Racial Fragmentation, Income Inequality and Social Capital: New Evidence from the US

Andrea Tesei*

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Abstract. Existing studies of social capital formation in US metropolitan areas have found that social capital 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 social capital. Also, racial fragmentation is no longer a significant determinant of social capital 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 social capital 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.

*PhD Candidate, Universitat Pompeu Fabra, Department of Economics; e-mail: andrea.tesei@upf.edu.
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1 Introduction

In the last decade, a large and influential literature has documented the detrimental effect of community heterogeneity on social capital formation across metropolitan areas in the US. Existing studies show that more racially fragmented and income unequal communities have lower levels of trust (Alesina and La Ferrara, 2002; Costa and Kahn, 2003; Putnam, 2007), group participation (Alesina and La Ferrara, 2000), public good provision (Alesina et al., 1999; Goldin and Katz, 1999) and civic engagement (Vigdor, 2004). 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 US will increase further.[1]

This paper reconsiders the existing evidence on the subject and argues that the focus of the current debate is partially misplaced. I emphasize 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 social capital formation across metropolitan areas in the US. My empirical work starts out by showing that racial fragmentation and overall income inequality have a statistically significant, negative effect on individual measures of social capital like trust and group participation, a result that is consistent with previous findings (Alesina and La Ferrara, 2002; Putnam, 2007; Alesina and La Ferrara, 2000). 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 social capital in metropolitan areas. Instead, what turns out to be key for social capital formation is the concurrence of differences in race and income.

My estimates show that individuals living in communities characterized by greater racial income inequality, report lower levels of trust, group membership and happiness. The estimated coefficients imply that a one standard deviation increase in racial income inequality reduces the average level of trust, group membership and happiness in the community by, respectively, 5%, 4% and 1% of their mean values. I also show that racial income inequality has a more detrimental effect in more racially fragmented communities and that minority groups always reduce trust more than the majority group when racial income inequality increases. These results are robust to alternative definitions of racial diversity, self-selection of individuals into different metropolitan areas and alternative treatments of the time dimen-

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

sion. The result also prevails when I instrument racial income inequality in MSAs by racial income inequality in each MSA if the average income level of every racial group was equal to their national average income levels. 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 more racially unequal communities the probability of meeting either identical or very different individuals is greater than in communities with lower racial disparities (where instead the probability of meeting individuals that are similar in at least one dimension is higher). Since the additional trust towards individuals similar in two dimensions does not compensate for the reduction in trust towards individuals different in two dimensions, the overall effect of greater racial income inequality on trust is negative.

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 inequality measures, such as the Gini index, is that it is perfectly decomposable.[2] 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. It is also worth noting that the correlation between the aggregate Theil index (the sum of the between-groups and within-groups components) and the Gini index for data in my sample is over 98%. This makes clear that there is no additional information conveyed by the Theil index *per se*, and that all the insights that derive from its use are a consequence of its perfect decomposability.

By exploiting the decomposability of the Theil index, I can estimate the effect of overall income inequality on social capital formation in different metropolitan areas, and then decompose this effect into the effects deriving from income inequality across racial groups and income inequality within racial groups. Figure 1A illustrates some of my main empirical findings using data on average trust and measures of community heterogeneity across metropolitan statistical areas. Panel (A) plots the average level of trust for Metropolitan

[2]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.

Statistical Areas[3] (MSA henceforth) over the period 1972-2008, 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 these measures of community heterogeneity, as documented in the literature. The graph, however, also illustrates that racial fragmentation and income inequality alone cannot account for the difference in average trust levels between similar cities, like San Francisco and Houston. While 40% of citizens 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 1B 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 these 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 or even triples of MSA in the US.[4] My analysis will thus focus on documenting this pattern in a systematic way.

The paper proceeds as follows. Section 2 briefly summarizes the relevant literature. Section 3 introduces the data and the measures of community heterogeneity used. Section 4 discusses the main results and robustness checks. Section 5 provides an interpretation for the results and derives further testable implications, which are formally derived in the conceptual framework in Appendix B. Section 6 concludes.

2 Related literature

Most of my empirical analysis focuses on trust, which is regarded as a fundamental dimension of social capital by all early proponents of the social capital theory (Coleman, 1988; Putnam, 1993; Fukuyama, 1996). The consensus is that social trust creates a common set of ethical norms that facilitate transactions and improve efficiency by reducing the level of uncertainty and the need for insurance. Numerous empirical studies provide support for

[3]The Metropolitan Statistical Area is a standard statistical definition from the federal Office of Management and Budget that includes one or more counties containing a city with a population of at least 50000 individuals.

[4]Figures 2A and 2B consider the triple San Diego, Raleigh-Durham and Jackson, MS.

this argument, showing that social capital and trust are associated with higher 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).

Trust is also the dimension of social capital on which the impact of community heterogeneity has been more thoroughly investigated. Alesina and La Ferrara (2002), using data from the US General Social Survey over the period 1974-1994, find that respondents living in more racially fragmented and income unequal communities report lower levels of trust. When both dimensions of heterogeneity are considered together they find that only racial fragmentation remains significant, leading them to conclude that people are more likely to trust others in an unequal city than in a racially fragmented one. Similar results are reported in Costa and Kahn (2003), who confirm the negative impact of both measures of community heterogeneity, but suggest that the crucial determinant of trust is income inequality. Putnam (2007) studies the effect of racial fragmentation on citizens' trust toward individuals of their own race and of different racial groups. He finds the effect to be negative on both out-group and in-group attitudes, concluding that inhabitants in diverse communities distrust their neighbours, regardless of the color of their skin. He also explicitly considers the possible interdependence between the level of racial fragmentation and the overall level of income inequality, but finds no significant interaction effects. Leigh (2006) analyzes the case of Australia and finds that only racial fragmentation, but not income inequality, matters to determine the level of trust. I complement these studies by showing that racial fragmentation and overall income inequality are necessary but not sufficient conditions for lower levels of trust and that the key aspect of heterogeneity in the community is its level of racial income inequality, which can be seen as an indicator of the concurrence of the two dimensions of heterogeneity emphasized in existing studies.

Other studies focusing on different dimensions of social capital, like group membership and happiness (Alesina and La Ferrara, 2000; Helliwell et al., 2010), are also closely related to my work. Their findings on the impact of community heterogeneity mirror those in the context of trust, positing an analogous argument for the negative impact of increased diversity on levels of participation and happiness. My work confirms the negative effect of diversity on these alternative dimensions of social capital, and provides additional insights by stressing the role of racial income inequality.

A number of recent theoretical studies has focused on the relation between community heterogeneity and measures of social capital (Alesina and La Ferrara, 2000; Tabellini, 2008;

Karlan et al., 2009), providing analytic support for the negative relation observed in the data. The key assumption in these models is that contacts among similar individuals happen at a faster rate than among dissimilar individuals. Such preference for similarity implies that, when individuals in a community are different in terms of race *or* income, their utility is lower and so is their level of cooperation, participation and trust. I extend this framework to allow individuals to differ in more than one dimension, both in race *and* income, and study the conditions under which the assumption of preference for similarity brings results consistent with my empirical findings.

While the literature on social capital formation has not explicitly investigated the role of racial income inequality, other strands of literature have done so. In the literature on government redistribution, for instance, Alesina et al. (2001) and Alesina and Glaeser (2005) argue that one of the key explanations for the redistribution gap between the US and Europe is that racial minorities are disproportionately represented among the poor in the US. This reflects in the perception of the poor as "other", and induces a lower propensity to redistribute than in Europe, where the difference between poor and non-poor does not have such a clear racial connotation. In a different context, students of social conflict also put racial income inequality at the center of their analysis, by considering racial disparities as an important focal point to exacerbate the level of political animosity. In particular, studies in this area have focused on the relation between racial income inequality and crime (Blau and Blau, 1982), proneness to city riots (Abu-Lughod, 2007) and even ethnic violence (Robinson, 2001; Stewart, 2003). My work shares with all of these studies the central attention given to racial income inequality, but focuses on its consequences on social capital formation.

Finally, relatively close to my study is a literature investigating the impact of alternative measures of racial heterogeneity on trust. Particularly relevant in this context is the work of Uslaner (2011), who argues that racial segregation, rather than fragmentation, is the appropriate dimension of heterogeneity to explain the level of trust in a community. His argument is that fragmented but integrated communities help to promote social interactions among different races, thus raising the level of trust by overcoming their perceived differences. Segregation, instead, always reduces trust because it isolates groups from each other, exaggerating their differences and reinforcing the in-group trust at the expense of the out-group (generalized) trust. An indirect confirmation of this point is provided by Stolle et al. (2008), who find that reported trust is higher for individuals that in diverse neighborhoods regularly interact with individuals of different races. My results show that segregation is indeed significantly related with social capital, but also suggest that its relevance is attenuated by the explicit consideration of the racial dimension of income inequality.

3 Data and descriptive statistics

The main source of data in this study is the General Social Survey (GSS henceforth) for the years 1972-2008.[5]. In each round, the GSS interviews about 1500 individuals on a broad range of topics, including demographic, behavioral 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 that "it depends" are coded as 0. Respondents who answer that "it depends" represent less than 5% of the total. Alternative codings assigning this intermediate category to the group of individuals who trust, do not alter the results. Similarly, dropping the intermediate group altogether does not change the results.

Doubts have been raised about the effective understanding of the trust question by GSS respondents. In particular, there is no agreement on whether the question elicits the level of trust or trustworthiness of individuals. Fehr et al. (2003) find a positive relation between affirmative answers to the trust question and actual trusting behavior in a controlled experiment, while both Glaeser et al. (2000) and Karlan (2005) find that more trusting individuals, as identified by their answers to the question regarding trust in others as asked by the GSS, behave in a more trustworthy but not more trusting manner. Following Alesina and La Ferrara (2002), I proceed by interpreting the answers in the most literal way, as the extent to which respondents believe that others can be trusted.

