Are Fairness Perceptions Shaped by Income Inequality? Evidence from Latin America*

Germán Reyes Leonardo Gasparini

June 11, 2021

Abstract

A common assumption in the literature is that the actual level of income inequality shapes people's views on distributive fairness. However, individuals do not directly observe income inequality (which often leads to large misperceptions), nor do they consider all inequities to be unfair. In this paper, we empirically assess the link between objective measures of income inequality and fairness views in a context of high but decreasing income inequality. To do this, we combine opinion poll data with harmonized data from household surveys for 18 Latin American countries over the 1997-2015 period. We find a strong and statistically significant relationship between income inequality and unfairness views both across countries and over time. Unfairness views evolved in the same direction as income inequality for 17 out of the 18 countries in our sample. On average, individuals who are older, unemployed, and left-wing are more likely to perceive the income distribution as very unfair. We also show that, conditional on income inequality, unfairness views predict individuals' propensity to mobilize and protest.

*Reyes: Cornell University (e-mail `gjr66@cornell.edu`). Address: 457 Uris Hall, Ithaca, New York 1485. (For correspondence and/or offprints). Gasparini: Centro de Estudios Distributivos, Laborales y Sociales (CEDLAS) - IIE-FCE, Universidad Nacional de La Plata and CONICETT (e-mail: `gasparinilc@gmail.com`).
For helpful comments, we thank Carolina García Domench, Giselle Del Carmen, Rebecca Deranian, Luis Laguinge, and two anonymous referees. A previous version of this article circulated as "Perceptions of Distributive Justice in Latin America during a Period of Falling Inequality." Errors and omissions are our own.

1 Introduction

Several theoretical and empirical papers rely on objective measures of income inequality to explain individual-level behaviors and outcomes.[1] Implicit in much of this literature is the assumption that inequality shapes individuals' beliefs about whether income distribution is fair, or fairness views, for short.[2] However, two pieces of evidence suggest that the link between inequality and fairness views is not straightforward. First, fairness views are not informed by objective measures of inequality—since these are not directly observable by individuals—but instead by perceived inequality. Research about how accurately people perceive income inequality shows large gaps between individuals' perceptions and the actual levels of inequality (Norton and Ariely, 2011; Kuziemko et al., 2015; Gimpelson and Treisman, 2018; Choi, 2019). Second, even absent any misperceptions, individuals do not consider all inequities to be unfair. Specifically, individuals largely accept income disparities derived from personal choices and effort, but deem inequities that are mostly driven by luck or chance as unfair (Cappelen et al., 2007; Alesina and Giuliano, 2011; Cappelen et al., 2013; Almås et al., 2020). Thus, the extent to which fairness perceptions are shaped by income inequality remains an important empirical question.

In this paper, we study the link between fairness views and income inequality in a particular scenario: a region of highly unequal countries—Latin America (LA)—but during a period of pronounced decline in inequality. First, we assess the extent to which fairness views are linked to income inequality, both across countries and over time. Then, we analyze how individual-level factors such as education, political ideology, and religious views relate to fairness views. Finally, we investigate the predictive power of fairness views for individuals' propensity to protest and mobilize.

In section 2, we describe the institutional context and our data. Our setting is Latin America, often regarded as one of the most unequal region in the world (Alvaredo and Gasparini, 2015). We focus on the 2000s, an unusual period in that income inequality saw a widespread decrease across countries in the region (Gasparini et al., 2011). To relate income inequality to fairness views, we combine data from two harmonization projects. Our source for income inequality data is SEDLAC, a project which increases cross-country comparability from official household surveys. These data enable us to compare the evolution of income inequality across countries and over time. The data on fairness perceptions come from public opinion polls conducted by Latinobarómetro in 18 LA countries since the 1990s. Crucially, the

[1] Examples include cooperation (Cozzolino, 2011), demand for redistribution (Meltzer and Richard, 1981; Finseraas, 2009), dishonesty (Neville, 2012), social cohesion (Alesina and Perotti, 1996), subjective wellbeing (Oishi et al., 2011), and trust (Gustavsson and Jordahl, 2008).

[2] For example, one important reason why social cohesion might be related to income inequality is that, as inequality increases, more individuals perceive the income distribution as unfair, making them more prone to mobilize. Similarly, we would not expect inequality to be negatively linked to subjective wellbeing if increases in income disparities were perceived as fair.

opinion polls asks individuals whether they believe the income distribution of their country is fair or unfair.

In section 3, we document a series of stylized facts about fairness views in the region. A strikingly high, albeit decreasing, share of the population believes the distribution of income is unfair. In 2002, almost nine out of ten individuals perceived the income distribution as unfair (86.6%). By 2015, this figure declined to 75.1%.[3] The reduction in unfairness perceptions was mainly driven by a decline in the share of individuals who hold strong unfairness beliefs, i.e., individuals who believe that the income distribution is very unfair as opposed to merely unfair.

Next, we link fairness views to income inequality. To do this, we study how the Gini coefficient—our main measure of inequality—correlates with fairness views across countries and over time. We find a strong linear correlation between the Gini coefficient and the percent of the population that perceives inequality as unfair across country-years. Fairness views evolved in the same direction as the Gini coefficient in 17 out of the 18 countries in our sample during the 2000s. The relationship between fairness views and inequality is driven by individuals with strong beliefs about unfairness.

We also calculate the elasticity of fairness views to changes in income inequality. A one percentage point decrease in the Gini is associated with a 1.4 percentage point decrease in the share of the population perceiving the distribution as unfair. Hence, the decline in the Gini coefficient exhibited during the 2000s—although remarkable by historical standards—was not enough to substantially modify the view of Latin Americans with respect to fairness in their societies. Despite improvements in the income distribution, three out of four citizens of the region still believe that the income distribution is unfair. Furthermore, holding constant this elasticity and the pace of inequality reduction of the 2000s, reducing the population that perceives income inequality as unfair to 50% would take roughly more than a decade.

Next, we investigate whether inequality measures other than the Gini coefficient have a stronger correlation with unfairness beliefs. This question is of interest in its own right given the discussion of whether income inequality should be measured with relative or absolute indicators. This is because relative and absolute indicators often provide different answers to important issues such as the distributive effects of globalization or trade openness (Ravallion, 2003; Atkinson and Brandolini, 2010). We take an agnostic approach and correlate a large number of relative and absolute measures of inequality with unfairness views. We find that relative indicators correlate more strongly with people's perceptions of unfairness. In contrast, absolute indicators tend to be *negatively* correlated with unfairness views. This is because in the booming years under analysis, absolute income gaps became wider in LA; yet perceptions about unfairness went down, consistently with a fall in relative income differences.

[3]This decline is particularly interesting considering that previous research highlights people's tendency to report perceptions of stable or increasing inequality, regardless of the actual evolution (Gimpelson and Treisman, 2018).

Understanding whether people think about distributive fairness through the lens of relative or absolute indicators has consequences about how we think of important issues such as the distributive effects of globalization

In section 4, we assess whether the correlation between the income inequality and fairness views is robust to controlling for observable variables and investigate which individual-level characteristics are predictive of fairness views. The relationship between unfairness views and the Gini coefficient is positive and statistically significant even after controlling for country fixed effects, year fixed effects, and a large set of individual-level characteristics. Conditional on income inequality, older, unemployed, and left-wing individuals are more likely to perceive income distribution as very unfair. These results are robust to alternative specifications. A Oaxaca-Blinder decomposition shows that the decline in unfairness perceptions during the 2000s is better accounted for by aggregate inequality trends rather than changes in the composition of the population.

In section 5, we analyze the link between fairness perceptions and the propensity to protest. A vast literature relates income inequality to social cohesion, conflict, and activism (for evidence in LA, see Gasparini et al., 2008). One might expect this link to be partly mediated by fairness views. Hence, we study whether, conditional on income inequality, fairness views have predictive power for social unrest. To do this, we measure individuals' likelihood of taking part of different political activities, such as participating in a demonstration, signing a petition, refusing to pay taxes, or complaining on social media. We find that for some political activities, such as complaining on social media, both fairness views and inequality have predictive power independent of each other; but other political activities are exclusively predicted by fairness views (such as signing a petition) or income inequality (such as refusing to pay taxes). This suggests both fairness views and income inequality are important determinants of the propensity to participate in political activities.

This paper contributes to the literature that links objective measures of the income distribution to individuals' perceptions of such measures. Previous papers have shown that individuals tend to misperceive their relative incomes (Cruces et al., 2013; Karadja et al., 2017; Hvidberg et al., 2020; Fehr et al., 2021) and other relevant features of the income distribution, such as the level of inequality, poverty, and mobility (Kuziemko et al., 2015; Page and Goldstein, 2016; Alesina et al., 2018; Fehr et al., 2020).[4] Evidence on the relationship between fairness perceptions and income inequality, particularly in LA, is rather scarce. To our knowledge, the only other paper that studies the link between inequality and fairness views in LA is Zmerli and Castillo (2015), although the focus of such a paper is on political

[4]Mismatches between beliefs and reality are important because there is mounting evidence that perceptions of facts, more than facts themselves, affect people's actions and decisions. For example, redistributive preferences are affected by perceptions of the income distribution more than by the actual distribution (Gimpelson and Treisman, 2018; Choi, 2019). Understanding what people believe about the income distribution is then important from a policy perspective. If there are mismatches between perceptions and reality, interventions that make information less costly might be desirable.

trust. Using the same data that we use, the authors find a positive association between unfairness views and the Gini. However, the authors only use data from one year, which means they cannot study the evolution of both variables over time, or control for unobserved heterogeneity at the country or year level, which, as we argue below, could generate a spurious correlation between income inequality and fairness views.[5] We contribute to this literature by providing novel empirical evidence linking fairness views to income inequality in a highly unequal region, but during a period of falling inequality.

This paper also contributes to the literature on inequality measurement. As noted above, this literature makes a crucial distinction between two types of indicators: the relative ones (such as the Gini coefficient) and absolute ones (such as the variance). The distributional consequences of policies often depend on how inequality is measured (Ravallion, 2003; Atkinson and Brandolini, 2010). Relative to previous papers, we contribute by assessing whether people think about distributive fairness through the lens of relative or absolute indicators. We show that relative indicators have a much stronger correlation with fairness views than absolute indicators.

Finally, we make a small contribution to the growing literature that relates income inequality—and more recently, measures of polarization—to conflict and political activism (Esteban and Ray, 2011; Esteban et al., 2012). Previous papers have shown that income inequality is predictive of conflict and social unrest. We contribute to this literature by showing that fairness views have predictive power for social unrest above and beyond income inequality (and vice-versa).

