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Trust, Racial Fragmentation and Income Inequality: New Evidence from the U.S.

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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. This result is consistent with a simple conceptual framework where concurrent differences in race and income are especially detrimental for trust formation. I find empirical support for further implications deriving from this assumption. In particular, I show that racial income inequality has a more detrimental effect in more racially fragmented communities and that trust falls more in minority groups than in the majority group when racial income inequality increases.

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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 2.6 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 the racial income inequality of each MSA with the value that would be observed if all racial groups in the community had a level of income equal to their national average. 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.

My empirical results are consistent with a simple conceptual framework where individuals can differ in both race and income, and trust falls at an increasing rate when individuals differ in both dimensions. In such a framework, an increase in racial income inequality reduces the average level of trust in the community. Intuitively, this happens because in racially income unequal communities a large share of population is either identical (same race and income) or very

[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.

different (different race and income). On the contrary, communities with lower racial disparities have a larger share of population that is similar in one dimension (same income but different race; same race but different income). If trust falls at increasing rates as diversity increases, the additional trust towards individuals similar in two dimensions does not compensate for the reduction in trust towards individuals different in two dimensions. As a result, the overall effect of greater racial income inequality on trust is negative and racially income unequal communities have, on average, lower levels of trust.

To estimate empirically the impact of income disparities between racial groups I measure income inequality by 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 separate the *between-groups* inequality, capturing the portion of overall inequality due to differences between different (racial) groups, from the *within-groups* inequality, capturing the portion due to income differences among individuals of the same (racial) group. By exploiting the decomposability of the Theil index, I can estimate the effect of overall income inequality on trust in different metropolitan areas, and then decompose this aggregate effect into the effects deriving from income inequality between racial groups and income 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 1973-2008, 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 in the U.S. 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; 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, the first to emphasize the negative effect of community heterogeneity on trust have been Alesina and La Ferrara (2002), who show 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 are documented by Costa and Kahn (2003) and Putnam (2007), who also distinguishes between the effect of racial fragmentation on trust in people of their own race and other races. He finds the effect to be negative on both out-group and in-group attitudes, concluding that inhabitants in heterogeneous communities distrust their neighbours, regardless of the colour of their skin. A similar pattern applies to other countries as well: Leigh (2006) analyzes the case of Australia and finds that racial fragmentation is negatively correlated with the level of trust, while Gustavsson and Jordahl (2008) find that trust in Sweden is negatively associated with differences in disposable income, especially among individuals in the bottom half of the income distribution. In the context of the U.S., a number of studies also find a similar negative correlation 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 analytic support for the negative relation between community heterogeneity and measures of social capital observed in the data. The fundamental assumption of these models is that individuals have a preference for similarity, a long-held belief in psychology and sociology (Allport 1954, Coleman 1990).[4] Under this assumption, individuals derive a lower utility from matching with others that are different in race *or* income, so 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 brings results consistent with my empirical findings.

It is finally worth noting that while studies on trust and social capital formation have not investigated the role of racial income inequality, other strands of literature have - implicitly or explicitly - considered it. Recent work by Alesina et al. (2012), in particular, finds a negative

[4] Allport (1954) for instance observes that "People mate with their own kind. They eat, play, reside in homogeneous clusters. They visit with their own kind, and prefer to worship together".

relation between income inequality between ethnic groups and different measures of regional development and public good provision in Africa, suggesting - in line with the argument in this paper - that what matters for development are the economic differences between groups rather than the level of fragmentation. Their results are consistent with studies from the social conflict literature which also consider racial income inequality one crucial trigger of political animosity, leading to several inefficient political and economic outcomes. In particular, existing studies show that racial income inequality exacerbates social turmoil (Abu-Lughod, 2007), violent crime (Blau and Blau, 1982) and ethnic violence (Robinson, 2001; Stewart, 2003). Also, the negative relation between racial income inequality and public good provision found by Alesina et al. (2012) is in line with existing explanations of the redistribution gap between the US and Europe (Alesina and Glaeser, 2005) and adds micro-based evidence to existing studies on the lower provision of public goods in countries characterized by greater racial income inequality (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 provides an interpretation for the results and derives further testable implications, which are formally derived in the conceptual framework 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 1973-2008.[5] In each round, the GSS interviews about 1500 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, sex, family income, working conditions, marital status, size of the place of residence and a dummy for the race of the respondent. The top panel of Table 1 reports summary statistics for these variables. From the GSS Sensitive Data files I identify the metropolitan areas in

[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 my 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.

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 104 different MSA, listed in Appendix Table A1. As the GSS is built to be nationally representative, many MSA (typically the smallest in terms of population) are only sampled in few rounds, and then replaced with comparable ones. Appendix Table A1 reports the number 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 diversity is measured using a Herfindahl-type fragmentation index that captures the probability that two randomly drawn individual 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 US 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 0.396 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.

[7] More than two thirds of GSS respondents can be associated to their MSA. A further 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 18733 individuals.

[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.

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:

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

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-hans 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 a 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

[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).

(Alesina and La Ferrara, 2002; 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:

$$Tr_{im} = \beta_1 X_{im} + \beta_2 RacFr_m + \beta_3 Ineq_m + \delta_1 Z_m + \alpha_{s(m)} + \tau_t + \epsilon_{im} \tag{2.4}$$

where X_{im} is the vector of individual characteristics reported in Table 1. Z_m is a set of community characteristics including the logarithm of the median income of each racial groups living in the MSA (and its squared term), the logarithm of the MSA size and the index of ethnic fragmentation. $RacFr_m$ is the measure of racial fragmentation and $Ineq_m$ is the measure of aggregate income inequality (calculated either by the Gini or by the Theil index). $\alpha_{s(m)}$ and τ_t are State and year fixed effects. Finally, ϵ_{im} 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:

$$Tr_{im} = \beta_1' X_{im} + \beta_2' RacFr_m + \gamma_1' BtwIneq_m + \gamma_2' WthIneq_m + \delta_1' Z_m + \alpha_{s(m)} + \tau_t + \eta_{im} \tag{2.5}$$

where all variables are defined as above, except for $BtwIneq_m$ which is the inequality between racial groups (calculated by the Theil index) and $WthIneq_m$ which is the inequality within racial groups (calculated by the Theil index). 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 income differences between races on trust. In addition, we will be interested in observing the variation of the coefficient of racial fragmentation (from β_2 to β_2') once the inequality between races is explicitly accounted for in equation (2.5). In line with previous studies (Alesina and La Ferrara, 2002; Costa and Kahn, 2003), the method of estimation is Probit, reporting marginal coefficients calculated at the means.[11]

[11] Estimating the model by least squares provides qualitatively identical results.

