Income Inequality and Income Segregation

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Abstract

Both income inequality and income segregation in the United States grew substantially from 1970 to 2000. Using data from the 100 largest metropolitan areas, we investigate whether and how income inequality affects patterns of income segregation along three dimensions—the spatial segregation of poverty and affluence; race-specific patterns of income segregation; and the geographic scale of income segregation. We find a robust relationship between income inequality and income segregation, an effect that is larger for black families than it is for white families. In addition, income inequality affects income segregation primarily through its effect on the large-scale spatial segregation of affluence, rather than by affecting the spatial segregation of poverty or by altering small-scale patterns of income segregation.

Introduction

After decades of decline, income inequality in the United States has grown substantially in the last four decades. The national Gini coefficient of household income inequality, for example, rose from .394 in 1970 to .403, .428, and .462 in 1980, 1990, and 2000, respectively.[1] At the same time, income segregation has grown as well (Jargowsky, 1996; Mayer, 2001b; Watson, 2009; Wheeler & La Jeunesse, 2006), though the details of how and why income segregation has grown have been much less thoroughly investigated than they have been for income inequality. Common sense and empirical evidence suggest that these trends are linked—greater inequality in incomes implies greater inequality in the housing and neighborhood "quality" that families or individuals can afford—but it is less clear in what specific ways income inequality affects income segregation.

Income segregation—by which we mean the uneven geographic distribution of income groups within a certain area—is a complex, multidimensional phenomena.[2] In particular, income segregation may be characterized by the spatial segregation of poverty (the extent to which the lowest-income households are isolated from middle- and upper-income households) and/or the spatial segregation of affluence (the extent to which the highest-income households are isolated from middle- and lower-income households). In addition, income segregation may occur at different geographic scales. High- and low-income households may be spatially far from one another or may be in economically homogeneous neighborhoods that are spatially near one another (Reardon, et al., 2008). And given the strong correlation between income and race in the U.S., income segregation is often empirically entangled with racial segregation, implying the necessity of examining income segregation separately by race as well as for the population as a whole.

Income segregation—and its causes and trends—is of interest to sociologists because income segregation may lead to inequality in social outcomes. Income segregation implies, by definition, that

[1] http://www.census.gov/hhes/www/income/histinc/p60no231_tablea3.pdf (retrieved 2 September, 2009).

[2] Throughout this paper, we focus on the spatial evenness dimension of income segregation (Massey & Denton, 1988; Reardon & O'Sullivan, 2004) because this dimension maps most closely onto our theoretical model of how income inequality is related to residential household income distribution patterns. Below we discuss the relationship of this dimension to patterns of concentration and exposure.

lower-income households will live, on average, in neighborhoods with lower average incomes than do higher-income households. If the average income of one's neighbors (and/or its correlates) indirectly affects one's own social, economic, or physical outcomes (and a large range of sociological theories predict such contextual effects; see, for example, Jencks & Mayer, 1990; Leventhal & Brooks-Gunn, 2000; Morenoff, 2003; Sampson, Raudenbush, & Earls, 1997; Sampson, Raudenbush, & Sharkey, 2008), then income segregation will lead to more unequal outcomes between low- and high-income households than their differences in income alone would predict. In a highly segregated region, then, higher-income households may be advantaged relative to lower-income households not only by the difference in their own incomes, but by the differences in their respective neighbors' incomes.

Given the potential consequences of income segregation on social, political, and health-related outcomes, it is important to understand how it is produced. In this paper, we seek to understand whether and how income inequality leads to income segregation. More specifically, we seek to understand if and how variation in income inequality—including variation in inequality among metropolitan areas, between racial groups, and over time—has shaped patterns of income segregation in the years 1970-2000. Despite the importance of understanding the connection between income inequality and income segregation, few studies have addressed these questions (for exceptions, see Mayer, 2000; Watson, 2009). Moreover, while these studies find that increasing income inequality leads to (or is at least correlated with) increasing income segregation, they do not investigate the ways in which income inequality is linked to income segregation in depth. As a result, these studies provide little or no information about income inequality's effects on the segregation of poverty and/or affluence, about racial differences in income segregation, or about how income inequality impacts the spatial scale of income segregation.

The research presented here investigates these issues. First, we describe a set of trends in average metropolitan area income segregation from 1970-2000, including overall trends, trends among white and black families separately, trends in the segregation of poverty and affluence, and trends in the geographic scale of segregation. We use a newly developed measure of rank-order income segregation that avoids the confounding of changes in the income distribution with changes in income segregation. Second, we estimate the effect of metropolitan area income inequality on overall metropolitan area income segregation during this time period. Third, we investigate in more detail how income inequality affects the geographic segregation of poverty and affluence, the extent to which it affects income segregation among white and black families differently, and the ways that it impacts the geographic scale of income segregation.

Background

Recent Growth in Income Inequality in the United States

20th century United States income inequality is characterized by a "U-shaped" trend (Nielsen & Alderson, 1997; Ryscavage, 1999). Income inequality was high in the first half of the century, reaching a peak in the late 1920s, when the top 10% of earners in the U.S. received 46% of all income and the top 1% of earners received nearly 20% of all income (Piketty & Saez, 2003). However, the Great Depression and World War II greatly depleted the share of income held by the highest earners and thus reduced income inequality substantially. By the end of World War II, the share of income received by the top 1% of earners was only 11% and by 1970, this figure was below 8%, a 60% decline from its high in 1928. In the 1970s and 1980s, income inequality began to rise again. By 2006, the share of income held by the top decile was 45% and the share held by the top 1% of earners was 18%, approaching inequality levels similar to the pre-World War II highs (Burkhauser, Feng, Jenkins, & Larrimore, 2009; Piketty & Saez, 2003, 2008).

The growth in income inequality in the past four decades has been driven largely by the growth of "upper-tail inequality"—dispersion in the relative incomes of those in the upper half of the income distribution—rather than by growth in "lower-tail inequality" (Autor, Katz, & Kearney, 2006, 2008; Piketty & Saez, 2003). This pattern is illustrated in Figure 1, which shows the changes in the household Gini index (a standard summary measure of income inequality), the 90/50 household income ratio (the ratio of the income of the household at the 90th percentile of the income distribution to that of the household at the 50th percentile), and the 50/10 household income ratio. The 90/50 ratio was 30% larger in 2007 than it was in 1967, while the 50/10 ratio was actually 6-7% smaller. This implies that the lower tail of the income distribution was compressed slightly (particularly in the early 1970s) while the upper tail was stretched.[3] Moreover, the growth in the household Gini index over the period very closely tracks the growth in the 90/50 ratio, indicating that the trend in the Gini index was driven largely—if not entirely—by growth in upper-tail inequality. Picketty and Saez (2003) argue that the notoriously sharp increase in CEO pay evident in recent decades is indicative of a general shift from an elite rentier class in the beginning of the 20th century to an elite "working rich" class today, leading to the exceptional rise in inequality in the upper tail of the distribution.[4] As we discuss below, this pattern of growth in income inequality has important implications for the effects of income inequality on income segregation.

Figure 1 here

Dimensions of Income Segregation

Income segregation—the uneven sorting of households or families among neighborhoods by income—is relatively ubiquitous in the U.S.[5] Anyone who has rented an apartment or bought a house understands that housing costs more in some neighborhoods than it does in others. Except for those few

[3] The trend in the 50/10 ratio we report here differs slightly than that reported by Autor, Katz, and Kearney, (2006, 2008), who find that the 50/10 ratio grew in the 1970s and early 1980s before flattening in the late l980s and 1990s. The discrepancy may arise from the fact that they describe trends in *individual*-level male and female wage inequality using CPS data while Figure 1 reports *household* income inequality. Regardless, in both cases, the dominant factor in producing income inequality growth in recent decades has been the growth of what they term "upper-tail inequality."

[4] A large body of research investigates the causes of the growth in income inequality in the United States since the 1970s. Economists have focused on declining labor union membership, the declining real value of the minimum wage, and the ways in which technological changes have differentially affected the productivity of workers (Card & DiNardo, 2002; Card, Lemieux, & Riddell, 2004; DiPrete, 2007; D. S. Lee, 1999; Levy & Murnane, 1992). Sociologists have investigated factors relating to changes in family structure, marital homogamy, and female labor force participation (Gottschalk & Danziger, 2005; Schwartz & Mare, 2005; Western, Bloome, & Percheski, 2008). In the interest of space, we do not review this literature here.

[5] Throughout this paper we are most interested theoretically in *household* income segregation (rather than *family* or *individual* income segregation), because households are primary residential units and so are most relevant to a discussion of segregation. Nonetheless, because of data limitations (e.g., the Census reports family income by race but not household income by race in some years), we use family income in much of our analysis. Although family income is generally higher on average than household income because many households only contain one person, the trends in inequality for families and households are very highly correlated (for trend in family Gini index, see http://www.census.gov/hhes/www/income/histinc/f04.html; for trend in household Gini index, see http://www.census.gov/hhes/www/income/histinc/p60no231_tablea3.pdf) (the correlation is 0.997, according to Moller, Alderson, & Nielsen, 2009, footnote 13). Likewise, the shape of the trends in metropolitan area family and household income segregation are similar as well (Watson, 2009; Wheeler & La Jeunesse, 2008).

with liquid wealth, income is a primary determinant of neighborhood affordability. Moreover, housing prices are tightly linked to the cost of nearby housing. Realtors, appraisers, and homebuyers use recent sale prices of comparable neighborhood real estate to gauge appropriate sale prices for nearby properties, which leads to positive feedback in local housing markets. And because mortgage loans are tied to income (the last few years notwithstanding), homebuyers' neighborhood options are constrained by their incomes. In principle, these mechanisms operate to place a (somewhat permeable) floor on the incomes of individuals who can afford to live in a given neighborhood, leading to a certain degree of residential sorting by income.

