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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.

JEL Classification: D31, F01, O15

Keywords: global inequality, development, inequality decomposition, labor markets

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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.

One question that has received much less attention is how the global *earnings* inequality has developed over the last decades. Focus in the previous literature has been on total income from all sources (labor, business and capital) and its distribution across households around the world (including old-age pensioners and adjustments for children). While such focus is indeed relevant in many distributional examinations, most people in the world still only have one single income source, labor earnings, and they earn this as working adults. Therefore, if one wants to understand the role of labor markets in shaping global inequality trends, examining the distribution of labor earnings among the world's working population is a natural starting point.

In this paper, we estimate the level of *global earnings inequality* and its trend over the past 45 years, from 1970 to 2015, and also decompose it across geographical, sectoral and occupational components. To the best of our knowledge, this is the first time such an analysis has been made. Our series are based on 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. We have constructed this database 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

[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

[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. These results are qualitatively robust to using different inequality measures, imputation methods, population weights, and PPP adjustments.

We also find that a combination of factors contributed to the fall in global earnings inequality in the 2000s. Income convergence between poorer and richer countries is key, particularly China's growth. Our occupational and sectoral data allow us to shed further light on these dynamics, and rising agricultural sector earnings in especially China and India appear to be particularly important. Inequality within occupations and sectors are found to contribute more to global inequality trends than do differences between them. This actually confirms the between-country convergence pattern, as it shows how earnings differences between managers in different countries are larger than between managers and workers in the same country. Additionally, inequality trends among industrial professions follow the global index closely, whereas services sector occupations exhibit a larger dispersion in within-occupation inequality levels and follow somewhat different trends. Such discrepancy between traded (industrial) and

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

non-traded (services) sectors indicates that trade globalization matters for global inequality, as do earnings changes in the agricultural sector. Finally, we find that the global gender gap decreases, but that this only has a marginal impact on earnings inequality 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 decreased 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 (agglomeration averages) from the United Nations (2017).

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.[13]

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

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] 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.

earnings available in the OWW database (Freeman and Oostendorp, 2012).[14] Thus, we have a 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.[15]

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,[16] as well as weekly working hours for our 15 different occupational profiles[17] and all countries and years available in the UBS *Prices and Earnings* reports.[18] All but two of the occupations are available from the 1970s, while call center agents and product managers are added during the 2000s.[19]

[14] 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, 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.

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

[16] 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.

[17] 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.

[18] 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. In a robustness check, we also try adjusting more outliers, finding that this does not affect the results.

[19] 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)

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.[20] Thus, to obtain a balanced panel, we extrapolate the missing country-occupation observations by the corresponding average sub-regional (or regional)[21] change for each occupation,[22] 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.[23] 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. This sample (Sample III) yields a total of 20,400 country-year-occupation observations for each of our

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.

[20] 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.

[21] 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).

[22] 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), yielding similar results.

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

different statistics, or 21,760 observations, including the unemployed category, and it has 100 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. 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).[24]

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. Such correlations are shown in Figure 1. 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.[25] 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.[26] The correlation

[24] Calculated as yearly earnings divided by weekly working hours times 52.

[25] 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.

[26] 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 managers with supervising or general foremen in the manufacture of industrial chemicals industry; engineers with

between occupational earnings in the two datasets is high (86 percent), and for hourly wages even higher (88 percent).[27]

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 two 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*. Figure 2 shows these comparisons for 15 countries from Europe, Asia and the Americas for which we found comparable series.[28] Overall, our estimated earnings inequalities are reassuringly similar to those available for other countries in the other sources in both levels

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.

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

[28] Our earnings inequality here includes added top earnings from the WID (see Section 6.2 below) in order to offer better comparability with the other sources at the country level. Appendix Figure A4 shows non-adjusted comparisons with Milanovic's (2016a) ALG series for 60 of our 66 covered countries (the ALG dataset 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., comparing country-level estimations of income or consumption Gini coefficients from various sources, as collected by Milanovic (2016a), with our measures of earnings inequality.

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 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

The evolution of global earnings inequality between 1970 and 2015 is presented in Figure 3.[29] 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 (which is in line with, e.g., Bick, Fuchs-Schündeln and Lagakos, 2016).

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 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.

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

[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.[30] 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 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

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

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).[31] 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]

Another way of depicting and understanding the evolution of inequality is to examine the rate of earnings growth across the distribution. Figure 7 depicts so-called non-anonymous growth incidence by country-occupation,[32] measured as the average annual percentage growth of each country-occupation's mean earnings between the 1970s and 2010s, ordered according to their initial 1970s rank in the global earnings distribution. To facilitate interpretation, we have marked some country-occupations that illustrate the earnings dispersion both within and across countries. During this long period, the average compounded global real earnings grew by approximately 0.5 percent annually. However, seen over the entire earnings distribution in the

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

[32] *Growth incidence curves* (GICs) were first formulated by Ravallion and Chen (2003).

1970s, the growth rates differ considerably. The lower half of the global distribution records mostly above-average earnings growth. In contrast, earnings growth in the upper half of the distribution was more often below average and, quite notably, for some country-occupations, real PPP-adjusted earnings growth was zero or even negative. While perhaps surprising, a recent study by Sacerdote (2017) similarly found that the growth of US real wages since the 1970s was essentially zero (with some variation due to the choice of price index).

[Figure 7 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 world regions and, for the first time in this literature, occupational groups and industrial sectors. In connection to this, we also present some more-fine-grained decompositions, depicting the evolution of earnings inequality within each of the different regions and occupations. Finally, we also do a counterfactual analysis, separately holding the different factors constant at their 1970 value over the investigated period, in order to isolate their relative importance for explaining the falling trend in global earnings inequality.

5.1 Country and regional decompositions

Figure 8 presents 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.[33] Looking first at the country-based decomposition in Figure 8a, 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

[33] 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 (2017).

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. Over the full 1970-2015 period, between-country inequality fell by almost 15 Gini points, while, at the same time, within-country inequality increased by five points, leading to the total decrease in global earnings inequality of almost ten Gini points. Looking only on the drop between 1997 and 2006, the opposing trends are even more pronounced, with a fall in between-country inequality of 17 Gini points and an increase in within-country inequality of eight points.

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 A5 in the appendix). We have also done similar analyses for the OECD versus non-OECD countries, finding that wage inequality 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.[34] Analyzing the decomposition trends within and between our different geographical regions (see Figure 8b), 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.

[Figure 8 about here]

Figure 9 displays regional earnings inequality trends in Africa, Asia, Europe, Latin America, Northern America and Oceania.[35] 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[36] 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

[34] This latter finding is in line with findings by Checchi, García-Peñalosa and Vivian (2016). Results available upon request.
[35] 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 A6 in the appendix. For a similar regional inequality analysis, see Ravallion (2014), which focuses on the developing world.
[36] 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.

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 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 9 about here]

5.2 Decompositions by occupations and sectors

A unique aspect of our global database is its labor market variables. We exploit this to decompose global earnings inequality by occupations and sectors. Figure 10a 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.[37] Between 1970 and 2015, inequality within occupations fell by eleven Gini points, while between-occupation inequality increased by one point. 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 10b, 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 10c and 10d, 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

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

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 typically more exposed to international competition, industrial earnings become compressed by globalization. By contrast, services sector earnings are to a larger extent determined by national conditions, and therefore, they respond much less to rising globalization.

[Figure 10 about here]

5.3 Counterfactual analysis

Another approach to analyzing explanatory factors is to run a counterfactual analysis. Here, this means that we keep different components of the global earnings inequality trend fixed at their initial 1970 value, one at a time, thereby analyzing the difference between actual inequality today compared to what it would have looked like had this factor not changed during the 1970-2015 period. These results are presented in Figure 11, showing that the most dominant component in explaining the fall in global earnings inequality is changes in gross hourly earnings. If gross wages had remained at their 1970 value during this period, the global inequality trend had essentially been flat. We can also see that changes in prices are important, although the impact of this factor is more volatile and, over the full period, relatively small. Changes in country-level populations have an opposing effect, driving the inequality trend upwards, while changes in taxes, working hours and within-country occupational populations have almost no impact on the global trend. The 2015 difference between the actual outcome and the counterfactual is -10 Gini points for gross wages, -2 points for prices and 2 points for country populations. Since changes in gross hourly earnings thus seem to be the main driver behind the global earnings inequality decile, the rest of this section focuses solely on that dimension.

[Figure 11 about here]

In Figure 12, we separately keep the 1970 gross wages fixed for the different regions, countries, sectors and occupations. Note that this figure only shows the difference between the actual outcome and the counterfactual with constant gross hourly earnings (the corresponding global inequality trends are shown in Figure A7 in the appendix). As clearly illustrated by this figure, earnings changes in Asia is the by far most important regional driver behind the fall in global earnings inequality. If Asian gross wages had remained constant since 1970, global inequality would have been 20 Gini points higher today. The most important countries are China and India, whose earnings changes, ceteris paribus, have reduced global inequality by nine and four Gini points, respectively, while wage changes in the United States (and Northern America) have had the opposing effect, driving global inequality up by two Gini points. Among the sectors, earnings changes in the agricultural and services sectors are the most dominant, although all three sectors contribute to the global inequality decrease since 2000. Wage changes among agricultural workers represent the most important occupation, implying a global inequality decrease of 10 Gini points, followed by female sales assistants, while changes among department managers have an upward-driving impact on global inequality.

[Figure 12 about here]

To summarize, cross-country convergence and earnings growth of especially China and agricultural workers, play a central role when one accounts for the drivers of global earnings inequality and, in particular, the downward trend since the late 1990s.

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, inequality indicators, geographical and occupational 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, adding top earnings from other sources, restricting the analysis to the urban and employed populations, and simulating earnings dispersion within occupations within countries. Some further robustness checks, using alternative imputations when generating the database, are presented in appendix Figure A8.[38]

6.1 Using different PPP-adjustments

[38] As shown in Figure A8 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. Finally, we also check that our results are not driven by extreme outliers, i.e., potential errors, by excluding all earnings observations that have changed by more than 100 percent over a three-year period, and instead linearly interpolate these observations, finding that this does not affect the results.

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 (Feenstra, Inklaar and Timmer, 2015).[39] 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.

[Figure 13 about here]

6.2 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 A9 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 A9 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.

[39] 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.

To account for earnings in the very top, we thus add national top earnings using data from the WID.[40] 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.[41] 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.[42] When missing, we impute these data using the same methods as described above, i.e., by linear interpolation and sub-regional or regional extrapolation.[43] 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.[44] Finally, we also try adding all income, i.e., the national top 5 percent average total income, including capital income and without adjusting for the earnings share of total income, available in the WID.[45]

The results from the top earnings addition are shown in Figure 13b. The Gini coefficient increases somewhat, from 58 to 59 in 2015, and this relatively small effect appears to be roughly the same regardless of how we impute the top incomes.

6.3 Restricting the analysis to global urban and working populations

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[40] 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.

[41] 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.

[42] 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.

[43] 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.

[44] 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 $Top5earnings = 2864 + 2.53 \cdot GDPpercapita$. The R^2 is 72 percent, which is higher than what Anand and Segal (2016) find for their model.

[45] 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.

Heterogeneity analyses with respect to populations, where we focus only on the global urban and global employed earnings inequalities, are presented in Figures 13c and 13d, respectively. 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 unemployment has increased.

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 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.[46] If we assume that this difference corresponds to the mean within-country-occupation inequality,[47] 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.

Global earnings inequality adjusted for within-country-occupations dispersion using this method is presented in Figure 14.[48] 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 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.

[46] See Figure 2.

[47] 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.

[48] 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.

We make this adjustment by using the gender composition in ILO's (2010, 2011) data on employment by sex and occupation[49] and by using the sectoral gender earnings gap in the UBS data.[50] 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.[51]

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. 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). A gender decomposition of the global earnings inequality trend is illustrated in Figure 15b, 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.

[Figure 15 about here]

7. Conclusions

The purpose of this study is to contribute to our understanding of global inequality and its trends 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

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[49] 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.

[50] 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.

