School of Economics and Finance

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Working Paper No. 737 January 2015 ISSN 1473-0278

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December 23, 2014

Abstract. Existing studies of trust formation in U.S. metropolitan areas have found that trust is lower when there is more income inequality and greater racial fragmentation. I add to this literature by examining the role of income inequality between racial groups (racial income inequality). I find that greater racial income inequality reduces trust. Also, racial fragmentation is no longer a significant determinant of trust once racial income inequality is accounted for. I also show that racial income inequality has a more detrimental effect in more racially fragmented communities and that trust falls more in minority groups when racial income inequality increases. The results hold under both least squares and instrumental variable estimation.

Keywords: Trust; Racial Income Inequality; U.S.

JEL Codes: D31; Z10; J15

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1. Introduction

In the last decade, a large and influential literature has documented the negative effect of community heterogeneity on the level of trust across metropolitan areas in the United States. Existing studies show, in particular, that individuals have lower levels of trust when they live in racially fragmented and income unequal communities (Alesina and La Ferrara, 2002; Costa and Kahn, 2003; Putnam, 2007). These findings have spurred a public debate about the workings of the American melting pot (e.g. Henninger, 2007; Jonas, 2007; Armour, 2003) and the debate is likely to continue as racial diversity in the U.S. will increase further.[1]

This paper reconsiders the existing evidence and emphasizes a neglected aspect of community heterogeneity that turns out to be important: the income inequality between racial groups. I show that racial income inequality is key for understanding the different levels of trust across Metropolitan Statistical Areas (MSA henceforth) in the United States.[2] My empirical work starts out by showing that racial fragmentation and overall income inequality have a statistically significant, negative effect on individual measures of trust, a result that is consistent with previous findings (Alesina and La Ferrara, 2002; Putnam, 2007). But I then find that these effects become statistically insignificant once I account for income inequality between racial groups. Hence, my empirical results indicate that it is not income inequality or racial fragmentation *per se* that reduce the level of trust in metropolitan areas. Instead, what turns out to be key for the level of trust is the concurrence of differences in race and income.

My estimates show that individuals living in communities characterized by greater racial income inequality have lower levels of trust. The estimated coefficients imply that a one standard deviation increase in racial income inequality is associated with a reduction in the average level of trust in the community of 2.8 percentage points, or 7% of its mean value. I also show that racial income inequality has a more detrimental effect in more racially fragmented communities and that minority groups reduce trust more than the majority group when racial income inequality increases. These results are robust to alternative definitions of racial diversity and alternative treatments of the time dimension. The results also prevail when I instrument racial income inequality with historical levels of cotton production in each MSA. Hence, the negative effect of racial income inequality on trust does not appear to be driven by reverse causation from low (interracial) trust to high inequality of average incomes across racial groups.

I consider two alternative explanations for my results. The first emphasizes the more intense competition induced by racial income inequality for access to valuable but limited resources, such as public education and welfare. This may foster prejudices and social stereotypes against competing others, ultimately reducing the overall level of trust in the community. The second explanation, instead, focuses on the well-documented preference for similarity of individuals, and the associated tendency to trust more those who are akin to themselves. While this ten-

[1] According to U.S. Census projections, by the year 2050 racial minorities will outnumber non-Hispanic Whites (Ortman and Guarneri, 2009).

[2] MSAs are defined by the US Federal Office of Management and Budget as geographic entities containing a core urban area of 50,000 or more population and consisting of one or more counties.

dency exists regardless of the context, the more frequent exposure to people of different race and socio-economic background leads individuals in more racially unequal communities to trust other people less, on average. I use individual-level data to try to distinguish between these two explanations and find empirical support only for the latter, based on the assumption of preference for similarity. This motivates the last part of the paper, where I qualify this assumption by showing, in particular, that racial income inequality reduces trust only if the preference for similarity of the individuals is *non-linear*, with trust falling at increasing rates towards those who are different both in race and income.

To estimate empirically the impact of income disparities between racial groups I measure income inequality with the Theil index (Theil, 1967). The main advantage of the Theil index over other measures of income inequality, such as the Gini index, is that it is perfectly decomposable.[3] This means that it is possible to distinguish the *between-groups* inequality, due to income differences between racial groups, from the *within-groups* inequality, due to income differences among individuals of the same racial group. This allows me to first estimate the effect of overall income inequality on trust in different metropolitan areas, and then decompose this aggregate effect into the effects deriving from inequality between racial groups and inequality within racial groups.

Figure 1.A illustrates some of my main empirical findings using data on average trust and measures of community heterogeneity across U.S. metropolitan areas. Panel (A) plots the average level of trust for MSA over the period 1973-2010, against their average level of racial fragmentation. Panel (B) plots it against their average level of income inequality. Both panels confirm the existence of an inverse relation between trust and the measures of community heterogeneity, as documented in the literature. The graph, however, also illustrates that racial fragmentation and income inequality alone cannot fully account for the difference in average trust levels between similar cities, like San Francisco and Houston. In spite of their very similar level of community heterogeneity, citizens in the two cities report different levels of trust: while 40% of those living in San Francisco say they can trust others, only 31% in Houston do so.

The explicit focus on racial income inequality provides an explanation for this difference. Figure 1.B plots on the horizontal axis the between-groups component of income inequality measured by the Theil index. The graph shows that the two cities are actually very different in this dimension. The share of overall inequality that is due to differences among races is twice as large in Houston as in San Francisco. This in turn seems to affect the level of trust in the two communities. In San Francisco, where the probability of meeting an individual of a different race but similar income level is relatively high, the level of trust is higher than in Houston, where belonging to a different race is also likely to be associated with a difference in income. The same pattern of apparent similarity, which is in reality masking an additional dimension of heterogeneity, is repeated over different pairs of MSA. My analysis will thus focus on documenting this pattern in a systematic way.

[3]The Gini index is perfectly decomposable only in the special case where the richest individual of one group is poorer than the poorest of the other.

The results in this paper are related to the literature on the determinants of trust. Trust is considered one of the fundamental aspects of social capital (Coleman, 1988; Putnam, 1993, 1995; Fukuyama, 1996), and several empirical studies have explored its influence on economic growth (Knack and Keefer, 1997; Zak and Knack, 2001; Algan and Cahuc, 2010), financial development (Guiso et al., 2004), trade (Guiso et al., 2009) and institutional quality (Knack, 2002).

In economics, Alesina and La Ferrara (2002) were the first to emphasize the negative effect of community heterogeneity on trust, showing that greater racial fragmentation and income inequality are associated with lower levels of trust in U.S. metropolitan areas. Between the two measures of heterogeneity, they find racial fragmentation to be more strongly (negatively) associated with trust, concluding that people are more likely to trust others in an economically unequal city rather than in a racially fragmented one. Similar results have been documented for the U.S. by Costa and Kahn (2003) and Putnam (2007), and by Leigh (2006) and Gustavsson and Jordahl (2008) for Australia and Sweden, respectively. Dinesen and Sonderskov (2014) show that the negative effect of racial heterogeneity on trust becomes even stronger in the immediate micro-context (within a radius of 80 meters of a given household).[4] A related strand of the literature finds a negative relationship between racial fragmentation, income inequality and other dimensions of social capital, such as group participation (Alesina and La Ferrara, 2000), civic engagement (Vigdor, 2004) and public good provision (Alesina et al., 1999; Goldin and Katz, 1999). I complement these studies by showing that the key correlate of trust is the level of racial income inequality, which can be seen as an indicator of the concurrence of the two dimensions of heterogeneity emphasized in previous work.

A related theoretical literature (Alesina and La Ferrara, 2000; Tabellini, 2008) provides analytical support for the negative relationship between community heterogeneity and measures of social capital observed in the data. The fundamental assumption of these models is that individuals prefer similarity - a long-held belief in psychology and sociology (Lazarsfeld and Merton, 1954; Coleman, 1988) - and derive a lower utility from matching with others that are different in race *or* income. This implies that in equilibrium heterogeneous communities are characterized by lower levels of cooperation, participation and trust. I consider an extension to this framework, allowing individuals to differ in more than one dimension, both in race *and* income, in order to study the conditions under which the assumption of preference for similarity is consistent with my empirical results.

While studies of trust and social capital formation have not investigated the role of racial income inequality, other strands of the literature have done so. Alesina et al. (2015), for example, find a negative relationship between ethnic inequality and regional development and public good provision in Africa. Their results are consistent with previous studies of social conflict, which emphasize the role of racial income inequality in triggering political animosity, leading

[4] While most empirical studies support the notion that diversity erodes trust, alternative perspectives - most notably Allport's 1954 contact theory - exist. Contact theory suggests that diversity fosters interethnic tolerance and social solidarity, and predicts that diversity should *increase* trust. Supporting studies for this argument include (Marschall and Stolle, 2004; Stolle et al., 2008).

to several inefficient political and economic outcomes, including social turmoil (Abu-Lughod, 2007), violent crime (Blau and Blau, 1982) and ethnic violence (Robinson, 2001; Stewart, 2005). The negative relationship between ethnic inequality and public good provision in Alesina et al. (2015) is also in line with explanations of the redistribution gap between U.S. and Europe (Alesina and Glaeser, 2005), and adds micro-based evidence to studies documenting the lower public good provision in countries with larger racial disparities (Baldwin and Huber, 2010).

The paper proceeds as follows. Section 2 introduces the data and the estimation framework. Section 3 discusses the main results and robustness checks. Section 4 investigates two alternative interpretations of the results and derives further testable implications, which are discussed formally in Appendix A. Section 5 concludes.

2. Data and Estimation Framework

2.1. Data

The main source of data in this study is the General Social Survey (GSS henceforth) for the years 1973-2010.[5] In each round, the GSS interviews about 1,500 individuals on a broad range of topics, including demographic, behavioural and attitudinal questions. The sample is built to be nationally representative, with primary sampling units represented by MSA and non-metropolitan counties stratified by region, age and race before selection (King and Richards, 1972). My main dependent variable, the measure of trust, is obtained from the following question: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?". I code as 1 individuals who answer "most people can be trusted", while those who answer "most people can't be trusted" or "it depends" are coded as 0. Respondents who report to trust others are 38% of the total.[6] The individual characteristics used in the estimation are also obtained from the GSS. These include variables on age, education, race, religion, gender, family income, working conditions, marital status, size of the place of residence and a dummy for the race of the respondent. The upper panel of Table 1 reports summary statistics for these variables. From the GSS Sensitive Data files I identify the metropolitan areas in which the respondents live, in order to match them with the measures of community heterogeneity calculated at the MSA level.[7] The respondents come from 110 different MSA, listed in Appendix Table A1. Since the GSS is built to be nationally representative, many MSA (typically the smallest ones in terms of population) are only sampled in few rounds, and then replaced with comparable ones. Appendix Table A1 reports the number

[5]The GSS was conducted yearly during the period 1972-1994, and every other year ever since. In three years (1979, 1981, 1992) the survey was not conducted. Individuals interviewed in 1972 are not included in the sample, due to lack of information about the MSA they live in.

[6]Respondents who answer that "it depends" represent less than 5% of the total. Alternative coding assigning the intermediate category to the group of individuals who trust does not alter the results. Similarly, dropping the intermediate group altogether does not change the results.

[7]More than two thirds of GSS respondents can be associated to their MSA. 39% of those who can be matched have missing data for trust. Cross availability with the individual characteristics of the respondents determines the final baseline sample of 20,056 individuals.

of years in which each MSA has been sampled as well as the total number of respondents for each MSA.