Income segregation has multiple dimensions. First, neighborhood sorting of families or households by income may produce the segregation of affluence and/or the segregation of poverty (by "segregation of affluence," we mean the uneven distribution of high-income and non-high-income households among neighborhoods, and by "segregation of poverty," we likewise mean the uneven distribution of low- and non-low-income households among neighborhoods).[6] Consider a stylized population made up of three types of families—high-, middle-, and low-income—who are distributed among three neighborhoods (See Table 1). Under scenario I, the low-income families all live in a single neighborhood, with no middle- or high-income neighbors, while the middle-and high-income families are evenly distributed between the other two neighborhoods—a situation where the segregation of poverty is greater than the segregation of affluence (high-income families have some non-high-income neighbors, but low-income families have only low-income neighbors). Under scenario II, the situation is reversed—the segregation of affluence is greater than the segregation of poverty. And finally, in scenario III, the segregation of both poverty and affluence are very high.

[6] Note that we mean to distinguish the terms "segregation of poverty" and "segregation of affluence" from the more commonly-used terms "concentrated poverty" and "concentrated affluence." The latter terms are often used to describe the income *composition* of *individual* neighborhoods (e.g., neighborhoods with poverty rates above 40% are sometimes described as being characterized by "concentrated poverty."), rather than patterns of the distribution of income across multiple neighborhoods in a city or region. In addition, we intend to identify "segregation of poverty" and "segregation of affluence" as aspects of the spatial evenness dimension of segregation, rather than as descriptions of the concentration dimension (Massey & Denton, 1988; Reardon & O'Sullivan, 2004). We can have high levels of "segregation of poverty" without the *spatial concentration* of poor households within one area of a region (for example, if low-income families live in many neighborhoods scattered throughout a metropolitan area, but not in the same census tracts as higher-income families).

Table 1 here

A second important dimension of income segregation is its relationship to patterns of racial segregation. Given the correlation of race and income in the U.S. and the high levels of racial segregation in many metropolitan areas, racial segregation alone could produce a certain degree of income segregation, even if there were no within-race income segregation at all. Moreover, the factors that affect income segregation and that link income inequality to income segregation may differ importantly across race/ethnic groups. Housing discrimination and residents' preferences for same- or different-race neighbors, for example, may also affect residential sorting. Until relatively recently, black families' neighborhood options were severely constrained by various discriminatory housing practices (steering by realtors, redlining by banks, rental discrimination, etc.), and even now these processes have not been entirely eradicated (Ross & Turner, 2005; South & Crowder, 1998; Turner & Ross, 2005; Turner, Ross, Galster, & Yinger, 2002; Yinger, 1995). Such practices meant that black and white families with identical incomes and assets, for example, had a very different set of residential options. This also likely meant that, historically, income inequality was not as tightly linked to income segregation for black families as it was for white families.

A third dimension of income segregation is its geographic scale (Reardon, et al., 2009; Reardon, et al., 2008). This refers to the extent to which the neighborhood sorting of households by income results from large-scale patterns of residential sorting (as would be the case if all high-income families live in the suburbs, and all low-income families live in the city) or from small-scale patterns of residential sorting (as would be the case if high- and low-income residents were distributed in a checkerboard pattern throughout a metropolis, with homogenously wealthy neighborhoods adjacent to homogeneously poor neighborhoods throughout the area). The extent to which income segregation is characterized by large or small geographic scales may have implications for the consequences of income segregation (a point indirectly supported by the results of Firebaugh & Schroeder, 2007). Reardon and colleagues argue, for example, that micro-scale residential segregation patterns are likely to affect pedestrian contact patterns and may be more consequential for children and the elderly, who are often more geographically constrained than young and middle-aged adults. Conversely, they argue, macro-scale segregation patterns may be more likely to affect the spatial distribution of economic, institutional, and political resources (Reardon, et al., 2009; Reardon, et al., 2008).

Patterns and Trends in Income Segregation

Most prior research on income segregation has focused on measuring overall income segregation, and has attended little to either the geographic scale of income segregation or the extent to which it is characterized by the segregation of poverty and/or affluence. Research on the trends in overall household or family income segregation generally indicate that metropolitan area income segregation grew, on average, from 1970 to 2000, though studies differ on the details of the timing and magnitude of the increase because of differences in the measures of income segregation used and the sample of metropolitan areas included (see Jargowsky, 1996, 2003; Massey & Fischer, 2003; Mayer, 2001b; Watson, 2009; Wheeler & La Jeunesse, 2006). In particular, income segregation appears to have grown most sharply in the 1980s. By many measures, income segregation, and particularly the segregation of poverty, declined in the 1990s (Jargowsky, 2003; Massey & Fischer, 2003; Yang & Jargowsky, 2006). In addition, studies that examine trends in income segregation by race generally find that income segregation among black families or households grew faster than it did among white families or households, particularly during the 1970s and 1980s (Jargowsky, 1996; Massey & Fischer, 2003; Watson, 2009; Yang & Jargowsky, 2006). Later in this paper we discuss the shortcomings of many of the measures of income segregation used in prior literature and present new evidence of trends in metropolitan area income segregation. We use a new measure of income segregation that addresses these shortcomings.

Potential Consequences of Income Segregation

There are many mechanisms through which income segregation might affect individual outcomes. The quality of public goods and local social institutions are affected by a jurisdiction's tax base and by the involvement of the community in the maintenance and investment of these public resources. If high-income households cluster together within a small number of neighborhoods or municipalities, they may be able to collectively better their own outcomes by pooling their extensive financial and social capital to generate resources of which only they can take advantage. Such income segregation may be self-reinforcing: low-income communities are often unable to generate enough social and human capital to overcome the strong incentive for wealthy communities to isolate themselves, because in homogenously high-income communities residents may be able to capitalize on their ability to provide high-quality public services at the lowest cost. Higher-income neighborhoods, therefore, may have more green space, better-funded schools, better social services, or more of any number of other amenities that affect quality of life. In addition, high- and low-income neighborhoods may differ in their social processes, norms, and social environments (Sampson, Morenoff, & Earls, 1999; Sampson, et al., 1997). Conversely, if high-income households are not clustered together, then they may help to fund social services and institutions that serve lower-income populations. Thus, the ability of high-income households to self-segregate affects the welfare of poor people and the neighborhoods in which they reside. Not only does this resource problem affect residents' current quality of life and opportunities, but it can also bridge generations—the income distribution in a community may affect the intergenerational transfer of occupational status through investment in locally financed institutions that serve children, such as schools (Durlauf, 1996).

Nonetheless, relatively little prior research has directly assessed the impacts of income segregation on individual outcomes. Several studies show that income segregation within states or metropolitan areas is associated with greater inequality in educational attainment between poor and non-poor individuals (Mayer, 2000; Quillian, 2007). Likewise, Mayer and Sarin (2005) show that greater state-level income segregation is associated with higher rates of infant mortality. A related body of research finds that metropolitan area racial segregation leads to greater racial inequality in labor market, educational, and health outcomes (Ananat, 2007; Cutler & Glaeser, 1997; Ellen, 2000; Osypuk & Acevedo-Garcia, 2008). Because racial segregation implies some level of income segregation (given the relatively large racial differences in income), and because income segregation is one plausible mechanism through which racial segregation may lead to racial inequality, the research showing that racial segregation increases racial disparities is consistent with the hypothesis that income segregation may lead to inequality of outcomes. In addition to the relatively small body of research directly investigating the effects of income segregation, a large body of recent research has attempted to investigate one potential mechanism through which segregation may affect individuals—the effect of living in a neighborhood with a high poverty rate. The empirical evidence for such 'neighborhood effects', however, remains both mixed and contested (see, for example, Clampet-Lundquist & Massey, 2008; Jencks & Mayer, 1990; Katz, Kling, & Liebman, 2007; Leventhal & Brooks-Gunn, 2000; Ludwig, et al., 2008; Rosenbaum & Popkin, 1991; Sampson, 2008; Sampson, et al., 1997; Sampson, et al., 2008; Waitzman & Smith, 1998a, 1998b). In sum, while theoretical arguments suggest that income segregation likely produces inequality in social outcomes, empirical research has yet to conclusively demonstrate this or to elucidate its mechanisms.

The Relationship between Income Inequality and Income Segregation

Processes Linking Income Inequality to Income Segregation

Despite the need for more and better research on the *effects* of income segregation, this paper focuses on an equally important topic—the *causes* of income segregation. Specifically, we investigate one potential cause—income inequality. Certainly income inequality is a necessary condition for income segregation. By definition, if there were no income inequality, there could be no income segregation because all individuals would have the same income and thus all neighborhoods would have the same income distribution. Nonetheless, income inequality is not alone sufficient to create income segregation. Rather, income segregation also requires the presence of income-correlated residential preferences, an income-based housing market, and/or housing policies that link income to residential location.

Three kinds of income-correlated residential preferences may lead to income segregation in the presence of income inequality: preferences regarding the socioeconomic characteristics of one's neighbors, preferences regarding characteristics of one's neighbors that are correlated with their income, and preferences regarding local public goods. If some or all households have preferences regarding the income level, educational attainment, or occupational status of their neighbors (that is, if at least some households prefer higher-income neighbors to lower-income neighbors), then households with similar incomes will be more likely to be neighbors than is expected by chance. Likewise, residential preferences based on neighborhood characteristics that are correlated with income may also produce income segregation. One obvious example is race. If households select neighborhoods based on the racial composition of that neighborhood and household income is correlated with race, then this would also produce income segregation, even in the absence of income-specific preferences.

