



Working Paper Series

Inequality convergence: How sensitive are results to the choice of data?

Nora Lustig
Daniel Teles

ECINEQ WP 2016 - 412

Inequality convergence: How sensitive are results to the choice of data?

Nora Lustig[†]

Daniel Teles

Tulane University, U.S.A.

Abstract

This paper examines the extent to which estimates of inequality convergence are sensitive to the choice of welfare concept, inequality indicator, database, country coverage, and time period. Moreover, we explore the sensitivity of the estimated rate of convergence by testing five hypotheses using a series of pair-wise F-tests. The main takeaways are as follows. First, estimates appear to be more sensitive to the choice of welfare concept than to the choice of inequality measure. Second, different international inequality databases frequently produce different results, even when the countries, the welfare concept, the inequality measure, and the time period are held constant. Third, while there is a rather large amount of evidence that estimated rates of convergence differ by region and by time, even this result is sensitive to the database that is used to perform the analysis.

Keywords: Inequality convergence, inequality databases, sensitivity analysis.

JEL Classification: C81, D31, D63.

[†]**Contact details.** N. Lustig: Samuel Z. Stone Professor of Latin American Economics, Tulane University, New Orleans, LA, USA; director of the CEQ institute; nonresident fellow of Center for Global Development and Inter-American Dialogue; Email: nlustig@tulane.edu. D. Teles: Tulane University, New Orleans, LA, USA; Email: dteles@tulane.edu.

1. Introduction

There is a growing wealth of data that describes income inequality. There are at least fifteen international income inequality databases (herewith, databases) that contain a wide range of inequality indicators for many countries and many years (Ferreira, Lustig and Teles, 2015; Alvaredo, Lustig, and Piketty, forthcoming). These databases are used for both academic and policy research (e.g., Atkinson and Bourguignon, 2014; Acemoglu et al., 2013; Piketty, 2014; and Ostry et al., 2014). Yet, the inequality indicators contained within these databases differ in substantial ways. The differences in their methodologies and the effects of their methodological differences on estimates of inequality levels and trends are the subject of a series of papers included in a special issue of the *Journal of Economic Inequality* (Ferreira and Lustig, 2015)³. We focus here on nine databases that contain from 1,065 to 9,124 inequality indicators for many countries and many years.

This paper examines the extent to which differences between databases of inequality indicators defined by welfare concept, inequality measure, data source, country coverage, and time period affect inequality convergence—the finding that inequality has fallen in what had been highly unequal countries and risen in countries that had been more egalitarian (Benabou, 1996; Bleaney and Nishiyamam 2003; and Ravallion, 2003). In particular, we analyze the sensitivity of the convergence result, both whether it exists and the rate at which it occurs, to choice of welfare concept (such as per capita consumption or equivalized household disposable income), inequality measure (Gini Coefficient, Theil Index, or Atkinson Index), the database used as source as well as the region over which convergence is estimated and the

³ This research began as an outgrowth of that work.

time period covered. This paper also estimates whether the rate of convergence has changed over time, and whether the results are more robust over some time periods than others.

Our data includes inequality indicators from nine sources. They are: “*All the Ginis*” (ATG);⁴ United Nations Economic Commission for Latin America and the Caribbean (ECLAC)’s *CEPALSTAT*; the Organization for Economic Co-operation and Development (OECD)’s *Income Distribution Database (IDD)*; the Center for Distributive, Labor and Social Studies (CEDLAS) at National University of La Plata (UNLP)’s *Socio-Economic Database for Latin America and the Caribbean (SEDLAC)*; the *Standardized World Income Inequality Database (SWIID)*;⁵ LIS Cross-National Data Center in Luxembourg; UNU-WIDER’s *World Income Inequality Database (WIID)*; the World Bank’s *World Development Indicators/POVCAL (WDI)*; and the *World Top Incomes Database (WTID)*.⁶ Six of our sources (CEPALSTAT, OECD IDD, SEDLAC, WDI, and WTID) directly estimate inequality measures from microdata, two (ATG and WIID) collect indicators from other sources, and one (SWIID) uses a large number of sources to estimate annual series of probability distributions for the Gini coefficients using multiple-imputation methods.

The indicators included in our dataset estimate inequality across a variety of inequality measures and welfare concepts. While the Gini coefficient is the most frequent inequality measure, our analysis covers datasets that include the Atkinson Index, the Theil Index, and the top one percent income share, top five percent income share, and inverted Pareto-Lorenz coefficient. These measures are used to describe inequality in pre-tax income, disposable income, and consumption on both a per capita and equivalized basis. The databases that

⁴ Produced by Branko Milanovic.

⁵ Produced by Frederick Solt.

⁶ Produced by Facundo Alvaredo, Tony Atkinson, Thomas Piketty, and Emmanuel Saez.

directly estimate inequality tend to have (broadly) consistent methodologies for defining their preferred welfare concepts. Those that do not—such as ATG and WIID—provide the researcher information with which he or she can decide how to construct panels with, hopefully, similar welfare concepts.

Our estimation framework follows Ravallion (2003) and estimates β convergence. Estimates of β convergence use regression procedures based on Ordinary Least Squares (OLS) to estimate the relationship between an initial level of inequality and the change in inequality over time. We test for inequality convergence by regressing observed changes in inequality on observed levels of inequality. We then test the sensitivity of the convergence results by holding the regression specification constant, while varying the panel of inequality indicators and performing a series of hypothesis tests to compare the estimates of the convergence rate produced by the different panels. Because measurement errors can bias the results towards convergence, we further follow Ravallion (2003) and use prior year's measurements of inequality as instrumental variables. It is important to note that we do not attempt to estimate a causal relationship between initial inequality and convergence or to explain the sources of inequality convergence. Moreover, we do not attempt to establish whether the convergence results are reflecting “true” convergence or just mere mean reversion. Rather, we focus specifically on how sensitive the convergence results are to the choice of inequality indicator.

With few exceptions, our estimates suggest that there is convergence in inequality levels. However, we find that the estimated rate of convergence varies significantly when we adjust our choice of data. Specifically, we find that the estimated rate of convergence is sensitive to the choice of which database is used as a source and which welfare concept is used from within a database. We also find that comparisons of the rates of inequality convergence

across regions are frequently sensitive to the choice of welfare concept, time period, and database used in the analysis. Similarly, comparisons of the rate of inequality convergence across time are sensitive to the choice of database used as a source.

This paper continues as follows. Section 2 provides an overview of the literature that has explored the question of inequality convergence. We present our empirical model and the rates of convergence estimated by our iterative analysis in section 3. In section 4, we present our primary contribution: a series of hypothesis tests that examine the extent to which inequality convergence results are sensitive to the choice of welfare concept, inequality measure, database, country coverage (by region), and time period. Section 5 discusses our findings and concludes.

2. Inequality Convergence: A Brief Review of the Literature

Over the last 30 years, existing research suggests that inequality has fallen in what had been highly unequal countries and risen in countries that had been more egalitarian (Benabou, 1996; Ravallion, 2003). This “inequality convergence” appears to be part of a broader convergence of income distributions; as global inequality has declined, within-country levels of inequality have become more similar (Bourguignon, 2015). As with any empirical study, however, the findings are subject to the strengths and weaknesses of the underlying data.

Global inequality convergence warrants further research for a number of reasons. First, the phenomenon is interesting in and of itself. It provides information on the distribution of income over time and explains the current trajectory of income inequality. By revisiting inequality convergence, we stand to gain a better understanding of whether the trends have changed. As levels of inequality have become more similar, has the rate of convergence slowed? Second, as explained by Benabou (1996) the neoclassical growth model predicts convergence in income distribution *among countries with similar fundamentals*. Therefore,

analysis of convergence in income inequality, along with a parallel line of literature examining convergence in income *levels*, produces evidence that either supports or contradicts existing theory. Third, the information is useful to policy makers. Trends in inequality affect decisions about economic investment, redistribution, and trade policy.

Given its importance, there have been several examinations of inequality convergence. Benabou (1996) provides the first examination of inequality convergence using (then preliminary) data from Deininger and Squire (1996) and LIS. He finds evidence of inequality convergence in the 1970s, but little evidence of convergence in the 1980s, and no evidence of convergence over the entire two-decade period. Bleaney and Nishiyama (2003) provide further evidence of convergence using Gini coefficients reported in WIID 1.0⁷. Bleaney and Nishiyama iterate their estimates using a “reliable data only” sample and a larger sample with “less reliable data” as well. Ravallion (2003) also finds evidence of convergence using data collected for an earlier project for the World Bank (Chen and Ravallion, 2001). He augments these results with a robustness check obtained using data from Li et al. (1998) based on Deininger and Squire (1996). Both Bleaney and Nishiyama (2003) and Ravallion (2003) find that while convergence itself is robust to the choice of database, the rate of convergence is highly sensitive.

Data reliability has been a central concern throughout the literature on inequality convergence. When Benabou (1996) first posed the question of inequality convergence he included the following caveat: “The paucity and sometimes poor quality of international data

⁷ Bleaney and Nishiyama (2003) use estimates for both income and expenditure in the same series, adding 6.6 to expenditure Ginis to compensate for the average income/expenditure difference. We use WIID 3.3 with separate time series for gross income, disposable income, and consumption. Further information on how we import data from WIID 3.3 is included in Appendix A: Incorporating Data from WIID 3.3.

on income distribution remain binding constraints here, as in all empirical work on these issues,” (p. 18). Similarly, Ravallion (2003) noted, “The shortage of comparable survey observations over time for many countries raises doubts about how well the trends have been estimated,” (p. 355).