The alternative measures of social capital that I consider, group membership and reported happiness, are also obtained from the GSS. The former is coded from answers to questions about membership in political groups, sport clubs, labor unions, religious groups, confraternities, etc. I code as 1 individuals who are members of at least one of such groups, and 0 otherwise. Among respondents, more than 70% of individuals belong to at least one group, the most represented being professional societies (14% of respondents are members).

[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.

My results are robust to different alternative exclusions of specific groups. Differently from the question about trust, that has been asked throughout all survey years, the question on membership has been interrupted in 1994, only to be resumed in 2004. This makes the number of observation for this alternative measure of social capital much smaller. The question on happiness, instead, has been consistently asked throughout the whole sample period 1972-2008 and is the measure with the most available observations in my study. It is possible to identify 26447 GSS respondents reporting their subjective level of happiness and living in a MSA with available measures of heterogeneity. This number is more than twice that of respondents reporting membership, and it is 40% higher than in the case of trust. I code as 1 individuals who say they are "happy" or "pretty happy", and with 0 those who say they are "not too happy". As with the previous variables, the results are robust to alternative codings.

Finally, from the GSS I also obtain all the individual controls used in the estimation. These include variables on age, education, race, sex, family income, working conditions, marital status and size of the place of residence, which have been shown to influence the level of perceived trust and group participation in previous studies. In addition, I also consider the family origin of the respondent, as recent work by Algan and Cahuc (2010) suggests that an important component of trust among second and third-generation Americans is inherited from their parents' country of origin.

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. I compute the measures at the MSA level to match them with the metropolitan areas in which the GSS respondents live[6]. 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:

$$Fragm_m = 1 - \sum_r S_{rm}^2$$

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

[6]More than two thirds of GSS respondents can be associated to the MSA in which they live. A further 39% of those who can be matched with their MSA have missing data for trust. This leaves us with a total of 21964 identified respondents. Cross availability with other control variables determines our final baseline sample of 18733 individuals. This is more than twice the amount of respondents in previous studies of social capital using the GSS.

Pacific Islander non-Hispanic; (iv) Native American non-Hispanic; (v) Other non-Hispanic; (vi) Hispanic.[7] The term S_{rm} represents the share of race r in the MSA.

Previous studies in the context of trust have used a slightly different classification, with no explicit consideration of the hispanic population. The reason for this choice is that the US Census does not identify Hispanic as a race, but rather as an ethnicity. Both Alesina and La Ferrara (2002) and Costa and Kahn (2003) thus associate Hispanic to the race category "Other", noting that there exists a high correlation (0.9) between those who define themselves as belonging to some "Other" race and their response to the ethnicity question as being "Hispanic". I choose instead to construct the six mutually exclusive categories outlined above and explicitly focus on the hispanic population. As it is evident from Table A1, while the overwhelming majority of individuals belonging to the "Other" category are indeed Hispanic, this by no means exhausts the whole hispanic population. In fact, only 42.2% Hispanic belong to the "Other" category, while 47.9% consider themselves as "White". Moreover, the almost 17 millions white Hispanics are likely to be amongst the poorest of their race category. By failing to consider their presence, both the level of racial fragmentation and income inequality between racial groups in a community are underestimated. Nonetheless, to show that the results are not driven by the racial classification adopted, I present results for both classifications and show that the estimates are stable across the two.

To maximize the comparability with previous literature I also consider an index of ethnic fragmentation, that is constructed analogously to the racial fragmentation index but uses ethnic origin rather than race. The original Census breakdown for ethnicity, reporting 35 categories of countries of origin, is aggregated into 10 main categories to avoid giving the same weight to very similar and very different ethnicities.[8]

The income inequality of a community is calculated using two different measures. The first is the Gini index, which is calculated starting from the family income of individuals for the four waves of Census 1970, 1980, 1990, 2000. The second is the Theil index, which represents the main focus of my analysis. The Theil index belongs to the generalized entropy class of inequality measures[9], and it is defined as:

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

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

[8]The aggregation procedure follows Alesina and La Ferrara (2002).

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

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 a given MSA, Y_m is total income in the MSA, and N_m is the total population in the MSA.

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

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

where all components are defined as above, with the exception 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 groups by summing the weighted logarithm of the ratio between their income and population shares.

As the equation shows, total income inequality can be represented as the sum of two separate terms. The first represents the amount of total inequality that is due to differences within racial groups. The second represents the amount that is due to differences between racial groups. Focusing on the latter term, notice that if the income share of a racial group is equal to its population share, the group does not contribute to between-groups inequality (the logarithm of income share over population share in the second term is equal to 0). On the contrary, if the income share of a racial group is bigger (smaller) than its population share, the group contributes positively (negatively) to between-groups inequality. Weighting by the income share ensures that the positive contributions are always higher than the negative.

A similar logic applies to the inequality within racial groups: if one of the n individuals of a racial group earns *one nth* 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). Overall, the index therefore evaluates the discrepancy between the distribution of income and the distribution of population both between and within different groups.

All measures of community heterogeneity (racial fragmentation, ethnic fragmentation and income inequality) are interpolated linearly through one Census year and another. 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 4.2 I check the robustness of my results to alternative arrangements of the time dimension and find similar results. Moreover, I show that the coincidence between the interpolated and the actual data (obtained from the American Community Survey of the US Census for the period 2003-2008) is very high, confirming that the interpolated measures have a high predictive power on the effective trend of community heterogeneity measures.

Table A2 highlights the correlations among the measures of heterogeneity discussed above. Some of the notable features in the data are the following. First, and most important, the correlation between the aggregate Theil index (the sum of the two components of between-groups and within-groups inequality) and the Gini index is over 98%. This shows 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. In second place, the between-groups inequality is correlated with trust and group membership, more than any other measure of heterogeneity. Finally, the between-groups inequality is also more correlated than aggregate inequality measures with the index of racial fragmentation.

4 Estimation Framework and Results

I start by considering the impact of community heterogeneity on trust according to the following specification, which closely replicates the one used in Alesina and La Ferrara (2002) and in other studies in this literature:

$$Tr_{ismt} = \alpha_s + \beta_1 X_{ismt} + \beta_2 Ineq_{smt} + \beta_3 Rac_{smt} + \beta_4 Ethn_{smt} + \delta_1 Z_{smt} + \tau_t + \epsilon_{ismt} \tag{4.1}$$

where α_s and τ_t are state and year fixed effects and X_{ismt} is the full set of individual controls reported in Table A3. Z_{smt} is a set of community characteristics, including the logarithm of the MSA median income (and its squared term), and the logarithm of the MSA size (community characteristics are reported in Table A4). ϵ_{ismt} is an error term that is clustered at the MSA level, to allow for arbitrary heteroskedasticity and serial correlation. The measures of community heterogeneity are first considered separately and then introduced simultaneously. The main coefficients of interest are β_2 and β_3.

In a second step, I augment the initial specification (4.1) by separately estimating the effect of between and within-groups inequality. This is done in the following regression:

$$Tr_{ismt} = \alpha_s + \beta_1' X_{ismt} + \gamma_1' (Btw\ Ineq)_{smt} + \gamma_2' (Wth\ Ineq)_{smt} + \beta_3' Rac_{smt} + \beta_4' Ethn_{smt} + \delta_1' Z_{smt} + \tau_t + \eta_{ismt} \tag{4.2}$$

where all variables are defined as above, except for the $(Btw\ Ineq)_{smt}$ which is the between racial groups component of income inequality and $(Wth\ Ineq)_{smt}$ which is the within component. Also in this case, the error term is clustered at the MSA level to allow for serial correlation and heteroskedasticity.

Further (minor) changes are also conducted on specification (4.2). First, I also estimate the impact of between-groups inequality under alternative definitions of racial diversity. In some specifications I thus replace the measure of racial fragmentation with those of polarization and segregation defined in Appendix A. Second, as I am also interested in other measures of social capital, in some specifications I replace trust with measures of group participation and reported happiness. Finally, in some estimations I replace the state and year fixed effects with state by year fixed effects. In this case, the identifying variation comes from differences in a given year between MSA belonging to the same state. This amounts to allowing for differences in State trends for the variables in the regression, providing a more stringent test for the results. In accordance with the previous literature, all the estimation results are from probit estimation, reporting marginal coefficients calculated at the means. All the results are also maintained if the estimation method adopted is ordinary least squares.

4.1 Baseline Results

Table 1 presents results for the baseline sample over the period 1972-2008. All columns control for individual characteristics[10] and state and year fixed effects. Columns (1) to (3) introduce the measures of community heterogeneity one at the time and find a negative and significant relation with trust for all of them. The estimated coefficients for racial fragmentation and income inequality are remarkably similar to those found in Alesina and La Ferrara (2002) for the period 1974-1994, suggesting that no substantial change in the effect of community heterogeneity has happened in the most recent period. Moving from the least racially fragmented MSA, where the index is 0.02, to the most heterogeneous where it is 0.72 the probability of trusting others decreases by 15 percentage points. Starting from the sample mean, an increase of one standard deviation decreases trust by 4 percentage points, or 11% of the sample mean. The effect is similar for income inequality: an increase by one standard deviation in the Gini index reduces trust by 5 percentage points, or 11% of the sample mean. The effect of ethnic fragmentation is weaker but still significant: in this case a

[10]The individual controls are the same used in the previous literature. The only exception is the variable "trauma", that has only been asked up to 1994 and would therefore reduce greatly the number of observations available.

one standard deviation increase implies a reduction in trust of slightly less than 2 percentage points, or 5% of the sample mean.

Column (4) includes the three measures of heterogeneity at the same time. Consistent with previous studies, the estimates show that racial fragmentation is a stronger predictor of trust than income inequality and ethnic fragmentation. The coefficients for the latter two become substantially lower and statistically insignificant, while the coefficient for racial fragmentation remains significant and not statistically different from the previous case in which it was estimated separately. Columns (5) to (7) replace the Gini index with the Theil index. In column (5) the Theil index is regressed alone. The coefficient is negative and significant at the 99% confidence level. The estimate suggests that moving from the least (0.13) to the most (0.58) unequal community reduces trust of 17 percentage points. A one standard deviation increase from the sample mean decreases trust by 3 percentage points, or 9% of the mean. Column (6) repeats the previous exercise of considering all the measures of heterogeneity simultaneously. As in the previous case, income inequality measured by the Theil index loses significance and the only variable that remains significantly associated with trust is racial fragmentation. The result is not surprising, given the high correlation between the Gini index and the aggregate Theil index discussed in the data section.

