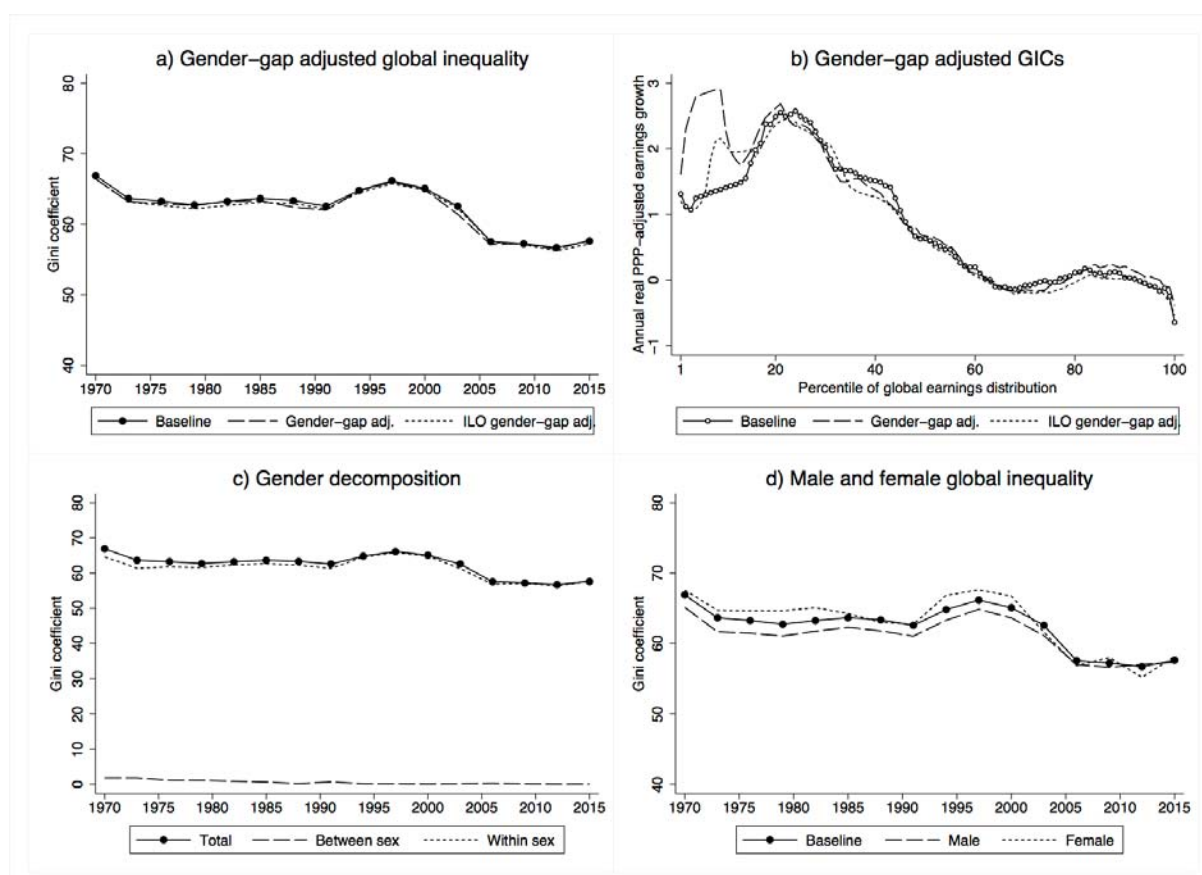
Notes: Calculations based on net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations. Gender-gap adjustment means that UBS sectoral earnings gender gaps are used and ILO gender-gap adjustment that ILO occupational earnings gender gaps (2000-2015) are used. a) Including the unemployed. b) Average annual percentile growth rate 1970s–2010s; excluding the unemployed; horizontal axis ranked according to earnings percentiles in 1970s; decade averages for 1970s and 2010s corresponding to the years 1970–1979 and 2006–2015, respectively. c) Using UBS sectoral earnings gender-gap adjustment. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient including the unemployed. d) Using UBS sectoral earnings gender-gap adjustment; including the unemployed

Sources: Authors' calculations based on data described in the text; ILO (2011).

Tables

Table 1: Coverage of the dataset.

	Sample	1970	1985	2000	2015	Mean
a) Number of countries represented in the database						
World	I	27	43	50	58	46.1
	II	66	66	66	66	66.0
Africa	I	1	3	3	3	2.4
	II	4	4	4	4	4.0
Asia	I	3	14	16	16	13.0
	II	21	21	21	21	21.0
Europe	I	16	17	20	29	21.1
	II	29	29	29	29	29.0
Latin America	I	4	6	7	6	6.1
	II	8	8	8	8	8.0
Northern America	I	2	2	2	2	2.0
	II	2	2	2	2	2.0
Oceania	I	1	1	2	2	1.4
	II	2	2	2	2	2.0
b) GDP (% of regional GDP represented in the database)						
World	I	79.5	84.6	94.7	91.7	88.3
	II	97.0	96.2	96.9	95.5	96.5
Africa	I	25.8	41.6	40.4	31.6	32.5
	II	57.2	43.6	48.0	53.2	48.9
Asia	I	43.4	73.5	91.8	86.9	78.5
	II	95.0	94.6	96.2	94.2	95.2
Europe	I	79.1	79.2	96.9	98.9	89.2
	II	99.4	99.3	99.1	98.9	99.2
Latin America	I	66.7	79.6	85.6	81.8	81.7
	II	84.0	84.0	87.8	89.6	86.8
Northern America	I	100.0	100.0	100.0	100.0	100.0
	II	100.0	100.0	100.0	100.0	100.0
Oceania	I	83.1	85.2	97.3	99.6	89.3
	II	96.9	96.9	97.3	99.6	97.4
c) Population (% of regional population represented in the database)						
World	I	24.9	50.0	72.5	71.0	54.9
	II	83.8	82.4	80.4	78.1	81.3
Africa	I	6.1	30.1	17.7	16.3	16.9
	II	34.1	33.7	32.8	31.8	33.1
Asia	I	5.2	45.2	80.2	78.6	52.9
	II	87.4	87.2	86.4	85.7	86.7
Europe	I	53.6	52.9	80.4	95.1	69.8
	II	95.9	95.6	94.8	95.1	95.2
Latin America	I	67.4	72.9	75.8	75.2	74.6
	II	79.9	80.7	80.7	80.7	80.6
Northern America	I	100.0	100.0	100.0	100.0	100.0
	II	100.0	100.0	100.0	100.0	100.0
Oceania	I	65.0	63.6	74.0	72.4	67.3
	II	79.6	76.7	74.0	72.4	75.7

Notes: First row for each region only includes the original UBS data (Sample I). Second row also includes the imputed data (Sample II). Last column shows average number of countries, current GDP and total population coverage over all years.
Sources: Authors' calculations based on data described in the text; World Bank (2016).

ONLINE APPENDIX TO

"Global earnings inequality, 1970-2015"

Hammar, Olle and Daniel Waldenström

May 2017

Appendix figures

Figure A1: Average earnings inequality around the world, 1970s and 2010s.
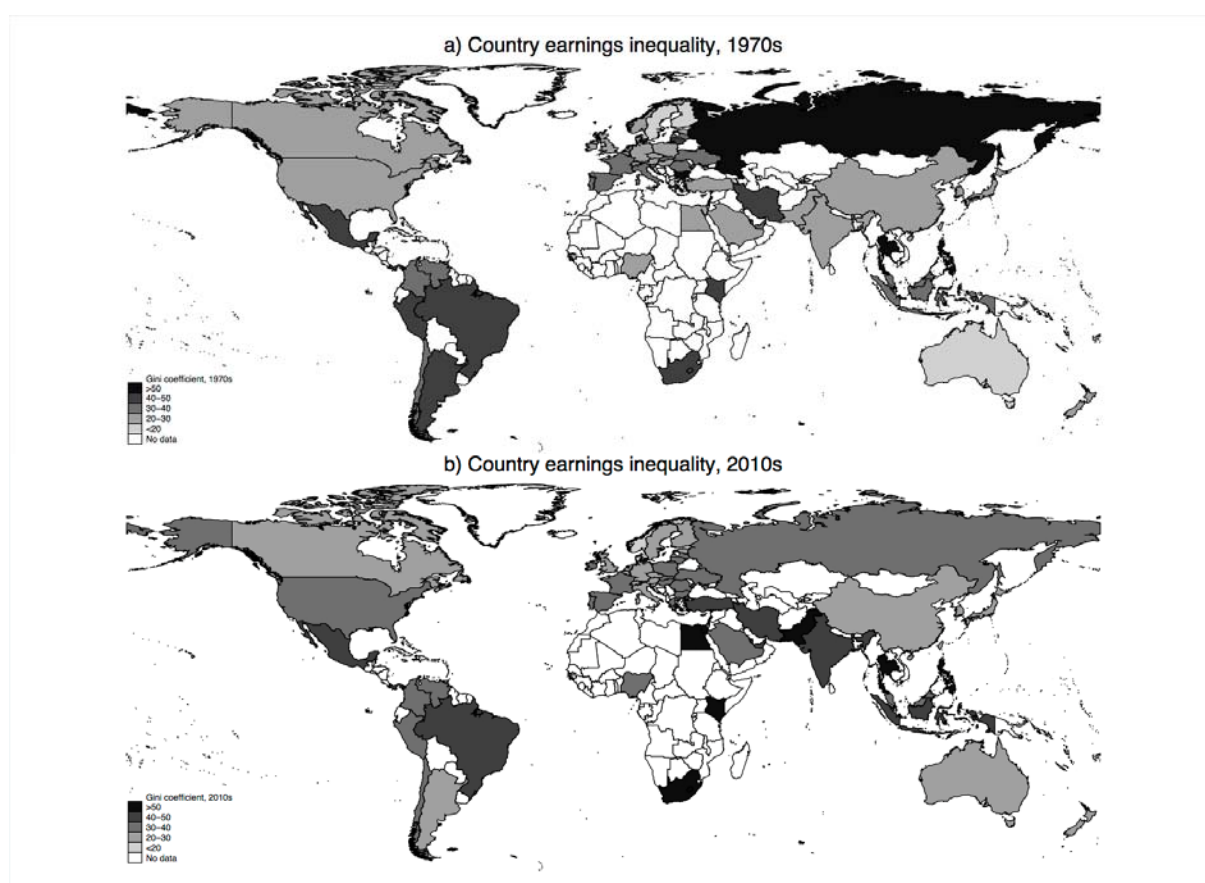
Notes: Average country-level Gini coefficients based on net yearly earnings and weighted by occupational group populations including the unemployed and the top 5 percent earnings added from the WID. Decade averages for 1970s and 2010s correspond to the years 1970-1979 and 2006-2015, respectively.
Sources: Authors' calculations based on data described in the text; WID (2016).