[51] 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.

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. In addition, instead of using a mix of differently composed household surveys from many different sources, we use one single consistent, and previously unutilized, source for our earnings data.

Our main finding is that global earnings inequality was stable between the 1970s and 1990s, dropped in the 1990s and the 2000s, and then stabilized again in the 2010s, almost 10 Gini points lower. The main driver behind the fall was the global income convergence between developed and developing countries, a finding that has also appeared in previous studies of global inequality. We document a rise in within-country dispersion that muted the convergence impact; while between-country inequality fell by 15 Gini points, within-country inequality rose by 5 points. Our occupational-sectoral data also allow us to examine labor-market related drivers, and we find that a large part of the decline was driven by rising agricultural earnings, especially in China and India. We also find that industry-sector occupations experienced an earnings convergence, which could indicate trade effects on 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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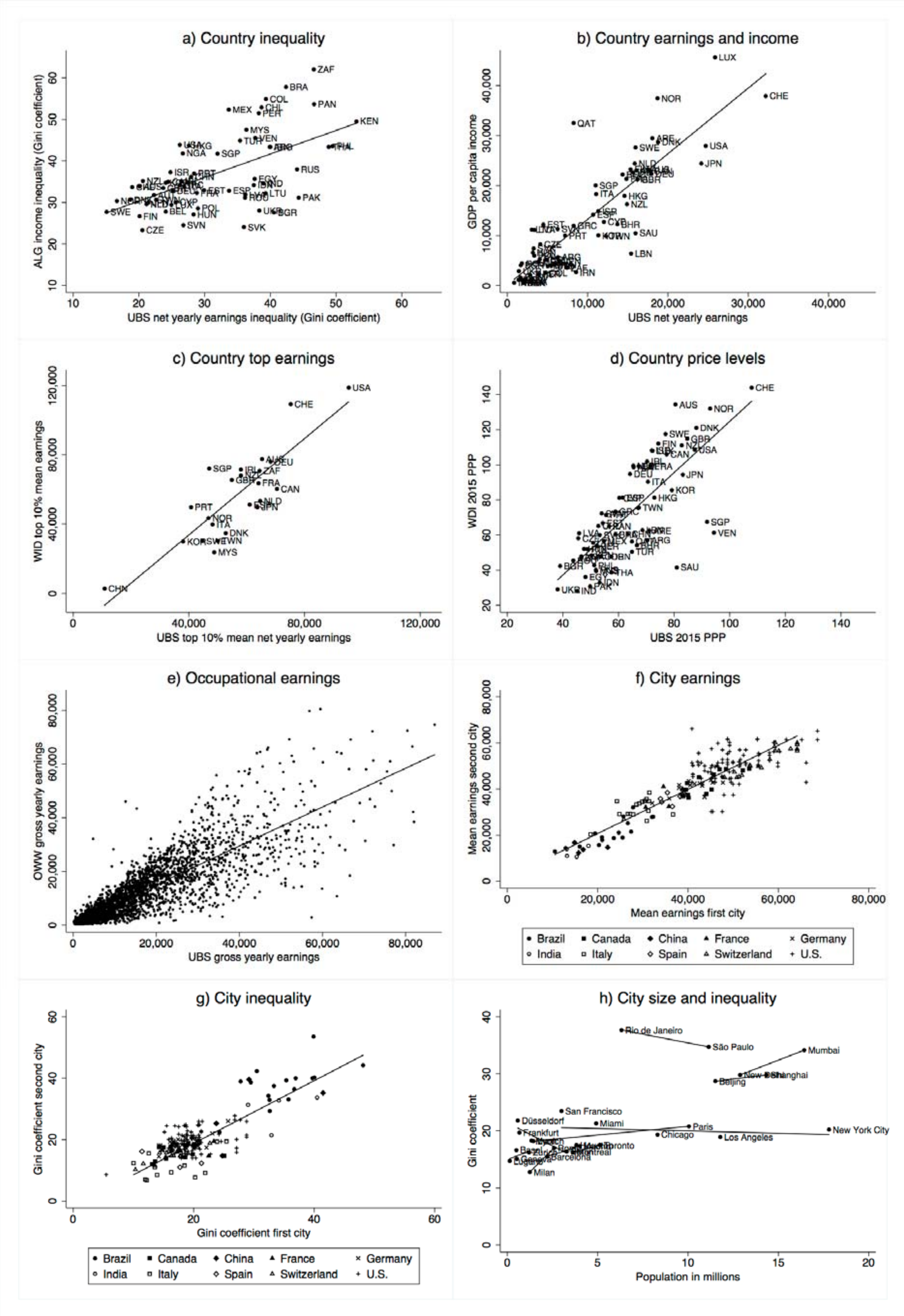
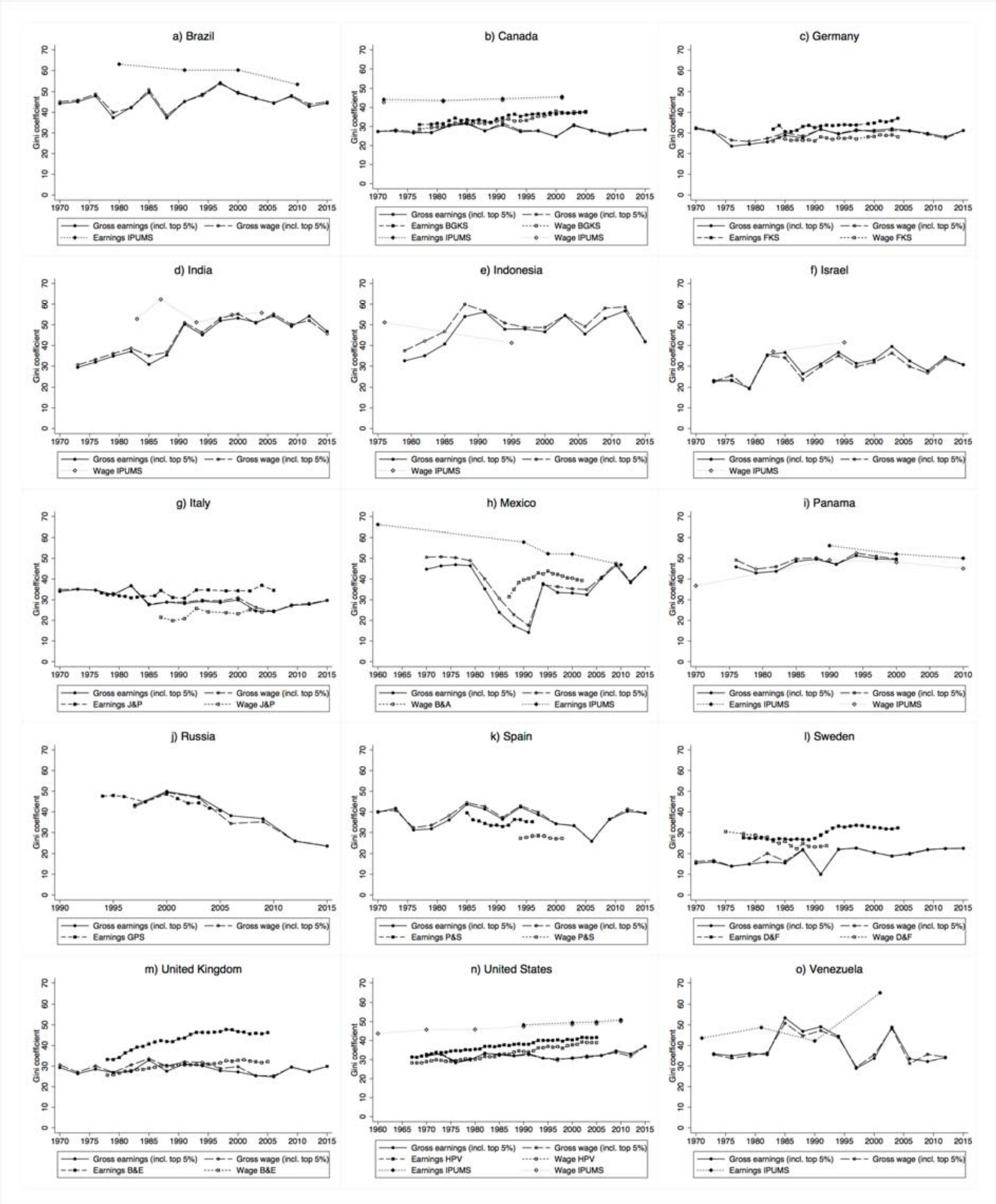
Figures

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).

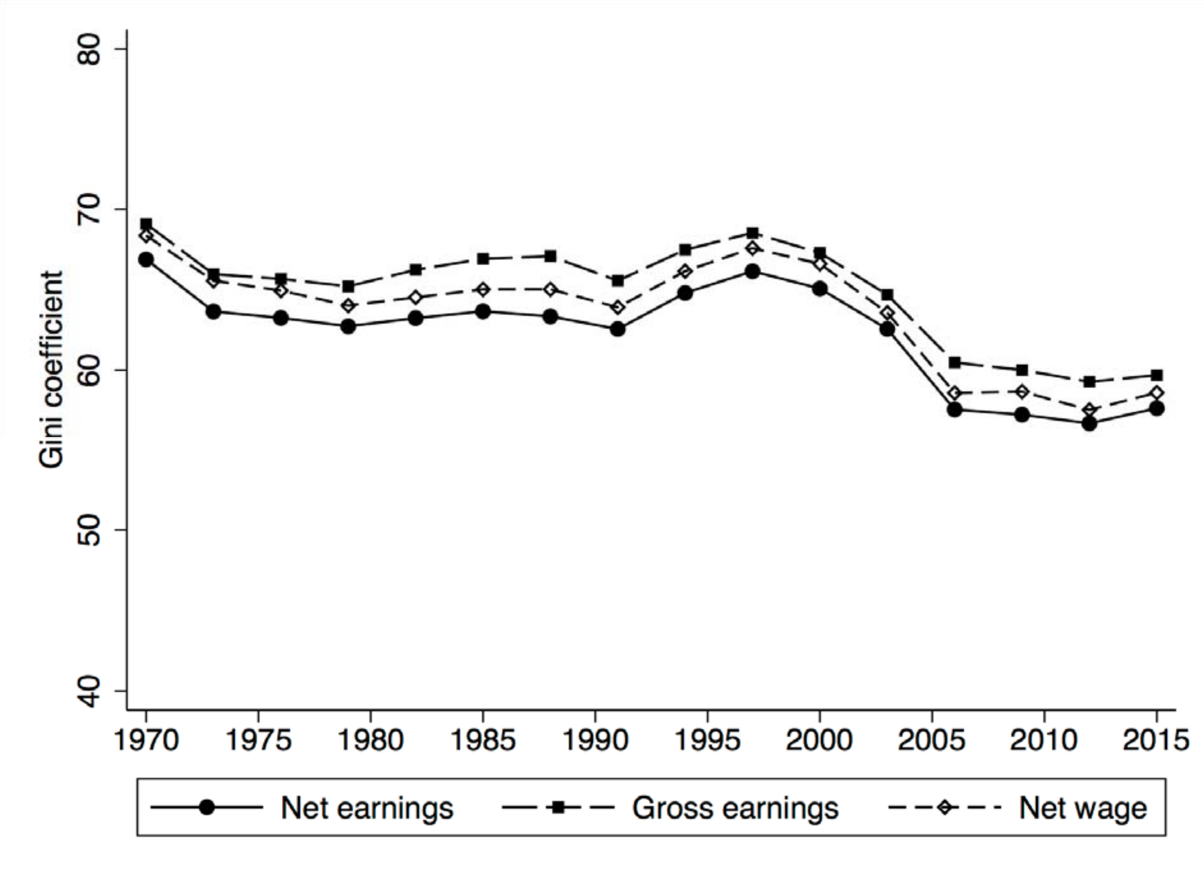
Figure 2: Some country-specific earnings inequality trends and comparisons.



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.

