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Documento de Trabajo Nro. 209
Abril, 2017
ISSN 1853-0168

www.cedlas.econo.unlp.edu.ar

Perceptions of distributive justice in Latin America during a period of falling inequality*

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April 2017

Abstract

In this paper we explore perceptions of distributive justice in Latin America during the 2000s and its relationship with income inequality. In line with the fall in income inequality in the region, we document a widespread, although modest, decrease in the share of the population that believes income distribution is unfair. The fall in the perception of unfairness holds across very heterogeneous groups of the population. Moreover, perceptions evolved in the same direction as income inequality for 17 out of the 18 countries for which microdata is available. Our analysis reveals unfairness perceptions are more correlated with relative measures of income inequality than absolute ones and that individual characteristics are correlated with distributive perceptions. On average, individuals that are older, more educated, unemployed, and left-wing tend to perceive income distribution as more unfair. We show that the decrease in unfairness perceptions during the last decade was due to changes in inequality, rather than to composition effects. Finally, we show that individuals that perceive income distribution as very unfair are more prone to mobilize and protest.

JEL Classification: D31, D63, D83

Keywords: Inequality, Fairness, Distributive Justice, Perceptions, Latin America

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* The authors would like to thank Carolina García Domench, Giselle Del Carmen and Rebecca Deranian for their support and thoughtful comments. The findings, interpretations, and conclusions in this paper are entirely those of the authors.

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1. Introduction

One of the most salient features of the 21st century is the rising concern for economic inequality, to the point that it is assessed as 'the defining challenge of our time.'[4] Inequality has been observed with concern by multilateral organizations, politicians and religious leaders.[5] The concerns about inequality are not only based on efficiency arguments, but especially on a moral ground. Anecdotal evidence suggests that concerns about inequality extend to the general population. For instance, protests such as 'Occupy Wall Street' are manifestations of the discontent with the wide income gaps. However, research on how the general population thinks about inequality, and how factors like age, gender, or education relate to our views on what is fair and unfair is still scarce.

Central to this paper is the concept of *social justice* or *fairness* and the underlying desire to live in a just world.[6] Since the seminal paper of Rabin (1993), the concept of fairness has been increasingly important in the field of Economics. Fehr and Schmidt (2003) provide an extensive review of the experimental evidence related with the desire for fairness. The authors show how in dictator games, participants share part of their endowments even though they could keep it all. Similarly, in ultimatum games, participants accept a monetary loss to penalize behavior that is not considered fair, and in gift exchange games, participants are averse to inequitable outcomes.

The desire for fairness seems to transcend cultural differences. Throughout Jerusalem, Ljubljana, Pittsburgh, Tokyo, the Machiguenga of the Peruvian Amazon, and 15 other small-scale societies, ultimatum game offers are always positive, and payoffs that are not considered fair are punished by rejecting positive offers at considerable rates.[7] Evidence from psychology suggests the desire for fairness is ingrained in human nature. Children as young as three years old react negatively to unfair distributions (Loblue et al, 2011),[8] and children's aversion to inequities also transcends borders (Blake et al., 2015). Insights from biology suggest preferences for fairness might have evolutionary origins. In their famous experiment, Brosnan and de Waal (2003) find that capuchin monkeys reject unequal payoffs, a finding that has been replicated in other species, such as dogs (Range et al., 2009) and birds (Wascher and Bugnayar, 2015). Bjornskov et al. (2013) show that people who perceive their society as fairer exhibit higher levels of subjective well-being and, in

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[4] See, for instance 'Remarks by the President on Economic Mobility,' The White House Office of the Press Secretary, Washington, D.C., December 4, 2013.

[5] During a visit to Bolivia in 2015, Pope Francis stated that: "*Working for a just distribution of the fruits of the earth and human labor is not mere philanthropy. It is a moral obligation.*"

[6] Benabou and Tirole (2005) show that this desire is so strong that people distorts their perceptions of reality in order to interpret it as fair.

[7] Evidence is provided in Roth et al. (1995), Henrich (2000) and Henrich et al. (2001), respectively.

[8] See also Fehr et al (2008) and Blake and McAuliffe (2011).

the context of distributive justice, Corneo and Fong (2008) find that US households put a monetary value on social justice of about a fifth of their disposable income.

In this paper we study the general population's beliefs about distributive justice, i.e., the perception of whether income distribution is fairly distributed, in the context of a pronounced decline in the income inequality in Latin America (LA), a highly unequal region. Our approach is to combine income microdata originated from household surveys with perceptions data from opinion polls surveys. We exploit the heterogeneity across years, countries, and individuals within countries to analyze how our views of fairness relate to the actual levels of income inequality.

Evidence of the relationship between fairness perceptions and income inequality, particularly in LA, is rather scarce. In Argentina, Rodriguez (2014) finds that people who consider their income to be fair tend to perceive lower levels of inequality. The work closest to this paper is CEPAL (2010), which shows that perceptions of distributive inequity in LA remained persistently high during the 1997-2007 period, consistent with the high levels of inequality of the region.

In the first part of the paper we document a series of stylized facts. After a decade of increasing disparities in LA, the 2000s saw a remarkable decrease in the levels of inequality. Despite this, the region continues to be one of the least egalitarian in the world, with levels of inequality comparable to those of Africa (Alvaredo and Gasparini, 2015). To the best of our knowledge, we are the first to show that unfairness perceptions fell during the 2000s in line with the evolution of income inequality, although we find that unfairness perceptions are not very responsive to changes in inequality. During the 2002-13 period, a 1 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 or very unfair.

The evolution of unfairness and inequality was consistent across countries: perceptions moved in the same direction as the Gini coefficient for 17 out of the 18 countries of the region for which microdata is available. We also show that this change was widespread across very heterogeneous groups of the population, and that the decline in unfairness perceptions was driven mainly by a reduction in the intensity of such beliefs (i.e., compared to ten years ago, fewer people perceive the distribution as very unfair).

Next we shed some light on the discussion of whether inequality should be measured with relative vs. absolute indicators by analyzing which indicators are more correlated with unfairness perceptions. We show that relative indicators—and in particular, the Gini coefficient—are the ones mostly correlated with people's perception of fairness.

In the second part of the paper we explore how individual factors and belief systems affect how inequality is perceived. We find that older, unemployed and more educated people are more likely to perceive income distribution as unfair. A decomposition exercise provides evidence on the relative contribution of composition effects vis-à-vis changes in aggregate inequality trends, to explain the decline in unfairness perceptions during the last decade. Regarding beliefs and unfairness, consistent with theories of fairness, we find that people leaning to the right of the political spectrum, Catholics, and optimists are more likely to believe income distribution is fair. Finally, we analyze the link between fairness perceptions and propensity to protest, and show some suggestive evidence that people that believe inequality is very unfair are more prone to mobilize.

The rest of the paper is organized as follows. In section 2 we document some stylized facts about distributive justice perceptions and the evolution of income inequality. In section 3, we shed some light on the discussion of whether income inequality should be measured with absolute or relative measures by studying the relationship between perceptions data with different indicators of income inequality. In section 4 we analyze whether individuals' unique background shape their perception of fairness, by analyzing how individuals' characteristics relate with perception of distributive justice; and compare the relative importance of the demographic variables vis-à-vis aggregate trends of inequality to explain the observed changes in fairness perceptions. In section 5 we analyze the relationship between different beliefs systems and unfairness, while in section 6 we explore the link between fairness perceptions and social cohesion. Section 7 concludes.

2. Income inequality and fairness: some stylized facts

Latin America has long been characterized as a region with high levels of income inequality, among the least egalitarian regions in the world. Out of the ten most unequal countries of the world for which household survey data is available eight of them are in LA, and the rest in Sub-Saharan Africa (World Bank, 2016), probably the most unequal region in the world (Alvaredo and Gasparini, 2015). Although the disparities between the poor and rich are still large, after a period of increasing inequality during the 1990s, the region experienced a 'turning point' in the 2000s, when income inequality saw a widespread decrease across the countries of the region.[9] The social gains in terms of inequality contrasts with what happened in other developing regions in the world, where the declines in inequality were much more modest (e.g., such as in the Middle East and North Africa), or even increased (such as in East Asia and Pacific, cf. Alvaredo and Gasparini, 2015, p. 29), and also contrasted with the increases in inequality experienced by developed countries (cf., Atkinson, Piketty and Saez, 2011).

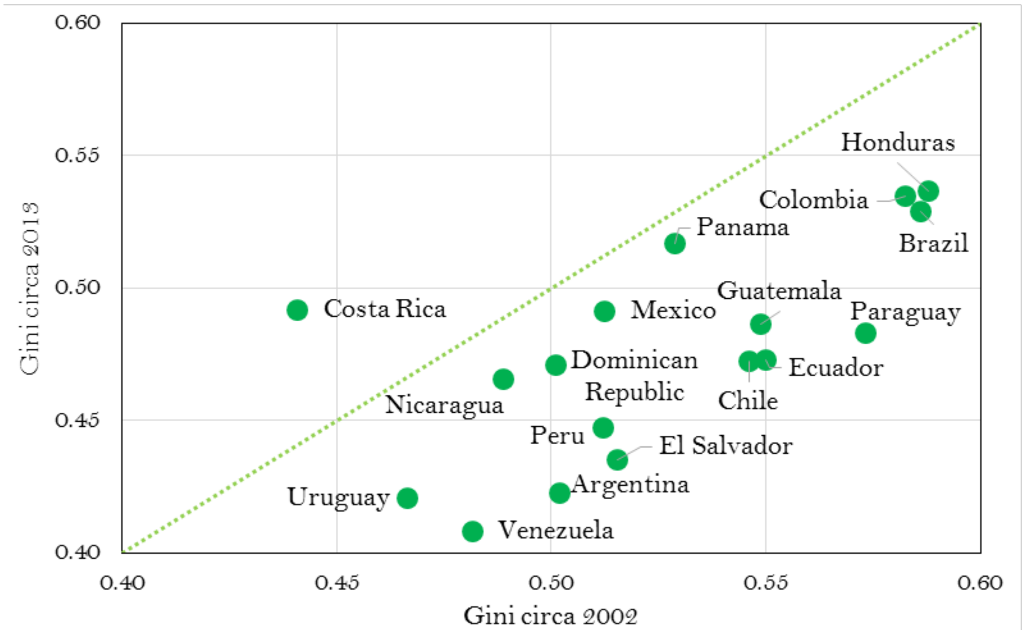
In this section we replicate the widespread decrease in income inequality in LA, and show how perceptions about fairness moved in the same direction. Our primary dataset for income inequality comes from a regional data harmonization efforts known as

[9] See Gasparini, Cruces and Tornarolli (2011), Gasparini and Lustig (2011) and Lustig, López-Calva and Ortiz-Juárez (2013).

SEDLAC (CEDLAS and World Bank), which increase the cross-country comparability from official household surveys.[10]

Figure 1 shows a scatterplot of the Gini coefficient of the per capita household income (in 2005 USD PPP) of 18 LA countries for which comparable data is available both at the beginning of the 2000s and one decade later (we use years close to 2002 and 2013). The Figure includes a 45 degree line denoting all the points for which the Gini coefficient is the same in both years, and points to the right of this line denote decreases in income inequality.

Figure 1. Gini coefficient circa 2002 and 2013



Note: This figure presents the Gini coefficient for 18 LA countries in 2002 and 2013. Due to household data unavailability or comparability issues, for some countries we use inequality data from adjacent years. In 2002, we use: Argentina 2004, Chile 2003, Guatemala 2006, and Peru 2004. In 2013 we use: Guatemala 2014, Mexico 2014 and Nicaragua 2014. Due to a break in data comparability, Costa Rica and Panama's 2002 Gini Coefficient were calculated with a linear interpolation. See Data Appendix for further details.

