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

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March 27, 2017

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

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

JEL Codes: D31; Z10; J15

* Thanks to Francesco Caselli, Antonio Ciccone, Federico Cingano, Francesco Fasani, Nicola Gennaioli, Albrecht Glitz, Eliana La Ferrara, Stephan Litschig, Aniol Llorente-Saguer, Marco Manacorda, Alan Manning, Barbara Petrongolo, Giacomo Ponzetto, Climent Quintana-Domeque, Marta Reynal-Querol, Joachim Voth, as well as seminar participants at CREI, Universitat Pompeu Fabra, Edinburgh University, Queen Mary University, Inter-American Development Bank, Universitat Autonoma de Barcelona, Universitat de Barcelona, Copenhagen University, CERGE-EI, Collegio Carlo Alberto, Royal Holloway University and Bank of Italy for useful comments and suggestions.

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1. Introduction

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

In this paper, I reconsider the existing evidence and emphasize the impact on trust of the income inequality between racial groups, arguably one of the defining features of American politics, with potentially negative social and economic consequences (Alesina et al., 2016).[2] I show that this additional dimension of community heterogeneity is key for understanding the different levels of trust across Metropolitan Statistical Areas (MSA henceforth) in the U.S. My empirical work starts out by showing that racial fragmentation and overall income inequality have a statistically significant, negative effect on individual measures of trust, a result that is consistent with previous findings (Alesina and La Ferrara, 2002; Putnam, 2007). But I then find that these effects become statistically insignificant once I account for racial income inequality. Hence, my empirical results indicate that it is not income inequality or racial fragmentation *per se* that reduce the level of trust in metropolitan areas. Instead, what turns out to be key for the level of trust is the concurrence of differences in race and income.

My estimates show that individuals living in communities characterized by greater racial income inequality have lower levels of trust. The estimated coefficients imply that a one s.d. increase in racial income inequality is associated with a reduction in the average level of trust in the community of 2.8 percentage points, or 7% of its mean value. I also show that racial income inequality has a more detrimental effect in more racially fragmented communities and that minority groups reduce trust more than the majority group when racial income inequality increases. These results are robust to alternative definitions of racial diversity and alternative treatments of the time dimension. The results also prevail when I instrument racial income inequality with a variant of the shift-share instrument (Bartik, 1991), which combines the initial occupational distribution by race at the local level with annual changes in industry payments at the national level. Hence, the negative effect of racial income inequality on trust does not appear to be driven by reverse causation from low (interracial) trust to high inequality of average incomes across racial groups.

I consider two alternative explanations for my results. The first emphasizes the competi-

[1] According to U.S. Census projections (Colby and Ortman, 2015), by the year 2050 more than half of all Americans will belong to a minority group (any group other than non-Hispanic Whites).

[2] Racial income differentials have been remarkably stable over the past 40 years and, as recently as 2014, Black and Hispanic families still only had 59 and 71 cents, respectively, for every dollar of White median household income.

tion for access to valuable but limited resources, such as public education and welfare. This may foster prejudices and social stereotypes against competing others, ultimately reducing the overall level of trust in the community. The second explanation, instead, focuses on the well-documented preference for similarity of individuals and the associated tendency to trust more those who are akin to themselves. While this tendency exists regardless of the context, the more frequent exposure to people of different race and socio-economic background leads individuals in more racially unequal communities to trust other people less, on average. I use individual-level data to try to distinguish between these two explanations and find empirical support only for the latter, based on the assumption of preference for similarity. This motivates the last part of the paper, where I qualify this assumption by showing, in particular, that racial income inequality reduces trust only if the preference for similarity is *non-linear*, with trust falling at increasing rates towards those who are different both in race and income.

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

Figure 1 illustrates some of my main empirical findings using data on average trust and measures of community heterogeneity across U.S. metropolitan areas.[4] Panel (A) plots the average level of trust for MSA over the period 1973-2010, against their average level of racial fragmentation. Panel (B) plots it against their average level of income inequality. Both panels confirm the existence of an inverse relation between trust and the measures of community heterogeneity, as documented in the literature. The graph, however, also illustrates that racial fragmentation and income inequality alone cannot fully account for the difference in average trust levels between similar cities, like San Francisco and Houston. In spite of their very similar level of community heterogeneity, citizens in the two cities report different levels of trust: while 40% of those living in San Francisco say they can trust others, only 31% in Houston do so.

The explicit focus on racial income inequality provides an explanation for this difference. Figure 2 plots on the horizontal axis the between-groups component of income inequality measured by the Theil index. The graph shows that the two cities are actually very different in this dimension. The share of overall inequality that is due to differences among races is twice as large in Houston as in San Francisco. This in turn seems to affect the level of trust in the two

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

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

communities. In San Francisco, where the probability of meeting an individual of a different race but similar income level is relatively high, the level of trust is higher than in Houston, where belonging to a different race is also likely to be associated with a difference in income. The same pattern of apparent similarity, which is in reality masking an additional dimension of heterogeneity, is repeated over different pairs of MSA. My analysis will thus focus on documenting this pattern in a systematic way.

The results in this paper are related to a recent literature in economics and political science investigating the consequences of between-groups inequality across countries. Baldwin and Huber (2010) show that countries characterized by greater inequality between groups have lower public goods provision, while Alesina et al. (2016) document a strong, negative cross-country relationship between ethnic inequality and real GDP per capita. Their results are consistent with previous studies in the social conflict literature, which stress the role of racial income inequality in fostering political hostility, with the potential to culminate in violent crime (Blau and Blau, 1982) and ethnic violence (Robinson, 2001; Stewart, 2005). Different from these studies, I employ a within-country approach and focus on one of the world's most established democracies to study the consequences of local racial income inequality on trust, one of the crucial dimensions of social capital (Coleman, 1988; Fukuyama, 1996; Putnam, 1995), which is considered a key ingredient for economic growth (Algan and Cahuc, 2010; Zak and Knack, 2001), financial development (Guiso et al., 2004) and institutional quality (Knack, 2002).

In economics, Alesina and La Ferrara (2002) were the first to emphasize the negative effect of community heterogeneity on trust, showing that greater racial fragmentation and income inequality are associated with lower levels of trust in U.S. metropolitan areas. Between the two measures of heterogeneity, they find racial fragmentation to be more strongly (negatively) associated with trust, concluding that people are more likely to trust others in an economically unequal city rather than in a racially fragmented one. Similar results have been documented for the U.S. by Costa and Kahn (2003) and Putnam (2007), and by Leigh (2006) and Gustavsson and Jordahl (2008) for Australia and Sweden, respectively. Dinesen and Sonderskov (2014) show that the negative effect of racial heterogeneity on trust becomes even stronger in the immediate micro-context (within a radius of 80 meters of a given household).[5] A related strand of the literature finds a negative relationship between racial fragmentation, income inequality and other dimensions of social capital, such as group participation (Alesina and La Ferrara, 2000), civic engagement (Vigdor, 2004) and public good provision (Alesina et al., 1999). I complement these studies by showing that the key correlate of trust is the level of racial income inequality, which can be seen as an indicator of the concurrence of the two dimensions of heterogeneity emphasized in previous work.

A related theoretical literature (Alesina and La Ferrara, 2000; Tabellini, 2008) provides an-

[5] While most empirical studies support the notion that diversity erodes trust, alternative perspectives - most notably Allport's 1954 contact theory - exist. Contact theory suggests that diversity fosters interethnic tolerance and social solidarity, and predicts that diversity should *increase* trust. Some empirical evidence in support of the argument is reported in Stolle et al. (2008).

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

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

2. Data and Estimation Framework

2.1. Data

The main source of data in this study is the General Social Survey (GSS henceforth) for the years 1973-2010.[6] In each round, the GSS interviews about 1,500 individuals on a broad range of topics, including demographic, behavioural and attitudinal questions. The sample is built to be nationally representative, with primary sampling units represented by MSA and non-metropolitan counties stratified by region, age and race before selection (King and Richards, 1972). My main dependent variable, the measure of trust, is obtained from the following question: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?". I code as 1 individuals who answer "most people can be trusted", while those who answer "most people can't be trusted" or "it depends" are coded as 0. Respondents who report to trust others are 38% of the total.[7] The individual characteristics used in the estimation are also obtained from the GSS. These include variables on age, education, race, religion, gender, family income, working conditions, marital status, size of the place of residence and a dummy for the race of the respondent. The upper panel of Table A.2 reports summary statistics for these variables. From the GSS Sensitive Data files I identify the metropolitan areas in which the respondents live, in order to match them with the measures

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

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

of community heterogeneity calculated at the MSA level.[8] The respondents come from 110 different MSA, listed in Table A.1. Since the GSS is built to be nationally representative, many MSA (typically the smallest ones in terms of population) are only sampled in few rounds, and then replaced with comparable ones. Table A.1 reports the number of years in which each MSA has been sampled as well as the total number of respondents for each MSA.