Figure A2: Agricultural worker earnings trend.
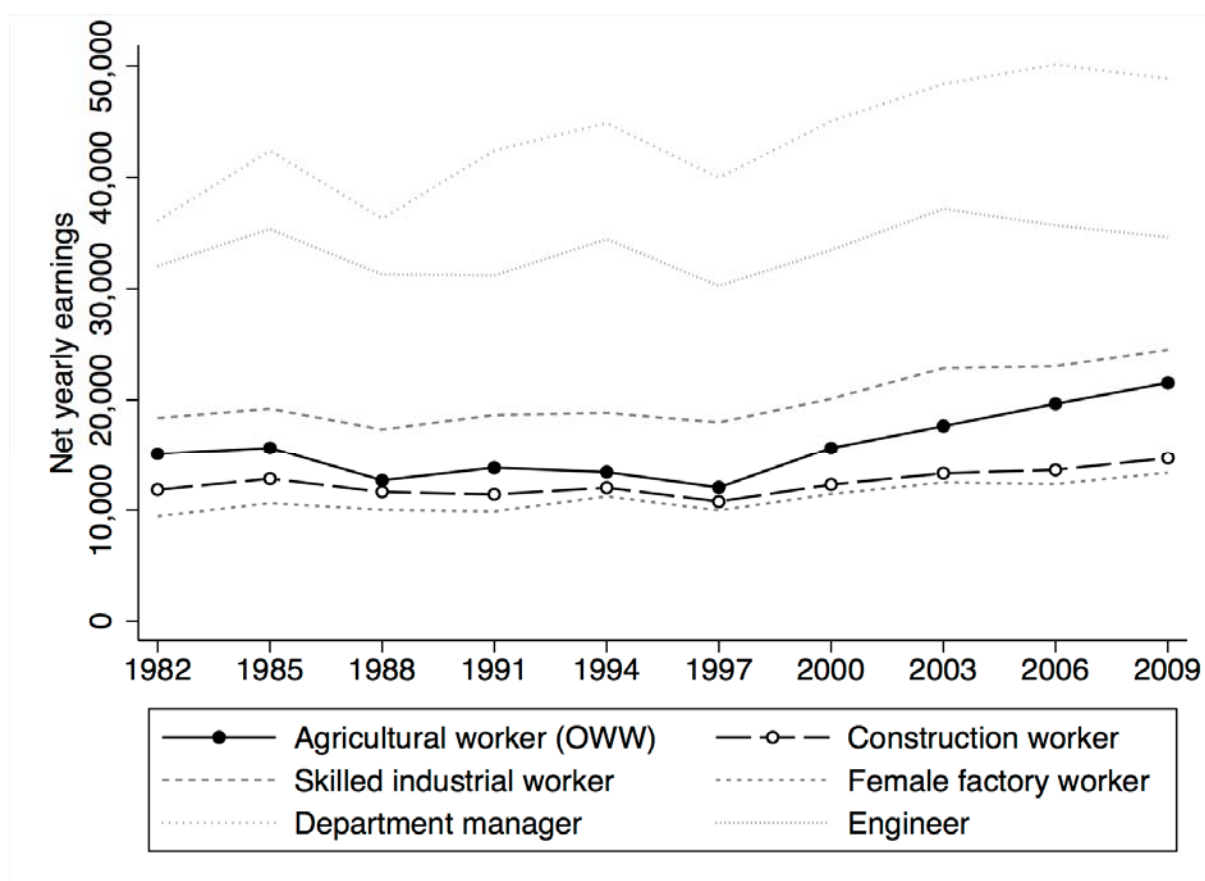
Note: Unweighted global average net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) per occupation in the agricultural and industrial sectors. Agricultural worker earnings based on the Occupational Wages around the World (OWW) database; other occupations based on the UBS.
Sources: Authors' calculations based on data described in the text; Freeman and Oostendorp (2012).

Figure A3: Occupational earnings correlations.

Note: Country-occupation average gross yearly earnings in current USD in the UBS and the Occupational Wages around the World (OWW) datasets.
Sources: Authors' calculations based on data described in the text; Freeman and Oostendorp (2012).

Figure A4: Country-level inequality trends and comparisons.
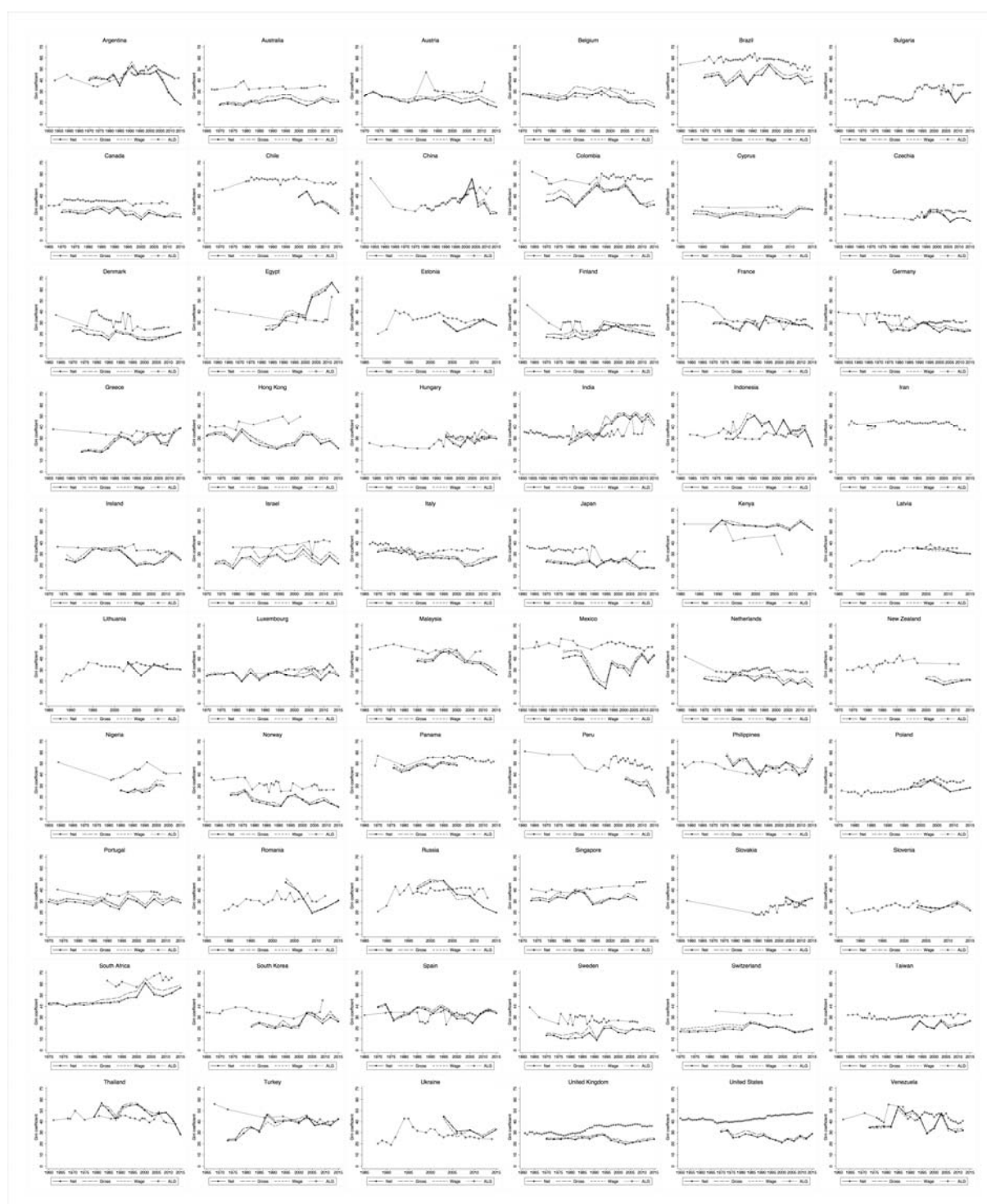
Notes: Net, gross and wage refer to this study and are country-level Gini coefficients based on net yearly, gross yearly and net hourly earnings, respectively, weighted by occupational group populations including the unemployed. Extrapolated years are excluded. All the Ginis (ALG) refers to Milanovic's (2016a) estimations of country-level income and/or consumption inequality.
Sources: Authors' calculations based on data described in the text; Milanovic (2016a).

Figure A5: Non-anonymous global growth incidence curve, 1970s-2010s.
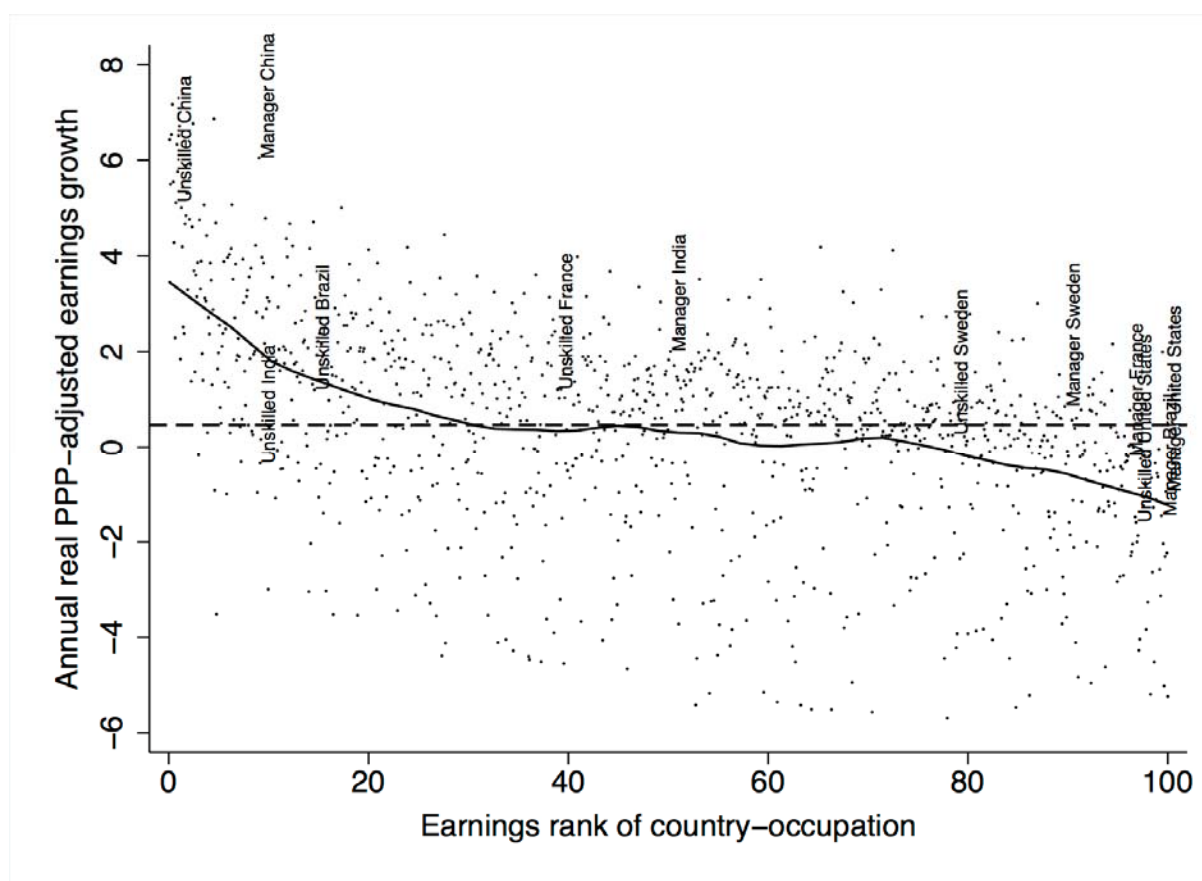
Notes: Average annual country-occupation growth rate 1970s-2010s in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), where each observation represents a country-occupation. Dashed line shows average annual earnings growth rate 1970s-2010s for all country-occupations, and solid line a smoothed local polynomial. Horizontal axis ranked according to country-occupation earnings ranks in 1970s. Decade averages for 1970s and 2010s correspond to the years 1970-1979 and 2006-2015, respectively.
Source: Authors' calculations based on data described in the text.

