Global Earnings Inequality, 1970–2018*

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Abstract:

We estimate trends in global earnings dispersion across occupational groups by constructing a new database that covers 68 developed and developing countries between 1970 and 2018. Our main finding is that global earnings inequality has fallen, primarily during the 2000s and 2010s, when the global Gini coefficient dropped by 15 points and the earnings share of the world's poorest half doubled. Decomposition analyses show earnings convergence between countries and within occupations, while within-country earnings inequality has increased. Moreover, the falling global inequality trend was driven mainly by real wage growth, rather than changes in hours worked, taxes or occupational employment.

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The world economy has undergone tremendous change over the past decades and questions about distributional consequences are often heard: Has the world become a more or less equal place? What are the main patterns underlying this development? Answering questions about global inequality is difficult since distributional data around the world are not always well-measured or comparable across countries and time. Despite this, a small research literature has estimated a global household income distribution by combining available information from household surveys, national accounts and administrative tax records (Milanovic, 2002, 2005, 2016; Anand and Segal, 2008, 2015, 2017; Bourguignon, 2015; Lakner and Milanovic, 2015; Alvaredo *et al.*, 2017).[1] The results so far are uncertain, but they suggest that global household income inequality (as measured by, for instance, the Gini coefficient) has decreased since the late 1990s, despite high income growth in the global top. They also find that a key driver behind this development has been an income convergence between poorer and richer countries.

In this paper, we construct a new global inequality dataset by using previously unexploited data on labour earnings in the working population that have been collected consistently around the world over the past fifty years. Our aim is to estimate the trend in *global earnings inequality* from 1970 to 2018 and to analyse underlying patterns and potential driving factors. Our contribution to the literature is threefold. First of all, we are the first to focus on labour earnings and wages among the global workforce, rather than on total incomes among households, when measuring global inequality. Second, we use data that were created with the explicit purpose to be comparable and consistent over both time and space, which contrasts with previously used global income datasets that are composed by mixing observations from distinct sources. Third, we observe labour market variables that allow us to decompose previously unexplored

[1] These studies, as well as ours, focus on *relative* inequality. For a discussion on *absolute* inequality, see Niño-Zarazúa *et al.* (2017) and Ravallion (2018*b*). Moreover, we follow the general practice within this literature by taking a cosmopolitan (rather than nationalistic) view on global inequality, which means that we value all people equally regardless of where they live.

dimensions of global inequality, for example, by occupations and sectors, comparing real wage rate growth with changes in labour supply, and pre- versus post-tax differences.

Our new database is based on two main sources: earnings survey data from the Union Bank of Switzerland's (UBS) *Prices and Earnings* (1970–2018) reports and labour market statistics from the International Labour Organization (ILO). The earnings data have been collected by the UBS using the same methodology in a total of 89 cities around the world, every three years since 1970. These data contain homogenous information about earnings, working hours and taxes in a total of 19 different occupations in 68 countries, which represents about 80% of the world's population and over 95% of the world's gross domestic product (GDP). The UBS data also contain local prices collected in the exact same location and time frame as the earnings data, which means that we can adjust for local price level differences. We create the global labour force by matching these UBS occupations to occupational employment statistics from the ILO (2010, 2018), using the *International Standard Classification of Occupations* (ISCO), together with unemployment data and country working age populations from the World Bank's (2018) *World Development Indicators* (WDI).

There are some important limitations with the UBS earnings data. First, in the UBS data, the observational units within a country are occupations, not individuals. This means that we will underestimate inequality both nationally and globally since we do not observe the individual earnings variation within each country-occupation.[2] A closely related problem is also that we only have earnings for a limited number of occupations and therefore lack variation both within and between missing occupations. Our main approach to examine how these issues affect our

[2] Note that the previous global inequality literature also uses grouped data but where, instead of country-occupations, their lowest level of observation is a country-decile or ventile. Since our baseline estimations include 20 occupations this means that the number of observational units are similar.

results is to compare our within-country series to corresponding microdata estimates for all countries with available data in the *Luxembourg Income Study* (LIS, 2017) and similar sources. These comparisons confirm that our levels of inequality are lower than the estimates using individual-level data, but also that we match the microdata-based within-country inequality trends remarkably well. Based on estimates from these comparisons, we are able to adjust our global inequality series for the missing dispersion within occupational groups (that is, both for missing occupations and for missing variation within occupations). We find that these adjustments increase our estimated level of global earnings inequality by relatively little (between one and four Gini points).

Second, another main limitation is that the UBS data have only been collected in major cities. The first implication of this urban coverage is that we lack certain rural-specific occupations, of which we add the most important one, namely agricultural sector earnings, from Freeman and Oostendorp's (2012) *Occupational Wages around the World* (OWW) database. The other implication is that we might still miss earnings variation, both within and between countries, if earnings levels within given occupations differ systematically between urban and rural areas. Our main approach to deal with this issue is to purchasing power parity (PPP)-adjust for urban prices at the local city level. Our (relatively strong) assumption is thus that any systematic differences in earnings between rural and urban areas would be fully captured by corresponding price differences. This assumption is supported by within-sample checks, where we compare price-adjusted earnings and inequality in cities of different sizes within the same country, and find no relationship between city population and earnings or inequality in our data. Nevertheless, it is still possible that, for example, urban earnings are relatively higher than rural earnings in developing, compared to developed, countries. If so, this would imply that we underestimate global inequality.

A third, and final, potential issue with the UBS data is limited coverage of top and bottom earnings. Comparisons with top earnings data from the *World Inequality Database* (WID, 2018) show that our data seem to cover top earnings reasonably well up to the top five percentiles. Moreover, when we add national top earnings from the WID to our data, we find that this has a very limited effect on our global earnings inequality estimates (which then increase by approximately one Gini point). At the lower end of the earnings distribution, we add the unemployed population in each country, which we assign zero earnings. However, our data and estimations do not include any earnings from the informal sector. While we cannot check the implications of this explicitly, we believe that it is plausible to assume that some of the workers who were officially registered as unemployed had some form of informal-sector earnings. If this is the case, this means that in our baseline analysis we ascribe them too low earnings and, as such, overestimate both country- and global-level earning inequality. In an alternative analysis, we therefore exclude the unemployed, instead focusing exclusively on the employed global workforce, finding that this yields only a slightly lower level of global inequality (approximately two Gini points lower).

Our main finding is that global earnings inequality has fallen during the past decades, after being stable at a high level from the 1970s until the 1990s. The decline occurred during the 2000s and 2010s, with the global Gini coefficient decreasing by 15 points (from 65 to 50) and the earnings share of the bottom half of the global distribution more than doubling (from 9% to 19%). Global inequality is lower for yearly earnings than for hourly wages, which suggests a negative relationship between earnings and hours worked at the global level. We also find that global post-tax inequality is approximately two Gini points lower than global pre-tax inequality. When decomposing global inequality into within- and between-country contributions, we find that earnings convergence across counties accounts for the entire fall in global inequality, primarily driven by high earnings growth in China and India. However, inequality within countries has increased since the 2000s, from representing about one-fifth to one-third of total global inequality. Counterfactual analyses, where we hold the 1970 values of different variables constant, show that the declining global inequality trend is driven mainly by relative changes in real wage rates rather than in labour supply, as reflected by hours worked and occupational employment shares, or in demographics. When we decompose the global earnings inequality trend across occupations and sectors, we find that the earnings growth of agricultural workers in China and low-skilled workers in India are particularly important and only slightly offset by rising managerial earnings in the United States. Finally, we observe a stronger earnings convergence in the traditionally traded (industrial) sector than in the non-traded (services) sector. While such an analysis lies outside the scope of this paper, this could indicate that trade globalization matters for global inequality trends.

The results of the study are robust to a number of sensitivity checks and alternations, including using alternative samples, inequality measures, imputation methods, populations, and PPP-adjustments (see the accompanying Online Appendix for further details). Comparing our results with the previous literature, we find that global inequality in earnings and wages are lower than global inequality in total incomes. The trends are similar, but with a slightly larger inequality decline for global earnings. While these deviations could be due to capital incomes, pensions and other transfers included in total household incomes, the overall similarities suggest that labour market outcomes stand for most of overall global inequality.