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

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

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

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

$$Theil_m = \sum_r \sum_i \frac{y_{irm}}{Y_m} ln \left(\frac{\frac{y_{irm}}{Y_m}}{\frac{1}{N_m}} \right) \tag{2}$$

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

As discussed in Bourguignon (1979), the indices of the generalized entropy class are the

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

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

only ones that satisfy the decomposability property.[10] By virtue of this, the Theil index can be rewritten as:

$$Theil_m = \sum_r \frac{y_{rm}}{Y_m} \left[\sum_i \frac{y_{irm}}{y_{rm}} ln \left(\frac{\frac{y_{irm}}{y_{rm}}}{\frac{1}{n_{rm}}} \right) \right] + \sum_r \frac{y_{rm}}{Y_m} ln \left(\frac{\frac{y_{rm}}{Y_m}}{\frac{n_{rm}}{N_m}} \right) \tag{3}$$

where all components are defined as in equation (2), with the addition of y_{rm}, which represents the income of racial group r, and n_{rm} which is the population of racial group r. In this form, the index explicitly compares the income and population distributions of different subgroups by summing the weighted logarithm of the ratio between their income and population shares. The first term on the right-hand side of equation (3) represents the amount of total inequality that is due to differences *within* racial groups, while the second represents the amount that is due to differences *between* racial groups. Focusing on the latter term, it is easy to see that if one racial group has the same income and population shares it does not contribute to the between-groups inequality of the MSA. On the contrary, if its income share is bigger (smaller) than its population share, the group contributes positively (negatively) to the between-groups inequality. Weighting by the income share of each racial group ensures that the positive contributions are always higher than the negative, so that the between-groups inequality term is always positive. A similar logic applies to the inequality within racial groups: if one of the n individuals of a racial group earns $1/n$-th of the total group income, his contribution to the within-groups inequality is equal to zero. If he earns more (less) than that, his contribution is positive (negative). As in the previous case, weighting by the income share of each individual ensures that the within-groups inequality term is always positive. Altogether, the Theil index thus evaluates the discrepancy between the distribution of income and the distribution of population both within and between different groups.

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

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

at the MSA level in all regressions, allowing for heteroskedasticity and arbitrary correlation in the error term. In section 3 I investigate the robustness of the results to alternative treatments of the time dimension.

2.2. Estimation framework

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

$$Tr_{imt} = \beta_1 X_{imt} + \beta_2 RacFr_{mt} + \beta_3 Ineq_{mt} + \delta_1 Z_{mt} + \alpha_{s(m)t} + \tau_t + \varepsilon_{imt} \tag{4}$$

where X_{imt} is the vector of individual characteristics reported in Table A.2, Z_{mt} is a set of community characteristics including the logarithm of the median income of each racial group in the MSA (and its squared term), the logarithm of the MSA size and the index of ethnic fragmentation, $RacFr_{mt}$ is the measure of racial fragmentation and $Ineq_{mt}$ is the measure of aggregate income inequality (calculated either by the Gini or by the Theil index), $\alpha_{s(m)t}$ and τ_t are state and year fixed effects. Finally, ε_{imt} is an error term that is clustered at the MSA level to allow for arbitrary heteroskedasticity and serial correlation.

In order to identify the impact of racial income inequality on trust, I expand the previous specification to separately estimate the effect of between- and within-groups inequality. This is done in the following regression:

$$Tr_{imt} = \tilde{\beta}_1 X_{imt} + \tilde{\beta}_2 RacFr_{mt} + \gamma_1 BtwIneq_{mt} + \gamma_2 WthIneq_{mt} + \tilde{\delta}_1 Z_{mt} + \alpha_{s(m)t} + \tau_t + \eta_{imt} \tag{5}$$

where all variables are defined as above, with the exception of $BtwIneq_{mt}$ that represents the inequality between racial groups and $WthIneq_{mt}$, the inequality within racial groups. As in the previous equation, the error term is clustered at the MSA level. The main coefficient of interest is γ_1, which captures the effect of greater racial income inequality on trust. In addition, I will be interested in observing the variation of the coefficient of racial fragmentation (from β_2 to $\tilde{\beta}_2$) once the inequality between races is explicitly accounted for. The method of estimation in the baseline specification is least squares. In section 3.2 I instrument the measures of racial income inequality and racial fragmentation and estimate two-stage least squares regressions.[11]

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

3. Empirical Results

3.1. Least squares estimation

Table 1 reports the estimates of the effect of community heterogeneity on trust for the period 1973-2010. I start by introducing the measures of community heterogeneity one at a time. Columns (1) and (2) show that both racial fragmentation and income inequality (measured by the Gini index) are negatively and significantly correlated with trust at the 99% level. The estimated coefficients are remarkably similar to those found by Alesina and La Ferrara (2002) for the period 1974-1994. The point estimate for racial fragmentation implies that, moving from the least to the most racially fragmented MSA the probability of trusting others decreases by 16 percentage points. Starting from the sample mean, a one s.d. increase in racial fragmentation reduces trust by 3.7 percentage points, or 10% of the sample mean. Similarly, the coefficient of income inequality implies that a one s.d. increase is associated with a reduction of trust of 9% of the sample mean. In column (3) I consider the two measures of community heterogeneity together. When doing so, the racial fragmentation coefficient remains statistically significant at the 95% level, while the income inequality coefficient drops substantially and becomes insignificant. In columns (4) and (5) I replace the Gini index with the Theil index. The results using the Theil index are similar to those obtained using the Gini index. Individually, the Theil index is negatively and significantly correlated with trust at the 95% level. When considered along with racial fragmentation it becomes insignificant and only the racial fragmentation coefficient remains negatively and significantly associated with trust.

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

Table 2 investigates the robustness of this result to alternative definitions of racial diversity. In columns (1) to (5) I replace the index of racial fragmentation with the individual shares of each racial group at a time. Since minorities are less trusting, the impact of fragmentation on trust may simply arise from compositional effects (Uslaner, 2008). The estimates show that trust is lower in the presence of larger Black and Hispanic minorities while it is higher for larger shares of the wealthier White and Asian groups, although the coefficients are not always statistically significant. Irrespective of the racial group considered, however, the coefficient of racial income inequality remains negative and highly significant in all columns, suggesting that the measure is not simply a proxy for larger population shares of groups with different levels of trust. In columns (6) and (7) I replace the index of racial fragmentation with an index of racial *segregation*.[12] Alesina and Zhuravskaya (2011) show the existence of a strong negative relationship between segregation and the level of trust in a cross-section of countries. Relatedly, Stolle et al. (2008) and Uslaner (2011) argue that, while fragmented but integrated communities may facilitate the repeated interactions among races raising their mutual trust, segregation reduces it by isolating groups from each other. In line with this argument, column (6) displays a negative and significant coefficient for racial segregation. The point estimate suggests that a one s.d. increase in segregation reduces trust by 3% of its mean value. The effect however becomes insignificant in column (7) when I include the measure of racial income inequality, which retains a negative coefficient significant at the 99% level. This suggests that the impact of racial income inequality is not limited to the sorting of individuals of different races across neighbourhoods on the basis of income. Indeed, the correlation between racial income inequality and segregation in the sample is only slightly positive (0.11).[13] Finally, columns (8) and (9) substitute the baseline indeces of racial fragmentation and inequality with similar ones calculated only on two groups (Whites versus non-Whites). The estimates using this alternative definition closely resemble those in the baseline model, confirming that the results also hold for broader racial definitions.[14]

Table 3 investigates alternative treatments of the time dimension. Columns (1) and (2) replace the state and year fixed effects with state X year fixed effects, allowing different states to follow different trends in the evolution of racial fragmentation and inequality. The results are similar to those in the baseline specification, except that racial fragmentation in column

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

[13] This is consistent with the theoretical results of Sethi and Somanathan (2004), who show that segregation happens at both high and low levels of racial income inequality if individuals care about the affluence and the racial composition of their neighborhoods.

[14] All results in the paper are robust to the Whites/non-Whites classification. Results available upon request.