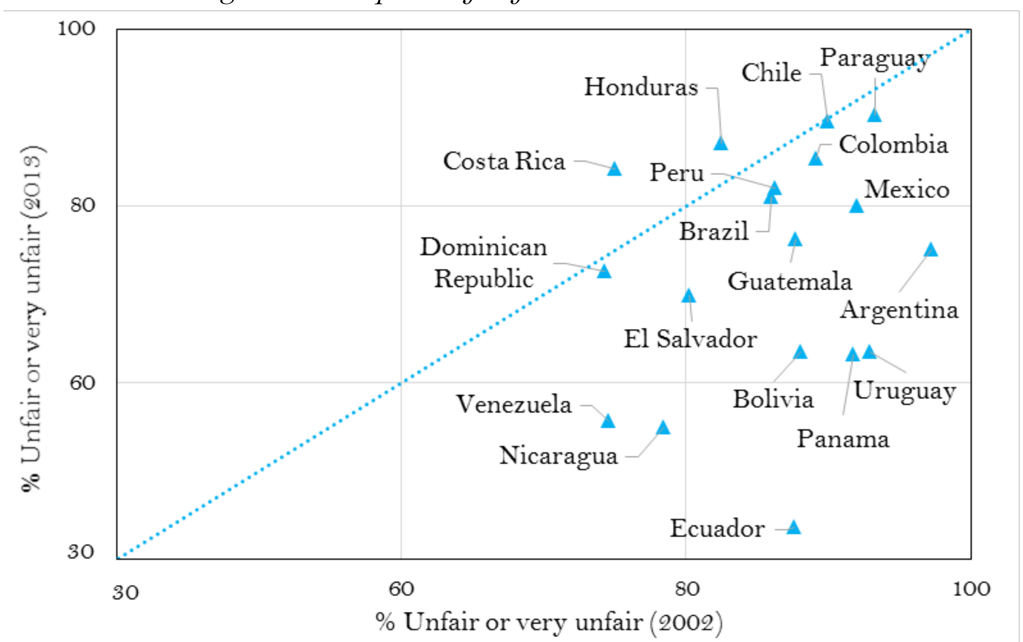
As is immediately apparent from Figure 1, with the exception of Costa Rica, all countries of the region experienced a decrease in income inequality. The regional trend is consistent with the cross-country evidence: the average Gini coefficient has decreased every year since the beginning of the decade, declining from 0.54 in 2000 to 0.47 in 2014. Moreover, as Rodríguez-Castelán et al. (2016) note, the decline in income inequality of the region is robust to the inequality indicator used and to the method of aggregation of the countries.

We complement the 'objective' evolution of income inequality with data from public opinions polls from Latinobarómetro, which has conducted surveys in 18 Latin American

[10] See Data Appendix for more details on the data sources.

countries since the 1990s, interviewing about 1,200 individuals per country about individual socioeconomic background and preferences regarding political and social issues (including inequality). The surveys are representative at the national level for the population over 18 years old.[11] 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 dichotomical variables reflecting whether the individual believes income distribution is unfair or very unfair.[12] Our baseline definition of unfairness perceptions includes all the individuals that perceived income distribution as unfair, i.e., we include those that answered both 'unfair' and 'very unfair', but also show the results are robust to a more narrow definition of unfairness (i.e., considering only those that answered 'very unfair'). Figure 2 shows the percentage of each country's population that believes income distribution is either unfair or very unfair in 2002 and 2013.

Figure 2. Perceptions of unfairness in 2002 and 2013



Note: This figure 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 in. Due to data unavailability in 2002, for the Dominican Republic we use 2007. See Data Appendix for further details.

There are several things to note about Figure 2. First, the percentage of the population that believes income distribution is unfair is strikingly high in both points in time. The regional average was as high as 86.6% in 2002 (with Argentina peaking at

[11] Latinobarómetro has been extensively used for research on several economic issues. For instance, Torgler (2003) uses this dataset to analyze tax morale and tax evasion in Latin America; Graham and Felton (2005) to analyze the relationship between inequality and subjective well-being; and Bonnet et al. (2012) to study satisfaction with the privatization of state-owned companies in Latin America.

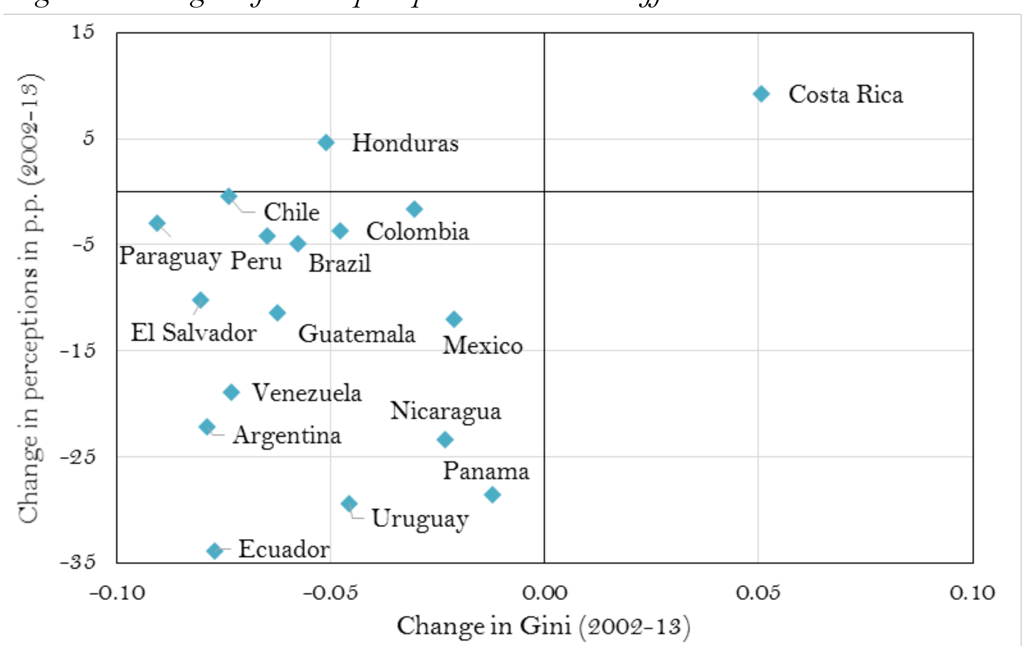
[12] Unfortunately, this question was not asked every year. We restrict our analysis to the years in which this question was asked: 1997, 2001, 2002, 2007, 2009, 2010, 2011, 2013, and 2015.

97.7% of the population, in the midst of a severe crisis). Even in Venezuela, the country with the smallest perception of unfairness in 2002, three out of four individuals (74.5%) perceived inequality as unfair in 2002. Although lower, the share of the population unsatisfied with income distribution was still astoundingly high in 2013, when about 72.8% of the population though inequality was unfair or very unfair.

Second, there was a widespread decrease in the share of the population that perceived income distribution as unfair. Relative to the previous decade, in 2013 fewer people perceived income distribution as unfair in 16 out of the 18 countries analyzed. The change in perceptions range from modest decreases, such as in Chile, where the decline was of less than one percentage point, to remarkable reductions, such as in Ecuador, where perceptions about unfairness declined from 87.5% to 38.6% in the 2002-13 period.

Lastly, with the exception of Honduras—where, despite falling inequality the population perceived the distribution as more unjust—in the rest of the countries both variables moved in the same direction. To see this more clearly, in Figure 3 we show jointly the change in the perceptions of unfairness (as measured by the percentage point change in the share of the population reporting income distribution is unfair or very unfair), and the change in the Gini coefficient during the 2002-13 period. As can be easily seen from Figure 3, most LA countries lie in the third quadrant, where both inequality and unfairness perceptions decreased.

Figure 3. Change in fairness perceptions and Gini coefficient between 2002 and 2013

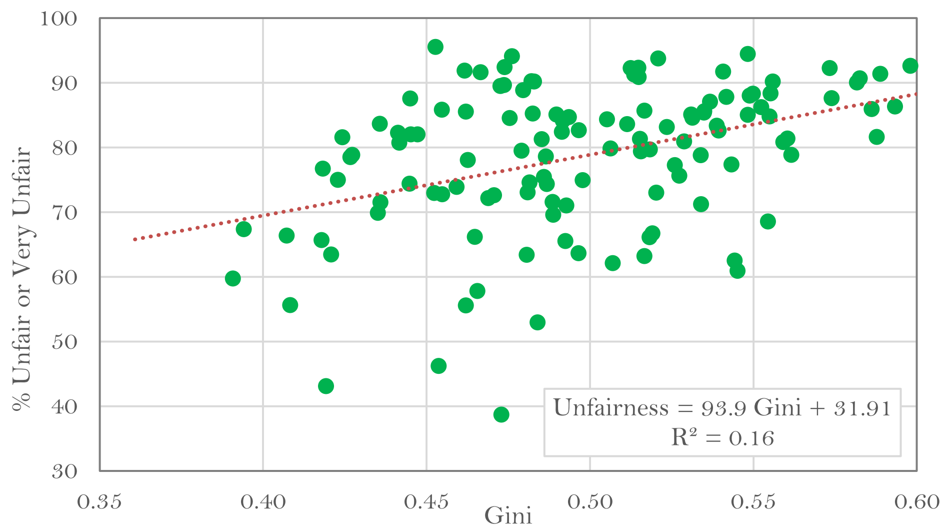


Note: This figure presents the percentage point change in the share of the population that believes income distribution is either unfair or very unfair between 2002 and 2013 (or close years), and the change in the Gini coefficient between 2002 and 2013 (or close years) for all LA countries. See Data Appendix for more detail.

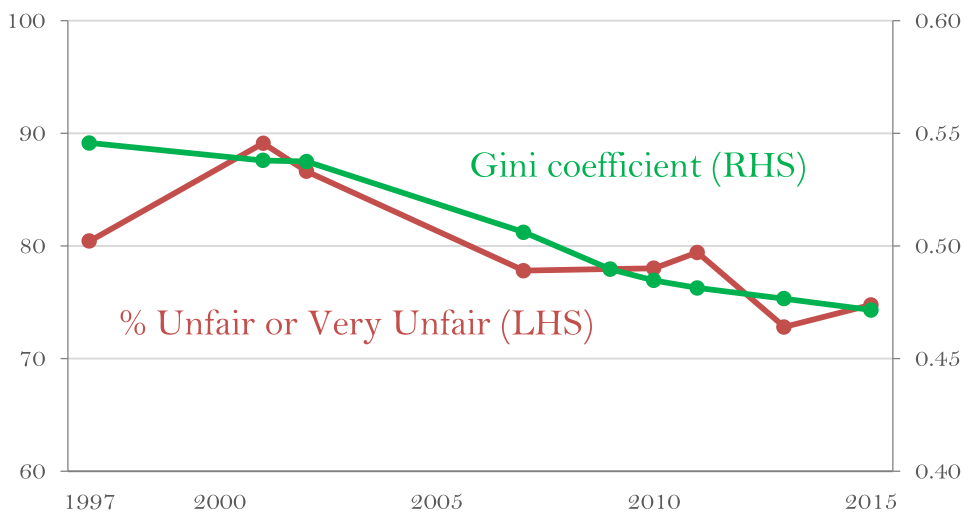
The relation between unfairness perceptions and the Gini coefficient is strong both across countries and time. In Figure 4 panel (a), we show the cross-country correlation between unfairness perceptions and income inequality in all the years for which both indicators are available, while in panel (b) we show the average regional trend over the 1997-2015 period.[13]

Figure 4.Unfairess perceptions and Gini coefficient in Latin America

a) *Across countries (Pooling all the countries and years)*



b) *Over time (Cross-country average, 1997-2015)*



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

Note: Panel (a) of this figure presents the cross-county correlation between unfairness perceptions and the Gini coefficient for 18 LA countries over the 1997-2015 period. The figure does not include data points that were calculated through linear interpolations. Panel (b) shows the unweighted average Gini coefficient of LA and unfairness perceptions since 1997. 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.

Figures 4a and 4b indicate that income inequality and unfairness perceptions are closely related. The linear correlation between the Gini coefficient and the unfairness perceptions across countries is 0.40, while the Spearman correlation between the ranking of countries is 0.42 (in both cases, $p<.01$). The correlation over time is stronger than across countries. The linear correlation of the series plotted in Figure 4.b is notably high (0.77), and the correlation between the Gini coefficient and perceptions is even higher if we consider the share of individuals that responded income distribution is very unfair (0.82).

Our results point to a low elasticity of unfairness perceptions to income inequality.[14] Pooling the data from all the countries we find that, during the 2002-13 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 or very unfair.[15] To put this number 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%.

The decrease in unfairness perceptions—from almost 90% in 2001 to 72.8% in 2013—does not seem to be driven by any particular group of the population, but is rather a widespread phenomenon. To see this, in Figure 5 we present the perceptions of fairness by dividing the population in many subgroups: according to their age, gender, educational achievement and labor status.