3. Baseline Results

Table 3 reports the estimates of the effect of community heterogeneity on trust for the period 1973-2008. 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 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 15 percentage points. Starting from the sample mean, a one standard deviation increase in racial fragmentation decreases trust by 4 percentage points, or 11% 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 11% 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 99% 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) to (5) confirm the results in Alesina and La Ferrara (2002): both racial fragmentation and income inequality are negatively related with 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 relation with trust. The estimated coefficient implies that moving from the community in which the between-groups inequality is at its minimum (0.014) to that in which it is at its maximum (0.064) reduces the level of trust by 11 percentage points. The null hypothesis that the coefficients of between and within- racial groups inequality are equal is rejected at the 95% confidence level, 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 half and becomes statistically insignificant, while the income inequality between races remains negatively and significantly correlated with trust at the 95% confidence level. The estimated coefficient is sizeable: starting from the mean, a one standard deviation increase in between-groups inequality reduces trust by 2.6 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 the main result to alternative definitions of racial diversity. Columns (1) to (5) substitute the racial fragmentation index by, respectively, the share of Whites, Blacks, Native Americans, Asians and Hispanics living in the MSA. These specifications account for the possibility that the level of trust is affected by the presence of some specific racial group, rather than by racial diversity *per se*. It is important to verify the robustness of the results based on these alternative specifications, in order to discard the possibility that the income inequality between groups is simply capturing the different population shares of more or less affluent racial groups in the community. The estimates in columns (1) and (4) indeed suggest that the level of trust in the MSA is higher when the share of the most affluent racial groups, Whites and Asians, is higher. Similarly, column (5) shows that the level of trust in the MSA is lower when the share of Hispanics, one of the least affluent racial groups, is higher. The shares of Blacks and Native Americans in columns (2) and (3) are estimated more imprecisely and do not appear to be significantly associated with the level of trust in the community. Irrespective of the racial group considered, the estimated coefficient of the between-groups inequality remains negative and significant in all columns in line with the results from the baseline specification. This is reassuring of the fact that the measure of racial income inequality is not only proxying for the larger population share of more affluent racial groups. In columns (6) and (7) I consider a measure of racial segregation, which captures the spatial isolation of different groups in the MSA. Some authors argue that racial segregation, and not fragmentation, is detrimental for the level of trust in the community. The argument is that fragmented (but integrated) communities facilitate the repeated interactions of individuals of different races, increasing their level of mutual trust by overcoming their perceived differences (Stolle et al., 2008). Segregation, instead, would always reduce trust by isolating groups from each other and exaggerating their differences (Uslaner, 2011).

To measure racial segregation I use the entropy index calculated by Iceland (2004) and 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.[12] The results in column (6) confirm the negative relation between segregation and trust in my sample. The estimated coefficient is significant at the 90% confidence level and implies a reduction of trust by 1 percentage point for a one standard devia-

[12]The index is expressed as:

$$Segr_m = \sum_r \sum_i \left(\frac{t_{im}}{T_m E_m}\right) s_{irm}\, ln\left(\frac{s_{irm}}{S_{rm}}\right) \tag{3.6}$$

where t_{im} is the number of citizens in Census tract (neighborhood) i of MSA m, T_m is the total number of individuals in MSA m, s_{irm} is the share of individuals of race r in Census tract i of MSA m, S_{rm} is the total share of individuals of race r in MSA m, and E_m is the entropy score defined as $\sum_r S_{rm} ln\left(\frac{1}{S_{rm}}\right)$. The index ranges between 0 and 1. When all Census tracts have the same composition as the overall MSA, the index is at its minimum. When each Census tract in the MSA is completely segregated, so that only one racial group is present, the index achieves its maximum.

tion increase in segregation. The relation, however, is not robust to the inclusion of the measure of racial income inequality in column (7): when this is explicitly accounted for, the index of segregation drops by three-quarter and becomes insignificant. The measure of racial income inequality instead remains negatively associated with the level of trust at the 99% confidence level. This suggests that its impact on trust is not limited to the social stratification induced by the choice of different neighborhoods of residence. Indeed, the correlation between the two variables in the sample is only slightly positive (0.14). This is in line with the theoretical results of Sethi and Somanathan (2004), who show that segregation is consistent with both high and low levels of racial income inequality, when individuals care about both the affluence and the racial composition of neighborhoods.

Table 5 presents estimates in which the impact of racial income inequality is identified based on alternative sources of variation. Columns (1) and (2) replace the State and year fixed effects with State-year fixed effects, allowing for different States to follow different trends in the evolution of racial fragmentation and racial income inequality. The specification exploits the cross-sectional variation in any given year in the level of trust and racial income inequality among 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. Columns (3) and (4) replace the State fixed effects with MSA fixed effects, allowing for unobserved time-invariant heterogeneity across MSA. The identification now comes from the variation over time within each MSA. I focus on MSA that are sampled in all GSS rounds, in order to have enough time variation to significantly estimate the parameters.[13] The sample consists of 9417 individuals, over half of the total number of respondents in the baseline specification. Column (3) shows that the results for racial fragmentation and total income inequality are not robust to the inclusion of the MSA fixed effects: the estimated coefficients are both statistically insignificant and with the wrong sign. Changes over time in the MSA's aggregate measures of diversity thus do not seem to be associated with a reduction of trust. This stands in contrast to the results in column (4), where the coefficient of income inequality between races retains its negative and statistically significant association with the level of trust. The point estimate is larger than in the baseline specification: a one standard deviation increase in racial income inequality is associated with a reduction of trust by 3.5 percentage points, or 9% of the mean value of trust. This result provides additional evidence of the detrimental effect of racial income inequality on trust after controlling for unobservable and time-invariant characteristics of different MSA.

Columns (5) to (8) replace the interpolated measures of racial fragmentation and income inequality with their original values calculated at different Census years. Columns (5) and (6)

[13]Since the GSS is a nationally representative sample, most MSA are only sampled in few rounds and then replaced with others comparable from the point of view of the national representativity (see Appendix Table A1). The MSA that are sampled in all GSS rounds are: Atlanta, Baltimore, Boston, Charlotte, Chicago, Columbus, Dallas, Denver, Detroit, Los Angeles, Minneapolis, New York, Philadelphia, Phoenix, Pittsburgh, San Diego, San Francisco, St. Louis, Washington.

assign the value calculated at the preceding Census year and held constant over the following decade, while columns (7) and (8) assign the value calculated at the closest Census year. Maintaining the measures of community heterogeneity constant reduces concerns of serial correlation introduced by the linear interpolation in the baseline specification. 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 together with the aggregate income inequality in columns (5) and (7). Its coefficient, however, becomes insignificant when the income inequality is partitioned into between- and within- groups inequality in columns (6) and (8). As in the baseline specification, only the between-groups 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 in the full sample.