(2) retains an independent effect on trust significant at the 90% level. The income inequality between races remains negatively and significantly correlated with trust at the 99% level. In the next columns I replace the interpolated measures of racial fragmentation and inequality with their original values calculated at different Census years. Keeping the measures of community heterogeneity constant reduces concerns of serial correlation introduced by linear interpolation. Columns (3) and (4) assign the value calculated at the preceding Census year and held constant over the following decade, while columns (5) and (6) assign the value calculated at the closest Census year. The results under both alternative definitions are very similar to the baseline, suggesting that the variation is mostly cross-sectional.

3.2. Instrumental variable estimation

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

To identify exogenous variation in racial income inequality at the MSA level I use a variant of the shift-share approach developed by Bartik (1991) and employed by Blanchard and Katz (1992) and Autor and Duggan (2003), among others. I predict the evolution of racial income shares - and the ensuing level of racial inequality - in each MSA, by interacting the initial occupational distribution by race at the local level with annual changes in industry payments at the national level. Specifically, I use the 1980 IPUMS Census data to construct MSA-specific racial employment shares in 68 two-digit industries (listed in Table A.4), for which I calculate the national-level evolution of annual payments over the period 1975-2010 using data from the Bureau of Labor Statistics.[15] Intuitively, MSA where minority workers were initially employed in industries that turned out to grow slowly over the following 30 years, will have higher predicted racial inequality compared to MSA where minorities were employed relatively more in industries that turned out to grow fast.

[15] I use 1980 as base year because information about occupation is missing for more than 50% of individuals in the 1970 Census IPUMS. For a similar application of Bartik shift-share instrument to local labor markets characterized along racial lines, see Bound et al. (1993).

National-level changes in industry payments between 1975 and 2010 are unlikely to be affected by local conditions in any given MSA and instead are arguably driven by international market competition and sectoral structural changes. Also, the detailed two-digit industry breakdown mitigates the concern that the instrument may simply be capturing underlying features of large macro industries like agriculture, whose specific characteristics - the nature of contracts or the working conditions - may historically affect the level of trust in the community.[16] Altogether, the shift-share methodology thus captures exogenous shifts in racial income inequality predicted by the initial MSA-specific industry mix, while avoiding the endogeneity associated with local occupational growth rates and other unobservable factors potentially correlated with both trust and racial inequality at the local level.

Table A.5 provides an illustration of the source of identifying variation in the data. The table reports the average employment shares - total and by race - for 8 selected two-digit industries, and the corresponding standard deviation for each race-industry pair. While there are clear differences in the occupational composition of races across industries, one can also appreciate the large variation across MSA within each race-industry pair, summarized by the standard deviation in brackets.[17] Such initial differences, associated with the different economic fortunes of each sector over the period, generate the cross-MSA variation used to identify the evolution of racial income inequality.

The instrument for racial fragmentation exploits the settlement patterns of immigrants based on pre-existing clusters, as in Card (2001). In particular, I predict flows of Hispanic and Asian immigrants based on their tendency to move to previously established enclaves. I thus multiply the initial shares of Hispanics and Asians in each MSA in 1970 by their national immigration inflows over the following decades, in order to obtain their predicted shares in each MSA. This isolates the exogenous supply-push component of Hispanic and Asian population shares, which are independent of MSA-specific levels of interracial trust. I then calculate a predicted racial fragmentation index, by replacing the actual shares of Hispanic and Asian population with the corresponding predicted shares based on earlier settlement locations.[18]

Columns (1) to (4) of Table 4 report estimates of the first-stage equations. The first two columns show the independent effect of each instrument on the corresponding endogenous regressor. The point estimate in column (1) suggests that a one s.d. increase in the predicted

[16] On average, each one of the 68 two-digit industries employs less than 1.5% of the total population and even the largest sector - Education - employs less than 9%.

[17] Perhaps not surprisingly, minority workers were initially overrepresented in low-pay sectors and in sectors that turned out to grow slowly during the following period (e.g. social services, whose average annual pay growth was 3.3%). They were instead disproportionately underrepresented in sectors that turned out to grow fast, like business services (average pay growth 4.9%). In spite of these broad compositional differences, there is considerable cross-MSA variation in employment within each race-industry pair. For example, against a national average of 3.2% Black population initially employed in business services the share in Phoenix was 4.5%, almost ten times larger than in neighboring Tucson (0.5%).

[18] Asians and, especially, Hispanics represent considerable shares of the U.S. population - 4.8% and 16.3%, respectively, according to the 2010 U.S. Census - and contribute significantly to the index of MSA racial fragmentation. Indeed, calculation of the racial fragmentation index excluding Asian and Hispanic population delivers an average level of racial fragmentation 28% lower than the baseline.

racial fragmentation index is associated with an increase in the actual index by 30% of the mean, an effect that is significant at the 99% level. The coefficient in column (2) instead suggests that a one s.d. increase in predicted racial inequality increases actual racial inequality by one fourth of its mean, an effect that is also significant at the 99% level. Columns (3) and (4) are the first-stage equations of the IV regression in column (7), where both endogenous regressors are included. Each instrument continues to significantly predict the corresponding endogenous regressor, and the point estimates are similar to the unconditional effects in the previous columns.

The remaining columns of Table 4 report the second-stage results. A comparison of the IV estimates in columns (5) and (6) with their OLS counterparts in Table 1 indicate that the effects of racial fragmentation and racial income inequality on trust are stronger (more negative) than what suggested by the non-instrumented estimates. The coefficients are statistically significant at the 99% and 95% level, respectively. In column (7) I consider the two instrumented regressors together. As in the baseline OLS regression, racial fragmentation becomes insignificant, while the index of racial income inequality remains negative and significant at the 90% level. The IV estimates in column (7) imply that a one s.d. increase in racial income inequality reduces trust by 6.1 percentage points, or 16% of its mean value. All IV columns report the Kleibergen-Paap F-statistic. In columns (7) the value is below the rule-of-thumb threshold used to define weak instruments. For this reason, I also report the p-values for two weak instruments robust significance tests, the Anderson-Rubin Chi-2 test and the Stock-Wright Lagrange Multiplier Chi-2 test, in which the standard errors are corrected to account for the extent to which the instruments are weak (Andrews and Stock, 2005). Both procedures test the joint significance of the endogenous variables and clearly reject the null hypothesis that the coefficients are statistically insignificant. Overall, the IV results confirm the negative effect of racial income inequality on trust and suggest that the effect is not driven by reverse causation from low (interracial) trust to high inequality of average incomes across racial groups. Since the OLS results provide a conservative estimate of the true effect, in the remainder I continue to present them along with the IV results, in order to show the consistency between the two sets of results.

4. Potential channels and implications

4.1. Interracial competition and preference for similarity

One way to understand the negative effect of racial income inequality on trust is to consider it part of a more general pattern of social prejudices and stereotypes against poor minorities, who are the main beneficiaries of redistributive policies. This is consistent with the sociological view that prejudice emerges as a defensive reaction from majority group members against challenges to their privileged position (Blalock, 1967) and with evidence showing that support for welfare is lower when recipients are of a different race (Alesina et al., 2001; Luttmer et al., 2001).

Under this interpretation, trust would be lower in racially unequal communities due to the more serious threat posed by minorities for access to valuable resources such as public education and welfare and to greater interracial competition for budget allocation.

Table 5 uses data from the GSS to investigate this explanation, by considering the relationship between racial income inequality, opposition to affirmative action programs and the extent of social stereotypes. If the above interpretation is correct and the decline in trust is linked to greater racial antagonism over the allocation of valuable resources, one should observe lower support for preferential policies and more pronounced social stereotypes where racial income inequality is higher. Columns (1) and (2) ask respondents of the White majority group whether they oppose affirmative action programs, while columns (3) and (4) ask whether they feel directly penalized by such programs. Contrary to the explanation based on interracial antagonism there is no evidence, neither in OLS or IV, that respondents in racially unequal communities are particularly opposed or feel especially threatened by policies granting preferential access to minority groups. Columns (5) to (8) move on to investigate the extent of prejudice and social stereotypes. I use a set of questions from the GSS that ask respondents to rate characteristics of individuals of different racial groups. I combine the answers and the race of the respondents to generate two dummy variables, which are equal to 1 if they think that individuals of other races are hard-working (columns 5 and 6) or intelligent (columns 7 and 8). In contrast to the interpretation based on interracial group competition, the estimates for racial income inequality turn out not to be significant in explaining either characteristics in both OLS and IV regressions. Overall, the results in Table 5 thus provide little support in favour of the interpretation based on interracial animosity fuelled by social stereotypes.