The remainder of the paper is organized as follows. Section 1 describes the data and construction of our *Global Earnings Inequality Database*. Section 2 presents the main trends, Section 3 their decomposition in different dimensions, and Section 4 concludes. Further details and validations as well as sensitivity and heterogeneity analyses are presented in the supplementary Online Appendix.

1. Data and Estimation Procedure

Our analysis builds on previous attempts to estimate global inequality by constructing an income distribution of the global population. Early attempts to do so used population-weighted national per capita incomes to measure the global distribution of income (for example, Deaton, 2010). This “Concept 2” of international inequality (Milanovic, 2005) captures between-country inequality, but neglects inequality within countries.[3] The more recent literature has instead used household income and consumption surveys from different countries compiled into a unified global population (Anand and Segal, 2015, 2017; Lakner and Milanovic, 2015).[4] In this paper we follow this latter “Concept 3” approach of global inequality (Milanovic, 2005), albeit with a slightly different focus. That is, we build on the measurement approaches of, for example, Lakner and Milanovic (2015), but construct a unified global distribution of earnings and wages (rather than total incomes or consumption) among occupational groups (instead of household quantiles). As such, our dataset is constructed by combining earnings data from the UBS surveys with occupational employment statistics from the ILO and country populations

[3] A comparison of this “Concept 2” of international (between-country) inequality in terms of labour earnings versus total income is presented in Figure C3 in the Online Appendix.

[4] A combination of the two concepts is used by, for example, Sala-i-Martin (2006). An overview of the early literature is provided in Anand and Segal (2008), whereas Ravallion (2018*a*) provides a review of two recent volumes by Bourguignon (2015) and Milanovic (2016).

from the World Bank.[5] This section briefly describes these data and the construction of our dataset. More detailed descriptions of the database are given in the Online Appendix.[6]

The key advantage of using the UBS earnings data is the comparability and consistency they offer across both time and space. Previous estimations of global inequality have merged household surveys from various countries and sources that often differ in sample definitions, observational unit (individuals or households), outcome measure (income or consumption), or time of measurement (Anand and Segal, 2008, 2015). Household surveys are also a fairly recent phenomenon which is why previous studies usually begin their analyses in the late 1980s. Our database covers a significantly longer time period as it includes the entire 1970s and 1980s as well as the most recent decade.[7]

Another advantage of the UBS data is that we can study global inequality along dimensions that have not been investigated before. For instance, we can compare the outcomes using yearly earnings versus hourly wages (that is, accounting for average weekly working hours) and pre- versus post-tax earnings. The previous global inequality studies differ from us in that they examine total income or consumption, which usually include earnings, pension income and also capital income, typically after taxes and transfers, and how they are distributed among all households including both working age adults and old-age pensioners. For this reason, if we were to encounter similar global inequality trends using our earnings data, this would quite

[5] A database somewhat similar to ours is the University of Texas Inequality Project (UTIP), which contains data on pay inequality within and between different countries and regions around the world (see, for example, Galbraith, 2007). That project, however, differs from us by focusing primarily on industrial wages and comparing national inequality levels rather than estimating a global earnings distribution. Moreover, the UTIP project estimates inequality between different manufacturing branches, rather than occupations.

[6] Online Appendix A contains details about the database and how we have constructed it. Appendix B presents a number of validation tests where we compare our data and inequality estimations with those available from other sources. Finally, Appendix C presents sensitivity analyses regarding the robustness of our findings.

[7] There are previous studies on global inequality that cover much longer time spans, but that use other data sources such as national accounts (for instance, Bourguignon and Morrisson, 2002, and Atkinson and Brandolini, 2010).

plausibly rule out strong influences from top capital incomes, pensions or other transfers. Another motivation for focusing solely on earnings and wage rates could, for instance, be that these outcomes are more closely connected to the distribution of human capital. As for the limitations with our data and analyses, we discuss them in the following sections.

1.1. Earnings, Taxes, Working Hours and Prices

The *Prices and Earnings* reports, collected by the UBS every third year between 1970 and 2018, represent a standardized price and earnings survey conducted locally by independent observers in a large number of cities around the world. In the latest edition (UBS, 2018), more than 75,000 data points were collected for the survey evaluation. The UBS data have previously been used by, for example, Braconier *et al*. (2005) to construct measures of wage costs and skill premia, and of selected wage gaps by Milanovic (2012). To our knowledge, our study is the first to use these data to construct broader measures of earnings inequality.

The UBS data collection involved questions on salaries, income taxes (including employee social security contributions) and working hours for a number of different occupational profiles that represent the structure of the working population in Europe. The underlying individual data 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. In total, the UBS survey provides an unbalanced panel of up to 89 cities in 68 countries (35 OECD members and 33 non-OECD countries) from 17 specific years covering a period of 48 years (that is, every third year between 1970 and 2018). The surveys cover four countries in Africa, 22 in Asia, 30 in Europe, eight in Latin America, two in Northern America and two in Oceania.[8]

[8] Throughout this paper, we use the United Nations' classification of macro geographical continental regions and geographical sub-regions (see Table A1 in the Online Appendix).

The data on gross and net yearly earnings in current United States dollar (USD) as well as weekly working hours cover 19 occupations in total (six from the industrial sector and 13 from the services sector), of which twelve occupations have available observations for all decades from the 1970s to the 2010s. For further description of the UBS *Prices and Earnings* data coverage, see Online Appendix A.

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 PPP. Fortunately, the UBS has compiled a price level index based on a common reference basket of more than 100 goods and services collected locally in all surveyed cities and years (where prices in New York City = 100). By dividing our earnings data by that index and deflating all years for inflation in consumer prices for the United States using WDI data (World Bank, 2018), we obtain earnings in constant New York City PPP-adjusted 2015 USD for all available occupations, cities and years.[9]

As discussed in the introduction, the UBS earnings data come in the form of occupational units and not individuals. Since we thereby lack earnings variation both within and between different occupations within these occupational groups, this is likely to bias the earnings dispersion downwards both within countries and at the global level. We examine the extent of this bias by comparing the country-level earnings inequality estimates in our data with equivalent estimates constructed from actual microdata in the LIS, the *Integrated Public Use Microdata Series* (IPUMS) and other sources. These comparisons reveal two main patterns: i) occupational inequality is lower than individual inequality within countries, and ii) this wedge appears to be

[9] As our baseline, we use this UBS price level index excluding rent. In alternative specifications, we instead use price level data from the *International Comparison Program* (ICP) 2011 in the *Penn World Tables* (PWT) as an alternative PPP source, as well as the UBS price level index including rent. We also report our results without PPP-adjustments (using current market exchange rates). While the choice of PPP seems important, it does not affect our overall results (see Figure C9 in the Online Appendix).

stable over time (see Sections B.5 and B.6 in the Online Appendix for comparisons in all countries with available microdata). We also apply Modalsli's (2015) correction method that adjusts for within-group inequality by imputing within-group dispersions, based on dispersion levels observed in the country microdata comparisons (see Section 3.4 below). This adjustment leads to an increase in the global Gini coefficient by a relatively small change, up to four points.