All in all, columns (1) to (6) confirm the results in Alesina and La Ferrara (2002): both racial fragmentation and income inequality are negatively correlated with trust and, amongst the two, racial fragmentation has the strongest relationship. This sets the basis for their finding that people are more likely to trust others in an unequal city than in a racially fragmented one. This conclusion however is challenged in column (7), which reports my main result. The regression exploits the decomposability of the Theil index to separate the aggregate income inequality into the two components of between and within-groups inequality. The separation has a strong impact on the coefficient of racial fragmentation, which drops by half and becomes statistically insignificant. Instead, income inequality between races emerges as the only negative and significant predictor of trust. Its coefficient, significant at the 95% confidence level, is sizable in magnitude. Everything else constant, moving from the community in which the between-groups inequality is at its minimum (0.001) to that in which it is at its maximum (0.079) reduces the level of trust by 10 percentage points. Starting from the mean, a one standard deviation increase in between-groups inequality reduces trust by 2 percentage points, or 5% of its mean value. The null hypothesis that the coefficients of between and within-groups inequality are equal is rejected at the 95% confidence level, ensuring that the model is different from the one in the previous column.

4.2 Robustness Checks

4.2.1 Alternative dimensions of social capital

Table 2 investigates the impact of racial income inequality on two other dimensions of social capital. Columns (1) to (5) start by focusing on the level of group membership in the MSA. The first three columns consider the measures of community heterogeneity separately, finding negative and significant coefficients for each of them. Compared to the baseline case of trust, the coefficient of racial fragmentation is smaller and less precisely estimated. On the contrary, the effect of income inequality is slightly stronger, while the index of ethnic fragmentation is substantially unchanged. In column (4) all measures of community diversity are considered together. Income inequality is the only one to be statistically significant (at the 95% confidence level). This coincides with the results in Alesina and La Ferrara (2000), who find that income inequality is a stronger predictor of membership than racial fragmentation. The estimated coefficient is also extremely similar to theirs (-0.474 compared to -0.468). Column (5) divides the total income inequality into within and between-groups inequality and finds, analogously to the case of trust, that the latter is the relevant component in predicting the amount of membership in the MSA. Compared to the baseline, the impact of inequality between racial groups is less precisely estimated (standard error 1.14), but implies a change in participation that is comparable in size. A one standard deviation increase in racial income inequality decreases participation by 2.4 percentage points.[11]

Columns (6) to (10) focus on the level of happiness reported by GSS respondents. Different from the previous cases, not all measures of community heterogeneity are significant predictors in the individual regressions. In particular, the aggregate level of income inequality reported in column (8) is not statistically significant at conventional levels. In addition, the size of the statistically significant coefficients is smaller than in previous cases. An increase by one standard deviation reduces happiness by only 1%, for both racial and ethnic fragmentation. In column (9) the three measures of heterogeneity are considered simultaneously. Only ethnic fragmentation remains statistically significant at the 90% level. Finally, column (10) separates the overall income inequality into its two components. As in the previous cases, racial income inequality stands as a significant predictor of reported happiness. The estimated coefficient however is smaller in size, and implies a reduction of only 1 percentage point for a one standard deviation increase.

[11] Substituting the dummy variable of group membership with the exact number of groups to which individuals participate provides similar results.

4.2.2 Reverse causality and sorting of individuals

The index of racial income inequality is increasing in the inequality of average incomes across racial groups. 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 least squares 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 MSAs by racial income inequality in MSAs if the average income level of each racial group was equal to their national average income levels.

Panel A of Table 3 presents two-stage least squares estimates of the effect of racial income inequality on trust. In column (1) I consider the full sample. The estimated coefficient for instrumented racial income inequality is statistically significant at the 90% confidence level and indicates a stronger (negative) effect of racial income inequality on trust than the least squares estimate. 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 least squares estimate. I also report the Kleinbergen-Paap F-statistic for the first stage regression. This statistic indicates that the instrument is weak (Stock et al., 2002). I therefore 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. Column (2) excludes observations with residuals in the top 5% in absolute value in the first stage regression. The first stage F-statistic is now much higher than in column (1) and no longer indicates instrument weakness. The effect of racial income inequality on trust is somewhat weaker than in column (1) but it is also more precisely estimated, and is significant at the 95% confidence level. Column (3) replaces the index of racial fragmentation with that of racial polarization.[12] The coefficient of racial income inequality remains negative and significant at the 95% confidence level. Hence, overall, the two-stage least squares results in Table 3 do not suggest that the negative least-squares 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.

Table 4 tackles a different possible source of endogeneity, generated by self-selection bias in the population composition. The problem originates from the possible sorting of individuals across MSAs on the basis of their personal income and human capital. The

[12]The index is described and defined in Appendix A.

negative correlation between trust and racial income inequality might then be the result of the migration of richer and more educated individuals of different races toward MSAs in which levels of social trust are higher. To account for differences in income levels of citizens belonging to the same racial group but living in different MSAs, columns (1) and (2) control for the median income of each racial group in the MSA. This does not affect the baseline results, but rather it strengthens the coefficient of the between-groups inequality. Under this specification, an increase in racial disparities by one standard deviation implies a reduction of more than 3% in the level of trust, or 8.5% of the trust sample average. Different from the baseline, the level of racial fragmentation also remains significant at the 90% level. Columns (3) and (4) control for differences in levels of human capital of racial groups in different communities. To do so, I include the shares of primary, secondary and tertiary education by race. Similar to the previous case, the inclusion of controls for human capital does not affect the baseline results, which confirm the negative and significant effect of between-groups inequality.

Columns (5) and (6) take a different approach to the problem of individuals' sorting, and restrict the sample to GSS respondents between 20 and 25 years of age. In this subsample, the problem of mobility across metropolitan areas is more easily avoided (Echenique and Fryer Jr, 2007). It is still possible that these individuals were born in metropolitan areas in which richer and more educated citizens of different races have migrated. However, the specification reduce concerns that richer and more educated GSS respondents have themselves moved toward areas with higher levels of social trust. Respondents between 20 and 25 years of age represent less than 10% of the total sample. Yet, also this restricted sample confirms the negative impact of racial income inequality.

Finally, columns (7) and (8) replace the state and year fixed effects with state-year fixed effects. Under this specification, the impact of racial income inequality is identified through differences between MSAs belonging to the same state, in a given year. This represents a more stringent test, as it allows different states to follow different trends in the evolution of racial income inequality and fragmentation. The pattern of results is unchanged and the negative effect of income inequality between racial groups remains significant at the 90% level, with a point estimate similar to that in previous specifications.

4.2.3 Alternative Measures of Heterogeneity

Table 5 checks the robustness of my results to alternative definitions of racial diversity, which are described in detail in Appendix A. Columns (1) to (3) consider an index of racial segregation, which captures the spatial isolation of different groups in the MSA. The measure adopted is the entropy index[13], calculated by Iceland (2004) and representing “the percentage of group’s population that would have to change residence for each neighborhood to have the same percentage of that group as the metropolitan area overall” (Iceland and Scopilliti, 2008). The results in column (1) confirm that segregation is negatively and significantly related to trust. An increase by one standard deviation in the amount of segregation reduces trust by almost 2%, and moving from the least segregated community (Provo-Orem, UT) to the most segregated (Detroit, MI) decreases trust by 8.2 percentage points. Controlling for the overall level of income inequality in column (2) reduces the coefficient of racial segregation, which still remains significant at the 90% confidence level. However, when explicitly considering the income inequality between racial groups in column (3), the index of segregation becomes insignificant, following the same pattern as the baseline measure of racial diversity. As in the baseline specification, only the between-groups inequality remains negatively and significantly (99%) related to the level of trust in the community. This suggests that income disparities between racial groups induce a more general social stratification than just the choice of the different neighborhoods to live in. Indeed, the correlation between the two variables in my sample is only slightly positive (0.11). This is in line with the theoretical results of Sethi and Somanathan (2004), who show that segregation and racial income inequality are characterized by an inverted U-shaped relation.

Columns (4) to (6) replace the index of racial segregation with a measure of racial polarization used in the literature of civil conflict (Esteban and Ray, 1994; Reynal-Querol, 2002). To the extent that social cohesion, and not only outright violence, is influenced by the level of community polarization, we expect a negative relation between this measure and the level of reported trust. Indeed, the effect of racial polarization on trust is substantial, and stronger than both alternative definitions of racial diversity considered. A one standard deviation increase in polarization reduces the amount of trust by almost 4 percentage points. The coefficient is almost unaffected by the inclusion of the aggregate Theil index in column (5) and remains significant at the 99% confidence level. Unlike the previous measures of diversity, the polarization index remains significant also in column (6), when the income inequality between groups is explicitly taken into account. The point estimate is somewhat lower, but still implies that moving from the least to the most polarized society, trust falls

[13]In a detailed review of six multi-group segregation indices, Reardon and Firebaugh (2002) conclude that the entropy index is the most satisfactory, as it the only measure to satisfy the *principle of transfer* on the basis of which the index declines when an individual of group r moves from census tract i to j, in which the proportion of individuals of type r is lower.

by more than 13 percentage points. Our main measure of interest, the income inequality between races, is also significant at the 95% confidence level, with an estimated effect that is lower than using the alternative definitions of racial diversity.