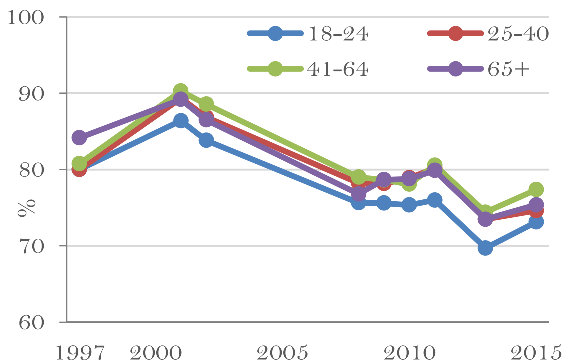
Figure 5 reveals some heterogeneity across groups. For instance, relatively younger population are less likely to perceive income distribution as unfair (panel a), while females are more likely to do so, although not consistently across time (panel b). Similarly, individuals with a higher educational achievement are more likely to belief income distribution is unfair, while the results according to employment status are mixed. Regardless of the different average beliefs, the perception of unfairness of all these groups consistently fell during the 2000s.

[14] The elasticity of unfairness perceptions to the Gini coefficient is calculated as: $\varepsilon = \Delta\%\text{Unfairness}/\Delta\%\text{Gini}$

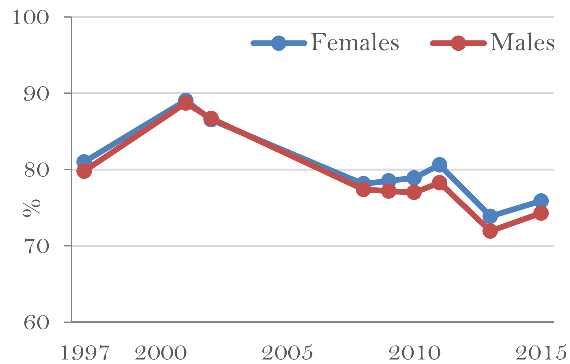
[15] The estimated elasticity is the combined effect of a higher elasticity of 'very unfair' perceived inequality (2.1) and a lower elasticity 'just unfair' perceived inequality (0.9).

Figure 5. Perceptions of unfairness in LA by subgroup, 1997-2015

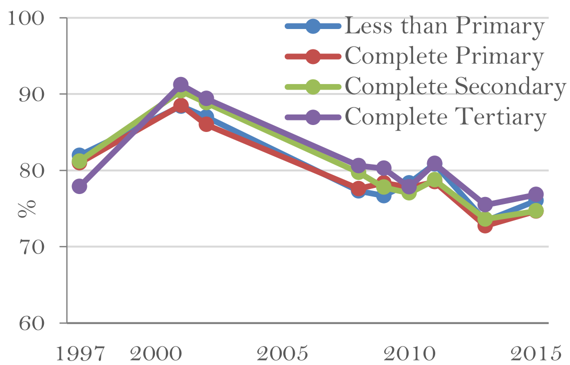
(a) By age:



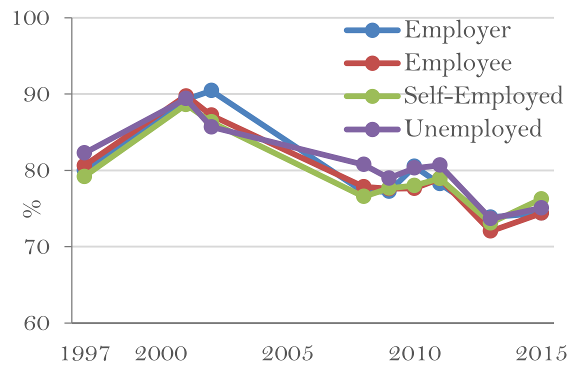
(b) By gender:



(c) By educational attainment:



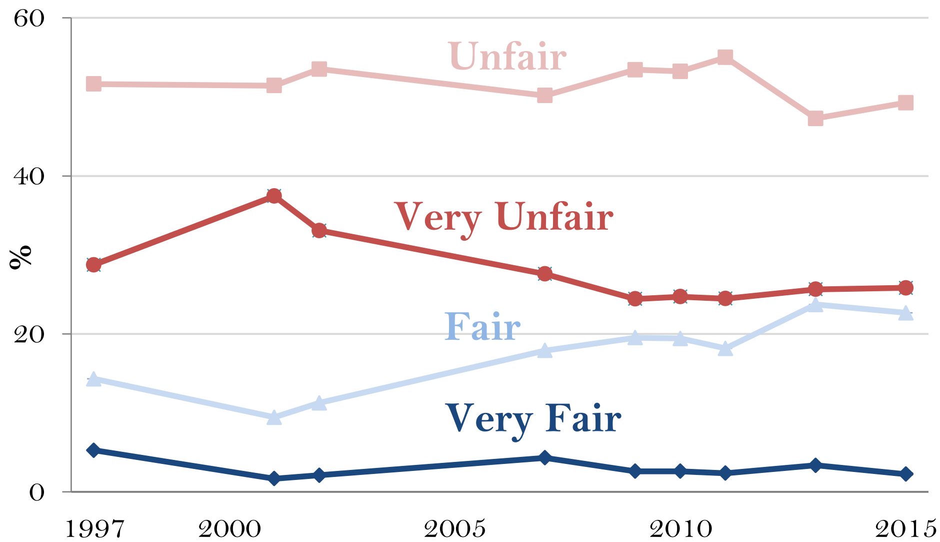
(d) By labor status:



Note: This figure presents the share of individuals that perceived income distribution as unfair or very unfair according to four categories of age (18-24; 25-40; 41-64 and 65+), gender, maximum educational achievement and labor status. Each line refers to the average of 18 LA countries for which data is available.

Not only injustice perceptions fell during the last decade, but the intensity of beliefs also diminished over time. To see this, Figure 6 shows the evolution of the different possible answers to the question of unfairness perceptions.

Figure 6. Intensity of unfairness perceptions in LA, 1997-2015



Note: This figure 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.

As can be seen from Figure 6, the decrease in unfairness perceptions was driven mainly by strong beliefs about unfairness (i.e., people that perceived inequality as very unfair). While in 2001, 37.4% of the population thought income distribution was very unfair, this figure decreased to 25% in 2015. In contrast, weak beliefs about unfairness (i.e., the population that responded income distribution was only 'unfair'), have been more volatile, remaining relatively constant during the 2000s (from 51.4% in 2001 to 49% in 2015). On the other hand, the share of the population believing in a fair distribution increased from a meager 9.5% in 2001 to a sizable 22.6% in 2015, while strong beliefs on fairness (i.e., 'very fair'), have remained under 5% throughout all the 2000s.

3. Is fairness absolute or relative?

In the previous sections we showed that a large, albeit decreasing, share of the population believes 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, the general population's views on income distribution might, in fact, be better captured with other indices.

The literature on inequality measurement makes a crucial distinction between two types of indicators: the relative (such as the Gini coefficient) and absolute ones (such as the Variance). The main distinction between them is that relative indicators fulfill the scale-invariant axiom, while the absolute indicators meet the translation-invariant axiom. In practical terms, this means that if the income of the entire population increases by the same percentage, relative indicators will remain unchanged, while absolute indicators might increase significantly. The question on which indicator should be used in practice has led to a heated debate in the literature. Milanovic (2016) provides several arguments to defend the use of relative indicators in practice, but the fact that they are better from a technical point of view does not say anything about how the general population perceives fairness.[16]

Understanding whether people think about distributive fairness through the lens of relative or absolute indicators is more than a technical measurement issue or an economist's whim. As Ravallion (2003) and Atkinson and Brandolini (2008) note, it has profound consequences about how we think of important issues such as the distributive effects of globalization or trade openness. As measured by absolute indicators, globalization has deteriorated the income distribution since the absolute income differences between the rich and the poor have increased, but under the lens of relative measurement, income inequality has been reduced, since the poor have grown proportionally more than the rich in relative terms.

We take an agnostic approach and let the data show which inequality indicators are more correlated with the perceptions of distributive justice. To do this, we calculate 13 different measures of income inequality for all the countries in our sample, and correlate all the indicators with the share of the population that believes income distribution is unfair over time.[17] Table 1 shows the results for the three different ways of calculating the correlation between the perceptions and inequality indicators at the regional level: (i) pooling all the data (i.e. taking simultaneously the indicators of all the countries and calculating the correlations with that pool of data, columns 1-3); (ii) calculating the average of the indicators across all the countries in every year, and then calculating the correlation between the average values of the indicators (columns 4-6); and (iii) calculating the correlations between inequality indicators and perceptions at the country level and then averaging the results (columns 7-9).

Our results suggest perceptions of unfairness are more correlated with relative indicators rather than absolute ones (Column 1 of Table 1). In fact, the Gini Coefficient—probably the most used inequality indicator in the literature—is the one with the highest

[16] Perhaps, the most disturbing instance of a mismatch between 'best practices' in inequality measurement theory and general perceptions is given by Amiel and Cowell (1992), who provide experimental evidence showing that many respondents do not agree with the Dalton-Pigou axiom, the backbone of all inequality indicators.

[17] The indicators are the Gini coefficient, the ratio between the 75th percentile and the 25th percentile, 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 1, 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.

explanatory power.[18] On average the Gini Coefficient explains about 10 percent of the variability of the perceptions about unfairness, as measured by the R-squared. On the other hand, the absolute indicators of inequality correlate negatively with the unfairness perceptions, and the explanatory power of such indicators is lower than of the relative indicators. It is interesting to note that indicators often mentioned in the mass media, such as the ratio between the richest 90% and the poorest 10% exhibit low explanatory power, although this may be due to mismeasurement of the top incomes. The results of the high correlation between unfairness perceptions and income inequality seems 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 close to zero (<0.1) 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 was greater than for translation invariance, reflecting greater support for relative inequality indicators. Moreover, the results are also consistent with graphical evidence that shows decreasing relative inequality, but rising absolute inequality during the 2000s in LA (Figure 4 and Figure 7, respectively). Since unfairness perceptions also declined over time, the relative indicators do a better job of tracing such evolution.

[18] The results are very similar if we exclude the observations with income equal to zero. For example, pooling all the data and excluding individuals with zero income changes the correlation of the Gini with the share of the population that perceives income distribution as either unfair or very unfair from 0.412 to 0.417.

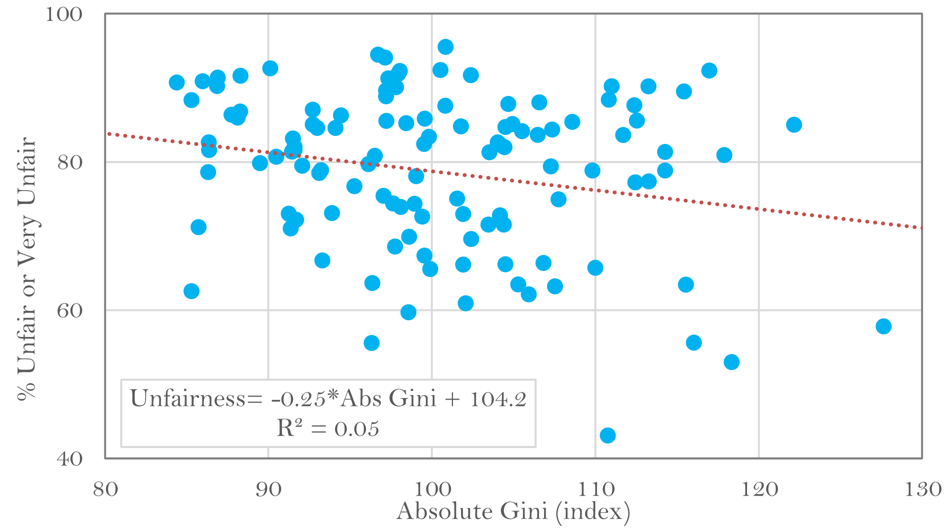
Table 1. Correlation between Inequality indicators and fairness perceptions, LA 1997-2015