An alternative explanation for the detrimental effect of racial income inequality on trust focuses on individual preferences. A long tradition in both psychology and sociology suggests that individuals have a strong tendency for homophily and prefer to associate with similar individuals (Coleman, 1988; Lazarsfeld and Merton, 1954).[19] The observation is also supported by a large body of experimental evidence (Bornhorst et al., 2010; Glaeser et al., 2000). Alesina and La Ferrara (2000) argue that such preference for similarity plays an indirect role on trust, by determining the propensity of individuals to join associations, unions and religious groups, whose social interactions are particularly conducive to generating high levels of interpersonal trust and reciprocity. Under this interpretation, citizens of heterogeneous communities are less likely to be members of a group due to the higher participation costs when other members are of different races and economic background. The lack of interaction, in turn, would exacerbate perceived differences further, reducing the level of trust in others.

In Table 6 I directly investigate this interpretation, by considering whether individuals exposed to greater racial disparities are less likely to be members of a group. The table presents

[19] The term "homophily" was coined by Lazarsfeld and Merton (1954). Several factors can potentially account for in-group bias, including similarity in preferences and tastes as well as networking arguments (Dixit, 2003; Tabellini, 2008).

regressions in which the dependent variable is a dummy variable equal to 1 if the respondent belongs to a group, and 0 otherwise.[20] The estimates in columns (1)-(3) show that racial income inequality reduces participation. A one s.d. increase in racial income inequality is associated with a reduction in group membership by 5.8 percentage points, or 15% of the sample mean. The result also holds when I instrument both measures of racial income inequality and fragmentation in column (4). Altogether, these results provide support for the interpretation based on the preference for similarity, whereby trust is lower in racially unequal communities because greater racial and income differences discourage interaction in social groups and mutual understanding among individuals. In the next section, I further investigate this assumption and consider its testable implications from the point of view of racial income inequality.

4.2. Characterization and testable implications

Models assuming a preference for similarity typically characterize individuals along one dimension: they are either similar in race or income (e.g. Alesina and La Ferrara, 2000; Tabellini, 2008). The focus on racial income inequality instead entails that individuals can be similar in more than one dimension: *identical* individuals have both the same race and income; *partially similar* individuals have either the same race or the same income; individuals that are *different* have no common element of similarity. This classification along multiple dimensions carries additional insights on the underlying features of the preference for similarity assumption. A formal analysis is reported in Appendix A, which presents a basic two-groups model of trust formation.[21] Here I offer a heuristic discussion of the conditions that must be satisfied in order for racial income inequality to reduce trust.

As a way of example, consider the two communities in Figure 3, where the population is perfectly split between Blacks and Whites and rich and poor. The only difference between the two is the way in which income is distributed across racial groups. In community A, half of each group is rich and half is poor. In community B, all Whites are rich and all Blacks are poor. Citizens in B therefore face twice as many identical and different individuals compared to A, where there is a larger share of partially similar individuals. From the empirical results in Section 3 we also know that trust is lower in B, where racial and economic identities coincide. These two observations combined imply that the doubling number of identical individuals in B - and the corresponding increase in trust - does *not* compensate for the doubling number of different individuals - and the corresponding reduction in trust. This in turn suggests that citizens have *non-linear* preferences for similarity: their trust falls at increasing rates as individuals become more different.

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

[21] Considering more than two groups would significantly complicate the analysis, without providing substantial additional insights. The two-groups model approximates the composition of the GSS sample in which Whites and Blacks account for roughly 90% of total individuals (see Table A.2).

The condition is derived analytically in Appendix A and is graphically summarized in Figure 4. 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 (trust towards those different in both dimensions is normalized to 0). The key condition for individual trust to be consistent with the empirical results is $w_2 < 2w_1$, reflecting the nonlinear relationship between trust and similarity. If the condition holds, at all levels of racial fragmentation and total income inequality, trust is lower when racial and income heterogeneity are combined rather than separated.

The non-linear relationship between trust and similarity carries additional implications that can be tested in the data. The first implication, formally derived in Appendix A, is that racial income inequality is more detrimental in more racially fragmented communities. Intuitively this happens because, when racial fragmentation is high, a large number of individuals become different in race and income as racial inequality increases.[22] This number is more limited in racially homogeneous communities, where instead a large portion of individuals - those in the racial majority group - become identical (same race and income) as racial inequality increases. As a consequence, the overall reduction in trust following an increase in racial income inequality is more contained in the latter community.[23] Figure 5 illustrates the point by plotting the change in trust associated with an increase in racial income inequality for communities at different levels of racial fragmentation.

The implication is tested in Table 7. The first two columns consider separately MSA below and above the median level of racial fragmentation. Column (1) shows that the coefficient of racial income inequality is insignificant in the sample of less fragmented MSA. For more fragmented MSA in column (2), instead, the effect is negative and statistically significant at the 95% level. Column (3) pools the observations together and interact the index of racial income inequality with two dummies for MSA above or below the median level of fragmentation. Also in this case, racial income inequality is associated with lower trust only in racially fragmented communities. The interaction term for communities above the median is significant at the 99% level. The result is confirmed also by the pooled IV estimates in column (4), where the interaction term remains significant at the 99% level.

A second implication of the non-linear relationship between trust and similarity concerns the impact of racial income inequality on different racial groups of the same community. In Appendix A, I show formally that minority groups are those who reduce trust most when racial income disparities increase. Intuitively, this depends on the different population shares of each group. The impact of racial income inequality is milder for members of the more populous groups, because these have many individuals to become identical with - based on the defini-

[22] Note that the number is maximized in the two hypothetical communities of the previous example, in which 50% the population belongs to one race and 50% belongs to the other.

[23] Indeed, from a theoretical point of view, the effect of racial income inequality becomes positive at extreme levels of racial homogeneity.

tion above - when racial income inequality increases. Minority groups members, instead, have fewer individuals to become identical with, and face a larger number of individuals who become different in both race and income when racial disparities increase. This implies a more pronounced reduction in their level of trust.

The implication is tested in Table 8. I identify the race of GSS respondents and estimate the impact of between-groups inequality for each racial group. The results in columns (1)-(5) show a negative effect of racial income inequality on trust for all groups, and generally confirm that the effect is stronger for racial minorities. In particular, the point estimates of between-groups inequality are more negative for all minorities (except for Blacks), compared to the White majority group. Column (6) pools all respondents together, interacting the measure of racial income inequality with dummies for their corresponding racial group. Under the pooled specification, for all groups except Native Americans the estimated effect is statistically significant. The coefficient of Whites is the most precisely estimated but its point estimate remains generally smaller in magnitude compared to those of the minority groups.[24]

Finally, Table 9 explores an additional dimension of the relationship between trust and similarity, which is closely related to the model in the Appendix but not explicitly derived there. If, as suggested by the theory, low levels of trust in racially unequal communities are due to the increasing diffidence towards individuals of different race and income, one should observe that only interracial trust decreases with racial inequality, but not trust towards individuals of the same race. Unfortunately, the GSS does not distinguish between own-race and interracial trust. I therefore exploit a different dataset, the Social Capital Benchmark Survey used by Putnam (2007), which distinguishes between the two dimensions. The sample size is similar to the GSS, although individuals are sampled from a smaller set of MSA (41 versus 110) and the data are only cross-sectional for the year 2000. I report results using both OLS and IV. Columns (1) and (2) focus on trust towards individuals of the same race, while columns (3) to (6) on two alternative definitions of interracial trust.[25] In line with the theory, the results indicate that only trust towards people of different races decreases when racial disparities increase. The estimated coefficients of racial income inequality on interracial trust in columns (4) and (6) are fifteen to twenty times larger (more negative) than the coefficient on own-race trust in column (2). Such heterogeneous response is consistent with the interpretation that trust falls at increasing rates as individuals become different in both race and income.

[24] The IV results are qualitatively similar, although the estimates are generally not statistically significant due to the limited sample size of most racial groups. There is also some evidence that the impact of racial income inequality on trust is increasing in individual income. These results are available upon request.

[25] In columns (3) and (4) I define a dummy variable equal to 1 if the respondent declares to trust very much all other racial groups, while in columns (5) and (6) I use the composite mean trust towards other racial groups defined by Putnam (2007).

5. Conclusions

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

References

Alesina, A., Baqir, R., and Easterly, W. (1999). Public goods and ethnic divisions. *Quarterly Journal of Economics*, 114(4):1243–1284.

Alesina, A., Glaeser, E., and Sacerdote, B. (2001). Why doesn't the united states have a european-style welfare state? *Brookings Papers on Economic Activity*, 2001(2):187–254.