Figure A6: Variants of growth incidence comparisons.
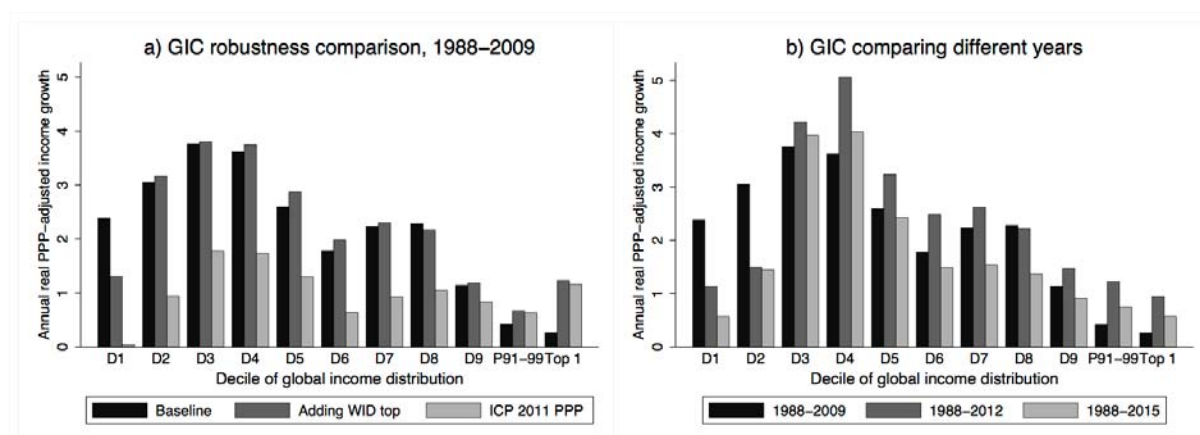
Notes: Annual decile growth rate in net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD (if nothing else specified), and weighted by working age populations excluding the unemployed. Horizontal axis ranked according to income quantiles in 1988, where D1-D9 are deciles, while P91-P99 and Top 1 are percentiles. a) Annual decile growth rate between 1988 and 2009. Adding WID top means that national top 5% earnings are added from the WID. For ICP 2011 PPP, prices are compared across countries in 2015 (using the 2011 ICP round from the WDI) and extrapolated using national inflation. b) Annual decile growth rate between 1988 and 2009, 2012 and 2015, respectively.
Sources: Authors' calculations based on data described in the text; WID (2016); World Bank (2016).

Figure A7: Within and between country decomposition: working hours and taxes.
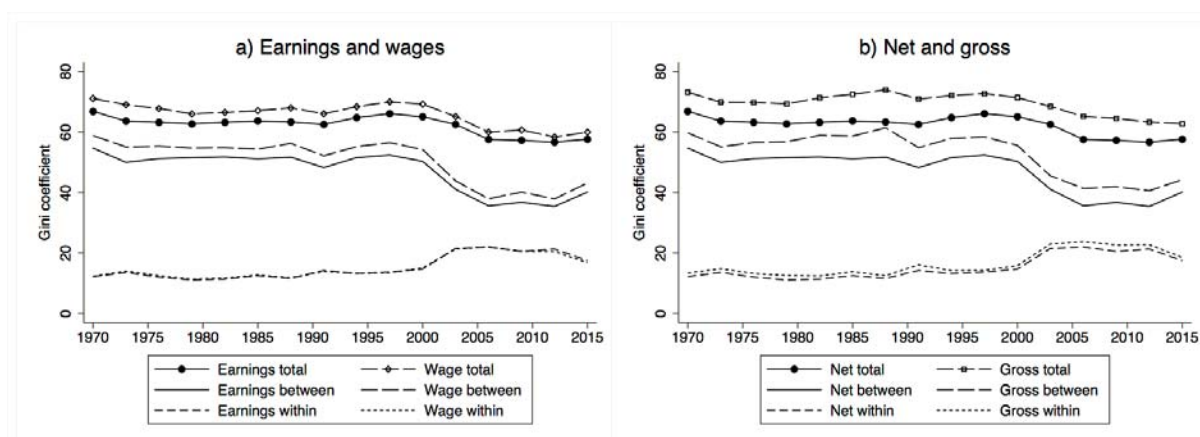
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD and weighted by working age populations. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient. a) Earnings refer to net yearly earning and wage to net hourly earnings. b) Net refers to yearly earnings post taxes and social security contributions, while gross refers to yearly earnings before such deductions have been made.
Source: Authors' calculations based on data described in the text.

Figure A8: Global earnings inequality excluding China and India.
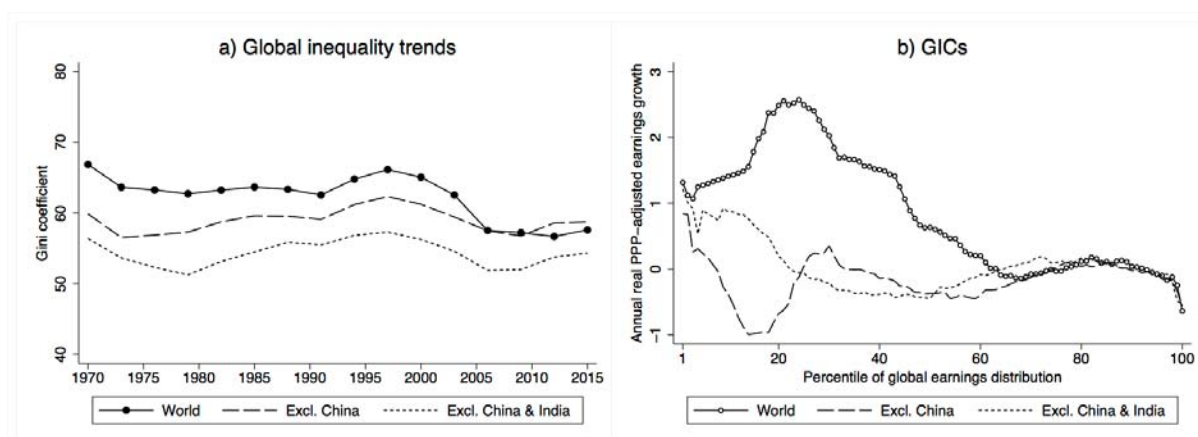
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations. a) Including the unemployed. b) Average annual percentile growth rate 1970s–2010s; excluding the unemployed; horizontal axis ranked according to earnings percentiles in 1970s; decade averages for 1970s and 2010s corresponding to the years 1970–1979 and 2006–2015, respectively.
Source: Authors' calculations based on data described in the text.

Figure A9: Regional earnings inequality, 1970–2015.
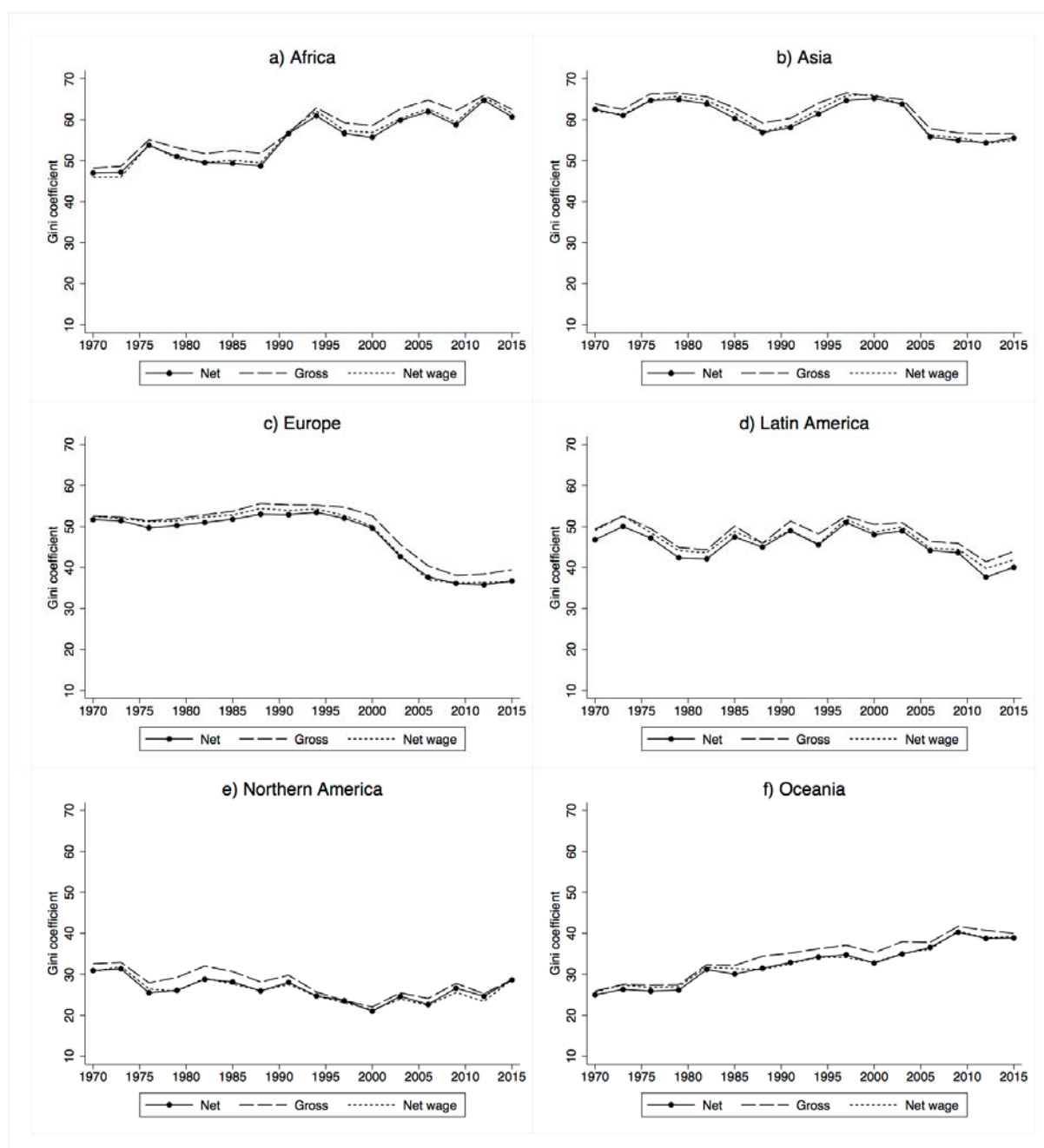
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD and weighted by working age populations including the unemployed. Net and gross refer to yearly earnings and net wage to hourly earnings.
Source: Authors' calculations based on data described in the text.