4.2.4 Alternative treatment of the time dimension

Table 6 and 7 address concerns about the data interpolation. First, I obtain data from the American Community Survey (ACS) of the US Census for the years 2003-2008 to check the relation between the interpolated measures and the actual data. Second, I repeat the estimation by fixing the heterogeneity measures at their Census level throughout the whole subsequent decade. Table 6 starts by analyzing the goodness of fit of interpolated and real data, in years in which the latter are available. I regress measures of community heterogeneity from the ACS on the interpolated measures of heterogeneity. All regressions include a full set of time fixed effects. The number of observations represents the MSA-years for which we have both interpolated and real data from the ACS. For all community measures the robust t-statistic is above 5, confirming that the interpolated measures have a high predictive power on the real trend of diversity measures. Table 7 instead checks the robustness of my results to an alternative treatment of the time dimension. In particular, I compute the heterogeneity measures at each Census year and maintain it throughout the following decade. Most of the results from the baseline specification are maintained. In particular, all heterogeneity measures are negative and significant predictors of trust levels in the community. Columns (5) and (7) also confirm that the only significant coefficient in the simultaneous regressions is that of racial fragmentation (99% significant). One important difference compared with the baseline specification is that racial fragmentation maintains independent explanatory power also in column (8), when the income inequality is divided into its two components. Finally, the between-groups inequality remains significant at the 90% level also when data are not interpolated.

4.2.5 Further robustness checks

Table 8 provides a series of further robustness checks for the results in the baseline sample. Columns (1) to (3) include the level of criminality in the respondents' MSA. This addresses the plausible concern that the negative impact of racial income inequality on trust is operating through an associated increase in criminality. I consider the number of serious crimes per 1000 persons obtained from the FBI Crime Statistics[14]. The inclusion of crime levels reduces the sample size by more than one third, as the crime data do not cover all MSA in my sample. The regressions in columns (1) and (2) show that crime is indeed a negative and significant predictor of trust levels in the community. Moving from the MSA with the lowest crime level to the one with the highest implies a reduction in average trust by almost 5%. The results on community heterogeneity, however, are not affected by the inclusion of crime. Racial fragmentation remains the only measure of diversity that is significantly related to trust, using both alternative indices of aggregate income inequality. However, when explicitly accounting for the income inequality between racial groups in column (3), the coefficients of both racial fragmentation and crime become insignificant, while the between-groups inequality is significant at the 99% confidence level. This provides a strong confirmation of the fact that racial income inequality affects social capital through more general channels than just by increasing the levels of criminality in the community. Columns (4) to (6) consider assigning respondents who answer the trust question "it depends" to the category of trusting individuals. The change involves 5% of total respondents, so that under this coding trusting individuals increase from 38% to 43% of the total. Column (4) considers all measures of community heterogeneity simultaneously using the Gini index of income inequality, while column (5) substitutes it with the Theil index. Column (6) divides the Theil index into its two components. The pattern of results is very similar to the baseline sample, and the estimated impact of the between-groups inequality is 35% higher under this coding. Finally, columns (7) to (9) consider the alternative racial classification used in previous studies and discussed in the data section. In both columns (7) and (8) the alternative index of racial fragmentation is a significant predictor of trust. In column (7) also the Gini index is significant at the 90% confidence level. One likely explanation is that, under the alternative classification of races, the collinearity of income inequality with the racial fragmentation index is reduced by the failure to allot part of the (white) hispanic population to its own racial group. As in the baseline sample, the coefficients of racial fragmentation drops by more than 50% in column (9), which explicitly considers the income inequality between racial groups. The latter is significant at the 95% confidence level, and the point estimate is very similar to that of the baseline sample.

[14]FBI Uniform Crime Reports 1985-2009. The data are originally at the county level, and are converted to MSA following the methodology outlined in Alesina and La Ferrara (2002).

4.2.6 Cultural versus Experiential Trust

Table 9 tests the two alternative hypothesis of cultural and experiential formation of trust suggested, respectively, by Algan and Cahuc (2010) and Uslaner (2008). The former authors argue that trust is mostly inherited and that the different level of trust among GSS respondents depends on their ethnic background. Uslaner (2008) instead considers the importance of day-to-day experience, in particular the impact of living among people who behave honestly and are themselves trusting.

Columns (1) to (3) start by testing the cultural foundation of trust. Column (1) includes the ethnicity of the respondents compared to the benchmark group of individuals (Swedish). The results are in line with those of Algan and Cahuc (2010) and show that US citizens of hispanic and mediterranean origins (Mexican, Italian, Portuguese, Spanish) trust significantly less than their fellow citizens of Swedish origin. Column (2) adds community characteristic, including aggregate income inequality, and shows that racial fragmentation remains a negative and significant predictor of trust levels in the MSA. Community characteristics seem orthogonal to the individual ethnicities, which maintain the same pattern observed in the previous column. Column (3) separates the MSA inequality into its two components and confirms the finding from Table 1: the coefficient of income inequality between racial groups is significant at the 90% level, whereas that of racial fragmentation drops by half and becomes insignificant.

Columns (4) to (6) test the experiential foundation of trust. Column (4) regresses trust on the shares of different ethnicities in the MSA and finds some confirmation for Uslaner's hypothesis: MSA with larger communities of high trusting individuals (like Belgian, Dutch, Austrian or French) display higher levels of average trust. On the contrary, areas characterized by larger communities of low trusting individuals such as the Spanish display lower average levels of trust. Column (5) introduces the community characteristics (excluding the ethnic fractionalization index which is highly collinear with its own components): neither racial fragmentation nor the aggregate income inequality are significant predictors of trust in the community once the ethnicity shares are taken into account. Column (6) splits aggregate income inequality into within and between-groups inequality and confirms the negative and significant impact of the latter. The coefficient is similar to that of the baseline sample and implies that a one standard deviation increase in income disparities between racial groups reduces trust by 1.7 percentage points.

5 Interpretation and further implications

5.1 Interpretation

The main result from the previous section is that communities characterized by greater racial income inequality have lower levels of social 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 social trust are lower when the two dimensions of economic and racial heterogeneity are combined, rather than separated.

In this section I outline a simple conceptual framework that helps to rationalize the underlying features of individual trust consistent with this pattern.[15] To do so, I start by considering two hypothetical communities in which 50% of the citizens are black and 50% are white, and 50% are rich and 50% poor (see Figure 3). The only difference between the two communities is the way in which income is distributed across racial groups. In the first community, for both blacks and whites, half of the group is rich and half is poor. In the second, all whites are rich and all blacks are poor. This amounts to say that the income inequality in the first community stems from differences *within* racial groups, while in the second it stems from differences *between* racial groups.

Suppose that individuals have a preference for similarity, so that they trust more those citizens who look similar to themselves.[16] The similarity can be in terms of both race and income, so that *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. It is easy to see that in the first community there is a lower amount of both identical and different individuals, but a greater amount of individuals that are partially similar, compared to the second in which all individuals are either identical or different.

For the sake of contrasting the overall amount of trust in the two communities, observe that moving from the first to the second requires making 25% of whites richer and 25% of blacks poorer. For any citizen of the first community, therefore, moving to the second means increasing by 25% the number of both identical and different individuals. If the individual preferences for similarity were linear, such change in the racial composition of

[15] A formal treatment of the results discussed in this section can be found in Appendix B.

[16] This assumption has a long tradition in both psychology and sociology. Allport (1954) for instance reports 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".

income inequality would have no impact, and the two communities would display the same overall amount of trust despite their differences. Under linear preferences, the increase in the number of identical individual would perfectly compensate for the increase in the number of different individuals.

The assumption of linearity, however, is inconsistent with the empirical results of the previous section. Communities like the second in our example, in which racial and economic identities coincide, have lower trust than communities like the first, in which racial and income identities are separated. What this suggests instead, is that preferences for similarity are nonlinear and fall at increasing rates as individuals become more different. If this is the case, we can rationalize why the overall level of trust is lower when racial and income heterogeneity are combined, rather than separated. With decreasing returns to similarity, a rise in the number of *identical* individuals, and the corresponding increase in individual trust, does not compensate for a rise of the same amount in the number of *different* individuals, and the corresponding decrease in individual trust. To go back to our example, this means that, from the point of view of any black or white individual in the second community, the 25% increase in people of the same race and income, does not compensate for the 25% increase in people of different race and income, leading to a lower amount of overall trust compared with the first community.

Figure 4 graphically summarizes the discussion above. 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 B).

5.2 Further implications

My results are consistent with a pattern of individual trust that falls at increasing rates as individuals become more different. This assumption yields further testable implications.

The first regards the different impact of income inequality between races for communities with different levels of racial fragmentation. In this context, the fact that trust towards different individuals decreases at increasing rates implies that a greater inequality between different races has a more detrimental effect in more racially fragmented communities.

To build intuition for this result, observe in first place that the two hypothetical communities described in the previous subsection represent the most racially fragmented societies one can think of in a setup with only two racial groups. Then, maintaining the same parameters w_1 and w_2 as before, consider a different pair of communities in which 80% of the citizens are white and only 20% are black. These communities are less racially fragmented than those in the previous subsection. As before, imagine that the only difference between the two 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 both groups are rich, and half are poor; in the second, all whites are rich and all blacks are poor).

Considering this pair of less fragmented communities, and repeating the previous experiment of increasing racial income inequality by moving from the first to the second, the effect on the overall amount of trust is still negative, but less than before. The reason is that in this case, due to the asymmetric racial composition of the communities, when racial income inequality increases, a greater amount of individuals in the more populous group become similar in two dimensions. In the current example, an additional 40% of white individuals has the same race and income in the second community compared to the first. This is much greater than the 25% increase in the previous example. Also, the increase in the number of citizens that are different in two dimensions is much more contained than before, only 10%. Of course the situation is inverted for citizens of the minority group, as moving from the first to the second community implies that they lose 40% of individuals that were similar in at least one dimensions, while gaining only 10% of individuals similar in both dimension. However, since they are the minority, their weight in the overall trust level of the society is smaller and the effect of the more populous group dominates. As a result, the overall amount of trust in the second society compared to the first is lower, as in the previous example, but the difference between the two communities is smaller than in the previous case in which the two communities were more racially fragmented.[17]

A second implication of the nonlinear relation between trust and similarity regards the impact of racial income inequality on different racial groups of the same community. Ap-

[17]Figure 5 in Appendix B graphically illustrates this point in the case of two races and two income levels per community.

pendix B formally shows that minority groups are those whose level of trust decreases the most when income disparities between racial groups increase. Intuitively, this depends on the different population share of each racial group. By increasing racial disparities, all groups reduce their amount of trust because, as we saw, the additional trust towards individuals of the same race and income does not compensate for the additional distrust towards those of different race and different income. However, the impact is milder for the most populous groups, because of the higher number of individuals that become similar in two dimensions when racial income inequality increases. On the contrary, minority groups are those who have more to lose when racial disparities increase. Since there are few people of the same race, when racial income inequality increases the additional number of those who can become similar in both income and race is lower than the number of those who become different under the two dimensions.