Preferences for public goods refer to the value households place on amenities that can be collectively purchased (e.g., public school quality, public parks, police services). Households that value such public goods will have incentives to live in communities with neighbors who both share these preferences and have high enough incomes to contribute to their collective purchase (through property taxes, for example). This can be seen as a manifestation of the Tiebout model of residential sorting, in which residents choose to live in municipalities that most closely match their ideal set of government services with their ability-to-pay (Tiebout, 1956). The Tiebout model predicts income segregation because households with similar preferences and ability-to-pay tend to form homogeneous communities. Differences among communities in public goods, income-related demographic characteristics, and in other social and cultural amenities may also lead to the development of neighborhood status hierarchies, or what one might call "neighborhood brands." The differentiation of communities along a status dimension in turn raises demand for those neighborhoods with the most desirable brands (and lowers demand for those with the least desirable brands). Thus, income differences may lead to the development of a rough status hierarchy among residential locations; this status hierarchy in turn may perpetuate income segregation by shaping household preferences.

Even in the presence of sizeable income inequality, however, the income-correlated preferences outlined above may be insufficient to produce income segregation. Income segregation requires as well the existence of a housing market based on residents' ability-to-pay or housing policies that sort households by income. For example, housing policies that constrain residential options for low-income households to public housing developments may directly affect the segregation of poverty by virtue of the spatial density and distribution of those options. More generally, income segregation results from a residential allocation or sorting process, which, in principle, is constrained by housing policy. Under a housing policy that allows sorting on the basis of preferences and ability-to-pay, residential segregation will likely be highly sensitive to changes in income inequality and income-related residential preferences because, in such a society, higher-income households will be able to outbid lower-income households for access to preferred neighborhoods. In addition, when higher-income households have greater influence than lower-income households over local political processes, they may have the capacity to create housing policies that perpetuate segregation by income, such as zoning laws that prohibit multifamily housing or require minimum lot sizes to build new structures.

Income Inequality and the Segregation of Poverty and Affluence

The above arguments suggest that, given the nature of the housing market, income inequality and income segregation are linked. Nonetheless, it is not clear if or how changes in income inequality might affect different aspects of income segregation, including the segregation of poverty and affluence. In order to build intuition about how income inequality may relate to income segregation, it is useful to consider how differences in income inequality are related to differences in income distributions. Figure 2 provides a stylized representation of two income distributions with equal aggregate incomes but that differ in their level of inequality. The solid lines describe the income distribution under a relatively low level of inequality (corresponding to a Gini index of 0.34), while the dashed lines describe the income distribution under a relatively high level of inequality (corresponding to a Gini index of 0.40).[7]

[7] The average level of income inequality across the 100 largest metropolitan areas in the years 1970-2000, as measured by the Gini index was 0.37, with a standard deviation of 0.03 (see Table 2 below for detail), so Gini indices of 0.34 and 0.40 correspond to metropolitan areas one standard deviation above and below the mean level of inequality in the period 1970-2000. Likewise, the average metropolitan area saw an increase in the Gini index from 0.35 to 0.40 from 1970 to 2000, so these distributions also correspond roughly to the magnitude of the average change over this period.

Moreover, the stylized income distributions depicted here differ only in the level of "upper-tail inequality"—the 50/10 income ratio is identical in both cases, but the 90/50 income ratio is 35% larger in the high-inequality case than in the low inequality case.[8] Note that the income distributions described in Figure 2 are not based on actual data. Rather they are stylized distributions that exemplify typical differences in income distributions—an exercise that highlights how the type and magnitude of inequality relates to important features of income distributions.

Figure 2 here

The left-hand panel of Figure 2 shows that the income distribution is more spread out at the high end under conditions of greater inequality. There is greater variation in income among high earners in the higher-inequality distribution than in the lower-inequality distribution. At the low end of the income distribution, however, increasing inequality actually *compresses* the income distribution, a result of the fact that income must be non-negative (at least in our stylized figures here).[9]

The difference in the effect of income inequality at the high and low ends of the income distributions is evident in the middle panel of Figure 2. For example, it is instructive to compare the incomes of households at the 20th and 30th percentiles in each scenario. In the lower-inequality distribution (solid line), the household at the 20th percentile has an income of $33,500 and the household at the 30th percentile has an income of $43,000, a difference of $9,500 and a ratio of 1.28. In the higher-inequality distribution (dashed line), the 20th and 30th percentile households have incomes of $29,000 and $37,000, respectively, a difference of $8,000 and a ratio of 1.28. That is, under high inequality, low-to-moderate income households of a given distance apart in income ranks have incomes that are actually *closer* together (and equally far apart if comparing incomes using ratios) than under low inequality. This implies that increases in income inequality of the type depicted here (that is, increases in inequality that leave the 50/10 ratio unchanged) will not increase, and may actually decrease income segregation among

[8] Because most of the change in income inequality from 1970 to 2000 was the result of changes in upper-tail inequality, we are particularly interested in investigating the effect of such changes on segregation patterns.
[9] While income can be negative, the number of households reporting negative income is generally quite small and has little effect on the income distribution.

low-income households (segregation of poverty). This is because increasing inequality (somewhat paradoxically) makes the incomes of low-income households more similar to one another.

The opposite is true at the high end of the income distribution. Comparing the incomes of the 70th and 80th percentile households under both the higher- and lower-inequality distributions, it is apparent that an increase in income inequality increases the difference in incomes between these households. In the lower-inequality distribution, the household at the 70th percentile has an income of $88,000 and the household at the 80th percentile has an income of $106,000, a difference of $18,000, and a ratio of 1.20. In the higher-income distribution, the 70th and 80th percentile households have incomes of $83,000 and $109,000, respectively, a difference of $26,000 and a ratio of 1.31. That is, an increase in upper-tail income inequality increases the difference in incomes between two moderate-to-high income households at given percentiles of the income distribution, making it less likely that they can afford to live in the same neighborhood. This implies that differences in income inequality that are due to differences in upper-tail inequality—as has been the case with changes in income inequality from 1970-2000—should lead to greater segregation of affluence but not necessarily to greater segregation of poverty.

Racial Differences in the Effects of Income Inequality

As we suggested above, income inequality may affect income segregation differently among black and white households because of the variation in housing markets available to each group. Racial discrimination in the housing market has meant that, historically at least, minority households (particularly black households) have had fewer residential options than white households with similar income and wealth. Even if black households had the same preferences and the same level of income inequality as white households, the racially discriminatory aspects of the housing market likely led to lower levels of income segregation among black households than among white households. This is because the segregation of black households compelled higher- and lower-income black households to live close to one another.

The black middle class grew rapidly from 1940 to 1990,[10] resulting in rising income inequality among black households (Farley & Frey, 1994; Son, Model, & Fisher, 1989). Until the passage of the Fair Housing Act in 1968 and the Home Mortgage Disclosure Act in 1975, however, discriminatory housing practices severely limited the residential mobility of middle-class black families (Farley & Frey, 1994). As a result, prior to 1970, income inequality among blacks was probably less tightly linked to income segregation than it was for whites. In the period from 1970-2000, however, the housing options available to middle-class blacks greatly expanded (though some housing discrimination persisted through this period; see Farley & Frey, 1994; Ross & Turner, 2005; Yinger, 1995), likely tightening the link between inequality and segregation among blacks over this period.

Empirical Predictions

The above arguments suggest several testable hypotheses. First, because the U.S. housing market is largely based on ability-to-pay, we predict that income inequality will be positively correlated with income segregation and that changes in income inequality with be positively associated with changes in income segregation. Second, because most of the change in income inequality has been the result of growth in upper-tail inequality, we predict that changes in income inequality will affect the segregation of affluence to a greater degree than it affects the segregation of poverty. Third, we predict that income inequality will have a stronger relationship with income segregation among black families than among white families during the period 1970-2000, when housing market constraints were substantially reduced for black households. Finally, although there is no existing research on the geographic scale of income segregation, we expect that income inequality leads to income segregation primarily by increasing the spatial distance between high- and low-income households (due to suburbanization of middle- and upper-income households, for example). Thus, we predict that income inequality will have a stronger relationship with macro-scale segregation patterns than with micro-scale segregation patterns.

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[10] Farley and Frey (1994) define middle class as having an income that is twice the poverty line. By this definition, just 1% of black households in 1940 were middle class, compared to 39% in 1970 and 47% in 1990.

There is little prior research regarding most of these hypotheses. Several existing studies demonstrate a positive association between income inequality and income segregation. Mayer (2001b) shows that the well-documented increase in income inequality from 1970-1990 resulted in an increase in segregation between census tracts within states—although the income variance within census tracts remained stable, the income variance between tracts grew, indicating an increase in between-tract income segregation. Wheeler and La Jeunesse (2008) largely corroborate these findings using metropolitan areas, rather than states, as the unit of analysis. They find that the average level of income segregation (measured as the between-block group share of income inequality) within metropolitan areas grew sharply in the 1980s and declined slightly in the 1990s, a pattern that is only partly consistent with the trend in steadily rising income inequality over the same period. Because their analysis is based on a simple comparison of trends, however, it indicates little about the causal relationship between income inequality and segregation.

A third recent study uses metropolitan area fixed-effects regression models to estimate the causal effect of metropolitan area income inequality on income segregation, demonstrating that income inequality has a strong effect on income segregation (Watson, 2009). Specifically, Watson finds that a one standard deviation rise in income inequality leads to a 0.4-0.9 standard deviation rise in income segregation. Moreover, Watson briefly investigates several additional aspects of the relationship between income inequality and income segregation. First, she finds that income inequality leads to increases in the segregation of both poverty and affluence (though the effect is slightly larger on the segregation of affluence). Second, she finds that income inequality has a weaker effect on income segregation among black families than in the population as a whole (contrary to our hypothesis above). Finally, her results suggest no effect of income inequality on suburbanization rates from 1970-2000, implying, perhaps, that income inequality does not affect the geographic scale of income segregation (though Watson notes that data limitations render these results merely "suggestive"). Nonetheless, while each of these three analyses provides some evidence regarding our hypotheses, they each rely on segregation measures that are not ideal. As we describe below, her preferred measure of segregation, the Centile Gap Index, does not allow clear comparisons across metro areas and years and it cannot be used to measure geographic scale. In our analyses below, we use a more appropriate measure of income segregation that allows us to more directly estimate the effects of inequality on the segregation of affluence and poverty and on the geographic scale of segregation.