Correlation with…	Pooling all the data			Averaging indicators			Averaging correlations		
	U. or V.U.	V.U.	U.	U. or V.U.	V.U.	U.	U. or V.U.	V.U.	U.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Gini coefficient	0.40	0.37	0.09	0.84	0.83	0.24	0.41	0.30	0.14
	(0.07)	(0.07)	(0.09)	(0.10)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Ratio 75/25	0.39	0.40	0.05	0.85	0.83	0.26	0.35	0.22	0.16
	(0.07)	(0.07)	(0.09)	(0.10)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Atkinson, A(0.5)	0.39	0.37	0.09	0.84	0.83	0.25	0.40	0.28	0.14
	(0.07)	(0.07)	(0.09)	(0.10)	(0.16)	(0.35)	(0.07)	(0.07)	(0.09)
Theil index, GE(1)	0.37	0.32	0.13	0.84	0.82	0.24	0.39	0.29	0.12
	(0.07)	(0.08)	(0.09)	(0.10)	(0.16)	(0.34)	(0.07)	(0.08)	(0.09)
Atkinson, A(1)	0.36	0.30	0.13	0.84	0.82	0.24	0.39	0.29	0.12
	(0.07)	(0.08)	(0.09)	(0.10)	(0.16)	(0.34)	(0.07)	(0.08)	(0.09)
Mean log deviation, GE(0)	0.33	0.37	-0.01	0.78	0.78	0.19	0.22	0.19	0.11
	(0.08)	(0.08)	(0.09)	(0.13)	(0.16)	(0.36)	(0.08)	(0.08)	(0.09)
Generalized entropy, GE(2)	0.32	0.17	0.25	0.80	0.78	0.25	0.37	0.29	0.13
	(0.07)	(0.09)	(0.08)	(0.11)	(0.17)	(0.34)	(0.07)	(0.09)	(0.08)
Coefficient Variation	0.30	0.36	-0.05	0.80	0.72	0.35	0.22	0.11	0.19
	(0.05)	(0.08)	(0.08)	(0.12)	(0.18)	(0.34)	(0.05)	(0.08)	(0.08)
Ratio 90/10	0.25	0.12	0.21	0.81	0.79	0.24	0.31	0.30	0.07
	(0.07)	(0.08)	(0.08)	(0.11)	(0.17)	(0.33)	(0.07)	(0.08)	(0.08)
Variance	-0.12	-0.01	-0.17	-0.28	0.05	-0.68	-0.07	0.07	-0.22
	(0.08)	(0.09)	(0.08)	(0.4)	(0.43)	(0.16)	(0.08)	(0.09)	(0.08)
Absolute Gini	-0.23	-0.10	-0.22	-0.71	-0.47	-0.63	-0.19	-0.06	-0.30
	(0.09)	(0.1)	(0.08)	(0.23)	(0.26)	(0.32)	(0.09)	(0.1)	(0.08)
Kolm, K(1)	-0.33	-0.18	-0.25	-0.80	-0.65	-0.49	-0.24	-0.13	-0.26
	(0.09)	(0.11)	(0.08)	(0.13)	(0.18)	(0.37)	(0.09)	(0.11)	(0.08)

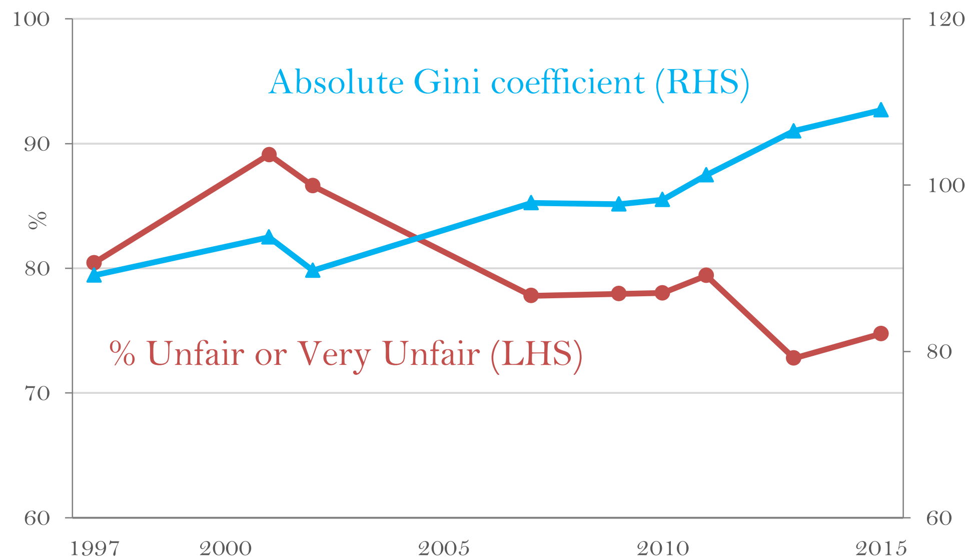
Note: U. or V.U. = % Unfair or Very Unfair; V.U. = % Very Unfair; U. = % Unfair. Standard Errors are reported in parenthesis, and were calculated with bootstrap (500 iterations).

Figure 7.Unfairess perceptions and Absolute Gini coefficient

c) Over countries (Pooling all the countries and years)



d) Over time (Cross country average, 1997-2015)



Note: Panel (a) of this figure presents the cross-county correlation between unfairness perceptions and the absolute Gini coefficient for all LA countries for which data is available over the 1997-2015 period. The absolute Gini was normalized so the average over the period is equal to 100 in every country. Figure does not include data points that were calculated through linear interpolations. Panel (b) shows evolution f the unweighted average absolute Gini and unfairness perceptions. 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.

4. Fairness through the eyes of people

In this section we explore how individuals' characteristics relate to their views on inequality. As shown in the previous section, most of the change in perceptions over the last decade was driven by the share of the population that perceived income distribution as being very unfair, thus we focus on explaining the correlates of such measure, although we also show the results for a broader definition of unfairness.

4.1 DATA

Our sample of individuals comes from pooling all LA countries from nine different waves of Latinobarómetro over the 1997-2015 period. Appendix Tables A1-A3 show basic descriptive statistics of the sample. Roughly half of respondents are women (50.9%), the average age was 39.4 (most interviewees—38%—were aged 25-40). Over half of the sample (57.3%) reported being married or in a civil union, and are adherents to Catholicism (70.7%).

About 90 percent of the sample are literate, the majority of respondents (76%) completed at least primary school, while a third of them (32.3%) had secondary education or more. Almost two thirds of the sample (64%) were part of the labor force, and 9.9% of them were unemployed. Access to basic services among respondents is relatively high: 87.6% of individuals had access to running water inside their dwelling and over two thirds (69.7%) reported that their dwellings had access to a flush toilet connected to waste-removal system (i.e., sewage). Ownership of durable goods ranges from low levels regarding cars and computers (27.3% and 29.6%, respectively) to high levels regarding fridges and mobile phones (79.2% and 76.4%).

To assess the differences between Latinobarómetro's sample and the household surveys' sample (SEDLAC), Appendix Table A4 compares a set of summary statistics in both datasets in 2013. To ensure comparability of the samples, we restrict the calculations to individuals aged over 18, and to countries with data available in both databases. In general, the samples are similar in observable characteristics. For instance, the average age in Latinobarómetro's reduced 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 subsample is more educated (46.1% of the population has secondary education or more, while this figure is 38.8% in Latinobarómetro).

4.2 ESTIMATION STRATEGY

To formally assess the relationship between individuals' characteristics and fairness perceptions, we run Logit regressions where the dependent variable takes the value 1 if the individual believes income distribution is very unfair and 0 otherwise. In the baseline specification, we assume that unfairness perceptions can be characterized according to the following equation:

$$Very\ Unfair_{ict} = \beta_0 + \beta_1\,\gamma_{ict} + \beta_2\,G_{ct} + \sum_c C_c + \sum_t T_t + \varepsilon_{ict}$$

where $Very\ Unfair_{ict}$ is the variable of interest, namely, whether the individual i of country c during year t believes income distribution is very unfair or not; γ is a vector of individual characteristics that includes the age, sex, civil status, education, and type of job; G_{ct} is the country's Gini coefficient; C is a vector of country and subnational fixed effects[19]; T is a vector of year fixed effects and ε_{ict} is the error term.

We are interested in the sign and magnitude of β_1 and β_2. The first of these coefficients captures the relationship between the individual's characteristics and unfairness perceptions. If unfairness is uncorrelated with observable characteristics, then this coefficient should not be statistically different from zero. On the other hand, β_2 captures the relationship between the Gini coefficient and the perceived fairness after controlling for an individual's covariables. If subjective measures of income inequality are significantly correlated with their objective counterparts, we would expect this coefficient to be positive and statistically different from zero.

4.3 Results

Table 2 summarizes the main results of the Logit regressions under different specifications. Column (1) presents the results controlling only for the Gini coefficient. Column (2) includes basic demographic indicators: age, age squared and gender. Column (3) incorporates dummies for civil status and educational variables, namely, literacy and maximum educational attainment. Column (4) includes dummies for labor market variables: labor force participation and unemployment. Column (5) incorporates access to basic services—running water and sewage—and asset ownership, namely ownership of a computer, washing machine, telephone and car. Column (6) replicates the same specification as column (5), but with Ordinary Least Squares (OLS). All specifications include country, subnational and year fixed effects.

Our first result is that the Gini coefficient has a positive and statistically significant relationship with unfairness perceptions, consistent with the evidence shown in the previous section. For example, in a country with average characteristics, a decrease of one point of the Gini coefficient (from 0.496 to 0.486), decreases in about half percentage point the share of the population that believes income distribution is very unfair. Such magnitude is quite similar with the Logit (column 5) and OLS (column 6) estimates, and does not vary much across different specifications (columns 1-5). It is important to stress that the interpretation is not causal. The relationship between income inequality and unfairness perceptions can go both ways. On one hand, higher inequality can increase the share of the population that believes distribution is unfair. But as more people perceive

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[19] Latinobarómetro's survey is representative in each country at the subnational level, so we include 380 subnational fixed effects to capture unobservable heterogeneities at this level.

income distribution as unfair, inequality can be affected through several channels (e.g., more demand for redistribution).

Table 2. Logit regressions of unfairness perceptions (very unfair) and individual characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Gini coefficient	0.603***	0.603***	0.595***	0.591***	0.575***	0.504***
	(0.064)	(0.064)	(0.064)	(0.064)	(0.065)	(0.064)
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 dummy		-0.001	-0.000	0.001	0.001	0.001
		(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married or civil union			-0.005*	-0.005*	-0.005*	-0.005*
			(0.003)	(0.003)	(0.003)	(0.003)
Literacy			-0.031***	-0.031***	-0.029***	-0.028***
			(0.006)	(0.006)	(0.006)	(0.006)
Complete Primary			-0.002	-0.002	0.002	0.001
			(0.004)	(0.004)	(0.004)	(0.004)
Complete Secondary			-0.005	-0.005	0.006	0.004
			(0.005)	(0.005)	(0.005)	(0.005)
Complete Tertiary			0.004	0.005	0.019***	0.016***
			(0.005)	(0.005)	(0.006)	(0.006)
Economically active dummy				-0.004	-0.004	-0.004
				(0.003)	(0.003)	(0.003)
Unemployed dummy				0.018***	0.017***	0.017***
				(0.005)	(0.005)	(0.006)
Sewage					0.000	0.000
					(0.003)	(0.003)
Computer					-0.008**	-0.008**
					(0.003)	(0.003)
Washing machine					-0.024***	-0.024***
					(0.004)	(0.004)
Landline					-0.010***	-0.009***
					(0.003)	(0.003)
Has access to a car					0.003	0.002
					(0.003)	(0.003)
Observations	150,144	150,144	149,119	149,116	145,039	145,104
% Unfair	27.77	27.77	27.74	27.74	27.70	27.69
Pseudo R-squared	0.0458	0.0469	0.0471	0.0471	0.0473	0.055

Note: This table presents estimates of the correlation between unfairness perceptions dummy variable that indicates if the individual believes income distribution is very unfair and individuals' characteristics. Columns 1 to 5 coefficients presents 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, while column 6 coefficients were estimated through Ordinary Least Squares regressions. All columns include country, subnational and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

Regressions results also suggest that, holding all other variables constant, older people tend to respond more often that income distribution is very unfair, although the relationship between age and unfairness perception is not linear. This result is similar to that of Bellemare et al. (2008), who find that young individuals have lower aversion to inequity than other groups in an experimental setting.