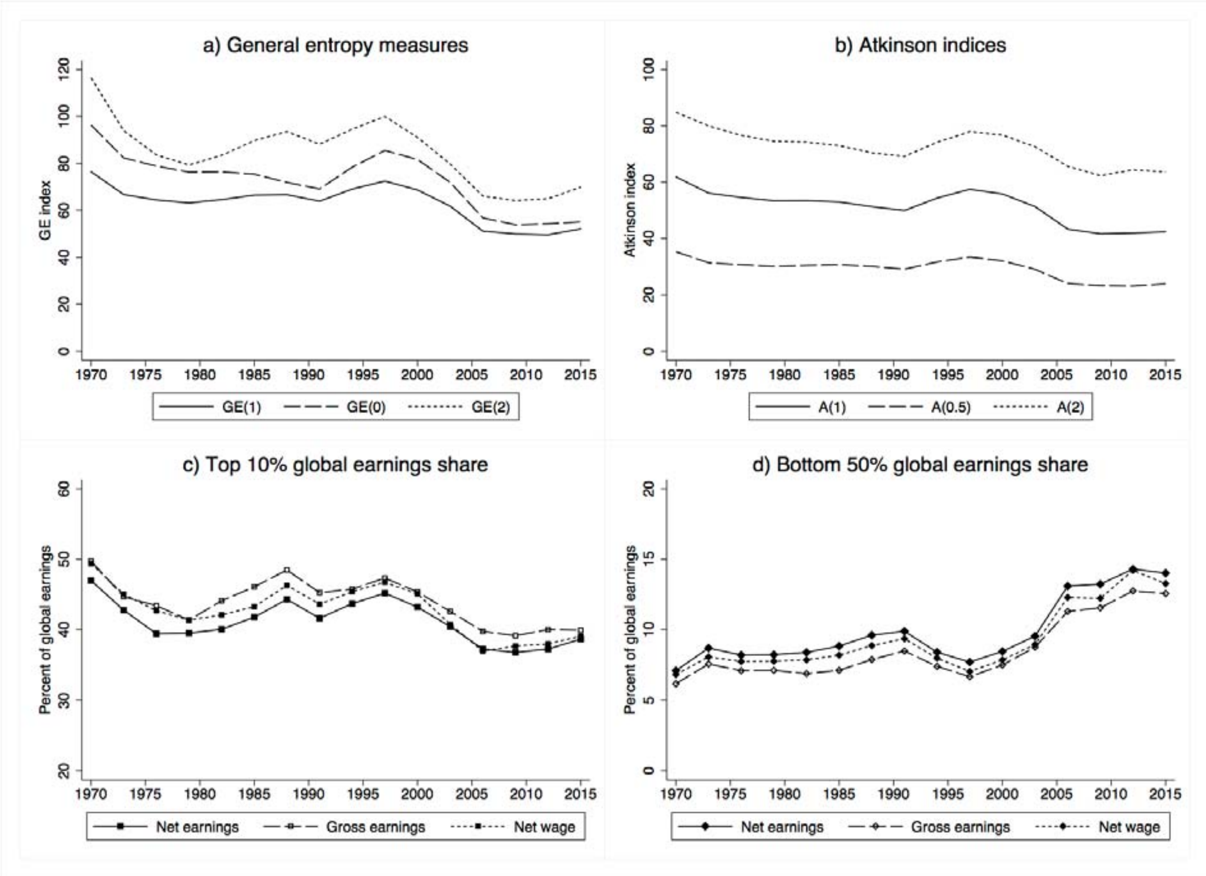
Sources: Authors' calculations based on data described in the text; Binelli and Attanasio (2010); Blundell and Etheridge (2010); Brzozowski, Gervais, Klein and Suzuki (2010); Domeij and Flodén (2010); Fuchs-Schündeln, Heathcote, Perri and Violante (2010); Gorodnichenko, Peter and Stolyarov (2010); Krueger and Sommer (2010); Jappelli and Pistaferri (2010); 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.



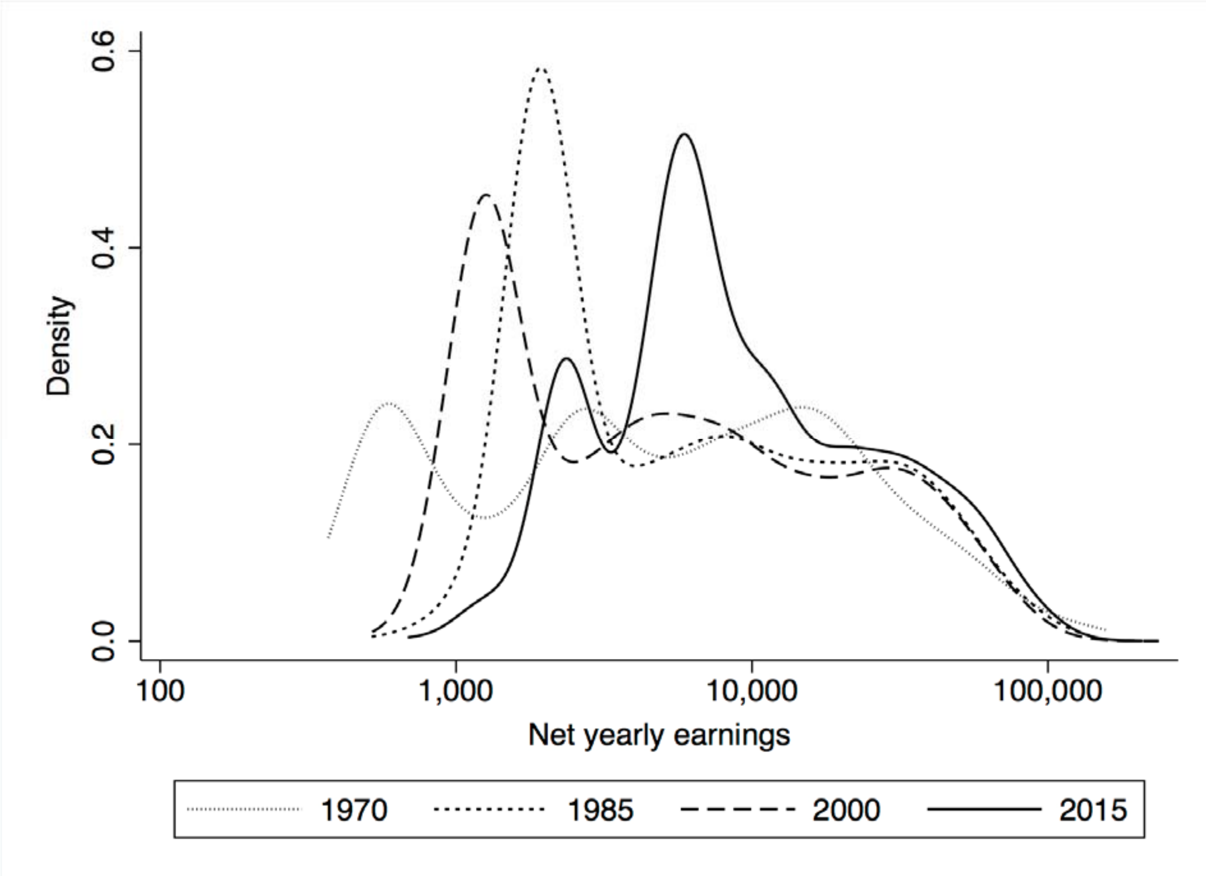
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD, weighted by working age populations and including the unemployed. Earnings refer to yearly earnings and wages to hourly earnings.
Source: Authors' calculations based on data described in the text.

Figure 4: Other measures of global earnings inequality trends.



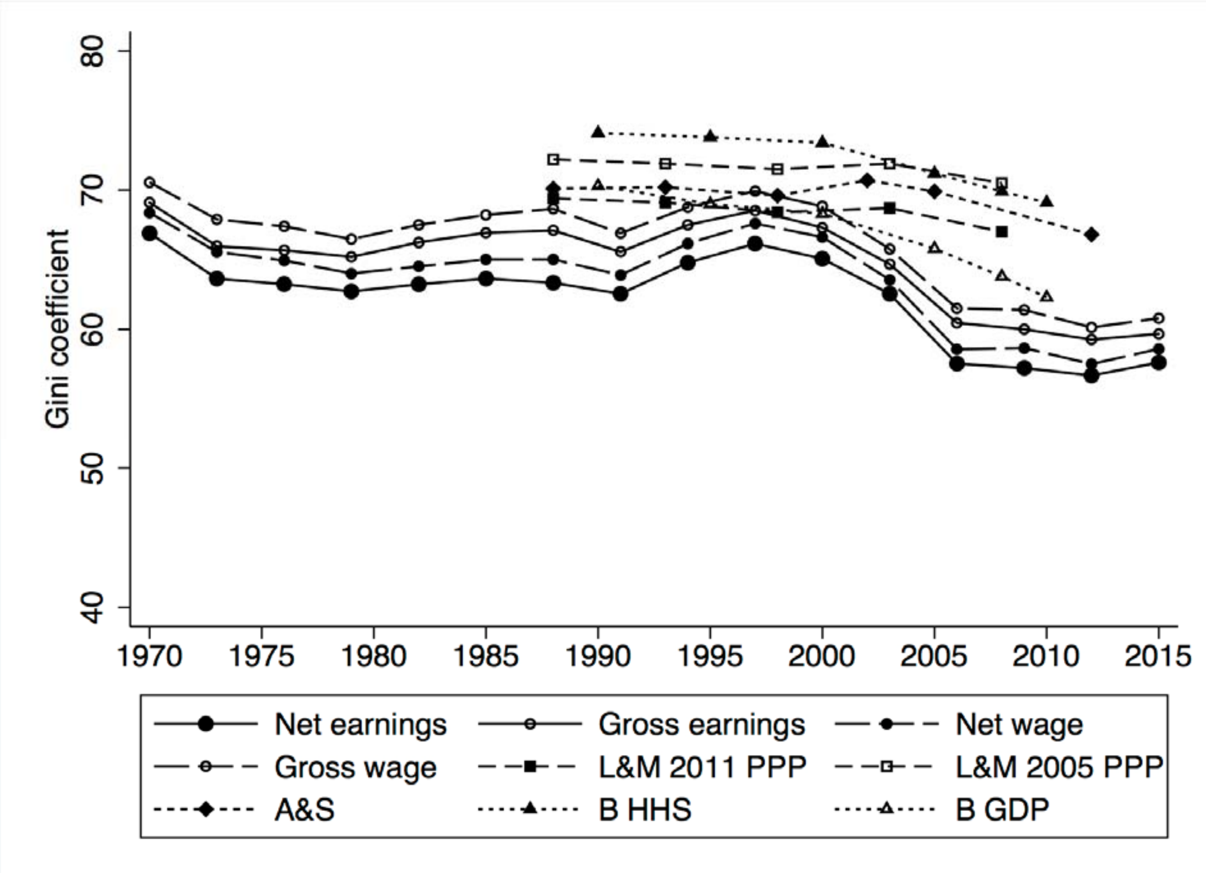
Notes: Calculations based on net yearly earnings (if nothing else specified), PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations, excluding the unemployed. Earnings refer to yearly earnings and wages to hourly earnings.
Source: Authors' calculations based on data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

Figure 5: Kernel densities over time.