1.2. Occupational Employment Statistics

To construct population-wide measures of earnings inequality, such as the Gini coefficient, we combine the occupational earnings with information about the relative proportions of each occupational group in the labour force of each country and over time, which implies that we are able to account for the changing occupational structure within each individual country. Data on employment by occupation are available in the ILO (2010, 2018) databases *LABORSTA* and *ILOSTAT*, where the economically active population in each country is disaggregated by occupational groups according to the latest version of the ISCO available for that year. We match each of our 19 UBS occupations with the most relevant of the ISCO categories and assign that category's population to the corresponding occupation.[10] Since the ILO occupational employment statistics include both paid employees and self-employed, this means that we assume that the UBS full-time employment earnings are representative for both of these groups.[11]

Because the UBS data are built on surveys conducted in cities, our earnings data lack representation of rural earnings and, in particular, occupations assigned to the ISCO agricultural

[10] See Table A2 in the Online Appendix. We have at least one occupation with UBS earnings data for each ISCO category, except for the agricultural group.
[11] For example, if self-employed workers in developing countries earn less than those that are dependently employed (within the same occupation), while self-employed workers in developed countries earn more than their dependently employed counterparts, this would mean that we underestimate the level of global earnings inequality.

category. To adjust for this and to make our earnings data representative for the total workforce within each country, we do several things: First, we add the occupational category "agricultural workers", to which we assign the average agricultural sector earnings in the OWW database (Freeman and Oostendorp, 2012). This makes a total of 20 occupational groups with earnings and population data for our broad panel of countries and years. Each country's occupational populations are then weighted so that they sum to the country's total employed working age population (aged 15–64), to which we also add an unemployed category with zero earnings (corresponding to the country's unemployed working age population), based on the World Bank's (2018) WDI.[12] Second, we PPP-adjust earnings using local city prices, collected at the same urban locations as the earnings. If, for example, urban earnings are higher than rural earnings, our assumption is thus that these differences will be captured by corresponding differences in prices. Finally, in the countries for which our UBS data cover more than one city, we compare earnings and inequality between cities of different sizes, and find no systematic relationship between city size and PPP-adjusted earnings or inequality (see Section B.4 in the Online Appendix). However, there could still be urban-rural differences that we do not capture by these adjustments and tests. Our guess is that a potential remaining bias would be in the direction of underestimating global inequality, as we expect such a real urban-rural earnings gap to be relatively larger in developing countries.[13]

An implication of the limited number of occupations in the UBS data is that we do not have full coverage of the very top and bottom of the earnings distributions. In the case of missing top earnings, we can compare our data with administrative top earnings data in the WID. This

[12] For 2018, we use data from 2017, because the 2018 WDI data were not yet available to use. For Taiwan, which is not included in the WDI, we instead use data from National Statistics Taiwan (2018).
[13] Few studies have systematically examined urban-rural inequality gaps around the world, but Eastwood and Lipton (2000) conclude that urban-rural income gaps in developing countries seem to follow overall inequality at the country level but to be trendless at the global level.

comparison shows that our observed professions represent top earnings levels relatively well up to the 95th percentile, and adding national top earnings from the WID does not change our results (except for yielding higher earnings growth in the absolute top of the global distribution).[14] In the bottom of the distribution, we add the unemployed and assign them zero earnings. Related to this, an important category that we do not capture is informal-sector earnings. To the extent that these workers are part of the unemployed population in the official statistics, we underestimate their actual earnings and thus overestimate inequality both nationally and at the global level.[15] In one of the sensitivity analyses, we exclude the unemployed and focus exclusively on the employed global working age population, which results in a slightly lower global inequality (see Section C.9 in the Online Appendix).

1.3. Estimation Procedure

In the original UBS data (Sample I), we have 836 country-year observations (for our 20 occupations, that makes 16,720 country-year-occupation observations).[16] 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.[17] To obtain a balanced panel, we extrapolate the missing country-occupation observations by the corresponding occupational earnings growth in neighbouring countries (or, more precisely, the average sub-regional or regional change for each occupation).[18] As such, we obtain full sample coverage with

[14] See Sections B.2, C.4 and C.10 in the Online Appendix.
[15] Estimates of the informal sector and its development around the world are scarce, but a survey by Charmes (2012) suggests that its relative importance has not changed much since the 1970s.
[16] This coverage refers to country means of the included cities, after linear interpolation for missing values within a series, with full occupational coverage and including the added agricultural category. In the very raw UBS data we have 11,806 city-year-occupation observations.
[17] This kind of adjustment is not done by, for instance, 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. A similar approach to ours, however, is used by Modalsli (2017).
[18] For a more detailed description of this procedure, see Online Appendix A. In alternative specifications, we instead extrapolate the missing observations with country GDP per capita growth, as well as using average and earliest or latest observed country-occupation growth rate, with similar results (Online Appendix Section C.12).

observations from all 68 countries for all 17 time periods, that is, every third year from 1970 to 2018 (Sample II). This gives a total of 1,156 country-year observations for each of the 20 occupations, and altogether 23,120 observations for each earnings and population measure.

In Table 1, we present the database coverage separating the two data samples just described.[19] Sample II covers approximately 80% of the world's population and over 95% of its GDP. Note that despite being smaller, the original observed UBS sample (Sample I) covers on average almost 60% of the global population and over 90% of the world's GDP.

[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 our missing countries, using GDP-per-capita-weighted average sub-regional or regional occupational earnings. This sample (Sample III) yields a total of 29,580 country-year-occupation observations for each of our different statistics (or 31,059 observations including the unemployed category), and has 100% global coverage. Sensitivity analyses show that our findings are not changed by excluding these latter imputations (see Figure C13 in the Online Appendix).

From these earnings and population data, we estimate the inequality of global, regional and country earnings over the entire period 1970–2018. Our main index of inequality is the Gini coefficient, but we have also assessed the inequality trends using other measures, such as top earnings shares and generalised entropy (GE) indices. Finally, we also estimate our different inequality indices for gross and net, yearly and hourly earnings (where hourly earnings

[19] For coverage in all years, see Table A4 in the Online Appendix.

inequality corresponds to what we will refer to as wage inequality). We have also validated our data by comparing them with those from other sources, finding relatively strong correlations (see Online Appendix B).

2. Main Results

The evolution of global earnings inequality between 1970 and 2018 is presented in Figure 1. Gini coefficients for three different earnings concepts are shown: gross annual earnings, net annual earnings, and net hourly wages. The level of inequality in gross earnings is approximately two 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 the findings of Bick *et al*., 2018). Looking at the trends over the period, all three measures offer a similar picture. Global earnings inequality was virtually flat over the 1970s, 1980s and 1990s. During these three decades, the global net earnings Gini coefficient was stable around 65%. A large decline is then recorded during the 2000s and 2010s. The fall over this period is sizeable: the net earnings Gini dropped from 65% in 2000 to 50% in 2018, that is, by 15 points in two decades.

[Figure 1 about here]

As a complement to the Gini coefficient, we present in Figure 2 two other inequality measures which illustrate the evolution of global earnings inequality in different parts of the global distribution: the global earnings shares of the global top decile and the global bottom 50%.[20]

[20] Figure C1 in the Online Appendix also shows the global earnings inequality trend using two other inequality indices, namely the GE and Atkinson indices, which yields very similar results. Moreover, Figure C2 presents another view of the evolution of inequality, depicting kernel densities of absolute earnings over this period.

These series both display a decline in global earnings inequality, or an increase in global earnings equality, over the studied period. The top decile share trend looks similar to the Gini trend, except for some more volatility during the 1970s and 1980s as well as a flatter trend during the 2010s. The share of the bottom half has more than doubled, from 9% of global earnings in 1970 to 19% today. As such, these series also indicate that the overall decline in global earnings inequality comes both from a relative decline of the top and a relative increase of the bottom of the global earnings distribution.

[Figure 2 about here]

Next, we examine how our global earnings inequality series relate to other estimates of global inequality: Figure 3 contrasts our gross and net earnings and wage Gini coefficients with the Gini coefficients for global income or consumption, as presented by Lakner and Milanovic (2015), Bourguignon (2015), and Anand and Segal (2017).[21] Some interesting results emerge from this comparison. First, the level of inequality we find in earnings is markedly lower than in surveyed income and consumption, with Gini coefficients being approximately seven percentage points lower. One important explanation for this gap is that our focus on the working age population implies that we exclude many low- or zero-earners such as students and retirees. Another reason is that our earnings data do not include incomes from capital, which are more unevenly distributed than income from labour, and transfers. Moreover, our data are based on occupational group averages instead of averages in income groups such as deciles.

[21] We use their inequality indices based on household surveys without imputed top income shares in order to increase the comparability across sources. While Anand and Segal (2017) PPP-adjust using the 2011 ICP round, Bourguignon (2015) uses the 2005 ICP round. As argued by Deaton and Aten (2017), using the ICP 2005 PPP is likely to overestimate global inequality. For Lakner and Milanovic (2015), we present their results using both the 2005 and 2011 ICP rounds.