Data and Methods

Measuring Income Segregation

To analyze income segregation it is necessary to first measure income segregation. While there is a rich literature discussing measures of segregation among unordered categorical groups, such as race or gender (see, for example, Duncan & Duncan, 1955; James & Taeuber, 1985; Reardon & Firebaugh, 2002; Reardon & O'Sullivan, 2004; Taeuber & Taeuber, 1965),[11] methods of measuring income segregation are much less well developed. Unlike race or gender, income is measured on a continuous (or at least an ordinal) scale, so measures of segregation that are appropriate for unordered categorical groups are not appropriate for measuring income segregation. We provide here a brief review of existing approaches to measuring income segregation and then describe the measure we will rely on, the rank-order information theory index (Reardon, Firebaugh, O'Sullivan, & Matthews, 2006).

Much of the small body of existing literature on income segregation in sociology has measured income segregation by using established measures of racial segregation, such as the dissimilarity index, applied to a small set of crude income categories (poor vs. non-poor, or upper, middle, and lower income). Examples of this approach are found in the literature in sociology (Fong & Shibuya, 2000; Massey, 1996; Massey & Eggers, 1993; Massey & Fischer, 2003), urban planning (Coulton, Chow, Wang, & Su, 1996; Pendall & Carruthers, 2003), economics (Jenkins, Micklewright, & Schnepf, 2006), and public health (Waitzman & Smith, 1998b). There are a number of serious deficiencies with this technique, including the substantial loss of information that results from treating income as categorical

[11] There is also a literature in geography and economics on the measurement of categorical segregation (see, for example, Echenique & Fryer, 2005; Mora & Ruiz-Castillo, 2003; Wong, 1993, 2002).

and the arbitrary nature of selecting a small number of cut points to categorize the data. Even if the exact income of families is unknown, the 16 income categories reported in the 2000 U.S. Census, for example, contain far more information than 2 or even 4 categories. Moreover, the income categories (as well as the meaning of a given dollar amount of income) change over time, so that categories defined in one decennial Census cannot be replicated in another.

A second approach to measuring income segregation defines segregation as a ratio of the between-neighborhood variation in mean income to the total population variation in income. Income segregation measures derived from this approach have used a number of different measures of income variation, including the variance of incomes (Davidoff, 2005; Wheeler, 2006; Wheeler & La Jeunesse, 2006), the standard deviation of incomes (Jargowsky, 1996, 1997), the variance of logged incomes (Ioannides, 2004), the coefficient of variation of incomes (Hardman & Ioannides, 2004), and Bourguignon's income inequality index (Ioannides & Seslen, 2002). Similarly, the Centile Gap Index (CGI) measures segregation as one minus the ratio of within-neighborhood variation in income percentile ranks to the overall variation in percentile ranks (Watson, 2006, 2009). Most well-known in sociology is Jargowsky's (1996, 1997) Neighborhood Sorting Index (NSI), which is defined as the square root of the ratio of the between-unit income variance to the total income variance.

Although the NSI and measures like it improve upon categorical measures of income segregation because they do not rely on arbitrary and changing dichotomizations of income distributions, they lack a key feature that is necessary for our purposes in this paper. In order to distinguish income *segregation* (the sorting of households by income among census tracts, independent of the income distribution) from income *inequality* (the uneven distribution of income among families), a measure of income segregation is required that is independent of income inequality. One way to achieve this is to use an income segregation measure that relies only on information about the rank-ordering of incomes among families, rather than information about actual dollar income amounts. A rank-order income segregation measure will be, by definition, invariant under any changes in income that leave families' residential location and income rank unchanged, regardless of how income inequality changes. Unfortunately, the Neighborhood

Sorting Index (NSI) (Jargowsky, 1996) does not satisfy this property, and so may confound changes in income inequality with changes in residential sorting by income, and may confound differences in income distributions across time, place, and groups with differences in segregation (Neckerman & Torche, 2007). More suitable for our purposes is the *rank-order information theory index* (H^R) (Reardon, et al., 2006), which measures the ratio of within-unit (tract) income rank variation to overall (metropolitan area) income rank variation.[12]

The Rank-Order Information Theory Index

Reardon and colleagues (2006) describe the rank-order information theory index in detail; we summarize its key features here. First, let p denote income percentile ranks (scaled to range from 0 to 1) in a given income distribution (that is $p = F(Y)$, where Y measures income and F is the cumulative income density function). Now, for any given value of p, we can dichotomize the income distribution at p and compute the residential (pairwise) segregation between those with income ranks less than p and those with income ranks greater than or equal to p. Let $H(p)$ denote the value of the traditional information theory index (James & Taeuber, 1985; Theil, 1972; Theil & Finezza, 1971; Zoloth, 1976) of segregation computed between the two groups so defined. Likewise, let $E(p)$ denote the entropy of the population when divided into these two groups (Pielou, 1977; Theil, 1972; Theil & Finezza, 1971). That is,

$$E(p) = p\log_2 \frac{1}{p} + (1-p)\log_2 \frac{1}{(1-p)} \tag{1}$$

and

[12] Reardon et al (2006) review a number of other measures of income segregation proposed in the literature, concluding that the rank-order information theory measure better isolates the sorting/unevenness dimension of income segregation than other measures, and ensures comparability over time and place, a feature most other measures lack. The Centile Gap Index (CGI) (Watson, 2006, 2009) shares many desirable features with H^R, but lacks several important features: it does not accommodate spatial information; it does not allow straightforward examination of the segregation of poverty and affluence; and it is insensitive to certain types of sorting among neighborhoods. These shortcomings render it less preferable than H^R.

$$H(p) = 1 - \sum_j \frac{t_j E_j(p)}{TE(p)},$$

(2)

where T is the population of the metropolitan area and t_j is the population of neighborhood j. Then the rank-order information theory index (H^R) can be written as

$$H^R = 2\ln(2)\int_0^1 E(p)H(p)dp$$

(3)

The rank-order information theory index ranges from a minimum of 0, obtained in the case of no income segregation (when the income distribution in each local environment (e.g. census tract) mirrors that of the region as a whole), to a maximum of 1, obtained in the case of complete income segregation (when there is no income variation in any local environment). Because the measure uses only information on the rank-ordering of household incomes within a metropolitan area, it is independent of the income distribution. As a result, it is possible to make meaningful comparisons across time, regardless of monetary inflation and changes in income inequality, and across metropolitan areas and population subgroups (such as racial groups), regardless of differences in their income distributions. To compare the levels of within-group income segregation among racial groups, we compute the rank-order information theory index for each racial group separately. For a detailed description of the computation of H^R from Census data, see the Appendix (Section 1).

Note that Equation (3) defines H^R as a weighted average of the binary income segregation at each point in the income distribution. The weights are proportional to the entropy $E(p)$, which is maximized when $p = 0.5$ and minimized at $p = 0$ or $p = 1$. In other words, if we computed the segregation between those families above and below each point in the income distribution and averaged these segregation values, weighting the segregation between families with above-median income and below-median income the most, we get the rank-order information theory index.[13] These weights have an intuitive appeal, as

[13] Reardon et al. (2006) show that the rank-order information theory index can also be written as one minus the ratio of within-neighborhood income rank-order variation to overall income rank-order variation. This formulation

they imply the extent of segregation between those above and below the median is more informative about overall residential sorting by income than is the extent of segregation between those above and below the 90^{th} percentile, for example.

Figure 3 provides an illustration of the information used in the calculation of H^R (see Equation 3 and Appendix Section 1), using family income data from the Chicago metropolitan area in 2000. The x-axis of Figure 3 corresponds to percentiles of the family income distribution in Chicago in the 2000 Census, with the values of the 15 specific Census income category thresholds marked for reference. For example, roughly 5% of families in Chicago had incomes less than \$10,000 and roughly 50% had incomes less than \$60,000. The circular markers at each income threshold indicate the between-tract segregation computed between two groups of families—those with incomes below the threshold and those with incomes equal to or greater than the threshold. So, for example, the value of the information theory index of segregation between families earning less than \$10,000 and those earning greater than or equal to \$10,000 was roughly 0.45 in Chicago in 2000. The markers indicate segregation levels for the 15 thresholds available in the 2000 Census. The solid line describes a fitted 4^{th}-order polynomial (our estimate of the function $H(p)$—see Appendix Section 1) through the measured segregation levels. In this example, the estimated rank-order information theory index is 0.298 (computed as the weighted average of the value of the fitted line over the range of percentiles from 0 to 1; see Equation 3). It is possible to compute a segregation profile like this for any metropolitan area in any year. More importantly, because $H(p)$ is a function of income percentiles rather than actual incomes, we can compare these profiles across metropolitan areas, racial groups, or years despite differences in their underlying income distributions.