The measures of community heterogeneity are obtained from the Integrated Public Use Microdata Series (IPUMS) 1% sample of the US Census for the years 1970, 1980, 1990, 2000. Racial fragmentation is measured using a Herfindahl-type of index that captures the probability that two randomly drawn individuals in a MSA belong to different races. The index is increasing in heterogeneity and is defined as:

$$RacFr_m = 1 - \sum_r S_{rm}^2 \tag{2.1}$$

where m indicates the MSA and r are race definitions which closely approximate the U.S. Census categories of 1990: (i) Whites non-Hispanic; (ii) Blacks non-Hispanic; (iii) Asian and Pacific Islander; (iv) Native American; (v) Hispanic.[8] The term S_{rm} represents the share of race r in the MSA. The mean MSA in my sample has a heterogeneity index of 0.403 with a standard deviation of 0.171. In order to maximize the comparability with previous studies (Alesina and La Ferrara, 2002), I also include in the regressions an index of ethnic fragmentation, calculated in a way analogous to the racial fragmentation index but using ethnic origin rather than race. The original Census breakdown for ethnicity, reporting 35 categories of countries of origin, is aggregated into 10 main categories in order to avoid giving the same weight to very similar and very different ethnicities.

I use two alternative measures of income inequality: the Gini index and the Theil index. The latter belongs to the generalized entropy class of inequality measures [9], it is bounded between 0 and 1 and measures the distance between the egalitarian state in which everybody has the same income, and the actual income distribution. Operationally, the Theil index is defined as:

$$Theil_m = \sum_r \sum_i \frac{y_{irm}}{Y_m} ln \left(\frac{\frac{y_{irm}}{Y_m}}{\frac{1}{N_m}} \right) \tag{2.2}$$

where m indicates the MSA and r the race of belonging. Thus, y_{irm} is the income of individual i belonging to racial group r in MSA m, Y_m is total income in the MSA, and N_m is the total population in the MSA.

As discussed in Bourguignon (1979) and Shorrocks (1980), the indices of the generalized entropy class are the only ones that satisfy the decomposability property.[10] By virtue of this, the Theil index can be rewritten as:

[8] The classification follows Iceland (2004) and Alesina et al. (2004).

[9] In particular, it corresponds to the generalized entropy index for a value of the parameter of distributional sensitivity α equal to 1.

[10] In order to satisfy the decomposability property, the measure of inequality should have an elementary consistency property: an increase in inequality in every subgroup of the population should be associated with an increase in the overall inequality index. This condition is not satisfied by the Gini index (Cowell, 2000).

$$Theil_m = \sum_r \frac{y_{rm}}{Y_m} \left[\sum_i \frac{y_{irm}}{y_{rm}} ln \left(\frac{\frac{y_{irm}}{y_{rm}}}{\frac{1}{n_{rm}}} \right) \right] + \sum_r \frac{y_{rm}}{Y_m} ln \left(\frac{\frac{y_{rm}}{Y_m}}{\frac{n_{rm}}{N_m}} \right) \tag{2.3}$$

where all components are defined as in (2.2), with the addition of y_{rm}, which represents the income of racial group r, and n_{rm} which is the population of racial group r. In this form, the index explicitly compares the income and population distributions of different subgroups by summing the weighted logarithm of the ratio between their income and population shares. The first term on the right-hand side of equation (2.3) represents the amount of total inequality that is due to differences *within* racial groups, while the second represents the amount that is due to differences *between* racial groups. Focusing on the latter term, it is easy to see that if one racial group has the same income and population shares it does not contribute to the between-groups inequality of the MSA. On the contrary, if its income share is bigger (smaller) than its population share, the group contributes positively (negatively) to the between-groups inequality. Weighting by the income share of each racial group ensures that the positive contributions are always higher than the negative, so that the between-groups inequality term is always positive. A similar logic applies to the inequality within racial groups: if one of the n individuals of a racial group earns $1/n$-th of the total group income, his contribution to the within-groups inequality is equal to zero. If he earns more (less) than that, his contribution is positive (negative). As in the previous case, weighting by the income share of each individual ensures that the within-groups inequality term is always positive. Altogether, the Theil index thus evaluates the discrepancy between the distribution of income and the distribution of population both within and between different groups.

The bottom panel of Table 1 reports the summary statistics for the measures of community heterogeneity, while Table 2 highlights their correlations. The most notable feature is the very high correlation (0.98) between the aggregate Theil index (the sum of the two components of between-groups and within-groups inequality) and the Gini index. This suggests that there is no additional information conveyed by the Theil index *per se*. Instead, its merit lies in its decomposability, which allows to account explicitly for the component of inequality due to differences between racial groups. Other relevant features of the table are the high correlation between the index of racial fragmentation and the between-groups inequality, as well as the negative correlation between the measure of trust and all measures of community heterogeneity. The measures of heterogeneity are interpolated linearly through one Census year and another, as in Alesina and La Ferrara (2002) and Costa and Kahn (2003). By construction, the interpolation introduces serial correlation in the estimates. To account for this, I cluster the standard errors at the MSA level in all regressions, allowing for heteroskedasticity and arbitrary correlation in the error term. In section 3 I investigate the robustness of my results to alternative treatments of the time dimension.

2.2. Estimation Framework

I start by considering the impact of community heterogeneity on trust of individual i in metropolitan area m according to the following specification:

$$Tr_{im} = \beta_1 X_{imt} + \beta_2 RacFr_{mt} + \beta_3 Ineq_{mt} + \delta_1 Z_{mt} + \alpha_{s(m)t} + \tau_t + \epsilon_{imt} \tag{2.4}$$

where X_{imt} is the vector of individual characteristics reported in Table 1. Z_{mt} is a set of community characteristics including the logarithm of the median income of each racial group in the MSA (and its squared term), the logarithm of the MSA size and the index of ethnic fragmentation. $RacFr_{mt}$ is the measure of racial fragmentation and $Ineq_{mt}$ is the measure of aggregate income inequality (calculated either by the Gini or by the Theil index). $\alpha_{s(m)t}$ and τ_t are state and year fixed effects. Finally, ϵ_{imt} is an error term that is clustered at the MSA level to allow for arbitrary heteroskedasticity and serial correlation.
In order to identify the impact of racial income inequality on trust, I then expand the previous specification to separately estimate the effect of between- and within-groups inequality. This is done in the following regression:

$$Tr_{imt} = \tilde{\beta_1} X_{imt} + \tilde{\beta_2} RacFr_{mt} + \gamma_1 BtwIneq_{mt} + \gamma_2 WthIneq_{mt} + \tilde{\delta_1} Z_{mt} + \alpha_{s(m)t} + \tau_t + \eta_{imt} \tag{2.5}$$

where all variables are defined as above, with the exception of $BtwIneq_{mt}$ which is the inequality between racial groups and $WthIneq_{mt}$ which is the inequality within racial groups. As in the previous equation, the error term is clustered at the MSA level. The main coefficient of interest is γ_1, which captures the effect of greater racial income inequality on trust. In addition, I will be interested in observing the variation of the coefficient of racial fragmentation (from β_2 to $\tilde{\beta_2}$) once the inequality between races is explicitly accounted for. The method of estimation in the baseline specification is least squares (LS). In section 3.2 I instrument the measures of racial income inequality and racial fragmentation and estimate two-stage least squares regressions (IV).[11]

3. Empirical Results

3.1. Least Squares Estimation

Table 3 reports the estimates of the effect of community heterogeneity on trust for the period 1973-2010. I start by introducing the measures of community heterogeneity one at a time. Columns (1) and (2) show that both racial fragmentation and income inequality (measured by

[11]Estimating the model by Probit as in previous studies (Alesina and La Ferrara, 2002; Costa and Kahn, 2003) provides qualitatively identical results.

the Gini index) are negatively and significantly correlated with trust at the 99% confidence level. The estimated coefficients are remarkably similar to those found by Alesina and La Ferrara (2002) for the period 1974-1994. The point estimate for racial fragmentation implies that, moving from the least to the most racially fragmented MSA the probability of trusting others decreases by 16 percentage points. Starting from the sample mean, a one standard deviation increase in racial fragmentation reduces trust by 3.7 percentage points, or 10% of the sample mean. Similarly, the coefficient of income inequality implies that a one standard deviation increase is associated with a reduction of trust of 9% of the sample mean. In column (3) I consider the two measures of community heterogeneity together. When doing so, the racial fragmentation coefficient remains statistically significant at the 95% confidence level, while the income inequality coefficient drops substantially and becomes insignificant. In columns (4) and (5) I replace the Gini index with the Theil index. The results using the Theil index are similar to those obtained using the Gini index. Individually, the Theil index is negatively and significantly correlated with trust at the 95% confidence level. When considered along with racial fragmentation it becomes insignificant and only the racial fragmentation coefficient remains negatively and significantly associated with trust.

Overall, columns (1)-(5) confirm the results in Alesina and La Ferrara (2002): both racial fragmentation and income inequality are negatively related to trust and, amongst the two, racial fragmentation has the strongest relationship. This sets the basis for their claim that people are more likely to trust others in an unequal city than in a racially fragmented one. This conclusion however is challenged in columns (6) and (7), where I exploit the decomposability of the Theil index. In column (6) I break down the aggregate income inequality into the two components of between- and within- racial groups inequality. As it turns out, only the former component has a negative and significant relationship with trust. The estimated coefficient implies that moving from the community with the lowest racial income inequality (0.001) to the one with the highest (0.061) reduces the level of trust by 11 percentage points. The null hypothesis that the coefficients of between- and within- groups inequality are equal is rejected at the 99% confidence level (t-stat 24.86), confirming that the disaggregated model is different from the aggregated one. In column (7) I further add to the two components of income inequality the index of racial fragmentation. Compared to column (5) the coefficient of racial fragmentation drops by more than half and becomes statistically insignificant, while that of racial income inequality remains negatively and significantly correlated with trust at the 99% confidence level. The estimated coefficient is sizeable: starting from the mean, a one standard deviation increase in racial income inequality reduces trust by 2.8 percentage points, or 7% of its mean value. The results in column (7) therefore suggest that it is not racial diversity *per se* to reduce the amount of trust, but rather the concurrence of racial and income disparities in the community.

Table 4 investigates the robustness of this result to alternative definitions of racial diversity. I start by considering the possibility, suggested by Uslaner (2008) among others, that the index of racial fragmentation represents a surrogate measure for the shares of minorities living in the

MSA. Since minorities are less trusting, the impact of fragmentation on trust may arise from compositional effects. In columns (1)-(5) I thus substitute the index of racial fragmentation with the shares of different racial groups living in the community. The estimates provide some support for the argument. In particular, the coefficients suggest that trust is lower when the shares of Black and Hispanic minorities are larger, albeit the coefficients are not statistically significant. Also, trust increases for larger shares of the more affluent White and Asian groups. Irrespective of the racial group considered, however, the coefficient of racial income inequality remains negative and significant in all columns, suggesting that the measure is not simply a proxy for larger population shares of groups with different levels of trust.

Columns (6) and (7) replace the baseline index of racial fragmentation with an index of racial *segregation*.[12] According to some authors, this is the relevant measure to consider when discussing the detrimental effect of diversity on trust (Stolle et al., 2008; Uslaner, 2011). The argument is that while fragmented but integrated communities facilitate the repeated interactions among races, potentially raising their mutual trust, segregation certainly reduces it by isolating groups from each other and exaggerating their perceived differences. In line with this explanation, column (6) displays a negative relationship between segregation and trust. The estimated coefficient is significant at the 90% confidence level and implies that a one standard deviation increase in segregation reduces trust by 3% of its mean value. The effect however becomes insignificant in column (7) when I include the measure of racial income inequality, which instead retains a negative coefficient significant at the 99% confidence level. This suggests that the effect of racial income inequality on trust is not only related to the sorting of individuals of different races across neighbourhoods on the basis of income. Indeed, the correlation between racial income inequality and segregation in the sample is only slightly positive (0.11). This is consistent with the theoretical results of Sethi and Somanathan (2004), who show that segregation happens at both high and low levels of racial income inequality if individuals care about the affluence and the racial composition of their neighborhoods.