The rest of the paper is organized as follows. In section 2, we provide institutional background on Latin America, describe the data, and provide descriptive statistics on our sample. In section 3, we establish a series of stylized facts about the relationship between income inequality and fairness views. In section 4, we analyze the individual-level determinants of fairness views. In section 5, we link fairness perceptions to social unrest. Section 6 concludes.

2 Institutional context, data, and descriptive statistics

This section provides institutional context on Latin America. We also describe our data and provide summary statistics on our sample.

[5]A related literature studies distributive issues in Latin America exploiting opinion surveys.CEPAL et al. (2010) uses Latinobarómetro data to document patterns of perceptions of distributive inequity during the 1997-2007 period. Rodríguez (2014) uses data from the International Social Survey Program to study inequality perceptions in Argentina, and finds that people who consider their income to be fair tend to perceive lower levels of inequality. Martínez Correa et al. (2020) use LAPOP data to explore the effect of immigration on preferences for redistribution in Latin America.

2.1 Institutional context

Latin America has long been characterized as a region with high levels of income inequality. Together with South-Saharan Africa, Latin America (LA) is one of the two most unequal regions in the world (Alvaredo and Gasparini, 2015; World Bank, 2016). Although the disparities between the poor and rich are still large, after a period of increasing inequality during the 1980s and 1990s, the region experienced a "turning point" in the 2000s, when income inequality saw a widespread decrease across the countries of the region.[6] The social gains in terms of inequality contrast with what happened in other developing regions in the world, where the declines in inequality were more modest (e.g., such as in the Middle East and North Africa), or even increased (such as in East Asia and Pacific, c.f. Alvaredo and Gasparini, 2015), and also contrasted with the increases in inequality experienced by developed countries (Atkinson et al., 2011).

2.2 Data

We use data on fairness views and income inequality from 18 LA countries over 1997-2015. The data comes from two data projects, known as Latinobarómetro and SEDLAC (Socio-Economic Database for Latin America and the Caribbean).

The data on fairness perceptions come from public opinion polls conducted by Latinobarómetro. Latinobarómetro has conducted opinion surveys in 18 LA countries since the 1990s, interviewing about 1,200 individuals per country about their socioeconomic background and preferences towards political and social issues. The survey was designed to be representative of the voting-age population at the national level (in most LA countries, population aged over 18). The key variable for our empirical analysis is individuals' fairness views. In every country, Latinobarómetro asks *"How fair do you think income distribution is in [country]? Very fair, fair, unfair or very unfair?"* Using this question, we construct dichotomic variables reflecting whether individuals believe income distribution is unfair or very unfair.[7]

Our source for income inequality data is SEDLAC, a joint project between CEDLAS-UNLP and The World Bank, which increases cross-country comparability from official household surveys. We use as the welfare indicator the total household per capita income in 2005 US$ (at purchasing power parity) per day. Whenever possible, we used comparable annual household surveys to estimate inequality indicators. However, some countries did not conduct surveys every year, and some of the household surveys available in certain countries are not comparable over time (usually due to important methodological changes; for instance, due to

[6] See Gasparini et al. (2011), Gasparini and Lustig (2011), and Lustig et al. (2013). The decline is robust to the inequality indicator used and to the method of aggregation of the countries (Rodríguez-Castelán et al., 2016).

[7] In Appendix Table B1 we show what percentage of the voting-age population is represented by the survey in each country for all the years in which the fairness question is available.

changes in the sampling scheme).[8] In Appendix B we describe some of the partial fixes we implemented to maximize the sample size.

2.3 Sample and summary statistics

For our regression analysis, we use individual-level data. Our sample of individuals comes from pooling the 11 different waves of the Latinobarómetro surveys over the 1997-2015 period.

Appendix Tables A1 and A2 show basic descriptive statistics of the sample. Roughly half of the respondents are men (49%) and the average age is 39.7. Over half of the sample (56.3%) reports being married or in a civil union, and adhering to Catholicism (68.0%). About 90% of the sample are literate, the majority of respondents (76%) completed at least primary school, while a third of them (33.6%) had completed secondary education or more. Almost two-thirds of the sample (64%) were part of the labor force, and 9.9% of the economically active individuals were unemployed. Access to basic services among respondents is relatively high: 88.8% of individuals had access to running water inside their dwelling and over two-thirds (69.6%) reported that their dwellings had access to a flush toilet connected to a waste-removal system (i.e., sewage). Ownership of durable goods ranges from relatively low levels regarding cars and computers (28.2% and 33.8%, respectively) to relatively high levels regarding fridges and mobile phones (79.2% and 80.6%).

To assess the differences between Latinobarómetro's sample and the household surveys' sample, Appendix Table A3 compares a set of variables available in both datasets during 2013. To ensure comparability across databases, we restrict the calculations to individuals over age 18, and to countries with data available in both harmonization projects. In general, the samples are similar in observable characteristics. For instance, the average age in Latinobarómetro's 2013 sample is 40.6 years, while in SEDLAC it is 42.7 years. Similarly, the percentage of males is 48.9% in Latinobarómetro and 47.6% in SEDLAC. The main difference arises from educational attainment. On average, the SEDLAC sample is more educated: 46.1% of the population has secondary education or more, while this figure is 38.8% in Latinobarómetro.

3 The relationship between fairness views and inequality

This section provides descriptive evidence on the evolution of fairness views in Latin America during the period under analysis. We then link fairness perceptions to income inequality both across countries and over time. Finally, we investigate whether absolute or relative measures of income inequality have more predictive power for fairness views.

[8] For Argentina and Uruguay, the inequality data correspond to urban areas only. See Appendix B.

3.1 The evolution of fairness views in LA during the 2000s

Figure 1 shows how fairness views evolved in the region over time (Panel A) and across countries (Panel B). Panel A plots the fraction of individuals who believe that the income distribution of their country is very unfair, unfair, fair, or very fair over the 1997-2015 period. To construct this figure, we average the responses across the 18 countries in our sample. Panel B shows the fraction of individuals who believe income distribution is either unfair or very unfair in each country during 2002 and 2015.

Figure 1, Panel A shows that a strikingly high, albeit decreasing, share of the population believes that the distribution of income is unfair. In 2002, almost nine out ten individuals perceived the income distribution as unfair (86.6%). By 2015, this figure declined to 75.1%. The decrease in unfairness perceptions was driven mainly by individuals with strong beliefs about unfairness (i.e., individuals who responded that income distribution was very unfair). While in 2001, 33.1% of the population perceived the income distribution as very unfair, this figure decreased to 25.8% in 2015. In contrast, weak beliefs about unfairness (i.e., the population that responded that income distribution was merely unfair) behaved more erratically, increasing in some years, and decreasing again by the end of the period. Overall, the share of individuals with weak beliefs about unfairness slightly declined during the 2000s, from 53.5% in 2002 to 49.2% in 2015. On the other hand, the share of the population believing in a fair distribution doubled from 11.3% in 2001 to a sizable 22.6% in 2015, while strong beliefs on fairness (i.e., "very fair"), remained below 5% throughout the 2000s.

Figure 1, Panel B shows that, while most individuals perceive the income distribution as unfair, fairness perceptions improved in most countries during 2002-2013. In all LA countries, a remarkably large share of the population perceived the income distribution as unfair in both 2002 and 2013. For example, in 2002, the share of unfairness perceptions ranged from 74.5% in Venezuela to 97.7% in Argentina (which, at the time, was in the midst of a severe economic crisis). A decade later, there was a widespread decrease in the share of the population that perceived income inequality as unfair. Relative to the previous decade, in 2013 a lower fraction of the population perceived the income distribution as unfair in 16 out of the 18 countries in our sample. The change in fairness perceptions ranged from modest decreases, like in Chile, where the decline was of less than one percentage point, to remarkable reductions, like in Ecuador, where perceptions about unfairness declined from 87.5% to 38.6%.

Appendix Figure A1 shows that the decline in unfairness perceptions was not driven by any particular group of the population but was rather a widespread phenomenon. To show this, we investigate how fairness views evolved for different subgroups of the population, according to the age, gender, educational achievement, and labor status of the individuals. This analysis reveals some heterogeneity across groups. For instance, relatively younger populations are less likely to perceive income distribution as unfair (Panel A), while females are more likely to do so, although not consistently across time (Panel B). Similarly, individuals with a higher educational achievement (Panel C) and the unemployed (Panel D) are more likely to believe income distribution is unfair. Regardless of the different average fairness views, the perception of unfairness of all these groups consistently fell during the 2000s.

Next, we explore the extent to which these changes in fairness views were accompanied by changes in the actual distribution of income experienced by countries.

3.2 Fairness perceptions and income inequality: some stylized facts

Figure 2 shows how fairness views evolved vis-à-vis changes in income inequality. Panel A plots a binned scatterplot of the Gini coefficient and unfairness views for all country-years in our sample. To construct this figure, we group the Gini coefficient of each country-year in bins of width equal to 0.02 Gini points and then calculate the average fairness perceptions in each bin. Panel B plots the percentage point change in unfairness perceptions between 2002 and 2013 against the change in the Gini coefficient over the same period.

Panel A shows unfairness perceptions and the Gini coefficient are strongly correlated across country-years. The linear correlation between the Gini coefficient and the overall unfairness perceptions across country-years is 0.93 ($p < 0.01$). The share of the population who perceive income as unfair or very unfair range from 63% in country-years with a Gini in the 0.40 bin (roughly, the average level of inequality observed in Venezuela during the 2000s), to 88% in country-years with a Gini in the 0.60 bin (roughly, the level of inequality observed in Honduras during the early 2000s).[9] The correlation between unfairness views and the Gini is driven by individuals who perceive inequality as very unfair. The correlation between perceptions of a very unfair distribution and the Gini coefficient is sizable and statistically significant. In contrast, the correlation between perceptions of a merely unfair distribution and the Gini is small and indistinguishable from zero.

Panel B shows that the evolution of fairness views mirrors the evolution of income inequality in most countries. In 17 out of the 18 countries in our sample, fairness views moved in the same direction as the Gini. The one exception is Honduras, where, despite falling inequality, the population perceived the distribution as more unjust. Most countries lie in the third quadrant, where both the Gini coefficient and unfairness perceptions decreased.[10]

In Appendix Figure A2 we show that the correlation between the Gini and unfairness views over time is also strong when pooling across countries. In this case, the linear correlation is

[9] An OLS regression of overall unfairness views on the Gini estimated on the plotted points yields an intercept of 28.2. This implies that, even on a society where all incomes are equalized, about 28% of the individuals would still perceive the income distribution as unfair. This exercise relies on the strong assumption that the relationship between fairness views and income inequality is linear throughout the support of the Gini distribution. While such relationship indeed appears as linear in Panel A, our data only covers a very narrow range of Gini coefficients (between 0.40 and 0.60). It is likely that the relationship stops being linear for Gini coefficients close to zero or one. Hence, this exercise is merely suggestive.