Alesina, A. and La Ferrara, E. (2000). Participation in heterogeneous communities. *Quarterly Journal of Economics*, 115(3):847–904.

Alesina, A. and La Ferrara, E. (2002). Who trusts others? *Journal of Public Economics*, 85(2):207–234.

Alesina, A., Michalopoulos, S., and Papaioannou, E. (2016). Ethnic inequality. *Journal of Political Economy*, 124(2):428–488.

Alesina, A. and Zhuravskaya, E. (2011). Segregation and the quality of government in a cross section of countries. *The American Economic Review*, 101(5):1872–1911.

Algan, Y. and Cahuc, P. (2010). Inherited trust and growth. *The American Economic Review*, 100(5):2060–2092.

Allport, G. (1954). *The Nature of Prejudice*. Addison-Wesley.

Andrews, D. W. and Stock, J. H. (2005). Inference with weak instruments. *Cowles Foundation Discussion Paper*, (1530).

Armour, S. (2003). Debate revived on workplace diversity. *USA Today*, page A1.

Autor, D. H. and Duggan, M. G. (2003). The rise in the disability rolls and the decline in unemployment. *Quarterly Journal of Economics*, pages 157–205.

Baldwin, K. and Huber, J. D. (2010). Economic versus cultural differences: Forms of ethnic diversity and public goods provision. *American Political Science Review*, 104(04):644–662.

Bartik, T. J. (1991). Boon or boondoggle? the debate over state and local economic development policies. *Who Benefits from State and Local Economic Development Policies*.

Blalock, H. M. (1967). *Toward a theory of minority-group relations*. Wiley.

Blanchard, O. J. and Katz, L. F. (1992). Regional evolutions. *Brookings papers on economic activity*, 1992(1):1–75.

Blau, J. and Blau, P. (1982). The cost of inequality: Metropolitan structure and violent crime. *American Sociological Review*, 47(1):114–129.

Bornhorst, F., Ichino, A., Kirchkamp, O., Schlag, K., and Winter, E. (2010). Similarities and differences when building trust: the role of cultures. *Experimental Economics*, 13(3):260.

Bound, J., Holzer, H. J., et al. (1993). Industrial shifts, skills levels, and the labor market for white and black males. *The Review of Economics and Statistics*, 75(3):387–96.

Bourguignon, F. (1979). Decomposable income inequality measures. *Econometrica*, 47(4):901–920.

Card, D. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64.

Colby, S. L. and Ortman, J. M. (2015). Projections of the size and composition of the us population: 2014 to 2060. *US Census Bureau*.

Coleman, J. (1988). Social capital in the creation of human capital. *American Journal of Sociology*, 94:95–120.

Costa, D. and Kahn, M. (2003). Civic engagement and community heterogeneity: An economist's perspective. *Perspective on Politics*, 1(1):103–111.

Cowell, F. A. (2000). Measurement of inequality. *Handbook of income distribution*, 1:87–166.

Dinesen, P. T. and Sonderskov, K. M. (2014). Ethnic diversity and social trust: Evidence from the micro-context. *American Sociological Review*, 80(3):550–573.

Dixit, A. (2003). Trade expansion and contract enforcement. *Journal of Political Economy*, 111(6):1293–1317.

Fukuyama, F. (1996). *Trust: The social virtues and the creation of prosperity*. Free Press.

Giuliano, L., Levine, D. I., and Leonard, J. (2009). Manager race and the race of new hires. *Journal of Labor Economics*, 27(4):589–631.

Glaeser, E., Laibson, D., Scheinkman, J., and Soutter, C. (2000). Measuring trust. *Quarterly Journal of Economics*, 115(3):811–846.

Guiso, L., Sapienza, P., and Zingales, L. (2004). The role of social capital in financial development. *The American Economic Review*, 94(3):526–556.

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

Henninger, D. (2007). The death of diversity. *The Wall Street Journal*.

Iceland, J. and Scopilliti, M. (2008). Immigrant residential segregation in US metropolitan areas, 1990–2000. *Demography*, 45(1):79–94.

Jonas, M. (2007). The downside of diversity. *The Boston Globe*.

King, B. and Richards, C. (1972). The 1972 NORC National Probability Sample. *Unpublished NORC memo*.

Knack, S. (2002). Social capital and the quality of government: Evidence from the States. *American Journal of Political Science*, 46(4):772–785.

Lazarsfeld, P. F. and Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. *Freedom and control in modern society*, 18(1):18–66.

Leigh, A. (2006). Trust, inequality and ethnic heterogeneity. *Economic Record*, 82(258):268–280.

Luttmer, E. F. et al. (2001). Group loyalty and the taste for redistribution. *Journal of Political Economy*, 109(3):500–528.

Putnam, R. (1995). Bowling alone: America's declining social capital. *Journal of Democracy*, 6(1):65–78.

Putnam, R. (2007). E Pluribus Unum: Diversity and community in the twenty-first century. The 2006 Johan Skytte Prize Lecture. *Scandinavian political studies*, 30(2):137–174.

Putnam, R. et al. (2001). Social capital benchmark survey, 2000. *Storrs, CT: Roper Center*.

Robinson, J. (2001). Social identity, inequality and conflict. *Economics of Governance*, 2(1):85–99.

Sethi, R. and Somanathan, R. (2004). Inequality and segregation. *Journal of Political Economy*, 112(6):1296–1321.

Stewart, F. (2005). *Horizontal Inequalities: A Neglected Dimension of Development*. Palgrave Macmillan.

Stolle, D., Soroka, S., and Johnston, R. (2008). When does diversity erode trust? Neighborhood diversity, interpersonal trust and the mediating effect of social interactions. *Political Studies*, 56(1):57–75.

Tabellini, G. (2008). The scope of cooperation: Values and incentives. *Quarterly Journal of Economics*, 123(3):905–950.

Theil, H. (1967). *Economics and information theory*. North-Holland Amsterdam.

Uslaner, E. (2008). *Does diversity drive down trust?* London: Routledge.

Uslaner, E. (2011). Trust, diversity, and segregation in the United States and the United Kingdom. *Comparative Sociology*, 10(2):221–247.

Vigdor, J. (2004). Community composition and collective action: Analyzing initial mail response to the 2000 Census. *Review of Economics and Statistics*, 86(1):303–312.

Zak, P. and Knack, S. (2001). Trust and growth. *The Economic Journal*, 111(470):295–321.

Figure 1 Similar Characteristics but Different Trust

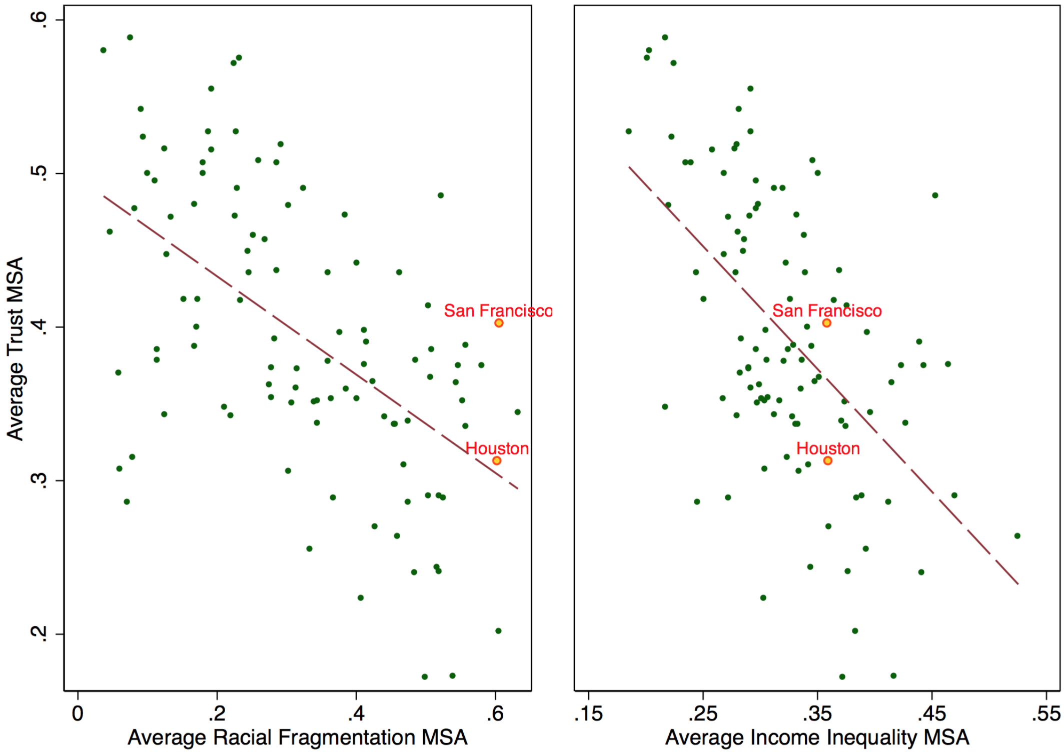


Figure 2 Are They Really Similar?