In Table 5 I check the robustness of the main result to alternative treatments of the time dimension. Columns (1) and (2) replace the state and year fixed effects with state-year fixed effects, allowing different states to follow different trends in the evolution of racial fragmentation and racial income inequality. The specification exploits the cross-sectional variation in each year between MSA belonging to the same state. The results are similar to those in the baseline specification, except that racial fragmentation in column (2) retains a significant and independent effect on trust. The income inequality between races also remains negatively and significantly correlated with trust at the 95% confidence level. In the next columns I replace the interpolated measures of racial fragmentation and income inequality with their original val-

[12] I use the entropy index calculated by Iceland and Scopilliti (2008). The index measures the percentage of one group's population that would have to change residence, in order for each neighbourhood to have the same percentage of that racial group as the MSA overall. The index ranges between 0 and 1. When all neighborhoods have the same composition as the overall MSA, the index is at its minimum. When each neighborhoods in the MSA is completely segregated, so that only one racial group is present, the index achieves its maximum.

ues calculated at different Census years. Keeping the measures of community heterogeneity constant reduces concerns of serial correlation introduced by the linear interpolation in the baseline specification. Columns (3) and (4) assign the value calculated at the preceding Census year and held constant over the following decade, while columns (5) and (6) assign the value calculated at the closest Census year. The results are similar to those using the interpolated measures. Racial fragmentation appears to be the only negative and significant predictor of trust when considered along with aggregate income inequality in columns (3) and (5). Its coefficient, however, becomes insignificant when the income inequality is partitioned into between- and within- groups inequality in columns (4) and (6). As in the baseline specification, only racial income inequality remains negatively and significantly associated with trust. The point estimates are similar to those obtained using the interpolated measures, suggesting that the variation is mostly cross-sectional.

3.2. Instrumental variable estimation

The previous results are suggestive of a negative effect of racial income inequality on trust. It is possible, however, that the causality of the relationship runs in the opposite direction, from low levels of trust to high racial income inequality. The index of racial income inequality in fact is increasing in the difference between the average incomes of racial groups, and such difference might itself be influenced by low levels of (interracial) trust.[13] This would be the case if, for example, employers engage in taste-based discrimination, preferring to hire individuals of their own race (Giuliano et al., 2009; Stoll et al., 2004). Similarly, the index of racial fragmentation could also be influenced by the level of trust if discriminated minorities decide to migrate towards other, more tolerant, communities. The least squares estimates would then be biased, as greater racial income inequality and fragmentation might partly be the consequence of low interracial trust in the MSA. I employ an instrumental variables procedure to address this reverse causality issue, using two separate instruments for the potentially endogenous measures of racial income inequality and racial fragmentation.

I instrument the index of racial income inequality in each MSA with the volume of local cotton production at the end of the 19th century. The instrument exploits the fact that labor-intensive cotton production in the Southern "Black Belt" was carried out through the forced labor of enslaved Black population. MSA in traditional cotton-producing areas were thus characterized by a disproportionate share of *poor* Black population.[14] This aspect has perpetuated over time

[13] The between-groups inequality in fact can be rewritten as:

$$BtwIneq_m = \sum_r \frac{y_{rm}}{Y_m}\, ln\left(\frac{\frac{y_{rm}}{Y_m}}{\frac{n_{rm}}{N_m}}\right) = \sum_r \frac{n_{rm}}{N_m}\,\frac{\overline{y_{rm}}}{\overline{y_m}}\, ln\,\left(\frac{\overline{y_{rm}}}{\overline{y_m}}\right)$$

where $\overline{y_{rm}}$ represents the average income of race r in the MSA and $\overline{y_m}$ is the average income in the MSA.

[14] While some Northern states (Delaware, New Jersey, D.C. and Maine) had an *overall* share of Black population comparable to that in the South, their share of *free* (and presumably richer) Black population was much

since the MSA continued to be heavily populated by the descendants of the Black workers, even after the decoupling between cotton and Black labor due to the mechanization of the picking process during the 1930s (Dattel, 2009). As a result, traditional cotton-producing MSA are still amongst the most racially income unequal communities in the U.S.

The historical volume of cotton production is measured by the number of cotton bales per Km^2 in each MSA. The data come from the 1889 U.S. Census on Agriculture.[15] The inclusion of state fixed effects in the first-stage regressions implies that the identifying variation comes from differences in the amount of cotton produced across MSA of the same state. The *within-state* variation is substantial. For example, cotton production in Tennesse ranged from 13 cotton bales per Km^2 in Memphis to 2 in Nashville and 0 in Knoxville and Johnson City. These historical differences translate into differences in current racial income inequality, which in Memphis is 3 times larger than in Nashville, and 10 times larger than in Knoxville and Johnson City.[16]

The instrument for racial fragmentation exploits the settlement patterns of immigrants based on pre-existing clusters, as in Card (2001). In particular, I predict flows of Hispanic and Asian immigrants based on their tendency to move to previously established enclaves. I thus multiply the initial shares of Hispanics and Asians in each MSA in 1970 by their national immigration inflows over the following decades, in order to obtain their predicted shares in each MSA. This isolates the exogenous supply-push component of Hispanic and Asian population shares, which are independent of MSA-specific levels of interracial trust. I then calculate a *predicted* racial fragmentation index, by replacing the actual shares of Hispanic and Asian population with the corresponding predicted shares based on earlier settlement locations.

The bottom panel of Table 6 reports the estimates from first-stage regressions. In all columns the coefficients of the instruments are significant at the 99% confidence level. Columns (1) and (2) show the independent effect of each instrument on the corresponding endogenous regressor. The point estimate in column (1) suggests that a one standard deviation increase in the predicted racial fragmentation index is associated with an increase in the actual racial fragmentation index by 30% of its average. The coefficient in column (2) instead suggests that MSA that were one standard deviation apart in terms of cotton production in 1889, differ by half of a standard deviation in terms of racial income inequality one century later. In numbers, this means that MSA that were producing 360 cotton bales per 100 km^2 (one standard deviation above the average production), today are 31% more racially unequal than the average MSA. Columns (3) and (4) include both instruments at the same time. Each instrument continues to significantly predict the corresponding endogenous regressor, and the point estimates are similar to the

higher, ranging from 46% to 98%, against an average 3% in the South (U.S. Census, 1850).

[15] The data are available at the county level from the United States Department of Agriculture. I attribute each county to the MSA of belonging.

[16] The suitability of the soil for cotton production is related to the outcrop of sedimentary units during the Cretaceous era. Submerged areas close to the shoreline at that time were, 100 millions years later, especially suitable for production. The shoreline curled through parts of the Southern states of Georgia, Alabama, Mississippi, Tennessee, North and South Carolina, making some areas of these states highly productive while others much less so. For a review of the relation between geological characteristics of the territory and a number of social, economic and political outcomes, see the webpage of Prof. Steven Dutch.

unconditional effects in the previous columns.

The upper panel of Table 6 reports the second-stage results. A comparison of the IV estimates with their LS counterparts in Table 3 reveals that the point estimates are never markedly different. If anything, the IV results in columns (1) and (2) indicate that the effects of racial fragmentation and racial income inequality on trust are stronger (more negative) than what suggested by the non-instrumented estimates. Both coefficients are statistically significant at the 99% confidence level. In column (3) I consider the two instrumented regressors together. As in the baseline LS regression, racial fragmentation becomes insignificant, while the index of racial income inequality remains negative and significant at the 95% confidence level. The *causal* IV estimate in column (3) thus implies that a one standard deviation increase in racial income inequality reduces trust of 3.4 percentage points, or 9% of its mean value. All columns report the Kleibergen-Paap F-statistic for the first-stage regressions. In all specifications, the Kleibergen-Paap F-statistic exceeds the relevant Stock-Yogo critical values, indicating that the instruments are strong predictors of the endogenous regressors. Since the value is close to the threshold in column (3), as a further check I also report the p-value for the Anderson-Rubin Chi-2 test, which is robust to the presence of weak instruments. In all specifications, the test clearly rejects the hypothesis that racial income inequality does not affect trust. Overall, the IV results confirm the negative effect of racial income inequality on trust, and suggest that the effect is not driven by reverse causation from low (interracial) trust to high inequality of average incomes across racial groups. Since the LS results provide a conservative estimate of the true effect, in the remainder I continue to present them along with the IV results, in order to show the consistency between the two sets of results.

4. Possible channels

4.1. Interracial competition

One way to interpret the negative effect of racial income inequality on trust is to argue that individuals have prejudices and classify others on the basis of social stereotypes. This view is consistent with sociological theories of interracial group-competition (Blumer, 1958; Blalock, 1967), which consider prejudice a defensive reaction from members of the majority group against challenges to their privileged position. The greater the perceived threat, the higher the hostility against threatening outsiders (Quillian, 1995). Under this interpretation, trust is lower in more racially unequal communities due to the greater menace posed by minorities for access to valuable resources, such as public education and welfare. This inter-group competition would foster hostility and prejudices, ultimately reducing trust in others, who are more likely to be of a different race and social background the greater the level of racial income inequality.

I start to investigate this explanation by testing one of its direct implications. If perceived group threats were important, one would expect political attitudes and behaviors, especially those concerning the allocation of resources, to be particularly disputed when racial income inequality is high. In particular, affirmative action programs granting preferential treatment to minority groups should find lower support in communities characterized by greater competition (Sidanius and Pratto, 2001).

In Table 7 I thus consider a set of questions from the GSS which explicitly ask respondents their opinion about the fairness of preferential policies, and check whether these opinions are affected by the extent of racial income inequality in the community of the respondents. I presents both LS and IV results for the full sample of individuals, as well as IV results for the sample of White respondents only. Columns (1)-(3) start by asking in general whether the respondents think that Blacks should overcome prejudice and make progresses without political favouritism. In all columns the coefficient of racial income inequality is insignificant, suggesting that racial disparities do not affect political views at this level of generality. Columns (4)-(6) more directly ask respondents their position about affirmative action policies. In this case the results provide some support for theories of interracial group-conflict. In particular, the IV specification of column (5) shows that opposition to affirmative action is stronger in more racially income unequal communities. The effect however disappears in column (6) for the sample of White respondents, who should instead be most concerned with race-targeted policies. Finally, columns (7)-(9) ask whether affirmative actions penalize members of the White majority. Also in this case, there is no evidence of a significant effect of racial income inequality on political opinions, neither in the full sample nor among White respondents. Altogether, Table 7 provides very scant evidence to support the political implications of group-conflict theories. This is consistent with the results of Oliver and Wong (2003) and Hopkins (2010), who also find no significant effect of racial threats on individual political attitudes, contrary to initial research on the subject (Pettigrew, 1959).

I complement this indirect (lack of) evidence with a more explicit test of the effect of racial income inequality on prejudices and social stereotypes. To this end, I use a set of questions from the GSS which ask to rate the characteristics of people in different racial groups. I focus in particular on whether the respondents think that people in a certain group tend to be hard-working or lazy, as well as unintelligent or intelligent.[17] I combine the answers and the race of the respondents to construct four dummy variables, which are equal to 1 if the respondent thinks that individuals of her own group or the other group are lazy or unintelligent. Simple mean comparisons suggest that respondents have a worse overall opinion of people of a different race, which are described as more lazy (12% vs. 3%) and unintelligent (18% vs. 6%) compared to individuals of their own race. A mean comparison test rejects the null hypothesis of means equality at the 99% confidence level (t-stats 22.4 and 21.6 respectively).