Figure A10: Regional growth incidence curves, 1970s-2010s.
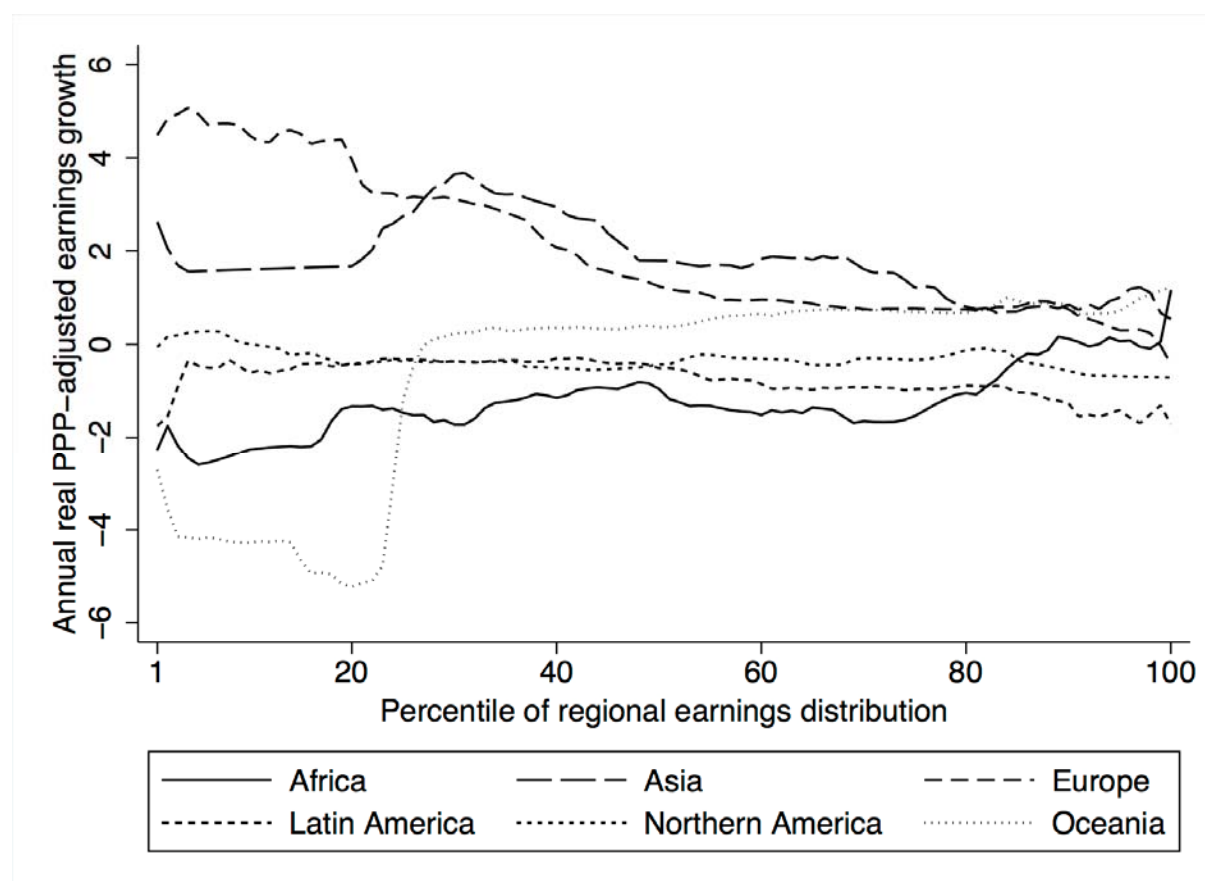
Notes: Average annual percentile growth rate 1970s-2010s in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and excluding the unemployed, per region. Horizontal axis ranked according to earnings percentiles in 1970s. Decade averages for 1970s and 2010s correspond to the years 1970-1979 and 2006-2015, respectively.
Source: Authors' calculations based on data described in the text.

Figure A11: Robustness checks: using alternative imputations.
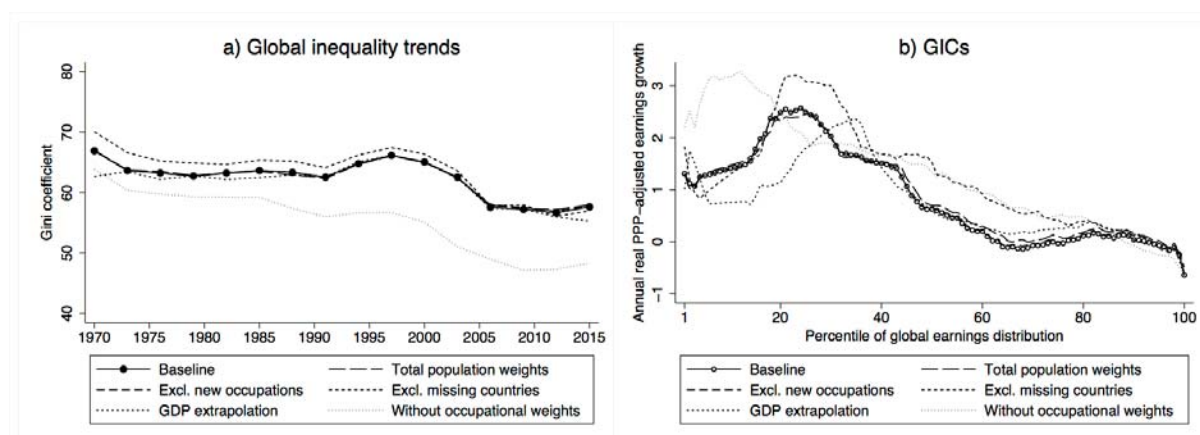
Notes: Calculations based on net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations. Total population implies that total country populations are used as weights instead of working age populations. New occupations refer to product managers and call center agents. Excluding missing countries means that countries not included in the UBS data are not imputed. For GDP extrapolation, missing earnings are extrapolated using GDP per capita growth and an adjustment factor of 0.87 to reflect empirically observed differences between national accounts and survey growth (World Bank, 2015), and GDP per capita growth is used instead of construction worker earnings growth for the agricultural worker extrapolation. Without occupational weights implies that all occupations within a country are assigned equal shares of the population (i.e., the ILO occupational data is not used). a) Including the unemployed. b) Average annual percentile growth rate 1970s–2010s; excluding the unemployed; horizontal axis ranked according to earnings percentiles in 1970s; decade averages for 1970s and 2010s corresponding to the years 1970–1979 and 2006–2015, respectively.
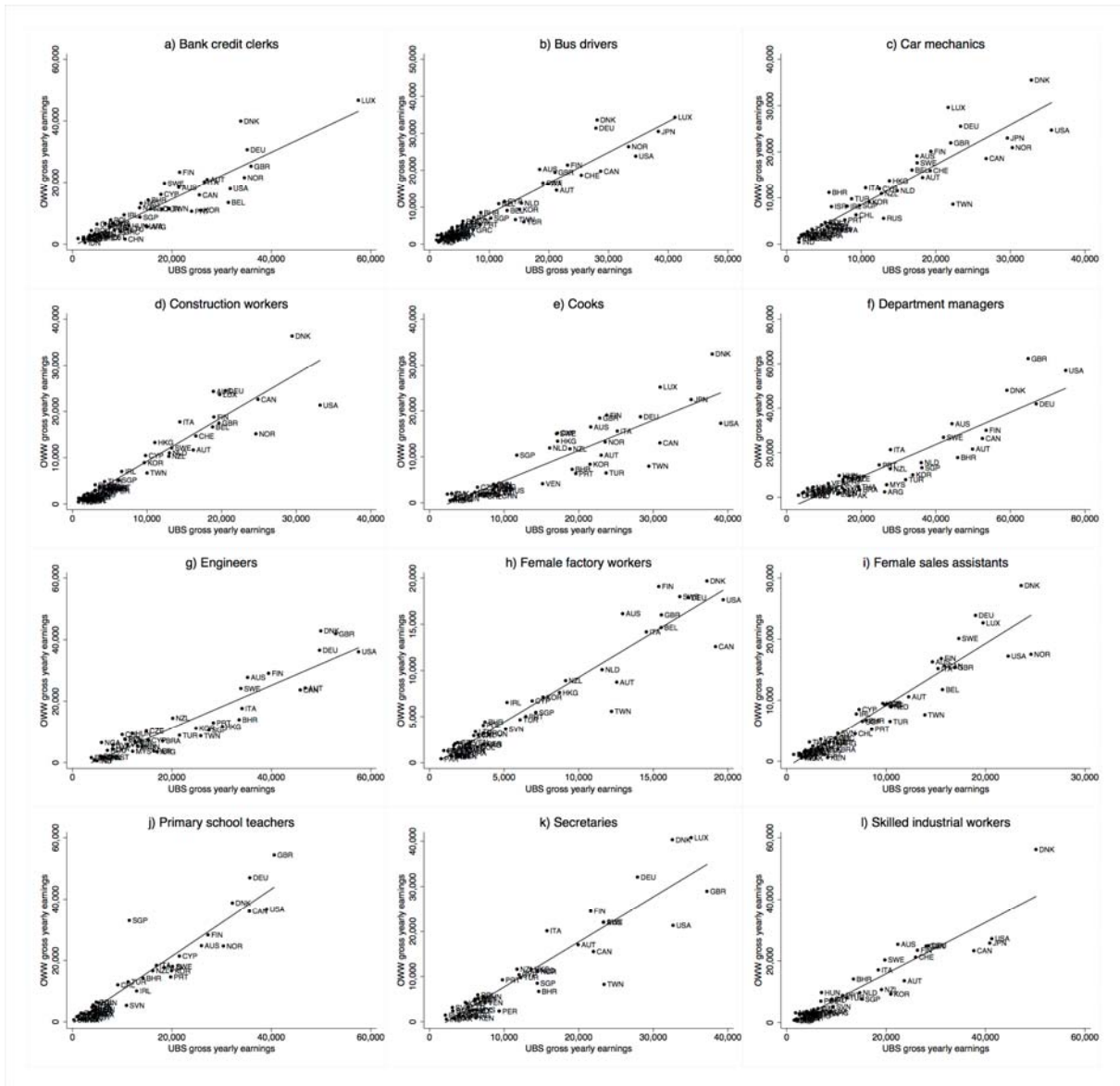*Sources:* Authors' calculations based on data described in the text; World Bank (2016).