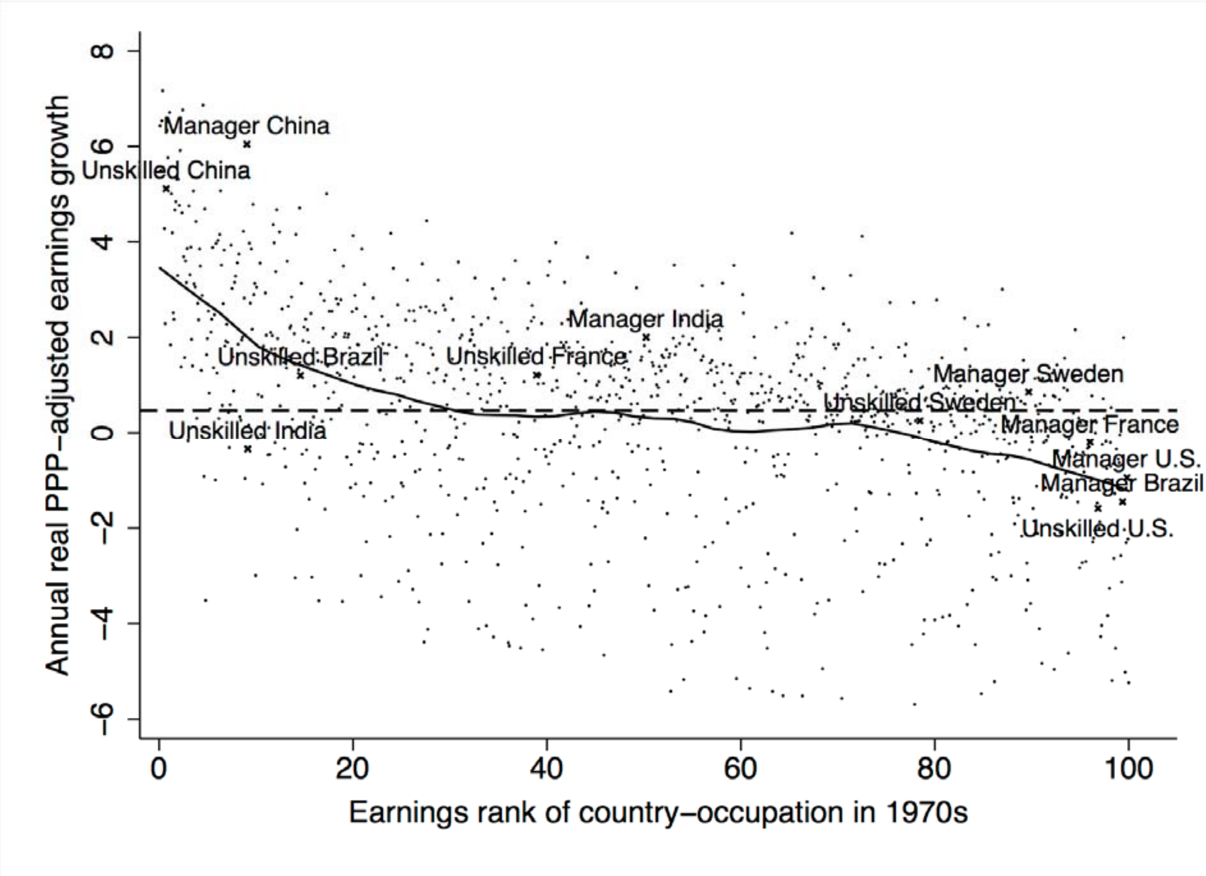
Notes: Density of log net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations, excluding the unemployed. Horizontal axis in log scale. Gaussian smoothing.
Source: Authors' calculations based on data described in the text.

Figure 6: Earnings versus income inequality comparisons.



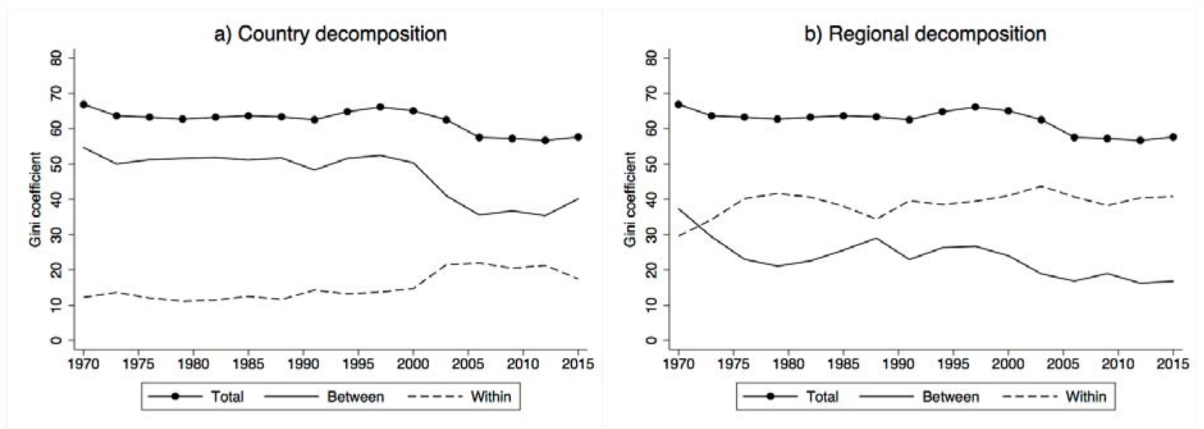
Notes: Net and gross earnings and wage inequality refer to this study and are based on yearly and hourly earnings, respectively, which are PPP-adjusted using UBS price levels in 2015 USD and weighted by working age populations including the unemployed. L&M refers to Lakner and Milanovic (2015). A&S refers 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: Non-anonymous growth incidence per country-occupation, 1970s-2010s.



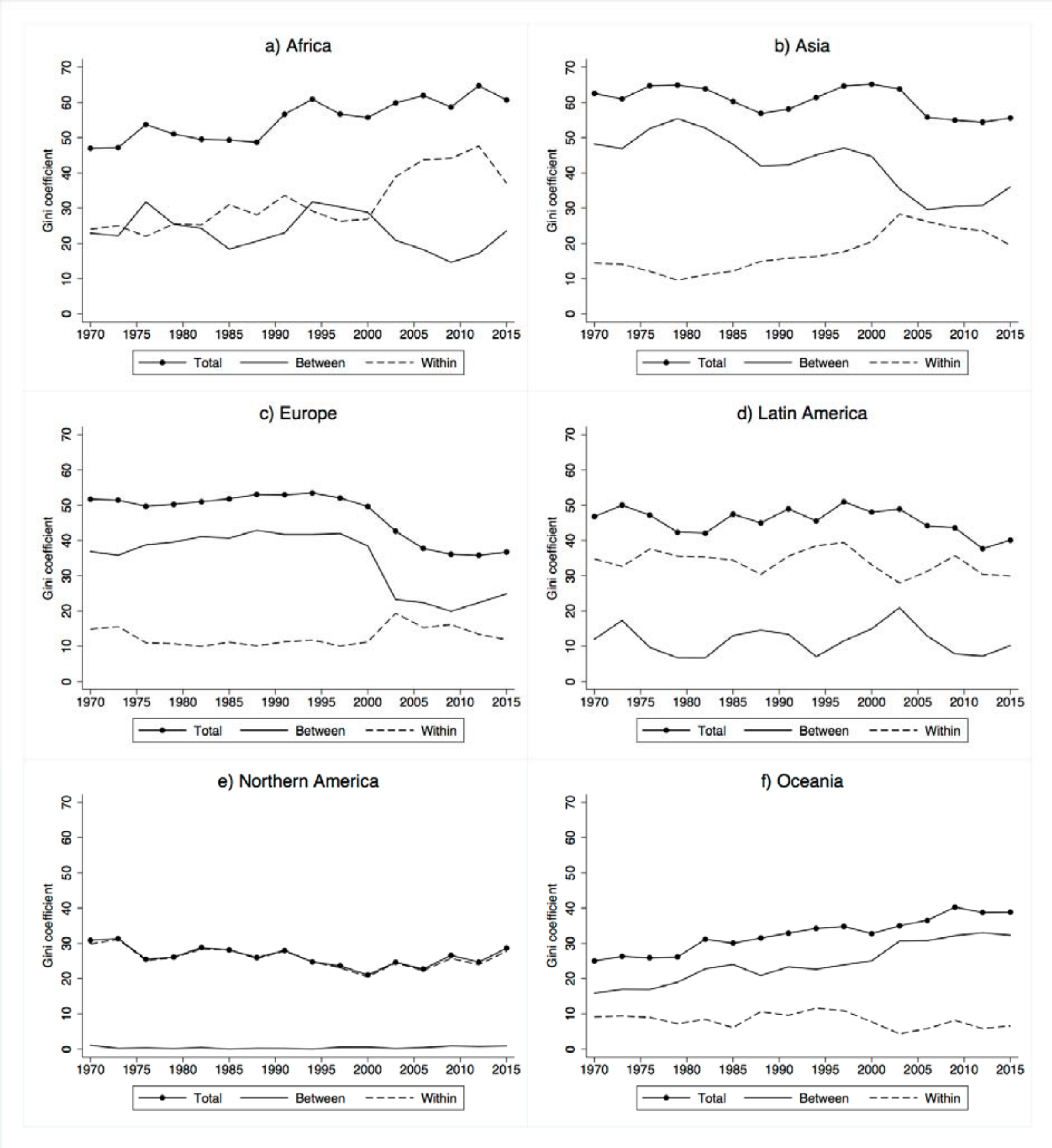
Notes: Average annual country-occupation growth rate 1970s-2010s in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), where each observation represents a country-occupation. Dashed line shows average annual earnings growth rate 1970s-2010s for all country-occupations, and solid line 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 8: Decomposing inequality within and between countries and regions.



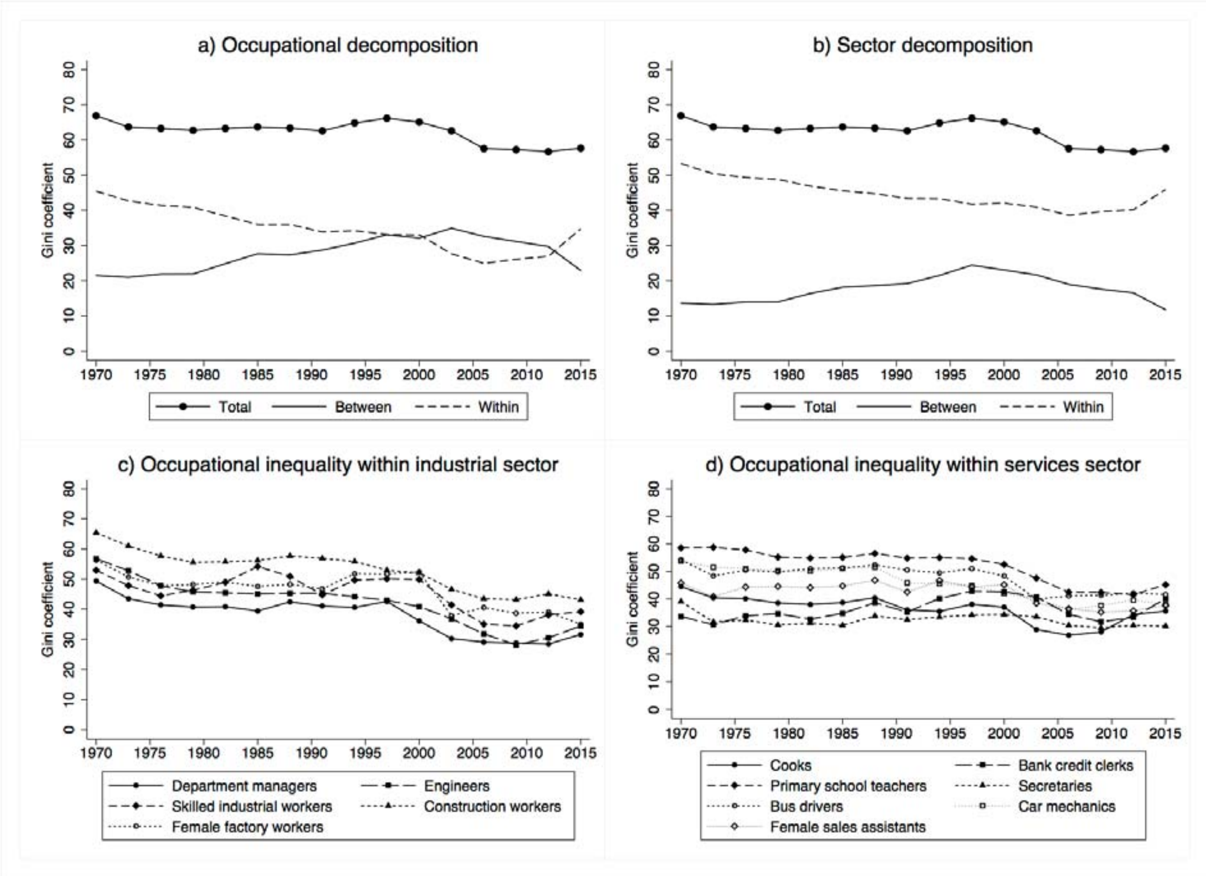
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations including the unemployed. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini 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 9: Earnings inequality in world regions and its country decomposition.