Figure 3 here

Once we have estimated the function $H(p)$ (as described in Appendix Section 1, Equation A2), we can also compute estimated values of segregation at any desired threshold. Suppose, for example, we

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makes clear that H^R is similar to the NSI and other variation-ratio measures of income segregation, save that H^R relies on income ranks rather than actual incomes. In particular, H^R is similar to Watson's Centile Gap Index (CGI). The CGI, however, cannot be written as a weighed sum of binary segregation measures, making is less useful for our purposes, as we describe below.

wish to estimate the segregation between families in the top 10 percent of the income distribution and all others. Even if there is not an income threshold in the Census data that corresponds exactly to the 90th percentile, we can estimate $H(.9)$ from the fitted polynomial (Equation A2). For example, even though there is no income threshold in Chicago that corresponds exactly to the 90th income percentile, we can compute the estimated value of $\hat{H}(.9) = 0.370$ from the estimated parameters of the fitted $H(p)$ profile in Figure 3. This will enable us to compute and compare the segregation levels of well-defined income groups even when the Census does not provide the exact information needed.

Finally, as Reardon et al. (2006) note, Equation (3) implies that we can easily compute spatial measures of income segregation by replacing $H(p)$ in (3) with its spatial analog, the spatial information theory index, $\widetilde{H}(p)$ (Reardon & O'Sullivan, 2004). The spatial information theory index takes into account the spatial proximity of neighborhoods and computes segregation as the variation in racial composition across individuals' 'local environments.' Following the work of Reardon and colleagues (B. A. Lee, et al., 2008; Reardon, et al., 2009; Reardon, et al., 2008), we compute spatial measures of income segregation using definitions of 'local' ranging from radii of 500 to 4000 meters in order to investigate the spatial scale of the effects of income inequality on income segregation. [14]

Measuring Income Inequality

We measure income inequality within each race group-metro-year with the Gini index (G). The Gini index measures the extent to which the actual income distribution deviates from a hypothetical distribution in which each person receives an identical share of total income. The measure ranges from 0, indicating perfect equality (where each individual receives an identical share of the distribution), to 1, indicating maximum inequality (where one individual holds all of the income). The estimation of G

[14] The spatial information theory index is analogous to the tract-based information theory index, but, rather than defining each family as living in a local environment defined by its census tract, the spatial index conceives of each family as located at the center of a (circular) egocentric local environment and measures segregation as the unevenness in the income distributions of these local environments. In computing the income distribution of a given family's local environment, nearby families are given more weight than less proximal families. We use the program *SpatialSeg* (Reardon & Matthews, 2008, available at www.pop.psu.edu/mss/mssdownload.cfm) to compute the spatial information theory index.

usually requires individual-level income data so that the cumulative income shares of individuals can be plotted against the cumulative population shares. However, publically-available Census data provides income data in categories, or bins, instead of as a metric measure. Thus, we compute the Gini index from Census data using a procedure described in detail in Nielsen and Alderson (1997).[15]

Data

This paper uses U.S. Census data from the 1970 Summary Tape Files 3A, the 1980 Summary Tape Files 3A, the 1990 Summary Tape Files 4A, and the 2000 Summary Files 3A (GeoLytics, 2004; Minnesota Population Center, 2004). For most of our analyses, we use data from the 100 metropolitan areas with the largest populations in 2000,[16] and use consistent metropolitan area definitions across census years to ensure comparability of the results over time (we use the OMB 2003 metropolitan area definitions, the first definitions based on the 2000 Census). Following Jargowsky (1996), however, we include in our analyses only cases in which there were at least 10,000 families of a given race group in a given metro in each of 1970, 1980, 1990 and 2000.[17] As noted earlier, throughout the paper we rely on tabulations of family income (because these are available separately by race) by census tract, except for the spatial analyses, for which we use tabulations of household income (because we do not conduct these analyses separately by race). For analyses of income segregation in the total population, our sample consists of 400 observations (100 metropolitan areas times 4 decades). For analyses using race-specific measures, our sample consists of 644 observations (100 metros times 4 decades for white income

[15] We use the prln04.exe program available at www.unc.edu/~nielsen/data/data.hlm.

[16] These 100 metropolitan areas together were home to 173 million residents in 2000, 62% of the U.S. total population, including 70% of non-Hispanic Blacks (23.6 million); 78% of Hispanics (27.6 million), and 89% of Asians (9 million). The metropolitan areas range in population from 11.3 million (New York-White Plains, NY-NJ) to 561,000 (Scranton--Wilkes-Barre, PA).

[17] For our analyses using spatial segregation measures, we use data from the 1980, 1990, and 2000 Censuses only, because large parts of many metropolitan areas were not tracted by the Census in 1970, making the computation of metropolitan area spatial segregation measures from 1970 error-prone. Although some parts of metropolitan areas were not fully tracted in 1980, untracted regions comprise only a small part of most metropolitan areas in 1980. Our results are robust to the exclusion of 1980 data.

segregation, and 61 metros times 4 decades for black income segregation).[18] In the Appendix (Section 2) we discuss the comparability of data across census years.

Results

Patterns and Trends in Income Inequality and Segregation

Before describing our strategy for estimating the effects of income inequality on income segregation, we present some descriptive data. Table 2 reports the average levels of income inequality and income segregation, by race, for the 100 largest metropolitan areas in the U.S. Overall, metropolitan area income inequality grew from 1970 to 2000, with the greatest increase occurring in the 1980s. Average metropolitan area income inequality grew more rapidly for blacks than whites, particularly in the 1970s, a pattern that reflects the continuing growth of the black middle class that began in the 1960s.

Table 2 here

Average metropolitan area income segregation followed a similar pattern, growing from 1970 to 2000, with the fastest increase occurring in the 1980s. For black families, income segregation grew rapidly in the 1970s and 1980s, at a rate more than three times faster than the corresponding growth of white income segregation. In fact, average black income segregation was about one-third of a standard deviation *lower* than white income segregation in 1970, but was about one standard deviation *higher* than white income segregation by 1990. As Figure 4 shows, these patterns suggest a relationship between income inequality and income segregation; for both black and white families, as well as for the total population, changes in income segregation appear to roughly mirror changes in income inequality.

Figure 4 here

The trends in metropolitan area income segregation reported in Table 2 and Figure 4 do not match the patterns found in some prior research. Watson (2009), for example, found that average metropolitan

[18] Family income data are not available separately for Hispanic and Asian families in 1970. In addition, because only 13 metropolitan areas contained at least 10,000 Asian families in 1980, 1990, and 2000, and only 36 of the 100 largest metropolitan areas contained at least 10,000 Hispanic families in 1980, 1990, and 2000, we do not include Asian and Hispanic families in our analyses (except insofar as they are included in the total population analyses).

area income segregation of all families, as measured by the Centile Gap Index, declined slightly in the 1970s and 1990s but rose sharply in the 1980s. Jargowsky (1996) and Yang and Jargowsky (2006), however, found that average metropolitan area income segregation of both white and black families, as measured by the Neighborhood Sorting Index, rose in the 1970s and 1980s, but declined sharply in the 1990s. Our estimated trends differ from these for two primary reasons. First, we use a different measure of income segregation than these prior studies, for reasons we describe above. Second, our estimates are based on the 100 largest metropolitan areas, while Watson (2009) uses 216 metro areas; Jargowsky (1996) uses 228 and 76 metropolitan areas for the white and black trends, respectively, from 1970-1990; and Yang and Jargowsky (2006) use 324 and 130 metropolitan areas for the white and black trends, respectively, from 1990-2000. Our restriction to the 100 largest metropolitan areas has substantial implications for the estimated trends, as is evident in Figure 5, which shows trends in income inequality and segregation for smaller metropolitan areas (those with at least 10,000 families of the relevant group in each year, excluding the 100 largest metropolitan areas). For small metropolitan areas, the trends in income inequality are very similar to those for large metropolitan areas, but the trends in income segregation are quite different. Income segregation in small metropolitan areas is, on average, much lower than for large metropolitan areas. In addition, income segregation in small metropolitan areas declined in both the 1970s and 1990s (among all families and for white families). Pooling the trends for large and small metropolitan areas would yield a trend similar to that described by Watson (2009)—declining average income segregation in the 1970s and 1990s and a sharp increase in average income segregation in the 1980s.

Figure 5 here

Although Table 2 and Figure 4 show changes in the average values of the rank-order information theory index from 1970 to 2000, they do not provide detail on the extent to which changes in income segregation are due to changes in the segregation of affluence and poverty. Figures 6-8 (for detail, see Appendix Section 3, Table A1) show average metropolitan area segregation profiles for 1970-2000. These enable us to examine the extent to which segregation has changed between the poor and non-poor and the rich and non-rich, for example.

Figure 6 here

Figure 6 shows the trend in the average income segregation profile across the 100 largest metropolitan areas from 1970-2000. First, note that in 1970, the poor were much less segregated from the non-poor than the rich were from the non-rich. Income segregation between the poor and non-poor (segregation of poverty) grew sharply between 1970 and 1980, however, while income segregation of the rich and non-rich (segregation of affluence) did not. In the 1980s, however, income segregation grew at all parts of the income distribution. In the 1990s, in contrast, income segregation grew only modestly, and only between families in the middle part of the income distribution. On average, the segregation of poverty and the segregation of affluence were relatively unchanged in the 1990s. These figures demonstrate that a single measure of income segregation may not fully convey the pattern of changes.

Figures 7 and 8 show the corresponding trends for white (Figure 7) and black families (Figure 8) separately. As we would expect, given the size of the white population, the trends for white income segregation are similar to those of the population as a whole. The trends in black family income segregation, however, are rather different. Black income segregation grew rapidly in the 1970s and 1980s at all parts of the black income distribution. Not only did low-income black families become more isolated from middle- and higher-income black families, but higher-income blacks became increasingly segregated from lower-and middle-income black families as well. In the 1990s, this trend ceased abruptly. In fact, the segregation of lower- and moderate-income black families from higher-income black families declined slightly in the 1990s.