[10] The fact that the Gini coefficient decreased for most countries in LA is consistent with previous empirical evidence (Gasparini et al., 2011; Gasparini and Lustig, 2011; Lustig et al., 2013).

equal to 0.80 ($p < 0.01$). Such a correlation is very similar if we consider the share of individuals who responded that income distribution is very unfair (0.79).[11]

We also calculate the elasticity of unfairness perceptions to income inequality.[12] During the 2002-2013 period, a one percentage point decrease in the Gini coefficient was associated with a 1.4 percentage point decrease in the share of the population perceiving the distribution as unfair. To put this figure in context, this means that, at the pace of inequality reduction of the 2000s, it would roughly take LA more than another decade to reduce the population that perceives income inequality as unfair to 50%.

3.3 Is fairness absolute or relative?

We have shown that a large, albeit decreasing, share of the population believes that income distribution is unfair, and that such levels and evolution are consistent with a high, but also declining Gini coefficient. Despite being the most widely used indicator to measure income inequality, fairness perceptions might be better captured with indices other than the Gini coefficient. We next explore this possibility.

The literature on inequality measurement makes a crucial distinction between two types of indicators: the relative ones (such as the Gini) and absolute ones (such as the variance). Relative indicators fulfill the scale-invariant axiom, while the absolute indicators meet the translation-invariant axiom.[13] The question of which indicator should be used in practice has led to a heated debate in the literature (Milanovic, 2016). This is because relative and absolute indicators often provide different answers to important issues such as the distributive effects of globalization or trade openness.[14]

To shed some light on this debate, we assess whether people think about distributive fairness through the lens of relative or absolute indicators. To do this, we take a data-driven approach. We calculate 13 different measures of income inequality for all the countries in our sample and correlate each inequality indicator with the share of the population that believes income distribution is unfair over time.[15]

[11] In 1997 Latinobarómetro had low coverage in large countries with relatively high levels of inequality (such as Brazil and Colombia), and did not survey other countries at all (such as the Dominican Republic). The increase in the coverage of the survey could drive part of the change in perceptions between 1997 and 2001.

[12] We calculate the elasticity of unfairness perceptions to the Gini coefficient, ε, as: $\varepsilon = \Delta\%\text{Unfairness}/\Delta\%\text{Gini}$.

[13] In practical terms, a proportional increase in the income of the entire population does not generate changes in income inequality as measured by relative indicators, but can provoke a large increase in inequality as measured by absolute indicators.

[14] As measured by absolute indicators, globalization has deteriorated the income distribution since the absolute income differences between the rich and the poor have increased. However, under the lens of relative measurement, income inequality has been reduced, since the poor's income has grown proportionally more than the income of the rich in relative terms.

[15] The indicators are the Gini coefficient, the ratio between the 75th percentile and the 25th percentile of the income distribution, the ratio between the 90th and 10th percentile, the Atkinson index with an inequality aversion parameter equal to 0.5 and 1, the mean log deviation, the Theil index, the Generalized entropy index, the coefficient of variation, the absolute Gini, the Kolm index with an inequity aversion parameter equal to

We calculate the correlation between unfairness perceptions and each inequality indicator at the regional level using three alternative aggregation methods. First, we calculate each correlation using the individual-level data and pooling all countries and years in our sample (columns 1-3). Second, we calculate the average unfairness views in each country-year, and then calculate the correlation between each inequality indicator and the average fairness views (columns 4-6). Third, we calculate the correlation between each inequality indicator and fairness views over time for each country separately (using the individual-level data), and then average the correlations across countries (columns 7-9). Table 1 shows the results.

Fairness views tend to be positively correlated with relative indicators and negatively correlated with absolute ones. In Table 1, column (1) shows the Gini is the indicator with the highest linear correlation.[16] On the other hand, the absolute indicators of inequality are negatively correlated with unfairness perceptions, and the overall magnitude of such correlations tends to be smaller.[17] The results of the high correlation between unfairness perceptions and income inequality seem to be driven by the population that perceives inequality as very unfair (columns 2, 5, and 8), rather than just unfair (columns 3, 6, and 9), as the correlations in the latter are relatively small for almost all indicators.

These results are consistent with experimental evidence from Amiel and Cowell (1992, 1999), who show that support for the scale-invariance axiom is greater than for translation invariance, reflecting greater support for relative inequality indicators. Moreover, the results are also consistent with previous evidence that documents decreasing relative inequality, but rising absolute inequality during the 2000s in LA. Since unfairness perceptions also declined over time, the relative indicators do a better job of tracing such evolution.

4 Individual-level fairness determinants

In this section, we study the individual-level correlates of fairness views. The purpose of this section is twofold. First, to assess whether the association between fairness views and income inequality is robust to the inclusion of controls. Second, to investigate what individual-level characteristics are systematically related to fairness views.

one, and the variance of the per capita household income (in 2005 PPP). These last three indices correspond to the absolute measures of inequality, while the other ten are relative measures.

[16]The results are very similar if we exclude the observations with income equal to zero. For example, pooling all the data and calculating the Gini without households with zero income barely changes the correlation between the Gini and the share of the population that perceives the income distribution as either unfair or very unfair, from 0.39 to 0.40.

[17]It is interesting to note that indicators sometimes mentioned in the mass media, such as the ratio between the richest 90% and the poorest 10%, exhibit low explanatory power. This may be due to mismeasurement of the top incomes.

4.1 Empirical design

To formally assess the relationship between individuals' characteristics and fairness perceptions, we estimate two-way fixed effects Logit models. This design controls for two important sources of heterogeneity that could drive the positive associations between inequality and fairness perceptions found in the previous section. First, we control for country-level heterogeneity. For example, countries with historically more extractive institutions could have both higher levels of income inequality and more negative fairness views as a legacy of such institutions. Insofar as institutions are stable over time, the country fixed effects deal with such potential bias. Second, we control for year-level heterogeneity. For example, in some particular years, macroeconomic events such as a financial crisis or a corruption scandal could increase income disparities and worsen fairness views, again generating a spurious correlation between inequality and fairness perceptions. Controlling for year fixed effects helps to alleviate such concerns.

Given that changes in fairness views over the last decade were driven by the share of the population that perceived income distribution as being very unfair (Figure 1), in our baseline specification we focus on explaining the determinants of strong unfairness beliefs (i.e., "very unfair"), although we also show the results for a broader definition of unfairness. We assume that unfairness perceptions can be characterized according to the following equation:

$$\text{Very Unfair}_{ict} = F(\lambda_c + \lambda_t + \gamma \text{Gini}_{ct} + \beta x_{ict}) \tag{1}$$

where the dependent variable, Very Unfair$_{ict}$ is equal to one if individual i believes the income distribution of country c during year t is very unfair, and zero otherwise. Equation (1) includes country fixed effects, λ_c; year fixed effects, λ_t; the country's Gini coefficient in year t, Gini$_{ct}$; and a vector of individual characteristics, x_{ict}, that includes age, age squared, sex, civil status, education, labor market status, an assets index, political ideology, and religious views.[18] In our baseline specification, $F(\cdot)$ is the logistic function. We cluster the standard errors at the country-by-year level.

We are interested in $\frac{\partial \text{Very Unfair}_{ict}}{\partial x_{ict}} = \beta f(\cdot)$ and $\frac{\partial \text{Very Unfair}_{ict}}{\partial \text{Gini}_{ict}} = \gamma f(\cdot)$. The first of these partial derivatives captures the relationship between the individuals' characteristics and their unfairness perceptions. Similarly, $\gamma f(\cdot)$ captures the relationship between the Gini coefficient and the perceived fairness after controlling for individual-level traits and fixed effects. The magnitude of the partial derivatives depends on the value of the covariables at which they are

[18] The assets index takes the value one if the individual reports having access to running water and sewerage, and owns a computer, a washing machine, a telephone, and a car. In household surveys, these variables tend to be correlated with household income, although the correlations are usually low. Unfortunately, we do not observe household income in the Latinobarómetro data. To measure political views, we rely on the question *"In politics, people normally speak of "left" and "right." On a scale where 0 is left and 10 is right, where would you place yourself?"* We interpret values closer to zero (ten) closer to a liberal (conservative) worldview. We measure religious views using a dummy that is equal to one for Catholicism—the predominant religion in the region—coding the rest of the religions (and lack of religion) as zero.

evaluated. We evaluate the marginal effects at the average values of the rest of the covariables.

4.2 Regression results

Table 2 summarizes the main results of the regressions under different specifications. Column (1) presents the results controlling only for the fixed effects and the Gini coefficient. Column (2) includes basic demographic indicators: age, gender, and civil status. Column (3) incorporates dummies for maximum educational attainment (the omitted category is completing primary education or less). Column (4) includes dummies for labor force participation and unemployment. Column (5) incorporates an index for access to basic services and asset ownership. Column (6) includes political and religious views.

Consistent with the evidence shown in section 3, the Gini coefficient has a positive and statistically significant relationship with unfairness perceptions. In a country with average characteristics, a decrease of one point in the Gini coefficient (from 0.49 to 0.48) decreases the share of the population that believes income distribution is very unfair by about half a percentage point. Such magnitude does not vary much across different specifications (columns (1)-(6)).[19]

Many individual-level covariates predict fairness views. Older people tend to respond more often that income distribution is very unfair, although the relationship between age and unfairness perception is non-linear. On average, males are just as likely as females to perceive income distribution as very unfair, while married individuals are slightly less likely to do so. Completing high school is negatively associated with perceptions of unfairness, although the magnitude of the coefficient is small. Being economically active does not seem to be correlated with unfairness views, but being unemployed does. On average, unemployed individuals are about two percentage points more likely to perceive income distribution as unfair than employed population. The assets index has a negative sign, suggesting relatively better-off individuals are less likely to view the income distribution as unfair, although the coefficient is not statistically different from zero. Ideologically conservative people are statistically less likely to perceive income distribution as very unfair, although the size of the effect is small (below half a percentage point). Finally, Catholics are less likely to perceive income distribution as very unfair.