On average, males are just as likely as females to perceive income distribution as very unfair, while married individuals are less likely to do so. Education seems to be correlated with perceptions of unfairness but only at the highest level of education—for those who have completed primary and secondary school, the coefficients are not statistically different from zero. Being part of the labor force does not seem to be correlated with perceptions of unfairness, but being unemployed does. On average, the unemployed population is more likely to perceive income distribution as unfair. The dummy variables for access to basic services and asset ownership have negative signs. In household surveys, these variables tend to be correlated with household income—although the correlations tend to be low—so a possible interpretation is that relatively richer people (as measured by access to services and assets), are less likely to perceive income distribution as very unfair.

Next, we run a similar set of regressions but, instead of considering only the people that responded that income distribution is 'very unfair,' we also consider the ones that answered only 'unfair.' The output of those regressions is reported in Table 3.

When we use the broader definition of unfairness the effect of education on perceptions of unfairness becomes stronger: in all the specifications, educational attainment is positively correlated with a sense of distributive unfairness. Moreover, the magnitude of the coefficient increases with the level of qualification: the coefficient of those with tertiary education complete is three times larger than those with only primary education complete. These results are similar to those of Rodriguez (2014), who finds that more years of education are associated with higher perceptions of inequality. The other two main differences with respect to the baseline set of regressions is that the civil status stops being statistically significant, and the male dummy becomes negative and statistically significant (in both cases consistently so across specifications).

As a robustness check we run the set of regressions reported in column (4), but using an alternative set of inequality indicators instead of the Gini coefficient. Those results are reported in Appendix Table A5. The result confirms the story of a positive and statistically significant correlation between income inequality and unfairness perceptions across a very different set of relative indicators (columns 1-4). Indeed, both 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, even after controlling for an individual's characteristics, while the absolute Gini (our absolute measure of inequality in the table) is negatively correlated with unfairness perceptions.

Table 3. Logit regressions of unfairness perceptions (all unfair) and individual characteristics

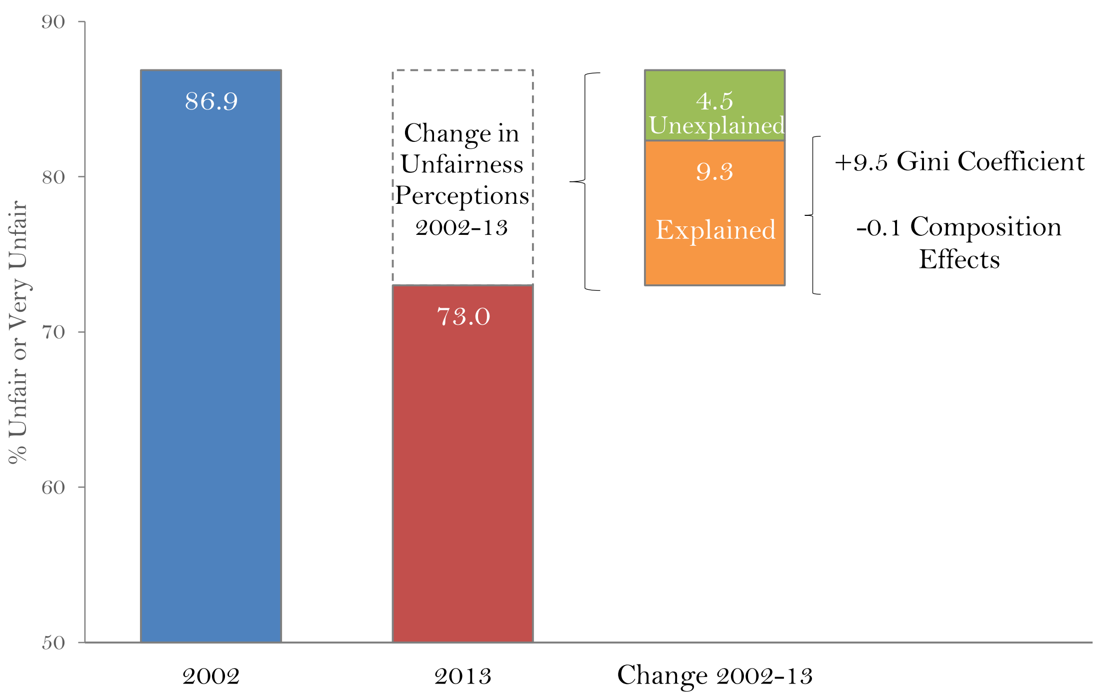
	(1)	(2)	(3)	(4)	(5)	(6)
Gini coefficient	0.423***	0.423***	0.412***	0.410***	0.410***	0.262***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.060)	(0.053)
Age		0.004***	0.004***	0.004***	0.004***	0.005***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age squared		-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male dummy		-0.013***	-0.013***	-0.012***	-0.012***	-0.012***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Married or civil union			-0.001	-0.001	0.000	-0.000
			(0.002)	(0.002)	(0.002)	(0.002)
Literacy			-0.013***	-0.013***	-0.011**	-0.014***
			(0.005)	(0.005)	(0.005)	(0.005)
Complete Primary			0.009***	0.009***	0.010***	0.012***
			(0.003)	(0.003)	(0.003)	(0.003)
Complete Secondary			0.016***	0.016***	0.020***	0.023***
			(0.004)	(0.004)	(0.004)	(0.004)
Complete Tertiary			0.024***	0.025***	0.030***	0.034***
			(0.005)	(0.005)	(0.005)	(0.005)
Economically active dummy				-0.003	-0.004	-0.004
				(0.003)	(0.003)	(0.003)
Unemployed dummy				0.018***	0.019***	0.018***
				(0.005)	(0.005)	(0.004)
Sewage					0.004	0.003
					(0.003)	(0.003)
Computer					0.000	0.001
					(0.003)	(0.003)
Washing machine					-0.017***	-0.019***
					(0.003)	(0.003)
Landline					0.002	0.000
					(0.003)	(0.003)
Has access to a car					-0.007***	-0.007**
					(0.003)	(0.003)
Observations	150,081	150,081	149,056	149,053	144,977	145,104
% Unfair	79.56	79.56	79.57	79.57	79.58	79.60
Pseudo R-squared	0.0674	0.0691	0.0694	0.0695	0.0702	0.070

Note: This table presents estimates of the correlation between unfairness perceptions dummy variable that indicates if the individual believes income distribution is unfair or very unfair and individuals' characteristics. Columns 1 to 5 coefficients presents 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, while column 6 coefficients were estimated through Ordinary Least Squares regressions. All columns include country, subnational and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

4.4 DECOMPOSING CHANGES IN UNFAIRNESS OVER TIME

One of the broad takeaways from the regressions results is that both the aggregate inequality trends and the individual's characteristics are associated with unfairness perceptions. A natural follow-up question is to ask what factors explain to a greater extent the reduction in the unfairness beliefs over the last decade: the observable characteristics of the individuals or the aggregate inequality trends. To analyze this point, we perform a basic Oaxaca-Blinder decomposition, taking 2002 and 2013 as the two 'groups' to be compared (see Appendix C for further detail on the Oaxaca-Blinder decomposition). The covariables included in the decomposition are analog to those of Column (4) in Table 2. The results are summarized in Figure 8.

Figure 8. Oaxaca-Blinder decomposition of unfairness perceptions in LA, 2002-2013



Note: This figure presents the estimates of the Oaxaca-Blinder decomposition. The dependent variable is a dummy that indicates whether the individual believes income distribution if unfair or not, and the regressors include the Gini coefficient, age, age squared, and dummy variables for: civil status, gender, literacy, maximum educational attainment, labor force participation and unemployment status. Results were calculated pooling data for 18 LA countries. The 'explained' part of the results refers to the endowment effects (changes in the value of the covariables), while the 'unexplained' refers to changes in the coefficients and the interaction terms.

During the 2002-13 period, the share of the population perceiving the distribution as unfair decreased 13.8 percentage points, from 86.8% to 73.0%.[20] The decomposition results suggest that a third of such change (4.5 percentage points) cannot be explained by

[20] These figures are slightly different from those presented in the previous section due to some observations having missing values in the covariables relevant for the decomposition.

changes in the covariate's values (i.e., changes in the X's of the regression), but rather are a consequence of changes in the elasticity of perceptions to each covariable (i.e., the β's of the regression), while the other two thirds (9.33 percentage points) can be explained by changes of the covariables' values.

Among the covariables included in the decomposition, the one that explains the decline in the unfairness perceptions is the change in the value of the Gini coefficient, and not changes in the composition of the groups. In fact, although marginal, the demographic component actually contributed to an *increase* in the unfairness perceptions. This is mostly due to changes in average age and educational attainment. Between 2002 and 2013 both the average age and the maximum educational attainment saw a modest increase in our sample, and since older and more educated individuals are more likely to perceive the distribution as unfair, these changes counteracted part of the decrease in unfairness perceptions.

5. Fairness and beliefs

Ingrained in any judgement of income distribution as unfair is an assessment of the sources of the inequalities. Theories of fairness suggests that societies that perceive that inequality arises from hard work and effort are less likely to perceive distribution as unfair, while societies that believe luck, connections and corruption are the main determinants of income are more prone to see inequality as unfair (see Alesina et al., 2001).[21] Understanding why some people perceive outcomes as a consequence of luck while other think it is due to effort is challenging, although the literature has provided a few clues.

First, political views matter. One of the clear dividing lines between the political 'left' and the 'right' is the views of to what extent luck determines incomes (which, in turn, affect preferences about the extent to which the government should intervene to redistributive from the rich to the poor as shown by Alesina and Giuliano, 2009). A second view is that beliefs are shaped by groups of interests (e.g., Glaeser, 2005). In particular, religion has been identified of a relevant group shaping beliefs (Bénabou and Tirole, 2005). In LA, we would expect Catholicism—the predominant religion—to affect fairness perceptions. Finally, sociology suggests that individuals with *motivated beliefs* are more likely to perceive hard work and effort as the ultimate determinants of success (e.g. Hochschild, 1981). In line with this research, we would expect people with a more optimistic life outlook to perceive income distribution as less unfair. Summarizing, we identify political views, religion and life outlook as some possible determinants of distributive justice perceptions. We test empirically whether these variables correlate with unfairness perceptions.

[21] This theory is supported by much experimental and empirical evidence. For a review of relevant literature, see Fehr and Schmidt (2001).

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 create a categorical variable for reported religion, coding the rest of the religions (and lack of religion) as zero. Finally, we proxy life outlook with the question: *"In the next 12 months do you think that, in general, the economic situation of your country will be much better, a little better, the same, a little worse or much worse than now?"* When using these questions we control for the current assessment of the country's situation to avoid any spurious correlation.[22] We interpret expectations that the country will be better (conditional on the present situation) as a positive life outlook.

Table 4 presents the main results. We control for individual characteristics in all the specifications, and include country and year fixed effects we well.

Table 4. Logit regressions of unfairness perceptions (very unfair) and individual beliefs

	(1)	(2)	(3)	(4)
Gini coefficient	0.490***	0.582***	0.343***	0.277***
	(0.072)	(0.065)	(0.074)	(0.083)
Self-reported Ideology	-0.002***			-0.002***
	(0.001)			(0.001)
Catholic religion		-0.008***		-0.008**
		(0.003)		(0.004)
Current economic situation of the country			-0.114***	-0.113***
			(0.002)	(0.003)
Positive Outlook			-0.042***	-0.040***
			(0.004)	(0.004)
Negative Outlook			0.076***	0.075***
			(0.004)	(0.004)
Observations	113,398	143,246	117,591	90,785
% Unfair	26.84	27.66	27.94	27.06
Pseudo R-squared	0.0487	0.0472	0.0874	0.0895

Note: This table presents estimates of the correlation between perception of distribution as very unfair and measures of individual values. 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 regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, and unemployment status, access to basic services and asset holding, as well as country, subnational and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

[22] Such assessment comes from the question: *"In general, how would you describe the country's present economic situation? Would you say it is…? (1) Good, (2) About average and (3) Bad."* We recode the variables so larger values correspond to a more positive assessment.

Our results suggest that, as expected, ideologically conservative people are, on average, less likely to perceive income distribution as very unfair (column 1). Catholics are less likely to perceive income distribution as very unfair, even after controlling for other observable individual characteristics (column 2). Finally, people with a more positive (and less negative) future outlook (column 3), are less likely to perceive inequality as unfair, even controlling for the country's current situation (as perceived by the individual). These results are robust to controlling for all the beliefs at the same time (column 4). The Gini coefficient is positive and statistically different from zero in all specifications, although the magnitude decreases notably when all the variables are included, suggesting part of the relationship between the Gini and unfairness perceptions is mediated through other beliefs.