The question, however, is whether these stereotypes correlate with the level of racial income inequality in the community of the respondents. This is investigated in Table 8, which reports both LS and IV estimates for each set of results. I start by considering opinions about laziness. The first two columns focus on individuals of the same group of the respondent, while the next

[17] The respondents are only asked about their opinion about Black and White individuals. I thus restrict the sample to respondents belonging to one of these two racial groups.

two columns on individuals of the other group. The IV results in columns (2) and (4) show that, in more racially unequal communities, respondents are more likely to consider both same-group and other-group individuals lazy. The point estimate for other-group individuals is twice as large as for same-group individuals, providing some support for the idea that stereotypes are exacerbated by interracial group-conflict. However, neither of the two coefficients is statistically significant, and they are not statistically different from each other. Columns (5)-(8) consider opinions about intelligence. The LS results in columns (5) and (7) show that respondents in racially income unequal communities are more likely to consider other people unintelligent, regardless of whether they belong to their same group or the other group. Both coefficients are significant at the 99% confidence, and they are not statistically different from each other. In column (6), the IV estimate for people of the same group turns negative and insignificant. For individuals of a different group in column (8) it remains positive, and larger in magnitude compared to LS, but is also not statistically significant.

Altogether, the results in Table 8 thus suggest that people in racially unequal communities have more negative opinions about their neighbours. This, however, is regardless of their group of belonging and there is no evidence that negative stereotypes are particularly targeted towards members of different racial groups. Together with the results in Table 7, this challenges the notion that negative stereotypes emerge as a reaction to perceived threats from competing different others, which in turn casts doubts on the idea that racial income inequality affects trust due to greater interracial competition.[18]

4.2. Preference for similarity

An alternative explanation for the detrimental effect of racial income inequality on trust is based on the observation that similarity affects the inclination towards others in several dimensions, including the propensity to trust. This view has a long tradition in both psychology and sociology (Lazarsfeld and Merton, 1954; Coleman, 1988), where it is often reffered to under the term of "homophily".[19] The observation is also supported by a large body of experimental evidence (Glaeser et al., 2000; Bornhorst et al., 2010). Several factors can potentially account for this in-group bias, including similarity in preferences and tastes as well as networking arguments (Dixit, 2003; Tabellini, 2008).

Alesina and La Ferrara (2000) suggest that homophily plays an indirect role on trust, by determining the propensity of individuals to join associations, unions and religious groups, whose social interactions are particularly conducive to generating high levels of interpersonal trust and reciprocity. Under this interpretation, citizens of heterogeneous communities are less likely to be members of a group and interact with individuals of different races and socio-economic background. The lack of interaction exacerbates their initial aversion towards those who are different, reducing their level of trust. One indirect way of assessing whether the

[18]A similar conclusion is reached by Rudolph and Popp (2010) and Oliver and Mendelberg (2000).

[19]The etymology of the term is: homo = self and philìa = love. The term "homophily" was coined by Lazarsfeld and Merton (1954). A review of the literature on homophily can be found in McPherson et al. (2001).

preference for similarity assumption holds in my data is therefore to check whether individuals exposed to greater racial disparities are less likely to be members of a group.

Table 9 thus presents regressions in which the dependent variable is a dummy variable equal to 1 if the respondent belongs to a group, and 0 otherwise.[20] The estimates in columns (1)-(3) show that racial income inequality reduces participation. A one standard deviation increase in racial income inequality is associated with a reduction in group membership by 3.4 percentage points. The result also holds when I instrument both measures of racial income inequality and fragmentation in column (4). Columns (5)-(7) compare the effect of racial income inequality on group participation in three of the most common forms of organization: unions, church groups and professional categories. The first two have a high degree of interaction amongst their members, whereas the third has a very low level of personal interaction. In line with the idea that individuals prefer to interact with their kin, the effect of racial income inequality is large and significant for unions and church organizations, but not for professional categories.

While these results are broadly supportive of the mechanism highlighted in Alesina and La Ferrara (2000), they don't necessarily establish a link between the level of trust and the preference for similarity of different individuals. A second and more stringent test comes from observing the effect of racial income inequality on the level of trust of two sets of individuals with arguably different levels of homophily. I use questions from the GSS to construct an indicator of the inclination of each respondent towards social and racial similarity. I measure preference for social similarity from answers on whether the government should engage in income redistribution to reduce inequality. I define a dummy variable which is equal to 1 for those who prefer same-income others and are strongly against redistribution. The preference for racial similarity is instead measured by answers to a set of questions regarding both abstract opinions and concrete behaviour towards different races.[21] For each question, I define a dummy variable which is equal to 1 for those who have a strong preference for same-race others. Finally, I separate respondents in two groups: those who prefer similarity in at least one of the two dimensions above, and those who don't. If the preference for similarity assumption were true, people in the first group should be more concerned by an increase in racial income inequality compared to individuals in the second group, who have weaker in-groups feelings.

Table 10 reports the coefficients for the two separate groups, defined on the basis of different combinations of preference for social and racial similarity. The results broadly support the preference for similarity assumption. The coefficients for those with stronger in-groups feelings are larger in magnitude in 7 out of 8 cases and the difference between the two groups is statistically significant in 5 out of 8 cases. This supports the view that racial income inequality affects trust

[20] About 70% of respondents report to be members of some group or organization. On average, respondents are members of 1.75 groups. The most frequent are church-affiliated groups (34% of respondents), sports groups (20%), professional societies (16%) and labor unions (15%).

[21] The questions range from being favourable to interracial marriage, to having invited someone of a different race at home for dinner recently. The exact definition for the questions included is reported in the notes to Table 10. The table includes all questions on racial attitude for which there are at least 1,000 respondents for each group.

more for individuals that are averse to social and racial mixing.

4.3. Characterization and testable implications

Models formalizing the preference for similarity assumption typically characterize individuals along one dimension: they are either similar in race or income (e.g. Alesina and La Ferrara, 2000; Tabellini, 2008). The focus on racial income inequality instead entails that individuals can be similar in more than one dimension: *identical* individuals have both the same race and income level; *partially similar* individuals have either the same race or the same income; individuals that are *different* have no common element of similarity. This classification along multiple dimensions carries additional insights on the underlying features of the preference for similarity. A formal analysis is reported in Appendix A, which presents a basic two-groups model of trust formation.[22] Here I offer a heuristic discussion of the conditions that must be satisfied in order for racial income inequality to reduce trust.

As a way of example, consider the two communities reported in Figure 2, where the population is perfectly divided between Blacks and Whites, and rich and poor. The only difference between the two is the way in which income is distributed across racial groups. In community A, for both Blacks and Whites, half of the group is rich and half is poor. In community B, all Whites are rich and all Blacks are poor. The empirical results in Section 3 show that trust is lower in community B, where racial and economic identities coincide. Also, Figure 2 shows that citizens of B face twice as many identical and different individuals compared to A, where there is a larger share of partially similar individuals. These two observations combined imply that the doubling of identical individuals in B - and the corresponding increase in trust - does *not* compensate for the doubling of different individuals - and the corresponding reduction in trust.

This suggests that citizens have *non-linear* preferences for similarity: their trust falls at increasing rates as individuals become more different. This condition is derived analytically from the model in Appendix A, and is graphically summarized in Figure 3. The x–axis plots the dimensions of similarity among citizens in the community, while the y–axis plots the corresponding amount of trust. I define w_2 as the amount of trust towards individuals similar in both race and income, and w_1 as the amount of trust towards those similar in only one dimension. The amount of trust towards individuals different in both dimensions is normalized to 0. The key condition for individual trust to be consistent with the empirical results is $w_2 < 2w_1$, reflecting the nonlinear relationship between trust and similarity. If this condition holds, then for any given amount of racial fragmentation and overall income inequality, the level of trust is lower when racial and income heterogeneity are combined rather than separated.

The non-linear preference for similarity carries additional implications that can be tested in the data. The first implication, formally derived in Appendix A, is that racial income inequality is more detrimental in more racially fragmented communities. Intuitively this happens because,

[22] Considering more than two groups would significantly complicate the analysis, without providing substantial additional insights. The two-groups model approximates the composition of the GSS sample in which Whites and Blacks account for roughly 90% of the total individuals (see Table 1).

in racially homogeneous communities, a larger number of individuals in the more populous group become identical when racial income inequality increases.[23] Clearly the situation is reversed for minority groups individuals, which are worse off compared to the case of racially fragmented communities. Since they represent a minority of the population, however, their weight in the overall level of trust of the community is smaller and the effect of the more populous group predominates. For the community as a whole, therefore, increases in racial income inequality imply progressively smaller reductions of trust as racial fragmentation decreases.[24] Figure 4 shows this point graphically, by plotting the variation in trust due to a rise in racial income inequality, for communities at different levels of racial fragmentation.

The implication is tested in Table 11. The first two columns distinguish between MSA below and above the median level of racial fragmentation. Column (1) shows that the coefficient of racial income inequality is insignificant in the sample of less fragmented MSA. For more fragmented MSA in column (2), instead, the effect is negative and statistically significant at the 95% confidence level. Compared to the average effect in Table 3, the estimated coefficient is 25% larger and implies a reduction of 9% of the mean value of trust for a one standard deviation increase in racial income inequality. Column (3) pools the observations together and includes the interactions of racial income inequality with two dummies for the MSA being above or below the median level of racial fragmentation. The results confirm that racial income inequality reduces trust only in racially fragmented communities. The interaction term for communities above the median is significant at the 99% confidence level. The result is also confirmed by the pooled IV estimates in column (4): the interaction term remains very similar in magnitude to the LS estimate and is statistically significant at the 90% confidence level.

A second implication of the non-linear relationship between trust and similarity concerns the impact of racial income inequality on different racial groups of the same community. In Appendix A, I show formally that minority groups are those who reduce trust most when racial income disparities increase. Intuitively, this depends on the different population shares of each group. The impact of racial income inequality is milder for members of the more populous groups, because they have many individuals to become identical with - based on the definition above - when racial income inequality increases. Minority groups members, instead, have fewer individuals to become identical with, and a larger number of individuals who become different in both race and income, when racial disparities increase. This implies a more pronounced reduction in their level of trust, when racial income inequality increases.

The implication is tested in Table 12. I identify the race of GSS respondents and estimate the impact of between-groups inequality for each of the different racial groups. The results in columns (1)-(5) show a negative effect of racial income inequality on trust for all groups, and confirm that the effect is stronger for racial minorities. In particular, greater racial income

[23]Note that the two hypothetical communities of the previous example, in which 50% the population belongs to one race and 50% belongs to the other, represent the most racially fragmented communities one can think of in a setup with only two racial groups.

[24]Indeed, the effect of racial income inequality becomes positive at extreme levels of racial homogeneity.

inequality has a negative but not significant effect in the sample of White respondents in column (1), while the estimated effect is 50% larger, and statistically significant, for the sample of Black individuals in column (2) and four times as large for the group of Hispanic respondents in column (5). In the case of Hispanics, a one standard deviation increase in between-groups inequality reduces trust by more than 8%. The remaining minority groups, Asians and Native Americans, have fewer respondents so that the estimated effect, while negative and with a large point estimate, is imprecisely estimated and not statistically significant. Column (6) pools all respondents together, interacting the measure of racial income inequality with dummies for their corresponding racial groups. Under the pooled specification, for all groups except Native Americans the estimated effect is statistically significant. The coefficient of Whites is the most precisely estimated but its point estimate remains generally smaller compared to those of the minority groups.

5. Conclusions

So far, the literature on the determinants of trust has neglected the role of income inequality along racial lines. I show that greater racial income inequality lowers the level of trust in U.S. metropolitan areas. Moreover, once racial income inequality is accounted for, racial fragmentation becomes a statistically insignificant determinant of trust in U.S. metropolitan areas. This suggests that it is not racial differences *per se* that matter for trust but racial differences that coincide with income differences. The result provides important insights for the debate on the workings of the American melting pot. In particular, it suggests that racial diversity is more detrimental when associated with income disparities between races and that, similarly, income inequality is more harmful when it has a marked racial connotation. My empirical results are consistent with a simple conceptual framework where trust decreases at increasing rates as individuals become more different. I also document empirical support for further implications deriving from this assumption. In particular, I show that income disparities between races have a more detrimental effect in more racially fragmented communities and that minority groups reduce trust more than the majority group when the inequality between races increases.