In an effort to limit data heterogeneity, a number of studies have focused on within-region or within-country inequality convergence across states or municipalities. Ezcurra and Pascual (2005) use data from the European Community Household Panel and find convergence within Europe. Gomes (2007) examines convergence inequality between Brazilian municipalities using data from the Joao Pinheiro Foundation’s 2003 Brazilian Human Development Report. He finds evidence of general convergence and convergence within the southern region toward a lower inequality level while the rest of the regions converge to a higher inequality level. Panizza (2001), Ezcurra and Pascual (2009), Lin and Huang (2012) and Ho (2015) all focus on convergence between U.S. states. Ezcurra and Pascual (2009) use data from Patrige et al. (1996, 1998) based on Census Bureau estimates. Lin and Huang (2012) and Ho (2015) use data from Frank (2009) based on the Internal Revenue Service (IRS) Statistics of Income. Panizza (2001), Ezcurra and Pascual (2009), and Lin and Huang (2012) all find evidence in support of convergence in income inequality among U.S. states. Lin and Huang (2012) iterate their analysis with top 1% share, Atkinson Index, Gini Coefficient, relative mean deviation, and Theil Index. Their analysis shows that the general finding of inequality convergence among U.S. states is robust across inequality measures. However, their research does not examine differences in the rates of convergence between inequality measures. Ho (2015) is unique in that the results do not support the conclusion that income inequality levels among states are converging.

The reliability and heterogeneity in inequality data that has been a significant concern through out the convergence literature is the subject of our research. We test the robustness of the convergence result across sources, measures, and welfare concepts. Differences in our estimates are analyzed in light of differences in the underlying methodologies.

3. Estimating Convergence

We iteratively estimate inequality convergence by regressing observed changes in inequality on observed levels of inequality. We use a common specification, but vary the panel of inequality indicators to encompass alternative databases, welfare concepts, inequality measures, time periods, and country coverage. Our estimation framework follows Ravallion (2003) and estimates β convergence. Estimates of β convergence use regression procedures based on Ordinary Least Squares (OLS) to estimate the relationship between an initial level of inequality and the change in inequality over time.

There are a number of alternative tests for convergence. Ezcurra and Pascual (2006, 2009) examine the dynamics of the entire income distributions of European countries and US states. However, the Ezcurra and Pascual methodology can be applied only to highly homogenous data. Lin and Huang (2012) and Ho (2015) each present novel methods to tests for convergence based on panel unit root tests. Both studies, however, rely on a long panel of state-level US inequality data from Frank (2009) to estimate convergence in state-level inequality within the US.⁸ While methods based upon unit root tests could theoretically be used to estimate cross-national convergence, similarly appropriate data is not available. Unit root tests require datasets that are longer and more complete (meaning fewer years with

⁸ Ho (2015) further subdivides tests for convergence into those that use a unit root or cointegration test and those that test for stationarity in mean inequality level differentials. That is, that states or countries are moving toward a common distribution.

missing data) than are generally found in the cross-national databases. Only SWIID provides such data at the national level, however, given that SWIID imputes every data point and employs a smoothing algorithm, we are not comfortable using it as a basis for this type of trend analysis.

Ezcurra and Pascual (2006) and Lin and Huang (2012), citing Quah (1993), criticize the econometric validity of the methodology employed by Benabou (1996), Ravallion (2003), and Gomes (2007), that tests the prediction of convergence from neoclassical growth using OLS-based estimates of β convergence. The intuition, from Quah (1993), is that beta tests cannot distinguish convergence from mean reversion. As an example, suppose each country has some “baseline” level of inequality that may be increasing or decreasing along a long-term trend line. Further suppose there exists a number of one-time events that increase or decrease inequality initially, with inequality gradually returning to the long-term trend line. Our methodology does not distinguish between convergence in baseline inequality trends and reversion back to a pre-shock trend line. However, for our purposes, this issue is not fundamental in the following sense. Our study should be viewed as an exercise designed to assess the sensitivity of convergence estimates to the choice of welfare concept, inequality metric, time period, and database.

We address the possibility that measurement error could bias estimates of convergence through the use of IV. Suppose an inequality indicator, θ , at time $t = 0$ is measured with error ε_0 . A change in inequality from $t = 0$ to $t = 1$ is then $\theta_1 + \varepsilon_1 - \theta_0 - \varepsilon_0$. OLS-based estimates of β convergence, such as those in this paper, compare the change in inequality, $\theta_1 + \varepsilon_1 - \theta_0 - \varepsilon_0$, to the initial level of inequality, $\theta_0 + \varepsilon_0$. If ε_0 is positive (negative), the independent variable is biased upward (downward) while the dependent variable is biased downward (upward). This would, in turn, bias β downward leading to an overestimate (that

is a more sharply negative estimate) of convergence. Following Ravallion (2003), we address this concern by using prior year's inequality indicators as instruments. In this example, the independent variable is now $\hat{\theta}_0(\theta_{-1} + \varepsilon_{-1})$. As long as the errors are not serially correlated, the bias is removed.

While our methodology is not ideal for determining the “true” rate of convergence, it is ideal for the comparison of panels of inequality indicators for the following reasons. First, since the focus of our work is to compare results across welfare concept, inequality measure, time, and databases, we want to use a methodology that resembles the most similar work: the tests for global inequality convergence by Benabou (1996), Bleaney and Nishiyama (2003), and Ravallion (2003). All three studies focus on β convergence. Second, most of the cross-national databases provide either short (as in the case of OECD IDD) or incomplete (as in the case of WDI) time series. As such, these databases are a better fit for a methodology based on cross-sectional inference than the time series approaches that have been used on long panels (such as those used by Lin and Huang (2012) and Ho (2015)). The Ravallion methodology allows us to include countries with as few as three estimates of inequality. Third, β convergence, by definition, estimates a convergence “rate”. The Ravallion methodology, therefore, allows us to examine not only whether the convergence result is robust across alternative specifications, but whether the rate of convergence is sensitive specifically to alternate sources, welfare concepts, and inequality measures.

We begin by defining Θ to be a panel of inequality indicators. Within a panel of indicators, let years be indexed $t = (0, 1, \dots, D)$ and let countries be indexed $i = (1, \dots, N)$ such that the inequality indicator for a given country in a given year is denoted as θ_{it} . Following Ravallion (2003) we assume that there is some true level of inequality, θ_{it}^* , that is measured with error such that $\theta_{it} = \theta_{it}^* + \varepsilon_{it}$.

Additionally, assume that each country has an underlying inequality trend $\tau_i(\theta_{i0}^*)$ defined by the equation:

$$\theta_{it}^* - \theta_{i1}^* = \tau_i(t - 1) + v_{it} \quad (i = 1, \dots, N; t = 2, \dots, D) \quad (1)$$

where v_{it} is a zero-mean, country and time specific error term that denotes true, short-term deviations from the time trend. Further assume that measurement error has a mean of zero and is serially independent such that $\theta_{it} = \theta_{it}^* + \varepsilon_{it}$. Finally, assume that there exists some linear approximation of the inequality trend such that

$$\tau_i \approx \alpha + \beta \theta_{i1}^* + \mu_i.$$

Then, we can rewrite equation 1 as:

$$\begin{aligned} \theta_{it} - \theta_{i1} &= \alpha(t - 1) + \beta \theta_{i1}(t - 1) + e_{it} \\ (i &= 1, \dots, N; t = 2, \dots, D) \end{aligned} \quad (2)$$

where e_{it} is a composite (heteroskedastic) error term defined:

$$e_{it} = v_{it} + \varepsilon_{it} - \varepsilon_{i1} + (t - 1)(\mu_i - \beta \varepsilon_{i1}).$$

Under the assumption that measurement errors are serially independent, we can use the inequality indicator from an earlier year, θ_{is} ($s < 1$) as an instrument for θ_{i1} and estimate equation 3 using an IV approach. Suppose, for example, we have estimates of the Gini coefficient for the years 1992, 1993, 1996, and 1997. We would use the Gini in 1992 as the instrument, denoting 1992 as $(t = 0)$ for the Gini in 1993 ($t = 1$), and run our regression

using observations of changes in inequality through 1995 ($t = 4$) and 1997 ($t = 5$). Similarly, if the Gini coefficient for 1992 is unavailable, the index for 1991 ($t = -1$) could serve as an instrument. To maximize the strength of our instruments, we use the closest, available, prior estimate of inequality.

Using this methodology, we estimate β -convergence iteratively, using each combination of welfare concept and inequality measure available in the nine databases listed in the introduction. Table 1 displays estimates for the period 1988 to 2012. In tables 2 and 3, the time frame is split in half, estimating convergence from 1988 to 2000 and from 2000 to 2012, respectively.⁹ In table 4, we use the same time frame as Ravallion (2003): 1983 to 1999. All estimates for the period 1988 to 2012 are negative (although not all are statistically significant) and therefore suggestive of convergence. For the time periods 1988 to 2000 and 1983 to 1999, we estimate *divergence* using OECD IDD's and LIS's measures of equivalized disposable income (although the LIS estimate is only statistically significant in the latter period). With this exception, however, our results generally confirm the existing findings in the literature.