Table 6 tackles the issue of reverse causation between racial income inequality and trust. The index of racial income inequality is increasing in the inequality of average incomes across racial groups.[14] Hence, greater racial income inequality in an MSA will partly reflect greater inequality of average incomes across racial groups in the MSA. It is possible that differences in average incomes across racial groups partly reflect low levels of interracial trust. This could result in the estimates being biased as greater racial income inequality might partly be the consequence of low (interracial) trust levels in the MSA. To overcome this potential source of reverse causation bias, I instrument racial income inequality in MSA by racial income inequality in MSA if the average income level of each racial group was equal to its national level.[15] Table 6 presents two-stage least squares estimates of the effect of racial income inequality on trust. In column (1) I run the baseline specification controlling for the measure of racial fragmentation in the MSA. The estimated coefficient for instrumented racial income inequality is statistically significant at the 99% confidence level and indicates a stronger (negative) effect of racial income inequality on trust compared to the non-instrumented estimates. Hence, if anything, the two-stage least squares result suggests that the effect of racial income inequality on trust is stronger than suggested by the non-instrumented estimates. In columns (2) to (6) I replace the index of racial fragmentation with the population shares of different racial groups. The estimates confirm the negative relation between racial income inequality and trust, and the estimated coefficients are generally larger than in the non-instrumented specifications. All columns report the Kleibergen-Paap F-statistic for the first stage regressions. The first-stage statistics

[14] Notice that the between-groups inequality can be rewritten as:

$$BtwIneq_m = \sum_r \frac{y_{rm}}{Y_m} \, ln \left(\frac{\frac{y_{rm}}{Y_m}}{\frac{n_{rm}}{N_m}} \right) = \sum_r \frac{n_{rm}}{N_m} \, \frac{\overline{y_{rm}}}{\overline{y_m}} \, ln \, \left(\frac{\overline{y_{rm}}}{\overline{y_m}} \right) \tag{3.7}$$

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.

[15] I thus calculate:

$$\frac{\overline{y_{r,us}}}{\overline{y_{us}}} = \frac{1}{m} \sum_m \frac{\overline{y_{rm}}}{\overline{y_m}}$$

and replace it in the previous equation (3.7) to substitute $\frac{\overline{y_{rm}}}{\overline{y_m}}$.

indicate that the instrument is a strong predictor of the actual racial income inequality. The Kleibergen-Paap F-statistics in all specifications exceed the relevant Stock-Yogo critical value. In column (2), where I control for the share of white population, however, the value is close to the Stock-Yogo threshold. As a further check on the validity of the instrumental variable strategy I thus also report the p-value for the Anderson-Rubin Chi-2 test, which is robust to the presence of weak instruments. This test clearly rejects the hypothesis that racial income inequality does not affect trust in all specifications. Hence, overall, the two-stage least squares results in Table 6 do not suggest that the negative effect of racial income inequality on trust is driven by reverse causation from low (interracial) trust to high inequality of average incomes across racial groups.

4. Interpretation and testable implications

4.1. Interpretation

The main result from the previous section is that communities characterized by greater racial income inequality have lower levels of trust. This 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. Overall, the result can be summarized by saying that levels of trust are lower when the two dimensions of economic and racial heterogeneity are combined, rather than separated. In Appendix A, I present a simple two-groups model that helps to rationalize the underlying features of individual trust consistent with this pattern.[16] Here I offer a heuristic discussion of the conditions that have to be satisfied in order for the empirical results to hold.

I build upon the assumption of preference for similarity, according to which individuals trust more those citizens who look similar to themselves. This is a popular interpretation of the detrimental effect of diversity on trust (Alesina and La Ferrara, 2002; Tabellini, 2008) and is supported by a large body of experimental evidence (Glaeser et al., 2000; Bornhorst et al., 2010). I allow individuals to 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; and individuals that are *different* have no common element of similarity.

The condition that turns out to be crucial to explain the negative relation between racial income inequality and trust observed in the data is that the preference for similarity is *non-linear*, with trust falling at increasing rates as individuals become more different. To understand why, consider the two hypothetical communities reported in Figure 2, in which 50% of the citizens are Blacks and 50% are Whites, and 50% are rich and 50% are poor. The only difference between

[16] 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).

the two communities is the way in which the 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. It is easy to see that in community A there is a lower amount of both identical and different individuals, but a greater amount of individuals that are partially similar, compared to community B in which all individuals are either identical or different. From the empirical results of the previous section we know that trust should be lower in community B, where racial and economic identities coincide, compared to community A, where racial and income identities are separated. This will only be true if trust falls at increasing rates as individuals become more different. Observe in fact that moving from A to B implies that 25% of Whites become richer and 25% of Blacks become poorer. For any citizen of A, therefore, moving to B means a 25% increase in the number of both identical and different individuals. If the individual preferences for similarity were linear, the increase in the number of different individuals (and the corresponding reduction in individual trust) would be perfectly offset by the increase in the number of identical individuals (and the corresponding increase in individual trust). The overall level of trust in the two communities would be identical despite their differences in the racial composition of income inequality, thus contradicting the empirical results of section 3. In order for the assumption of preference for similarity to be consistent with the data, it must instead be the case that the 25% increase in people of the same race and income in community B does *not* compensate for the 25% increase in people of different race and income, leading to an overall decrease in the level of trust compared with community A. This is true only insofar trust falls at increasing rates as individuals become more different or, in other words, if the preference for similarity is non-linear.
Figure 3 graphically summarizes the discussion. 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. It is natural to assume that $w_2 > w_1$. For simplicity, I also normalize to 0 the amount of trust towards individuals different in both dimensions. The key condition for individual trust to be consistent with the observed empirical data is $w_2 < 2w_1$, reflecting the nonlinear relation between trust and similarity discussed above. 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. This condition will emerge analytically from the formal conceptual framework (see Parametric Assumption B in Appendix A).

4.2. Testable implications

The non-linear preference for similarity carries additional implications that can be tested in the data. Their empirical verification, in turn, can be used as an indirect validation of the non-linear relationship between trust and similarity.
The first implication is that racial income inequality is more detrimental for trust in more

racially fragmented communities. To understand why this is the case, let's compare the two communities of the previous example with a pair of more racially homogeneous communities, in which 80% of the citizens are Whites and only 20% are Blacks.[17] As before, imagine that the only difference between the two communities lies in the racial composition of income inequality and that the distributional pattern they follow is the same as before: in the first community, half of the members of each group are rich and half are poor, while in the second all Whites are rich and all Blacks are poor. In spite of the similarities with the previous example, repeating the exercise of moving from the first to the second community (thus raising the level of racial income inequality) in this case yields a smaller reduction in the total level of trust. The reason is that a larger amount of individuals in the more populous group now become identical when racial inequality increases: indeed, for the white majority, moving from the first to the second community implies a 40% increase in the number of identical individuals. This is larger than the 25% increase in the previous example. Similarly, the additional number of individuals becoming different in two dimensions is much more contained than before, only 10%. The example captures a more general pattern: when racial income inequality increases, individuals in the majority group are always better off if the level of racial fragmentation is lower, since this means there is a larger pool of individuals to become identical with. Clearly the situation is reversed for citizens of the black minority, as moving from the first to the second community for them now implies having 40% less individuals that are similar in one dimension, and only 10% more individuals that are similar in both dimensions. Compared to the previous case of more racially fragmented communities, then, racial minority groups are now worse off when racial income inequality increases. However, since they represent a minority of the population, their weight in the overall level of trust of the community is smaller and the effect of the more populous group dominates. For the community as a whole, therefore, the increase in racial income inequality implies a smaller reduction in the level of trust compared to the previous case of greater racial fragmentation.[18]