Figure A12: Top earnings correlations.
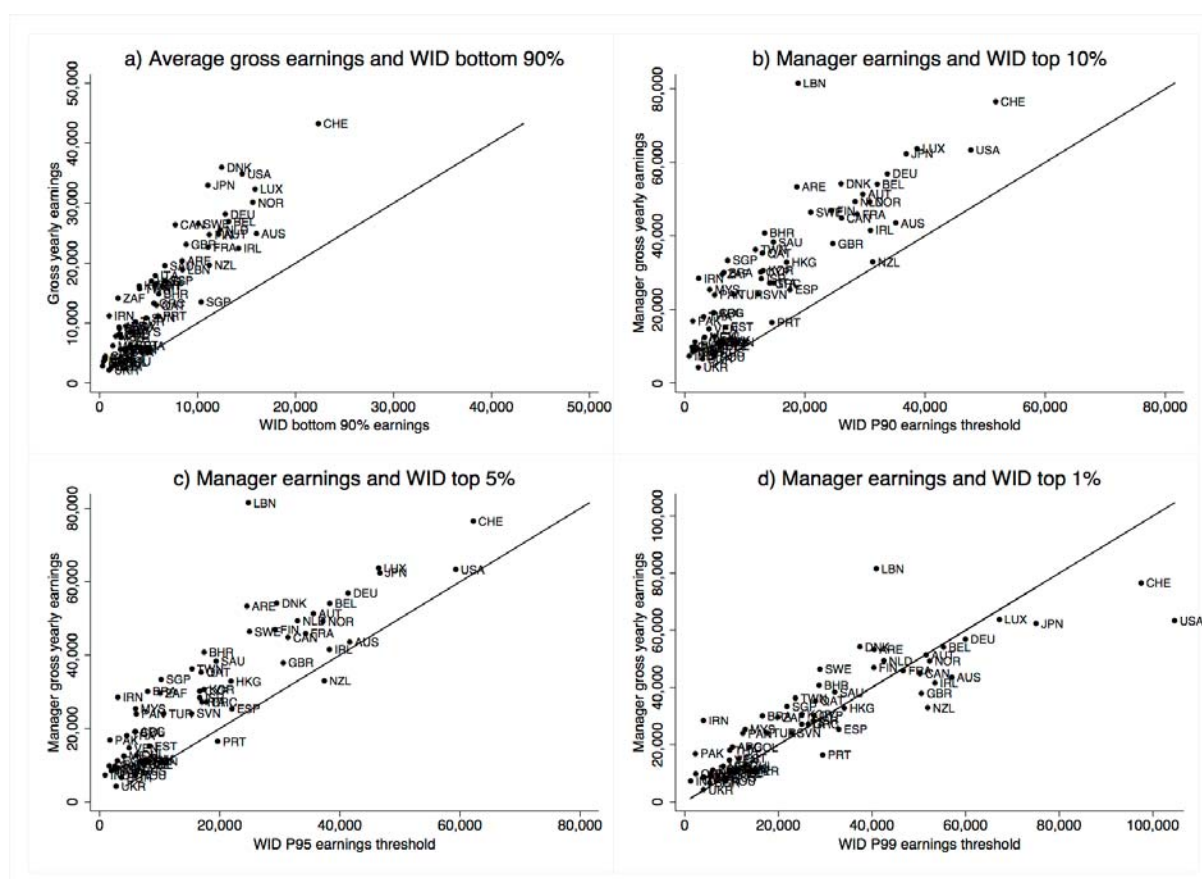
Notes: Correlations between mean and top earnings in the WID and UBS. Solid line indicates 45 degree line, with equal earnings in the WID and UBS data.
Sources: Authors' calculations based on data described in the text; WID (2016).

Appendix tables

Table A1: Countries included in the UBS data.

Country	Cities	Years
Africa		
Eastern Africa		
Kenya	Nairobi	1988–2015
Northern Africa		
Egypt	Cairo	1982–1991, 2000, 2009–2015
Southern Africa		
South Africa	Johannesburg	1970–2015
Western Africa		
Nigeria	Lagos	1985–1994, 2003
Asia		
Eastern Asia		
China	Beijing, Shanghai	1997–2015
Hong Kong	Hong Kong	1970–2015
Japan	Tokyo	1970–2015
South Korea	Seoul	1982–2015
Taiwan	Taipei	1991–2015
South-Eastern Asia		
Indonesia	Jakarta	1979–2015
Malaysia	Kuala Lumpur	1985–1991, 1997–2015
Philippines	Manila	1976–2015
Singapore	Singapore	1973–2009
Thailand	Bangkok	1979–1988, 1994–2015
Southern Asia		
India	Mumbai, New Delhi	1973, 1982–2015
Iran	Tehran	1976–1979
Pakistan	Karachi	2003
Western Asia		
Bahrain	Manama	1976–1988, 1994–2015
Cyprus	Nicosia	1988–2000, 2006–2015
Israel	Tel Aviv	1973–2003, 2009–2015
Lebanon	Beirut	1970–1973
Qatar	Doha	2009–2015
Saudi Arabia	Jeddah	1979–1988
Turkey	Istanbul	1973–1988, 1997–2015
United Arab Emirates	Abu Dhabi, Dubai	1979–1988, 1994–2015
Europe		
Eastern Europe		
Bulgaria	Sofia	2003–2015
Czechia	Prague	1994–1997, 2003–2015
Hungary	Budapest	1994–2015
Poland	Warsaw	1997–2015
Romania	Bucharest	2003–2015
Russia	Moscow	1997–2015
Slovakia	Bratislava	2003–2015
Ukraine	Kiev	2003–2015
Northern Europe		
Denmark	Copenhagen	1970–2015

Estonia	Tallinn	2003–2015
Finland	Helsinki	1970–2015
Ireland	Dublin	1976–2015
Latvia	Riga	2003–2015
Lithuania	Vilnius	2003–2015
Norway	Oslo	1970–2015
Sweden	Stockholm	1970–2015
United Kingdom	London	1970–2015
Southern Europe		
Greece	Athens	1970–2015
Italy	Milan, Rome	1970–2015
Portugal	Lisbon	1970–1976, 1982–2015
Slovenia	Ljubljana	2003–2015
Spain	Barcelona, Madrid	1970–2015
Western Europe		
Austria	Vienna	1970–2015
Belgium	Brussels	1970–2015
France	Lyon, Paris	1970–2015
Germany	Berlin, Düsseldorf, Frankfurt, Munich	1970–2015
Luxembourg	Luxembourg	1970–2015
Netherlands	Amsterdam	1970–2015
Switzerland	Basel, Geneva, Lugano, Zurich	1970–2015
Latin America		
Central America		
Mexico	Mexico City	1970–2015
Panama	Panama City	1976–2000
South America		
Argentina	Buenos Aires	1970–2015
Brazil	Rio de Janeiro, São Paulo	1970–2015
Chile	Santiago de Chile	2000–2015
Colombia	Bogotá	1970–2015
Peru	Lima	2003–2015
Venezuela	Caracas	1973–2012
Northern America		
Northern America		
Canada	Montreal, Toronto	1970–2015
United States	Chicago, Houston, Los Angeles, Miami, New York City, San Francisco	1970–2015
Oceania		
Australia and New Zealand		
Australia	Sydney	1970–2015
New Zealand	Auckland	2000–2015

Source: UBS (1970-2015).

Table A2: Occupations included in the UBS data.

Occupation	Years	ISCO-58	ISCO-68	ISCO-88	ISCO-08
Industrial sector					
Managers					
Department manager	1973–2015	1	2	1 (12)	1 (12)
Technicians and associate professionals					
Engineer	1979–2015	0	0–1	3	3
Plant and machine operators and assemblers					
Female factory worker	1976–2015	7–8	7–9	8 (81)	8 (81)
Skilled industrial worker	1976–2015	7–8	7–9	8 (81)	8 (81)
Elementary occupations					
Construction worker	1976–2015	7–8	7–9	9	9
Services sector					
Managers					
Product manager	2003–2015	1	2	1 (12)	1 (12)
Professionals					
Primary school teacher	1970–2015	0	0–1	2	2
Clerical support workers					
Bank credit clerk	1970–2015	2	3	4 (42)	4 (42)
Call center agent	2006–2015	6	3	4 (42)	4 (42)
Secretary	1970–2015	2	3	4 (41)	4 (41)
Services and sales workers					
Cook	1979–2015	9	5	5 (51)	5 (51)
Female sales assistant	1979–2015	3	4	5 (52)	5 (52)
Craft and related trades workers					
Car mechanic	1970–2015	7–8	7–9	7	7
Plant and machine operators and assemblers					
Bus driver	1970–2015	6	7–9	8 (83)	8 (83)

Note: ISCO level 2 in parentheses.
Sources: UBS (1970-2015); ILO (2010, 2011).

Table A3: Coverage of the dataset.