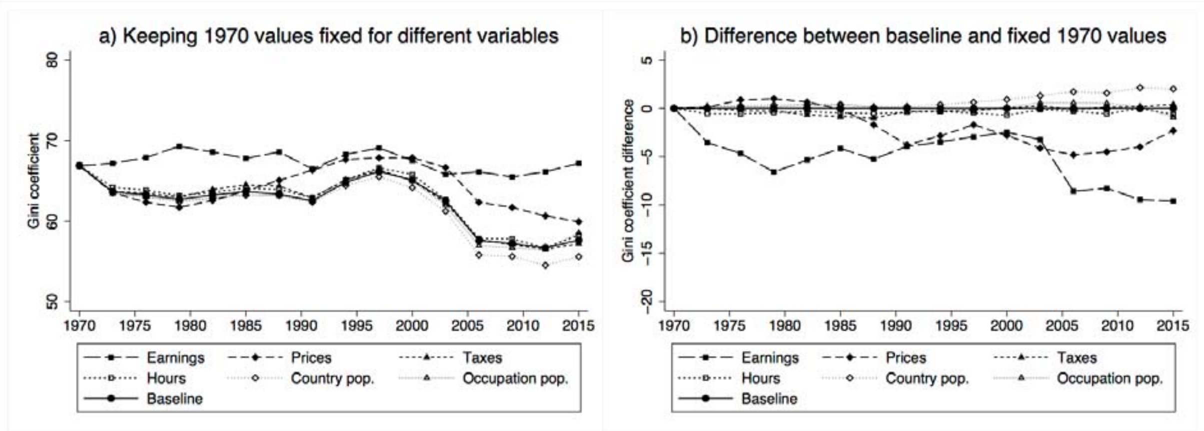
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations including the unemployed. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total regional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

Figure 10: Occupational and sectoral decompositions of global earnings inequality.



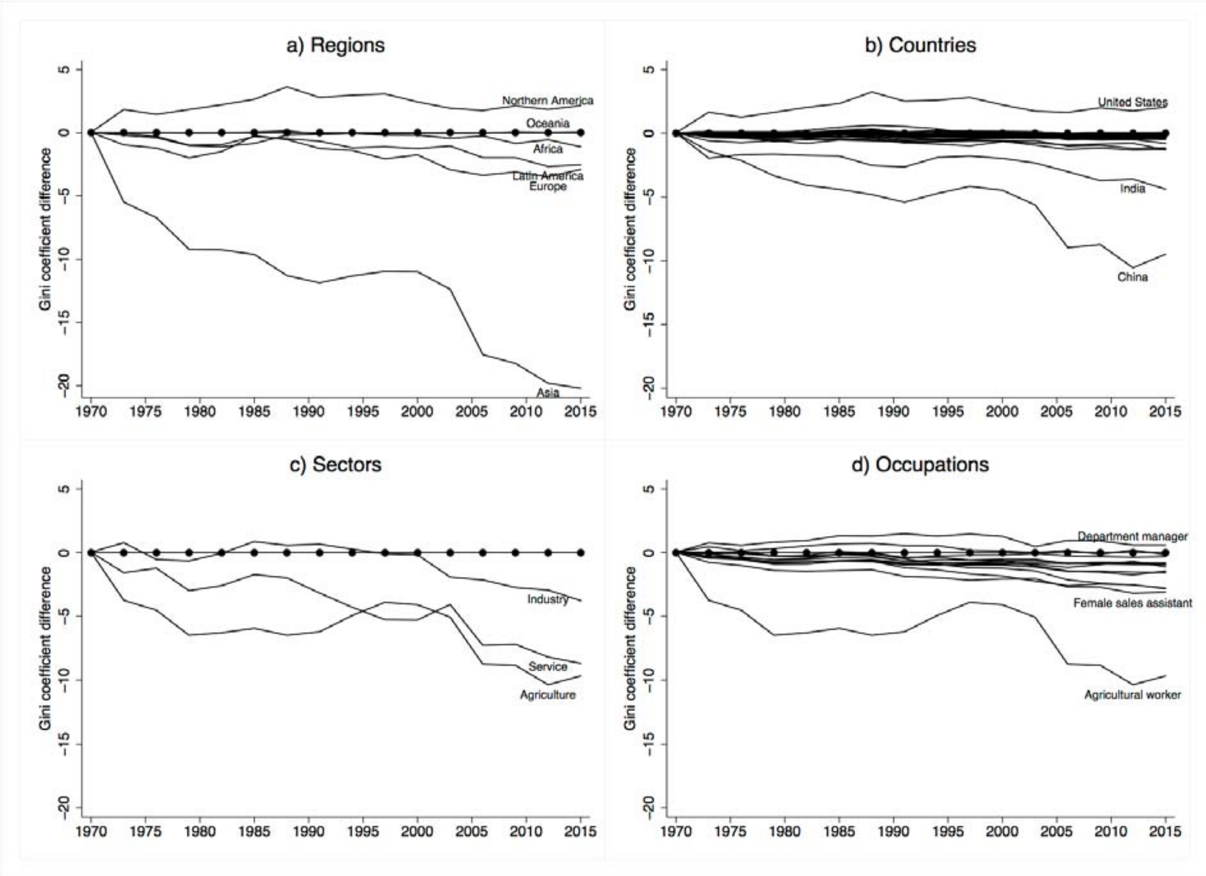
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations. a) and b) Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient 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 11: Counterfactual analysis: holding different factors constant.



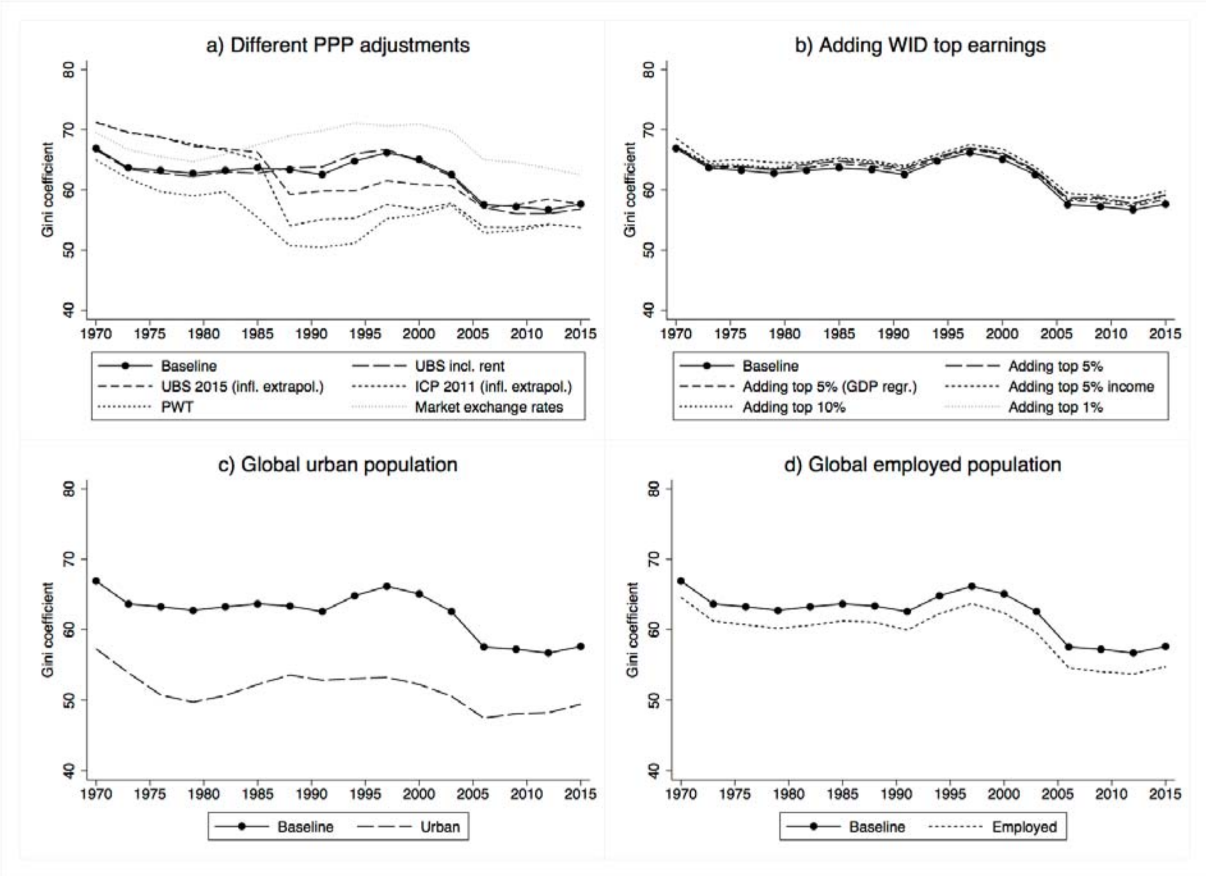
Note: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and including the unemployed. Earnings imply holding gross hourly earnings (wage) constant.
Source: Authors' calculations based on data described in the text.

Figure 12: Difference between actual Gini and counterfactual Gini with fixed 1970 earnings.



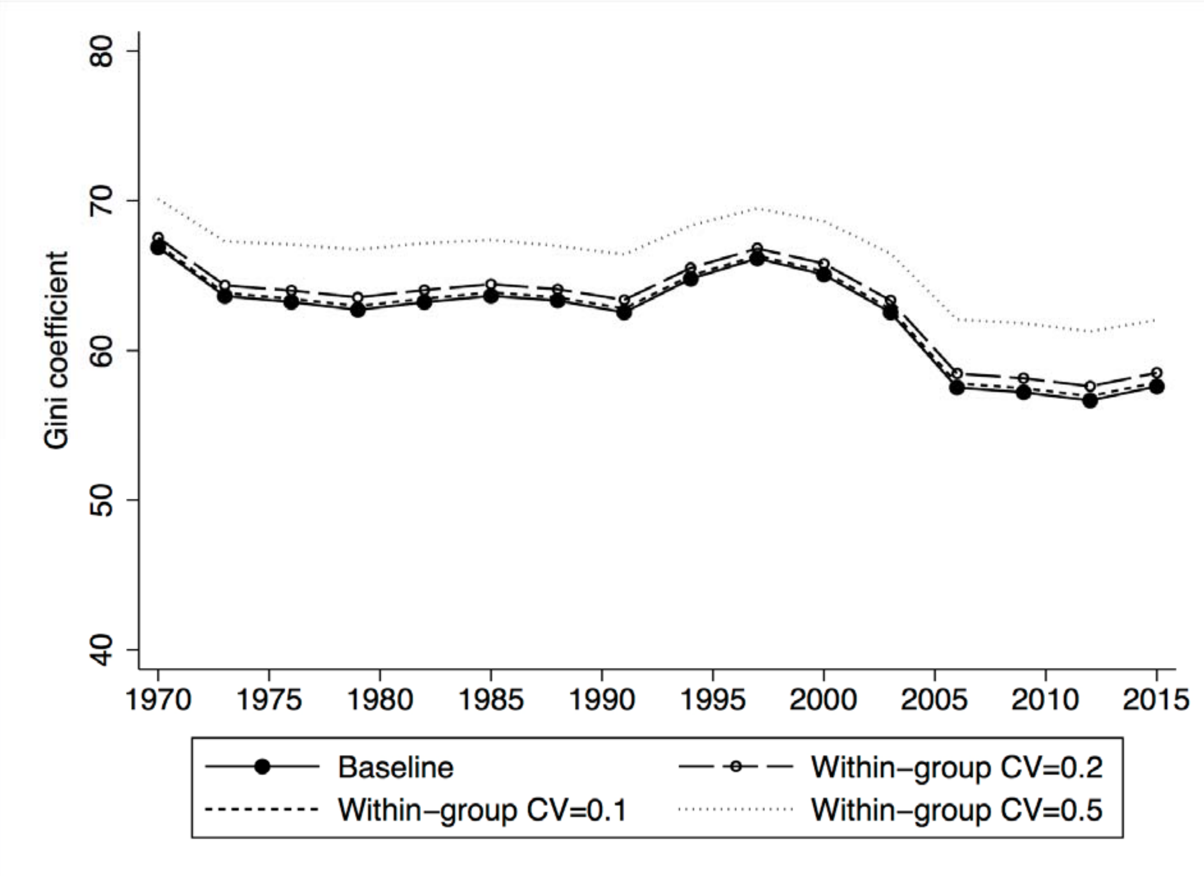
Note: Difference between actual global earnings inequality and counterfactual with gross hourly earnings (wage) held constant. Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and including the unemployed.
Source: Authors' calculations based on data described in the text.