The implication is tested in Table 7, where I check for the heterogeneous effect of racial income inequality on trust, based on the level of racial fragmentation of the different communities. I start by dividing the sample cross-sectionally, and distinguish among MSA below and above the median level of racial fragmentation. In line with the discussion above, for less racially fragmented MSA in column (1) there is no evidence of a detrimental effect of greater racial income inequality on trust. For more racially fragmented MSA in column (2), instead, the effect is negative and statistically significant at the 99% confidence level. The estimated coefficient is nearly four times larger than in the other group, and it implies a 5.6% reduction in trust for a one standard deviation increase in racial income inequality. Column (3) pools the observations together and include the interaction of racial income inequality with a dummy for the MSA

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

[18] Figure 4 in Appendix A shows graphically the variation in the level of trust when racial income inequality increases, as a function of the level of racial fragmentation of the community.

being above or below the median level of racial fragmentation. The results confirm those in the previous two columns: greater racial income inequality is detrimental for trust only in more racially fragmented communities. Next, I divide the sample over time considering the effect of racial income inequality before and after 1990.[19] Since racial fragmentation in the U.S. has considerably increased over the past two decades (in the data, the average index of fragmentation for the period 1973-1989 is 0.33, increasing to 0.44 for the period 1990-2008), the effect of racial income inequality on trust is expected to be more negative during the more recent period. Column (4) confirms that before 1990, in the period of lower racial fragmentation, the income inequality between races is not significantly correlated with the level of trust. On the contrary, column (5) shows that after 1990 the coefficient becomes negative and statistically significant at the 99% confidence level. Finally, column (6) pools together all observations, adding the interaction of racial income inequality with a dummy for pre/post 1990. The results confirm that the detrimental effect of racial income inequality is driven by the more recent period of greater racial fragmentation in the U.S. Overall, Table 7 therefore confirms both cross-sectionally and over time that the more racially fragmented a community is, the more detrimental the effect of greater racial income inequality.

A second implication of the non-linear relation between trust and similarity relates to 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 whose level of trust decrease the most when income disparities between racial groups increase. Intuitively, this depends on the different population shares of each racial group. By increasing racial disparities, all groups reduce their average level of trust because the additional trust towards individuals of the same race and income does not compensate for the additional distrust towards individuals of different race and income. However, the impact is milder for the more populous groups, because of the larger number of individuals becoming identical when racial income inequality increases. On the contrary, minority groups reduce trust more when racial disparities increase. Since there are fewer individuals of their same race, when racial income inequality increases the number of individuals to become identical with is lower, while the number of those who become different in both race and income is higher.

The second implication is tested in Table 8. I identify the race of GSS respondents and estimate the impact of between-groups inequality for each of the different racial subgroups. A stronger impact of racial income inequality is expected for respondents belonging to racial minorities, while the effect should be milder for those belonging to the most populous group. The results in columns (1) to (5) show a negative effect of greater racial income inequality on trust for all racial groups, and confirm that the effect is stronger in the case of racial minorities. In particular, greater racial income inequality has a negative but not significant effect in the sample of white respondents in column (1), while the estimated effect is fifty percent larger, and

[19]The threshold is chosen in order to make the two periods as uniform as possible in terms of sample size. Fixing the threshold at 1994, which maximizes comparability with Alesina and La Ferrara (2002), whose sample covers the period 1974-1994, yields similar results.

statistically significant, for the sample of black individuals in column (2) and four times larger 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 in the sample 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 of different races together, interacting the measure of racial income inequality with dummies for their corresponding racial groups. Under the pooled specification, the coefficient of white individuals is more precisely estimated and becomes significant at the 95% confidence level. Yet, its point estimate remains generally smaller compared to those of the other minority groups, providing some additional evidence in support of the second implication of the conceptual framework.

4.3. Within Groups Inequality

While the main point of the paper is on the effect of income inequality between races on trust, it is also instructive to consider the role of the income inequality *within* races, in order to shed further light on the assumption of preference for similarity. Under this assumption, an increase in within-groups income inequality has two opposite effects on the level of trust of the community: first, it reduces trust by making initially identical individuals different in the income dimension. Second, it enhances trust by making initially different individuals similar in the income dimension. 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 greater within-groups inequality on trust 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 will only reduce 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 racial groups. Depending on the degree of concavity of the preference for similarity assumption as well as on the number of individuals of different races who share the same income level after an increase of within-groups inequality, the overall impact on trust in racially fragmented MSA may even be positive.[20]
Table 9 investigates the impact of within-groups inequality on trust. 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 where he lives. 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, depending on whether it is associated with an increase in the number of individuals of other races having the same level of income of the respondent.

[20] In this respect, notice that the positive coefficients of within-groups inequality in Table 7 for the group of more racially fragmented MSA are consistent with the argument.

Column (1) shows on the whole sample of individuals that only the inequality within one's own group 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 at the 99% confidence level in line with the results from the baseline specification. The inequality within one's own racial groups also remains negative and significant at the 90% level. Column (3) also adds the index of racial fragmentation in the MSA, whose inclusion leaves the coefficient of one's own group inequality virtually unchanged. Columns (4) and (5) divide the sample based on the difference between the income level of the majority group and that of other racial groups. Under the preference for similarity assumption, the more similar the income levels are the more citizens should reduce their trust when the income inequality within other groups increases. As a matter of fact, 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 living in MSA where the income differences between races are large, instead, greater income inequality within other groups should be less detrimental and may even increase their level of trust. In this case, in fact, a greater income dispersion within other groups raises the probability of income overlaps between individuals of different races, leading to an increase in the number of partially similar individuals. The results in columns (4) and (5) provide support for the argument: individuals in MSA characterized by similar income levels reduce their trust when the inequality within other races increases. The estimated effect is significant at the 95% confidence level. On the contrary, individuals living in MSA characterized by large income differences between racial groups increase their level of trust when the inequality within other races increases.

5. Conclusions

So far, the literature on the determinants of trust has neglected the role of income inequality along racial lines (racial income inequality). 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. This sheds some light on the functional form of the preference for similarity assumption, a popular interpretation of the detrimental effect of diversity on trust, suggesting that the relation between trust and diversity changes non-linearly when individual can differ in more than one dimension. 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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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.[21] 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:

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

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 $(1 - \alpha_1)p$.

[21] 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.