	World		Africa		Asia		Europe		L. America		N. America		Oceania	
	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2	S1	S2
Number of countries represented in the database														
1970	27	66	1	4	3	21	16	29	4	8	2	2	1	2
1973	32	66	1	4	7	21	16	29	5	8	2	2	1	2
1976	35	66	1	4	8	21	17	29	6	8	2	2	1	2
1979	38	66	1	4	12	21	16	29	6	8	2	2	1	2
1982	41	66	2	4	13	21	17	29	6	8	2	2	1	2
1985	43	66	3	4	14	21	17	29	6	8	2	2	1	2
1988	45	66	4	4	15	21	17	29	6	8	2	2	1	2
1991	41	66	4	4	11	21	17	29	6	8	2	2	1	2
1994	44	66	3	4	13	21	19	29	6	8	2	2	1	2
1997	48	66	2	4	16	21	21	29	6	8	2	2	1	2
2000	50	66	3	4	16	21	20	29	7	8	2	2	2	2
2003	59	66	3	4	16	21	29	29	7	8	2	2	2	2
2006	57	66	2	4	15	21	29	29	7	8	2	2	2	2
2009	60	66	3	4	17	21	29	29	7	8	2	2	2	2
2012	59	66	3	4	16	21	29	29	7	8	2	2	2	2
2015	58	66	3	4	16	21	29	29	6	8	2	2	2	2
Total	*737*	*1,056*	*39*	*64*	*208*	*336*	*338*	*464*	*98*	*128*	*32*	*32*	*22*	*32*
GDP (% of regional GDP represented in the database)														
1970	79.5	97.0	25.8	57.2	43.4	95.0	79.1	99.4	66.7	84.0	100.0	100.0	83.1	96.9
1973	82.0	97.2	27.8	54.5	65.1	96.3	78.7	99.4	75.5	85.4	100.0	100.0	80.3	96.5
1976	79.9	96.6	21.4	53.5	57.6	95.0	78.3	99.4	79.6	85.4	100.0	100.0	85.7	96.8
1979	81.6	96.5	22.3	50.8	71.6	94.7	78.1	99.4	79.6	85.2	100.0	100.0	83.5	96.3
1982	83.4	96.2	32.8	50.7	76.2	94.7	77.9	99.3	79.7	85.2	100.0	100.0	86.4	97.2
1985	84.6	96.2	41.6	43.6	73.5	94.6	79.2	99.3	79.6	84.0	100.0	100.0	85.2	96.9
1988	87.8	96.9	44.3	44.3	83.4	96.2	84.5	99.5	81.3	85.7	100.0	100.0	80.9	96.4
1991	88.5	96.5	40.6	40.6	78.2	94.3	90.3	99.6	84.2	89.1	100.0	100.0	85.5	96.8
1994	90.2	97.0	35.2	46.3	82.8	95.8	92.6	99.6	83.4	88.9	100.0	100.0	82.0	96.1
1997	94.1	96.8	28.9	48.9	91.5	95.8	97.5	99.1	82.8	89.1	100.0	100.0	84.2	97.0
2000	94.7	96.9	40.4	48.0	91.8	96.2	96.9	99.1	85.6	87.8	100.0	100.0	97.3	97.3
2003	95.5	96.9	35.9	47.4	91.8	96.1	99.0	99.0	84.3	85.0	100.0	100.0	98.6	98.6
2006	93.8	96.3	25.4	47.0	87.3	95.0	98.8	98.8	87.0	87.5	100.0	100.0	98.7	98.7
2009	93.7	95.8	33.9	44.9	89.0	94.9	98.8	98.8	87.5	88.1	100.0	100.0	98.7	98.7
2012	92.0	95.2	31.4	51.4	86.5	93.9	98.8	98.8	88.7	89.4	100.0	100.0	98.7	98.7
2015	91.7	95.5	31.6	53.2	86.9	94.2	98.9	98.9	81.8	89.6	100.0	100.0	99.6	99.6
Mean	*88.3*	*96.5*	*32.5*	*48.9*	*78.5*	*95.2*	*89.2*	*99.2*	*81.7*	*86.8*	*100.0*	*100.0*	*89.3*	*97.4*
Population (% of regional population represented in the database)														
1970	24.9	83.8	6.1	34.1	5.2	87.4	53.6	95.9	67.4	79.9	100.0	100.0	65.0	79.6
1973	40.9	83.6	6.0	33.9	32.9	87.5	53.5	95.9	71.7	80.1	100.0	100.0	64.9	79.3
1976	27.2	83.4	5.9	33.8	9.8	87.5	53.8	95.8	72.4	80.3	100.0	100.0	64.5	78.8
1979	31.2	83.1	5.8	33.8	17.6	87.4	52.1	95.8	72.6	80.5	100.0	100.0	64.3	78.1
1982	48.1	82.8	14.8	33.8	44.4	87.3	53.2	95.7	72.8	80.6	100.0	100.0	64.1	77.4
1985	50.0	82.4	30.1	33.7	45.2	87.2	52.9	95.6	72.9	80.7	100.0	100.0	63.6	76.7
1988	50.3	82.1	33.6	33.6	45.3	87.1	52.7	95.5	72.9	80.8	100.0	100.0	63.6	76.3
1991	48.1	81.6	33.4	33.4	41.9	86.8	52.3	94.6	72.9	80.8	100.0	100.0	63.2	75.9
1994	48.1	81.2	24.4	33.2	43.4	86.6	55.5	94.6	72.9	80.8	100.0	100.0	62.6	75.3
1997	71.7	80.8	9.3	33.0	80.5	86.5	81.5	94.7	72.9	80.7	100.0	100.0	62.0	74.7
2000	72.5	80.4	17.7	32.8	80.2	86.4	80.4	94.8	75.8	80.7	100.0	100.0	74.0	74.0
2003	77.3	80.0	24.3	32.6	83.7	86.3	94.8	94.8	80.2	80.7	100.0	100.0	73.6	73.6
2006	72.2	79.6	8.9	32.3	79.5	86.1	94.9	94.9	80.2	80.7	100.0	100.0	73.2	73.2
2009	72.8	79.1	16.7	32.0	79.4	86.0	94.9	94.9	80.1	80.7	100.0	100.0	72.9	72.9
2012	72.1	78.7	16.5	31.9	78.9	85.8	95.0	95.0	80.1	80.7	100.0	100.0	72.6	72.6
2015	71.0	78.1	16.3	31.8	78.6	85.7	95.1	95.1	75.2	80.7	100.0	100.0	72.4	72.4
Mean	*54.9*	*81.3*	*16.9*	*33.1*	*52.9*	*86.7*	*69.8*	*95.2*	*74.6*	*80.6*	*100.0*	*100.0*	*67.3*	*75.7*

Notes: First column for each region only includes the original UBS data (Sample 1); second column also includes the imputed data (Sample 2). *Sources:* Authors' calculations described in the text; World Bank (2016).

Table A4: Average earnings inequality per country, 1970–2015.

	Gini coefficient (%)				Kakwani index (%)
	Net earnings	Gross earnings	Net wage	Gross wage	Tax progressivity
Sweden	15.1	17.7	15.7	18.1	5.0
Norway	16.7	18.2	17.0	18.2	3.0
Denmark	18.7	20.8	18.6	20.7	3.1
Switzerland	19.0	20.2	21.1	22.2	4.0
Finland	20.1	23.4	21.4	24.6	6.6
Australia	20.1	22.7	20.4	22.9	8.0
Czechia	20.5	21.6	19.6	20.5	3.8
New Zealand	20.6	22.0	20.7	22.0	5.0
Netherlands	21.2	22.6	21.7	22.8	3.2
Japan	21.4	22.1	21.7	22.3	3.3
Austria	22.3	24.9	22.7	25.2	5.9
Taiwan	22.6	23.7	23.1	24.1	8.6
United Kingdom	23.7	24.6	24.8	25.7	2.7
Belgium	24.1	27.3	24.4	27.5	5.5
South Korea	24.1	25.8	25.0	26.6	11.4
Canada	24.5	26.7	24.8	26.9	5.9
Israel	24.8	29.4	24.0	28.2	11.8
Luxembourg	24.9	26.2	27.3	28.2	4.7
Germany	25.2	25.9	26.1	26.4	1.3
Cyprus	25.6	27.5	27.8	29.6	9.1
United States	26.2	27.7	26.0	27.3	4.2
Greece	26.3	27.9	26.9	28.2	6.5
Ireland	26.5	27.4	28.2	29.0	3.6
Nigeria	26.7	27.3	29.0	29.8	6.5
Slovenia	26.8	28.1	29.1	30.5	2.5
Italy	26.9	29.1	27.4	29.4	6.3
Hong Kong	27.6	28.9	29.9	31.1	20.4
China	28.0	28.8	28.4	29.2	3.8
Hungary	28.3	32.1	28.4	32.2	7.6
Portugal	28.4	31.0	30.7	33.0	10.3
France	28.8	30.3	29.0	30.2	5.3
Poland	29.0	29.6	28.3	28.9	1.8
Estonia	29.9	30.5	30.0	30.7	1.7
Singapore	32.0	33.4	33.0	34.3	5.1
Saudi Arabia	32.6	32.5	35.9	35.8	-1.5
Mexico	33.7	36.4	36.9	39.4	17.9
Spain	33.7	35.2	34.3	35.7	6.3
Turkey	35.4	36.8	35.4	36.9	3.1
Slovakia	36.0	37.3	35.6	36.8	4.1
Romania	36.2	38.7	35.9	38.5	5.7
Latvia	36.2	36.5	35.7	36.0	0.9
Malaysia	36.4	38.0	38.4	40.1	8.8

Indonesia	37.5	37.9	40.5	40.9	11.9
Egypt	37.6	39.4	38.5	40.7	8.3
Venezuela	37.7	38.6	37.3	38.2	9.8
Peru	38.2	40.1	39.1	40.9	10.4
Ukraine	38.3	39.5	37.3	38.4	6.4
United Arab Emirates	38.4	38.4	39.0	39.0	5.7
Bahrain	38.6	38.5	39.9	39.8	-12.5
Chile	38.7	39.5	39.1	40.0	3.3
India	39.0	42.4	40.0	43.3	39.4
Lithuania	39.3	39.7	38.8	39.1	1.0
Colombia	39.3	42.4	40.2	43.2	18.5
Argentina	39.9	40.5	40.7	41.3	2.5
Iran	40.0	40.5	38.4	39.0	1.1
Qatar	40.1	40.1	44.0	44.0	
Bulgaria	40.6	41.5	39.5	40.5	3.2
Brazil	42.4	45.6	42.9	46.1	15.2
Russia	44.1	44.6	42.5	43.1	2.0
Pakistan	44.3	45.2	45.5	46.2	5.2
South Africa	46.6	49.5	47.2	50.1	8.5
Panama	46.7	48.2	48.1	49.5	8.3
Thailand	48.9	49.9	49.1	50.1	11.7
Philippines	49.5	51.6	49.7	51.9	14.2
Lebanon	49.8	49.3	48.9	48.3	-4.0
Kenya	53.1	54.1	53.5	54.5	4.9

Notes: Calculations based on earnings weighted by occupational group populations including the unemployed. Earnings refer to yearly and wage to hourly earnings.
Source: Authors' calculations based on data described in the text.