We conduct three robustness checks. First, in Appendix Table A4 we use a broader measure of unfairness as the dependent variable. Instead of considering only the people who responded that income distribution is very unfair, we also consider the ones who answered only unfair. When we use the broader definition of unfairness, the magnitude of the coefficient

[19]It is important to stress that the interpretation is not necessarily causal. The relationship between income inequality and unfairness perceptions can go both ways. On the one hand, higher inequality can increase the share of the population that believes distribution is very unfair. But as more people perceive income distribution as very unfair, the income distribution can be affected through several channels (e.g., more corruption or social unrest).

on the Gini declines. Given the relatively large standard errors, the 95% confidence interval on the Gini coefficient includes the zero; but the interval also includes the estimated magnitudes in our baseline set of regressions (Table 2). In other words, when we use the broader measure of unfairness, our estimates become less informative. This is because strong unfairness views are more strongly correlated to income inequality than weak unfairness views (Table 1 and Figure 2).[20]

As a second robustness check, in Appendix Table A5 we run a specification similar to the one in column (6) of Table 2, but using an alternative set of inequality indicators instead of the Gini coefficient. We find a positive correlation between income inequality and unfairness perceptions across all relative measures of inequality (columns (1)-(4)). The Gini coefficient calculated without households with zero income, the Atkinson index, the Theil index, and the Generalized Entropy indicator are consistently correlated with unfairness and all the coefficients are statistically different from zero at the usual levels. In contrast, the absolute Gini (our absolute measure of inequality in the table) is negatively correlated with unfairness perceptions, although the coefficient is statistically indistinguishable from zero.

As a final robustness check, in Appendix Table A6 we estimate equation (1) using a linear probability model (LPM) instead of a Logit. The choice of a LPM is consistent with the visual evidence shown in Figure 2, Panel A, where fairness views seems to be linearly related to the Gini coefficient. Overall, we find that the magnitude of the correlations is quite similar in the LPM and the Logit regressions. For example, in the specification with the larger set of controls (column (6)), the marginal effect of the Gini coefficient is 0.68 using the Logit (Table 2) and 0.63 using the LPM (Appendix Table A6).

4.2.1 Decomposing changes in fairness views over time. Both aggregate inequality and individual-level characteristics are associated with fairness perceptions. Next, we ask which of these two factors mainly explain (in an accounting sense) the reduction in unfairness beliefs over the last decade. To do this, we perform a Oaxaca-Blinder decomposition, taking 2002 and 2013 as the two groups to be compared (see Appendix C for details on the Oaxaca-Blinder decomposition). In the decompositions, we use the broad definition of unfairness perceptions as the dependent variable and include controls for demographics, educational attainment, labor market status, assets, political views, and religion. Figure 3 shows the results.

During the 2002-2013 period, the share of the population perceiving the distribution as

[20] The effect of some individual-level characteristics are also different when using the broader definition of unfairness views. The effect of completing college on perceptions of unfairness becomes strong and statistically significant. Civil status stops being statistically significant, while the male dummy becomes negative and statistically significant (in both cases consistently so across specifications). The coefficient on the assets index becomes larger and statistically different from zero. Finally, the effect of political ideology and religious views become statistically indistinguishable from zero. These results suggest that the population that perceives the income distribution as very unfair tends to be different in observable variables than the population that believes the income distribution is merely unfair.

unfair decreased 14 percentage points, from 87% to 73%. The decomposition results suggest that about 28% of such a change (4 percentage points) is accounted for by changes in the elasticity of fairness views to each covariable (i.e., changes in the values of the coefficients in the regression), while the other 72% can be explained by changes in the covariables' values. Among the covariables included in the decomposition, the one that mainly explains the decline in the unfairness perceptions is the change in the value of the Gini coefficient, which accounts for 88.9% of the explained component. In contrast, changes in the composition of the population only account for 11.1% of the explained component. This result suggests that the decline in unfairness views during the 2000s in Latin America seems to be mainly driven by changes in income inequality, and not by changes in the composition of the population.

5 The predictive power of fairness views for social unrest

There is a vast literature that relates economic inequality—and more recently, measures of polarization—to social cohesion, conflict, and activism.[21] Arguably, the relationship between income inequality and conflict is mediated by fairness views. That is, individuals mobilize partly because they believe existing inequities are not fair. However, a given level of income inequality might not be seen as unfair by some individuals due to, for example, misperceptions of the actual level of inequality (Gimpelson and Treisman, 2018) or a perception that income gaps are mainly driven by differences in talent or effort (Alesina et al., 2001). For these reasons, a regression that links social unrest to income inequality can contain a substantial amount of measurement error. We sidetrack these issues by directly measuring the link between social unrest and fairness views.

We measure social unrest using the opinion polls data. Specifically, for several political activities, Latinobarómetro asks repondents whether they (i) Have ever done a given activity; (ii) Would do the activity; or (iii) Would never do the activity. We investigate eight different types of demonstrations: making a complaint on social media, making a complaint on the media, signing a petition, protesting with authorization, protesting without authorization, refusing to pay taxes, participating in riots, and occupying land, factories or buildings.[22] We also use an index of political participation which takes the value one if the individual engaged in tax evasion, an illegal protest, signed a petition, or complained on the media, and zero otherwise.[23] For each activity (and the index), we consider two measures of social unrest. First, we use an indicator that takes the value one if an individual reports having done the

[21]For instance, in LA, Gasparini et al. (2008) find a strong empirical correlation between inequality and conflict, as well as polarization and conflict. Most of previous studies linking inequality and conflict are based on cross-country regressions, and therefore have a notably smaller sample size than our analysis.

[22]Unfortunately, Latinobarómetro asked these question in only a few years, so our sample size for these regressions is an order of magnitude smaller than in the previous regressions.

[23]We use those four measures to construct the index because we do not have data on the other political activities during 2015. Other years have data on fewer political activities.

activity in the past. Second, we use a dummy that takes the value one if the individual did the activity in the past or reports that she is willing to do the activity, and zero otherwise.

Table 3, Panel A shows unfairness perceptions correlate with taking part in political activities in the past. We find positive and statistically significant effects for complaining on social media (column (1)) and signing a petition (column (3)). Conditional on income inequality, individuals who perceive the income distribution as very unfair are 1.6 percentage points more likely to have complained through social media in the past (from a baseline of 7.8%) and 1.3 percentage points more likely to have signed a petition in the past (from a baseline of 18.6%). The rest of the effects tend to be positive although not statistically different from zero. Conditional on fairness views, we find a statistically significant correlation between the Gini and complaining on social media (column (1)), taking part in an authorized demonstration (column (5)), and the composite index (column (9)). The effect of income inequality on the rest of the activities is statistically indistinguishable from zero.

Table 3, Panel B shows the results when the dependent variable also includes the willingness to take part in the political activities. The set of political activities predicted by fairness views are somewhat different than in Panel A. In Panel B, we find positive and statistically significant effects for complaining through media (either social media or traditional media, columns (1) and (2), respectively) and refusing to pay taxes (column (6)). The magnitude of the coefficients that are statistically significant tends to be larger. For example, the effect of unfairness views on the propensity to complain on social media is twice as large in Panel B than in Panel A (3.3 vs. 1.6 percentage points, correspondingly). Finally, we find that—holding fairness views constant—income inequality is predictive of refusing to pay taxes (column (4)). The effect of income inequality on the rest of the political activities is not statistically different from zero.

These results show there are political activities for which fairness views and income inequality have predictive power independent of each other (like complaining through social media), but also activities that are exclusively predicted by income inequality (like participating in an unauthorized protest) or fairness views (like signing a petition). This suggests both fairness views and income inequality capture different channels through which changes in the income distribution can affect social unrest.

6 Conclusions

In this paper we analyze perceptions of distributive justice in a context of falling income inequality. We show that fairness beliefs moved in line with the evolution of objective inequality indicators: both unfairness perceptions and income inequality declined across countries and over time in our sample. Some individual-level characteristics, such as unemployment status and political ideology, are systematically correlated to fairness views. Fairness views have predictive power for social unrest above and beyond income inequality (and vice-versa).

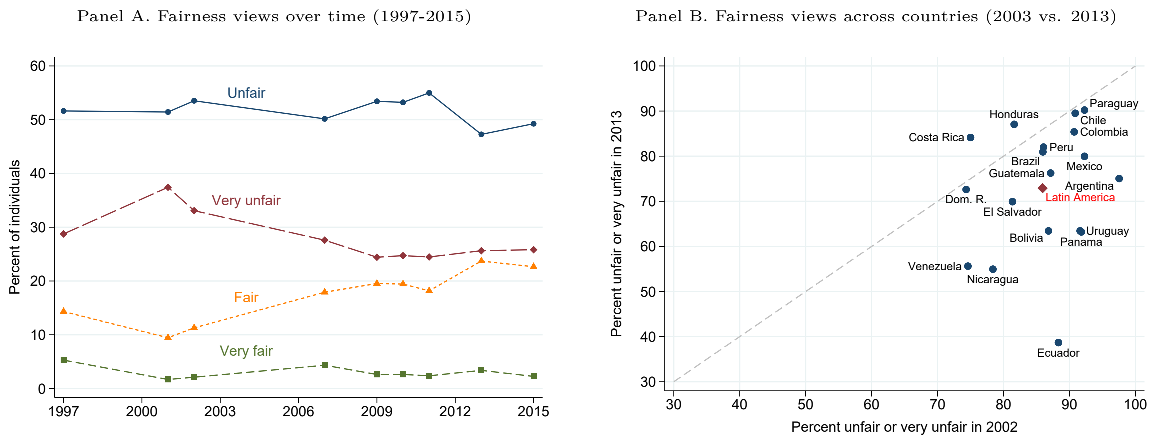
Our findings are relevant for both researchers and policymakers. For researchers, our results suggest that, in some contexts, one can proxy fairness views using relative measures of income inequality, such as the widely used Gini coefficient. This is reassuring, since inequality measures are much more widely available than fairness views in standard datasets.

For policymakers, our findings warn about concerning levels of dissatisfaction with existing income disparities. Three in four LA citizens believe income distribution is unfair, and such perceptions have proved to be relatively inelastic to a relatively large improvement in the income distribution. If fairness perceptions are interpreted as preferences for some leveling of income, our results suggest a striking majority is in favor of reducing the existing disparities between the rich and the poor, while very few people believe the current distribution is fair and income disparities should remain the same. A second actionable insight for policymakers is that fairness views act as a thermometer of individuals' latent propensity to engage in political activities. Thus, if policymakers want to prevent social unrest, they ought to pay attention to the evolution of fairness views and take preventive measures before unfairness becomes the ubiquitous view.

A caveat with our results is that we cannot disentangle whether most individuals believe income distribution is unfair because (i) individuals have inaccurate views about the levels of income inequality (perhaps, believing that the distribution of income is more unequal than it actually is); or (ii) individuals accurately assess the level of inequality, but believe that the process that generates such inequities is not fair. Disentangling these two channels is a challenge for future research.