Figures 7 & 8 here

The tables and figures above describe patterns and trends in income segregation using "aspatial" measures of segregation. These measures treat census tracts as discrete, spatially anonymous units and so are not fully sensitive to changing spatial patterns of segregation. In particular, they are insensitive to the spatial scale of segregation—they do not indicate the extent to which segregation levels are due to the large or small scale spatial patterning of families in residential space. Figure 9 reports average segregation profiles similar to those in Figures 6-8, but using the spatial information theory index (Reardon & O'Sullivan, 2004) computed at a range of spatial scales instead of the tract-based information theory index used in the figures above.

In particular, Figure 9 shows the average spatial information theory index household[19] income segregation threshold profile computed using radii of 500, 1000, 2000, and 4000 meters for the 100 largest metropolitan areas in 2000. These radii correspond roughly to local environments ranging from 'pedestrian' in size (500 m radius) to those that are considerably larger (4000 m radius)—the size of a large high-school attendance zone, for example—larger in scale than the neighborhoods in which most people attend church, shop, and do much of their socializing (Reardon, et al., 2008). In addition, Figure 9 shows the macro/micro segregation ratio (dashed line, with scale on the right-hand axis), which measures the proportion of micro-scale segregation (segregation among 500m radius local environments) that is due to macro-scale segregation patterns (segregation among 4000m radius environments). This ratio can be interpreted as a measure of the geographic scale of segregation, with larger values indicating that more of the measured segregation is due to the separation of groups over large distances (Reardon, et al., 2009; Reardon, et al., 2008).

Figure 9 here

Two key patterns are evident in Figure 9. First, spatial income segregation patterns are very similar to the aspatial patterns shown in Figure 6. Segregation of high-income households from other households is, in general, higher than the segregation of low-income households from other households, regardless of the radius at which segregation is measured. Second, this pattern appears to be largely, if not entirely, due to the fact that upper-income households are much more segregated at a large geographic scale than are lower-income households. For high-income households, 60% or more of segregation patterns are due to macro-scale segregation—presumably the concentration of high-income households in wealthy suburban and exurban areas. For low-income households, 40% or less of segregation patterns are

[19] We are able to use household income for the spatial measures rather than family income because we do not analyze spatial patterns for black and white families separately. As noted above, family and household income segregation are highly correlated.

due to macro-scale segregation; this implies that the poor are less concentrated spatially than the wealthy in most metropolitan areas.

In sum, our descriptive analyses reveal several important trends. First, average metropolitan area income inequality and segregation both grew from 1970-2000, though the growth in income segregation was much larger for black families than for white families. Second, income segregation grew at all parts of the income distribution from 1970-2000, though at different times and at different rates for black and white families. Most of the growth in income segregation occurred between 1970 and 1990. Nonetheless, both the segregation of poverty and the segregation of affluence were much higher in 2000 than they had been in 1970 for white and black families alike. And third, the segregation of affluence is generally greater than the segregation of poverty in the 100 largest metropolitan areas, a pattern that appears to be driven by the macro-scale segregation of the highest earners from others. In the next section of the paper, we investigate the extent to which variation in income inequality can explain these patterns.

Estimating the Effects of Income Inequality on Income Segregation

We estimate the effect of income inequality on income segregation using a set of fixed-effects regression models. The models rely on 644 metro-group-year cases, as noted above. Because each observation in the data corresponds to a specific metropolitan area, decade, and race group, there are three potential sources of variation in income inequality—variation across decades (within each metro-by-group cell), variation among metropolitan areas (within each decade-by-group cell), and variation between race groups (within each metro-by-decade cell).[20] We use three different fixed effects models, each relying on a different source of variation in income inequality, to estimate the effect of income inequality on segregation over time, across race groups, and across metropolitan areas, respectively.

In addition we wish to ensure that our estimates of the effect of inequality on segregation are not

[20] Only 61 of the 100 metropolitan areas have this latter variation, because we include observations for black families in the sample only for the 61 metropolitan areas where there are at least 10,000 black families in each of the four Census years.

biased by any confounding metropolitan-level covariates that are correlated with both inequality and segregation. Based on previous research, we control for metropolitan demographic characteristics, housing market pressures and housing stock, intra- and inter-metropolitan mobility, population growth, labor market characteristics, and family structure[21] (Abramson, Tobin, & VanderGoot, 1995; Jargowsky, 1996; Massey & Eggers, 1993; Pendall & Carruthers, 2003; Watson, 2009; Wheeler, 2006; Wilson, 1987). Notably, because the U.S. Census does not provide information on family wealth, we are unable to include controls for metro- year- and race-specific aspects of the distribution of wealth in our models. Although wealth is only modestly correlated with income, it plays a key role in residential location because it enables families to buy housing in communities where their current income may be insufficient, and provides a financial cushion during unstable times, such as temporary unemployment, illness, or divorce, and so enables families to remain in their home when their income cannot support them (Wolff, 2006). Nonetheless, research suggests that wealth may not be a significant factor in neighborhood migration patterns (Sharkey, 2008), although it is a stronger predictor of neighborhood choice for blacks than it is for non-Hispanic whites (Crowder, South, & Chavez, 2006).

In the first set of regression models (models 1 and 2), we estimate the effect of changes in inequality on changes in segregation, including both metropolitan area-by-group fixed effects and decade fixed effects. These models have the form

$$H_{mgy} = \alpha \cdot I_{mgy} + \Gamma_{mg} + \Delta_y + \mathbf{X}_{my}\mathbf{B} + \mathbf{W}_{mgy}\mathbf{\Psi} + \epsilon_{mgy} \, , \tag{4}$$

where m indexes metropolitan areas, g indexes race groups, y indexes Census years, and where H_{mgy} and I_{mgy} indicate the rank-order segregation and income inequality, respectively, in metropolitan area m for group g in year y. The models include metropolitan area-by-group (Γ_{mg}) and decade (Δ_y) fixed effects. The coefficient α on inequality from this model indicates the average within-metro-group

[21] More specifically, to control for these factors in our models, we include metropolitan-level population counts of each race group, percent older than 65 and younger than 18 years-old, percent with at least a high school diploma by race, percent foreign born, percent in the manufacturing sector, percent in the managerial/professional sector, percent in finance, insurance, and real estate, percent in the construction sector, percent unemployed by race, per capita income by race, intra- and inter-metropolitan mobility, percent new housing construction, and percent female-headed households by race. The data sources for and construction of each of these variables are described in the Appendix (Section 2) in more detail.

association (over time) between inequality and segregation, net of any secular trend common to all metropolitan areas and race groups. Model 2 includes a set of metro-year and group-metro-year covariates ($\mathbf{X}_{my}$ and $\mathbf{W}_{mgy}$) as control variables in addition to the fixed effects. We compute bootstrapped standard errors in all of the regression models to take into account the clustered nature of the observations.

In the second set of models (Model 3 and 4), we estimate the effect of differences in income inequality between race groups on income segregation, using metropolitan area-by-year fixed effects and group-specific dummy variables. These models have the form

$$H_{mgy} = \alpha \cdot I_{mgy} + \Gamma_{my} + \Delta_g + \mathbf{W}_{mgy}\mathbf{\Psi} + \epsilon_{mgy} , \qquad (5)$$

where Γ_{my} and Δ_g are metropolitan area-by-year and group-specific fixed effects, respectively. The coefficient α on inequality from this model indicates the average within-metro-year association (between race groups) between inequality and segregation, net of any average differences in inequality and segregation between race groups across metropolitan areas and time. Model 4 includes a small set of group-metro-year covariates as control variables as well as the fixed effects.

In the third set of models (Model 5 and 6), we estimate the effect of differences in income inequality among racial groups on income segregation, using metropolitan area and group-by-year fixed effects. These models have the form

$$H_{mgy} = \alpha \cdot I_{mgy} + \Gamma_{gy} + \Delta_m + \mathbf{X}_{my}\mathbf{B} + \mathbf{W}_{mgy}\mathbf{\Psi} + \epsilon_{mgy} , \qquad (6)$$

where Γ_{gy} and Δ_m are group-by-year and metropolitan area fixed effects, respectively. The coefficient α on inequality from this model indicates the average within-group-year association (across metropolitan areas) between inequality and segregation, net of any average differences in inequality and segregation among metropolitan areas across groups and decades. Model 6 includes a set of group-metro-year and metro-year covariates as control variables as well as the fixed effects. Because the three models rely on different sources of variation in income inequality, each relies on a different key assumption in order to support a causal claim about the effect of income inequality on income segregation.[22] As a result, if the three sets of models produce similar results, we can rule out many potential sources of bias. As an additional set of sensitivity checks, we estimate a set of models for each race group separately, and a set for each decade separately.

Main Effects of Income Inequality on Income Segregation

Table 3 reports the estimates from the models described in Equations (3)-(5) above. Of primary interest here are the estimated coefficients on the Gini index in Models 2, 4, and 6, which include the full set of covariates as well as the fixed effects. Model 2 yields an estimated association of 0.467 (*s.e.*= 0.060; p<.001) between income inequality and income segregation, net of the model's fixed effects and covariates. In other words, a change of one point in a group's income inequality is associated with a change of roughly a half a point in income segregation. Note also that Model 1 implies that changes in income inequality alone do not fully explain the trends in income segregation—even after controlling for income inequality, within-group income segregation grew, on average, by 0.013 points in the 1970s and by another 0.015 points in the 1980s.