Table A5: Country earnings inequality, 1970–2015.

| | **Gini coefficient (%), net earnings** | | | | | | | | | | | | | | | |
	1970	**1973**	**1976**	**1979**	**1982**	**1985**	**1988**	**1991**	**1994**	**1997**	**2000**	**2003**	**2006**	**2009**	**2012**	**2015**
Argentina	40.3	42.0	41.2	40.7	44.2	35.2	46.7	52.6	45.8	45.8	45.6	48.4	40.4	29.2	22.2	18.1
Australia	17.7	18.5	17.9	17.0	20.7	19.1	21.4	22.1	24.0	23.3	19.6	17.1	19.7	23.2	20.0	20.7
Austria	26.0	29.5	25.1	24.5	21.2	19.9	21.8	23.6	21.7	24.6	22.0	19.2	20.5	22.8	18.7	15.9
Bahrain	*39.2*	*39.2*	43.1	44.2	34.5	35.6	33.0	38.7	46.1	42.6	41.8	39.9	39.7	34.5	30.8	34.9
Belgium	27.4	26.8	24.6	23.4	21.9	23.2	28.8	27.3	27.1	30.6	25.0	24.5	20.2	19.2	19.3	16.1
Brazil	42.4	43.5	44.8	35.1	39.6	44.4	36.0	44.6	44.8	53.6	46.1	41.6	41.4	44.2	36.9	38.9
Bulgaria	*52.6*	*54.0*	*50.6*	*50.3*	*49.2*	*50.0*	*42.9*	*40.1*	*42.6*	*39.2*	*38.7*	31.1	30.1	19.9	28.5	29.1
Canada	25.7	26.0	24.6	24.7	27.8	28.7	24.7	29.5	22.9	23.8	19.0	25.2	23.3	21.9	22.1	21.4
Chile	*40.7*	*40.4*	*40.8*	*39.4*	*45.6*	*42.5*	*43.2*	*42.7*	*40.8*	*37.2*	39.2	44.1	32.5	34.8	30.0	24.7
China	*26.0*	*25.6*	*23.6*	*18.9*	*18.3*	*18.1*	21.7	20.9	29.7	34.1	41.8	54.8	30.7	33.7	24.5	25.0
Colombia	35.3	36.3	39.6	36.9	30.6	37.4	43.4	49.3	43.8	44.9	45.9	48.9	41.1	33.3	30.6	32.3
Cyprus	*32.4*	*30.5*	*29.4*	*24.0*	*27.1*	*29.2*	24.3	23.8	20.8	24.2	22.9	21.7	22.4	20.4	28.8	28.0
Czechia	*21.3*	*21.0*	*19.0*	*19.7*	*18.6*	*19.6*	*18.8*	*19.9*	20.8	26.2	26.1	22.8	16.8	20.1	20.5	17.6
Denmark	22.5	23.7	19.7	19.1	18.6	14.6	22.1	19.9	19.3	15.5	14.7	14.3	16.7	17.5	19.4	21.3
Egypt	*22.2*	*23.2*	*22.5*	*24.0*	24.2	23.8	27.6	34.7	36.8	35.5	34.7	53.2	55.8	59.4	66.5	57.8
Estonia	*30.6*	*31.0*	*27.3*	*27.2*	*27.0*	*27.4*	*30.6*	*27.2*	34.9	37.0	*38.2*	31.6	22.4	26.2	32.9	27.5
Finland	17.1	16.6	15.5	15.8	18.1	15.1	16.7	19.1	28.5	27.1	26.3	23.6	22.7	21.0	19.7	18.5
France	29.2	29.3	28.5	24.9	22.7	31.1	29.1	23.8	36.0	34.0	31.8	30.7	28.8	28.0	28.2	24.9
Germany	30.3	30.7	23.4	24.5	23.6	23.3	25.1	29.7	29.1	24.7	21.6	25.2	23.4	23.3	22.1	22.9
Greece	17.9	19.1	18.3	17.8	20.9	27.2	31.1	29.6	24.0	26.7	32.2	33.4	25.2	23.6	34.7	38.9
Hong Kong	32.0	33.6	32.8	27.1	35.6	27.8	23.9	21.9	20.5	23.2	23.6	33.2	33.4	24.8	27.5	21.0
Hungary	*26.2*	*26.5*	*27.2*	*27.3*	*27.2*	*29.5*	*31.7*	*32.3*	31.0	25.2	22.1	30.5	25.3	31.4	30.3	29.6
India	*25.1*	24.4	27.7	30.8	33.7	28.3	34.2	41.6	43.0	49.3	51.0	47.3	51.2	44.8	49.7	41.9
Indonesia	*42.3*	*40.7*	*33.7*	29.6	29.2	34.9	47.0	50.5	40.6	45.2	33.9	46.6	34.1	31.2	37.2	22.9
Iran	*39.0*	*40.4*	41.5	40.6	38.5	*43.1*	37.1	34.3	35.6	29.3	*37.8*	43.7	43.3	44.2	*48.9*	42.9
Ireland	*24.1*	*24.6*	25.0	22.5	26.6	34.3	33.8	32.7	33.4	27.0	19.5	21.2	20.5	23.0	30.5	24.7
Israel	*23.4*	21.4	21.6	17.1	26.6	27.6	21.1	27.7	29.7	23.8	25.9	34.2	26.3	20.5	28.4	21.4
Italy	31.8	33.2	32.2	30.6	34.1	24.9	26.5	26.3	26.2	25.8	25.7	18.9	19.7	22.1	24.7	27.4
Japan	23.1	22.2	21.5	21.3	20.2	22.3	23.0	18.3	22.3	25.4	22.8	26.1	21.7	16.9	18.2	17.6
Kenya	*49.2*	*49.0*	*49.6*	*49.6*	*48.5*	*50.6*	50.7	60.7	56.6	56.0	55.3	54.4	55.9	51.7	59.6	52.0
Latvia	*38.5*	*38.2*	*37.1*	*37.4*	*37.4*	*36.8*	*38.3*	*35.9*	36.6	39.5	*38.4*	35.0	34.5	34.5	30.8	30.1
Lebanon	35.4	38.9	*44.0*	41.4	43.5	48.1	*54.3*	*59.3*	60.6	59.2	*60.1*	53.2	52.6	49.0	*50.6*	47.0
Lithuania	*43.7*	*43.5*	*42.3*	*42.6*	*42.4*	*42.2*	*44.0*	41.2	44.8	42.3	*40.7*	37.1	24.8	35.3	30.8	30.5
Luxembourg	24.5	26.0	25.9	27.4	19.6	27.6	20.7	25.4	28.7	25.6	24.5	23.5	26.3	20.8	28.1	24.7
Malaysia	*38.6*	*37.1*	*33.2*	27.7	*33.1*	38.0	37.1	38.3	45.4	46.7	41.8	36.8	35.8	35.8	30.5	25.7
Mexico	40.6	41.8	43.0	42.4	33.7	21.7	17.3	13.5	36.0	32.2	31.8	24.8	37.5	43.2	36.6	42.9
Netherlands	22.2	20.6	19.9	19.3	25.8	25.2	24.7	20.2	24.5	24.0	22.8	16.7	20.7	17.5	19.7	15.0
New Zealand	*17.8*	*18.2*	*18.4*	*17.1*	20.2	17.7	22.3	27.2	27.0	25.8	22.0	19.9	16.7	18.7	20.3	20.9
Nigeria	*21.4*	*21.9*	*20.9*	*22.5*	*20.9*	25.8	24.3	27.1	24.1	25.3	30.5	29.9	*37.7*	*34.5*	29.6	*30.3*