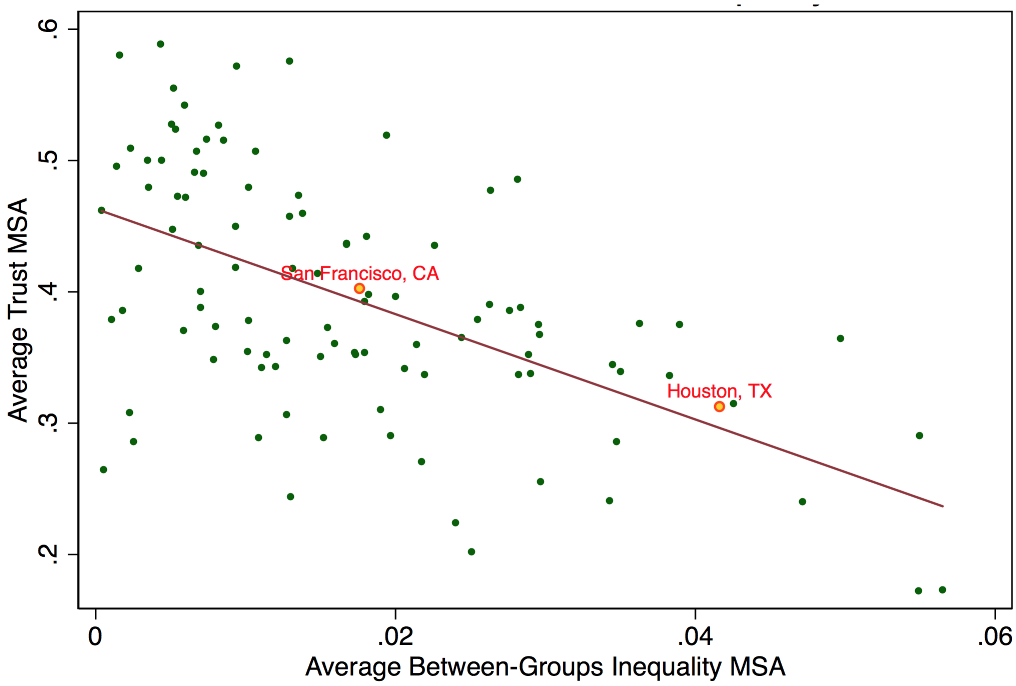


Figure 3 Two Hypothetical Communities

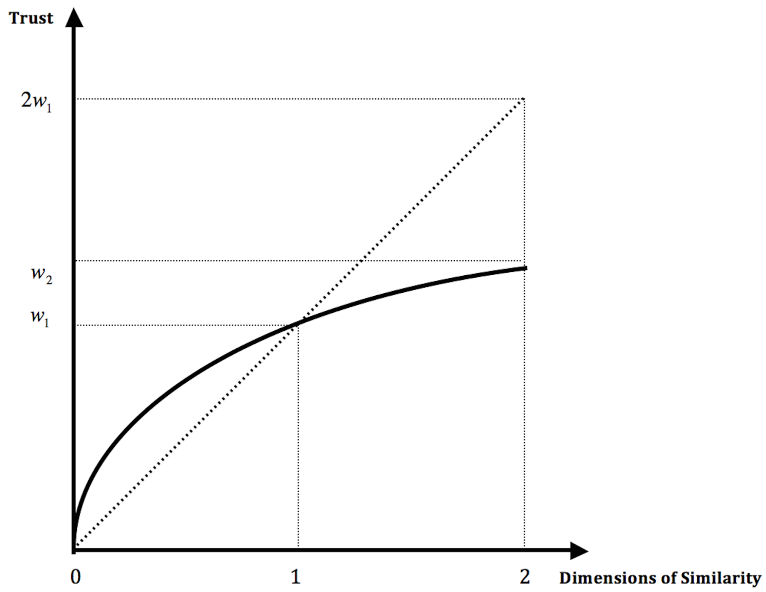
Community A

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

Community B

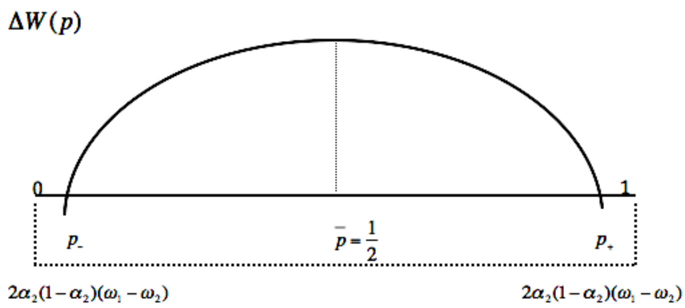
	White	Black	Tot. Ineq.
Rich	50	0	50
Poor	0	50	50
Rac. Fr.	50	50	

Figure 4 Trust and Dimensions of Similarity



Note: The Figure plots the relationship between trust and similarity, identifying the condition under which greater racial inequality is associated with lower levels of trust. w_1 represents the amount of trust towards individuals similar in one dimension (either race or income), w_2 towards individuals similar in both dimensions, while trust towards individuals different in both dimensions is normalized to 0.

Figure 5 Plot of Δ_1 at different levels of p



Note: The Figure illustrates the relationship between racial income inequality and changes in the level of trust at different levels of racial fragmentation.

Table 1 Baseline Results 1973-2010

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

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise (Source: GSS cumulative data file 1973-2010). All measures of community heterogeneity refer to the MSA of the respondent: *Rac Fr* is the index of racial fragmentation; *Gini* is the total income inequality calculated by the Gini index; *Theil* is the total income inequality calculated by the Theil index; *Btw Theil* is the income inequality *between* racial groups calculated by the Theil index; *Wth Theil* is the inequality *within* racial groups calculated by the Theil index. All specifications include state and year fixed effects. The measures of community heterogeneity are calculated from: IPUMS 1% sample of U.S. Census 1970, 1980, 1990, 2000. Further details on their construction are in Section 2. All regressions also include the following individual controls: age, age^2, log (real income), $educ \leq 12$ years, $educ \geq 16$ years, religion, female, married, full-time, part-time, divorced, children, Black, Native American, Asian, Hispanic (Source: GSS cumulative data file 1973-2010); as well as the following community controls: log MSA size, index of ethnic fragmentation, log (median income) by race, log $(median\ income)^2$ by race. Source: IPUMS 1% sample of U.S. Census (1970, 1980, 1990, 2000). *Significantly different from zero at the 90 percent confidence, ** 95 percent confidence, *** 99 percent confidence.

Table 2 Alternative Definitions of Racial Heterogeneity

	Individual Racial Shares					Segregation		Heterogeneity (2 groups)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Btw Theil	-1.524***	-1.775***	-2.083***	-2.027***	-1.863***		-2.038***		-2.349***
	(0.544)	(0.487)	(0.385)	(0.358)	(0.421)		(0.408)		(0.560)
Wth Theil	0.243	0.214	0.211	0.188	0.225		0.201		0.178
	(0.153)	(0.151)	(0.149)	(0.152)	(0.149)		(0.149)		(0.141)
Share w	0.106*								
	(0.056)								
Share b		-0.120							
		(0.082)							
Share na			1.006						
			(1.053)						
Share a				0.402**					
				(0.157)					
Share h					-0.085				
					(0.051)				
Rac Seg						-0.107**	-0.036		
						(0.052)	(0.050)		
$Rac\ Fr_{w/nw}$								-0.185**	-0.009
								(0.071)	(0.080)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,056	20,056	20,056	20,056	20,056	20,056	20,056	20,056	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise. Columns (1)-(5) separately control for the population share of each racial group in the MSA. Columns (6)-(7) include the entropy index of racial segregation. Columns (8)-(9) re-calculate the measures of community heterogeneity based on two groups only: Whites and non-Whites. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 3 Alternative Treatment of Time Dimension