The first implication is tested empirically in Table 10. The table investigates whether more racially fragmented communities are more negatively affected by greater inequality between racial groups. I start by dividing the sample cross-sectionally, separating the MSAs below the median level of racial fragmentation from those above the median. Columns (1) and (2) show that, for less fragmented MSA, racial diversity is detrimental for trust, while there is no significant effect of between-groups inequality. This is in line with the predictions above, as in racially homogeneous communities the amount of individuals becoming similar in both race and income when racial income inequality increases is such as to compensate the increase in the number of individuals becoming different in both dimensions. On the contrary, columns (3) and (4) show that for highly fragmented MSA, between-groups inequality has a significant effect on trust. The sign is as expected, in line with the framework above. The coefficient of between-groups inequality is more than twice that observed in the group of less fragmented communities, and it is significant at the 99% confidence level. In this sample, an increase by one standard deviation in racial disparities between racial groups reduces trust by more than 4%. Notice also that the positive coefficient of within-groups inequality in column (2) is not inconsistent with my conceptual framework. Greater within-groups inequality reduces the number of individuals similar in two dimensions, but it also increases the number of individuals similar in one dimension. In racially fragmented communities the second effect prevails, so that the overall effect on trust is positive.

Columns (5) to (8) split the sample over time, looking at the effect of between and within-groups inequality before and after 1994.[18] As the average racial fragmentation after

[18]I use 1994 as the threshold year in order to maximize comparability with Alesina and La Ferrara (2002)

1994 is 37% higher than before, the effect of both components is expected to be stronger in the latter period. This is indeed what the data show, following a pattern similar to the cross-sectional separation. Columns (6) shows that before 1994, in the period of lower racial fragmentation, the between-groups inequality is not a significant predictors of trust. On the contrary, after 1994 the coefficient is statistically significant and has the expected sign, as shown in column (8). This finding confirms that the more racially fragmented a community is, the more detrimental the effect of increasing racial income inequality.

Table 11 tests the second implication of the outlined conceptual framework, regarding the heterogeneous impact of racial income inequality on the trust levels of racial groups with different sizes. I identify the race of GSS respondents and estimate the impact of between-groups inequality in each of the different subsamples.[19] 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 confirm these expectations, by showing a negative effect of greater racial income inequality for all racial groups, but 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, while the effect is roughly three times as large, and statistically significant, for both Black and Hispanic respondents. In the case of Blacks, a one standard deviation increase in between-groups inequality reduces trust by 6.5%, while in the case of Hispanics the reduction is more than 8%. The other minority groups, Asian and Indian Americans, have fewer respondents, so that their effect is estimated imprecisely and it is not statistically significant.

6 Conclusions

So far, the literature on the determinants of trust and social capital formation has neglected the role of income inequality along racial lines (racial income inequality). I show that greater racial income inequality lowers social capital in US metropolitan areas. Moreover, once racial income inequality is accounted for, racial fractionalization becomes a statistically insignificant determinant of social capital in US metropolitan areas. This suggests that it is not racial differences per se that matter for social capital formation but racial differences that coincide with income differences. My empirical results are consistent with a simple conceptual framework where social capital formation decreases at increasing rates as individuals

and Costa and Kahn (2003) whose samples cover the period 1974-1994. Fixing the threshold at 1990, which maximizes the sample comparability in terms of observations between the two periods, yields similar results.

[19] Around 20% of respondents do not report their race, and therefore can't be included in the estimation.

become more different. I also document empirical support for further implications deriving from this assumption. In particular, I show that income disparities between racial groups have a more detrimental effect in more racially fragmented communities and that minority groups always reduce trust more than the majority group when the inequality between races increases.

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A Alternative measures of racial diversity

In addition to the racial and ethnic fragmentation indices commonly adopted in the literature on social capital, I also test my results using two other measures of community diversity constructed from the US Census. The first is an index of racial polarization, defined as:

$$Polar_m = 1 - \sum_r \left(\frac{1/2 - S_{rm}}{1/2} \right)^2 S_{rm}$$

The index measures the extent to which the community's racial composition is different from the bipolar distribution, representing the highest amount of possible polarization in the society. In a society characterized by only two racial groups, the polarization index is equal to the racial fragmentation index up to a scalar (Garcia-Montalvo and Reynal-Querol (2005)). When there are more than two groups, the relation between the two measures breaks down. This is the result of their different weighting schemes. While both the polarization and the fragmentation index estimate the probability that two randomly chosen individuals belong to different groups, the former weighs the probability by the different groups size while the latter does not.

The second alternative measure of diversity is a racial segregation index. I use the *entropy* index, calculated by Iceland (2004) from US Census data:

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

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 $\sum_r S_{rm} ln \left(\frac{1}{S_{rm}} \right)$. Basically, the entropy index represents the weighted average deviation of each Census tract's racial diversity from the MSA-wide racial diversity, expressed as a fraction of the total MSA's racial diversity. 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.

B 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.[20] 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:

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

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

and

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

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

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

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:

$$\begin{aligned} W = {} & \left\{\left[\alpha_1^2 + (1-\alpha_1)^2\right]\omega_2 + 2\alpha_1(1-\alpha_1)\omega_1\right\}p^2 + \\ & + \left\{\left[\alpha_2^2 + (1-\alpha_2)^2\right]\omega_2 + 2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 + \\ & + 2\left[\alpha_1\alpha_2 + (1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p)\,. \end{aligned} \tag{B.3}$$

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 $(\alpha_1, \alpha_2) = (0,1)$ 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

$$\begin{aligned}\Delta_1 = &\left\{\left[(\alpha_1^2-1)+(1-\alpha_1)^2\right]\omega_2+2\alpha_1(1-\alpha_1)\omega_1\right\}p^2+ \\ &+\left\{\left[(\alpha_2^2-1)+(1-\alpha_2)^2\right]\omega_2+2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2+ \\ &+2\left[\alpha_1\alpha_2+(1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p) \; = \\ &=2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2+ \\ &+2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2+ \\ &+2\left[\alpha_1\alpha_2+(1-\alpha_1)(1-\alpha_2)\right]\omega_1 p(1-p)\end{aligned} \tag{B.4}$$

as a function p, α_1 and α_2. 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

$$\begin{aligned}\Delta_2 = &\left\{\left[\alpha_1^2+(1-\alpha_1)^2\right]\omega_2+2\alpha_1(1-\alpha_1)\omega_1\right\}p^2- \\ &-\left\{\left[\alpha_2^2+(1-\alpha_2)^2\right]\omega_2+2\alpha_2(1-\alpha_2)\omega_1\right\}(1-p)^2 \; = \\ &=2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2- \\ &-2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2\,.\end{aligned} \tag{B.5}$$

I shall now pursue the analysis under the following

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

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

Observe that

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

Therefore, under assumption (A) the difference Δ_1 becomes simply (see (B.4)):

$$\begin{aligned}\Delta_1 &= 2\alpha_2(1-\alpha_2)\left\{(\omega_1-\omega_2)\left[p^2+(1-p)^2\right]\,+2\omega_1 p(1-p)\right\} \; = \\ &=2\alpha_2(1-\alpha_2)\left[-2\omega_2p^2+2\omega_2 p+(\omega_1-\omega_2)\right]\,.\end{aligned} \tag{B.6}$$

Let me now make the following

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

If (B) is satisfied, it is immediately seen from (B.6) 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 (B.6):

Let assumption (A) be satisfied.

(a) 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 $[0, 1/2]$.*

(b) If (B) fails, then the difference Δ_1 is always negative.

Figure 5 below 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. On the other hand, Δ_1 is zero when $\alpha_2 = 0$ - namely, when the between-groups inequality is maximum, whereas the within-groups inequality is zero - and increases when the within-groups inequality does (whereas the between-groups inequality decreases). These results represent the formal counterpart of the first two implications discussed qualitatively in section 5.

Let me now address the quantity Δ_2. If assumption (A) holds, it reads simply (see (B.5)):

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

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* $[0, 1/2]$. This result represents the formal counterpart of the third implication discussed qualitatively in section 5.