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Figure 1 A. Similar Characteristics but Different Trust

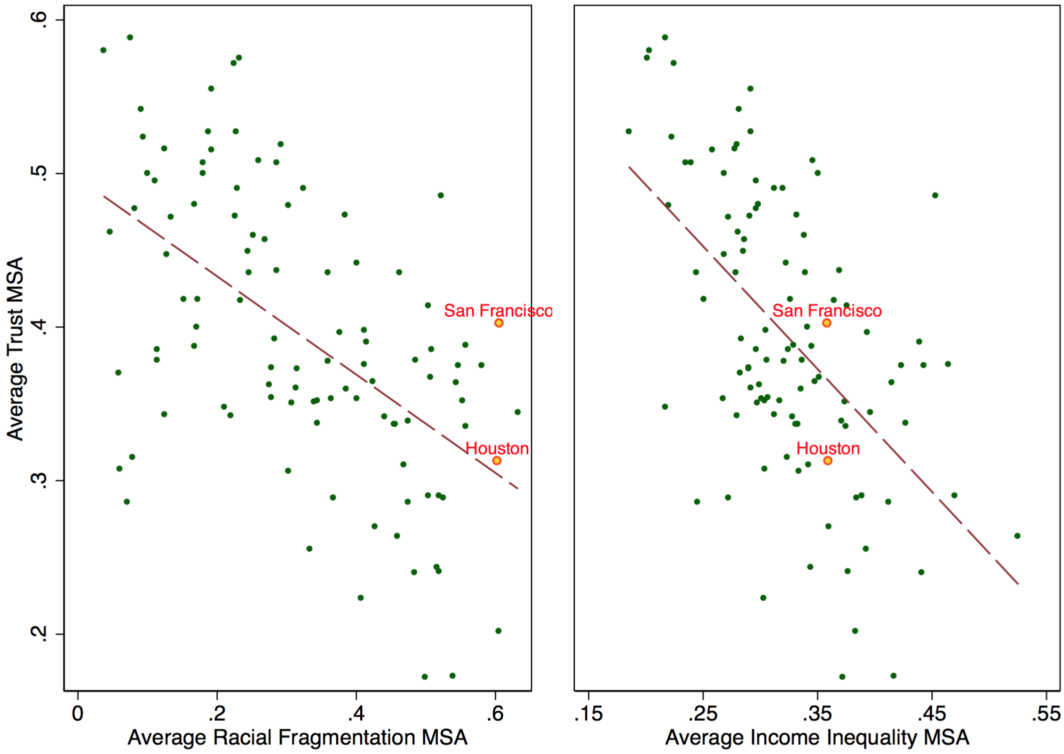

Figure 1 B. Are They Really Similar?

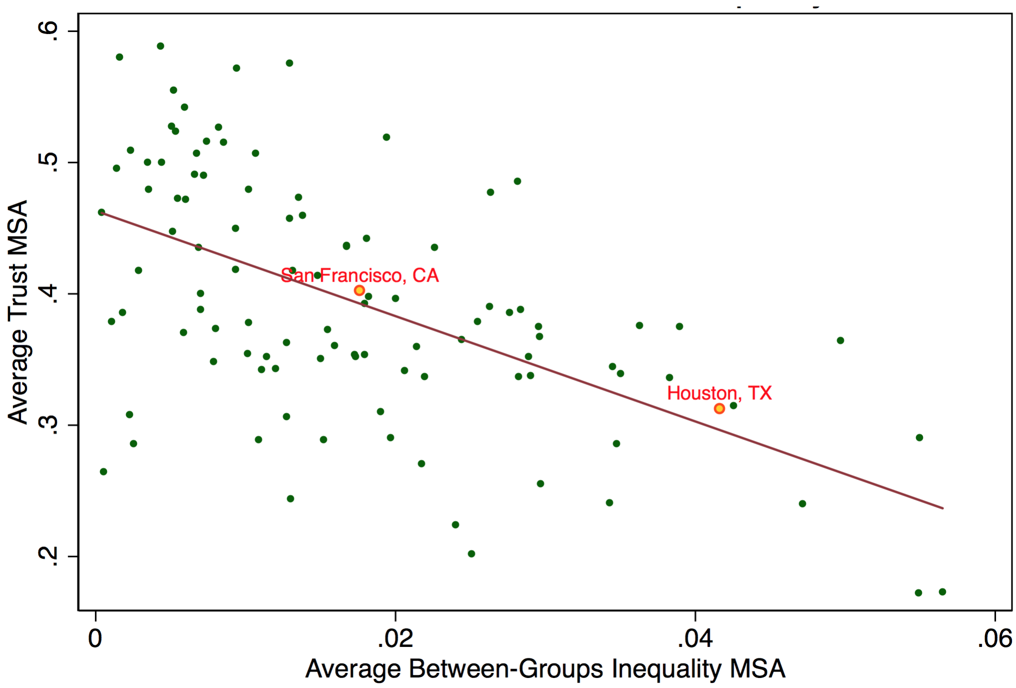

Figure 2. Two Hypothetical Communities

Community A

	White	Black	Tot. Ineq.
Rich	25	25	50
Poor	25	25	50
Rac. Fr.	50	50	

Community B

	White	Black	Tot. Ineq.
Rich	50	0	50
Poor	0	50	50
Rac. Fr.	50	50	

Figure 3. Trust and Dimensions of Similarity

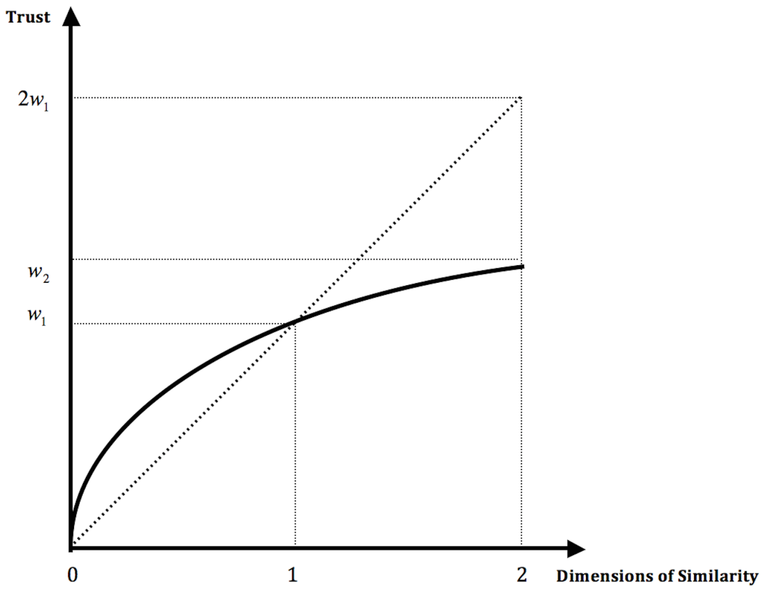

Figure 4. Plot of Δ_1 at different levels of p

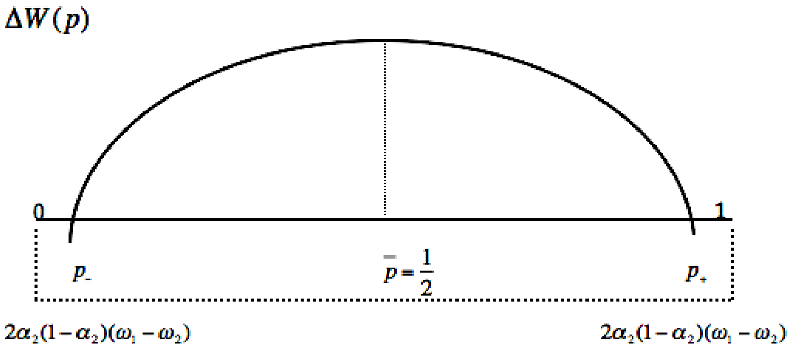

Table 1. Summary Statistics

	Individual Characteristics		
	Avg.	Std. Dev.	Observations
Trust	.381	.485	22804
Age	44.70	17.09	22804
Female	.559	.496	22804
Educ $\leq$ 12 *years*	.204	.403	22804
Educ $\geq$ 16 *years*	.252	.434	22804
Log (*Real Income*)	10.03	.990	20499
White	.744	.436	22804
Black	.148	.355	22804
Native American	.029	.168	22804
Asian	.021	.145	22804
Hispanic	.056	.231	22804
Full Time	.516	.499	22804
Part Time	.102	.303	22804
Religious	.888	.316	22804
Married	.515	.499	22804
Divorced	.167	.373	22804
Member	.697	.459	10620
Memb. Union	.145	.352	10513
Memb. Church	.331	.471	10536
Memb. Prof.	.166	.372	10508
$Lazy_{\ own}$	.030	.171	4696
$Lazy_{\ oth.}$	.115	.319	4696
$Unint._{\ own}$	.061	.240	4087
$Unint._{\ oth}$	.175	.380	4087
Black No Fav.	.704	.456	4911
Oppose Aff. Act.	.815	.388	4706
White pen. Aff. Act.	.652	.476	5201
	Community Characteristics		
Rac Fr	.403	.171	22633
Gini	.419	.051	22633
Theil	.340	.085	22633
Btw Theil	.021	.015	22633
Wth Theil	.318	.075	22633
Rac Seg	.304	.125	22726
Ethn Fr	.749	.102	22633
Rac Fr Pred	.396	.167	22633
Cotton Bales ($100's$)	.999	2.64	22804
Log (*Size*)	4.14	2.13	22526
$Log\ (median\ inc._{\ w})$	10.56	.513	22633
$Log\ (median\ inc._{\ b})$	9.98	.569	22633
$Log\ (median\ inc._{\ na})$	10.12	.653	22633
$Log\ (median\ inc._{\ a})$	10.48	.618	22633
$Log\ (median\ inc._{\ h})$	10.11	.494	22633

Table 2: Correlations among Measures of Heterogeneity

Variables	Trust	Gini	Theil	Wth Ineq	Btw Ineq	Rac Fr
$Trust$	1.000					
$Gini$	-0.261	1.000				
$Theil$	-0.252	0.981	1.000			
$Wth\ Ineq$	-0.231	0.965	0.989	1.000		
$Btw\ Ineq$	-0.268	0.717	0.702	0.629	1.000	
$Rac\ Fr$	-0.266	0.612	0.578	0.511	0.719	1.000

Table 3. Baseline 1973-2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LS	LS	LS	LS	LS	LS	LS
Rac Fr	-0.221***		-0.162**		-0.189***		-0.072
	(0.039)		(0.070)		(0.065)		(0.076)
Gini		-0.691***	-0.236				
		(0.205)	(0.284)				
Theil				-0.298**	-0.039		
				(0.117)	(0.152)		
Btw Theil						-2.059***	-1.814***
						(0.367)	(0.539)
Wth Theil						0.120	0.231
						(0.143)	(0.154)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,056	20,056	20,056	20,056	20,056	20,056	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Gini* is the total income inequality calculated by the Gini index; *Theil* is the total income inequality calculated by the Theil index; *Btw Theil* is the income inequality *between* racial groups calculated by the Theil index; *Wth Theil* is the inequality *within* racial groups calculated by the Theil index. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census (1970, 1980, 1990, 2000). *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 4. Alternative Definitions of Racial Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LS	LS	LS	LS	LS	LS	LS
Btw Theil	-1.524***	-1.775***	-2.083***	-2.027***	-1.863***		-2.077***
	(0.544)	(0.487)	(0.385)	(0.358)	(0.421)		(0.406)
Wth Theil	0.243	0.214	0.211	0.188	0.225		0.201
	(0.153)	(0.151)	(0.149)	(0.152)	(0.149)		(0.149)
Share w	0.106*						
	(0.056)						
Share b		-0.120					
		(0.082)					
Share na			1.006				
			(1.053)				
Share a				0.402**			
				(0.157)			
Share h					-0.085		
					(0.051)		
Rac Seg						-0.082*	-0.019
						(0.049)	(0.046)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,056	20,056	20,056	20,056	20,056	20,056	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Btw Theil* is the measure of income inequality *between* racial groups; *Wth Theil* is the measure of income inequality *within* racial groups; *Share w* is the share of Whites; *Share b* is the share of Blacks; *Share na* is the share of Native Americans; *Share a* is the share of Asians; *Share h* is the share of Hispanics; *Rac Seg* is the entropy index of racial segregation. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2008); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 5. Alternative Treatment of Time Dimension