	State Time Trend		Previous Census		Closest Census	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Rac Fr	-0.310***	-0.150*	-0.194***	-0.067	-0.198***	-0.054
	(0.066)	(0.089)	(0.066)	(0.082)	(0.069)	(0.082)
Theil	-0.042		-0.082		-0.044	
	(0.184)		(0.158)		(0.168)	
Btw Theil		-2.240***		-1.759***		-2.080***
		(0.678)		(0.617)		(0.559)
Wth Theil		0.315		0.108		0.255*
		(0.215)		(0.159)		(0.151)
State FE	No	No	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes
State X Year FE	Yes	Yes	No	No	No	No
Observations	20,056	20,056	20,056	20,056	20,056	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise. Columns (1)-(2) include state X year fixed effects. Columns (3)-(4) assign to the measures of community heterogeneity their value calculated at the previous Census year and maintained constant during the following decade. Columns (5)-(6) assign to the measures of community heterogeneity their value at the closest Census year. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 4 Instrumental Variable Estimation

	First-stage (OLS)				IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Rac Fr	*Btw Theil*	*Rac Fr*	*Btw Theil*	Trust		
Rac Fr Pred	0.743***		0.631***	0.048***			
	(0.123)		(0.145)	(0.010)			
Btw Theil Pred		0.127***	0.107	0.074***			
		(0.021)	(0.117)	(0.025)			
Rac Fr					-0.253***		0.116
					(0.054)		(0.242)
Btw Theil						-2.104**	-4.045*
						(0.919)	(2.416)
Wth Theil						0.127	0.390*
						(0.203)	(0.235)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F-stat	–	–	–	–	36.64	35.97	2.89
Anderson-Rubin P-val	–	–	–	–	0.00	0.03	0.00
Stock-Wright LM P-val	–	–	–	–	0.00	0.08	0.02
Observations	20,056	20,056	20,056	20,056	20,056	20,056	20,056

Note: Columns (1)-(4) report first-stage (OLS) regressions of *Rac Fr* and *Btw Theil* on the predicted index of racial fragmentation *Rac Fr Pred* and the predicted racial income inequality *Btw Theil Pred*. Details on the construction of the instruments are reported in Section 3.2. Columns (5)-(7) report Two Stages Least Squares (IV) regressions of equations (4) and (5) in the text, where the dependent variable is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise. The values in brackets are Huber robust standard errors clustered at the MSA level. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 5 Perceived Threats and Stereotypes

	Oppose affirmative action		Affirmative action penalizes Whites		Hard-workers other groups		Intelligent other groups	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Rac Fr	0.083	-0.235	0.128	-0.708	-0.002	-0.814	0.040	0.836
	(0.114)	(0.581)	(0.117)	(0.858)	(0.141)	(1.196)	(0.156)	(1.302)
Btw Theil	-0.295	1.942	-0.112	6.003	0.015	6.637	-0.223	-4.464
	(0.773)	(4.625)	(0.763)	(6.777)	(0.835)	(10.211)	(0.869)	(10.838)
Wth Theil	0.021	-0.124	-0.250	-0.572	-0.222	-0.618	0.076	0.060
	(0.193)	(0.465)	(0.238)	(0.598)	(0.267)	(0.690)	(0.264)	(0.810)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,085	7,085	7,495	7,495	6,608	6,608	5,786	5,786

Note: The method of estimation in odd-numbered columns is Least Squares and in even-numbered columns is Two Stages Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable is a dummy equal to 1 if the respondent: opposes affirmative action policies (columns 1 and 2); thinks affirmative action policies penalize Whites (columns 3 and 4); consider individuals of different racial groups to be hard-working (columns 5 and 6) or intelligent (columns 7 and 8). Columns (1)-(4) restrict to the sample of White respondents only. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 6 Membership in Associations

	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	IV
Rac Fr	-0.040		0.198	0.393
	(0.096)		(0.136)	(0.279)
Btw Theil		-2.903**	-3.880***	-7.618*
		(1.257)	(1.417)	(4.605)
Wth Theil		0.217	0.086	0.344
		(0.305)	(0.317)	(0.532)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	12,146	12,146	12,146	12,146

Note: The method of estimation in columns (1)-(3) is Least Squares, in column (4) is Two Stages Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent is member of at least one group, and 0 otherwise. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 7 Racial Income Inequality and Fractionalization

	Below Median	Above Median	Pooled Below-Above	
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	IV
$Rac\,Fr$	-0.080	-0.213*		
	(0.121)	(0.126)		
$Btw\,Theil$	1.818	-2.238**		
	(1.487)	(1.079)		
$Wth\,Theil$	-0.036	0.234		
	(0.260)	(0.218)		
$Rac\,Fr_{bel}$			-0.154	-0.167
			(0.093)	(0.121)
$Rac\,Fr_{abo}$			-0.178	-0.116
			(0.114)	(0.095)
$Btw\,Theil_{bel}$			1.521	0.028
			(1.318)	(2.097)
$Btw\,Theil_{abo}$			-2.155***	-3.260***
			(0.509)	(1.225)
$Wth\,Theil_{bel}$			-0.156	0.114
			(0.191)	(0.278)
$Wth\,Theil_{abo}$			0.302**	0.514**
			(0.141)	(0.233)
$Below$			0.241**	0.277***
			(0.093)	(0.088)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	10,325	9,731	20,056	20,056

Note: The method of estimation in columns (1)-(3) is Least Squares, in column (4) is Two Stages Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise. Column (1) considers the subsample of MSA below the median level of racial fragmentation; column (2) the subsample of MSA above. Columns (3)-(4) consider the full sample, interacting measures of community heterogeneity with the dummy variable *Below*, which is equal to 1 if the MSA level of racial fragmentation is below the median, and 0 otherwise. All specifications include country and year fixed effects, plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 8 Racial Income Inequality and Size of the Groups

	Whites	Blacks	Ind. Am.	Asian	Hispanic	Pooled Races
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Rac Fr	-0.076	-0.275*	0.804*	0.182	0.235	
	(0.099)	(0.166)	(0.437)	(0.900)	(0.279)	
Btw Theil	-1.753**	-0.523	-6.439*	-8.036*	-5.104***	
	(0.711)	(1.066)	(3.316)	(4.346)	(1.766)	
Wth Theil	0.304*	0.085	-0.786	1.509	0.941	
	(0.177)	(0.336)	(0.941)	(1.405)	(0.644)	
$Btw\ Theil_w$						-1.711***
						(0.589)
$Btw\ Theil_b$						-1.516*
						(0.789)
$Btw\ Theil_{na}$						-2.426
						(1.735)
$Btw\ Theil_a$						-4.244*
						(2.150)
$Btw\ Theil_h$						-2.354**
						(1.139)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,015	2,887	592	421	1,141	20,056

Note: The method of estimation is Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The dependent variable in all columns is a dummy equal to 1 if the respondent reports to trust others, and 0 otherwise. Columns (1)-(5) consider subsamples of respondents based on their race. Column (6) pools all respondents and interacts the income inequality between racial groups with the corresponding racial identity dummy of each respondent. $Btw\ Theil_w$ thus represents the interaction of *Btw Theil* with the dummy variable White, equal to one if the individual identifies himself as White. Analogous definitions apply to the other interaction terms. The interactions of *Rac Fr* and *Wth Theil* with racial identity dummies are also included (but not reported) in the specification in column (6). All specifications include state and year fixed effects plus the entire set of individual and community controls as in Table 1. See also notes to Table 1.

Table 9 Own-Race and Interracial Trust

	Own-race		Interracial		Composite Interracial	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Rac Fr	-0.136	-0.072	-0.134	-0.017	-0.073	0.003
	(0.155)	(0.111)	(0.138)	(0.116)	(0.168)	(0.117)
Btw Theil	0.075	-0.072	-0.506	-1.253***	-2.342*	-1.894**
	(1.109)	(0.525)	(1.017)	(0.476)	(1.368)	(0.893)
Wth Theil	-0.150	-0.082	-0.010	0.067	0.021	-0.160
	(0.151)	(0.231)	(0.109)	(0.216)	(0.167)	(0.275)
Observations	16,543	13,438	16,673	13,544	16,673	13,544

Note: The method of estimation in odd-numbered columns is Least Squares and in even-numbered columns is Two Stages Least Squares. The values in brackets are Huber robust standard errors clustered at the MSA level. The source of the data is the Social Capital Benchmark Survey, 2000 (Putnam et al., 2001). The dependent variable in columns (1)-(2) is a dummy equal to 1 if the respondent reports to trust individuals of her own racial group; in columns (3)-(4) is a dummy equal to 1 if the respondent reports to trust individuals of all other racial groups; in columns (5)-(6) is the composite mean trust across 3 of the following 4 groups - Whites, Blacks, Asians, Hispanics (excluding only the respondent's own group). All specifications include the entire set of individual and community controls as in Table 1. See also notes to Table 1.