As a robustness check, we run the same set of regressions, but using as the dependent variable all unfairness perceptions. These results are shown in Appendix Table A6. We find that the relationship between Catholicism and unfairness loses its significance, while the self-reported ideology actually changes its sign, which suggests these two results—religion and political ideology—are driven by the population with strong beliefs about unfairness. The rest of the results remain unchanged. As noted previously, we are not inferring any causal relationship out of these results, but rather establishing strong empirical associations as stylized facts. For example, it could be the case that a negative life outlook increases the unfairness perceptions, or that an unfair distribution of income makes people more negative about life in general, or that both variables are caused by a third (omitted) variable.

6. Unfairness and Social Unrest

There is a vast literature that relates economic inequality—and more recently, measures of polarization—to social cohesion, conflict, and activism.[23] More recently, some papers have argued that models that include 'objective' measures of inequality to explain social phenomena such as conflict could be misleading since people do not directly observe the income distribution (or the Gini coefficient), but rather take decisions based on their perceptions of it (e.g. Gimpelson and Treisman, 2015). Thus, this evidence suggests *perceived* inequality, and not *actual* inequality, should be the relevant regressor in the models that relate social unrest with inequality. To understand what this implies from an empirical point of view, it is useful to take the measurement-error perspective. Let's assume perceived inequality is equal to real inequality plus an error term:

$$\text{Perceived inequality} = \text{Inequality} + \text{Error}$$

If the population's perception of inequality corresponds to the actual level of inequality, then $\varepsilon = 0$, and the estimations we would obtain of the relationship between

[23] For instance, in LA, Gasparini et al. (2008) find a strong empirical correlation between inequality and conflict, as well as polarization and conflict.

conflict and inequality would be unbiased. However, research about how accurately people perceive income inequality reveals systematic cognitive biases. The seminal paper of this strand of the literature is Norton and Ariely (2011), who find individuals dramatically underestimated the current level of inequality.[24] Gimpelson and Treisman (2015) show that ordinary people have little idea about the levels of inequality, its evolution over time, and their place in the income distribution. Individuals consistently arrive to misperceptions of inequality, regardless of the data source, operationalization, and measurement method. In a survey experiment, Cruces et al. (2013) find systematic biases in perceptions of own income rank: a significant portion of relatively poor individuals place themselves in higher positions than they actually occupy. This evidence suggests that the mean of the error term will not necessarily be zero. Thus, if we use the 'objective inequality,' instead of the perceived one as explanatory variable in regressions, the measurement error becomes part of the error term in the regression equation, creating an attenuation bias.

In this section we test whether unfairness perceptions are positively correlated with social unrest, exploiting the fact that both perceptions and stated activism vary at the individual level.[25] We rely on the following question from Latinobarómetro: *"On a scale from 1 to 10 where 1 means "not at all" and 10 "very", how willing would you be to demonstrate and protest about…? (a) Higher wages and better working conditions; (b) Improvement in healthcare and education; (c) Exploitation of natural resources; and (d) To defend democratic right."*

Figure 9 shows the simple cross-country correlations between unfairness perceptions at the country level and the average index of the different measures of stated activism in 2015. Visual evidence suggests that unfairness measures tend to be positively correlated with the social unrest measures, although in some cases the correlation is small.

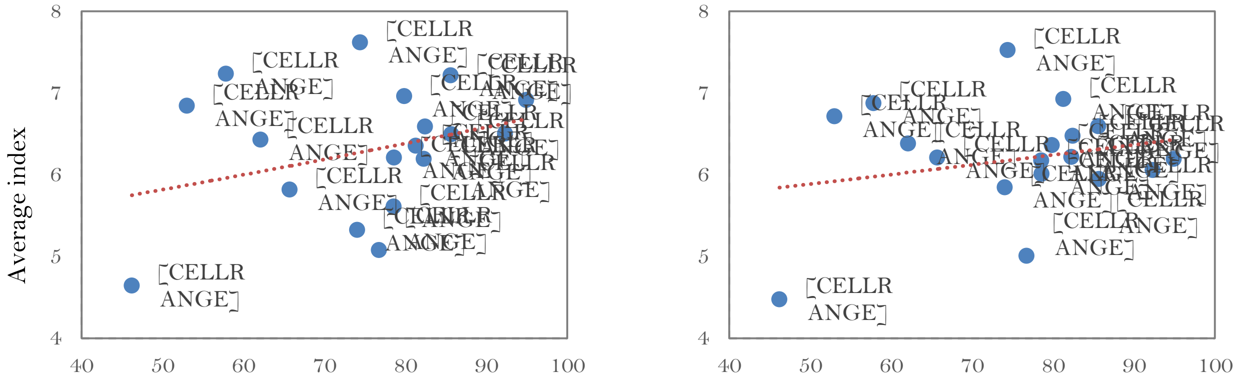
Figure 9. Perceptions of unfairness (very unfair) and stated activism in LA, 2015 (%)

(a) Better working conditions

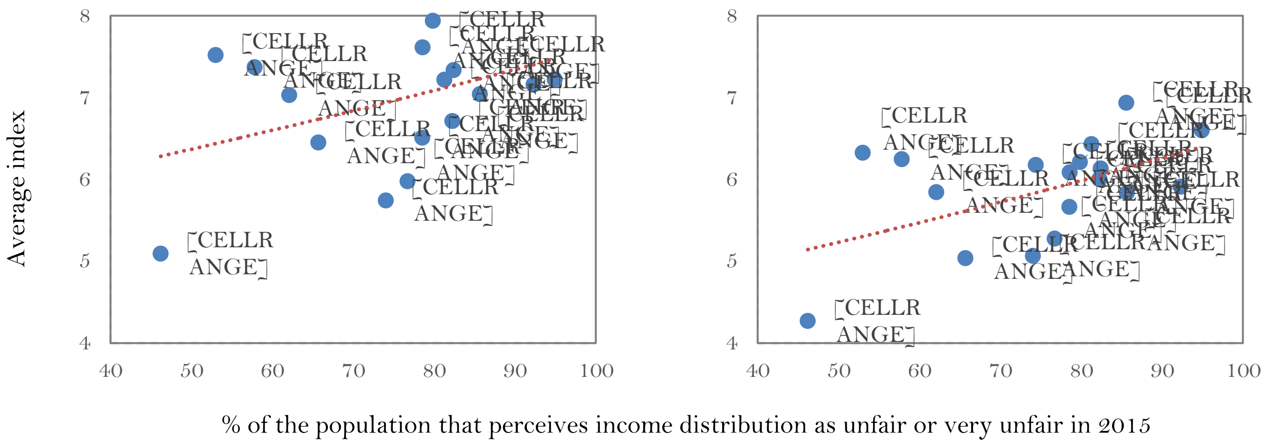
(b) To defend democratic right

[24] Perhaps more interestingly, individuals constructed ideal distributions that were far more equitable than even their erroneously low estimates of the actual distribution.

[25] Most of previous studies linking inequality and conflict are based on cross-country regressions, and therefore have a notably smaller sample size.



(c) Improvement in healthcare and education (d) Exploitation of natural resources



To formally assess the relationship between unfairness and activism, we run OLS regressions, where we use each of the social unrest measures as dependent variables and unfairness perceptions (as very unfair) as the main regressor, including the usual individual and fixed effect controls. Table 5 shows the main results.

Table 5 .OLS regressions of unfairness perceptions (very unfair) and stated activism

	Higher wages and better work (1)	Democratic rights (2)	Healthcare and education (3)	Natural resources (4)
Very Unfair	0.290***	0.117**	0.247***	0.149***
	(0.045)	(0.046)	(0.043)	(0.046)
Gini coefficient	-10.273***	-16.791***	-15.445***	-13.062***
	(2.767)	(2.673)	(2.565)	(2.721)
Constant	9.703***	12.894***	12.113***	10.719***
	(1.213)	(1.182)	(1.133)	(1.196)
Individual controls	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓
Observations	35,534	35,221	35,651	35,268

% Unfair	24.89	24.72	24.85	24.80
Adjusted R-squared	0.101	0.0875	0.113	0.0808

Note: This table presents estimates of the correlation between measures of demonstrations and unfairness perceptions (very unfair). Coefficients were estimated through OLS. Column (1) presents the results for higher wages and better working conditions. Column (2) to defend democratic right. Column (3) for improvement in healthcare and education. Column (4) for exploitation of natural resources. All regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, unemployment status, access to basic services and asset holding, as well as country, subnational and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses.

Table 5 suggests that the population that perceives distribution as very unfair is more prone to actively demonstrate. Each of the four reasons to mobilize has positive and statistically different from zero coefficients. The magnitude of the coefficients suggest this effect is larger in the case of protests for jobs, health and education, compared to exploitation of natural resources or to defend democratic rights, where the size of the coefficients is half as large. Table 5 also suggests that, on average, people are less prone to protest in countries with relatively higher levels of inequality. As with previous results, the relationship can go either way. For instance, relatively unequal countries might, in fact, have higher levels of inequality due to a lower propensity of its citizens to manifest against such disparities.

Although these results are encouraging, the analysis relies on 'willingness' to demonstrate. However, people might state they are very eager to protest, while in practice they might not do it. To partially overcome this issue, we analyze the relationship between unfairness and actually having mobilized in the past. In particular, we consider six different types of demonstrations: making a complaint to the media, making a complaint on social networks, signing a petition, refusing to pay taxes and being part of an authorized or unauthorized demonstration. We recode these variables so they take a value equal to 1 if the individual stated she had a past of mobilization, and 0 otherwise. Cross-country visual evidence is provided in Appendix Figure A9 while regression results are shown in Table 6.

Overall, both visual and regression analysis suggests unfairness perceptions are positively and significantly correlated with a past of activism. With the exception of illegal activities (columns 1 and 4),[26] and making a complaint to the media, all other coefficients have the expected sign and are statistically significant. In Appendix Tables A7 and A8 we replicate Tables 5 and 6 regressions, but using as the regressor of interest the population that perceived distribution as unfair or very unfair. We observe two main differences. First, some of the coefficients stop being statistically different from zero (e.g., columns 3 and 4 from Table 5). Second, some of the coefficients actually turn negative and

[26] Perhaps, the lack of results with respect to illegal activities (columns 1 and 4) could be due to measurement error, as there are no incentives to report a past of doing illegal activities accurately.

statistically significant (e.g., column 2 from Table 5, and columns 1-3 from Table 6). These two facts together suggest that activism is driven by the population with strong views about inequality (i.e., very unfair), and not by those who perceive it as just unfair.

Even though a strikingly high share of the population shares the view that income distribution is unfair, the fight against inequality does not seem to be a top priority among LA citizens. Every year, Latinobarómetro asks respondents what they think is their country's most important problem. Although there is a lot of heterogeneity both across countries and across time, insecurity and unemployment are consistently listed as the top priorities. In these rankings, reducing the high disparities between the rich and the poor is usually listed in the bottom half of the priorities, under other issues like 'education' or 'corruption.'

Table 6. Logit regressions of unfairness perceptions (very unfair) and past activism

	Refuse to pay taxes	Signing a petition	Taking part in authorized demonstrations	Taking part in unauthorized demonstrations	Make a complaint to the media	Make a complaint through the social media
	(1)	(2)	(3)	(4)	(5)	(6)
Very Unfair	0.003	0.012***	0.008**	-0.003	0.004	0.013***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Gini coefficient	0.098**	0.361***	0.118	0.139***	0.251***	0.287***
	(0.045)	(0.093)	(0.076)	(0.042)	(0.055)	(0.049)
Individual controls	✓	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	18,141	51,036	51,580	18,422	18,406	18,192
% Unfair	25.89	28.70	28.70	25.94	25.90	25.95
Pseudo R-squared	0.0110	0.0706	0.0705	0.0251	0.0267	0.0733

Note: This table presents estimates of the correlation between measures of past demonstrations and unfairness perceptions (very unfair). 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. Column (1) presents the results for refusing to pay taxes. Column (2) for signing a petition. Column (3) for unauthorized demonstrations. Column (4) authorized demonstrations. Column (6) making a complaint to the media and Column (6) complaining in social media. All regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, and unemployment status, as well as country, and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

A highly speculative reading of this section is that, the way in which this higher propensity to mobilize could manifest is not with direct demonstrations against inequality (like in the Occupy Wall Street movement), but rather in demonstrations against other types of inequalities (such as inequality in access to education or health), or against the underlying causes of it (such as low wages of some specific segments of the population).