These estimates provide a first pass at answering the question, “is there inequality convergence?” Generally, we find that there is. In the next section, we go further, and ask whether the rate of inequality convergence is sensitive to the choice of data. In our sensitivity analysis, we use the same databases, welfare concepts, and inequality measures. As such these estimates also provide a baseline for the pair-wise comparisons in section 4. We alter the data in only one way as we move from the tests of convergence presented here to the

⁹ These time periods were selected to maximize the number of observations available in a panel while keeping the number of countries in the panel relatively stable over time. There is far less data available prior to the mid-1980s.

pairwise hypothesis tests that follow: the pair-wise tests use only data from countries that appear in both panels (i.e., both OECD and LIS disposable income or both WIID income and WIID consumption).

4. Hypothesis Testing

In order to understand how specific methodological and data choices affect estimates of convergence, we begin by defining inequality indicators along three dimensions. In addition to the typical distinctions of how welfare is defined (i.e., consumption or income and per capita or equivalized) and by which inequality measure (Gini, Theil, and so on) is used, given the main focus of our paper we also define each inequality indicator by the database from which it is drawn. Additionally, of course, each indicator is defined by a country and year. A panel of indicators, Θ , can similarly be described along the dimensions of the welfare concept, inequality measure, and source along with the set of countries and years included within it. Thus, let Θ_{wmjIT} be the panel of indicators using welfare concept w and inequality measure m , from database j , covering the set of countries I and time period T . Moreover, let $\hat{\beta}_{wmjIT}$ be the estimate of β -convergence produced from panel Θ_{wmjIT} .

Using this notation, we set about testing a set of five “straw man” hypotheses associated with variation in welfare concepts, w , inequality measures, m , databases, j , sets of countries, I , and time periods, T , while holding everything else equal. In each case, we make pair-wise comparisons between panels using F-tests with the null hypothesis that the estimated rate of convergence, $\hat{\beta}_{wmjIT}$, would be the same using either panel. We limit our analysis to pair-wise comparisons in which each panel includes at least ten countries and at least 30 observations. We call these set of five “straw man” hypotheses A, B, C, D, and E; they are described in detail below. We then analyze the results of these five sets of hypothesis tests with particular regard to how different databases can yield different conclusions even in the

cases in which the welfare concept, the inequality measures, the countries, and the time period are kept the same.

Hypotheses Set A: changing the welfare concept

We begin by estimating convergence with different welfare concepts that appear in the same database, while holding the inequality measure, country coverage, and time period constant. We then test the null that the estimated rates of convergence are identical. Formally our hypothesis is as follows:

Given any two panels of inequality indicators θ_{vmjIT} and θ_{wmjIT} , with identical inequality measures m , sources j , sets of countries I , and time periods T , the estimated rate of convergence is constant across welfare concepts, v and w ; $\hat{\beta}_{vmjIT} = \hat{\beta}_{wmjIT}$.

We are able to test this hypothesis using six pairwise, within-databases comparisons. As an example, we compare estimates using SEDLAC's Theil Index estimates of equivalized income inequality to SECLAC's Theil Index estimates of per capita income inequality. Where there is sufficient data, these comparisons are made over the four time periods discussed in section 3—1988 to 2012, 1988 to 2000, 2000 to 2012, and 1983-1999—for a total of 20 hypothesis tests. Results appear in table 5.

In five out of the 20 cases, the null hypothesis of constant beta coefficients across panels can be rejected at a 5% significance level. We apply 12 tests of hypothesis A using data from SEDLAC. In each case, we fail to reject the hypothesis that the estimated rate of convergence is identical whether the welfare concept employed is equivalized disposable income or per capita disposable income. In five of the other eight tests, however, we find that estimates of convergence are not equivalent across welfare concepts.

Using data from either SWIID or OECD IDD leads to the conclusion that, at least prior to 2000, the rate of convergence has been significantly higher when the welfare concept is based on pre-tax income than when it is based upon post-tax income. Using these two databases, we reject the null five times out of seven. As we noted in the prior section, using the time period from 1983 to 1999, data from OECD IDD suggests convergence in pre-tax and transfer income inequality and divergence in disposable income inequality.

Examining our initial estimates created using WDI data, we find that estimates of income inequality convergence differ from estimates of consumption inequality convergence. For the period from 2000 to 2012 (table 3), the point estimate for the rate of income inequality convergence is -0.030 with a standard error of 0.004. In contrast, the point estimate for consumption inequality convergence is 0.009 with a standard error of 0.009. Yet, only a small subset of Eastern European Countries (Bulgaria, Estonia, Hungary, Latvia, Lithuania, Slovak Republic, and Slovenia) appear in both the income and consumption panels. As such, it remains unclear whether the different point estimates are driven by the choice of welfare concept or the variation in the countries included in the panels.

Hypotheses Set B: changing the inequality measure

Our second hypothesis estimates convergence with different inequality measures that appear within the same database and tests whether the estimated rates of convergence are equal.

Formally our hypothesis is as follows:

Given any two panels of inequality indicators Θ_{wljIT} and Θ_{wmljIT} , with identical welfare concepts w , sources j , sets of countries I , and time periods T , but different inequality measures the estimated rate of convergence is constant across inequality measures, l and m ;

$$\hat{\beta}_{wljIT} = \hat{\beta}_{wmljIT}.$$

For example, under Hypothesis B, we test whether the estimated rate of β convergence is the same whether we use CEPAL estimates of per capita total current income inequality using the Gini coefficient or using the Theil index. Again, we iterate our tests over up to four time periods where data is available and produce 33 unique tests of Hypothesis B.

Results for tests of hypothesis B appear in table 6. Even if alternative inequality measures constantly pointed to the same qualitative conclusions, we might find that estimates of the convergence rates are very sensitive to the choice of inequality measure. Yet, we are only able to reject the null of identical β coefficients in two of 33 cases. This result is consistent with the robustness checks presented in Lin and Huang (2012).

Hypotheses Set C: changing the database used as a source

Our third hypothesis compares estimates of convergence using different databases. Here, we construct panels from pairs of databases such that the welfare concept, inequality measure, and country coverage are identical. We then compare, for example, rates of convergence estimated with LIS and OECD. We examine four different time periods and five different welfare measures to produce a total of 60 tests of Hypothesis C, stated formally as follows.

Given any two panels of inequality indicators Θ_{wmjIT} and Θ_{wmkIT} , with identical welfare concepts, w , inequality measures, m , sets of countries, I , and time periods, T , the estimated rate of convergence is constant across data sources, j and k ; $\hat{\beta}_{wmjIT} = \hat{\beta}_{wmkIT}$.

Hypothesis C, which initially drove this research, posits that our estimates of convergence are unaffected by the choice of database, provided that the welfare concept and inequality measure are held constant. We run 60 tests of this hypothesis, all of which compare panels that employ the Gini coefficient, and reject the null 25 times.

Our analysis shows that estimates produced using LIS and OECD are similar. We therefore cannot reject the hypothesis that the two databases yield the same estimated rate of convergence (provided we use an analogous indicator). LIS and OECD are similar in a number of ways. Both focus on economically advanced countries, calculate inequality from micro-data, and provide estimates of equivalized household disposable income. Their major difference is that LIS standardizes microdata from income surveys in-house prior to calculating inequality, while OECD IDD calculates inequality in conjunction with national statistical offices.

Comparison between SWIID and its source material provides interesting results. SWIID imputes complete time series using a variety of inputs including LIS, OECD IDD, SEDLAC, WDI, ATG, and WIID. The final SWIID time series is built to impute “LIS-comparable net income inequality” indicators (Solt, 2016, forthcoming). Additionally, SWIID employs a moving average formula to avoid “unrealistic” jumps in inequality from one year to the next—unless those jumps are documented by LIS.¹⁰ Yet, using three of the four time periods for our panels, we reject the hypothesis that estimates of convergence in equivalized disposable income are constant between SWIID and LIS. Focusing on the net income inequality indicators, we similarly reject the hypothesis that estimates of convergence in equivalized disposable income are constant when comparing SWIID with WIID over two of the four time periods and when comparing SWIID with OECD IDD over three of the four time periods. Conversely, we find that estimates produced using SWIID are generally similar to those produced using SEDLAC (with the 1983 to 1999 time period an exception). We also

¹⁰ Inequality levels can jump significantly during crises. As such it is unclear whether this smoothing process produces more or less accurate estimates.

fail to reject the null in any of the comparisons between the SWIID and OECD IDD panels of pre tax and transfer income inequality.

When we test for the equality of estimates produced from panels that aggregate various welfare concepts together, we reject eight of 12 tests. The income and consumption inequality estimates in WDI are estimated by the World Bank using either grouped or micro data. ATG and WIID, however, aggregate Gini estimates from multiple sources. Panels constructed using these sources, therefore, include both aggregated welfare concepts, and aggregated methods of treating the microdata. As such, these rejections are consistent with the rejection of five of 12 tests of hypothesis A which suggests variation in estimates created using alternative welfare concepts within the same IDD.

Hypotheses Set D: changing the region of analysis

Hypothesis D examines whether the estimated rate of convergence is constant across regions of the world. Here there are two questions of interest. First, is there variation in convergence across regions? We are interested in, for example, whether countries within Latin America and the Caribbean are converging at the same rate as countries in Sub-Saharan Africa. Second, do different databases produce different conclusions with regards to these sort of pair-wise comparisons? Specifically, the hypothesis can be stated as follows:

Given any two panels of inequality indicators Θ_{wmjHT} and Θ_{wmjIT} , with identical welfare concepts, w , inequality measures, m , sources, j , and time periods, T , the estimated rate of convergence is constant across regional country sets H and I ; $\hat{\beta}_{wmjHT} = \hat{\beta}_{wmjIT}$.