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:

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

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:

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

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

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

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:

$$\begin{aligned} \Delta_1 = &\left\{\left[(\alpha_1^2 - 1) + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 + \\ &+ \left\{\left[(\alpha_2^2 - 1) + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 + \\ &+ 2\left[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p) = \\ &= 2\alpha_1(1-\alpha_1)(\omega_1 - \omega_2)p^2 + \\ &+ 2\alpha_2(1-\alpha_2)(\omega_1 - \omega_2)(1-p)^2 + \\ &+ 2\left[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p) \end{aligned} \tag{A.9}$$

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:

$$\begin{aligned}\Delta_2 &= \left\{\left[\alpha_1^2 + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 - \\ &- \left\{\left[\alpha_2^2 + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 = \\ &= 2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2 - 2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2 .\end{aligned} \tag{A.10}$$

I shall now pursue the analysis under the following:

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

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.9)):

$$\begin{aligned}\Delta_1 &= 2\alpha_2(1-\alpha_2)\left\{(\omega_1-\omega_2)\left[p^2+(1-p)^2\right] + 2\omega_1 p(1-p)\right\} = \\ &= 2\alpha_2(1-\alpha_2)\left[-2\omega_2 p^2 + 2\omega_2 p + (\omega_1-\omega_2)\right] .\end{aligned} \tag{A.11}$$

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.11) 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.11):

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 observing that the region of positivity of Δ_1 (if (A) and (B) are satisfied) is centered 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.

Let's now address the quantity Δ_2. If assumption (A) holds, it reads simply (see (A.10)):

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

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.

Figure 4. Plot of Δ_1 at different levels of p

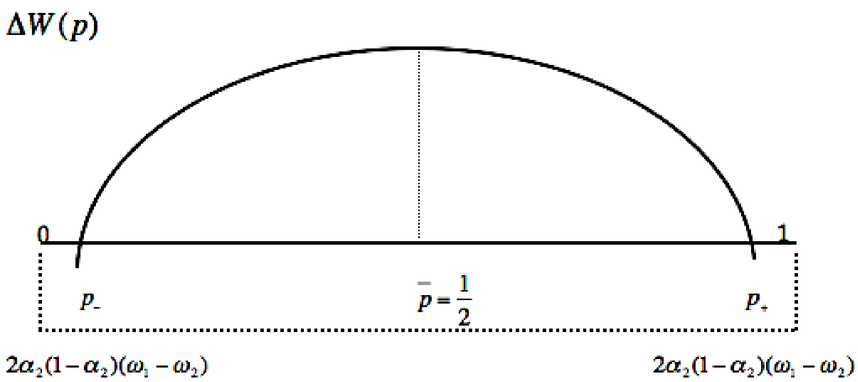

Figure 1 A. Similar Characteristics but Different Trust

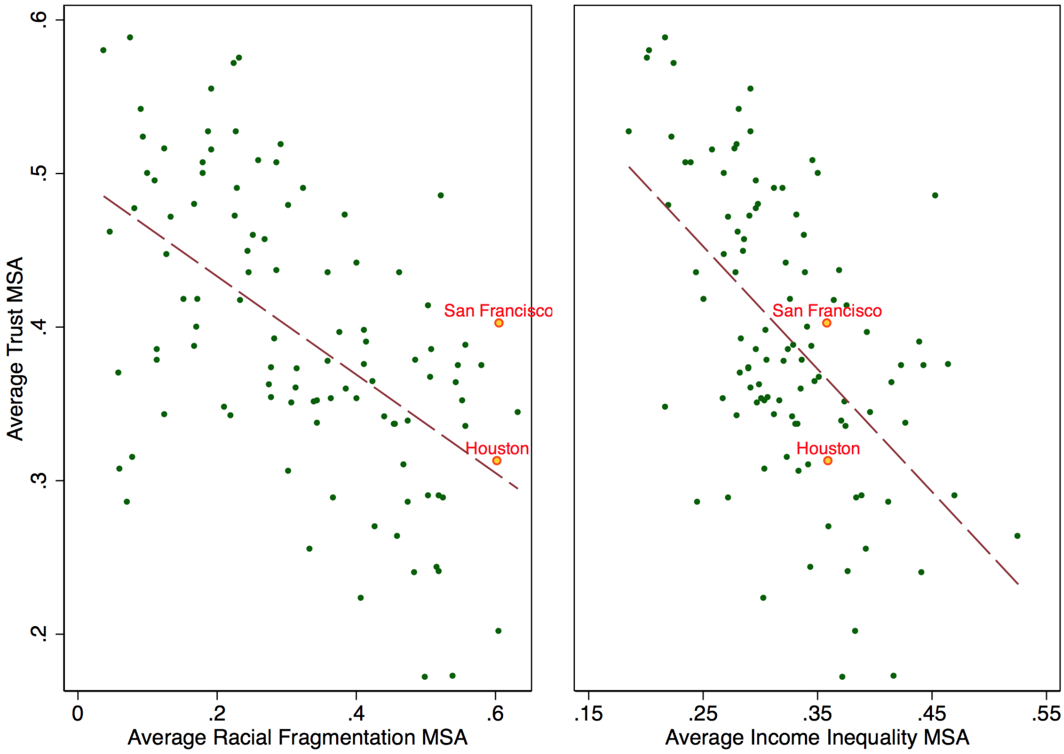

Figure 1 B. Are They Really Similar?