	State Time Trend		Previous Census		Closest Census	
	(1)	(2)	(3)	(4)	(5)	(6)
	LS	LS	LS	LS	LS	LS
Rac Fr	-0.309***	-0.148	-0.194***	-0.066	-0.198***	-0.054
	(0.066)	(0.090)	(0.066)	(0.083)	(0.069)	(0.083)
Theil	-0.042		-0.082			-0.044
	(0.184)		(0.158)		(0.168)	
Btw Theil		-2.254***		-1.763***		-2.083***
		(0.682)		(0.617)		(0.561)
Wth Theil		0.317		0.109		0.255*
		(0.215)		(0.159)		(0.151)
State FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	No	No	No	No
Observations	20,056	20,056	20,056	20,056	20,056	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Theil* is the total income inequality calculated by the Theil index; *Btw Theil* is the income inequality *between* racial groups; *Wth Theil* is the inequality *within* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2008); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 6. Instrumental Variable Estimation

	(1) IV	(2) IV	(3) IV	
Rac Fr	-0.253***		-0.011	
	(0.054)		(0.131)	
Btw Theil		-2.441***	-2.670***	
		(0.473)	(0.956)	
Wth Theil		0.179	0.304*	
		(0.152)	(0.162)	
State FE	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	
Kleibergen-Paap F-stat	36.64	56.24	7.56	
Anderson-Rubin p-value	0.001	0.001	0.001	
		First-Stage Regressions		
	Rac Fr	*Btw Theil*	*Rac Fr*	*Btw Theil*
Rac Fr Pred.	0.743***		0.636***	0.048***
	(0.123)		(0.140)	(0.010)
Hist. Cotton Prod.		0.265***	0.205	0.186***
		(0.035)	(0.181)	(0.040)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	20,056	20,056	20,056	20,056

Note: The method of estimation in the upper panel is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in the upper panel is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the income inequality *between* racial groups; *Wth Theil* is the inequality *within* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. The bottom panel reports the corresponding first-stage regressions. *Rac Fr Pred.* is the predicted index of racial fragmentation, based on earlier settlements location of Hispanic and Asian population. *Hist. Cotton Prod.* is 100's bales per Km^2, from the 1889 U.S. Census on Agriculture. Further details on the construction of the instruments are in Section 3.2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 7. Threat from Minorities and Political Opinion

	No favouritism for Blacks			Oppose affirmative action			Affirmative action penalizes Whites		
	Full sample		Whites only	Full sample		Whites only	Full sample		Whites only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	LS	IV	IV	LS	IV	IV	LS	IV	IV
Rac Fr	0.027	0.021	0.229	-0.033	-0.260*	0.048	0.167*	-0.038	0.384***
	(0.140)	(0.222)	(0.238)	(0.076)	(0.151)	(0.129)	(0.092)	(0.165)	(0.144)
Btw Theil	1.386	0.965	-0.675	0.744	2.255**	-0.070	-0.017	1.192	-1.344
	(1.054)	(1.842)	(1.902)	(0.503)	(1.113)	(0.920)	(0.603)	(1.040)	(1.011)
Wth Theil	-0.366	-0.291	-0.277	-0.141	-0.155	-0.222	-0.265	-0.236	-0.183
	(0.304)	(0.270)	(0.305)	(0.161)	(0.176)	(0.164)	(0.200)	(0.214)	(0.234)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat		15.11	17.99		15.66	18.02		15.64	18.58
Anderson-Rubin p-value		0.061	0.910		0.692	0.538		0.400	0.114
Observations	7,361	7,361	5,124	7,085	7,085	4,967	7,495	7,495	5,322

Note: The method of estimation in columns (1), (4), (7) is Least Squares (LS); in columns (2), (3), (5), (6), (8), (9) is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in columns (1)-(3) is *Black Favouritism*, coded one for individuals who think that Blacks should overcome prejudice without political favouritism, and zero otherwise; in columns (4)-(6) is *Affirmative Action*, coded one for individuals who think that Blacks should not be given preference in hiring and promotion, and zero otherwise; in columns (7)-(9) is *White Penalized*, coded one for individuals who think it is likely that a White won't get a job or promotion while an equally or less qualified Black gets one, and zero otherwise. (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the measure of income inequality *between* racial groups; *Wth Theil* is the measure of income inequality *within* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2008); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 8. Stereotypes

	Lazy same group		Lazy other group		Unintelligent same group		Unintelligent other group	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LS	IV	LS	IV	LS	IV	LS	IV
Rac Fr	-0.012	-0.160	-0.015	-0.110	-0.170**	-0.155	-0.005	-0.132
	(0.046)	(0.136)	(0.111)	(0.284)	(0.071)	(0.173)	(0.104)	(0.240)
Btw Theil	-0.099	1.376	0.900	2.616	1.188***	-0.357	1.545***	2.405
	(0.282)	(0.992)	(0.600)	(2.083)	(0.380)	(1.217)	(0.547)	(1.790)
Wth Theil	0.065	-0.056	-0.427**	-0.642***	-0.020	0.240	-0.674***	-0.704***
	(0.075)	(0.115)	(0.196)	(0.231)	(0.133)	(0.170)	(0.182)	(0.223)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat		3.37		3.37		2.97		2.97
Anderson-Rubin p-value		0.084		0.024		0.032		0.082
Observations	6,608	6,608	6,608	6,608	5,786	5,786	5,786	5,786

Note: The method of estimation in columns (1), (3), (5), (7) is Least Squares (LS); in columns (2), (4), (6), (8) is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in columns (1)-(2) is *Lazy Same Group*, coded one for individuals who think that people of their own racial group are lazy, and zero otherwise; in columns (3)-(4) is *Lazy Other Group*, coded one if they think that people of a different racial group are lazy, and zero otherwise; in columns (5)-(6) is *Unintelligent Same Group*, coded one if they think that people of their own racial group are unintelligent, and zero otherwise; in columns (7)-(8) is *Unintelligent Other Group*, coded one if they think that people of a different racial group are unintelligent, and zero otherwise. (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the measure of income inequality *between* racial groups; *Wth Theil* is the measure of income inequality *within* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2008); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 9. Membership in Associations

	Member of at least one association				Unions	Church	Professional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LS	LS	LS	IV	IV	IV	IV
Rac Fr	-0.028		0.170	0.465*	0.088	0.680**	0.189
	(0.089)		(0.125)	(0.267)	(0.139)	(0.318)	(0.133)
Btw Theil		-1.355	-2.219*	-6.538**	-3.844***	-7.117**	-1.220
		(0.983)	(1.156)	(3.043)	(1.159)	(3.472)	(1.781)
Wth Theil		-0.145	-0.234	-0.042	0.232	-0.270	-0.043
		(0.277)	(0.285)	(0.363)	(0.236)	(0.399)	(0.220)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat				11.40	11.42	11.42	11.42
Anderson-Rubin p-value				0.035	0.000	0.018	0.258
Observations	12,597	12,597	12,597	12,597	12,493	12,515	12,486

Note: The method of estimation in columns (1)-(3) is Least Squares (LS), in columns (4)-(7) is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in columns (1)-(4) is *Membership*, coded one for individuals who are members of at least one group, and zero otherwise (Source: GSS cumulative data file 1973-2010). Columns (5)-(7) refer to membership in specific groups. All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the measure of income inequality *between* racial groups; *Wth Theil* is the measure of income inequality *within* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2008); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 10. Racial Income Inequality and Preference for Similarity

		IV coeff. of *Btw Theil*		$\beta_0 = \beta_1$	Fraction of Yes
		(1)	(2)	(3)	(4)
		Yes	No		
[1]	Against redistribution/ Against interracial marriage	-9.202***	-0.921	0.09	0.26
		(3.388)	(1.813)		
[2]	Against redistribution/ Racist has right to teach	-1.855	-1.687	0.46	0.51
		(1.756)	(1.839)		
[3]	Against redistribution/ Whites have right to segregated neighborhood	-13.333**	-3.288*	0.01	0.19
		(5.228)	(1.918)		
[4]	Against redistribution/ No opposite race for dinner	-5.046**	-2.018	0.10	0.64
		(2.502)	(4.719)		
[5]	Against redistribution/ Black should not push	-6.830	-6.171*	0.05	0.29
		(4.532)	(3.718)		
[6]	Against redistribution/ Against children to school with opposite race	-2.238	-5.222	0.18	0.43
		(4.633)	(4.645)		
[7]	Against redistribution/ Against busing	-5.440*	-2.885	0.02	0.66
		(2.927)	(5.351)		
[8]	Against redistribution/ Allow racist books	-3.002	-1.728	0.21	0.40
		(2.598)	(1.922)		

Note: The method of estimation in columns (1)-(2) is Two Stages Least Squares (IV). Column (1) reports the coefficient of *Btw Theil* for the sample of respondents with strong in-group preferences; column (2) for the sample of respondents with weak in-group preferences. Column (3) tests whether the two coefficients are statistically different. Column (4) reports the fraction of individuals with strong in-group preferences, for each separate question. All regressions include the full set of individual and community controls used in the baseline specification, as well as state and year fixed effects. *Against redistribution* is coded one for individuals who say that "the government should not concern itself with reducing income difference between the rich and the poor". In each row, this variable is matched with a dummy variable reflecting interracial attitudes. In [1] the dummy is equal to one if the respondent thinks that "there should be laws against marriages between blacks and whites". In [2] if the respondent thinks that "a person who believes that blacks are genetically inferior should be allowed to teach in a college or university". In [3] if the respondent agrees strongly that "white people have a right to keep blacks out of their neighborhoods if they want to, and blacks should respect that right". In [4] if "during the last few years, no one in the respondent's family has brought a friend of the opposite race home for dinner". In [5] if the respondent agrees strongly that "blacks shouldn't push themselves where they're not wanted". In [6] if the respondent "would have any objection to sending his/her children to a school where half of the children are of the opposite race". In [7] if the respondent "in general opposes the busing of black and white school children from one school district to another". In [8] if the respondent thinks that "racist books should be allowed in libraries". *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 11. Racial Income Inequality and Fractionalization

	Below Median	Above Median	Pooled Below-Above	
	(1)	(2)	(3)	(4)
	LS	LS	LS	IV
Rac Fr	-0.087	-0.196		
	(0.120)	(0.131)		
Btw Theil	1.759	-2.277**		
	(1.482)	(1.095)		
Wth Theil	-0.014	0.269		
	(0.261)	(0.218)		
$Rac\ Fr_{\ bel}$			-0.119	0.275
			(0.093)	(0.317)
$Rac\ Fr_{\ abo}$			-0.183	-0.094
			(0.117)	(0.230)
$Btw\ Theil_{\ bel}$			1.169	-7.904
			(1.305)	(6.117)
$Btw\ Theil_{\ abo}$			-2.036***	-2.081*
			(0.498)	(1.174)
$Wth\ Theil_{\ bel}$			-0.134	0.596
			(0.192)	(0.617)
$Wth\ Theil_{\ abo}$			0.307**	0.440**
			(0.140)	(0.202)
Below			0.250***	0.034
			(0.095)	(0.176)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat				2.141
Anderson-Rubin p-value				0.002
Observations	10,442	9,614	20,056	20,056