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Norway	21.9	22.1	25.1	16.2	15.0	13.4	11.8	11.6	20.5	22.3	17.3	13.1	14.8	16.9	13.7	10.9
Pakistan	*23.2*	*24.9*	*28.4*	*28.3*	*32.3*	*28.8*	*34.1*	*43.0*	*38.0*	*54.3*	*64.2*	60.0	*67.0*	*60.7*	*64.9*	*56.7*
Panama	*45.7*	*45.4*	45.8	42.2	44.0	47.7	48.9	45.8	50.3	48.8	48.3	*41.5*	*48.5*	*50.3*	*44.8*	*48.7*
Peru	*46.5*	*47.0*	*47.5*	*46.4*	*46.6*	*44.6*	*47.1*	36.7	34.8	32.3	*31.3*	36.0	33.3	30.4	30.3	21.1
Philippines	*61.0*	*61.2*	56.6	47.7	52.9	54.2	45.1	38.5	47.7	45.9	45.9	50.9	46.9	40.3	42.6	54.0
Poland	*30.2*	*30.8*	28.5	28.8	28.1	30.3	24.2	28.0	30.9	28.8	29.2	35.2	30.7	24.9	26.6	28.4
Portugal	29.6	27.3	29.9	29.3	28.2	26.3	30.3	25.5	22.9	32.6	29.8	24.4	31.7	26.6	31.2	28.7
Qatar	*39.2*	*35.4*	*37.8*	*38.1*	*38.5*	*37.6*	*37.5*	*40.6*	*44.2*	*46.3*	*45.7*	*45.8*	*41.5*	*39.4*	*35.3*	*38.8*
Romania	*33.8*	*36.0*	*35.4*	*37.4*	*38.4*	*41.3*	*38.9*	*39.2*	*39.2*	*42.4*	*36.4*	47.1	38.8	19.2	24.2	30.8
Russia	*53.2*	*53.2*	*51.2*	*51.3*	*50.7*	*52.7*	*48.4*	*46.0*	*43.9*	*41.7*	48.0	49.0	36.2	35.0	24.6	19.7
Saudi Arabia	*28.8*	*25.4*	*27.4*	*24.1*	*26.0*	*38.3*	*31.6*	*35.1*	*37.9*	*39.0*	*37.6*	*37.7*	*33.3*	*33.3*	*33.3*	*31.9*
Singapore	*33.4*	30.5	31.1	29.5	33.9	32.5	39.5	37.6	27.1	28.5	32.5	31.7	34.4	31.5	*31.1*	26.8
Slovakia	*40.7*	*40.6*	*37.0*	*37.3*	*36.3*	*37.6*	*35.0*	*35.3*	*39.1*	*40.7*	*41.4*	33.2	30.4	28.1	30.5	32.7
Slovenia	*32.4*	*32.7*	*27.1*	*26.1*	*27.3*	*27.8*	*29.0*	*25.3*	*24.3*	*27.6*	*29.2*	24.4	20.2	24.4	28.7	21.7
South Africa	42.4	43.0	40.0	42.1	41.3	42.4	43.0	43.2	44.0	47.6	48.1	60.6	50.5	49.0	51.8	56.7
South Korea	*23.0*	*21.8*	*22.3*	*21.9*	21.4	24.6	21.2	20.1	22.2	20.4	22.2	33.4	30.3	24.5	29.8	26.3
Spain	39.1	41.9	26.9	30.3	32.9	38.6	37.1	33.4	39.2	35.1	28.7	29.0	24.6	32.9	36.1	33.8
Sweden	13.5	13.4	10.8	10.4	11.1	11.7	15.7	9.2	19.9	20.4	16.3	15.4	19.4	18.2	19.1	17.2
Switzerland	17.0	16.8	16.9	17.1	17.2	19.4	19.2	18.4	24.6	23.2	20.4	21.2	19.9	16.5	16.9	19.1
Taiwan	*21.8*	*21.5*	*22.3*	*19.9*	*23.6*	*24.6*	*22.4*	19.1	26.5	21.4	19.9	26.1	20.3	22.5	23.5	26.6
Thailand	*57.2*	*54.6*	*53.1*	44.4	56.9	50.0	43.0	53.4	54.8	55.3	50.4	45.2	47.0	48.3	40.5	28.2
Turkey	*22.1*	22.8	23.2	29.3	34.7	30.4	46.0	39.3	40.5	40.8	38.6	44.8	36.8	37.9	36.4	42.3
Ukraine	*37.5*	*38.4*	*38.6*	*38.9*	*38.7*	*40.5*	*41.9*	*43.4*	*42.9*	*44.9*	*41.8*	44.3	31.0	32.0	25.8	32.8
United Arab Emirates	*34.5*	*33.9*	*33.4*	32.5	34.0	31.9	38.5	44.0	46.2	41.0	42.1	37.5	41.4	38.4	43.7	40.9
United Kingdom	24.5	24.1	23.9	24.9	23.7	25.2	24.3	27.0	27.7	23.0	21.4	19.6	20.9	21.9	23.1	24.0
United States	30.8	31.7	25.3	26.0	28.6	27.9	25.9	27.6	24.8	23.3	20.9	24.4	22.3	26.7	24.6	28.8
Venezuela	*34.3*	34.8	35.1	35.5	35.1	53.6	46.8	49.8	43.4	28.9	33.5	47.5	33.5	30.3	31.8	*29.6*

Note: Calculations based on net yearly earnings weighted by occupational group populations including the unemployed. Imputed observations in italics.
Source: Authors' calculations based on data described in the text.

Table A6: Country-level pairwise correlations: inequality, earnings and prices.

a) Inequality correlations (%)	All the Ginis income	Gini net earnings	Gini gross earnings
Gini net earnings	46.8***		
	(798)		
Gini gross earnings	47.3***	99.0***	
	(798)	(1,056)	
Gini net wage	48.7***	98.7***	97.6***
	(798)	(1,056)	(1,056)

b) Income and earnings correlations (%)	GDP per capita	Net earnings	Gross earnings
Net earnings	87.9***		
	(1,056)		
Gross earnings	89.0***	98.2***	
	(1,056)	(1,056)	
Hourly wage	89.2***	99.2***	98.3***
	(1,056)	(1,056)	(1,056)

c) Price levels correlations (%)	UBS PPP	UBS 2015 PPP	ICP 2011 PPP
UBS 2015 PPP	91.4***		
	(1,056)		
ICP 2011 PPP	86.5***	91.3***	
	(1,056)	(1,056)	
PWT PPP	87.0***	84.4***	91.6***
	(990)	(990)	(990)

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Number of observations in parentheses. Calculations weighted by occupational group populations including the unemployed. a) All the Ginis refers to interpolated values of Milanovic (2016a). b) GDP per capita in current USD. c) For UBS 2015 PPP and ICP 2011 PPP, prices are compared across countries in 2015 (for ICP 2011 using the 2011 ICP round from the WDI) and extrapolated using national inflation. For UBS PPP and PWT PPP, prices are compared across countries each year.

Sources: Authors' calculations based on data described in the text; Feenstra, Inklaar and Timmer (2015); Milanovic (2016a); World Bank (2016).

Table A7: Basic distributional facts.

a) Global inequality

	Gini coefficient (%)			GE index (%)		
	Net earnings	**Gross earnings**	**Net wage**	**GE(0) Theil-L (MLD)**	**GE(1) Theil-T**	**GE(2)**
1970	66.9	69.1	68.4	96.3	76.4	116.5
1973	63.6	66.0	65.6	82.3	66.7	93.9
1976	63.2	65.7	64.9	78.8	64.4	83.6
1979	62.7	65.2	64.0	76.3	63.1	79.3
1982	63.2	66.2	64.5	76.4	64.5	83.4
1985	63.7	66.9	65.0	75.4	66.5	89.7
1988	63.3	67.1	65.0	71.9	66.6	93.5
1991	62.6	65.6	63.9	69.1	63.8	88.2
1994	64.8	67.5	66.2	78.4	69.0	94.6
1997	66.2	68.5	67.6	85.5	72.4	100.0
2000	65.1	67.3	66.6	81.6	68.7	91.0
2003	62.6	64.7	63.6	71.9	61.7	79.7
2006	57.5	60.5	58.6	56.7	51.1	66.0
2009	57.2	60.0	58.7	53.8	49.9	64.1
2012	56.7	59.3	57.5	54.2	49.5	64.9
2015	57.6	59.7	58.6	55.0	52.0	69.8
1970-2015 change (%)	-13.9	-13.6	-14.3	-42.9	-31.9	-40.0

b) Regional Gini indices (%)

	Africa	**Asia**	**Europe**	**Latin America**	**Northern America**	**Oceania**
1970	47.0	62.6	51.7	46.8	30.9	25.0
1973	47.2	61.0	51.4	50.0	31.3	26.3
1976	53.8	64.7	49.7	47.2	25.5	25.9
1979	51.0	64.9	50.2	42.4	26.1	26.1
1982	49.5	63.9	51.0	42.1	28.8	31.2
1985	49.3	60.3	51.8	47.5	28.1	30.0
1988	48.7	56.8	53.0	45.0	25.9	31.5
1991	56.6	58.1	52.9	49.0	28.0	32.9
1994	60.9	61.4	53.4	45.5	24.7	34.2
1997	56.7	64.7	52.0	50.9	23.6	34.8
2000	55.7	65.2	49.6	48.0	21.0	32.7
2003	59.8	63.8	42.6	48.9	24.6	34.9
2006	61.9	55.8	37.7	44.1	22.7	36.5
2009	58.7	54.9	36.1	43.6	26.6	40.3
2012	64.7	54.4	35.8	37.6	24.7	38.7
2015	60.7	55.6	36.7	40.1	28.6	38.8
1970-2015 change (%)	29.2	-11.2	-29.0	-14.3	-7.4	55.3

c) Global Theil index decomposition within and between countries and occupations (%)

GE(1) by countries		GE(1) by occupations	

	Within country	Between country	Between (%) contribution	Within occupation	Between occupation	Between (%) contribution
1970	14.0	62.5	81.7	51.8	24.6	32.1
1973	14.3	52.4	78.6	44.7	22.0	33.0
1976	12.2	52.2	81.0	42.1	22.3	34.6
1979	11.2	51.9	82.3	41.1	22.0	34.9
1982	11.6	52.9	82.0	39.2	25.4	39.3
1985	13.1	53.4	80.4	37.5	28.9	43.5
1988	12.2	54.4	81.7	37.8	28.8	43.2
1991	14.6	49.3	77.2	34.5	29.3	45.9
1994	14.1	55.0	79.6	36.4	32.6	47.3
1997	15.0	57.4	79.3	36.2	36.2	50.0
2000	15.5	53.1	77.4	34.8	33.8	49.3
2003	21.2	40.5	65.6	27.3	34.4	55.8
2006	19.5	31.6	61.8	22.2	28.9	56.6
2009	17.9	32.0	64.2	22.7	27.1	54.4
2012	18.6	30.9	62.4	23.6	25.9	52.4
2015	15.8	36.3	69.7	31.3	20.7	39.8
1970-2015 change (%)	13.1	-41.9	-14.7	-39.5	-15.7	23.7

d) Global percentile earnings shares and average net yearly earnings (in PPP-adjusted 2015 USD)

	Top and bottom earnings shares (%)			Top and bottom earnings (2015 USD)		
	Bottom 50%	Top 10%	Top 1%	Bottom 50%	Top 10%	Top 1%
1970	7.1	47.0	7.2	1,753	58,104	122,621
1973	8.7	42.8	6.7	2,830	69,822	144,363
1976	8.2	39.4	6.8	2,418	61,171	102,203
1979	8.2	39.5	6.3	2,515	62,298	101,340
1982	8.4	40.0	6.9	2,020	49,431	84,424
1985	8.8	41.8	6.6	2,233	55,080	92,497
1988	9.6	44.3	5.9	2,170	50,289	82,395
1991	9.9	41.6	6.8	2,312	49,669	83,497
1994	8.4	43.7	7.3	2,032	53,288	88,379
1997	7.7	45.2	7.2	1,632	48,087	82,441
2000	8.5	43.2	6.7	1,971	51,092	79,599
2003	9.5	40.4	6.4	2,718	57,852	91,931
2006	13.1	37.2	5.9	3,727	53,574	86,695
2009	13.2	36.8	5.8	3,883	54,085	87,081
2012	14.3	37.2	5.9	4,911	65,860	103,352
2015	14.0	38.6	6.2	4,288	60,155	96,116
1970-2015 change (%)	97.8	-17.7	-14.2	144.7	3.5	-21.6

Notes: Calculations based on net yearly earnings (if nothing else specified), which are PPP-adjusted using UBS price levels in 2015 USD and weighted by working age populations. Earnings refer to yearly earnings and wage to hourly earnings. Gini indices include the unemployed; GE indices and percentiles exclude the unemployed.
Source: Authors' calculations based on data described in the text.