Figure 13: Varying price indices, adding top earnings and using alternative populations.



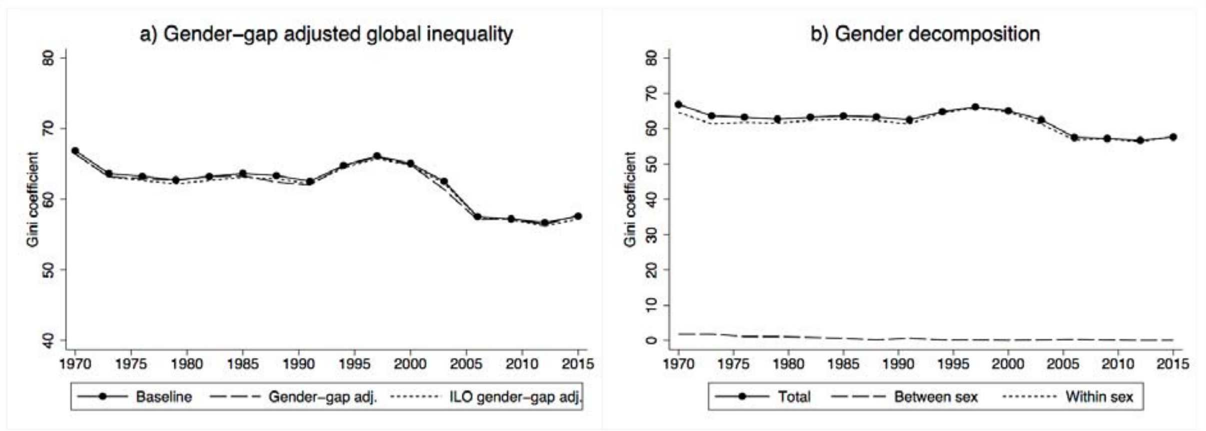
Notes: Calculations based on net yearly earnings, PPP-adjusted using UBS price levels in 2015 USD (if nothing else specified), and weighted by working age populations including the unemployed (if nothing else specified). a) Baseline implies UBS PPP excluding rent. For UBS 2015 and ICP 2011, prices are 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) 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 ($Top5income = 4431 + 3.71 \cdot GDPpercapita$). c) 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. d) Employed means that the unemployed are excluded.
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 including the unemployed. 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. b) 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.
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

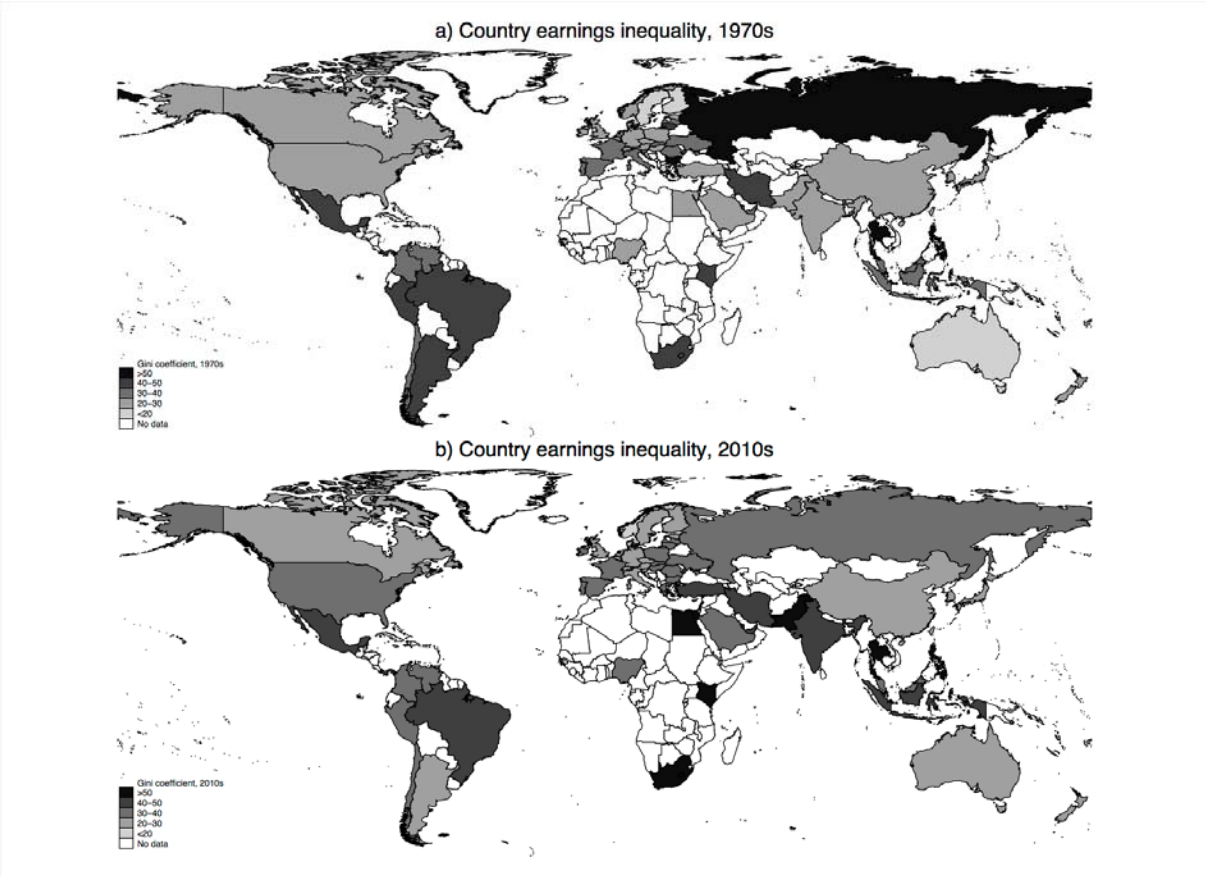
“Global earnings inequality, 1970-2015”

Hammar, Olle and Daniel Waldenström

June 2017

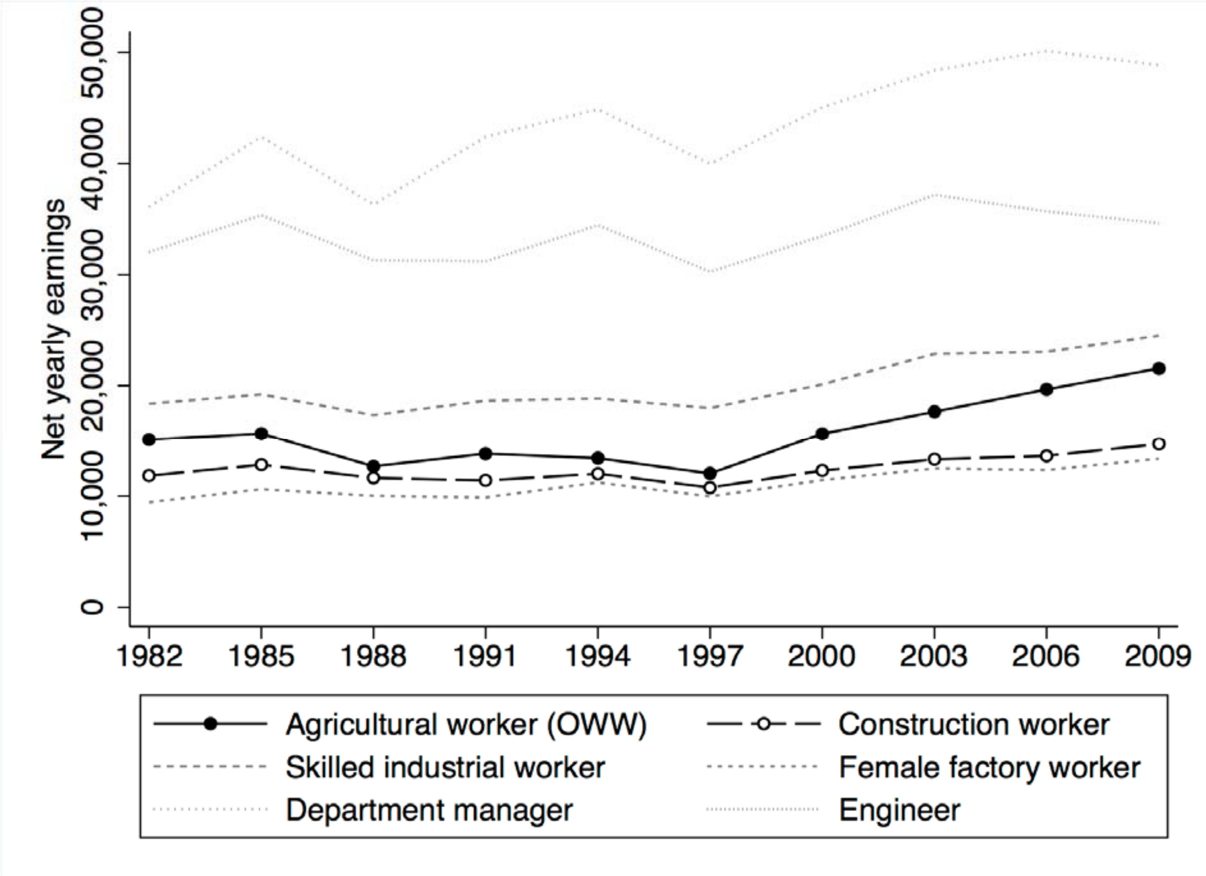
Appendix figures

Figure A1: Average earnings inequality around the world, 1970s and 2010s.