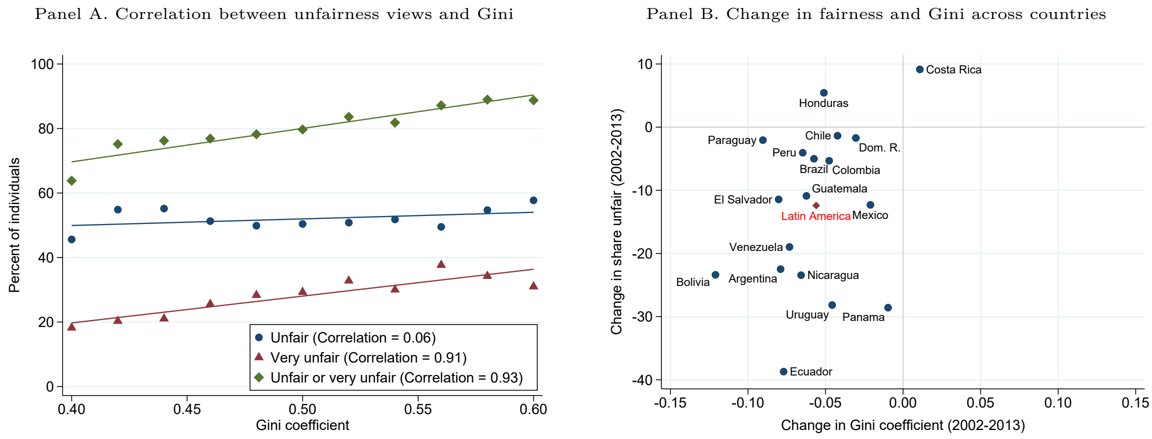
Figures and tables

Figure 1: Fairness views in Latin America over time and across countries



Notes: Panel A presents the average across 18 LA countries of the share of individuals that perceived income distribution as very unfair, unfair, fair, and very fair over the 1997-2015 period. Panel B presents the percentage of the population that believes income distribution is either unfair or very unfair in 2002 and 2013 for all LA countries for which data is available. Due to data unavailability in 2002, for the Dominican Republic we use 2007. See Appendix B for further details.

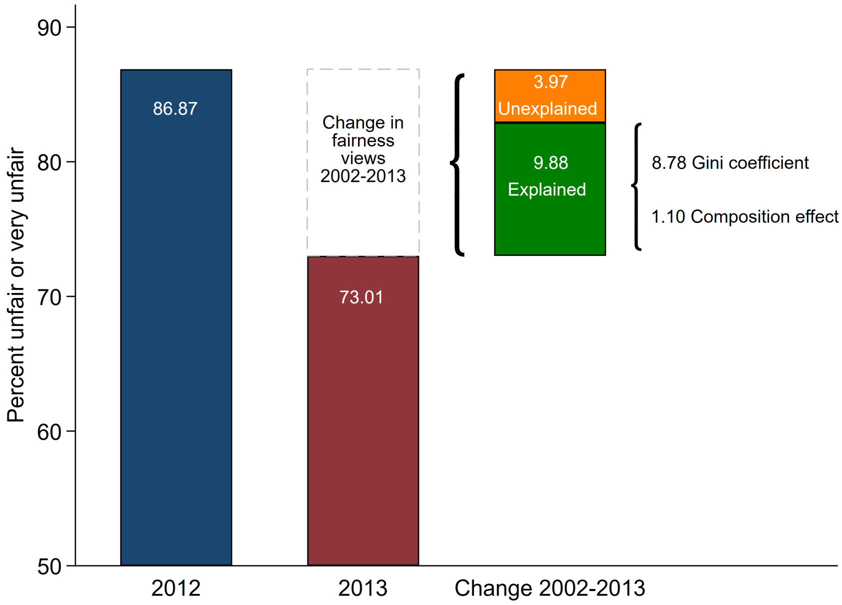
Figure 2: Fairness views and income inequality in Latin America



Notes: Panel A shows a binned scatterplot of the Gini coefficient and fairness views for all country-years in our sample. To construct this figure, we group the Gini coefficient of each country-year in bins of width equal to 0.02 Gini points and then calculate the average fairness perceptions in each bin.

Panel B plots the percentage point change in the share of the population that believes income distribution is either unfair or very unfair between 2002 and 2013 (or close years), and the change in the Gini coefficient between 2002 and 2013 (or close years) for all LA countries. Due to a break in data comparability or household data unavailability, for some countries, we use inequality data from adjacent years. In 2002, we use: Argentina 2004, Chile 2003, Costa Rica 2010, Ecuador 2003, Guatemala 2006, Nicaragua 2001, Panama 2008, and Peru 2004. In 2013 we use: Guatemala 2014, Mexico 2014, Nicaragua 2014, and Venezuela 2012. See Appendix B for more details.

Figure 3: Oaxaca-Blinder decomposition of unfairness perceptions, 2002-2013



Notes: This figure presents the estimates of the Oaxaca-Blinder decomposition (see Appendix C). The dependent variable is a dummy that indicates whether the individual believes income distribution is unfair or very unfair. The regressors include the Gini coefficient, age, age squared, and dummy variables for: civil status, gender, literacy, maximum educational attainment, labor force participation, unemployment status, an assets index, political ideology, and religious views. The "explained" part of the results refers to changes in the value of the covariables, while the "unexplained" refers to changes in the coefficients and the interaction terms.

Table 1: Correlation between inequality indicators and fairness views, 1997-2015

	Individual-level data			Country-by-year level data			Averaging correlations across countries		
	U. or V.U. (1)	V.U. (2)	U. (3)	U. or V.U. (4)	V.U. (5)	U. (6)	U. or V.U. (7)	V.U. (8)	U. (9)
Gini coefficient	0.39	0.36	0.10	0.84	0.82	0.25	0.39	0.28	0.15
	(0.07)	(0.07)	(0.09)	(0.10)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Theil index	0.39	0.38	0.05	0.85	0.82	0.27	0.33	0.20	0.18
	(0.07)	(0.07)	(0.09)	(0.09)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Atkinson, A(0.5)	0.38	0.35	0.10	0.84	0.82	0.25	0.37	0.26	0.15
	(0.07)	(0.07)	(0.09)	(0.10)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Atkinson, A(1)	0.36	0.30	0.13	0.84	0.82	0.25	0.38	0.28	0.13
	(0.07)	(0.08)	(0.09)	(0.10)	(0.16)	(0.34)	(0.07)	(0.08)	(0.09)
Mean log deviation	0.35	0.29	0.14	0.84	0.82	0.25	0.38	0.28	0.13
	(0.07)	(0.08)	(0.09)	(0.10)	(0.16)	(0.34)	(0.07)	(0.08)	(0.09)
Coefficient Variation	0.33	0.36	0.00	0.78	0.78	0.19	0.18	0.20	0.10
	(0.08)	(0.08)	(0.09)	(0.13)	(0.16)	(0.36)	(0.08)	(0.08)	(0.09)
Ratio 75/25	0.29	0.15	0.24	0.80	0.78	0.26	0.36	0.29	0.12
	(0.07)	(0.09)	(0.08)	(0.11)	(0.17)	(0.33)	(0.07)	(0.09)	(0.08)
Generalized entropy	0.29	0.35	-0.04	0.80	0.72	0.35	0.18	0.09	0.19
	(0.05)	(0.08)	(0.08)	(0.11)	(0.18)	(0.34)	(0.05)	(0.08)	(0.08)
Ratio 90/10	0.23	0.10	0.21	0.81	0.79	0.25	0.30	0.30	0.07
	(0.07)	(0.08)	(0.08)	(0.11)	(0.17)	(0.32)	(0.07)	(0.08)	(0.08)
Variance	-0.08	-0.01	-0.12	-0.25	0.10	-0.71	-0.06	0.04	-0.12
	(0.07)	(0.08)	(0.08)	(0.39)	(0.43)	(0.14)	(0.07)	(0.08)	(0.08)
Absolute Gini	-0.21	-0.10	-0.18	-0.71	-0.46	-0.64	-0.18	-0.10	-0.22
	(0.09)	(0.10)	(0.08)	(0.23)	(0.26)	(0.31)	(0.09)	(0.10)	(0.08)
Kolm, K(1)	-0.31	-0.18	-0.22	-0.80	-0.64	-0.50	-0.22	-0.16	-0.22
	(0.09)	(0.10)	(0.08)	(0.12)	(0.18)	(0.37)	(0.09)	(0.10)	(0.08)

Notes: U. or V.U. stands for "Unfair or Very Unfair"; V.U. stands for "Very Unfair"; U. stands for "Unfair." In columns (1)-(3), we calculate each correlation using the individual-level data and pooling all countries and years in our sample. In columns (4)-(6), we calculate the average unfairness views in each country-year, and then calculate the correlation between each inequality indicator and the average fairness views. In columns (7)-(9), we calculate the correlation between each inequality indicator and fairness views over time for each country separately (using the individual-level data), and then average the correlations across countries. Standard Errors are reported in parenthesis and were calculated with bootstrap (500 iterations).

Table 2: Logit regressions of unfairness perceptions (very unfair) and individuals' characteristics

	Baseline (1)	Demog. (2)	Education (3)	Labor status (4)	Assets (5)	Ideology, Religion (6)
Gini	0.679***	0.674***	0.678***	0.680***	0.678***	0.684***
	(0.227)	(0.225)	(0.225)	(0.225)	(0.225)	(0.223)
Age		0.004***	0.004***	0.004***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared		−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male		−0.002	−0.002	−0.001	−0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married		−0.006*	−0.006**	−0.006*	−0.006*	−0.005
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Finished HS			−0.010*	−0.009*	−0.008*	−0.006
			(0.005)	(0.005)	(0.005)	(0.005)
Finished coll.			−0.001	0.000	0.002	0.006
			(0.007)	(0.007)	(0.006)	(0.006)
In labor force				−0.003	−0.003	−0.002
				(0.004)	(0.004)	(0.003)
Unemployed				0.020***	0.019***	0.019***
				(0.007)	(0.007)	(0.007)
Assets index					−0.009	−0.007
					(0.006)	(0.006)
Conservative						−0.003*
						(0.002)
Catholic						−0.011***
						(0.004)
N	167,436	166,105	164,662	164,436	164,436	164,436

Notes: This table presents estimates of the relationship between a dummy variable that indicates if the individual believes income distribution is very unfair and individuals' characteristics. Coefficients show the marginal effects at the mean values of the rest of the variables and were estimated through Logit regressions, weighting by individual's probability of being interviewed. All columns include country and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors clustered at the country-by-year level in parentheses.