Second, the trend in inequality is relatively similar and points in the same direction: A decrease in recent decades from high and relatively stable levels in the late 1980s and 1990s to a lower level in the late 2000s and early 2010s. A main takeaway from these comparisons is thus that the overall levels and trends of global inequality are strikingly similar when we only include labour earnings (that is, excluding incomes from capital, pensions and other transfers) among the global workforce instead of total incomes among households. Yet, looking at magnitudes, the decrease is larger in earnings than in total income and consumption. A plausible explanation for this difference could be an increasing role of capital that counteracts the convergence in earnings. Another possible explanation could be welfare system expansions in developing countries where, for example, old people do not have to work but instead get pensions (and hence lower incomes). A related analysis is also presented in Section C.3 in the Online Appendix, where we compare the "Concept 2" of international inequality (Milanovic, 2005) using country-mean earnings versus GDP per capita to estimate between-country inequality for labour earnings and total incomes, respectively. This analysis confirms that the convergence between countries has also been larger for labour earnings than for GDP per capita.

[Figure 3 about here]

Growth incidence curves (GIC), showing the rate of earnings growth across the distribution, offer another way of examining the evolution of inequality (Ravallion and Chen, 2003). Figure 4 depicts a so-called non-anonymous GIC by country-occupation, 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, on average, global real

(PPP-adjusted) earnings grew by approximately 1% annually. However, seen over the entire earnings distribution in the 1970s, the growth rates differ considerably. The lower half of the global distribution recorded 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.[22] The anonymous GIC,[23] depicted in Figure C4 in the Online Appendix, shows a similar pattern with above-average growth in the lower part of the global earnings distribution and below-average growth in its upper part. Because the UBS data are likely to lack observations in the very top of the distribution, we have also done this analysis adding national top earnings from the WID, which generates a pattern similar to Lakner and Milanovic's (2015) "elephant curve" with relatively high growth rates in the very top of the global distribution (see Section C.4 in the Online Appendix).

[Figure 4 about here]

3. Decomposing Global Inequality Trends

The next part of our analysis is to account for the potential drivers of the global earnings inequality trends, as documented above. Our approach to this 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 sectors. Then we do counterfactual analyses by holding different factors and variables constant at their 1970 value in order to isolate their

[22] While perhaps surprising, a recent study by Sacerdote (2017) similarly found that, since the 1970s, the growth of real wage rates in the United States has been close to zero (with some variation due to the choice of price index).
[23] The corresponding GIC for global incomes or consumption, as depicted in Lakner and Milanovic (2015), is sometimes referred to as the "elephant curve" (Corlett, 2016; Lakner and Milanovic, 2016).

relative importance for the trends over time. Finally, we examine how global earnings inequality responds to simulating earnings dispersion within the occupational groups within countries. Some further analyses and more fine-grained decompositions, for instance, depicting the evolution of earnings inequality within each of the different regions as well as within the different occupations, are presented in Online Appendix C.

[Figure 5 about here]

3.1. Country and Regional Decompositions

The two upper panels of Figure 5 present Gini decomposition results with respect to countries and regions, respectively.[24] Looking first at the country-based decomposition in Figure 5a, the major part of the inequality can be attributed to earnings differences between countries. Over time, however, this between-inequality component has become less important, while the relative importance of the within-country component has increased. Over the investigated period, between-country inequality fell by 24 Gini points while, at the same time, within-country inequality increased by nine points, leading to the total decrease in global earnings inequality of 15 Gini points. Note also that since our earnings data are based on occupational group averages and thus lack within-group dispersion, the within-country inequality is likely to be underestimated (see Section 3.4). Analysing the decomposition trends within and between world regions, we can also see in Figure 5b 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.

[24] Gini decompositions calculated using Yitzhaki and Lerman's (1991) method as described in Frick *et al*. (2006), with the overlapping term included in the within component. For an alternative decomposition method, see Modalsli (2017). Theil index decompositions give qualitatively the same results (Online Appendix Table A7).

3.2. Decompositions by Occupations and Sectors

A unique aspect of our global database is its labour market variables. We exploit them to decompose global earnings inequality by occupations (Figure 5c) and sectors (Figure 5d). Both within- and between-occupation inequality have decreased over this period, and the decline in within-occupation inequality accounts for most of the fall in global earnings inequality. Between 1970 and 2018, inequality within occupations fell by twelve Gini points, and between-occupation inequality by three points. This result goes well with the country-based analysis, since the large within-occupation inequality also reflects large earnings differences across countries.[25] The sectoral decomposition divides the world's workers into the agricultural, industrial and services sectors. It shows that the within-sector component dominates the between-sector level of inequality, but that most of the fall in the inequality trend can be explained by earnings convergence between sectors.

3.3. Counterfactual Analysis

An alternative way to examine the role of explanatory factors is by counterfactual analysis. We do this by keeping different components of the global earnings inequality trend fixed at their initial 1970 value, one at a time, and then analyse the difference between the actual global inequality outcome and the counterfactual outcome if this factor had not changed during the 1970–2018 period. The results in Figure 6 show that the most dominant component behind the fall in global earnings inequality is changes in earnings, or more exactly, gross hourly wages. If gross wages had remained at their 1970 values during this period, the global net earnings inequality trend would have been essentially flat. Changes in prices, influencing through their role for PPP-adjustments, matter during some periods, but less when considering the full period impact. Within-country occupational employment shares (that is, changes in the occupational

[25] For the evolution of earnings inequality within each different occupation, see Figure C7 in the Online Appendix.

structure) have also contributed to the fall in global inequality since the mid-1990s, albeit to a relatively small extent. Changes in country-level populations have a small but opposing impact, driving the inequality trend upwards. Changes in taxes and working hours have almost no impact on the global trend. The 2018 difference between the actual outcome and the counterfactual is minus 15 Gini points for wages, minus four points for prices, minus two points for occupational employment and plus one points for country populations. Since changes in gross hourly wages thus seem to be the main driver behind the global earnings inequality decline, in the rest of this section we focus solely on that dimension.

[Figure 6 about here]

As a next step, we keep the 1970 wages fixed for the different regions, countries, sectors and occupations, one at a time. Figure 7 shows differences between the actual global inequality outcome and each of these inequality counterfactuals holding gross hourly wages constant. As clearly illustrated by this figure, earnings changes in Asia are by far the 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 27 Gini points higher today. The most important countries are China and India, whose wage changes, ceteris paribus, have reduced global inequality by twelve and eight Gini points, respectively. Wage changes in the United States, and Northern America, have had the opposing effect, driving global inequality up by three Gini points. Among the sectors, all three sectors contribute to the global inequality decrease, although their relative importance has changed over time. During the 1970s and 1980s, wage changes in the agricultural sector contributed most to the global inequality decline, while during the late-1990s and early-2000s industry was the dominant sector, followed by services during the most recent decade. Wage changes among agricultural and construction workers represent the most important occupational groups, implying a global inequality decrease of six and five Gini points, respectively, while changes among department managers have had an upward-driving impact on global inequality. Doing the same analysis for each country-occupation separately further emphasises the special role played by agricultural workers in China and construction workers in India (see Figure C8 in the Online Appendix).

[Figure 7 about here]

To summarize, cross-country convergence and real wage growth, especially in China, seem to account for most of the global earnings inequality trend and, in particular, the fall in global inequality since the turn of the millennium. We check the robustness of these findings by conducting a variety of sensitivity and heterogeneity analyses (presented in Online Appendix C).[26] Overall, these checks show that our results seem to be robust, but that the early-period estimates are associated with a higher degree of uncertainty.

3.4. Within-Group Dispersion Adjustment

Finally, we examine how sensitive our results are for the lack of earnings dispersion within the country-occupational groups. Because our data emanate from occupational averages, they do not capture any earnings differences among workers within the same occupation in the same country, nor between the occupations included and not included in our data.[27] While we cannot know exactly how large the bias from this omitted within-group dispersion is at the global level, Modalsli (2015) suggests a correction method to adjust for this (applied to historical social

[26] These include, but are not limited to, analyses using different PPP-adjustments, workforce and population definitions, top-earnings and gender-gap adjustments, as well as alternative samples and imputations.
[27] Note that this problem is not unique to our dataset, as essentially all studies of global inequality are based on grouped data (usually in the form of country-deciles or ventiles) and, in this regard, also underestimate within-country-group dispersion.

tables). His method imposes a number of distributional assumptions, but could still be informative about plausible implications of our missing within-group dispersion.