Table 3 here

Model 4, which relies on variation in income inequality between white and black families within the same metropolitan area and year, yields an estimated association between inequality and segregation

[22] The models that include metro-by-group fixed effects rely on the assumption that changes in income inequality within a metropolitan area and race group over time are exogenous, conditional on secular trends common to all groups and metropolitan areas and the set of included covariates in the model. The models that include metro-by-year fixed effects rely on the assumption that differences between white and black income inequality within the same metropolitan area and decade are exogenous, once we have accounted for differences in income inequality between white and black families that are common across metropolitan areas and time and differences in inequality that are associated with differences in the covariates included in the model. And finally, the models that include group-by-year and metropolitan area fixed effects rely on the assumption that differences in income inequality within a given year and for a given race group are exogenous, once we have accounted for stable differences among metropolitan areas and differences associated with the covariates in the model. None of these three assumptions are likely to be perfectly true, but each model is somewhat insulated against threats to another. If we are worried about temporal confounding biasing the estimates from the first models, for example, we can examine the second and third set of models, each of which relies on cross-sectional variation across groups or metropolitan areas. If we are worried about unobserved group-specific factors, such as a correlation between employment sector and preferences for neighbors, biasing the estimates in the second set of models, we can look to the first and third set of models, each of which relies only on within-group variation (over time or across metropolitan areas).

of 0.783 (*s.e.*=0.125; *p*<.001), somewhat larger than the estimate from model 2. Note that Model 3 implies that income inequality alone more than accounts for the differences in income segregation between black and white families. Model 3 implies that income segregation among black families is *lower*, on average, than among white families within the same metropolitan area and year, given the same level of income inequality.

Finally, Model 6 yields an estimated association between income inequality and income segregation of 0.502 (*s.e.*=0.110; *p*<.001). Thus, each of the three models yields estimated coefficients on income inequality that imply inequality has a positive effect on income segregation. To get a sense of the magnitude of these effects, note that an effect of 0.500 (roughly that found in Models 2 and 6) implies that the changes in income inequality from 1970 to 2000 shown in Table 2 account for roughly 40% of the average change in black income segregation, 80% of the average change in white income segregation, and 60% of the average change in overall income segregation. Put differently, a one-standard deviation change in income inequality leads to roughly one-quarter of a standard deviation change in income segregation.[23]

To ensure that the estimates from Models 2, 4, and 6 are not driven by one particular race group or decade, we fit an additional set of models for each race group separately, and another set of models for each decade separately. The results of these models are shown in Table 4. In each model, the coefficient on inequality is positive and statistically significant. In the group-specific models, the coefficients range from 0.450 to 0.561; in the decade-specific models, the coefficients range from 0.624 to 0.732. Thus, across all the models shown in Tables 3 and 4, we find that income inequality has a large and positive association with income segregation, regardless of whether we rely on temporal, between-group, or between-metropolitan area variation to identify this association, and regardless of which groups or

[23] These are computed from the 1970-2000 changes in inequality and segregation shown in Table 2. For example, income inequality among all families grew by 0.048 from 1970-2000. If the effect of income inequality on segregation were 0.500, this would imply a change in income segregation of $0.048 \cdot 0.5 = 0.024$, which is roughly 70% of the observed total change (0.033) in income segregation from 1970-2000. Likewise, the standard deviation of income inequality within a given year was roughly 0.025, on average, while the standard deviation of income segregation was roughly 0.050. This implies that an effect of 0.500 corresponds to an effect size of 0.25.

decades we use in the sample.[24]

Table 4 here

Effects of Income Inequality on the Segregation of Poverty and Affluence

One advantage of the information theory index is that it enables us to investigate whether income inequality more strongly affects income segregation through the segregation of poverty or the segregation of affluence. To answer this, we fit models identical to models 2, 4, and 6 above but using income segregation measured at a set of income percentiles (the 5th, 10th, 25th, 50th, 75th, 90th, and 95th percentiles) rather than the rank-order information theory index as the outcome. In addition, we fit these models separately by race (as in Table 3), again using segregation measured at a set of percentiles as the outcome variables.

The estimates from these models are reported in Figures 10 and 11 (for details, see Appendix Section 3, Table A2). Figure 10 shows that income inequality has little or no significant impact on the segregation of the very poorest families of a metropolitan area from all other families, but has large and significant effects on the segregation of moderate- to high-income families from those with lower incomes. This pattern holds across the three models. In other words, income inequality appears to be much more strongly linked to the segregation of affluence than to the segregation of poverty.

Figure 10 here

The same general pattern is true when we investigate the effects of income inequality on income segregation for white and black families separately, as shown in Figure 11. However, the effect of inequality on the segregation of affluence is much stronger for black families than for white families.

[24] In additional analyses not shown here, we estimate the same set of models on a sample of smaller metropolitan areas (those not included in the 100 largest metropolitan areas, but with at least 10,000 families). This sample includes 179 metropolitan areas (176 of which have at least 10,000 white families, and 15 of which have at least 10,000 black families in each year 1970-2000). The estimates from models on these samples yield much smaller coefficient estimates (on the order of $\hat{\alpha} = 0.200$ in each model). This suggests that the effects of income inequality on income segregation are much stronger in large metropolitan areas than in smaller ones, a finding that may help explain the difference in the trends in income segregation in small relative to large metropolitan areas observed in Figures 4 and 5 above.

That is, in metropolitan areas and years when black income inequality is largest, the highest-earning 10 percent of black families are much more segregated from the lower 90 percent of black families than when and where black income inequality is low.

Figure 11 here

Effects of Income Inequality on Spatial Segregation Patterns

Our third set of analyses investigates whether income inequality produces macro- and/or micro-scale income segregation patterns. For these analyses, we focus on the relationship between overall income inequality and *household* income segregation, rather than race-specific family income inequality and segregation. As above, we focus on the 100 largest metropolitan areas in 2000. We fit models that include metropolitan area and year fixed effects and a set of metropolitan area-by-year covariates (the models are identical to those specified in Column 1 of Table 4, save for the different outcome and the fact that we use data only from years 1980-2000).

In order to investigate the geographic scale of the effects of income inequality, we fit these models using five different measures of spatial segregation: four using different radii and one using the measure of "net micro segregation" described by Lee et al (2008). Our rationale for this is as follows. The level of segregation among micro-environments (local environments of 500 meter radius) can be thought of as made up of two non-negative components: a component that is due to macro-scale segregation patterns—that is, segregation among macro-environments (local environments of 4000 meter radius)—plus a component that is due to micro-scale variation in neighborhood composition over and above the macro-scale patterns. By definition, then, the effect of inequality on segregation among micro-scale environments will be equal to the sum of its effect on macro-scale segregation and its effect on net micro segregation. Thus, by comparing the effect estimates across the outcome measures, we can infer the geographic scale at which income inequality affects segregation. For example, if inequality affects segregation among micro-environments much more than it affects segregation among macro-environments, then the effect of segregation must operate primarily to increase the small-scale spatial patterning of income (net micro segregation). Conversely, if inequality affects segregation among micro- and macro-scale environments equally, then the effect of segregation must operate primarily to increase the macro-scale spatial patterning of income (and have no effect on small-scale pattering).

Our estimates of these different effects are shown in Table 5. The key result in Table 5 is the consistency of the point estimates of the effect of inequality (reading across rows of the Table), regardless of the radius used to define a household's local environment. In each model, and regardless of the span of years, income inequality has a significant effect on macro-scale segregation (4000-meter-radius local environments), and a roughly similar-sized effect on smaller-scale segregation (though the latter estimates are not always statistically significant due to large standard errors). Moreover, the effect of income inequality on net micro-scale segregation (the difference between 500-meter and 4000-meter radius segregation, shown in the 5th column of Table 5) is indistinguishable from zero in these models, implying that the effect of income inequality on segregation operates entirely through its effect on macro segregation. In other words, income inequality affects income segregation by shaping residential patterns at a large spatial scale, rather than by increasing the block-to-block sorting of households by income.

Table 5 here

In Figure 12, we present the results of an analysis that combines features of two of the preceding analyses. Here we report the effects of income inequality on spatial household income segregation at specific percentiles of the income distribution and using different local environment radii to compute spatial segregation. The left-hand panel of Figure 12 shows that income inequality has a large positive effect on the spatial segregation of affluence but a negative effect on the spatial segregation of extreme poverty (the bottom 5% of the income distribution) when segregation is computed among local environments of 500 meter radius. The center panel indicates that income inequality has a similar effect on macro-scale segregation, except in the bottom quartile of the income distribution. The right-hand panel of Figure 12 describes the portion of the effect of income inequality on 500-meter radius segregation that is not due to macro-scale segregation effects (mathematically, this effect is the difference between the two effects in the left and center of the Figure). Except for the effects on the segregation of poverty, these net-micro-scale effects are indistinguishable from zero. Income inequality does, however, appear to reduce the segregation of extreme poverty by reducing the small-scale patterning of the segregation of the very poor, a finding consistent with the fact that income inequality may actually compress the lower part of the income distribution. As we note above, when the lower part of the income distribution is compressed, low-income households at different percentiles of the income distribution may be more likely to be able to afford to live in the same neighborhoods, leading to lower income segregation. In sum, Figure 12 suggests that income inequality affects income segregation primarily by increasing the macro-scale separation of the affluent from all others. As income inequality grows, this suggests, the middle and upper-middle class become increasingly concentrated together at relatively large distances from those with lower incomes.

Figure 12 here

Discussion and Conclusions

Our analysis yields four main findings. First, we reproduce the finding in Watson (2009) and Mayer (2001b) linking income inequality to income segregation. Using a set of fixed-effects regression models, we show that there is a strong and robust relationship between within-race metropolitan area income inequality and within-race metropolitan area income segregation, net of secular trends, stable between-race differences, and stable differences among metropolitan areas. Our estimates indicate that a one standard deviation increase in income inequality leads to a quarter of a standard deviation increase in income segregation, an effect roughly half the size of that found by Watson (2009). Nonetheless, these effects are large enough to be substantially meaningful—they imply that increasing income inequality was responsible for 40-80% of the changes in income segregation from 1970-2000. The strength and consistency of our results across a wide range of model specifications suggests this is a robust relationship, at least among large metropolitan areas in the decades from 1970-2000. The estimated effect, however, is much weaker among small metropolitan areas. Moreover, it is important to keep in mind that this analysis investigates the effect of income inequality in an era of rising inequality. It is not clear to what extent these findings generalize to eras of lower, or stable, inequality.