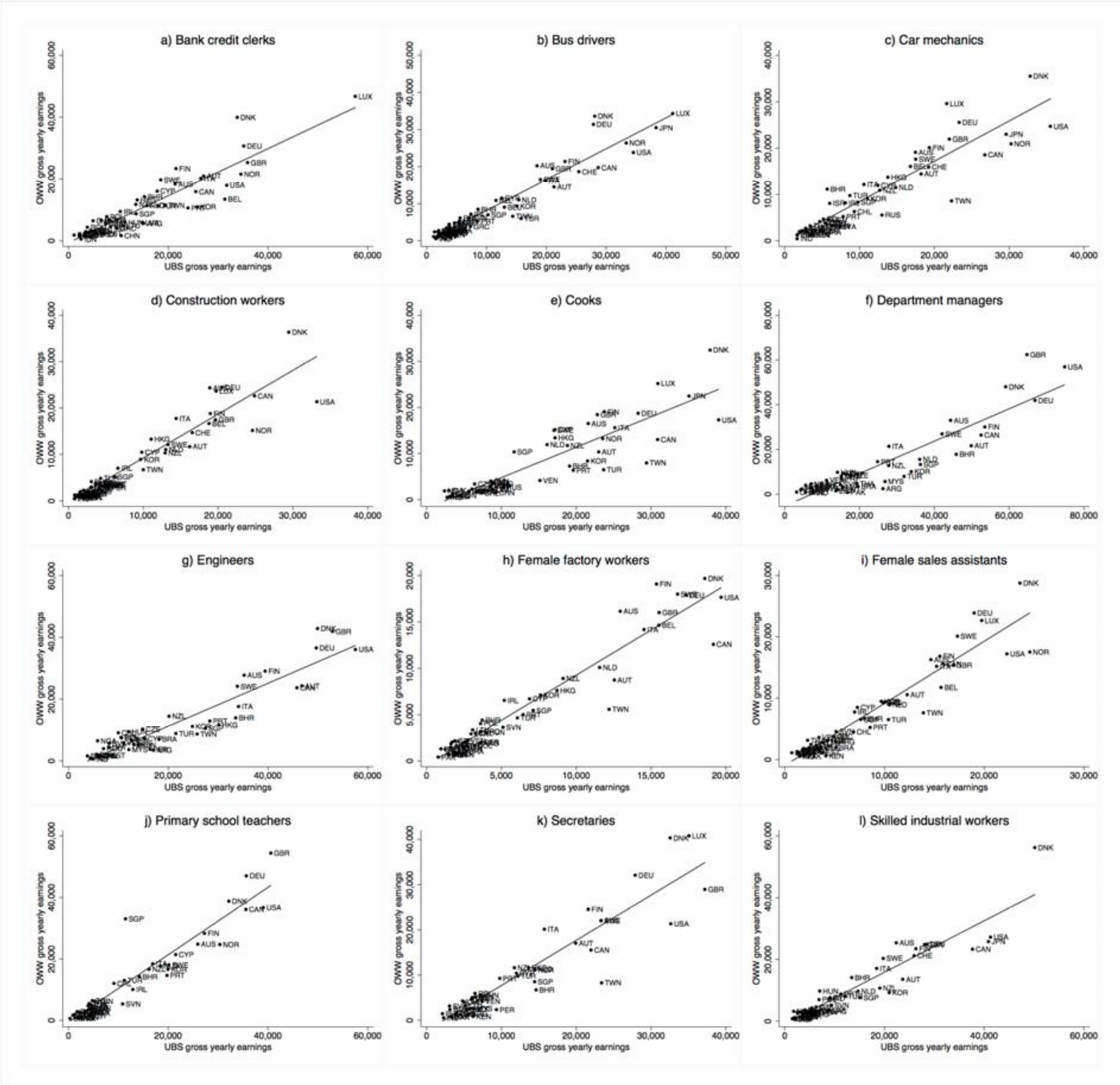
Notes: Average country-level Gini coefficients based on net yearly earnings and weighted by occupational group populations including the unemployed and the top 5 percent earnings added from the WID. Decade averages for 1970s and 2010s correspond to the years 1970-1979 and 2006-2015, respectively.
Sources: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

Figure A2: Agricultural worker earnings trend.



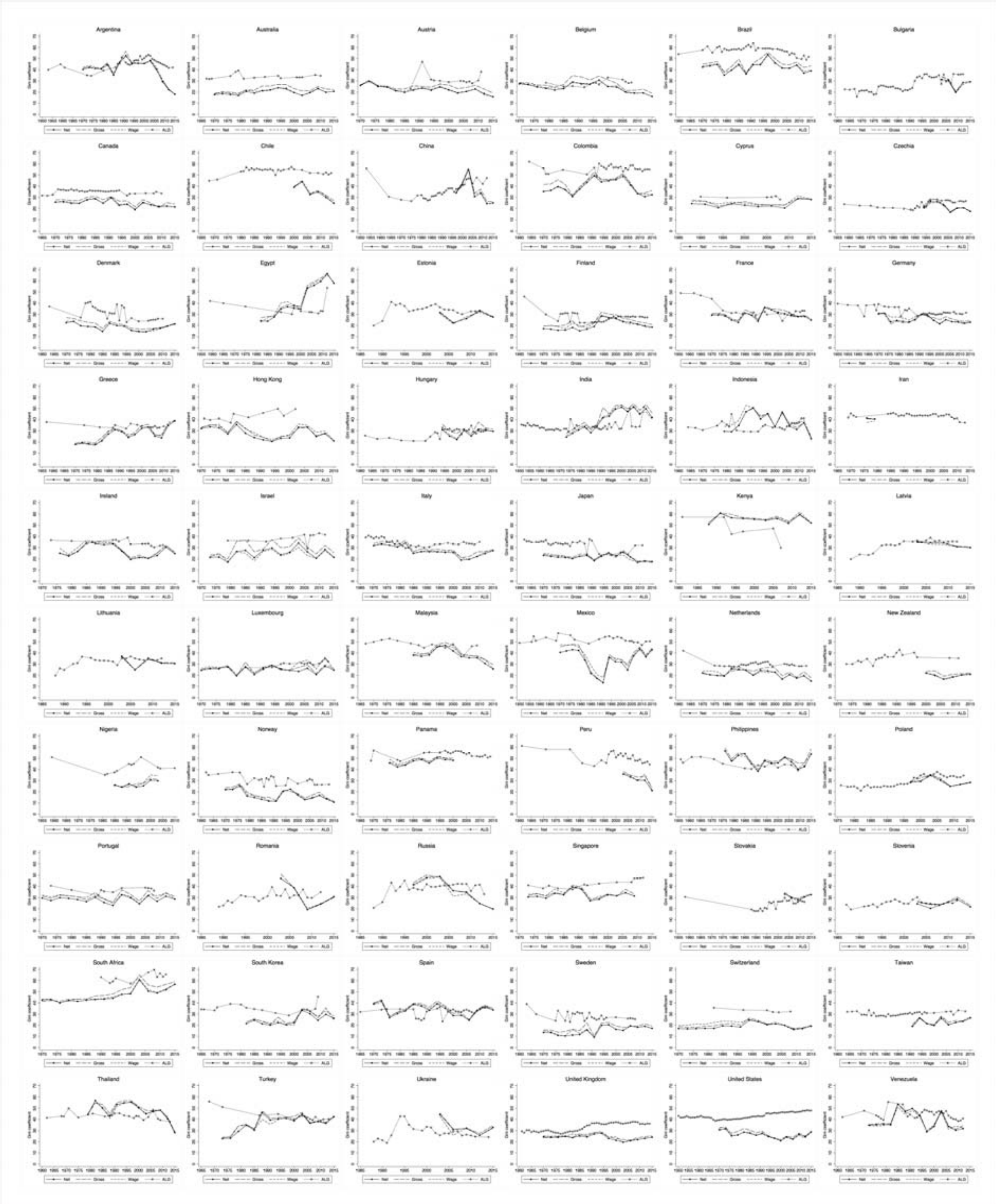
Note: Unweighted global average net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) per occupation in the agricultural and industrial sectors. Agricultural worker earnings based on the Occupational Wages around the World (OWW) database; other occupations based on the UBS.
Sources: Authors'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

Figure A3: Occupational earnings correlations.



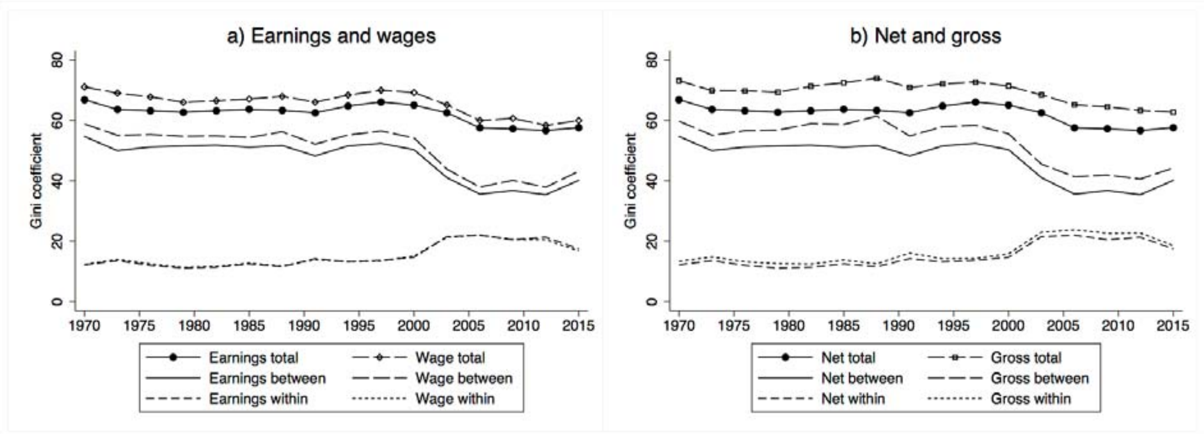
Note: Country-occupation average gross yearly earnings in current USD in the UBS and the Occupational Wages around the World (OWW) datasets.
Sources: Authors' calculations based on data described in the text; Freeman and Oostendorp (2012).

Figure A4: Country-level inequality trends and comparisons.



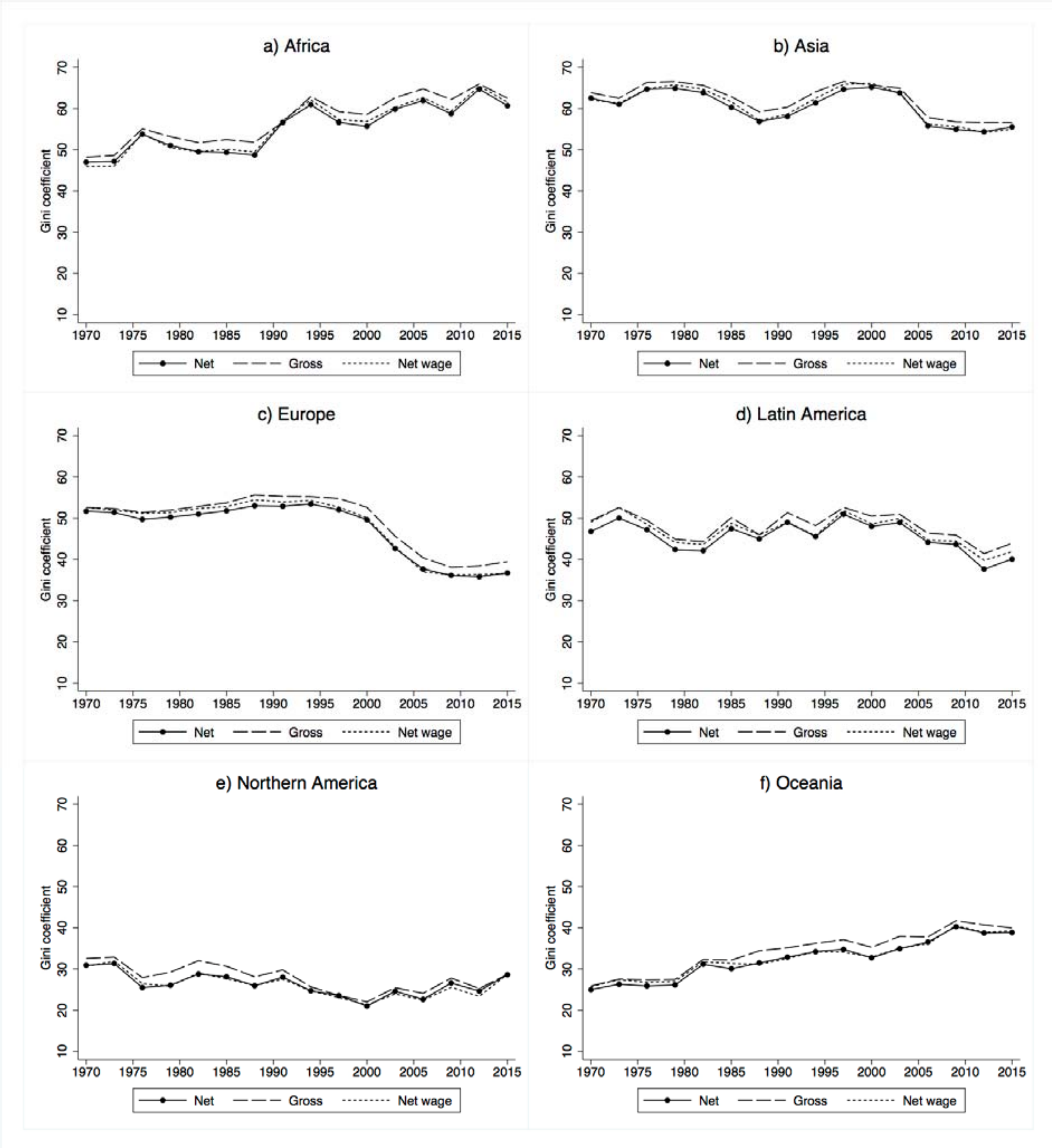
Notes: Net, gross and wage refer to this study and are country-level Gini coefficients based on net yearly, gross yearly and net hourly earnings, respectively, weighted by occupational group populations including the unemployed. Extrapolated years are excluded. All the Ginis (ALG) refers to Milanovic's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

Figure A5: Within and between country decomposition: working hours and taxes.