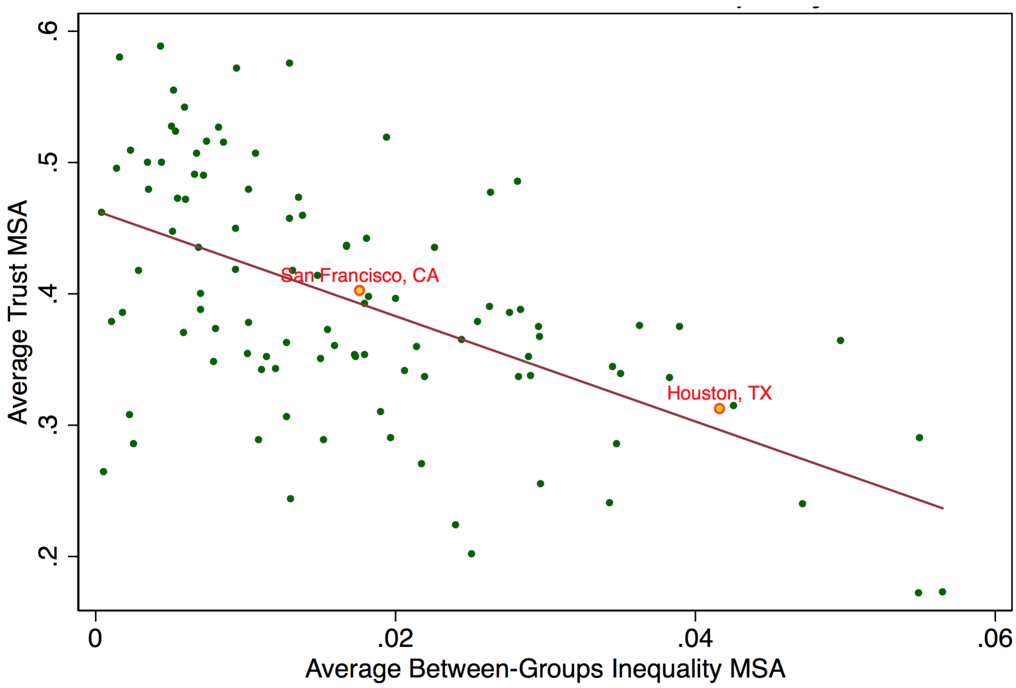

Figure 2. Two Hypothetical Communities

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

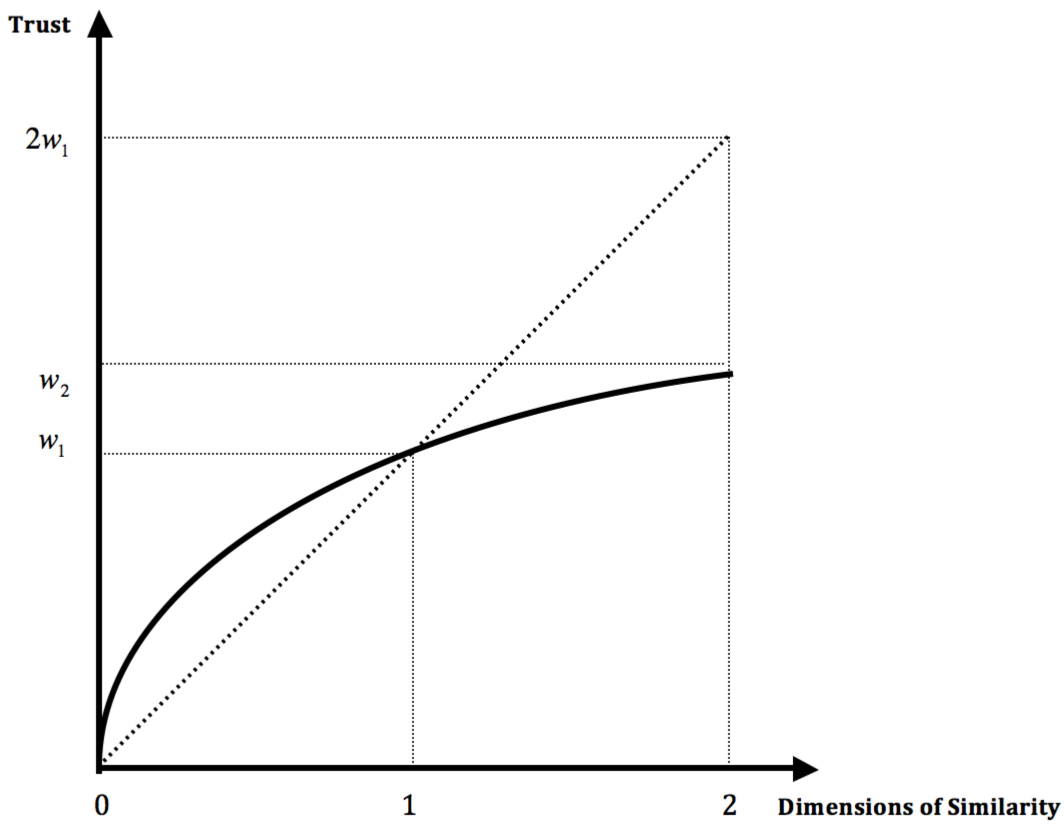

Table 1. Summary Statistics

	Individual Characteristics		
	Avg.	Std. Dev.	Observations
$Trust$	0.382	0.486	21867
Age	44.748	17.153	33583
$Married$	0.516	0.5	34004
$Female$	0.557	0.497	34004
$Educ \leq 12\ years$	0.206	0.404	34004
$Educ \geq 16\ years$	0.256	0.437	34004
$Log\ (Real\ Income)$	10.028	0.988	29335
$Log\ (size)$	4.142	2.122	32434
$Full\ Time$	0.511	0.5	34004
$Part\ Time$	0.103	0.304	34004
$Divorced$	0.163	0.369	34004
$Children$	0.389	0.487	34004
$White$	0.744	0.437	33733
$Black$	0.148	0.355	33733
$Native\ American$	0.028	0.166	33733
$Asian$	0.022	0.145	33733
$Hispanic$	0.057	0.232	33733
	Community Characteristics		
$RacFr$	0.396	0.171	33753
$Ethnfr$	0.745	0.1	33753
$Gini$	0.416	0.049	33753
$Theil$	0.335	0.082	33753
$Btw\ Theil$	0.021	0.014	33753
$Wth\ Theil$	0.314	0.072	33753
$Log\ (median\ inc._{white})$	10.535	0.504	33753
$Log\ (median\ inc._{black})$	9.958	0.563	33753
$Log\ (median\ inc._{nat.\ am.})$	10.087	0.628	33753
$Log\ (median\ inc._{asian})$	10.47	0.651	33753
$Log\ (median\ inc._{hisp.})$	10.093	0.494	33753

Table 2: Correlations among Measures of Heterogeneity

Variables	Trust	Gini	Theil	Wth Ineq	Btw Ineq	Rac Fr
Trust	1.000					
Gini	-0.350	1.000				
Theil	-0.308	0.983	1.000			
Wth Ineq	-0.252	0.966	0.990	1.000		
Btw Ineq	-0.489	0.758	0.731	0.629	1.000	
RacFr	-0.490	0.666	0.624	0.556	0.763	1.000

Table 3. Baseline 1973-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RacFr	-0.214***		-0.146**		-0.202***		-0.101
	(0.040)		(0.069)		(0.069)		(0.087)
Gini		-0.860***	-0.508				
		(0.240)	(0.309)				
Theil				-0.334**	-0.083		
				(0.138)	(0.167)		
Btw Theil						-2.319***	-1.870***
						(0.490)	(0.690)
Wth Theil						0.109	0.189
						(0.170)	(0.179)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18733	18733	18733	18733	18733	18733	18733

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). All measures of community heterogeneity refer to the MSA of the respondent: *RacFr* 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. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US 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)
Btw Theil	-1.424**	-1.540***	-1.902***	-2.065***	-1.228**		-2.260***
	(0.661)	(0.495)	(0.455)	(0.385)	(0.517)		(0.533)
Wth Theil	0.0873	-0.011	0.003	0.067	0.003		0.154
	(0.172)	(0.174)	(0.177)	(0.164)	(0.169)		(0.179)
Share w	0.143**						
	(0.0683)						
Share b		-0.098					
		(0.094)					
Share na			0.136				
			(1.195)				
Share a				0.489***			
				(0.127)			
Share h					-0.114*		
					(0.068)		
RacSeg						-0.090*	-0.023
						(0.054)	(0.055)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18733	18733	18733	18733	18733	18733	18733