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.[28] In order to estimate the size of this within-group dispersion, we use the country-level microdata available from Krueger *et al*. (2010), the LIS (2017) and IPUMS International (Minnesota Population Center, 2018). Comparing the levels of microdata-estimated inequality with our estimations based on occupational groups, we find that the former is, on average, eleven Gini points higher for earnings (and five Gini points higher for wages), for the 41 countries available in the microdata sources (see Figure B6 in the Online Appendix). If we assume that this difference corresponds to the mean inequality within the country-occupational groups,[29] the corresponding within-group CVs would be approximately 0.2 for earnings and 0.1 for wages (thus indicating a positive relationship between earnings and hours worked within country-occupations). Constructing comparable country-inequality series by calculating mean earnings per ISCO group from the LIS microdata yields some support for this assumption and do not show any systematic trend in this within-group dispersion (see Section B.6 in the Online Appendix).

[28] 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%, respectively). However, since earnings are generally less dispersed than income, and since occupational groups might be more narrowly defined than other social groups, it is plausible that the within-group dispersion in our data would rather be somewhere between the lower CV of 0.1 (corresponding to a within-group Gini coefficient of 6%) and 0.5.

[29] We thus assume that our occupational data capture the within-country between-occupations inequality and that the microdata estimations capture the total within-country inequality (both within and between occupations), while the overlap category is assumed to be negligible.

Figure 8 presents global earnings inequality adjusted for within-country occupational-group dispersion using this method.[30] As is immediately visible, assuming a within-group CV of 0.1 does not change the global Gini coefficients at all, while CVs of 0.2 and 0.5 increase the global earnings inequality by approximately one and four Gini points, respectively. Even if this suggests that total earnings inequality is somewhat higher than our baseline estimates show, it does not change the overall picture that global earnings inequality has decreased over time.

[Figure 8 about here]

4. Conclusions

The purpose of this study has been to shed further light on global inequality by studying new and previously unexploited data on occupational earnings in a large panel of countries covering the past fifty years. Our focus on the global distribution of labour earnings and wages appears to be a unique contribution to the literature, and it also allows us to decompose global inequality and its trend in various dimensions that have not been analysed before.

Our main finding shows that global earnings inequality was stable during the 1970s–1990s, after which it fell during the 2000s–2010s. In 2018, the global earnings Gini coefficient was 15 points lower than it was in 1970, which accounts to a fall by around one quarter. Decomposing this inequality decline, we found that it was mainly driven by earnings convergence between developed and developing countries. Over the same period, within-country dispersion increased and counteracted the convergence impact (that is, while between-country inequality fell by 24 Gini points, within-country inequality rose by 9 points). When decomposing inequality trends

[30] We first compute the adjustments excluding the unemployed, then weight total inequality (with the unemployed) by the ratio between the adjusted estimates and our unadjusted measures of inequality (without the unemployed).

across occupational and sectoral dimensions, we found that the inequality decline was largely driven by rising earnings among agricultural and low-skilled industrial workers, especially in China and India, while rising earnings among American and European top-earnings professions only slightly offset this equalization. Moreover, industry-sector occupations experienced stronger earnings convergence than those in services, which suggests that trade could potentially have an important impact on global inequality. To identify the determinants of global inequality more rigorously would require complementary data and other analytical approaches, which lies beyond the scope of the present study. In ongoing work, we hope to shed further light on these and related issues. What we have shown in this study, however, is that it seems to be real wage growth rather than changes in labour supply or demographics that dominates the global inequality trend. To conclude, we thus find that, over the investigated period, global earnings and wage growth has been pro-poor.

Altogether, we hope that our study and the new database that we have constructed will spur further analysis on the links between national, regional and global labour markets and their role for global distributional outcomes.

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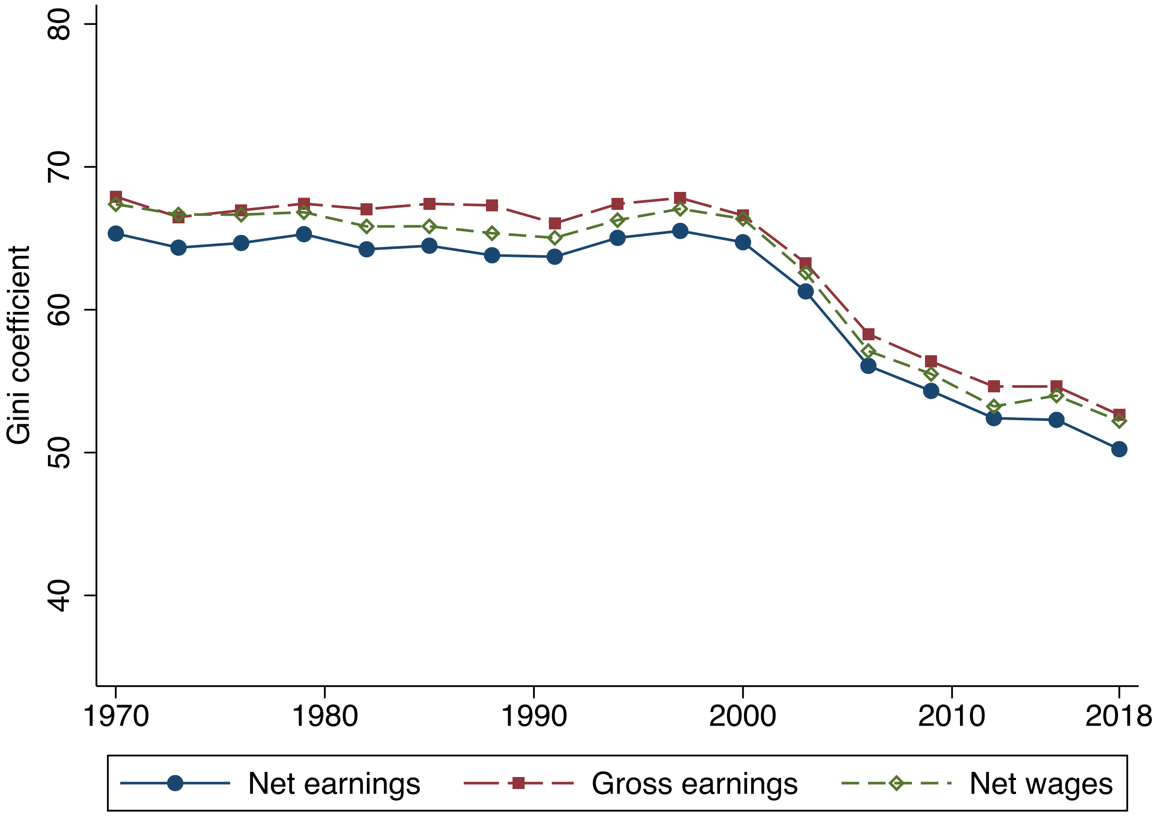
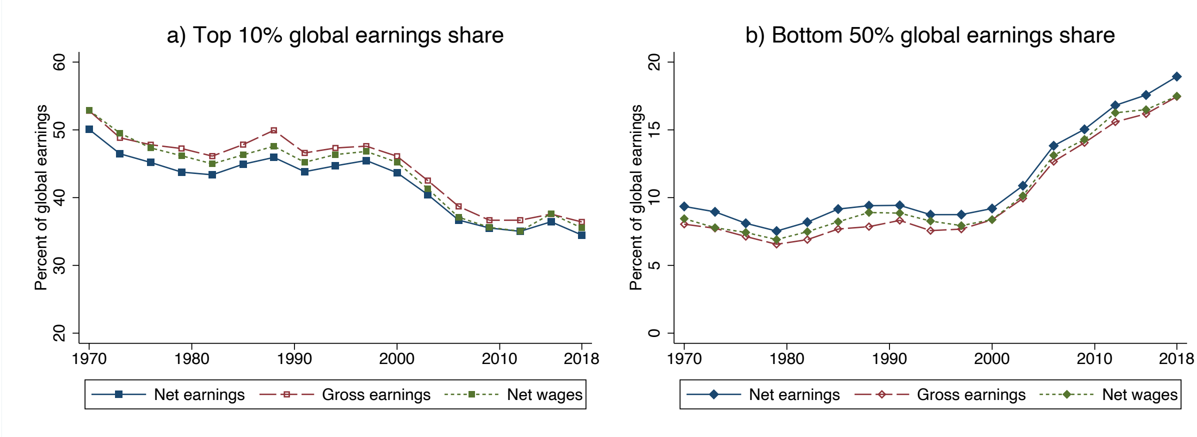
Figures