To test this hypothesis we make pair-wise comparisons between regions while holding the inequality measure (always the Gini coefficient), welfare concept, time period, and source database constant. We test hypothesis D using the following sources and income concepts:

WDI estimates of income inequality, WDI estimates of consumption inequality, WIID estimates of per capita disposable income inequality, SWIID estimates of market income inequality, and SWIID estimates of net market income inequality. By varying the time periods over which we estimate convergence, we produce a total of 191 pair-wise comparisons between the following regions: Advanced Economies, East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, the Middle East and North Africa, South Asia, and Sub-Saharan Africa. Given the focus of this paper, we then compare whether the results of the hypothesis tests vary whether we use WDI, WIID, or SWIID.

We reject the null of equal rates of convergence in 111 of 193 tests. This includes 15 tests using data from WDI, eight tests using data from WIID, and 168 tests using data from SWIID. We find that results vary even within databases when the income concept or time period varies. For example, using panels of WDI/POVCAL income inequality Gini coefficients, we compare rates of convergence between panels of Latin American countries with panels of advanced economies across four time periods. Strikingly, we reject the null of equal rates of convergence for the period 1988 to 2000, but fail to reject the null for the period 1983 to 1999. Similarly, for the period 1988 to 2012, the panel of WDI/POVCAL consumption inequality Gini coefficients leads to the rejection of the hypothesis that convergence rates are the same in Europe and Central Asia as in advanced economies, but fail to reject that hypothesis when using income inequality Gini coefficients. The 168 tests performed using SWIID include 103 in which we reject the null hypothesis. More often than not, estimated convergence rates differ by region. Yet this finding is highly sensitive to the specific panel employed to test it.

Hypotheses Set E: changing time periods

Finally, we test whether the estimated rate of convergence is constant across time. Here, we hold the source database, welfare concept, inequality measure, and group of countries constant while estimating the rate of convergence over two different time frames.

Given any two panels of inequality indicators Θ_{wmjIS} and Θ_{wmjIT} , with identical welfare concepts, w , inequality measures, m , databases, j , and sets of countries, I , the estimated rate of convergence is the same over time periods S and T ; $\hat{\beta}_{wmjIS} = \hat{\beta}_{wmjIT}$.

We make pair-wise comparisons between the time periods 1988 to 2012, 1988 to 2000, 2000 to 2012, and 1983-1999—six total comparisons—using 27 different sets of inequality indicators. In total we estimate 153 test of hypothesis E. We then compare whether the hypothesis is accepted or rejected using each database.

We reject hypothesis E, the proposition that estimated convergence rates remain constant as the time period under study varies, 57 out of 153 times. Here, there is frequently consistency across welfare concepts and inequality measures for a given comparison within a given database. For example, we consistently fail to reject the null that convergence rates from 1988 to 2000 were equal convergence rates from 2000 to 2012 when using SEDLAC and CEPAL while we reject null using either the Gini coefficient or the Atkinson Index contained in LIS. Surprisingly, however, the panels made up of SEDLAC or CEPAL data lead to rejection of the null hypothesis in five out of seven tests when we compare 1983 to 1999 with 2000 to 2012. As another example, WTID data allows for the rejection of the null that the rate of convergence of the top one percent of incomes was the same from 1988-2000 and from 2000-2012. However, we fail to reject the same null hypothesis using either the top five percent income share or the inverted Pareto Lorenz coefficient.

In summary, this analysis explores the sensitivity of the estimated rate of convergence by testing five hypotheses using a series of pair-wise F-tests. The main findings of this sensitivity analysis are summarized in table 8. The main takeaways are as follows. First, estimates appear to be more sensitive to the choice of welfare concept than to the choice of inequality measure. Second, different databases frequently produce different results, even when the countries, the welfare concept, the inequality measure, and the time period are held constant. Third, while there is a rather large amount of evidence that estimated rates of convergence differ by region and by time—Hypotheses D and E are rejected 58% and 37% of the time—even this result is sensitive to the database that is used to perform the analysis.

5. Conclusions

The purpose of our paper is to assess the extent to which inequality analysis is sensitive to the choice of the data. We use iterative estimation of inequality convergence as a means to this end. We examine the sensitivity of our estimates of convergence to the choice of welfare concept, inequality measure, the database used as a source, as well as the region over which convergence is estimated and the time period covered.

We use data from nine databases with various welfare concepts, inequality measures, and country coverage. Overall, our estimates are generally supportive of the concept of inequality convergence (or mean reversion since—strictly speaking—we cannot distinguish between the two). Although not all of our estimates are statistically significant, we only rule out convergence using OECD IDD's measure of equivalized disposable income for the periods 1988 to 2000 and 1983 to 1999 and LIS's measure of equivalized disposable income for 1983 to 1999. These specific results are notable for two reasons. First, the fact that any of our estimates are statistically significant and positive provides a contrast with the existing literature. Second, for the period of 1988 to 2000 and 1983 to 1999 we find different results

within the same database using alternate welfare concepts. That is, we find divergence (we reject a null of convergence) using OECD disposable income and we find convergence (we reject a null of no convergence) using OECD pre-tax and transfer income.

We examine this phenomenon more rigorously in our tests of Hypothesis A. We reject five of twenty tests in which we hold the time period, database, countries, and inequality measure constant, but vary the welfare concept. More specifically, where we compare welfare concepts that differ between pre-tax (or market) and post-tax (or disposable) income, we reject five of seven tests. On the other hand, using SEDLAC, we do not reject the null that estimated rates of convergence vary depending on whether the welfare concept is per capita or disposable income.

In contrast with our other results, cross-sectional estimates of inequality convergence appear to be relatively consistent across inequality measures. While the Gini coefficient is used most prominently, we find little evidence to suggest that estimates would change significantly if the analysis were built on panels of Atkinson or Theil indices nor do our findings suggest a significant differentiation between using the top one percent income share or the top five percent income share. We should caution, however, that these inequality measures provide different information about the distribution of income and that while we find little evidence to suggest that the choice of measure alters large cross-sectional analysis, this does not mean that the metrics are interchangeable.

Estimates are highly sensitive to the source of the data. Even when the welfare concept and inequality measure are the same, and the countries used in the analysis are identical, results occasionally differ. We would therefore recommend that, where possible, all cross-national inequality studies test the sensitivity of their findings across multiple sources. Alternatively, we ought to regard any finding based on a single database as preliminary.

Of these findings, the most interesting may be the sensitivity of the convergence result to the choice of welfare concept. Yet, it may come as no surprise to researchers who focus on the relationship between fiscal policy and inequality. The Commitment to Equity Project, for example, provides a series of country-by-country examinations of the relationship between fiscal redistributions and economic inequality (Lustig and Higgins, 2013). One conclusion that can be drawn from this research, and others like it, is that fiscal redistribution is driven by country-specific institutional characteristics and politics (Lustig, Pessino, and Scott, 2013). As such we should expect that any analysis of trends in inequality would be sensitive to whether one uses market income, disposable income, or consumption as the primary welfare concept. Any analysis based on inequality trends should therefore be very precise about the welfare concept that is being used and we should remain cautious about use of inequality indicators based upon broadly defined or poorly understood welfare concepts.

Finally, our results display the importance of panel construction and its effect on results. While the depth and breadth of inequality data continues to grow, large gaps remain. Adjusting, even slightly, the time period being studied or the regions included can alter estimates by a statistically significant margin. As such, researchers ought to be very specific about the choices that they make in constructing panels of inequality indicators and very humble about the external validity of their results.

References

- Acemoglu, D., Naidu, S., Restrepo, P., and Robinson, J. A. (2013). Democracy, redistribution and inequality. Working Paper 19746, National Bureau of Economic Research.
- Atkinson, A. and Bourguignon, F., editors (2015). *Handbook of Income Distribution*, volume 2A-2B of *Handbook of Income Distribution*. Elsevier, 1 edition.
- Benabou, R. (1996). Inequality and growth. In *NBER Macroeconomics Annual 1996, Volume 11*, pages 11–92. MIT Press.
- Bleaney, M. and Nishiyama, A. (2003). Convergence in income inequality: differences between advanced and developing countries. *Economics Bulletin*, 4(22):1–10.
- Bourguignon, F. (2015). *The Globalization of Inequality*. Princeton University Press.
- Deininger, K. and Squire, L. (1996). A new data set measuring income inequality. *The World Bank Economic Review*, 10(3):565–591.
- Ezcurra, R. and Pascual, P. (2009). Convergence in income inequality in the united states: a nonparametric analysis. *Applied Economics Letters*, 16(13):1365–1368.
- Ferreira, F. H. and Lustig, N., editors (2015). *Special Issue on “Appraising Cross-National Income Inequality Databases”*, volume 13. Springer.
- Frank, M. W. (2009). Inequality and growth in the United States: Evidence from a new state-level panel of income inequality measures. *Economic Inquiry*, 47(1):55–68.
- Gomes, F. (2007). Convergence in income inequality: the case of Brazilian municipalities. *Economics Bulletin*, 15(15):1–9.
- Ho, T.-w. (2015). Income inequality may not converge after all: Testing panel unit roots in the presence of cross-section cointegration. *The Quarterly Review of Economics and Finance*, 56:68–79.
- Li, H. and Zou, H.-f. (1998). Income inequality is not harmful for growth: theory and evidence. *Review of development economics*, 2(3):318–334.
- Lin, P.-C. and Huang, H.-C. (2012). Convergence in income inequality? evidence from panel unit root tests with structural breaks. *Empirical Economics*, 43(1):153–174.
- Lustig, N., and Higgins, S. (2013). Commitment to Equity Assessment (CEQ): Estimating the Incidence of Social Spending, Subsidies, and Taxes-Handbook. Subsidies, and Taxes-Handbook (September 1, 2013).
- Lustig, N., Pessino C., and Scott, J. (2013). The Impact of Taxes and Social Spending on Inequality and Poverty in Argentina, Bolivia, Brazil, Mexico, Peru and Uruguay: An Overview. CEQ Working Paper No. 13, Center for Inter-American Policy and Research and Department of Economics, Tulane University and Inter-American Dialogue
- Ostry, M. J. D., Berg, M. A., and Tsangarides, M. C. G. (2014). *Redistribution, inequality, and growth*. International Monetary Fund.
- Partridge, J. S., Partridge, M. D., and Rickman, D. S. (1998). State patterns in family income inequality. *Contemporary Economic Policy*, 16(3):277–294.
- Partridge, M. D., Rickman, D. S., and Levernier, W. (1996). Trends in us income inequality: evidence from a panel of states. *The Quarterly Review of Economics and Finance*, 36(1):17–37.