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). 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 white population; *Share b* is the share of black population; *Share na* is the share of native american population; *Share a* is the share of asian population; *Share h* is the share of hispanic population; *RacSeg* is the entropy index of racial segregation. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 5. Alternative Sources of Variation

	State Time Trend		MSA FE		Previous Census		Closest Census	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RacFr	-0.346***	-0.251**	0.166	0.193	-0.214***	-0.120	-0.218***	-0.105
	(0.080)	(0.103)	(0.169)	(0.183)	(0.071)	(0.091)	(0.075)	(0.093)
Theil	-0.126		0.044		-0.170		-0.079	
	(0.205)		(0.441)		(0.174)		(0.185)	
Btw Theil		-1.643**		-2.733**		-1.679**		-1.987***
		(0.748)		(1.211)		(0.729)		(0.683)
Wth Theil		0.126		0.821		0.016		0.202
		(0.240)		(0.512)		(0.184)		(0.180)
State FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
State*Year FE	Yes	Yes	No	No	No	No	No	No
MSA FE	No	No	Yes	Yes	No	No	No	No
Observations	18658	18658	9417	9417	18733	18733	18733	18733

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). All measures of community heterogeneity refer to the MSA of the respondent: *RacFr* 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 calculated by the Theil index; *Wth Theil* is the inequality *within* racial groups calculated by the Theil index. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US 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)	(2)	(3)	(4)	(5)	(6)
Btw Theil	-5.872***	-4.954**	-3.969***	-3.878***	-3.701***	-3.884***
	(1.982)	(1.943)	(0.673)	(0.737)	(0.699)	(1.001)
Wth Theil	0.539**	0.471**	0.439**	0.444**	0.400**	0.432**
	(0.261)	(0.227)	(0.186)	(0.194)	(0.187)	(0.193)
RacFr	0.196					
	(0.158)					
Share w		-0.098				
		(0.151)				
Share b			0.017			
			(0.097)			
Share na				0.684		
				(1.148)		
Share a					0.395***	
					(0.153)	
Share h						0.003
						(0.084)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18733	18733	18733	18733	18733	18733
R-squared	0.128	0.129	0.130	0.130	0.130	0.130
Kleibergen-Paap	22.92	13.99	58.09	80.33	83.00	59.09
Anderson-Rubin Chi-2 p-value	0.001	0.001	0.000	0.000	0.000	0.000

Note: The method of estimation is two-stage 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 1973-2008). 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; *RacFr* is the index of racial fragmentation; *Share w* is the share of white population; *Share b* is the share of black population; *Share na* is the share of native american population; *Share a* is the share of asian population; *Share h* is the share of hispanic population. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US Census (1970, 1980, 1990, 2000). *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 7. First Implication: Racial Income Inequality and Fractionalization

	(1)	(2)	(3)	(4)	(5)	(6)
	Below Median	Above Median	Pooled Below-Above	Pre-1990	Post-1990	Pooled Pre-Post
RacFr	-0.093	-0.098		-0.085	-0.214	
	(0.142)	(0.135)		(0.124)	(0.156)	
Btw Theil	-1.049	-4.040***		1.680	-2.703***	
	(1.660)	(0.795)		(1.357)	(0.992)	
Wth Theil	-0.028	0.820***		-0.658***	0.693**	
	(0.309)	(0.233)		(0.234)	(0.284)	
$RacFr_{bel}$			-0.143			
			(0.107)			
$RacFr_{abo}$			-0.113			
			(0.130)			
$Btw\ Theil_{bel}$			-1.162			
			(1.264)			
$Btw\ Theil_{abo}$			-1.950**			
			(0.766)			
$Wth\ Theil_{bel}$			-0.068			
			(0.233)			
$Wth\ Theil_{abo}$			0.236			
			(0.177)			
Below			0.340***			
			(0.111)			
$RacFr_{pre90}$						-0.088
						(0.093)
$RacFr_{post90}$						-0.150
						(0.094)
$Btw\ Theil_{pre90}$						-1.011
						(1.100)
$Btw\ Theil_{post90}$						-1.852***
						(0.709)
$Wth\ Theil_{pre90}$						-0.299
						(0.259)
$Wth\ Theil_{post90}$						0.383*
						(0.199)
$Pre-1990$						0.418***
						(0.094)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9694	9039	18733	9245	9488	18733

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). All measures of community heterogeneity refer to the MSA of the respondent: *RacFr* is the index of racial fragmentation; *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. *Below* is a dummy variable equal to one if the MSA level of racial fragmentation is below the median, 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 measures of community heterogeneity interacted with the dummy *Above*, which is equal to one if the MSA level of racial fragmentation is above the median, and zero otherwise. $Pre-1990$ is a dummy variable equal to one if the year is before 1990, zero otherwise. $RacFr_{pre90}$, $Btw\ Theil_{pre90}$, $Wth\ Theil_{pre90}$ are the measures of community heterogeneity interacted with the dummy $Pre-1990$. $RacFr_{post90}$, $Btw\ Theil_{post90}$, $Wth\ Theil_{post90}$ are the measures of community heterogeneity interacted with the dummy $Post-1990$, which is equal to one if the year is 1990 or later, and zero otherwise. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 8. Second Implication: Racial Income Inequality and Groups' Size

	(1)	(2)	(3)	(4)	(5)	(6)
	Whites	Blacks	Ind Am	Asian	Hispanic	Pooled Races
$RacFr$	-0.141	-0.120	1.033**	-1.212	0.313	
	(0.108)	(0.135)	(0.411)	(0.944)	(0.419)	
Btw $Theil$	-1.433	-2.120**	-3.885	-7.334	-5.589**	
	(0.899)	(1.030)	(3.473)	(4.699)	(2.654)	
Wth $Theil$	0.236	0.285	-0.173	1.454	1.735**	
	(0.205)	(0.370)	(0.909)	(1.573)	(0.845)	
Btw $Theil_w$						-1.790**
						(0.757)
Btw $Theil_b$						-3.013*
						(1.796)
Btw $Theil_{na}$						-3.920*
						(2.196)
Btw $Theil_a$						-4.940*
						(2.648)
Btw $Theil_h$						-1.179
						(1.235)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14103	2711	521	353	965	18653

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). All measures of community heterogeneity refer to the MSA of the respondent: $RacFr$ 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 measure of income inequality *between* racial groups with the dummy variable White, which is equal to one if the individual identifies himself as White, and zero otherwise. Same definition for *Btw* $Theil_b$, *Btw* $Theil_{na}$, *Btw* $Theil_a$ and *Btw* $Theil_h$, which are interacted with the corresponding identity dummies. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 9. Within-Groups Inequality