Figure 1: *Global Earnings Inequality, 1970–2018.*



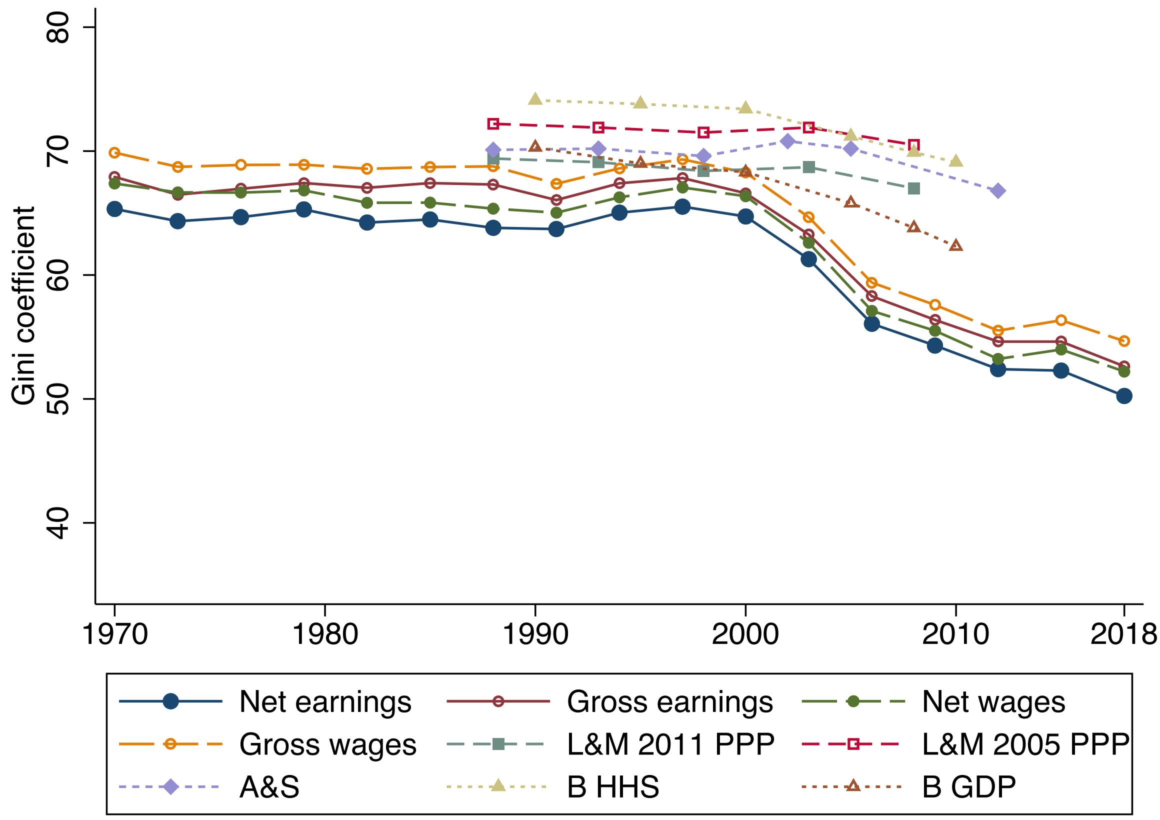
Notes: Calculations based on PPP-adjusted earnings using UBS price levels in 2015 USD, weighted by working age populations and including the unemployed. Earnings refer to yearly earnings and wages to hourly earnings. *Source:* Authors' calculations based on data described in the text.

Figure 2: *Top and Bottom Global Earnings Shares.*



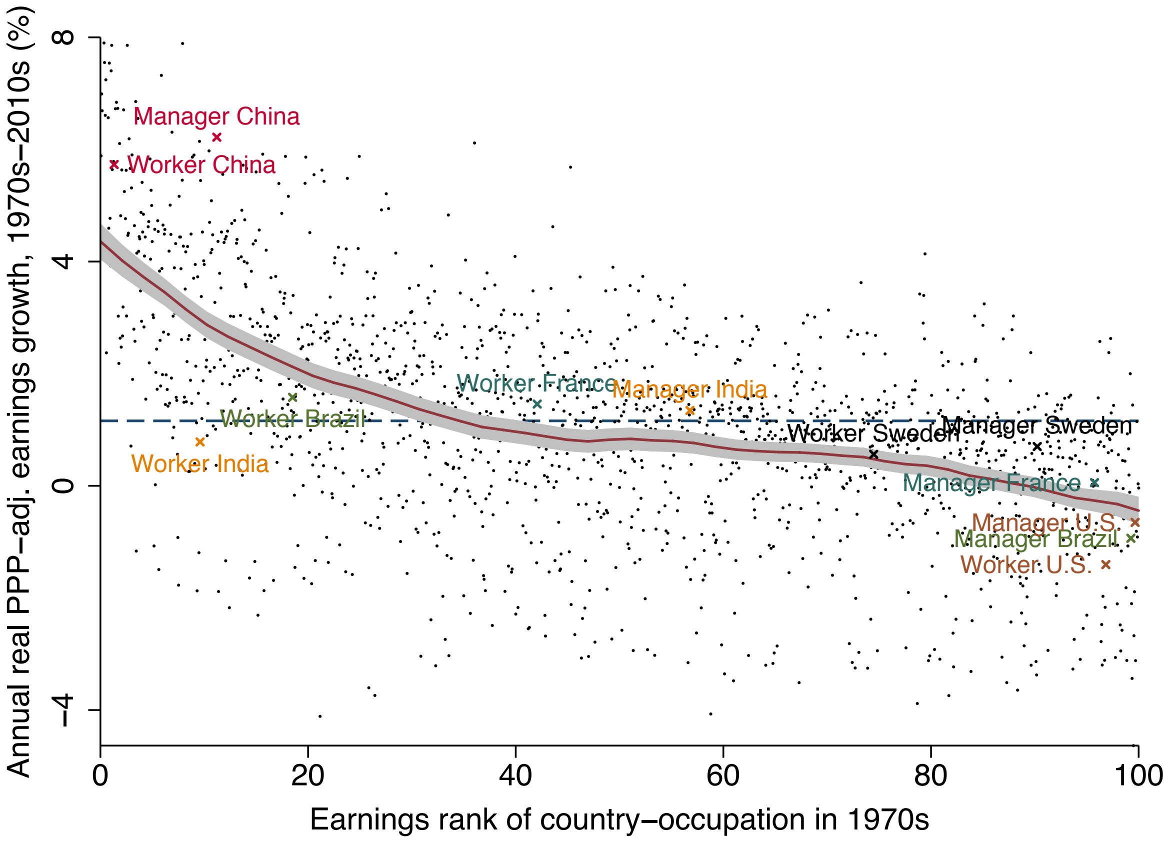
Notes: Calculations based on net yearly earnings (if nothing else specified), PPP-adjusted using UBS price levels in 2015 USD, and weighted by working age populations, excluding the unemployed. Earnings refer to yearly earnings and wages to hourly earnings.
Source: Authors' calculations based on data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