Note: The method of estimation in columns (1)-(3) is Least Squares (LS), in column (4) is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the income inequality *between* racial groups; *Wth Theil* is the inequality *within* racial groups. *Below* is a dummy variable equal to one if the MSA level of racial fragmentation is below the median, and zero otherwise. $RacFr_{bel}$, $Btw\ Theil_{bel}$, $Wth\ Theil_{bel}$ are the measures of community heterogeneity interacted with the dummy *Below*. $RacFr_{abo}$, $Btw\ Theil_{abo}$, $Wth\ Theil_{abo}$ are the corresponding measures for MSA above the median level of racial fragmentation. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 12. Racial Income Inequality and Size of the Groups

	Whites	Blacks	Ind Am	Asian	Hispanic	Pooled Races
	(1)	(2)	(3)	(4)	(5)	(6)
	LS	LS	LS	LS	LS	LS
Rac Fr	-0.075	-0.275*	0.810*	0.200	0.240	
	(0.099)	(0.166)	(0.436)	(0.909)	(0.281)	
Btw Theil	-1.758**	-0.525	-6.497*	-8.133*	-5.142***	
	(0.713)	(1.066)	(3.316)	(4.433)	(1.773)	
Wth Theil	0.305*	0.085	-0.781	1.508	0.932	
	(0.177)	(0.335)	(0.941)	(1.404)	(0.644)	
$Btw\ Theil_w$						-1.718***
						(0.591)
$Btw\ Theil_b$						-1.521*
						(0.789)
$Btw\ Theil_{na}$						-2.454
						(1.739)
$Btw\ Theil_a$						-4.259*
						(2.149)
$Btw\ Theil_h$						-2.361**
						(1.140)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,015	2,887	592	421	1,141	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Btw Theil* is the measure of income inequality *between* racial groups; *Wth Theil* is the measure of income inequality *within* racial groups; $Btw\ Theil_w$ is the interaction of the income inequality *between* racial groups with the dummy variable White, equal to one if the individual identifies himself as White. Same definition applies to $Btw\ Theil_b$, $Btw\ Theil_{na}$, $Btw\ Theil_a$ and $Btw\ Theil_h$, which are interacted with the corresponding racial identity dummies. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Appendix to
Trust and Racial Income Inequality: Evidence from the U.S.

A. Formal conceptual framework

I consider a community consisting of two racial groups, labelled by $i = 1, 2$. I suppose that there is a fraction $p \in [0, 1]$ of individuals belonging to the first racial group and a fraction $1-p$ of individuals of the second. Therefore, the level of racial fragmentation of the community is represented by the parameter p: increasing p from 0 to 1/2, the racial fragmentation increases from the minimum to the maximum value.

To introduce the within-groups inequality I suppose that within each racial group there is a fraction α_i of rich and a fraction $1 - \alpha_i$ of poor ($\alpha_i \in [0, 1]; i = 1, 2$). For the rich the level of income is assumed to be the same, and similarly for the poor. I shall be particularly interested in two extreme cases:

(*i*) $\alpha_1 = 1$, $\alpha_2 = 0$ (or $\alpha_1 = 0$, $\alpha_2 = 1$): in this case the between-groups inequality is maximum, whereas the within-groups inequality is minimum;

(*ii*) $\alpha_1 = \alpha_2 = 1/2$: conversely, in this case the between-groups inequality is minimum, whereas the within-groups inequality is maximum.

For every racial group, I shall denote by $\omega_2 > 0$ the level of trust of each individual towards another individual *both* of the same race *and* of the same income. On the other hand, I shall denote by $\omega_1 > 0$ the level of trust towards another individual *either* of the same race, yet of different income, *or* of the same income, yet of different race.[25] Clearly, it is natural to assume $\omega_2 > \omega_1$, as I do in the following. Finally, I suppose to be equal to zero the level of trust towards individuals *both* of different race *and* of different income.

On these grounds, the expected trust level from a random match *for a rich* belonging to the *first* racial group is the following:

$$W_1^{(r)} = [\alpha_1\omega_2 + (1-\alpha_1)\omega_1]\, p + \alpha_2\omega_1(1-p)\,,$$

whereas *for a rich* belonging to the *second* racial group is:

$$W_2^{(r)} = [\alpha_2\omega_2 + (1-\alpha_2)\omega_1]\,(1-p) + \alpha_1\omega_1 p\,.$$

Similarly, the expected trust levels *for the poor* belonging to each racial group are, respectively:

$$W_1^{(p)} = [(1-\alpha_1)\omega_2 + \alpha_1\omega_1]\, p + (1-\alpha_2)\omega_1(1-p)\,,$$

[25] This assumption is only made for simplicity. A third level of trust $\omega_3 \neq \omega_1$, towards individuals of the same income but of different race, could be easily dealt with.

and:

$$W_2^{(p)} = [(1-\alpha_2)\omega_2 + \alpha_2\omega_1]\,(1-p) + (1-\alpha_1)\omega_1 p\,.$$

Clearly, the share of rich individuals belonging to the first racial group in the total population of the community is $\alpha_1 p$, whereas the share of the poor of the same racial group is $(1-\alpha_1)p$. Therefore, the *expected trust level* W_1 *of the first racial group* is obtained multiplying $W_1^{(r)}$ by the population share $\alpha_1 p$ and $W_1^{(p)}$ by the population share $(1-\alpha_1)p$ and summing over the two terms. This gives:

$$W_1 = \left\{\left[\alpha_1^2 + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 + [\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)]\,\omega_1 p(1-p)\,.$$

Similarly, the *expected trust level* W_2 *of the second racial group* is obtained multiplying $W_2^{(r)}$ by the population share $\alpha_2(1-p)$ and $W_2^{(p)}$ by the population share $(1-\alpha_2)(1-p)$ and summing over the two terms. This gives:

$$W_2 = \left\{\left[\alpha_2^2 + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 + [\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)]\,\omega_1 p(1-p)\,.$$

Then, the *total trust level* $W := W_1 + W_2$ *of the community* has the following expression:

$$\begin{aligned} W = &\left\{\left[\alpha_1^2 + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 + \\ &+ \left\{\left[\alpha_2^2 + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 + \\ &+ 2\,[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)]\,\omega_1 p(1-p)\,. \end{aligned} \tag{A.6}$$

In the following I address the dependence of W on the quantities p, α_1 and α_2, to investigate how the total level of trust in the community is affected by different levels of racial diversity, between-groups inequality and within-groups inequality. As observed above, increasing p from 0 to 1/2 increases the racial diversity of the model community from its minimum to its maximum, while changing the values of the couple (α_1, α_2) from $(1, 0)$ to $(1/2, 1/2)$ the limit situations concerning between-groups and within-groups inequality are obtained. In this connection, observe that for both $(\alpha_1, \alpha_2) = (1, 0)$ and $(\alpha_1, \alpha_2) = (0, 1)$ (i.e. when racial income inequality is at its maximum) the total trust level is simply:

$$\tilde{W} = \omega_2\left[p^2 + (1-p)^2\right]\,.$$

Instead of studying the total trust level itself, it seems natural to address its change with respect the extreme situation represented by $\tilde{W}$.

Thus I shall study the difference $\Delta_1 := W - \tilde{W}$, namely:

$$\begin{aligned}\Delta_1 = &\left\{\left[(\alpha_1^2 - 1) + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 + \\ &+ \left\{\left[(\alpha_2^2 - 1) + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 + \\ &+ 2\left[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p) \; = \\ &= 2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2 + \\ &+ 2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2 + \\ &+ 2\left[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p)\end{aligned} \tag{A.7}$$

as a function p, α_1 and α_2. Δ_1 thus captures the additional trust of the community when it moves away from the extreme case of maximum racial income inequality. Observe that the expression of W is invariant under the transformation $p \to 1-p$, $\alpha_1 \to \alpha_2$, as it must be.

Another relevant quantity I shall address is the *difference* $\Delta_2 := W_1 - W_2$ *between the trust levels of the two racial groups*, namely:

$$\begin{aligned}\Delta_2 = &\left\{\left[\alpha_1^2 + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 - \\ &- \left\{\left[\alpha_2^2 + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 \; = \\ &= 2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2 - 2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2 \, .\end{aligned} \tag{A.8}$$

I shall now pursue the analysis under the following:

Parametric Assumption (A): $\quad \alpha_1 + \alpha_2 = 1 \qquad (\alpha_1, \alpha_2 \in [0, 1/2])\,,$

The reason of the above assumption is that it is satisfied in the extreme cases (i)-(ii) mentioned at the beginning of this section - namely, $(\alpha_1, \alpha_2) = (1, 0)$ and $(\alpha_1, \alpha_2) = (1/2, 1/2)$. In fact, if (A) holds, I can connect the case $(\alpha_1, \alpha_2) = (1, 0)$ to $(\alpha_1, \alpha_2) = (1/2, 1/2)$ by increasing α_2 from 0 to 1/2 (accordingly, α_1 decreases from 1 to 1/2). Therefore, making assumption (A) and increasing α_2 from 0 to 1/2 is a simple way in the model to decrease the between-groups inequality while increasing the within-groups inequality.

Observe that:

$$\alpha_1 = 1 - \alpha_2\,, \quad 1 - \alpha_1 = \alpha_2 \quad \text{if } (A) \text{ holds}\,.$$

Therefore, under assumption (A) the difference Δ_1 becomes simply (see (A.7)):

$$\begin{aligned}\Delta_1 &= 2\alpha_2(1-\alpha_2)\left\{(\omega_1-\omega_2)\left[p^2 + (1-p)^2\right] + 2\omega_1 p(1-p)\right\} = \\ &= 2\alpha_2(1-\alpha_2)\left[-2\omega_2 p^2 + 2\omega_2 p + (\omega_1 - \omega_2)\right]\,.\end{aligned} \tag{A.9}$$

Let's now make the following:

Parametric Assumption (B): $\omega_1 < \omega_2 < 2\omega_1\,.$

If (B) is satisfied, it is immediately seen from (A.9) that the difference Δ_1 vanishes at two values of the parameter p, namely

$$p = p_{\pm} := \frac{\omega_2 \pm \sqrt{\omega_2(2\omega_1 - \omega_2)}}{2\omega_2} \quad .$$

The following result is also an immediate consequence of equality (A.9):

Let assumption (A) be satisfied. If (B) holds, the difference Δ_1 is positive in the interval $(p_-, p_+) \subseteq (0,1)$, zero at $p = p_{\pm}$ and negative elsewhere. Moreover,

- *the interval (p_-, p_+) is centered at $p = 1/2$ and only depends on the values of ω_1 and ω_2. It extends to the whole interval $(0,1)$ in the limiting case $\omega_1 = \omega_2$ and shrinks to the point $\{1/2\}$ in the limiting case $\omega_2 = 2\omega_1$;*
- *for every fixed $p \in (p_-, p_+)$, the difference Δ_1 increases when α_2 increases in the interval $[0, 1/2]$.*

Figure 4 plots the graph of Δ_1 at different levels of p. Is it worth noting that the region of positivity of Δ_1 (if (A) and (B) are satisfied) is centred at the value $p = 1/2$, namely where the racial fragmentation is maximum. Given the definition of Δ_1, this means that the benefit of moving away from a situation of extreme racial income inequality is maximum when the community is at the highest level of racial fragmentation. Clearly, the opposite is also true: the reduction of trust due to increasing racial income inequality is maximum when racial fragmentation is at its highest. This result represents the formal counterpart of the first implication discussed qualitatively in section 4.3.