7. Concluding remarks

There is a growing body of evidence showing that many of the decisions agents make are not based on objective economic indicators, but rather on how these are perceived. Understanding what people believe about the income distribution is crucial from a policy perspective—not only from a traditional view, in which a just income distribution is seen as a pure public good (Thurow, 1971) and is therefore underprovided by unregulated free-market economy, but also because interventions that make information less costly can have welfare-improving effects (Roemer, 2003) if there are mismatches between perceptions and reality.

In this paper we analyzed the perceptions of distributive justice in a context of falling income inequality. 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 all incomes should be the same.

The positive news is that beliefs moved in line with the evolution of objective indicators: both unfairness perceptions and income inequality declined both across countries and time. The bad news is that three in four LA citizens believe income distribution is unfair, and such perceptions have proved to be quite inelastic to changes in income distribution. What happened during the 2000s in terms of inequality reduction was remarkable, but recent evidence suggests the pace of inequality reduction is not going to be the same in the near future. As inequality reduction in LA stagnates, one can wonder if an income distribution that the majority of the population thinks is unfair can be a steady state in the long run.

We believe that, compared to the vast literature on inequality measurement, as well as its causes and consequences, relatively little emphasis has been given to how inequality is perceived by the general population. This paper intends to bridge this gap in the research agenda. We present the characterization of fairness perceptions in LA not as conclusions but as a starting point for researchers who are interested in income inequality perceptions. The results of this paper also raise a number of puzzling questions for future research: Where do people think the unfairness of income distribution stems from? What has been the role of mass media in shaping these beliefs? Does the general population think separately about the 'micro-justice' (i.e., the income I receive is fair) and the 'macro-justice' of overall patterns of inequality? Would fairness perceptions change if individuals are confronted with accurate information about income distribution? We hope future research helps to clarify these questions.

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Appendix A: Additional Figures and Tables

Table A1. Descriptive statistics of the sample pooling data 1997-2015

Variables	Mean	Standard Dev.	Observations
Sociodemographic variables			
Age	39.49	16.18	167,420
Male (%)	49.08	0.50	167,436
Catholic religion (%)	70.70	0.46	165,329
Married or civil union (%)	57.30	0.49	166,121
City > 1 Million Inhabitants. (%)	50.43	0.50	150,224
Education and Labor market			
Literate (%)	89.95	0.30	165,925
Secondary education or more (%)	32.38	0.47	165,925
Parents with secondary education (%)	16.77	0.37	132,792
Economically active (%)	64.07	0.48	167,091
Unemployed (% Labor Force)	9.95	0.30	167,091
Access to services			
Access to a sewage (%)	69.73	0.46	164,743
Access to running water (%)	87.67	0.33	146,354
Asset ownership			
Car (%)	27.29	0.45	164,521
Computer (%)	29.63	0.46	164,719
Fridge (%)	79.22	0.41	146,686
Homeowner (%)	73.65	0.44	165,650
Mobile (%)	76.49	0.42	114,297
Washing machine (%)	51.72	0.50	165,195
Landline (%)	45.14	0.50	165,108

Source: Author's elaboration based on Latinobarómetro.

Table A2. Unfairness perceptions by population group pooling data 1997-2015, in %

Category	Perception of income distribution				Total
	Very unfair	Unfair	Fair	Very fair	
All	28.0	51.6	17.5	2.9	100
Gender					
Female	28.1	52.2	16.8	2.8	100
Male	27.9	51.0	18.1	3.0	100
Age group					
15-24	25.3	52.0	19.6	3.1	100
25-40	28.3	51.3	17.3	3.0	100
41-64	29.2	51.7	16.3	2.8	100
65+	28.8	51.6	17.1	2.5	100
Civil Status					
Married	28.2	51.9	17.1	2.8	100
Not married	27.7	51.3	17.9	3.1	100
Religion					
Catholic	28.2	51.7	17.2	2.9	100
Not catholic	27.5	51.5	18.1	2.9	100
Education level					
Less than Primary	28.7	50.9	17.3	3.0	100
Complete Primary	27.6	51.6	17.9	3.0	100
Complete Secondary	27.6	52.1	17.7	2.6	100
Complete Tertiary	28.7	52.9	15.6	2.8	100
Type of employment					
Employee	28.1	51.5	17.5	2.9	100
Employer	27.1	52.5	17.5	2.8	100
Self-employed	27.9	51.1	17.9	3.2	100
Unemployed	30.6	51.5	14.9	2.9	100
City size					
100,000 to 1,000,000	26.2	51.7	19.1	2.9	100
More than 1,000,000	29.4	51.2	16.8	2.6	100
Under 100,000	26.5	52.7	18.5	2.4	100

Source: Author's elaboration based on Latinobarómetro.

Table A3. Unfairness perceptions by geographical location pooling data 1997-2015, in %

Category	Perception of about income distribution				
	Very unfair	Unfair	Fair	Very fair	Total
City size					
Under 100,000	26.5	52.7	18.5	2.4	100
100,000 to 1,000,000	26.2	51.7	19.1	2.9	100
More than 1,000,000	29.4	51.2	16.8	2.6	100
Country					
Argentina	38.38	50.66	10.14	0.83	100
Bolivia	17.77	55.87	23.88	2.48	100
Brazil	31.81	53.75	12.94	1.50	100
Chile	40.20	49.94	8.42	1.45	100
Colombia	35.13	51.21	11.40	2.26	100
Costa Rica	23.18	53.55	20.12	3.15	100
Dominican Rep.	32.45	46.49	17.51	3.56	100
Ecuador	21.55	47.58	27.38	3.49	100
El Salvador	22.67	53.04	20.58	3.71	100
Guatemala	28.26	51.37	16.70	3.66	100
Honduras	28.86	53.46	14.27	3.41	100
Mexico	32.18	49.86	15.22	2.74	100
Nicaragua	18.94	51.67	24.23	5.16	100
Panama	27.23	48.11	20.29	4.36	100
Paraguay	37.32	48.92	11.91	1.86	100
Peru	24.83	62.01	11.79	1.37	100
Uruguay	18.26	57.50	22.61	1.64	100
Venezuela	23.53	42.89	26.64	6.94	100

Source: Author's elaboration based on Latinobarómetro.

Table A4. Comparison of descriptive statistics in Latinobarómetro and SEDLAC, 2013

	Mean		Standard Dev.	
	Latinob.	SEDLAC	Latinob.	SEDLAC
Sociodemographic				
Age	40.59	42.68	16.43	17.25
Male (%)	48.97	47.63	0.50	0.50
Married or civil union (%)	56.77	36.41	0.50	0.48
Education and Labor market				
Literate (%)	91.18	92.17	0.28	0.27
Secondary education or more (%)	38.83	46.11	0.49	0.50
Economically active (%)	65.14	68.66	0.48	0.46
Unemployed (%)	5.78	4.08	0.23	0.20
Assets and Services				
Access to a sewage (%)	68.76	63.41	0.46	0.48
Car (%)	26.37	21.09	0.44	0.41
Computer (%)	46.55	47.82	0.50	0.50
Fridge (%)	82.76	88.89	0.38	0.31
Homeowner (%)	74.09	69.64	0.44	0.46
Mobile (%)	86.91	91.78	0.34	0.27
Washing machine (%)	60.49	56.88	0.49	0.50
Landline (%)	40.22	39.47	0.49	0.49

Source: 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 A5. Regressions of unfairness perceptions (very unfair) and different inequality indicators

	(1)	(2)	(3)	(4)	(5)
Gini coefficient (no zero income)	0.605***				
	(0.065)				
Atkinson, A(1)		0.182***			
		(0.045)			
Theil index, GE(1)			0.165***		
			(0.023)		
Generalized entropy, GE(2)				0.010***	
				(0.002)	
Absolute Gini					-0.000***
					(0.000)
Age	0.005***	0.005***	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 dummy	0.001	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Married or civil union	-0.005*	-0.005*	-0.005*	-0.005*	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Literacy	-0.031***	-0.032***	-0.032***	-0.032***	-0.032***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Complete Primary	-0.002	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Complete Secondary	-0.005	-0.004	-0.004	-0.004	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Complete Tertiary	0.005	0.006	0.006	0.007	0.007
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Economically active dummy	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Unemployed dummy	0.018***	0.018***	0.018***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	149,116	149,116	149,116	149,116	149,116
% Unfair	27.74	27.74	27.74	27.74	27.74
Pseudo R-squared	0.0471	0.0467	0.0469	0.0468	0.0466

Note: This table presents estimates of the correlation 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, subnational and year fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

Table A6. Logit regressions of unfairness perceptions (unfair or very unfair) and individual beliefs

	(1)	(2)	(3)	(4)
Gini coefficient	0.541***	0.418***	0.207***	0.331***
	(0.071)	(0.060)	(0.060)	(0.072)
Self-reported Ideology	0.002***			-0.000
	(0.000)			(0.001)
Catholic religion		-0.003		-0.001
		(0.002)		(0.003)
Current economic situation of the country			-0.107***	-0.116***
			(0.002)	(0.002)
Positive Outlook			-0.065***	-0.067***
			(0.003)	(0.003)
Negative Outlook			0.050***	0.054***
			(0.003)	(0.004)
Observations	113,298	143,190	117,532	90,705
% Unfair	78.25	79.56	80.30	79.08
Pseudo R-squared	0.0729	0.0701	0.142	0.146

Note: This table presents estimates of the correlation between perception of distribution as very unfair and measures of individual values. 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 regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, and unemployment status, access to basic services and asset holding, as well as country, subnational and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

Table A7. OLS regressions of unfairness perceptions (unfair or very unfair) and stated activism

	Higher wages and better work	Democratic rights	Healthcare and education	Natural resources
	(1)	(2)	(3)	(4)
Unfair	0.139***	-0.113***	0.052	-0.036
	(0.042)	(0.042)	(0.040)	(0.042)
Gini coefficient	-10.347***	-16.790***	-15.498***	-13.082***
	(2.771)	(2.676)	(2.569)	(2.724)
Constant	9.687***	12.981***	12.136***	10.771***
	(1.215)	(1.184)	(1.135)	(1.198)
Individual controls	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓
Observations	35,534	35,221	35,651	35,268
% Unfair	73.57	73.47	73.50	73.49
Adjusted R-squared	0.0998	0.0875	0.112	0.0805