Table 3: Logit regressions of unfairness perceptions (very unfair) and activism

	Complain on social media (1)	Complain on media (2)	Sign a petition (3)	Authorized protest (4)	Unauth. protest (5)	Refuse to pay taxes (6)	Participate in riots (7)	Occupy land or buildings (8)	Activism composite index (9)
Panel A. Have done the activity in the past									
Very unfair	0.016^{***}	0.005	0.013^{**}	0.011	−0.001	0.004	0.002	0.003	0.006
	(0.004)	(0.004)	(0.006)	(0.007)	(0.004)	(0.005)	(0.002)	(0.002)	(0.013)
Gini	0.322^{*}	0.209	−0.123	−0.060	0.164^{*}	0.105	0.015	−0.054	0.643^{*}
	(0.175)	(0.182)	(0.287)	(0.149)	(0.092)	(0.089)	(0.034)	(0.040)	(0.336)
Mean Dep. Var.	0.078	0.072	0.186	0.080	0.046	0.043	0.011	0.015	0.251
Panel B. Have done the activity in the past or would do the activity									
Very unfair	0.033^{**}	0.031^{*}	−0.012	0.025	0.016	0.024^{**}	−0.003	−0.001	0.011
	(0.015)	(0.017)	(0.008)	(0.025)	(0.014)	(0.010)	(0.006)	(0.008)	(0.015)
Gini	0.627	0.603	−0.597	0.162	0.452	0.629^{*}	0.039	0.014	0.954
	(0.786)	(0.842)	(0.479)	(0.661)	(0.446)	(0.328)	(0.107)	(0.147)	(0.695)
Mean Dep. Var.	0.413	0.477	0.527	0.296	0.210	0.187	0.063	0.084	0.688
N	18,605	18,827	52,704	17,475	18,846	18,553	16,823	16,779	18,155

Notes: This table presents estimates of the relationship between unfairness views (very unfair) and the likelihood of taking part in different political activities. Column (9) shows a composite index which takes the value one if the individual engaged in tax evasion, an illegal protest, signed a petition, or complained in the media, and zero otherwise. Coefficients display the marginal effects at the mean values of the rest of the variables and were estimated through Logit regressions, weighting by individuals' probability of being interviewed. All regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, unemployment status, assets index, political ideology, and religion. The regressions in column (3) also controls for country and year fixed effects. The rest of the political activities are available in only one year and thus we cannot include fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors clustered at the country-by-year level in parentheses.

References

Alesina, A. and P. Giuliano (2011). Preferences for redistribution. In *Handbook of social economics*, Volume 1, pp. 93–131. Elsevier.

Alesina, A., E. Glaeser, and B. Sacerdote (2001). Why doesn't the us have a european-style welfare system? Technical report, National bureau of economic research.

Alesina, A. and R. Perotti (1996). Income distribution, political instability, and investment. *European economic review 40*(6), 1203–1228.

Alesina, A., S. Stantcheva, and E. Teso (2018). Intergenerational mobility and preferences for redistribution. *American Economic Review 108*(2), 521–54.

Almås, I., A. W. Cappelen, and B. Tungodden (2020). Cutthroat capitalism versus cuddly socialism: Are americans more meritocratic and efficiency-seeking than scandinavians? *Journal of Political Economy 128*(5), 000–000.

Alvaredo, F. and L. Gasparini (2015). Recent trends in inequality and poverty in developing countries. *Handbook of Income Distribution 2*, 697–805.

Amiel, Y. and F. Cowell (1999). *Thinking about inequality: Personal judgment and income distributions.* Cambridge University Press.

Amiel, Y. and F. A. Cowell (1992). Measurement of income inequality: Experimental test by questionnaire. *Journal of Public Economics 47*(1), 3–26.

Atkinson, A. B. and A. Brandolini (2010). On analyzing the world distribution of income. *The World Bank Economic Review 24*(1), 1–37.

Atkinson, A. B., T. Piketty, and E. Saez (2011). Top incomes in the long run of history. *Journal of Economic Literature 49*(1), 3–71.

Cappelen, A. W., A. D. Hole, and B. Sørensen, Erikand Tungodden (2007). The pluralism of fairness ideals: An experimental approach. *American Economic Review 97*(3), 818–827.

Cappelen, A. W., J. Konow, E. Sørensen, and B. Tungodden (2013). Just luck: An experimental study of risk-taking and fairness. *American Economic Review 103*(4), 1398–1413.

CEPAL, N. et al. (2010). América latina frente al espejo: dimensiones objetivas y subjetivas de la inequidad social y el bienestar en la región.

Choi, G. (2019). Revisiting the redistribution hypothesis with perceived inequality and redistributive preferences. *European Journal of Political Economy 58*, 220–244.

Cozzolino, P. J. (2011). Trust, cooperation, and equality: a psychological analysis of the formation of social capital. *British Journal of Social Psychology 50*(2), 302–320.

Cruces, G., R. Perez-Truglia, and M. Tetaz (2013). Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment. *Journal of Public Economics 98*, 100–112.

Esteban, J., L. Mayoral, and D. Ray (2012). Ethnicity and conflict: An empirical study. *American Economic Review 102*(4), 1310–42.

Esteban, J. and D. Ray (2011). Linking conflict to inequality and polarization. *American Economic Review 101*(4), 1345–74.

Fehr, D., J. Mollerstrom, and R. Perez-Truglia (2021). Your place in the world-relative income and global inequality.

Fehr, D., D. Mueller, and M. Preuss (2020). Social mobility perceptions and inequality acceptance. *Working Paper*.

Finseraas, H. (2009). Income inequality and demand for redistribution: A multilevel analysis of european public opinion. *Scandinavian Political Studies 32*(1), 94–119.

Gasparini, L., G. Cruces, L. Tornarolli, and D. Mejía (2011). Recent trends in income inequality in latin america. *Economia 11*(2), 147–201.

Gasparini, L., M. Horenstein, E. Molina, and S. Olivieri (2008). Income polarization in latin america: Patterns and links with institutions and conflict. *Oxford Development Studies 36*(4), 461–484.

Gasparini, L. and N. Lustig (2011). The rise and fall of income inequality in latin america. Technical report, Documento de Trabajo.

Gimpelson, V. and D. Treisman (2018). Misperceiving inequality. *Economics & Politics 30*(1), 27–54.

Gustavsson, M. and H. Jordahl (2008). Inequality and trust in sweden: Some inequalities are more harmful than others. *Journal of Public Economics 92*(1-2), 348–365.

Hvidberg, K. B., C. Kreiner, and S. Stantcheva (2020). Social position and fairness views. Technical report, National Bureau of Economic Research.

Karadja, M., J. Mollerstrom, and D. Seim (2017). Richer (and holier) than thou? the effect of relative income improvements on demand for redistribution. *Review of Economics and Statistics 99*(2), 201–212.

Kuziemko, I., M. I. Norton, E. Saez, and S. Stantcheva (2015). How elastic are preferences for redistribution? evidence from randomized survey experiments. *American Economic Review 105*(4), 1478–1508.

Lustig, N., L. F. Lopez-Calva, and E. Ortiz-Juarez (2013). Declining inequality in latin america in the 2000s: The cases of argentina, brazil, and mexico. *World development 44*, 129–141.

Martínez Correa, J., L. J. Peñaloza Pacheco, and L. C. Gasparini (2020). Latin american brotherhood?: immigration and preferences for redistribution. *Documentos de Trabajo del CEDLAS*.

Meltzer, A. H. and S. F. Richard (1981). A rational theory of the size of government. *Journal of Political Economy 89*(5), 914–927.

Milanovic, B. (2016). *Global inequality: A new approach for the age of globalization*. Harvard University Press.

Neville, L. (2012). Do economic equality and generalized trust inhibit academic dishonesty? evidence from state-level search-engine queries. *Psychological Science 23*(4), 339–345.

Norton, M. I. and D. Ariely (2011). Building a better america—one wealth quintile at a time. *Perspectives on psychological science 6*(1), 9–12.

Oishi, S., S. Kesebir, and E. Diener (2011). Income inequality and happiness. *Psychological science 22*(9), 1095–1100.

Page, L. and D. G. Goldstein (2016). Subjective beliefs about the income distribution and preferences for redistribution. *Social Choice and Welfare 47*(1), 25–61.

Ravallion, M. (2003). The debate on globalization, poverty and inequality: why measurement matters. *International affairs 79*(4), 739–753.

Rodríguez, S. A. (2014). Percepciones de desigualdad socioeconómica: Un estudio exploratorio para el caso argentino. *Revista de Ciencias Sociales 27*(34), 93–118.

Rodríguez-Castelán, C., L. F. López-Calva, N. Lustig, and D. Valderrama (2016). *Understanding the dynamics of labor income inequality in Latin America*. The World Bank.

World Bank (2016). Poverty and shared prosperity 2016: Taking on inequality.

Zmerli, S. and J. C. Castillo (2015). Income inequality, distributive fairness and political trust in latin america. *Social science research 52*, 179–192.

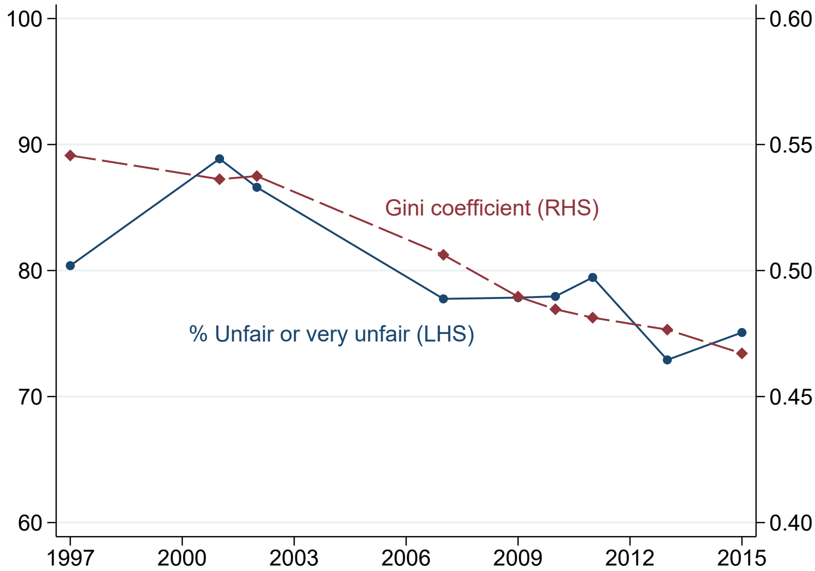
Appendix

A Additional Figures and Tables

Figure A1: Perceptions of unfairness by subgroup, 1997-2015

Notes: This figure presents the share of individuals that perceived income distribution as unfair or very unfair according to four categories of age (15-24; 25-40; 41-64 and 65+), gender, maximum educational attainment, and employment status. Each line refers to the cross-country average.

Figure A2: Fairness views and Gini in LA over time



Notes: This figure plots the unweighted average Gini coefficient of LA and unfairness perceptions over the 1997-2015 period. To ensure the same set of countries is analyzed over time, a linear extrapolation of inequality indicators was made in the years in which income microdata was not available (see Appendix B).