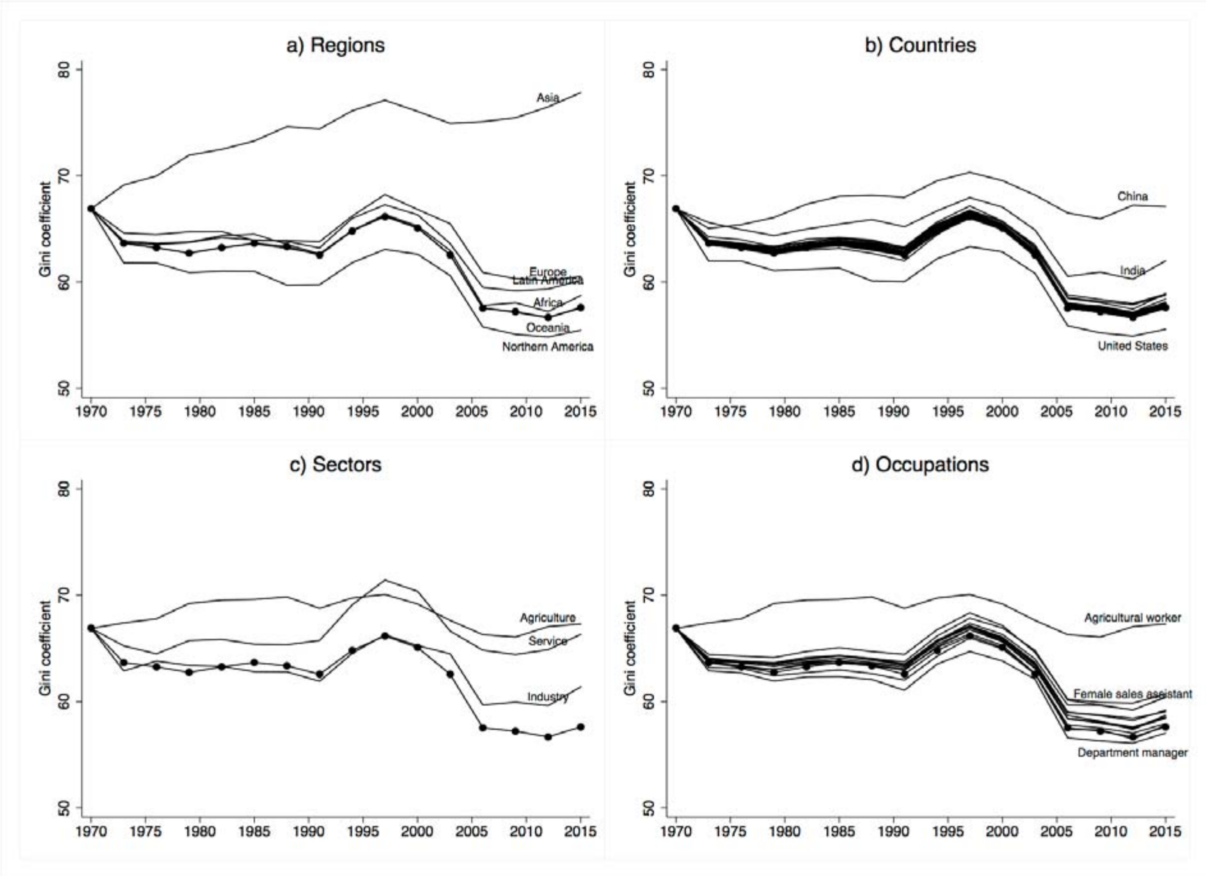
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD and weighted by working age populations. Within and between decompositions calculated as their Theil index, GE(1), contributions excluding the unemployed scaled by total global Gini coefficient. a) Earnings refer to 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 A6: Regional earnings inequality, 1970–2015.



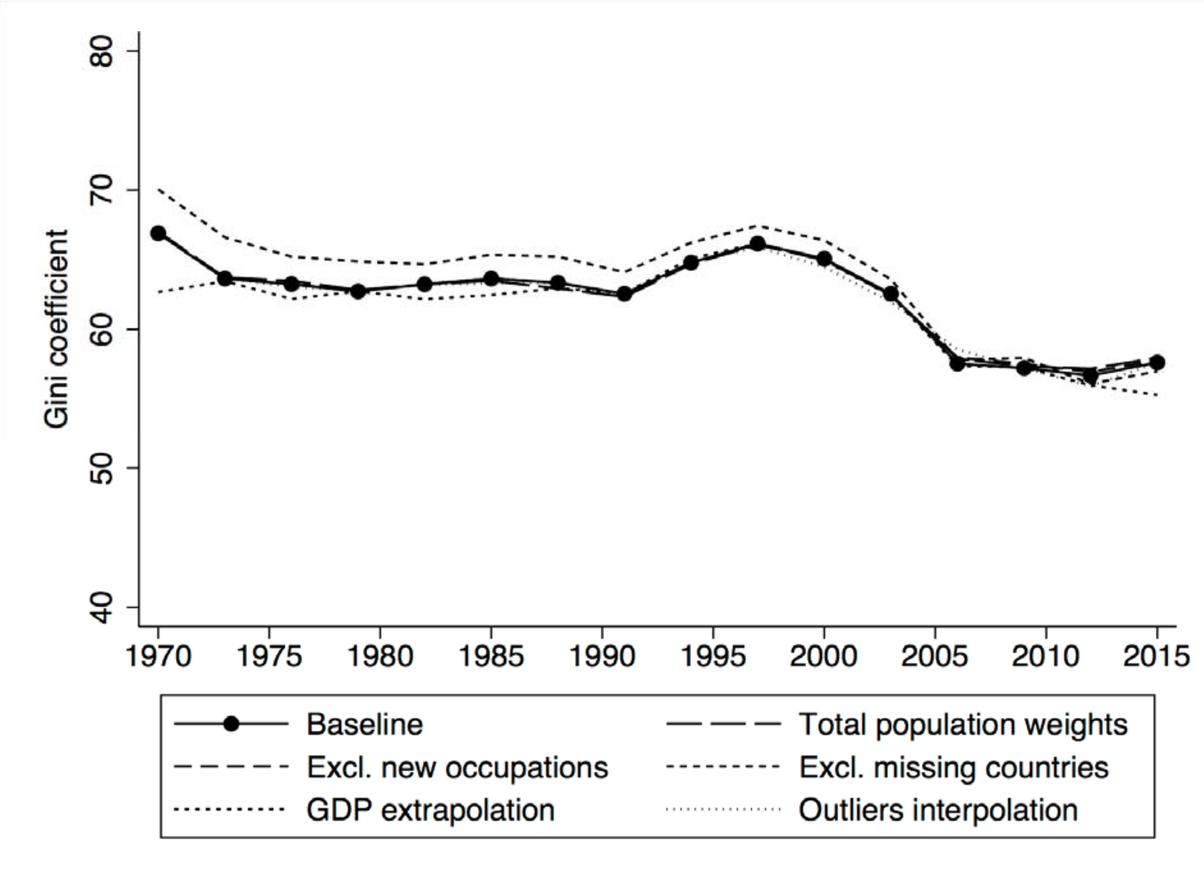
Note: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD and weighted by working age populations including the unemployed. Net and gross refer to yearly earnings and net wage to hourly earnings. *Source:* Authors' calculations based on data described in the text.

Figure A7: Fixed 1970 earnings for different regions, countries, sectors and occupations.



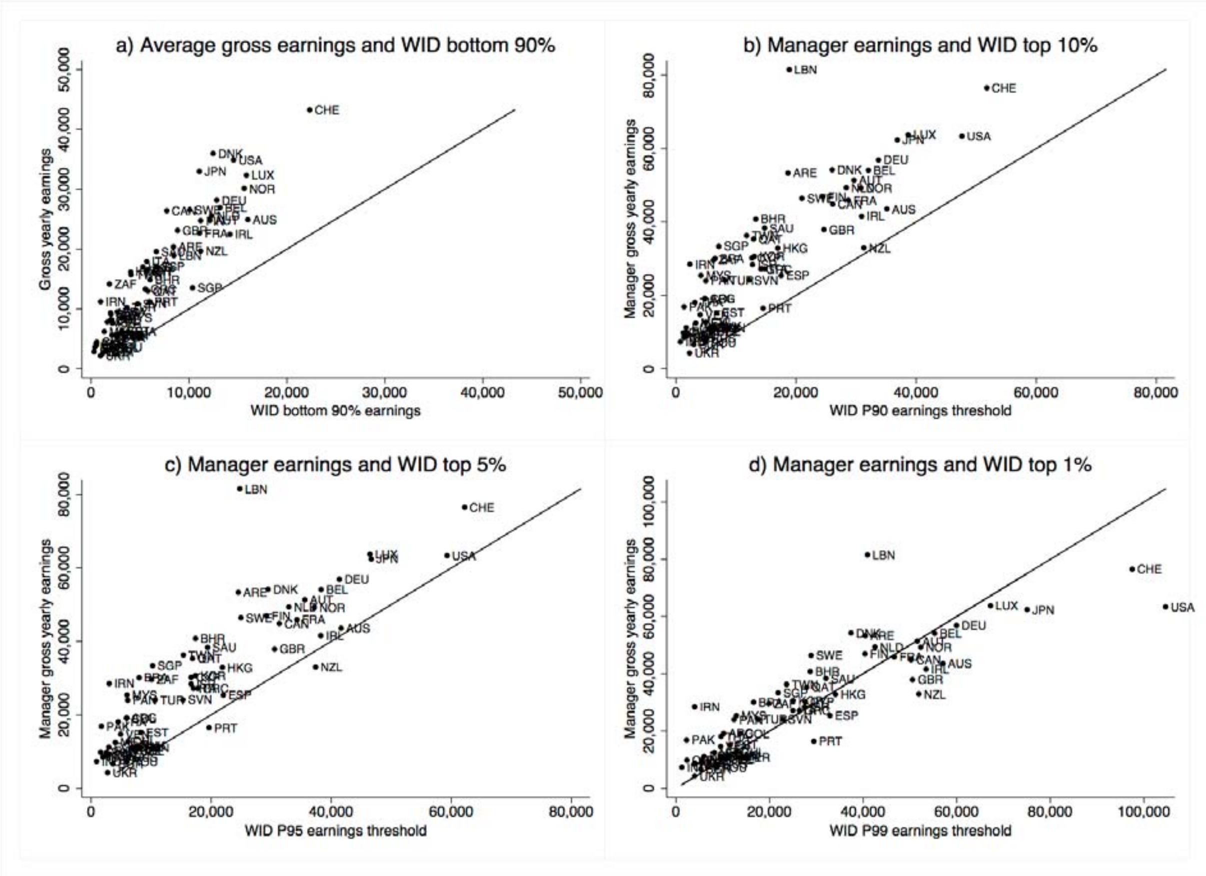
Note: Counterfactual global earnings inequality trends with gross hourly earnings (wage) held constant. Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and including the unemployed.
Source: Authors' calculations based on data described in the text.

Figure A8: 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 including the unemployed. 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. For outlier interpolation, we drop all earnings observations with a three-year change larger than 100 percent, and instead interpolate these observations linearly.
Sources: Authors' calculations based on data described in the text; World Bank (2016).

Figure A9: 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*

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.