	(1)	(2)	(3)	(4)	(5)
$Wth\ Theil_{own}$	-0.197**	-0.156*	-0.155*	0.052	-0.407***
	(0.100)	(0.095)	(0.095)	(0.105)	(0.150)
$Wth\ Theil_{oth}$	-0.181	-0.025	0.035	-0.462**	0.719***
	(0.134)	(0.152)	(0.166)	(0.195)	(0.252)
$Btw\ Theil$		-1.883***	-1.515**	-2.022**	1.131
		(0.558)	(0.730)	(1.000)	(1.575)
$RacFr$			(0.090)	(0.108)	(0.151)
			(0.090)	(0.108)	(0.152)
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	18653	18653	18653	9360	9282

Note: The method of estimation is Probit. Reported are marginal Probit coefficients calculated at the means. 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 1973-2008). All measures of community heterogeneity refer to the MSA of the respondent: $Wth\ Theil_{own}$ is the measure of income inequality *within* the respondent's own 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; $RacFr$ is the index of racial fragmentation. The measures of community heterogeneity are calculated from: IPUMS 1% sample of US 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, 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 US Census 1970, 1980, 1990, 2000. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Appendix Table A1. MSAs in GSS Sample, 1973-2008

Name	Avg. Trust	Avg. Racial Fragm.	Avg. Ineq.	Years in GSS	Respondents
Akron	.51	.18	.23	5	73
Albany-Schenectady-Troy	.47	.14	.27	8	106
Allentown-Bethlehem-Easton	.45	.13	.27	11	161
Appleton-Oskosh-Neenah	.58	.04	.2	6	69
Atlanta	.38	.49	.34	22	375
Atlantic City	.29	.37	.27	8	97
Austin	.38	.55	.44	5	88
Baltimore	.34	.44	.33	22	334
Bellingham	.51	.26	.35	6	116
Binghamton	.38	.11	.31	3	74
Birmingham	.22	.41	.3	13	161
Boston	.44	.28	.37	22	387
Buffalo-Niagara Falls	.34	.22	.28	19	263
Burlington	.46	.05	.28	5	78
Charleston-N.Charleston	.29	.47	.41	16	210
Charlotte-Gastonia-Rock Hill	.34	.46	.33	22	431
Chicago	.39	.51	.32	22	1035
Cincinnati-Hamilton	.38	.41	.46	9	157
Cleveland	.35	.34	.3	21	290
Columbia	.37	.42	.35	5	85
Columbus, GA	.24	.52	.38	8	108
Columbus, OH	.31	.3	.33	22	340
Corpus Christi	.17	.54	.42	5	81
Dallas-Fort Worth	.37	.51	.35	22	406
Dayton-Springfield	.45	.25	.28	8	109
Denver-Boulder	.47	.38	.33	22	408
Des Moines	.38	.12	.3	11	148
Detroit	.35	.4	.3	22	541
Eau Claire	.48	.08	.3	6	88
Eugene-Springfield	.5	.11	.3	8	109
Evansville	.34	.12	.31	5	70
Flint	.48	.3	.22	5	73
Fort Lauderdale-Hollywood-Pompano Beach	.29	.53	.38	6	97
Fort Wayne	.5	.18	.27	13	156
Fresno	.35	.55	.32	13	176
Grand Rapids	.46	.25	.34	11	185
Harrisburg-Lebanon–Carlisle	.42	.15	.25	8	79
Hartford-Bristol-Middleton- New Britain	.44	.25	.24	5	62
Houston-Brazoria	.31	.6	.36	21	368
Indianapolis	.37	.28	.29	11	142
Jackson, MI	.31	.08	.32	6	108
Jackson, MS	.17	.5	.37	8	99
Jacksonville	.4	.41	.31	8	88
Johnson City-Kingsport–Bristol	.31	.06	.3	8	104
Kansas City	.36	.27	.3	14	196
Knoxville	.39	.17	.34	12	178
Lakeland-Winterhaven	.35	.31	.3	8	134
Lansing	.46	.27	.29	5	81
Little Rock–North Little Rock	.35	.36	.27	5	82
Long Branch-Asbury Park	.57	.22	.22	6	84
Los Angeles-Long Beach	.34	.63	.4	22	1115
Lynchburg	.25	.33	.39	5	98

Appendix Table A1. MSAs in GSS Sample, 1973-2008 (continued)

Name	Avg. Trust	Avg. Racial Fragm.	Avg. Ineq.	Years in GSS	Respondents
Madison	.54	.09	.28	8	131
Manchester	.59	.08	.22	8	119
Memphis	.29	.5	.47	6	100
Miami-Hialeah	.2	.6	.38	18	208
Milwaukee	.52	.29	.28	8	131
Minneapolis-St. Paul	.53	.19	.29	22	353
Modesto	.24	.52	.34	5	74
Nashville	.4	.38	.39	14	280
New Haven-Meriden	.35	.28	.31	13	144
New Orleans	.36	.54	.41	15	206
New York-Northeastern	.34	.56	.37	22	2098
Norfolk-VA Beach–Newport News	.31	.47	.34	12	174
Oklahoma City	.38	.36	.32	19	249
Orlando	.36	.31	.29	6	100
Philadelphia	.36	.39	.34	22	651
Phoenix	.44	.4	.32	22	353
Pittsburgh	.42	.17	.33	22	409
Portland	.49	.23	.31	17	259
Providence-Fall River-Pawtucket	.48	.17	.3	8	98
Provo-Orem	.52	.13	.28	8	126
Racine	.53	.23	.19	6	74
Raleigh-Durham	.34	.47	.37	3	59
Reading	.52	.09	.22	5	84
Richland-Kennewick-Pasco	.34	.34	.43	3	83
Richmond-Petersburg	.34	.46	.33	14	205
Riverside-San Bernardino	.44	.46	.28	13	193
Rochester	.44	.36	.34	14	239
Saginaw-Bay City-Midland	.56	.19	.29	13	119
St. Louis	.37	.31	.29	22	400
San Antonio	.38	.58	.42	3	56
San Diego	.41	.5	.38	22	314
San Francisco-Oakland-Vallejo	.4	.61	.36	22	701
Santa Barbara	.49	.52	.45	6	70
Savannah	.24	.48	.44	3	75
Seattle-Everett	.49	.32	.32	17	249
Springfield	.5	.1	.35	5	76
Springfield-Holyoke-Chicopee	.51	.19	.26	6	66
Stamford	.57	.23	.2	6	73
Syracuse	.4	.17	.34	5	60
Tacoma	.47	.22	.29	6	72
Tampa-St. Petersburg-Clearwater	.35	.34	.37	17	256
Topeka	.51	.28	.24	5	75
Tucson	.29	.52	.39	6	69
Tuscaloosa	.26	.46	.52	3	72
Waco	.27	.43	.36	13	174
Washington	.39	.56	.33	22	446
West Palm Beach-Boca Raton-Delray Beach	.39	.41	.44	5	41
Wheeling	.37	.06	.28	8	108
Wichita Falls	.39	.28	.28	6	79
Worcester	.42	.23	.36	9	151
York	.29	.07	.25	6	70
Youngstown-Warren	.35	.21	.22	6	92