Table A1: Descriptive statistics of our sample

	Mean (1)	Standard Dev. (2)	Observations (3)
Panel A. Sociodemographic			
Age	39.75	16.23	225,551
Male (%)	48.97	0.50	225,567
Married or civil union (%)	56.27	0.50	224,081
Catholic religion (%)	68.01	0.47	222,790
Ideology (10 = right-wing)	5.48	2.64	131,980
Panel B. Education and Labor market			
Literate (%)	90.31	0.30	224,056
Secondary education or more (%)	33.65	0.47	224,056
Parents with secondary education (%)	17.43	0.38	184,884
Economically active (%)	64.14	0.48	225,222
Unemployed (% Labor Force)	9.89	0.30	225,222
Panel C. Access to services			
Access to a sewage (%)	69.59	0.46	222,530
Access to running water (%)	88.83	0.31	204,340
Panel D. Asset ownership			
Car (%)	28.21	0.45	222,338
Computer (%)	33.79	0.47	222,645
Fridge (%)	79.22	0.41	146,686
Homeowner (%)	73.92	0.44	223,603
Mobile (%)	80.61	0.40	172,253
Washing machine (%)	54.71	0.50	223,122
Landline (%)	42.28	0.49	222,968

Note: Author's elaboration based on Latinobarómetro. To calculate the statistics we pooled the data from the 18 LA countries in our sample over the 1997-2018 period.

Table A2: Fairness views by population group

	% of individuals who believe income distribution is:			
	Very unfair (1)	Unfair (2)	Fair (3)	Very fair (4)
All	28.2	51.6	17.3	2.9
Panel A. Gender				
Female	28.3	52.2	16.7	2.8
Male	28.0	51.1	17.9	3.0
Panel B. Age group				
15-24	25.2	52.0	19.7	3.1
25-40	28.5	51.3	17.2	3.0
41-64	29.5	51.7	16.0	2.8
65+	29.2	51.6	16.6	2.5
Panel C. Civil status				
Married	28.3	51.9	17.0	2.8
Not married	27.9	51.4	17.7	3.1
Panel D. Religion				
Catholic	28.2	51.7	17.2	2.9
Not catholic	28.0	51.5	17.5	3.0
Panel E. Education level				
Less than Primary	27.7	51.6	17.7	3.0
Complete Primary	27.9	52.2	17.4	2.6
Complete Secondary	29.1	53.2	15.0	2.7
Complete Tertiary	29.0	50.8	17.1	3.1
Panel F. Type of employment				
Employee	28.3	51.5	17.2	2.9
Employer	24.3	53.9	19.0	2.8
Self-employed	28.0	51.4	17.5	3.1
Unemployed	30.3	51.6	15.1	3.0
Panel E. Country				
Argentina	38.17	50.74	10.26	0.83
Bolivia	18.01	56.13	23.39	2.48
Brazil	31.95	53.71	12.85	1.49
Chile	40.20	49.93	8.42	1.45
Colombia	35.15	51.20	11.40	2.26
Costa Rica	23.20	53.55	20.13	3.12
Dominican Rep.	32.31	46.52	17.61	3.56
Ecuador	21.45	47.46	27.58	3.51
El Salvador	22.73	53.16	20.45	3.65
Guatemala	28.29	51.34	16.70	3.66
Honduras	28.87	53.42	14.33	3.38
Mexico	32.15	49.75	15.32	2.78
Nicaragua	18.69	51.88	24.33	5.11
Panama	27.39	48.01	20.25	4.34
Paraguay	38.31	48.80	10.95	1.93
Peru	25.03	61.89	11.70	1.38
Uruguay	18.22	57.51	22.64	1.64
Venezuela	23.51	42.96	26.62	6.92

Note: Author's elaboration based on Latinobarómetro. To calculate the statistics we pooled the data from the 18 LA countries in our sample over the 1997-2018 period.

Table A3: Descriptive statistics in Latinobarómetro and SEDLAC, 2013 (selected countries)

	Mean		Standard Dev.		Observations	
	Latinob. (1)	SEDLAC (2)	Latinob. (3)	SEDLAC (4)	Latinob. (5)	SEDLAC (6)
Panel A. Sociodemographic						
Age	40.59	42.68	16.43	17.25	14,855	1,004,894
Male (%)	48.97	47.63	0.50	0.50	14,855	1,004,894
Married or civil union (%)	56.77	36.41	0.50	0.48	14,804	915,117
Panel B. Education and Labor market						
Literate (%)	91.18	92.17	0.28	0.27	14,855	1,004,744
Secondary education or more (%)	38.83	46.11	0.49	0.50	14,855	1,001,672
Economically active (%)	65.14	68.66	0.48	0.46	14,855	1,004,718
Unemployed (%)	5.78	4.08	0.23	0.20	14,855	1,004,718
Panel C. Assets and Services						
Access to a sewage (%)	68.76	63.41	0.46	0.48	13,799	975,726
Car (%)	26.37	21.09	0.44	0.41	11,612	643,350
Computer (%)	46.55	47.82	0.50	0.50	12,747	894,003
Fridge (%)	82.76	88.89	0.38	0.31	12,763	894,003
Homeowner (%)	74.09	69.64	0.44	0.46	14,761	1,003,306
Mobile (%)	86.91	91.78	0.34	0.27	12,754	896,079
Washing machine (%)	60.49	56.88	0.49	0.50	11,816	848,350
Landline (%)	40.22	39.47	0.49	0.49	12,736	896,425

Note: Author's elaboration based on Latinobarómetro and SEDLAC. Summary statistics were calculated on a restricted sample (individuals aged over 18) to ensure comparability between both datasets, pooling data from 14 countries in 2013: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Honduras, Panama, Peru, Paraguay, and Uruguay.

Table A4: Logit regressions of unfairness perceptions (unfair) and individual characteristics

	Baseline (1)	Demog. (2)	Education (3)	Labor status (4)	Assets (5)	Ideology, Religion (6)
Gini	0.344	0.347	0.341	0.338	0.340	0.355
	(0.220)	(0.220)	(0.221)	(0.221)	(0.220)	(0.223)
Age		0.004***	0.004***	0.004***	0.004***	0.004***
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared		−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male		−0.014***	−0.014***	−0.013***	−0.012***	−0.009***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married		−0.000	−0.000	0.000	0.000	0.000
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Finished HS			0.004	0.004	0.006	0.009**
			(0.005)	(0.005)	(0.005)	(0.005)
Finished coll.			0.010*	0.011*	0.016***	0.020***
			(0.006)	(0.006)	(0.006)	(0.006)
In labor force				−0.003	−0.004	−0.003
				(0.003)	(0.003)	(0.003)
Unemployed				0.021***	0.021***	0.021***
				(0.005)	(0.005)	(0.005)
Assets index					−0.019***	−0.017***
					(0.006)	(0.006)
Conservative						0.001
						(0.002)
Catholic						−0.001
						(0.003)
N	167,436	166,105	164,662	164,436	164,436	164,436

Notes: This table presents estimates of the relationship between a dummy variable that indicates if the individual believes income distribution is unfair or very unfair and individuals' characteristics. Columns show the marginal effects at the mean values of the rest of the variables and were estimated through Logit regressions, weighting by individuals' probability of being interviewed. All columns include country and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors clustered at the country-by-year level in parentheses.

Table A5: Logit regressions of unfairness perceptions (very unfair) and different inequality indicators

	(1)	(2)	(3)	(4)	(5)
Gini (no zero income)	0.708***				
	(0.223)				
Atkinson, A(1)		0.341**			
		(0.164)			
Theil index			0.246***		
			(0.080)		
Generalized entropy				0.019***	
				(0.007)	
Absolute Gini					−0.001
					(0.001)
Age	0.004***	0.004***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married	−0.005	−0.005	−0.005	−0.005	−0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Finished HS	−0.006	−0.006	−0.005	−0.005	−0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Finished coll.	0.006	0.006	0.007	0.007	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
In labor force	−0.002	−0.002	−0.002	−0.002	−0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployed	0.019***	0.020***	0.018***	0.018***	0.020***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Assets index	−0.007	−0.007	−0.007	−0.006	−0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Conservative	−0.003*	−0.003*	−0.003*	−0.003*	−0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Catholic	−0.011***	−0.011***	−0.011***	−0.011***	−0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	164,436	164,436	164,436	164,436	164,436

Notes: This table presents estimates of the relationship between a dummy variable that indicates whether the individual believes income distribution is very unfair and individuals' characteristics controlling for different inequality indicators. Coefficients present the marginal effects at the mean values of the rest of the variables and were estimated through Logit regressions, weighting by individuals' probability of being interviewed. All columns include country and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors clustered at the country-by-year level in parentheses.

Table A6: OLS regressions of unfairness perceptions (very unfair) and individual characteristics

	Baseline (1)	Demog. (2)	Education (3)	Labor status (4)	Assets (5)	Ideology, Religion (6)
Gini	0.621^{***}	0.623^{***}	0.622^{***}	0.623^{***}	0.623^{***}	0.627^{***}
	(0.222)	(0.222)	(0.220)	(0.220)	(0.219)	(0.218)
Age		0.004^{***}	0.004^{***}	0.004^{***}	0.004^{***}	0.004^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared		-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male		−0.002	−0.002	−0.001	−0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married			-0.006^{**}	-0.005^{*}	-0.005^{*}	−0.005
			(0.003)	(0.003)	(0.003)	(0.003)
Finished HS			-0.010^{**}	-0.010^{**}	-0.009^{*}	−0.007
			(0.005)	(0.005)	(0.005)	(0.005)
Finished coll.			−0.002	−0.001	0.001	0.005
			(0.007)	(0.007)	(0.006)	(0.006)
In labor force				−0.003	−0.003	−0.002
				(0.003)	(0.003)	(0.003)
Unemployed				0.020^{***}	0.020^{***}	0.019^{***}
				(0.007)	(0.007)	(0.007)
Assets index					−0.009	−0.007
					(0.006)	(0.006)
Conservative						-0.003^{*}
						(0.002)
Catholic						-0.011^{***}
						(0.004)
N	167,436	167,420	164,662	164,436	164,436	164,436

Notes: This table presents estimates of the correlation between a dummy variable that indicates if the individual believes income distribution is unfair or very unfair and individuals' characteristics. Coefficients were estimated through OLS regressions, weighting by individuals' probability of being interviewed. All columns include country and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors clustered at the country-by-year level in parentheses.

B Data appendix

The numbers presented in this paper are based on two harmonization projects, known as Latinobarómetro and SEDLAC (Socio-Economic Database for Latin America and the Caribbean). In this Appendix, we describe how we make both sources compatible.

Our perceptions data come from Latinobarómetro, which has conducted opinion surveys in 18 LA countries since the 1990s, interviewing about 1,200 individuals per country about individuals' socioeconomic background, and preferences towards political and social issues. Although the survey is conducted every year, not all years include the question regarding the fairness of income distribution. The survey was designed to be representative at the national level of the voting-age population (in most LA countries, population aged over 18). In Table B1 we show what percentage of the voting-age population is represented by the survey in each country for all the years in which the fairness question is available.