Figure 5. Plot of Δ_1 at different levels of p

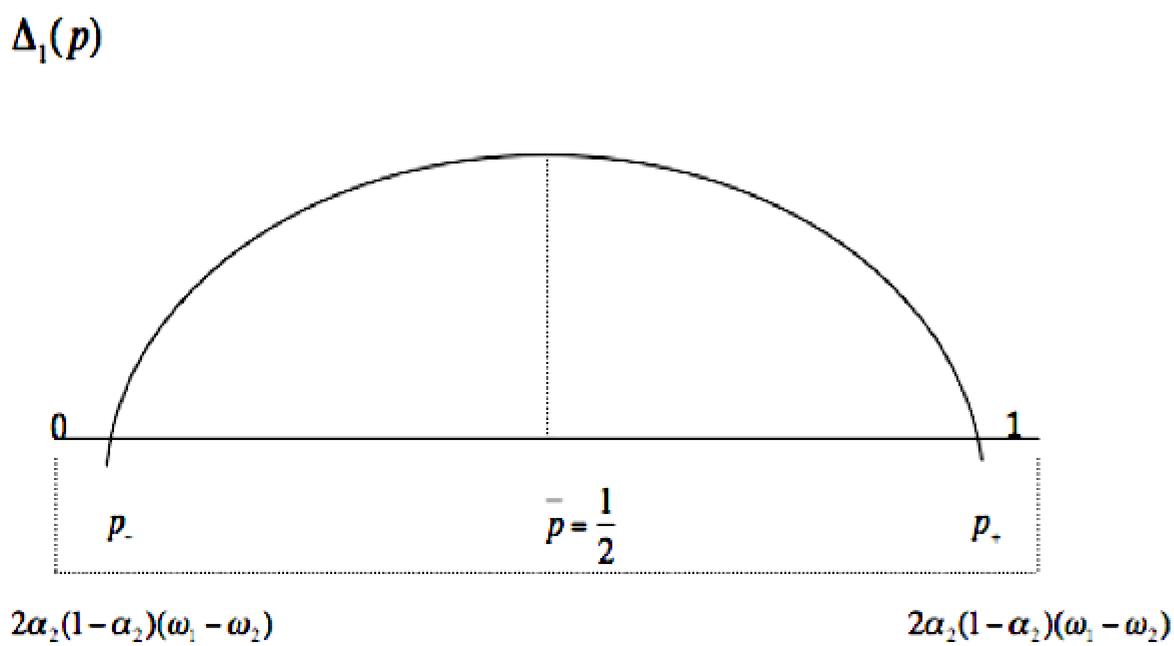

Table 1. Baseline 1972-2008

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Racfr$	-0.209***			-0.147**		-0.202***	-0.117
	(0.04)			(0.06)		(0.06)	(0.08)
$Ethnfr$		-0.183***		-0.010		-0.007	-0.048
		(0.07)		(0.09)		(0.09)	(0.09)
$Gini$			-0.933***	-0.432			
			(0.23)	(0.33)			
$Theil$					-0.385***	-0.020	
					(0.14)	(0.17)	
$Btw\ Theil$							-1.311**
							(0.67)
$Wth\ Theil$							0.127
							(0.18)
Observations	18733	18733	18733	18733	18733	18733	18733

Note: The dependent variable is $Trust$, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 2. Alternative Dimensions of Social Capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
			Group Membership					Happiness		
Racfr	-0.090*			0.053	0.146	-0.056**			-0.024	0.018
	(0.05)			(0.08)	(0.12)	(0.03)			(0.04)	(0.04)
Ethnfr		-0.152*		-0.138	-0.157		-0.112**		-0.095*	-0.116*
		(0.08)		(0.11)	(0.12)		(0.05)		(0.06)	(0.06)
Theil			-0.474**	-0.474**				-0.072	0.025	
			(0.19)	(0.23)				(0.08)	(0.10)	
Btw Theil					-1.890*					-0.660**
					(1.14)					(0.34)
Wth Theil					-0.344					0.112
					(0.22)					(0.11)
Observations	11645	11645	11645	11645	11645	26447	26447	26447	26447	26447

Note: The dependent variable in columns (1) to (5) is *Membership*, coded one for individuals who belong to *at least* one group among those surveyed in the GSS, and zero otherwise. The dependent variable in columns (6) to (10) is *Happiness*, coded one for individuals who say they are happy, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 3. IV-2SLS, First Stage and Reduced Form

	Panel A: IV-2SLS. Dependent variable: *Trust*		
	(1)	(2)	(3)
	Full	5% |res| f.s.	Full
Btw Theil	-9.488*	-7.742**	-2.112**
	(5.33)	(3.32)	(0.95)
Wth Theil	0.493	0.396	0.231
	(0.34)	(0.26)	(0.18)
Racfr	0.529	0.465	
	(0.43)	(0.31)	
Polar			-0.086*
			(0.05)
Observations	18733	17864	18733
Kleinbergen-Paap F-statistic	5.76	12.30	24.27
Anderson-Rubin Chi-2 p-value	0.0014	0.0011	0.0117
	Panel B: First Stage. Dependent variable: *Btw Theil*		
Btw Theil Pred.	0.443**	0.509***	0.838***
	(0.18)	(0.15)	(0.17)
Wth Theil	0.049**	0.053***	0.086***
	(0.02)	(0.01)	(0.02)
Racfr	0.055***	0.060***	
	(0.01)	(0.01)	
Polar			0.009
			(0.01)
Observations	18733	17864	18733
	Panel C: Reduced Form. Dependent variable: *Trust*		
Btw Theil Pred.	-4.207***	-3.939***	-1.769**
	(1.32)	(1.22)	(0.71)
Wth Theil	0.030	-0.013	0.049
	(0.16)	(0.18)	(0.15)
Racfr	0.010	-0.000	
	(0.08)	(0.08)	
Polar			-0.106**
			(0.04)
Observations	18733	17864	18733

The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). Column (1) estimates over the full sample and controls for racial fragmentation. Column (2) excludes the observations whose residuals are in the top 5% (in absolute value) in the first stage. Column (3) estimates over the full sample and controls for racial polarization. All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. The method of estimation is two-stage least squares. The values in brackets are Huber robust standard errors clustered at the metropolitan area level. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 4. Self-Selection

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Income by Race		Educ. by Race		20-25 years		State-Year FE	
	LS	LS	LS	LS	LS	LS	LS	LS
Racfr	-0.299***	-0.171*	-0.182***	-0.101	-0.370*	-0.123	-0.238***	-0.143
	(0.08)	(0.10)	(0.07)	(0.09)	(0.21)	(0.27)	(0.08)	(0.10)
Ethnfr	0.036	-0.059	-0.039	-0.084	0.289	0.187	0.065	-0.012
	(0.09)	(0.10)	(0.10)	(0.10)	(0.26)	(0.27)	(0.09)	(0.11)
Theil	0.021		-0.268		-0.409		-0.102	
	(0.17)		(0.19)		(0.51)		(0.21)	
Btw Theil		-2.253***		-1.554**		-3.824*		-1.849*
		(0.87)		(0.77)		(2.22)		(0.99)
Wth Theil		0.347*		-0.094		-0.179		0.167
		(0.19)		(0.20)		(0.53)		(0.23)
Med. Inc. Race	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Educ. Race	No	No	Yes	Yes	No	No	No	No
State FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No
State-Year FE	No	No	No	No	No	No	Yes	Yes
Observations	17912	17912	18169	18169	1434	1434	17831	17831

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). Columns (1)-(2) replace the MSA median income level with the MSA median income level of each race. Columns (3)-(4) include the shares of primary, secondary and tertiary education for all racial groups in the MSA. Columns (5)-(6) restrict the sample to GSS respondents between 20 and 25 years of age. Columns (7)-(8) replace state and year fixed effects, by state-year fixed effects. All specifications also include the logarithm of the MSA size and all the individual characteristics reported in Table A3. The MSA median income level is included in all specification, except for columns (1)-(2). 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. All regressions, except those in columns (7)-(8), control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 5. Alternative Measures of Racial Diversity

	(1)	(2)	(3)	(4)	(5)	(6)
		Racial Segregation			Racial Polarization	
Segregation	-0.150***	-0.099*	-0.051			
	(0.05)	(0.05)	(0.05)			
Polarization				-0.181***	-0.175***	-0.144***
				(0.03)	(0.04)	(0.04)
Ethnfr		-0.115	-0.106		0.005	-0.008
		(0.08)	(0.07)		(0.08)	(0.08)
Theil		-0.231			-0.062	
		(0.16)			(0.15)	
Btw Theil			-1.837***			-1.043**
			(0.48)			(0.53)
Wth Theil			0.102			0.108
			(0.18)			(0.18)
Observations	18645	18645	18645	18733	18733	18733

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3, except for *Segregation* and *Polarization*, that are described in Appendix A. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). Columns (1) to (3) consider racial segregation. Columns (4) to (6) consider racial polarization. All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 6 Comparison Interpolated and Actual Data

	(1)	(2)	(3)	(4)	(5)
	Racfr ACS	*Gini ACS*	*Theil ACS*	*Btw Theil ACS*	*Wth Theil ACS*
Racfr	0.747*** (0.04)				
Gini		0.339*** (0.06)			
Theil			0.286*** (0.04)		
Btw Theil				0.421*** (0.04)	
Wth Theil					0.235*** (0.04)
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	521	521	521	521	521

Note: The dependent variable in column (1) is racial fragmentation; in column (2) the Gini index; in column (3) the aggregate Theil; in column (4) the *between-groups* Theil; in column (5) the *within-groups* Theil. Source: American Community Survey 2003-2008. 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. All regressions control for year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 7. Diversity Measures Fixed at Census Years

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Racfr	-0.322***			-0.344***		-0.345***	-0.275***
	(0.05)			(0.09)		(0.09)	(0.09)
Ethnfr		-0.178*		0.084		0.069	0.028
		(0.11)		(0.12)		(0.11)	(0.12)
Gini			-1.180***	-0.356			
			(0.29)	(0.39)			
Theil					-0.470***	-0.206	
					(0.15)	(0.23)	
Btw Theil							-1.488*
							(0.90)
Wth Theil							0.003
							(0.31)
Indiv. Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18089	14341	17426	14341	18089	14341	14341

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). The variables' values in the Census years are kept fixed throughout the decade, until the next Census. All specifications also include the logarithm of the MSA size, the MSA median income level by race and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 8. Further Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Control for Crime			Alternative Trust			Alternative Race		
Crime	-0.298*	-0.307*	-0.265						
	(0.16)	(0.17)	(0.18)						
Racfr	-0.199**	-0.269***	-0.137	-0.138**	-0.163**	-0.042	-0.100*	-0.148**	-0.096
	(0.09)	(0.10)	(0.10)	(0.07)	(0.07)	(0.08)	(0.06)	(0.06)	(0.07)
Ethnfr	0.036	0.051	-0.036	-0.062	-0.059	-0.117	-0.065	-0.085	-0.083
	(0.13)	(0.13)	(0.14)	(0.10)	(0.10)	(0.10)	(0.08)	(0.08)	(0.08)
Gini	-0.360			-0.093			-0.557*		
	(0.42)			(0.34)			(0.33)		
Theil		0.083			0.058			-0.090	
		(0.26)			(0.18)			(0.19)	
Btw Theil			-1.830***			-1.772**			-1.458**
			(0.68)			(0.75)			(0.72)
Wth Theil			0.345			0.269			0.007
			(0.29)			(0.19)			(0.20)
Observations	11354	11354	11354	18733	18733	18733	18733	18733	18733