- Piketty, T. (2014). *Capital in the twenty-first century*. The Belknap Press of Harvard University Press, Cambridge Massachusetts.
- Quah, D. (1993). Galton's fallacy and tests of the convergence hypothesis. *The Scandinavian Journal of Economics*, pages 427–443.
- Ravallion, M. (2003). Inequality convergence. *Economics Letters*, 80(3):351–356.
- Solt, F. (2016). The standardized world income inequality database. *Social Science Quarterly*, forthcoming.

*Tables***Table 1: Convergence Estimates 1988-2012**

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality Measure (<i>m</i>)	Slope		Intercept		N
			Coefficient	Std error	Coefficient	Std error	
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient	-0.026	(0.004)	0.014	(0.002)	177
CEPALSTAT	Per Capita Total Current Income	Theil Index	-0.032	(0.005)	0.018	(0.003)	177
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)	-0.024	(0.004)	0.010	(0.002)	177
LIS	Equivalized Disposable Household Income	Gini Coefficient	-0.010	(0.003)	0.004	(0.001)	86
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	-0.005	(0.004)	0.001	(0.001)	86
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient	-0.037	(0.005)	0.018	(0.002)	201
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	-0.010	(0.002)	0.004	(0.001)	224
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	-0.038	(0.003)	0.019	(0.001)	220
SEDLAC	Per Capita Disposable Household Income	Theil Index	-0.045	(0.005)	0.023	(0.003)	220
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	-0.040	(0.003)	0.015	(0.001)	220
SEDLAC	Household Equivalized Income	Gini Coefficient	-0.037	(0.003)	0.018	(0.001)	220
SEDLAC	Household Equivalized Income	Theil Index	-0.044	(0.005)	0.021	(0.002)	220
SEDLAC	Household Equivalized Income	Atkinson Index (1)	-0.040	(0.003)	0.014	(0.001)	220
Top Incomes	Income	Top 1% Share	-0.009	(0.003)	0.205	(0.022)	340
Top Incomes	Income	Top 5% Share	-0.004	(0.003)	0.280	(0.060)	282
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	-0.011	(0.007)	0.037	(0.013)	397
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	-0.006	(0.002)	0.003	(0.001)	540
WDI/POVCAL	Per Capita Income	Gini Coefficient	-0.008	(0.001)	0.004	(0.001)	339
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	-0.012	(0.005)	0.004	(0.002)	317
ATG	Welfare Concept Varies	Gini Coefficient	-0.015	(0.001)	0.007	(0.001)	1054
WIID	Household Equivalized Gross Income	Gini Coefficient	-0.036	(0.006)	1.722	(0.271)	184
WIID	Household Equivalized Disposable Income	Gini Coefficient	-0.008	(0.001)	0.329	(0.036)	489
WIID	Household Per Capita Disposable Income	Gini Coefficient	-0.019	(0.003)	0.539	(0.080)	519
WIID	Household Per Capita Expenditure	Gini Coefficient	-0.025	(0.009)	0.902	(0.326)	65
WIID	Average of Multiple Welfare Concepts	Gini Coefficient	-0.015	(0.002)	0.581	(0.074)	1151
SWIID	Market Income	Gini Coefficient	-0.037	(0.001)	0.018	(0.001)	2661
SWIID	Net Market Income	Gini Coefficient	-0.025	(0.001)	0.011	(0.000)	2662

Table 2: Convergence Estimates 1988-2000

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Slope		Intercept		N
			Coefficient	Std error	Coefficient	Std error	
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient	-0.036	(0.014)	0.022	(0.007)	38
CEPALSTAT	Per Capita Total Current Income	Theil Index	-0.045	(0.022)	0.031	(0.013)	38
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)	-0.030	(0.017)	0.016	(0.006)	38
LIS	Equivalized Disposable Household Income	Gini Coefficient	0.007	(0.011)	-0.001	(0.004)	19
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	0.009	(0.015)	-0.000	(0.004)	19
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient	-0.053	(0.033)	0.030	(0.014)	19
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	0.018	(0.005)	-0.004	(0.001)	44
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	-0.045	(0.008)	0.024	(0.004)	57
SEDLAC	Per Capita Disposable Household Income	Theil Index	-0.073	(0.022)	0.038	(0.011)	57
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	-0.049	(0.008)	0.021	(0.003)	57
SEDLAC	Household Equivalized Income	Gini Coefficient	-0.044	(0.008)	0.023	(0.004)	57
SEDLAC	Household Equivalized Income	Theil Index	-0.071	(0.021)	0.034	(0.009)	57
SEDLAC	Household Equivalized Income	Atkinson Index (1)	-0.049	(0.008)	0.020	(0.003)	57
Top Incomes	Income	Top 1% Share	-0.021	(0.007)	0.305	(0.058)	157
Top Incomes	Income	Top 5% Share	-0.026	(0.008)	0.707	(0.152)	130
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	0.005	(0.011)	0.013	(0.020)	179
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	-0.013	(0.006)	0.007	(0.003)	115
WDI/POVCAL	Per Capita Income	Gini Coefficient	-0.021	(0.007)	0.011	(0.004)	80
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	-0.030	(0.016)	0.012	(0.006)	30
ATG	Welfare Concept Varies	Gini Coefficient	-0.026	(0.004)	0.013	(0.002)	376
WIID	Household Equivalized Gross Income	Gini Coefficient	0.000	(0.011)	0.426	(0.332)	24
WIID	Household Equivalized Disposable Income	Gini Coefficient	-0.009	(0.006)	0.436	(0.176)	158
WIID	Household Per Capita Disposable Income	Gini Coefficient	0.000	(0.006)	0.250	(0.235)	131
WIID	Household Per Capita Expenditure	Gini Coefficient	-0.027	(0.014)	0.969	(0.542)	22
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	-0.010	(0.005)	0.460	(0.210)	395
SWIID	Market Income	Gini Coefficient	-0.056	(0.003)	0.029	(0.001)	1123
SWIID	Net Market Income	Gini Coefficient	-0.037	(0.002)	0.017	(0.001)	1123

Table 3: Convergence Estimates 2000-2012

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Slope		Intercept		N
			Coefficient	Std error	Coefficient	Std error	
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient	-0.013	(0.012)	0.002	(0.007)	96
CEPALSTAT	Per Capita Total Current Income	Theil Index	-0.038	(0.008)	0.009	(0.005)	96
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)	-0.017	(0.012)	0.001	(0.005)	96
LIS	Equivalized Disposable Household Income	Gini Coefficient	-0.033	(0.009)	0.011	(0.003)	11
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	-0.042	(0.012)	0.009	(0.003)	11
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient	-0.032	(0.019)	0.016	(0.008)	140
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	-0.016	(0.005)	0.005	(0.002)	128
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	-0.042	(0.012)	0.016	(0.006)	119
SEDLAC	Per Capita Disposable Household Income	Theil Index	-0.060	(0.010)	0.021	(0.006)	119
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	-0.051	(0.010)	0.013	(0.004)	119
SEDLAC	Household Equivalized Income	Gini Coefficient	-0.042	(0.012)	0.015	(0.006)	119
SEDLAC	Household Equivalized Income	Theil Index	-0.061	(0.010)	0.019	(0.006)	119
SEDLAC	Household Equivalized Income	Atkinson Index (1)	-0.052	(0.011)	0.012	(0.004)	119
Top Incomes	Income	Top 1% Share	0.006	(0.008)	0.064	(0.084)	126
Top Incomes	Income	Top 5% Share	-0.017	(0.007)	0.498	(0.157)	107
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	0.010	(0.011)	-0.010	(0.021)	151
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	-0.023	(0.003)	0.007	(0.002)	248
WDI/POVCAL	Per Capita Income	Gini Coefficient	-0.030	(0.004)	0.009	(0.002)	154
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	0.009	(0.009)	-0.004	(0.003)	162
ATG	Welfare Concept Varies	Gini Coefficient	-0.023	(0.004)	0.007	(0.002)	390
WIID	Household Equivalized Gross Income	Gini Coefficient	-0.114	(0.016)	5.447	(0.716)	111
WIID	Household Equivalized Disposable Income	Gini Coefficient	-0.025	(0.003)	0.695	(0.086)	228
WIID	Household Per Capita Disposable Income	Gini Coefficient	-0.011	(0.011)	0.178	(0.353)	270
WIID	Household Per Capita Expenditure	Gini Coefficient	-0.081	(0.023)	3.315	(0.811)	20
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	-0.038	(0.005)	1.380	(0.187)	477
SWIID	Market Income	Gini Coefficient	-0.032	(0.003)	0.014	(0.002)	1116
SWIID	Net Market Income	Gini Coefficient	-0.031	(0.002)	0.011	(0.001)	1117