Let's now address the quantity Δ_2. If assumption (A) holds, it reads simply (see (A.8)):

$$\begin{aligned}\Delta_2 &= 2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)\left[p^2-(1-p)^2\right] = \\ &= 2\alpha_2(1-\alpha_2)(\omega_2-\omega_1)(1-2p)\,.\end{aligned}$$

Then I have the following result:

Let assumption (A) be satisfied and $\omega_1 < \omega_2$. Then for any $\alpha_2 \in [0, 1/2]$

$$W_1 > W_2 \quad \Leftrightarrow \quad p < 1/2\,.$$

Moreover, for every fixed $p < 1/2$ the difference $W_1 - W_2$ increases when α_2 increases in the interval $[0, 1/2]$.

Thus, when racial income inequality decreases (i.e. when α_2 increases) the minority group increases its level of trust more than the majority group. Clearly, the opposite is also true: when racial income inequality increases, the minority group reduces its level of trust more than the majority group. This represents the formal counterpart of the second implication discussed qualitatively in section 4.3.

B. Within Groups Inequality

While the focus of the paper is on the effect of racial income inequality on trust, it is also instructive to consider the role of income inequality *within* races. This sheds further light on the assumption of preference for similarity. An increase in within-groups inequality has two opposite effects on the level of trust of the community: on the one hand, it reduces it by making initially identical individuals different in income. On the other, it increases it by making initially different individuals similar in income. The overall impact is ex-ante ambiguous, and which of the two effects prevails crucially depends on the exact income distribution of the different racial groups. Irrespective of the distributional aspects, however, the impact of within-groups inequality is comparatively more adverse in racially homogeneous MSA. Indeed, in the extreme case in which all individuals belong to the same racial group, greater within-group inequality only reduces the number of identical individuals, univocally decreasing the level of trust. In racially fragmented MSA, instead, this negative effect can be partially or completely offset by the increasing income overlaps between individuals of different races. Depending on the degree of concavity of the individuals' preference for similarity, the overall impact on trust in racially fragmented MSA may even be positive.[26]

The impact of within-groups inequality on trust is investigated in Appendix Table A2. For each respondent in the sample, based on the racial group of belonging, I calculate the income inequality within his own racial group as well as the income inequality within the other racial groups in the MSA. Under the assumption of preference for similarity, an increase in the former is unambiguously detrimental for the level of trust of the respondent, whereas an increase in the latter has ambiguous effects. Column (1) shows that only the own group inequality reduces the amount of trust, while the effect of greater inequality within other groups is negative but not statistically significant. A one standard deviation increase in the inequality within one's own group reduces trust by 1.7 percentage points, an effect that is significant at the 95% confidence level. Column (2) adds the income inequality between racial groups, which is negative and significant in line with the results from the baseline specification. The inequality within one's own racial group remains negative and significant at the 95% level. Column (3) adds the index of racial fragmentation in the MSA, whose inclusion does not affect the point estimate of own group inequality, which remains significant at the 90% level. Column (4) shows the corresponding IV specification, which further confirms the detrimental effect of greater own group inequality.

Columns (5) and (6) split MSA based on the difference between the income level of the majority group and the other racial groups. The smaller this difference, the more citizens should reduce their trust when income inequality within other groups increases. Indeed, in the extreme case of all races having the same average income, greater inequality within other groups would only increase the number of different individuals, unambiguously reducing the level of trust. For citizens in MSA with large income differences between races, instead, greater

[26] In this regard, the observation is consistent with the positive coefficients of within-groups inequality in columns (3) and (4) of Table 11.

income inequality within other groups should be less detrimental and may even increase their level of trust. In this case greater income dispersion within other groups raises the probability of income overlaps between individuals of different races, increasing the number of partially similar individuals. The results in columns (5) and (6) support the argument, both under LS and IV: individuals in MSA with similar income levels reduce their trust when the inequality within other races increases. The estimated effect is significant at the 90% confidence level. On the contrary, individuals in MSA with large income differences between races increase their trust when the inequality within other races increases, and reduce it when the inequality in their own group increases.

Appendix Table A2. Within-Groups Inequality

					Below	Above
	(1) LS	(2) LS	(3) LS	(4) IV	(5) LS	(6) LS
$Wth\ Theil_{own}$	-0.162**	-0.134**	-0.123*	-0.110*	0.019	-0.334***
	(0.068)	(0.065)	(0.065)	(0.066)	(0.087)	(0.086)
$Wth\ Theil_{oth}$	-0.106	0.042	0.090	0.123	-0.225*	0.468**
	(0.095)	(0.106)	(0.113)	(0.110)	(0.122)	(0.176)
$Btw\ Theil$		-1.835***	-1.552***	-2.693**	-1.313*	-0.112
		(0.431)	(0.590)	(1.109)	(0.766)	(0.940)
$Rac\ Fr$			-0.072	0.006	-0.237**	-0.103
			(0.074)	(0.142)	(0.092)	(0.125)
Kleibergen-Paap F-stat				7.621		
Anderson-Rubin p-value				0.001		
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,056	20,056	20,056	20,056	10,180	9,876

Note: The method of estimation in columns (1), (2), (3), (5), (6) is Least Squares (LS), in column (4) is Two Stages Least Squares (IV). The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is $Trust$, coded one for individuals who say they can trust others, and zero otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: $Rac\ Fr$ is the index of racial fragmentation; $Wth\ Theil_{own}$ is the measure of income inequality *within* the respondent's racial group; $Wth\ Theil_{oth}$ is the measure of income inequality *within* the other racial groups, excluding the respondent's own group; $Btw\ Theil$ is the measure of income inequality *between* racial groups. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, White, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table A1. MSAs in GSS Sample, 1973-2010

Name	Avg. Trust	Avg. Racial Fragm.	Avg. Ineq.	Respondents
Akron, OH	.51	.18	.23	73
Albany-Schenectady-Troy, NY	.47	.14	.27	106
Allentown-Bethlehem-Easton, PA	.45	.13	.27	160
Anchorage, AK	.31	.47	.27	52
Appleton-Oskosh-Neenah, WI	.58	.04	.2	69
Atlanta, GA	.37	.49	.34	397
Atlantic City, NJ	.29	.37	.27	97
Austin, TX	.38	.55	.44	88
Baltimore, MD	.34	.44	.33	348
Bellingham, WA	.51	.26	.35	115
Biloxi-Gulfport, MS	.18	.35	.35	77
Binghamton, NY	.4	.12	.31	91
Birmingham, AL	.22	.41	.3	161
Boston, MA	.44	.29	.38	406
Buffalo-Niagara Falls, NY	.34	.22	.28	263
Burlington, VT	.46	.05	.28	78
Charlotte-Gastonia-Rock Hill, NC	.33	.47	.34	453
Chicago, IL	.38	.51	.33	1069
Cincinnati-Hamilton, OH	.37	.43	.47	161
Clarksville- Hopkinsville, KY	.25	.35	.36	16
Cleveland, OH	.36	.34	.31	300
Columbia, SC	.37	.42	.35	85
Columbus, GA	.24	.52	.38	108
Columbus, OH	.31	.31	.34	360
Dallas-Fort Worth, TX	.36	.51	.36	424
Dayton-Springfield, OH	.45	.25	.28	109
Denver-Boulder, CO	.47	.39	.34	420
Des Moines, IA	.42	.11	.3	163
Detroit, MI	.34	.41	.31	557
Eau Claire, WI	.48	.08	.3	88
Eugene-Springfield, OR	.5	.11	.3	109
Evansville, IN	.37	.13	.31	54
Flint, MI	.48	.3	.22	73
Fort Lauderdale-Hollywood-Pompano Beach, FL	.29	.53	.38	97
Fort Wayne, IN	.5	.18	.27	156
Fresno, CA	.35	.55	.32	176
Grand Rapids, MI	.46	.26	.35	198
Green Bay, WI	.43	.05	.2	19
Harrisburg-Lebanon–Carlisle, PA	.42	.15	.25	79
Hartford-Bristol-Middleton- New Britain, CT	.44	.25	.24	62
Houston-Brazoria, TX	.3	.62	.37	490
Indianapolis, IN	.37	.28	.29	142
Jackson, MS	.17	.5	.37	99
Jacksonville, FL	.4	.41	.31	88
Johnson City-Kingsport–Bristol, TN	.31	.06	.3	104
Kansas City, MO	.36	.27	.3	196
Knoxville, TN	.39	.17	.34	178
Lafayette, LA	.3	.42	.57	50
Lansing, MI	.46	.27	.29	80
Lexington-Fayette, KY	.5	.21	.5	16
Little Rock–North Little Rock, AR	.35	.36	.27	82
Long Branch-Asbury Park, NJ	.57	.22	.22	84
Los Angeles-Long Beach, CA	.35	.63	.4	1165
Lynchburg, VA	.25	.33	.39	98
Madison, WI	.54	.09	.28	131

Table A1. MSAs in GSS Sample, 1973-2010 (continued)

Name	Avg. Trust	Avg. Racial Fragm.	Avg. Ineq.	Respondents
Manchester, NH	.59	.08	.22	119
Memphis, TN	.29	.5	.47	100
Miami-Hialeah, FL	.2	.6	.38	207
Milwaukee, WI	.52	.29	.28	131
Minneapolis-St. Paul, MN	.54	.19	.3	368
Modesto, CA	.24	.52	.34	72
Montgomery, AL	.14	.47	.35	125
Nashville, TN	.39	.39	.41	307
New Haven-Meriden, CT	.35	.28	.31	144
New Orleans, LA	.36	.55	.42	215
New York-Northeastern NJ	.34	.56	.38	2173
Norfolk-VA Beach–Newport News, VA	.31	.47	.34	174
Oklahoma City, OK	.38	.36	.32	247
Orlando, FL	.36	.31	.29	100
Philadelphia, PA	.37	.39	.34	683
Phoenix, AZ	.44	.41	.33	362
Pittsburgh, PA	.41	.17	.33	417
Portland, OR	.48	.24	.32	279
Providence-Fall River-Pawtucket, RI	.48	.17	.3	98
Provo-Orem, UT	.52	.13	.28	126
Racine, WI	.53	.23	.19	74
Raleigh-Durham, NC	.44	.48	.38	78
Reading, PA	.52	.09	.22	84
Richland-Kennewick-Pasco, WA	.34	.35	.43	104
Richmond-Petersburg, VA	.32	.46	.35	274
Riverside-San Bernardino,CA	.44	.46	.28	192
Rochester, NY	.44	.37	.35	252
Sacramento, CA	.47	.43	.31	123
Saginaw-Bay City-Midland, MI	.56	.19	.29	119
St. Louis, MO	.37	.32	.29	414
San Antonio, TX	.38	.58	.43	64
San Diego, CA	.42	.51	.38	323
San Francisco-Oakland-Vallejo, CA	.41	.61	.37	738
Santa Barbara, CA	.49	.52	.45	70
Savannah, GA	.22	.48	.45	89
Seattle-Everett, WA	.48	.33	.32	261
Springfield, MO	.5	.1	.35	76
Springfield-Holyoke-Chicopee, MA	.51	.19	.26	66
Stamford, CT	.57	.23	.2	73
Syracuse, NY	.4	.17	.34	59
Tacoma, WA	.47	.22	.29	72
Tampa-St. Petersburg-Clearwater, FL	.35	.34	.38	266
Texarkana, AR	.14	.36	.44	76
Topeka, KS	.51	.28	.24	75
Tucson, AZ	.29	.52	.39	68
Tulsa, OK	.22	.42	.46	64
Tuscaloosa, AL	.27	.46	.53	93
Waco, TX	.27	.43	.36	173
Washington, DC	.39	.56	.34	464
West Palm Beach-Boca Raton-Delray Beach, FL	.39	.41	.44	41
Wheeling, WV	.37	.06	.28	108
Wichita Falls, TX	.39	.28	.28	79
Worcester, MA	.4	.24	.37	163
York, PA	.29	.07	.25	70
Youngstown-Warren, OH	.35	.21	.22	92

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