Note: The dependent variable is *Trust*. In columns (1) to (3) and (7) to (9) it is coded one for individuals who say they can trust others, and zero otherwise. In columns (4) to (6) it is coded one for individuals who say they can trust others or that "it depends", and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). Columns (1) to (3) also include the number of serious crimes per 1000 persons. Source: FBI Uniform Crime Reports 1985-2009. Columns (7) to (9) follow the alternative classification of racial groups discussed in Section 3. All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 9. Inherited vs Experiential Trust

	Respondent Ethnicity			Ethnicity Share in the MSA		
	(1)	(2)	(3)	(4)	(5)	(6)
Racfr		-0.191***	-0.112		-0.117	-0.066
		(0.07)	(0.08)		(0.08)	(0.08)
Ethnfr		-0.031	-0.069			
		(0.09)	(0.09)			
Theil		0.037			0.028	
		(0.19)			(0.19)	
Btw Theil			-1.144*			-1.244*
			(0.65)			(0.69)
Wth Theil			0.174			0.204
			(0.19)			(0.21)
Africa	-0.088	-0.086	-0.086	-1.178	-0.697	0.199
Austria	-0.054	-0.050	-0.050	4.839*	4.527*	5.206**
Canada	-0.027	-0.015	-0.015	5.304	4.546	3.508
Czech Republic	-0.016	-0.034	-0.034	-1.176	-0.823	-1.036
Denmark	0.045	0.051	0.052	-0.797	-0.869	-1.043
United Kingdom	0.020	0.016	0.017	0.217	0.152	0.134
Finland	-0.027	-0.019	-0.019	-2.842	-2.865	-3.371
France	-0.006	-0.007	-0.007	1.063***	1.007***	0.925**
Germany	-0.031	-0.037	-0.037	0.166	0.091	0.119
Hungary	-0.036	-0.043	-0.042	1.339	0.888	1.057
Ireland	0.019	0.014	0.014	0.118	-0.003	0.052
Italy	-0.064*	-0.064*	-0.063*	0.143	0.123	0.090
Netherlands	-0.049	-0.050	-0.051	0.781***	0.691***	0.533***
Norway	0.038	0.045	0.046	-0.873	-0.964	-1.085*
Poland	-0.056	-0.062	-0.062	0.124	0.088	0.038
Portugal	-0.116**	-0.123**	-0.123**	-0.655	-0.719	-0.672
Mexico	-0.095***	-0.092**	-0.091**	-0.031	-0.006	0.105
Russia	-0.064	-0.062	-0.062	-0.309	-0.053	-0.236
Spain	-0.088**	-0.080*	-0.080*	-3.997*	-3.871*	-4.187*
Switzerland	0.025	0.022	0.022	4.270*	3.926*	3.655
Yugoslavia	-0.100	-0.104	-0.104	-4.718	-3.723	-3.897
India	-0.171***	-0.152***	-0.151***	2.847	3.394*	3.829**
Belgium				11.544**	11.345**	6.434
Sweden				0.995	0.911	1.305
Observations	13030	13030	13030	18733	18733	18733

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). All specifications also include the logarithm of the MSA size, the MSA median income level and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 10. Racial Inequality and Fractionalization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Below Median		Above Median		Pre-1994		Post-1994	
Racfr	-0.260**	-0.188	-0.330**	-0.147	-0.242**	-0.174	-0.452**	-0.296
	(0.13)	(0.18)	(0.14)	(0.15)	(0.12)	(0.13)	(0.20)	(0.21)
Ethnfr	-0.174	-0.186	0.237	0.101	0.082	0.064	0.204	0.003
	(0.12)	(0.12)	(0.17)	(0.17)	(0.16)	(0.16)	(0.18)	(0.21)
Theil	0.035		0.187		-0.340		0.384	
	(0.27)		(0.27)		(0.33)		(0.35)	
Btw Theil		-1.454		-3.186***		-1.577		-2.661*
		(2.18)		(0.85)		(1.27)		(1.58)
Wth Theil		0.091		0.773***		-0.238		0.942**
		(0.30)		(0.24)		(0.36)		(0.43)
Observations	9021	9021	8889	8889	10908	10908	6150	6150

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). Columns (1)-(2) consider MSA below the median racial fragmentation level. Columns (3)-(4) MSA above the median racial fragmentation level. Columns (5)-(6) consider years until 1994. Columns (7)-(8) years after 1994. All specifications also include the logarithm of the MSA size, the MSA median income level by race and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 11. Racial Inequality and Population Groups

	(1) Whites	(2) Blacks	(3) Ind Am	(4) Asian	(5) Hispanic
Racfr	-0.182	0.030	0.899**	-5.616***	0.285
	(0.12)	(0.18)	(0.42)	(1.26)	(0.44)
Ethnfr	-0.089	-0.003	-1.162**	-0.649	-0.607
	(0.12)	(0.22)	(0.49)	(1.46)	(0.38)
Btw Theil	-1.553	-4.526***	-0.978	-7.718	-5.705**
	(1.01)	(1.74)	(4.57)	(6.26)	(2.67)
Wth Theil	0.455*	0.415	-0.544	-2.703	1.953**
	(0.24)	(0.60)	(1.06)	(2.38)	(0.85)
Observations	10829	1967	502	266	954

Note: The dependent variable is *Trust*, coded one for individuals who say they can trust others, and zero otherwise. Source: GSS cumulative data file 1972-2008. The explanatory variables are described in detail in Section 3. Source: IPUMS 1% sample of US Census (1970, 1980, 1990, 2000). All specifications also include the logarithm of the MSA size, the MSA median income level by race and all the individual characteristics reported in Table A3. 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. All regressions control for state and year fixed effects. *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table A4. Summary Statistics. Community Characteristics

	mean	median	sd	min	max	count
Trust	.38	0	.48	0	1	21964
Member	.70	1	.46	0	1	13203
Happy	.87	1	.33	0	1	30984
Ln Median Income	10.41	10.48	.469	8.69	11.25	21715
Ln Median Income sq	108.62	110.00	9.68	75.55	126.78	21715
Racial Fragmentation	.39	.41	.17	.02	.72	21715
Ethnic Fragmentation	.74	.75	.09	.38	.98	21715
Racial Segregation	.31	.31	.12	.04	.59	21715
Racial Polarization	.61	.68	.21	.05	.98	21812
Gini	.42	.41	.05	.27	.55	21715
Total Theil	.33	.32	.08	.13	.58	21715
Between Theil	.02	.02	.01	.00	.08	21715
Within Theil	.31	.30	.07	.13	.56	21715

Table A3. Summary Statistics. Individual Characteristics

	mean	median	sd	min	max	count
Ln Median Income	10.02	10.14	.97	5.61	11.87	19096
Cohort	1946.16	1949	19.47	1884	1990	21873
Age 30	.22	0	.41	0	1	21964
Age 3039	.23	0	.42	0	1	21964
Age 5059	.13	0	.34	0	1	21964
Age 60	.22	0	.41	0	1	21964
Married	.51	1	.49	0	1	21964
Female	.55	1	.49	0	1	21964
Black	.15	0	.36	0	1	21964
Educ 12	.20	0	.40	0	1	21964
Educ 16	.24	0	.43	0	1	21964
Full	.51	1	.49	0	1	21964
Part	.10	0	.30	0	1	21964
Divorced	.16	0	.37	0	1	21964
Prot	.54	1	.49	0	1	21964
Cath	.27	0	.44	0	1	21964
Jew	.02	0	.16	0	1	21964
Ln Size	4.16	3.98	2.10	0	8.98	21057

Figure 1 A. Similar Characteristics but Different Trust

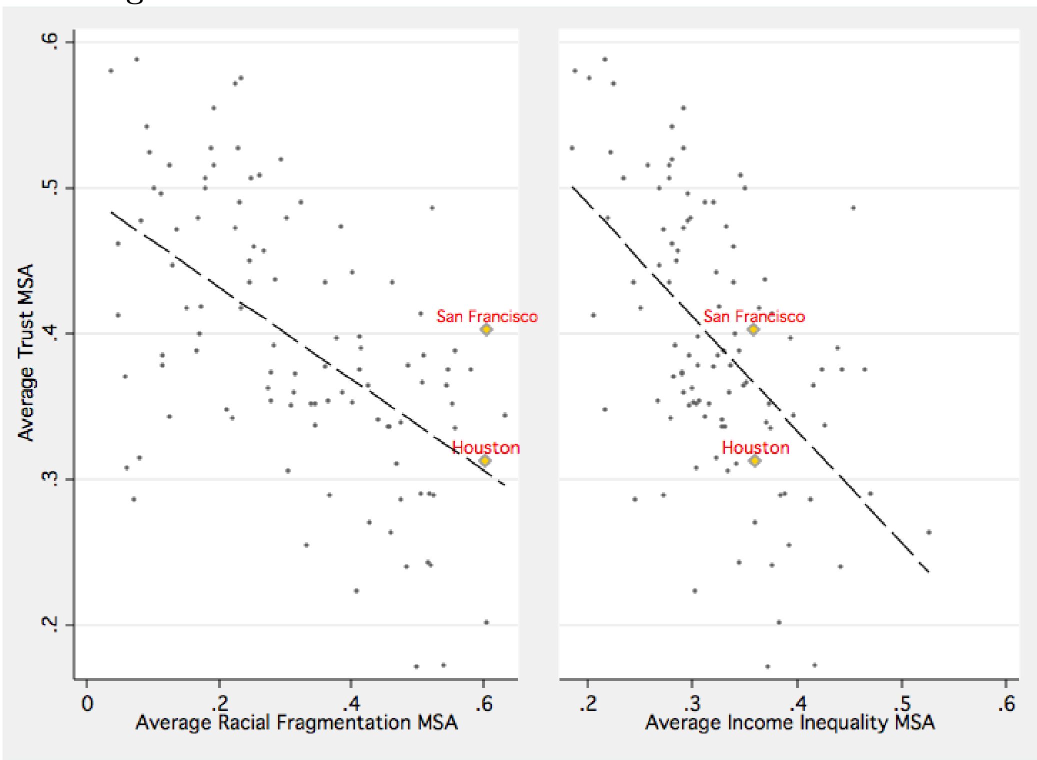

Figure 1 B. Are They Really Similar?