Table 4: Convergence Estimates 1983-1999

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Slope		Intercept		N
			Coefficient	Std error	Coefficient	Std error	
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient	-0.028	(0.016)	0.017	(0.008)	26
CEPALSTAT	Per Capita Total Current Income	Theil Index	-0.043	(0.025)	0.030	(0.015)	26
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)	-0.021	(0.019)	0.011	(0.007)	26
LIS	Equivalized Disposable Household Income	Gini Coefficient	0.009	(0.003)	-0.001	(0.001)	37
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	0.007	(0.005)	0.000	(0.001)	37
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient	-0.066	(0.015)	0.032	(0.007)	32
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	0.016	(0.003)	-0.004	(0.001)	57
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	-0.008	(0.009)	0.007	(0.004)	54
SEDLAC	Per Capita Disposable Household Income	Theil Index	-0.017	(0.029)	0.015	(0.013)	54
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	-0.009	(0.009)	0.007	(0.003)	54
SEDLAC	Household Equivalized Income	Gini Coefficient	-0.005	(0.009)	0.006	(0.004)	54
SEDLAC	Household Equivalized Income	Theil Index	-0.013	(0.029)	0.012	(0.012)	54
SEDLAC	Household Equivalized Income	Atkinson Index (1)	-0.007	(0.010)	0.006	(0.003)	54
Top Incomes	Income	Top 1% Share	-0.008	(0.007)	0.180	(0.041)	215
Top Incomes	Income	Top 5% Share	-0.009	(0.007)	0.333	(0.120)	182
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	-0.010	(0.008)	0.037	(0.013)	250
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	-0.010	(0.005)	0.005	(0.002)	148
WDI/POVCAL	Per Capita Income	Gini Coefficient	-0.009	(0.004)	0.005	(0.002)	107
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	-0.017	(0.011)	0.006	(0.004)	42
ATG	Welfare Concept Varies	Gini Coefficient	-0.022	(0.003)	0.011	(0.001)	504
WIID	Household Equivalized Gross Income	Gini Coefficient	-0.025	(0.010)	1.272	(0.413)	39
WIID	Household Equivalized Disposable Income	Gini Coefficient	-0.002	(0.003)	0.231	(0.085)	186
WIID	Household Per Capita Disposable Income	Gini Coefficient	-0.013	(0.003)	0.649	(0.103)	150
WIID	Household Per Capita Expenditure	Gini Coefficient	-0.041	(0.012)	1.648	(0.435)	33
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	-0.018	(0.003)	0.891	(0.132)	497
SWIID	Market Income	Gini Coefficient	-0.044	(0.002)	0.022	(0.001)	1383
SWIID	Net Market Income	Gini Coefficient	-0.027	(0.002)	0.012	(0.001)	1383

Table 5: F Statistics for Tests of Hypothesis A

Metric (m)	Source (j)	Welfare Concepts (w vs. v)	Time Period (T)			
			1988-2012	1988-2000	2000-2012	1983-1999
Gini Coefficient	WDI	Income vs. Consumption	1.821 (0.180)			
Gini Coefficient	SEDLAC	Equivalized Income vs Per Capita Income	0.042 (0.838)	0.000 (0.986)	0.000 (1.000)	0.059 (0.808)
Atkinson Index (1)	SEDLAC	Equivalized Income vs Per Capita Income	0.003 (0.958)	0.000 (0.982)	0.008 (0.929)	0.035 (0.853)
Theil Index	SEDLAC	Equivalized Income vs Per Capita Income	0.038 (0.846)	0.006 (0.937)	0.005 (0.946)	0.010 (0.922)
Gini Coefficient	SWIID	Net Income vs. Market Income	49.800 (0.000)	25.768 (0.000)	0.046 (0.830)	44.630 (0.000)
Gini Coefficient	OECD	Disposable Income vs. Total Income	24.343 (0.000)		0.541 (0.462)	28.976 (0.000)

P-values in parentheses. Tests only performed where there were at least 10 countries and 30 observations in each subset.

Table 6: F Statistics for Tests of Hypothesis B

Welfare Concept (w)	Source (j)	Inequality Measures (l vs. m)	Time Period (T)			
			1988-2012	1988-2012	1988-2012	1988-2012
Per Capita Total Current Income	CEPAL	Gini Coefficient vs. Theil Index	0.968 (0.326)	0.108 (0.743)	3.151 (0.077)	
Per Capita Total Current Income	CEPAL	Atkinson Index (1) vs. Theil Index	1.518 (0.219)	0.283 (0.596)	2.189 (0.141)	
Per Capita Total Current Income	CEPAL	Gini Coefficient vs. Atkinson Index(1)	0.119 (0.730)	0.078 (0.781)	0.075 (0.784)	
Per Capita Disposable Household Income	SEDLAC	Gini Coefficient vs. Atkinson Index(1)	0.412 (0.521)	0.179 (0.673)	0.333 (0.564)	0.004 (0.947)
Per Capita Disposable Household Income	SEDLAC	Gini Coefficient vs. Atkinson Index(1)	0.601 (0.439)	0.198 (0.658)	0.419 (0.518)	0.012 (0.914)
Per Capita Pre-tax Income	WTID	Top five percent Income Share vs. Inverted Pareto Lorenz Coefficient	2.064 (0.151)	7.189 (0.008)	3.354 (0.069)	0.000 (0.997)
Per Capita Pre-tax Income	WTID	Top one percent Income Share vs. Inverted Pareto Lorenz Coefficient	0.268 (0.605)	4.742 (0.030)	0.143 (0.706)	0.001 (0.979)
Per Capita Total Current Income	WTID	Top one percent Income Share vs. Top five percent Income Share	0.647 (0.422)	0.344 (0.558)	0.940 (0.333)	0.000 (0.995)
Per Capita Disposable Household Income	LIS	Gini Coefficient vs. Atkinson Index(1)	1.277 (0.260)	0.020 (0.889)	0.325 (0.576)	0.122 (0.728)

P-values in parentheses. Tests only performed where there were at least 10 countries and 30 observations in each subset.

Table 7: F-Statistics for Tests of Hypothesis C

Welfare Concept (<i>w</i>)	Inequality Measure (<i>m</i>)	Source (<i>j</i> vs. <i>k</i>)	Time Period (<i>T</i>)			
			1988-2012	1988-2012	1988-2012	1988-2012
Equivalized Disposable or Net Household Income	Gini Coefficient	LIS vs. OECD IDD	0.014	1.206	0.089	1.613
			(0.905)	(0.277)	(0.766)	(0.208)
Equivalized Disposable or Net Household Income	Gini Coefficient	SWIID vs. LIS	0.085	6.227	5.568	21.179
			(0.771)	(0.013)	(0.020)	(0.000)
Equivalized Disposable or Net Household Income	Gini Coefficient	SWIID vs. OECD IDD	12.025	17.293	1.895	55.831
			(0.001)	(0.000)	(0.169)	(0.000)
Equivalized Disposable or Net Household Income	Gini Coefficient	SWIID vs. SEDLAC	0.040	2.491	0.063	10.619
			(0.842)	(0.116)	(0.803)	(0.001)
Equivalized Disposable or Net Household Income	Gini Coefficient	SWIID vs. LIS and SEDLAC	1.903	1.156	1.926	21.930
			(0.168)	(0.283)	(0.166)	(0.000)
Equivalized Disposable or Net Household Income	Gini Coefficient	WIID vs. LIS	0.108	0.421	0.199	11.618
			(0.742)	(0.517)	(0.656)	(0.001)
Equivalized Disposable or Net Household Income	Gini Coefficient	WIID vs. OECD IDD	0.168	2.035	0.062	25.613
			(0.682)	(0.156)	(0.804)	(0.000)
Equivalized Disposable or Net Household Income	Gini Coefficient	WIID vs. SEDLAC	0.083	1.844	11.524	0.808
			(0.774)	(0.180)	(0.001)	(0.372)
Equivalized Disposable or Net Household Income	Gini Coefficient	WIID vs. LIS and SEDLAC	5.184	1.017	4.041	4.103
			(0.023)	(0.315)	(0.046)	(0.044)
Equivalized Disposable or Net Household Income	Gini Coefficient	WIID vs. SWIID	19.726	1.313	4.524	2.445
			(0.000)	(0.252)	(0.034)	(0.118)
Per Capita Expenditure or Consumption	Gini Coefficient	WIID vs. WDI/POVCAL	1.089	0.111	24.787	0.057
			(0.298)	(0.742)	(0.000)	(0.812)
Per Capita Disposable Household Income	Gini Coefficient	WIID vs. SEDLAC	0.463			
			(0.497)			
Equivalized Market or Pre Tax and Transfer Income	Gini Coefficient	SWIID vs. OECD IDD	0.044		2.827	0.667
			(0.834)		(0.093)	(0.415)
Aggregated Welfare Concepts	Gini Coefficient	WIID vs. ATG	0.291	5.645	8.923	0.577
			(0.589)	(0.018)	(0.003)	(0.448)
Aggregated Welfare Concepts	Gini Coefficient	WIID vs. WDI/POVCAL	20.747	0.190	8.555	7.941
			(0.000)	(0.663)	(0.004)	(0.005)
Aggregated Welfare Concepts	Gini Coefficient	ATG vs. WDI/POVCAL	26.212	6.318	0.050	9.784
			(0.000)	(0.012)	(0.824)	(0.002)

P-values in parentheses. Tests only performed where there were at least 10 countries and 30 observations in each subset.