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

A. Formal conceptual framework

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

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

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

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

For every racial group, I shall denote by $\omega_2 > 0$ the level of trust of each individual towards another individual *both* of the same race *and* of the same income. On the other hand, I shall denote by $\omega_1 > 0$ the level of trust towards another individual *either* of the same race, yet of different income, *or* of the same income, yet of different race.[26] 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:

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

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

and:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

$$\begin{aligned}\Delta_2 = & \left\{ \left[\alpha_1^2 + (1-\alpha_1)^2 \right] \omega_2 + 2\alpha_1(1-\alpha_1)\omega_1 \right\} p^2 - \\ & - \left\{ \left[\alpha_2^2 + (1-\alpha_2)^2 \right] \omega_2 + 2\alpha_2(1-\alpha_2)\omega_1 \right\} (1-p)^2 = \\ & = 2\alpha_1(1-\alpha_1)(\omega_1-\omega_2)p^2 - 2\alpha_2(1-\alpha_2)(\omega_1-\omega_2)(1-p)^2 .\end{aligned} \tag{A.3}$$

I shall now pursue the analysis under the following:

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

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

Observe that:

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

Therefore, under assumption (A) the difference Δ_1 becomes simply (see (A.2)):

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

Let's now make the following:

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

If (B) is satisfied, it is immediately seen from (A.4) that the difference Δ_1 vanishes at two values of the parameter p, namely

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

The following result is also an immediate consequence of equality (A.4):

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

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

Figure 4 plots the graph of Δ_1 at different levels of p. Is it worth noting that the region of positivity of Δ_1 (if (A) and (B) are satisfied) is centred at the value $p = 1/2$, namely where the racial fragmentation is maximum. Given the definition of Δ_1, this means that the benefit of moving away from a situation of extreme racial income inequality is maximum when the community is at the highest level of racial fragmentation. Clearly, the opposite is also true: the reduction of trust due to increasing racial income inequality is maximum when racial fragmentation is at its highest. This result represents the formal counterpart of the first implication discussed qualitatively in section 4.2.

Let's now address the quantity Δ_2. If assumption (A) holds, it reads simply (see (A.3)):

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

Then I have the following result:

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

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

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

Thus, when racial income inequality decreases (i.e. when α_2 increases) the minority group increases its level of trust more than the majority group. Clearly, the opposite is also true: when racial income inequality increases, the minority group reduces its level of trust more than the majority group. This represents the formal counterpart of the second implication discussed qualitatively in section 4.2.

Table A.1 MSA in GSS Sample, 1973-2010

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

Table A.1 (continued) MSA in GSS Sample, 1973-2010

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

Table A.2 Summary Statistics

	Avg.	Std. Dev.	Observations
		Individual Outcomes	
$Trust$	.381	.485	22804
$Oppose\ Aff.\ Act.$	.815	.388	4706
$White\ pen.\ Aff.\ Act.$	.652	.476	5201
$Hard-working_{\ oth.}$	.223	.416	7640
$Intelligent._{\ oth}$	.292	.454	6696
$Member$	.697	.459	10620
		Individual Characteristics	
Age	44.70	17.09	22804
$Female$	.559	.496	22804
$Educ \leq 12\ years$	.204	.403	22804
$Educ \geq 16\ years$	.252	.434	22804
$Log\ (Real\ Income)$	10.03	.990	20499
$Full\ Time$	.516	.499	22804
$Part\ Time$	.102	.303	22804
$Religious$	.888	.316	22804
$Married$	.515	.499	22804
$Divorced$	.167	.373	22804
$White$	.744	.436	22804
$Black$	.148	.355	22804
$Native\ American$	.029	.168	22804
$Asian$	.021	.145	22804
$Hispanic$	.056	.231	22804
		Community Characteristics	
$Rac\ Fr$	.403	.171	22633
$Gini$	.419	.051	22633
$Theil$	.340	.085	22633
$Btw\ Theil$	.021	.015	22633
$Wth\ Theil$	.318	.075	22633
$Rac\ Seg$	.304	.125	22726
$Ethn\ Fr$	.749	.102	22633
$Rac\ Fr\ Pred$	.396	.167	22633
$Btw\ Theil\ Pred\ (Bartik)$	.018	.013	22633
$Log\ (Size)$	4.14	2.13	22526
$Log\ (median\ inc._{\ w})$	10.56	.513	22633
$Log\ (median\ inc._{\ b})$	9.98	.569	22633
$Log\ (median\ inc._{\ na})$	10.12	.653	22633
$Log\ (median\ inc._{\ a})$	10.48	.618	22633
$Log\ (median\ inc._{\ h})$	10.11	.494	22633

Table A.3 Correlations among Measures of Heterogeneity

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

Table A.4 MSA 2-digit Industries

SIC Code	*SIC Industry*	*SIC Code*	*SIC Industry*
7	Agricultural services	49	Electric, gas, and sanitary services
10	Metal mining	50	Wholesale trade, durable goods
12	Coal mining	51	Wholesale trade, nondurable goods
13	Oil and gas extraction	52	Building materials and garden supplies
14	Nonmetallic minerals, except fuels	53	General merchandise stores
15	General building contractors	54	Food stores
16	Heavy construction, except building	55	Automotive dealers and service stations
17	Special trade contractors	56	Apparel and accessory stores
20	Food and kindred products	57	Furniture and home furnishings stores
21	Tobacco products	58	Eating and drinking places
22	Textile mill products	59	Miscellaneous retail establishments
23	Apparel and other textile products	60	Depository institutions
24	Lumber and wood products	61	Nondepository institutions
25	Furniture and fixtures	63	Insurance carriers
26	Paper and allied productss	64	Insurance agents, brokers, and service
27	Printing and publishing	65	Real estate
28	Chemicals and allied products	67	Holding and other investment offices
29	Petroleum and coal products	70	Hotels and other lodging places
30	Rubber and miscellaneous plastics products	72	Personal services
31	Leather and leather products	73	Business services
32	Stone, clay, and glass products	75	Auto repair, services, and parking
33	Primary metal industries	76	Miscellaneous repair services
34	Fabricated metal products	78	Motion pictures
35	Industrial machinery and equipment	79	Amusement and recreation services
36	Electronic and other electrical equipment	80	Health services
37	Transportation equipment	81	Legal services
38	Instruments and related products	82	Educational services
39	Miscellaneous manufacturing industries	83	Social services
40	Railroad transportation	84	Museums and botanical and zoological gardens
41	Local and interurban passenger transit	86	Membership organizations
42	Trucking and warehousing	87	Engineering and management services
44	Water transportation	89	Services, nec
45	Transportation by air	94	Administration of Human Resources
47	Transportation services	95	Environmental Quality and Housing

Table A.5 MSA Industry Composition 1980 (selected industries)

SIC Industry	*Total* Share	*Whites* Share	*Blacks* Share	*Ind.Am.* Share	*Asians* Share	*Hispanics* Share
Educational services	0.089 [0.022]	0.089 [0.022]	0.096 [0.052]	0.090 [0.155]	0.116 [0.137]	0.083 [0.078]
Health services	0.086 [0.017]	0.081 [0.016]	0.122 [0.060]	0.058 [0.086]	0.151 [0.148]	0.085 [0.070]
Business services	0.035 [0.010]	0.035 [0.010]	0.032 [0.020]	0.040 [0.056]	0.027 [0.038]	0.030 [0.024]
Insurance carriers	0.030 [0.010]	0.031 [0.010]	0.030 [0.062]	0.020 [0.069]	0.022 [0.042]	0.019 [0.021]
Social services	0.020 [0.005]	0.018 [0.005]	0.037 [0.022]	0.038 [0.082]	0.009 [0.016]	0.022 [0.022]
Engineering and management services	0.019 [0.007]	0.021 [0.008]	0.011 [0.010]	0.018 [0.039]	0.018 [0.020]	0.015 [0.020]
Electronic and other electrical equipment	0.018 [0.015]	0.018 [0.015]	0.020 [0.026]	0.011 [0.022]	0.027 [0.040]	0.021 [0.028]
Hotels and other lodging places	0.015 [0.010]	0.013 [0.009]	0.023 [0.024]	0.022 [0.058]	0.018 [0.057]	0.023 [0.061]

Note: The table reports information on the share of population - total and by race - employed in 8 selected two-digit SIC industries in 1980. For each race-industry pair it is reported the average occupational share and its standard deviation (in square brackets).