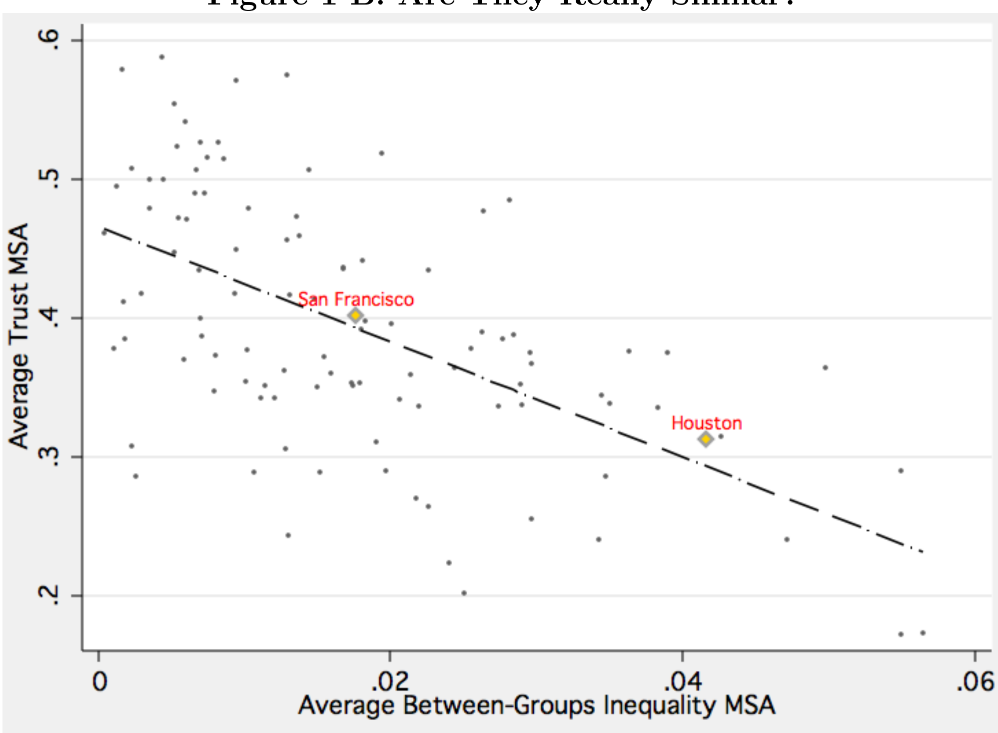

Figure 2A. Similar Characteristics but Different Trust

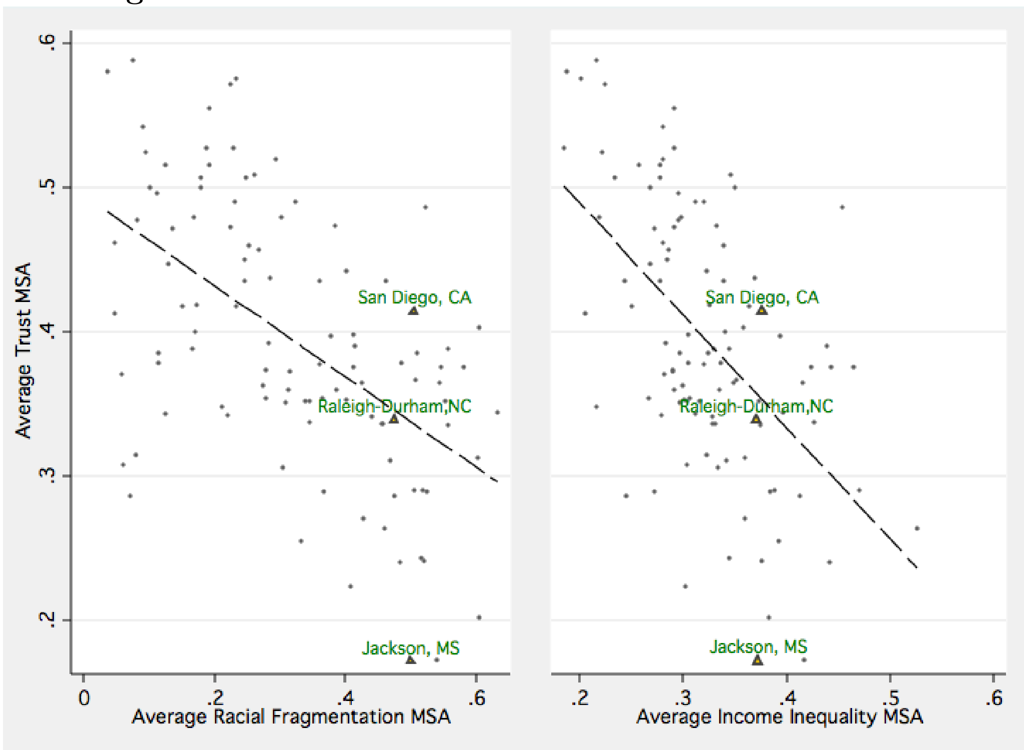

Figure 2B. Are They Really Similar?

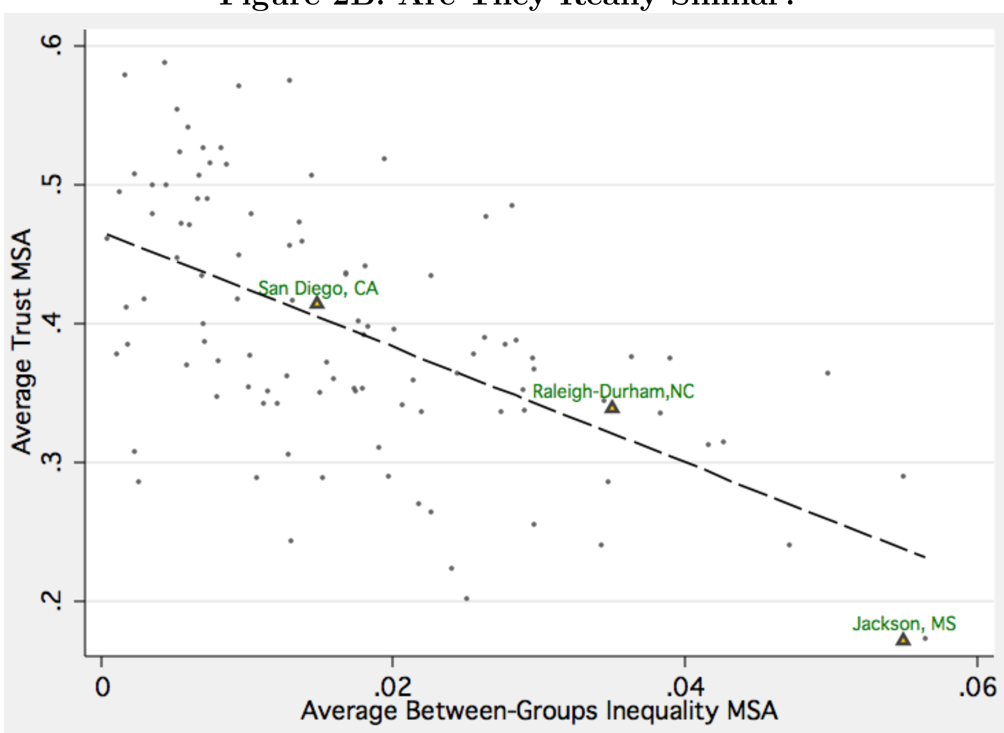

Table A1. Hispanic in the Population

	Hispanic	% Hispanic	% US	Not Hispanic	% Not Hispanic	% US
Any Race	35,305,818	100	12.5	246,116,088	100	87.5
One Race	33,081,736	93.7	11.8	241,513,942	98.1	85.8
White	16,907,852	47.9	6.0	194,552,774	79.1	69.1
Black	710,353	2.0	0.3	33,947,837	13.8	12.1
Am Indian	407,073	1.2	0.1	2,068,883	0.8	0.7
Asian	119,829	0.3	0.1	10,123,169	4.1	3.6
Other	14,891,303	42.2	5.3	467,770	0.2	0.2
Two Race	2,224,082	6.3	0.8	4,602,146	1.9	1.6

Table A2. Correlations 1972-2008

	Trust	*Gini*	*Theil*	*Wth Th*	*Btw Th*	*Rac ICE*	*Rac ALF*	*Segr*	*Pol*
Trust	1								
Gini	-0.35	1							
Theil	-0.30	0.98	1						
Wth Th	-0.25	0.96	0.99	1					
Btw Th	-0.51	0.77	0.74	0.65	1				
Rac ICE	-0.49	0.66	0.62	0.55	0.77	1			
Rac ALF	-0.50	0.72	0.68	0.62	0.80	0.94	1		
Segr	-0.31	-0.22	-0.25	-0.31	0.10	0.12	0.14	1	
Pol	-0.60	0.51	0.46	0.39	0.67	0.91	0.88	0.26	1

Figure 3. Two hypothetical communities

First Community

	White	Black	Inequality
Rich	50%	0%	50%
Poor	0%	50%	50%
Race	50%	50%	

Second Community

	White	Black	Inequality
Rich	25%	25%	50%
Poor	25%	25%	50%
Race	50%	50%	

Figure 4. Trust and dimensions of similarity