Figure 3: *Global Earnings versus Income Inequality.*



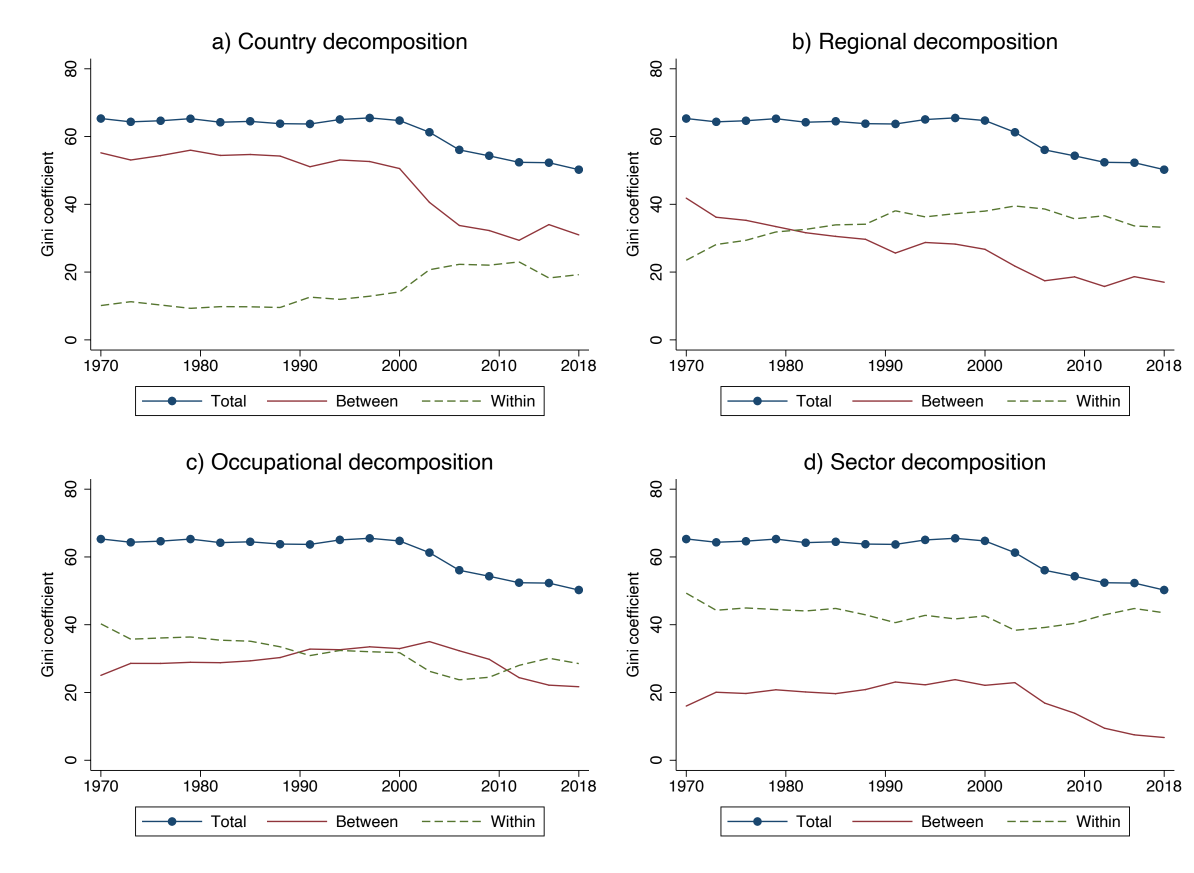
Notes: Net and gross earnings and wage inequality refer to this study and are based on yearly and hourly earnings, respectively, which are PPP-adjusted using UBS price levels in 2015 USD and weighted by working age populations including the unemployed. "L&M" refers to Lakner and Milanovic's (2015) estimations using the ICP 2005 and 2011 PPP, respectively. "A&S" refers to Anand and Segal's (2017) estimations without top incomes (using the ICP 2011 PPP). "B" refers to Bourguignon's (2015) estimations based on household surveys and data rescaled by GDP per capita, respectively (using the ICP 2005 PPP).
Sources: Authors' calculations based on data described in the text; Anand and Segal (2017); Bourguignon (2015); Lakner and Milanovic (2015).

Figure 4: *Non-Anonymous Growth Incidence per Country-Occupation, 1970s–2010s.*



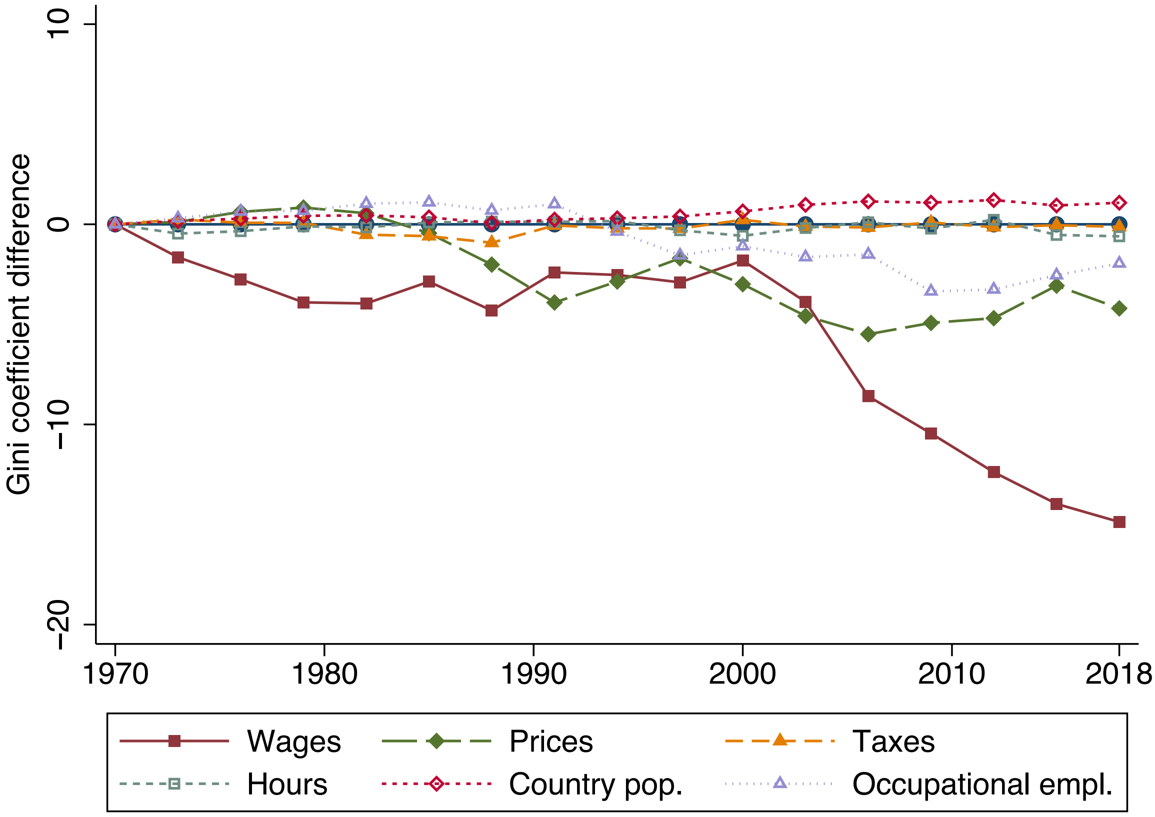
Notes: Average annual country-occupation growth rate 1970s–2010s in net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), where each observation represents a country-occupation. Dashed line shows average annual earnings growth rate 1970s–2010s for all country-occupations, and solid line 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 2009–2018, respectively. "Manager" refers to department managers and "Worker" to construction workers.
Source: Authors' calculations based on data described in the text.

Figure 5: *Decomposing Inequality by Countries, Regions, Occupations and Sectors.*