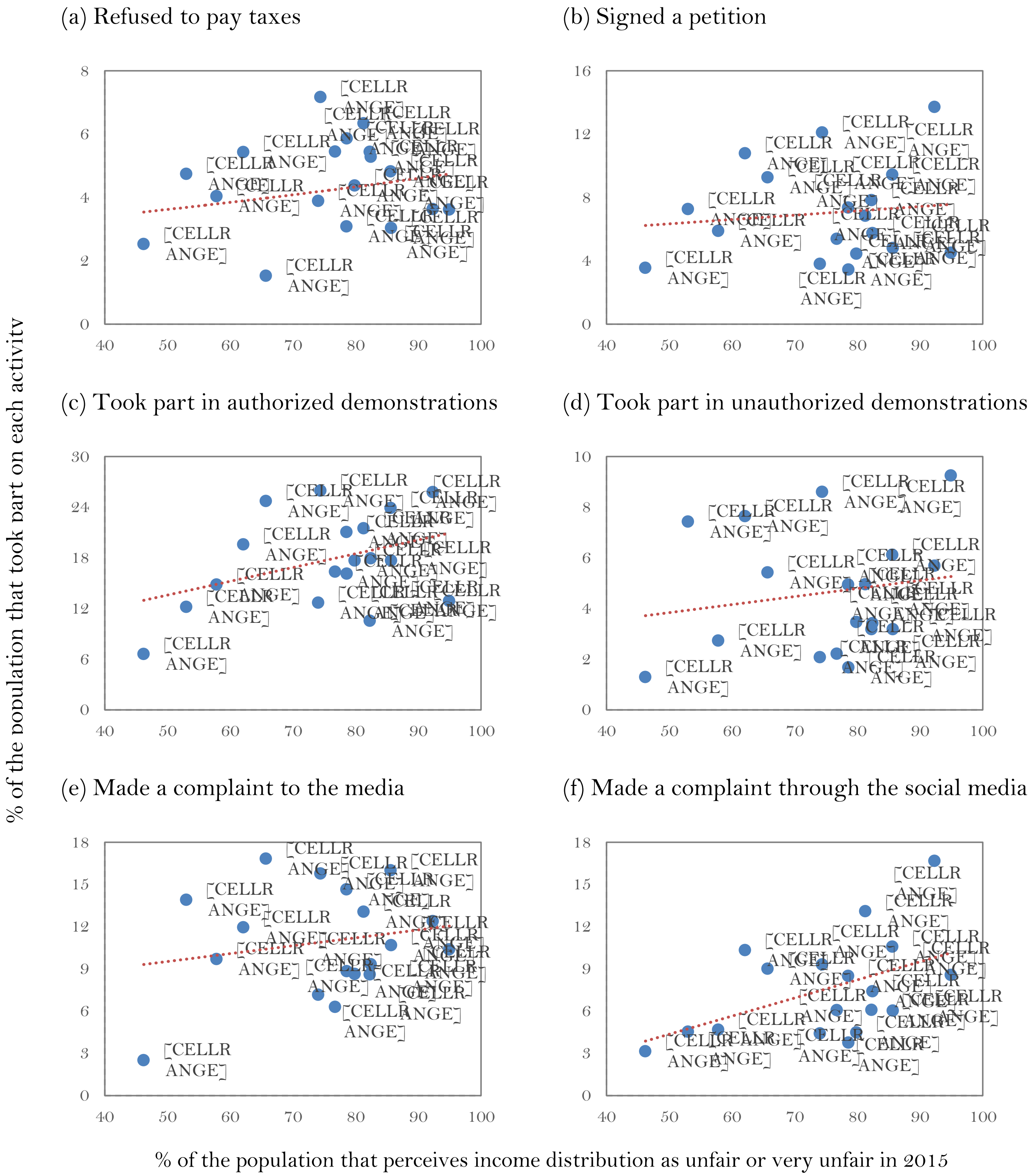
Note: This table presents estimates of the correlation between measures of demonstrations and unfairness perceptions (unfair or very unfair). Coefficients were estimated through OLS. Column (1) presents the results for higher wages and better working conditions. Column (2) to defend democratic right. Column (3) for improvement in healthcare and education. Column (4) for exploitation of natural resources. All regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, unemployment status, access to basic services and asset holding, as well as country, subnational and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

Table A8. Logit regressions of unfairness perceptions (unfair or very unfair) and past activism

	Refuse to pay taxes	Signing a petition	Taking part in authorized demonstrations	Taking part in unauthorized demonstrations	Make a complaint to the media	Make a complaint through the social media
	(1)	(2)	(3)	(4)	(5)	(6)
Unfair	-0.009***	-0.015***	-0.014***	-0.004	0.001	0.011**
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Gini coefficient	0.111**	0.389***	0.139*	0.139***	0.256***	0.297***
	(0.046)	(0.093)	(0.076)	(0.043)	(0.055)	(0.049)
Individual controls	✓	✓	✓	✓	✓	✓
Fixed Effects	✓	✓	✓	✓	✓	✓
Observations	18,141	51,036	51,580	18,422	18,406	18,192
% Unfair	75.05	79.70	79.77	75.18	75.23	75.16
Pseudo R-squared	0.0120	0.0706	0.0708	0.0253	0.0266	0.0727

Note: This table presents estimates of the correlation between measures of past demonstrations and unfairness perceptions (unfair or very unfair). 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. Column (1) presents the results for refusing to pay taxes. Column (2) for signing a petition. Column (3) for unauthorized demonstrations. Column (4) for authorized demonstrations. Column (5) make a complaint to the media and Column (6) complain in social media. All regressions control for age, squared age, gender, civil status, maximum educational attainment, labor force participation, and unemployment status, as well as country, and yearly fixed effects. ***, ** and * denote significance at 10%, 5% and 1% levels, respectively. Heteroskedasticity-robust standard errors in parentheses.

Figure A9 Perceptions of unfairness (unfair and very unfair) and past activism in LA, 2015 (%)



Appendix B: About the data

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 comes from Latinobarómetro, which has conducted opinion surveys in 18 LA countries since the 1990s, interviewing about 1,200 individuals per country about individual socioeconomic background, and preferences towards political and social issues. Although the survey is conducted every year, not all years include the question regarding 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 Rep.	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

Note: This table presents the percentage of the voting age population represented each year in Latinobarómetro overtime. The regional average was calculated by weighting each country's population. N/A means the survey was not conducted in that particular country.

Since our goal is to analyze how unfairness perceptions evolved vis-à-vis changes in income inequality, we put a lot of effort in trying to get income inequality data for each data point for which we have perceptions data available.

Our source for income inequality data is SEDLAC, a joint effort of the World Bank and CEDLAS at the National University of La Plata in Argentina. SEDLAC increases cross-country comparability of selected findings from official household surveys. The welfare indicator used is the total household per capita income in 2005 US$ (PPP) per day. The inequality measures we use include households with zero incomes unless otherwise noted (results are similar with the exclusion of these households). For Argentina and Uruguay, the inequality data corresponds to urban areas only.

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 across time, usually due to important methodological changes (for instance, due to changes in the sampling scheme or in the set of variables available).

To increase the number of observations available (without pushing the data too much), we made to two partial fixes. First, we filled the data gaps using household surveys of 'close' years in which previously unused data was available. 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 corresponds to a year in which the perceptions question was not asked (and therefore, inequality data is not needed in that year).

Table B2. Circa years used to fill data gaps

Country	Year without household data	Data point used instead
All	2015	2014
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
Mexico	1997	1998
Mexico	2001	2000
Mexico	2007	2006
Mexico	2009	2008
Mexico	2011	2012
Nicaragua	1997	1998
Nicaragua	2007	2005

Venezuela	2013	2012

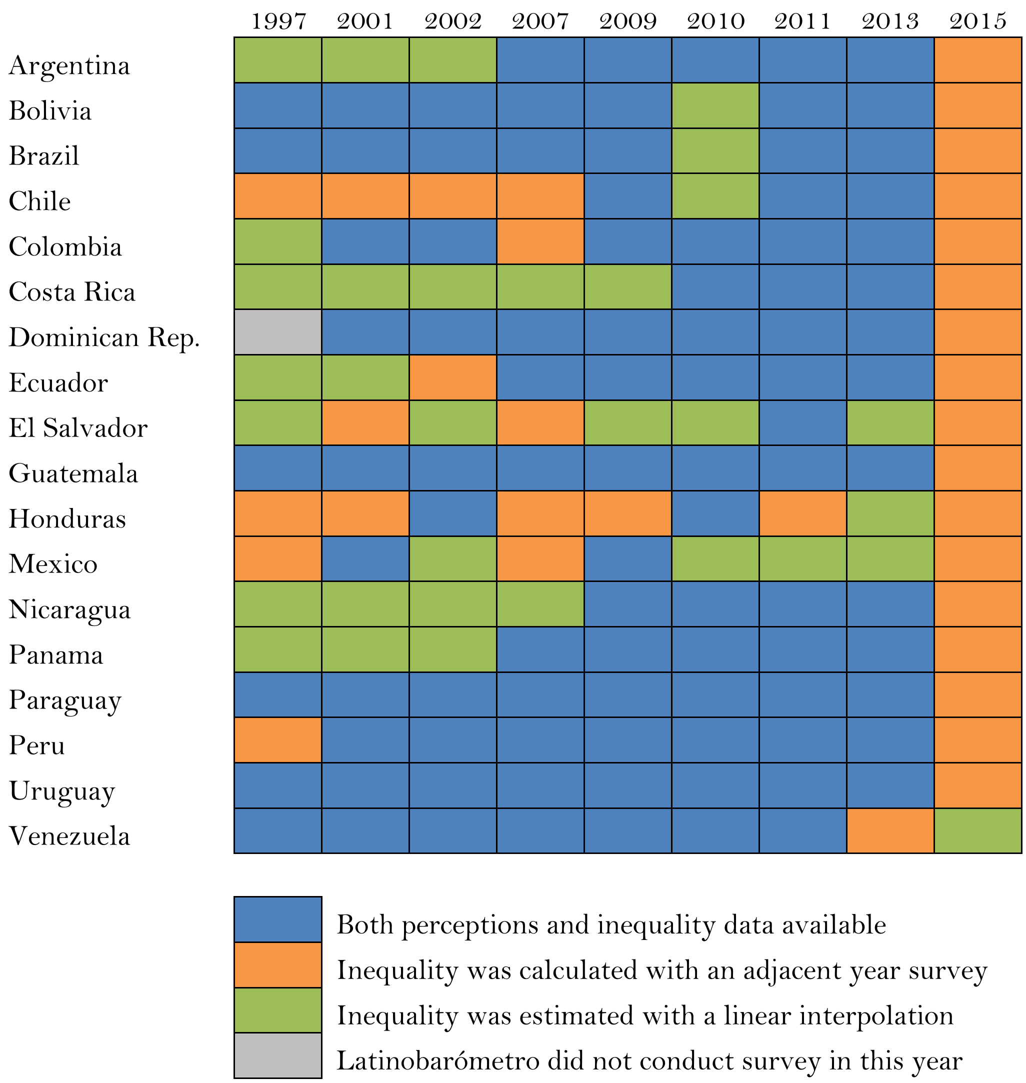
Finally, for some countries, a few years had perceptions data available but no comparable household survey overtime and no 'close year' available. In this case, and in order to analyze the same set of countries every year, interpolation was applied to the inequality indicators.

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 (about a fifth of the 161 data points we have available). The majority of our inequality data points (59%) were calculated using a household surveys from the same year in which the perceptions polls were conducted (Table B1), while the remaining 21% of our inequality indicators were calculated using households surveys from adjacent years (Table B2). A summary of the data sources used in every year in which perceptions data is available is provided in Figure B1.

Figure B1. Summary of the data used in every country/year



Appendix C: The Oaxaca-Blinder Decomposition

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

$$Unfair_t = \beta_t X_t + \varepsilon_t \quad ; \quad t \in \{2002, 2013\} \tag{C.1}$$

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 1 if the year is 2013, then, the mean difference in unfairness perceptions between both years is given by:

$$\Delta^{\mu} = E(Unfair_{2013}|D_{2013} = 1) - E(Unfair_{2002}|D_{2013} = 0) \tag{C.2}$$

Since the regression line that comes from estimating the parameters in equation C.2 above meets the property of passing through the sampling means, we have:

$$\overline{Unfair}_{2002} = \hat{\beta}_{2002}\,\bar{X}_{2002} \quad \& \quad \overline{Unfair}_{2013} = \hat{\beta}_{2013}\,\bar{X}_{2013} \tag{C.3}$$

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., the β remained constant), then the unfairness perceptions in 2013 could be expressed as:

$$\overline{Unfair}^{C}_{2013} = \hat{\beta}_{2002}\,\bar{X}_{2013} \tag{C.4}$$

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

Replacing the expected value of the covariables in equation (C.2) by the sample averages, the difference in the perceptions between both years can be expressed as:

$$\Delta^{\mu} = \hat{\beta}_{2013}\bar{X}_{2013} - \hat{\beta}_{2002}\bar{X}_{2002}$$

$$\Delta^{\mu} = \hat{\beta}_{2013}\bar{X}_{2013} - \hat{\beta}_{2002}\bar{X}_{2002} + \hat{\beta}_{2002}\bar{X}_{2013} - \hat{\beta}_{2002}\bar{X}_{2013}$$

$$\Delta^{\mu} = \underbrace{\hat{\beta}_{2002}(\bar{X}_{2013} - \bar{X}_{2002})}_{\hat{\Delta}^{\mu}_{X}} + \underbrace{\bar{X}_{2013}(\hat{\beta}_{2013} - \hat{\beta}_{2002})}_{\hat{\Delta}^{\mu}_{S}} \tag{C.5}$$

The first term of equation (C.5.), usually known as the "composition effect," captures the difference between the average perceptions in 2002 and the counterfactual perceptions 2013 if 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 the educational attainment, age or income inequality).

In turn, the second term of equation (C.5)—what can be thought of as a "perceptions structure effect"—reflects the difference between the average perceptions in 2013, and the counterfactual perceptions in 2002 with the observable attributes of 2013. Therefore, this component reflects changes in perceptions that are due to changes in the elasticity of the different covariables between both years.

In the main text of the paper we exploit the additive linearity assumption of the decomposition, and report the sole effect of changes in the Gini coefficient.