Table 8 Summary of Results

Hypothesis		Tests	Rejections
A	All else equal, estimates are identical across welfare concepts	20	5
B	All else equal, estimates are identical across inequality measures	33	2
C	All else equal, estimates are identical across data sources	60	25
D	All else equal, estimates are identical across regional subsets of countries	191	111
E	All else equal, estimates are identical across time periods	153	57

Appendix A: Incorporating Data from WIID 3.3

The World Income Inequality Database (WIID) is a secondary source database that collects inequality indicators from a variety of sources. WIID data is characterized by welfare definition, unit of analysis, income share unit, and a number of variables that describe the breadth or coverage of the inequality estimate. We use WIID 3.3, released in September of 2015.

In our analysis, we only use inequality indicators that are classified as including all age groups and all regions within a country. We then divide the dataset into four groups by welfare definition; they are consumption, gross income, disposable income, and other. We then expand the dataset from four categories to 12 based on whether the unit of analysis is household, person, or other. We further divide the dataset, from 12 categories to 36 based on whether the indicators are calculated either using household adult equivalence scales, by individual or household per capita, or some other equivalency scale. Finally, we expand from 36 categories to 144 based on quality rating: high, medium, low, or unknown. Where multiple estimates exist for the same welfare definition, scale, quality, country, and year, we average the indicators together. The result is 144 unique panels of inequality estimates based on WIID 3.3.

We then limit the number of panels by using a choice by precedence approach to 48 by collapsing along the dimension of unit of analysis into panels of country, year, welfare definition, and equivalence scale. Within each cell we keep the best available indicator, categorizing the best unit of analysis as person, the second best unit of analysis as household, and the worst unit of analysis as other. We further limit the number of panels by merging all panels that list the welfare metric as “other” whether they are measured using household adult equivalence scales, by individual or household per capita, or some other equivalency scale. This reduces the number of panels to 40. That is, for each level of quality there are ten unique panels:

(1) disposable household equivalent income, (2) gross household equivalent income, (3) household equivalent expenditure, (4) disposable household per capita income, (5) gross household per capita income, (6) per capita expenditure, (7) other disposable income, (8) other gross income, (9) other expenditure, and (10) other.

Next, within each of the ten categories above, we replace metrics of medium, low, or unknown quality with better quality metrics when possible. After this process the high quality panels are subsets of the medium quality panels, the medium quality panels are subsets of the low quality panels, and the low quality panels are subsets of the unknown quality panels. Unless otherwise stated, we the figures that appear in this paper are based on the medium quality panels.

Table A1: F-Statistics for Tests of Hypothesis D using WDI and WIID

Regional Comparison (<i>H</i> vs. <i>I</i>)	Time Period (<i>T</i>)	SOURCE (<i>J</i>) Welfare Concept (<i>w</i>)		
		WDI/POV/CAL Income	WDI/POV/CAL Consumption	WIID Per Capita Disposable Income
Advanced Economies vs. East Asia and Pacific	1988-2012		3.353 (0.072)	
Advanced Economies vs. Europe and Central Asia	1988-2000			1.319 (0.253)
Advanced Economies vs. Europe and Central Asia	2000-2012			5.205 (0.023)
Advanced Economies vs. Europe and Central Asia	1988-2012	0.248 (0.620)	3.900 (0.050)	0.096 (0.757)
Advanced Economies vs. Europe and Central Asia	1983-1999			0.319 (0.573)
Advanced Economies vs. Latin America and the Caribbean	1988-2000	6.934 (0.010)		1.399 (0.240)
Advanced Economies vs. Latin America and the Caribbean	2000-2012	10.114 (0.002)		
Advanced Economies vs. Latin America and the Caribbean	1988-2012	14.866 (0.000)		1.097 (0.295)
Advanced Economies vs. Latin America and the Caribbean	1983-1999	0.114 (0.736)		
Advanced Economies vs. Sub-Saharan Africa	1988-2012		8.454 (0.005)	
East Asia and Pacific vs. Europe and Central Asia	2000-2012		0.086 (0.769)	
East Asia and Pacific vs. Europe and Central Asia	1988-2012		0.311 (0.578)	
East Asia and Pacific vs. Sub-Saharan Africa	2000-2012		0.108 (0.746)	
East Asia and Pacific vs. Sub-Saharan Africa	1988-2012		10.980 (0.001)	
Europe and Central Asia vs. Latin America and the Caribbean	1988-2000			0.010 (0.923)
Europe and Central Asia vs. Latin America and the Caribbean	1988-2012	1.548 (0.215)		1.198 (0.276)
Europe and Central Asia vs. Sub-Saharan Africa	2000-2012		1.184 (0.279)	
Europe and Central Asia vs. Sub-Saharan Africa	1988-2012		7.453 (0.007)	

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.

Table A2: F-Statistics for Tests of Hypothesis D using SWIID Market Income Gini

Regional Comparison (<i>H</i> vs. <i>I</i>)	Time Period (<i>T</i>)			
	1988-2000	2000-2012	1988-2012	1983-1999
Advanced Economies vs. East Asia and Pacific	1.478 (0.225)	0.023 (0.880)	21.374 (0.000)	1.189 (0.276)
Advanced Economies vs. Europe and Central Asia	1.223 (0.269)	18.315 (0.000)	2.623 (0.106)	0.423 (0.516)
Advanced Economies vs. Latin America and the Caribbean	1.307 (0.253)	1.456 (0.228)	5.685 (0.017)	0.365 (0.546)
Advanced Economies vs. Middle East and North Africa	15.623 (0.000)	2.215 (0.138)	0.468 (0.494)	22.552 (0.000)
Advanced Economies vs. South Asia	21.316 (0.000)	18.956 (0.000)	31.541 (0.000)	9.970 (0.002)
Advanced Economies vs. Sub-Saharan Africa	0.714 (0.398)	5.145 (0.024)	6.026 (0.014)	3.118 (0.078)
East Asia and Pacific vs. Europe and Central Asia	0.026 (0.872)	20.340 (0.000)	22.892 (0.000)	0.014 (0.905)
East Asia and Pacific vs. Latin America and the Caribbean	5.516 (0.020)	1.802 (0.181)	5.947 (0.015)	0.096 (0.757)
East Asia and Pacific vs. Middle East and North Africa	6.481 (0.012)	2.593 (0.110)	10.812 (0.001)	17.669 (0.000)
East Asia and Pacific vs. South Asia	14.595 (0.000)	18.154 (0.000)	10.592 (0.001)	7.260 (0.008)
East Asia and Pacific vs. Sub-Saharan Africa	0.301 (0.584)	6.007 (0.015)	5.397 (0.020)	0.519 (0.472)
Europe and Central Asia vs. Latin America and the Caribbean	3.952 (0.048)	4.784 (0.029)	9.535 (0.002)	0.016 (0.900)
Europe and Central Asia vs. Middle East and North Africa	2.936 (0.088)	2.890 (0.090)	3.518 (0.061)	14.330 (0.000)
Europe and Central Asia vs. South Asia	11.081 (0.001)	39.713 (0.000)	35.413 (0.000)	6.513 (0.011)
Europe and Central Asia vs. Sub-Saharan Africa	0.332 (0.565)	3.643 (0.057)	9.864 (0.002)	0.377 (0.540)
Latin America and the Caribbean vs. Middle East and North Africa	27.300 (0.000)	0.090 (0.764)	1.477 (0.225)	17.208 (0.000)
Latin America and the Caribbean vs. South Asia	28.146 (0.000)	23.272 (0.000)	21.210 (0.000)	7.573 (0.006)
Latin America and the Caribbean vs. Sub-Saharan Africa	4.623 (0.032)	0.455 (0.500)	0.011 (0.917)	0.801 (0.371)
Middle East and North Africa vs. South Asia	6.436 (0.013)	23.991 (0.000)	25.463 (0.000)	0.285 (0.594)
Middle East and North Africa vs. Sub-Saharan Africa	13.906 (0.000)	0.088 (0.767)	1.675 (0.196)	14.811 (0.000)
South Asia vs. Sub-Saharan Africa	18.999 (0.000)	29.664 (0.000)	20.704 (0.000)	5.835 (0.016)

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.