Table B1: Coverage of each country's population in Latinobarómetro overtime (in %)

	1997	2001	2002	2007	2009	2010	2011	2013	2015
Argentina	68	75	75	100	100	100	100	100	100
Bolivia	32	52	100	100	100	100	100	100	100
Brazil	12	100	100	100	100	100	100	100	100
Chile	70	70	70	100	100	100	100	100	100
Colombia	25	71	51	100	100	100	100	100	100
Costa Rica	100	100	100	100	100	100	100	100	100
Dominican Republic	N/A	N/A	N/A	100	100	100	100	100	100
Ecuador	97	97	100	100	100	100	100	100	100
El Salvador	65	100	100	100	100	100	100	100	100
Guatemala	100	100	100	97	100	100	100	100	100
Honduras	100	100	100	98	100	99	99	99	99
Mexico	93	88	95	100	100	100	100	100	100
Nicaragua	100	100	100	100	100	100	100	100	100
Panama	100	100	100	99	99	99	99	99	99
Paraguay	46	46	46	100	100	100	100	100	100
Peru	52	52	100	100	100	100	100	100	100
Uruguay	80	80	80	100	100	100	100	100	100
Venezuela	100	100	100	100	93	100	100	100	100
Weighted average	68	86	91	100	100	100	100	100	100

Since our goal is to analyze how unfairness perceptions evolved vis-à-vis changes in income inequality, we put a lot of effort into trying to get income inequality data for each data point for which we have perceptions data available. To increase the number of observations available (without pushing the data too much), we made two partial fixes. First, we filled the data gaps using household surveys of relatively close years in which previously unused data were available (see Appendix Table B2). For instance, Chile conducts household surveys on average every two years. We have perceptions data in 1997 but no income inequality data for the same year. Therefore, we use the inequality data from the adjacent year (1998) to compare the perceptions data from 1997. As noted previously, we only do this process of using data from close years if the data from the adjacent year correspond to a year in which the perceptions question was not asked (and therefore, inequality data are not needed in that year).

Table B2: Circa years used to fill data gaps

Country	Year without household data	Data point used instead
Chile	1997	1998
Chile	2001	2000
Chile	2002	2003
Chile	2007	2006
Colombia	2007	2008
Ecuador	2002	2003
El Salvador	1997	1998
Guatemala	2001	2000
Guatemala	2015	2014
Mexico	1997	1998
Mexico	2001	2000
Mexico	2007	2006
Mexico	2009	2008
Mexico	2011	2012
Mexico	2015	2014
Nicaragua	1997	1998
Nicaragua	2007	2005
Nicaragua	2015	2014
Venezuela	2013	2012

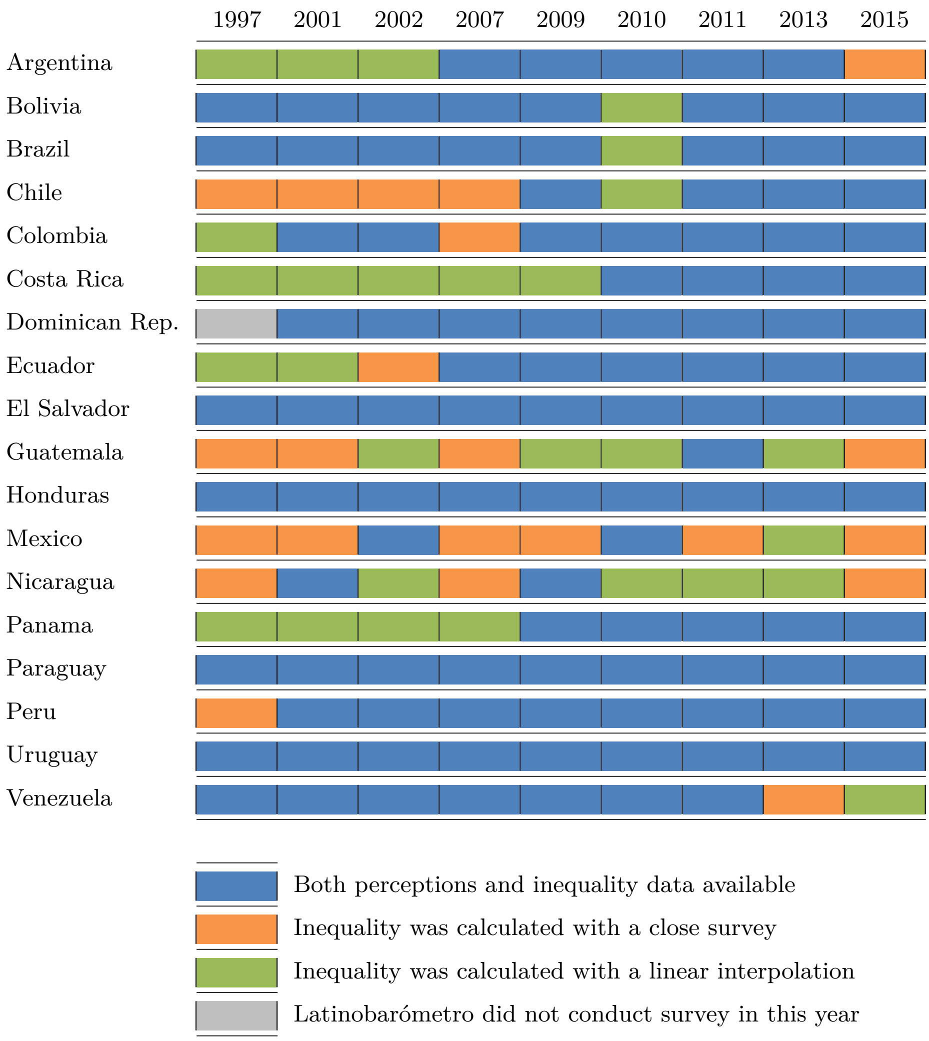
Our second partial fix involves interpolating inequality indicators for some years. For some countries, a few years had perceptions data available but no comparable household survey over time and no close year available. In this case, and to analyze the same set of countries every year, interpolation was applied to the inequality indicators (see Appendix Table B3).

Table B3: Years in which inequality indicators were calculated with a linear interpolation

Country	Years interpolated
Argentina	1997, 2001, and 2002
Bolivia	2010
Brazil	2010
Chile	2010
Colombia	1997
Costa Rica	1997, 2001, 2002, 2007, and 2009
Ecuador	1997, 2001
Guatemala	1997, 2002, 2009, 2010, and 2013
Mexico	2013
Nicaragua	2002, 2010, 2011, and 2013
Panama	1997, 2001, 2002, and 2007
Peru	1997, 2001, 2002
Venezuela	2015

Overall, the years in which income inequality was calculated using linear interpolations represent a relatively small share of the total data points (17% of total). The majority of our inequality data points (69%) are calculated using a household survey from the same year in which the perceptions polls were conducted, while the remaining 14% of our inequality indicators are calculated using household surveys from adjacent years. Table B4 summarizes the data sources used in every year in which perceptions data are available.

Table B4: Summary of the data used in every country-year



B.1 Imputation of missing values for the regression analysis

Two of our individual-level variables (political ideology and religion) have many missing values in some country-years. To deal with this in our regressions, we imputed the average value of each variable to individuals with a missing value. In those cases, we included in the regression a dummy that takes the value one if the value of the variable was imputed and zero otherwise. The results are similar if we do not impute the values, but the sample size of the regressions are smaller.

C The Oaxaca-Blinder Decomposition

The starting point to decompose changes in unfairness perceptions between 2002 and 2013 is the following equation:

$$\text{Unfair}_t = \beta_t X_t + \varepsilon_t \quad \text{for} \quad t \in \{2002, 2013\} \tag{C1}$$

where t indicates the year in which perceptions are captured, and X denotes all the explanatory variables defined in the regressions (mainly, demographics factors and the Gini coefficient). Defining D_{2013} as a dummy variable that takes the value one if the year is 2013, then, the mean difference in unfairness perceptions between both years is given by:

$$\Delta^\mu = \mathbb{E}(\text{Unfair})_{2013}|D_{2013} = 1) - \mathbb{E}(\text{Unfair})_{2002}|D_{2013} = 0) \tag{C2}$$

Since the regression line that comes from estimating the parameters in equation (C2) above meets the property of passing through the sampling means, we have:

$$\overline{\text{Unfair}}_t = \hat{\beta}_{2002}\bar{X}_{2002} \quad \text{and} \quad \hat{\beta}_{2013}\bar{X}_{2013} \tag{C3}$$

Where $\bar{X}_t$ is the vector of the average values of the explanatory variables in year t, and $\hat{\beta}$ the vector of estimated coefficients. If the relationship between the explanatory variables and the perceptions of fairness did not change during the 2002-13 period (i.e., if the β remained constant), then the unfairness perceptions in 2013 could be expressed as:

$$\overline{\text{Unfair}}_t^c = \hat{\beta}_{2002}\bar{X}_{2013} \tag{C4}$$

where the superscript C indicates this value comes from a counterfactual exercise.

Replacing the expected value of the covariables in equation (C2) by the sample averages, the difference in the perceptions between both years can be expressed as:

$$\begin{aligned}
\Delta^\mu &= \hat{\beta}_{2002}\bar{X}_{2002} - \hat{\beta}_{2013}\bar{X}_{2013} \\
&= \hat{\beta}_{2002}\bar{X}_{2002} - \hat{\beta}_{2013}\bar{X}_{2013} + \hat{\beta}_{2002}\bar{X}_{2013} - \hat{\beta}_{2002}\bar{X}_{2013} \\
&= \underbrace{\hat{\beta}_{2002}(\bar{X}_{2013} - \bar{X}_{2002})}_{\equiv\hat{\Delta}_X^\mu} + \underbrace{\bar{X}_{2013}(\hat{\beta}_{2013} - \hat{\beta}_{2002})}_{\equiv\hat{\Delta}_S^\mu}
\end{aligned} \tag{C5}$$

The first term of equation (C5) is usually known as the "composition effect." This effect captures the difference between the average perceptions in 2002 and the counterfactual perceptions 2013 had the $\hat{\beta}$'s—i.e., the elasticity of perceptions to the different covariables—remained constant during the 2002-13 period. In other words, this first term captures only differences in the endowments of characteristics that determine unfairness perceptions (such as educational attainment, age, or income inequality).

The second term of (C5) can be thought of as a “fairness views structure effect.” This effect reflects the difference between the average fairness views in 2013, and the counterfactual fairness views in 2002 with the observable attributes of 2013. Thus, this component reflects changes in fairness views that are due to changes in the elasticity of the different covariables between both years.