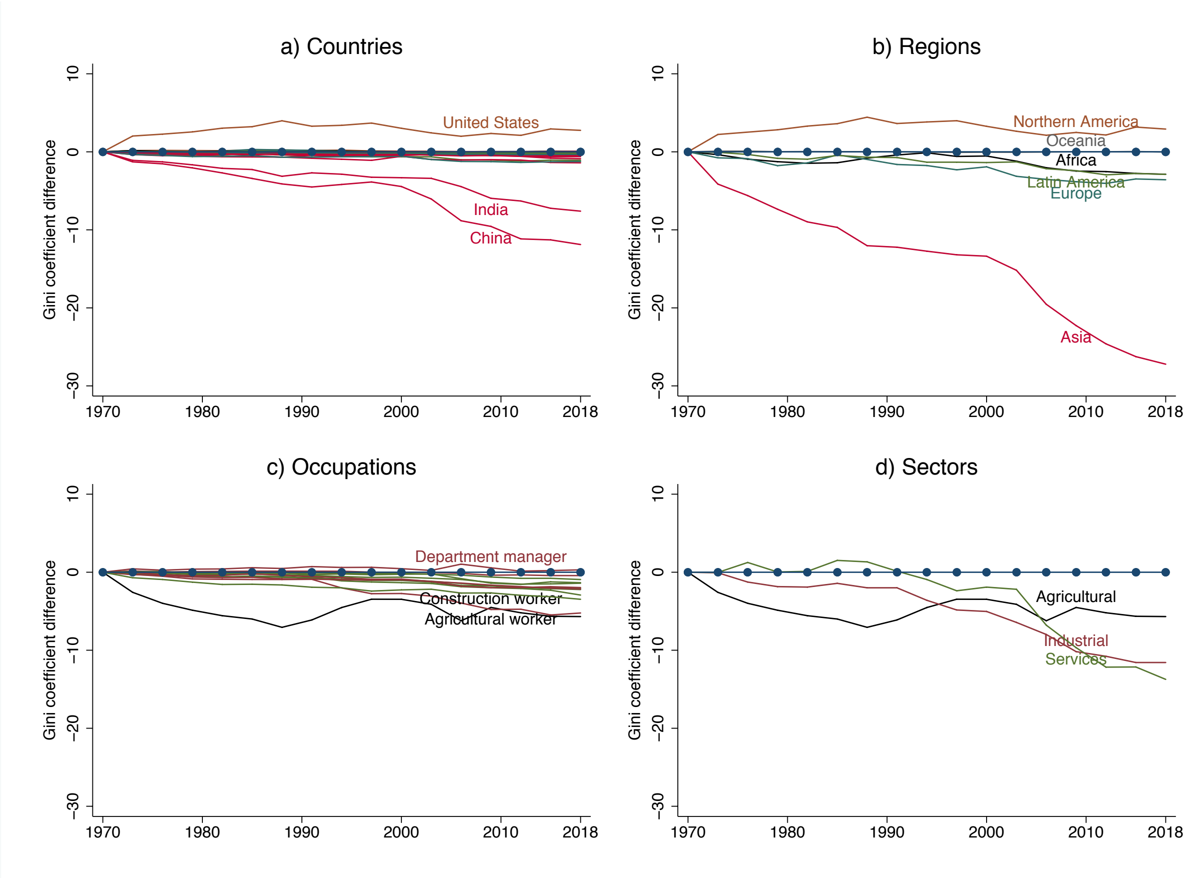
Notes: Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD) and weighted by working age populations including the unemployed. Gini decompositions calculated using Yitzhaki and Lerman's (1991) method as described in Frick *et al*. (2006), with overlapping index included in "within". Decompositions calculated excluding the unemployed but scaled by total global Gini coefficient including the unemployed. b) Regional decomposition refers to Africa, Asia, Europe, Latin America, Northern America and Oceania. d) Sector decomposition refers to agricultural, industrial and services sectors.
Source: Authors' calculations based on data described in the text.

Figure 6: *Counterfactual Analysis: Impact of Holding Factors Constant at 1970 Values.*



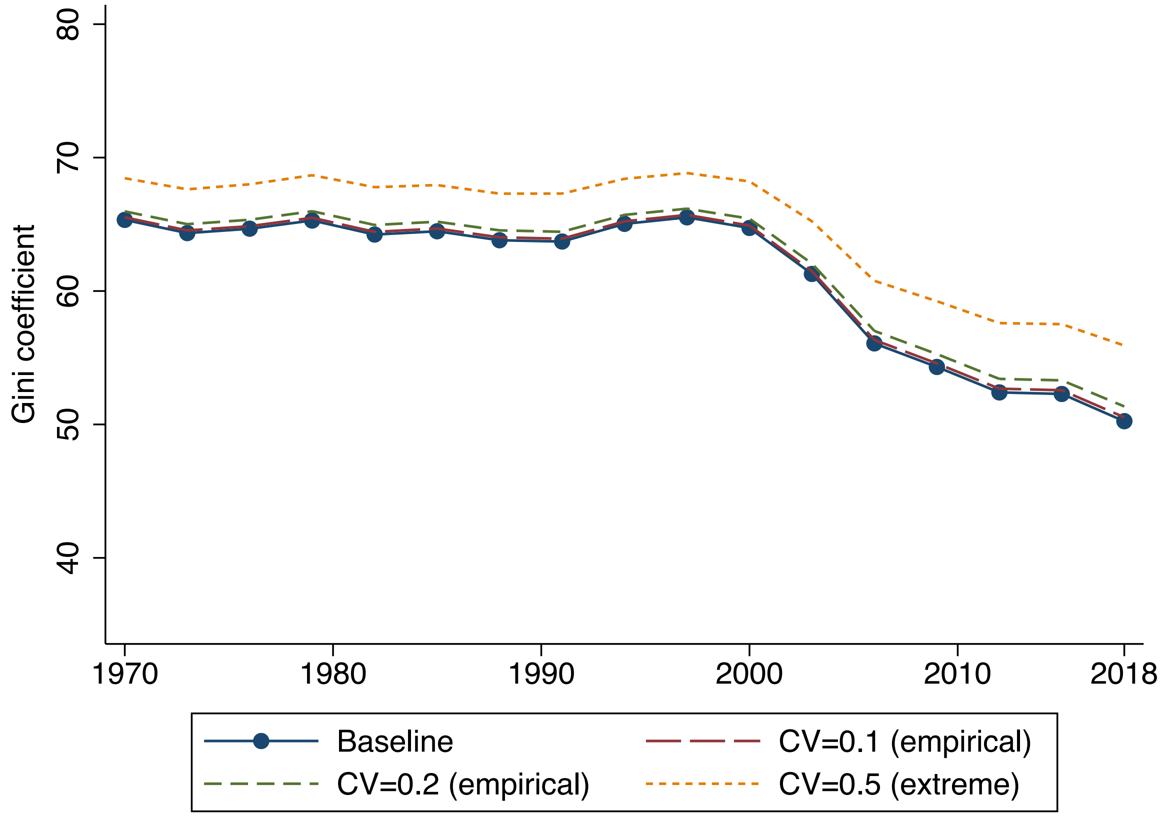
Notes: Figure shows difference between actual baseline global earnings inequality and counterfactual inequality keeping 1970 values fixed for the different variables. Calculations based on net yearly earnings (PPP-adjusted using UBS price levels in 2015 USD), weighted by working age populations and including the unemployed.
Source: Authors' calculations based on data described in the text.

Figure 7: *Difference between Actual Gini and Counterfactual Gini with Fixed 1970 Wages.*



Notes: Figure shows difference between actual global earnings inequality and counterfactual inequality with 1970 gross hourly wages 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 8: *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. CV implies that country-occupations are assigned within-group earnings distributions with CVs 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.

Tables

Table 1: *Coverage of the Dataset.*

	Sample	1970	1994	2018	Mean
a) Number of countries represented in the database					
World	I	27	48	63	49.2
	II	68	68	68	68.0
Africa	I	1	4	4	3.1
	II	4	4	4	4.0
Asia	I	3	16	18	14.4
	II	22	22	22	22.0
Europe	I	16	19	30	21.8
	II	30	30	30	30.0
Latin America	I	4	6	7	6.5
	II	8	8	8	8.0
Northern America	I	2	2	2	2.0
	II	2	2	2	2.0
Oceania	I	1	1	2	1.4
	II	2	2	2	2.0
b) GDP (% of regional GDP represented in the database)					
World	I	82	92	94	90.5
	II	97	97	96	96.5
Africa	I	24	47	46	40.1
	II	53	47	46	47.7
Asia	I	44	87	92	82.0
	II	95	96	95	95.5
Europe	I	87	92	99	92.8
	II	100	100	99	99.4
Latin America	I	67	83	82	81.6
	II	84	89	90	87.0
Northern America	I	100	100	100	100.0
	II	100	100	100	100.0
Oceania	I	83	82	98	89.5
	II	97	96	98	97.1
c) Population (% of regional population represented in the database)					
World	I	25	51	75	59.3
	II	85	83	79	82.4
Africa	I	6	33	32	25.3
	II	34	33	32	33.2
Asia	I	5	46	81	58.3
	II	89	89	88	88.7
Europe	I	54	55	96	71.5
	II	97	95	96	95.9
Latin America	I	67	73	75	74.7
	II	80	81	80	80.5
Northern America	I	100	100	100	100.0
	II	100	100	100	100.0
Oceania	I	65	62	72	67.2
	II	79	75	72	75.1

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 (2018).