Table A3: F-Statistics for Tests of Hypothesis D using SWIID Net Income Gini

Regional Comparison (<i>H</i> vs. <i>I</i>)	Time Period (<i>T</i>)			
	1988-2000	2000-2012	1988-2012	1983-1999
Advanced Economies vs. East Asia and Pacific	6.638 (0.010)	0.647 (0.422)	44.879 (0.000)	18.632 6.638
Advanced Economies vs. Europe and Central Asia	31.981 (0.000)	9.570 (0.002)	135.842 (0.000)	34.568 31.981
Advanced Economies vs. Latin America and the Caribbean	12.000 (0.001)	3.199 (0.074)	25.126 (0.000)	8.456 12.000
Advanced Economies vs. Middle East and North Africa	3.082 (0.080)	0.312 (0.577)	5.989 (0.015)	4.770 3.082
Advanced Economies vs. South Asia	8.053 (0.005)	28.455 (0.000)	16.592 (0.000)	9.058 8.053
Advanced Economies vs. Sub-Saharan Africa	12.145 (0.001)	1.113 (0.292)	39.470 (0.000)	12.159 12.145
East Asia and Pacific vs. Europe and Central Asia	6.696 (0.010)	1.673 (0.197)	4.804 (0.029)	1.874 6.696
East Asia and Pacific vs. Latin America and the Caribbean	0.227 (0.634)	0.611 (0.435)	13.712 (0.000)	1.072 0.227
East Asia and Pacific vs. Middle East and North Africa	10.811 (0.001)	0.001 (0.977)	16.305 (0.000)	16.605 10.811
East Asia and Pacific vs. South Asia	16.028 (0.000)	16.756 (0.000)	0.157 (0.692)	32.448 16.028
East Asia and Pacific vs. Sub-Saharan Africa	0.010 (0.921)	0.006 (0.939)	9.320 (0.002)	0.394 0.010
Europe and Central Asia vs. Latin America and the Caribbean	5.076 (0.025)	0.121 (0.728)	9.790 (0.002)	5.558 5.076
Europe and Central Asia vs. Middle East and North Africa	33.813 (0.000)	1.084 (0.299)	11.675 (0.001)	23.671 33.813
Europe and Central Asia vs. South Asia	38.878 (0.000)	12.539 (0.000)	2.712 (0.100)	47.262 38.878
Europe and Central Asia vs. Sub-Saharan Africa	9.578 (0.002)	3.188 (0.075)	3.560 (0.059)	3.901 9.578
Latin America and the Caribbean vs. Middle East and North Africa	15.891 (0.000)	0.459 (0.499)	0.988 (0.321)	11.951 15.891
Latin America and the Caribbean vs. South Asia	21.414 (0.000)	11.807 (0.001)	6.535 (0.011)	22.076 21.414
Latin America and the Caribbean vs. Sub-Saharan Africa	0.464 (0.496)	1.007 (0.316)	1.053 (0.305)	0.171 0.464
Middle East and North Africa vs. South Asia	1.436 (0.234)	13.085 (0.000)	8.334 (0.004)	0.118 1.436
Middle East and North Africa vs. Sub-Saharan Africa	15.151 (0.000)	0.001 (0.979)	3.273 (0.071)	13.844 15.151
South Asia vs. Sub-Saharan Africa	20.639 (0.000)	21.270 (0.000)	4.781 (0.029)	26.335 20.639

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.

Table A3: F Statistics for Tests of Hypothesis E (1/3)

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Time Periods (<i>S</i> vs. <i>T</i>)	
			1988-2000 vs. 2000-2012	1988-2000 vs. 1988-2012
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient	1.684	0.562
CEPALSTAT	Per Capita Total Current Income	Theil Index	0.077	0.327
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)	0.408	0.147
LIS	Equivalized Disposable Household Income	Gini Coefficient	7.913	2.413
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	7.206	0.877
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient		
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	21.128	26.443
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	0.043	0.717
SEDLAC	Per Capita Disposable Household Income	Theil Index	0.299	1.606
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	0.014	1.091
SEDLAC	Household Equivalized Income	Gini Coefficient	0.035	0.777
SEDLAC	Household Equivalized Income	Theil Index	0.167	1.548
SEDLAC	Household Equivalized Income	Atkinson Index (1)	0.039	1.149
Top Incomes	Income	Top 1% Share	6.148	2.539
Top Incomes	Income	Top 5% Share	0.731	6.676
Top Incomes	Income	Inverted Pareto Lorenz Coefficient		
Top Incomes	Income and Consumption Mixed	Gini Coefficient	0.092	1.449
WDI/POVCAL	Per Capita Income	Gini Coefficient	2.122	1.197
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	1.247	2.885
WDI/POVCAL	Welfare Concept Varies	Gini Coefficient	4.646	1.244
ATG	Household Equivalized Gross Income	Gini Coefficient	0.177	6.138
WIID	Household Equivalized Disposable Income	Gini Coefficient	37.063	9.521
WIID	Household Per Capita Disposable Income	Gini Coefficient	6.353	0.036
WIID	Household Per Capita Disposable Income	Gini Coefficient	0.705	7.890
WIID	Household Per Capita Expenditure	Gini Coefficient	4.084	0.019
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	15.075	0.871
SWIID	Market Income	Gini Coefficient	27.986	35.161
SWIID	Net Market Income	Gini Coefficient	2.651	19.612

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.

Table A4: F Statistics for Tests of Hypothesis E (2/3)

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Time Periods (<i>S</i> vs. <i>T</i>)	
			1988-2000 vs. 1983-1999	2000-2012 vs. 1988-2012
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient		1.095 (0.296)
CEPALSTAT	Per Capita Total Current Income	Theil Index		0.384 (0.536)
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)		0.273 (0.602)
LIS	Equivalized Disposable Household Income	Gini Coefficient	0.044 (0.834)	6.558 (0.012)
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	0.024 (0.876)	10.307 (0.002)
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient		0.069 (0.794)
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	0.074 (0.786)	1.206 (0.273)
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	9.788 (0.002)	0.106 (0.744)
SEDLAC	Per Capita Disposable Household Income	Theil Index	2.410 (0.124)	1.829 (0.177)
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	11.249 (0.001)	0.887 (0.347)
SEDLAC	Household Equivalized Income	Gini Coefficient	10.108 (0.002)	0.146 (0.703)
SEDLAC	Household Equivalized Income	Theil Index	2.614 (0.109)	2.292 (0.131)
SEDLAC	Household Equivalized Income	Atkinson Index (1)	11.352 (0.001)	1.134 (0.288)
Top Incomes	Income	Top 1% Share	1.965 (0.162)	3.021 (0.083)
Top Incomes	Income	Top 5% Share	2.927 (0.088)	2.435 (0.119)
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	1.295 (0.256)	2.462 (0.117)
Top Incomes	Income	Gini Coefficient		
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	0.106 (0.745)	19.585 (0.000)
WDI/POVCAL	Per Capita Income	Gini Coefficient	1.961 (0.163)	30.639 (0.000)
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	0.476 (0.493)	3.879 (0.049)
ATG	Welfare Concept Varies	Gini Coefficient	0.559 (0.455)	4.016 (0.045)
WIID	Household Equivalized Gross Income	Gini Coefficient	3.020 (0.087)	21.755 (0.000)
WIID	Household Equivalized Disposable Income	Gini Coefficient	1.310 (0.253)	38.915 (0.000)
WIID	Household Per Capita Disposable Income	Gini Coefficient	3.683 (0.056)	0.453 (0.501)
WIID	Household Per Capita Expenditure	Gini Coefficient	0.660 (0.420)	5.429 (0.022)
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	1.643 (0.200)	17.391 (0.000)
SWIID	Market Income	Gini Coefficient	10.621 (0.001)	1.408 (0.235)
SWIID	Net Market Income	Gini Coefficient	11.738 (0.001)	7.609 (0.006)

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.

Table A5: F Statistics for Tests of Hypothesis E (3/3)

Source (<i>j</i>)	Welfare Concept (<i>w</i>)	Inequality measure (<i>m</i>)	Time Periods (<i>S</i> vs. <i>T</i>)	
			2000-2012 vs. 1983-1999	1988-2012 vs. 1983-1999
CEPALSTAT	Per Capita Total Current Income	Gini Coefficient		
CEPALSTAT	Per Capita Total Current Income	Theil Index		
CEPALSTAT	Per Capita Total Current Income	Atkinson Index (1)		
LIS	Equivalized Disposable Household Income	Gini Coefficient	19.810	(0.000)
LIS	Equivalized Disposable Household Income	Atkinson Index (1)	15.391	(0.000)
OECD IDD	Equivalized Pre Tax and Transfer Income	Gini Coefficient	2.102	(0.149)
OECD IDD	Equivalized Disposable Household Income	Gini Coefficient	28.631	(0.000)
SEDLAC	Per Capita Disposable Household Income	Gini Coefficient	5.212	(0.024)
SEDLAC	Per Capita Disposable Household Income	Theil Index	2.014	(0.158)
SEDLAC	Per Capita Disposable Household Income	Atkinson Index (1)	9.064	(0.003)
SEDLAC	Household Equivalized Income	Gini Coefficient	5.738	(0.018)
SEDLAC	Household Equivalized Income	Theil Index	2.515	(0.115)
SEDLAC	Household Equivalized Income	Atkinson Index (1)	9.822	(0.002)
Top Incomes	Income	Top 1% Share	1.652	(0.200)
Top Incomes	Income	Top 5% Share	0.691	(0.406)
Top Incomes	Income	Inverted Pareto Lorenz Coefficient	2.231	(0.136)
WDI/POVCAL	Income and Consumption Mixed	Gini Coefficient	4.313	(0.038)
WDI/POVCAL	Per Capita Income	Gini Coefficient	14.799	(0.000)
WDI/POVCAL	Per Capita Consumption	Gini Coefficient	3.493	(0.063)
ATG	Welfare Concept Varies	Gini Coefficient	0.092	(0.762)
WIID	Household Equivalized Gross Income	Gini Coefficient	22.752	(0.000)
WIID	Household Equivalized Disposable Income	Gini Coefficient	38.466	(0.000)
WIID	Household Per Capita Disposable Income	Gini Coefficient	0.036	(0.850)
WIID	Household Per Capita Expenditure	Gini Coefficient	2.401	(0.128)
SWIID	Average of Multiple Welfare Concepts	Gini Coefficient	10.707	(0.001)
SWIID	Market Income	Gini Coefficient	9.262	(0.002)
SWIID	Net Market Income	Gini Coefficient	3.323	(0.068)
			0.583	(0.445)

P-values in parentheses. Tests only performed where there were at least 30 observations in each subset.