One might be concerned that our estimated effects are subject to various forms of bias. For example, despite our efforts to use a range of modeling strategies to protect our estimates from unobserved confounding, the estimated associations here may nonetheless be biased by the presence of some unaccounted-for factors that shape both income inequality and income segregation. The consistency of the results across three sources of variation, however, strongly suggest a causal relationship. More importantly, one might worry that the estimated associations represent the effects of segregation on inequality, rather than the other way around. Certainly there is reason to suspect that income segregation may engender increased income inequality, by providing differential access to quality schooling, high-paying labor markets, and differential social capital. However, many mechanisms that would drive such effects would require considerable time to take effect (schooling effects would not manifest as increased income inequality for many years, for example), so we think these are less plausible explanations for our findings. Nonetheless, we test the hypothesis of reverse causality by reversing our regressions (using inequality as the dependent variable and segregation as an independent variable in Models 2, 4, and 6). In each case, the estimated associations between segregation and inequality are positive and statistically significant, but much smaller in magnitude than the effects we report.[25]

Our second main finding is that income inequality affects income segregation primarily by affecting the segregation of affluence, rather than the segregation of poverty. Although the segregation of poverty increased from 1970-2000 for both white and black families, as well as for all families, very little of this change is attributable to changes in income inequality. Indeed, income inequality affects the relative incomes of lower-income households only to a small degree—and may actually compress the low end of the income distribution. This suggests that changes in income inequality would be expected to have little effect on the segregation of poverty. Our estimates of the effect of income inequality on spatial segregation, in fact, suggest that income inequality may slightly *reduce* the spatial segregation of low-

[25] While inequality explains 1/2-2/3 of the variation in segregation, segregation only explains 1/5 of the variation in inequality.

income households. Given that income inequality does not seem to drive the patterns of the segregation of poverty, we suspect that the segregation of poverty is more a result of housing policy than of income inequality. Through the 1980s, federal and metropolitan housing policies fostered the development of high-density housing for low-income families. These policies are likely responsible for much of the growth of the segregation of poverty over that time. Likewise, the growth in scattered site low-income and mixed-income housing in the 1990s, coupled with the demolition of some large, high-density public housing projects, may account for the stabilization of the segregation of poverty in the 1990s.

Third, we find that the relationship between income inequality and income segregation differs for black and white families. In 1970, income segregation among black families was lower than among white families. This is likely the result of the ghettoization of minorities that took place, particularly in Northern and Midwestern American cities, during the post-WWII suburbanization boom. Because of housing discrimination, black families were largely denied access to suburban areas, leaving both middle- and lower-income black families living in relative proximity in urban areas. The passage of housing and lending anti-discrimination legislation in the 1970s, however, began to reduce the prevalence of housing discrimination, making a wider range of neighborhood options available to middle-income black families. As a result, income segregation among black families rose steeply from 1970-1990, as the growing black middle class was able to move into previously inaccessible suburban areas. By 1980, in fact, income segregation among black families was higher than among white families. In this era, black income inequality is strongly related to the segregation of high-income black families in neighborhoods separate from lower-income black families. Although this growth in income segregation among black families is a result of both the growing black middle class and reductions in housing discrimination—both signs of progress since the 1960s—it nonetheless may have negative consequences. Given high levels of racial segregation in U.S. cities, the growth of income segregation among black families results in the increasing racial and socioeconomic isolation of lower-income black families in neighborhoods of concentrated disadvantage (Wilson, 1987).

Finally, we find that the effects of income inequality on income segregation are driven primarily by the effects of inequality on macro-scale patterns of segregation. Coupled with our earlier finding regarding the effects of inequality on the segregation of affluence, this means that income inequality appears to increase income segregation largely by inducing the highest-earning families to move far away from lower-income households. The expansion of suburban and exurban areas in the last few decades, facilitated by the growth of the highway system and the movement of many high-skill industries to the suburban ring, has allowed families to move farther away from metropolitan cores while still engaging in the high-skill labor market. The fact that the effect of income inequality on income segregation is much weaker in small metropolitan areas is consistent with this explanation. Because macro-scale segregation is often not possible in small metropolitan areas, inequality may have little room to affect income segregation. If one of the key amenities that high-income families desire to purchase is space—large lots, very low-density housing, and access to parks and undeveloped open space—then they will be much more able to do so in large metropolitan areas.

In sum, our analyses show that income inequality has a strong and robust effect on income segregation, but that this effect is more nuanced in form that one might initially expect. In fact, income inequality appears to be responsible for a specific aspect of income segregation—the large-scale separation of the affluent from lower-income households and families. It does not, however, appear to be responsible for patterns of segregation of poverty (for that, housing policy is likely to blame). Nor is it responsible for patterns of small-scale income segregation, such as those seen resulting from the gentrification of urban neighborhoods adjacent to poor, non-gentrifying neighborhoods.

The macro-scale spatial segregation of high-income households from middle- and low-income households may have important and far-reaching consequences, particularly given that the top 10% of earners in the U.S. now receive 45% of all income. The segregation of these high-income households in communities spatially far from lower-income households may reduce the likelihood that high-income residents will have social, or even casual, contact with lower-income residents. This in turn may make it less likely that they are willing to invest in metropolitan-wide public resources that would benefit residents of all income levels, such as transportation networks, utilities, parks, services, and cultural amenities. Moreover, the spatial separation of the affluent and poor implies that there will be few opportunities for disadvantaged families to benefit from local spillover of public goods. The distance between affluent and lower-income communities make it unlikely that disadvantaged families will be able to take advantage of the local schools, parks, and services in which affluent communities invest. Although most sociological theory and research regarding the spatial distribution of income has focused on the effects of concentrated *poverty* on residents of poor neighborhoods, the findings here suggest that a better understanding of the effects of concentrated *affluence* on residents far from affluent communities is needed as well. The segregation of affluence may directly affect the resources available to residents of both poor and lower-income neighborhoods.

Given the evidence that income inequality has sizeable effects on income segregation, it is plausible that income segregation may mediate the effects of income inequality on social outcomes. A large body of research has linked income inequality to negative health outcomes such as increased morbidity, mortality, and infant death, as well as to negative effects on educational attainment, crime rates, social capital, network ties, and political institutions (see Neckerman & Torche, 2007 for a review). Although some scholars have argued that income segregation may serve as a mechanism that links income inequality to some of these negative social outcomes (Mayer, 2002; Mayer & Sarin, 2005; Neckerman & Torche, 2007), the scant research on this topic has produced mixed results. Mayer and Sarin (2005) explicitly test this hypothesis and show that income segregation is one mechanism that links income inequality to infant mortality at the state level. On the other hand, other research finds that economic segregation does not mediate the relationship between income inequality and mortality (Lobmayer & Wilkinson, 2002) or between income inequality and the distribution of educational attainment (Mayer, 2001a). Clearly the role of income segregation as a mediator between income inequality and various social outcomes warrants further investigation, as does the direct impact of income segregation on other forms of social inequality.

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Table 1: Stylized Patterns of Income Segregation

	Neighborhood		
	A	B	C
Scenario I: Segregation of Poverty			
Low-Income	100	0	0
Middle-Income	0	50	50
High-Income	0	50	50
Scenario II: Segregation of Affluence			
Low-Income	50	50	0
Middle-Income	50	50	0
High-Income	0	0	100
Scenario III: Segregation of Poverty and Affluence			
Low-Income	100	0	0
Middle-Income	0	100	0
High-Income	0	0	100

Table 2: Income Inequality and Income Segregation Trends, by Race, 100 Largest Metropolitan Areas, 1970-2000

	Income Inequality (Gini Index)					**Income Segregation (rank-order H)**				
Group	1970	1980	1990	2000	Change	1970	1980	1990	2000	Change
Black	0.376	0.410	0.430	0.436	0.060	0.099	0.133	0.173	0.170	0.071
	(0.018)	(0.017)	(0.030)	(0.024)		(0.029)	(0.036)	(0.042)	(0.044)	
White	0.344	0.341	0.369	0.384	0.040	0.110	0.117	0.132	0.139	0.029
	(0.028)	(0.020)	(0.026)	(0.025)		(0.039)	(0.043)	(0.043)	(0.046)	
Black-White Difference	0.032	0.069	0.061	0.052	0.020	-0.011	0.016	0.041	0.031	0.042
All Families	0.352	0.360	0.384	0.400	0.048	0.124	0.134	0.152	0.157	0.033
	(0.029)	(0.023)	(0.026)	(0.025)		(0.044)	(0.052)	(0.050)	(0.051)	

Notes: Standard deviations in parentheses. Sample includes 100 largest metropolitan areas (according to 2000 population). For blacks, sample includes 61 of 100 metropolitan areas with at least 10,000 black families in each census 1970-2000.

Table 3: Estimated Effects of Income Inequality on Income Segregation, 1970-2000

	Source of Variation in Income Inequality					
	Temporal Variation Within Metro-by-Race Cells		Between-Race Variation Within Metro-by-Year Cells		Between-Metro Variation Within Race-by-Year Cells	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Gini Index	0.385 ***	0.467 ***	0.431 ***	0.783 ***	0.286 **	0.502 ***
	(0.059)	(0.060)	(0.069)	(0.125)	(0.103)	(0.110)
Year=1980	0.013 ***	0.029 ***				
	(0.002)	(0.009)				
Year=1990	0.028 ***	0.032 **				
	(0.003)	(0.012)				
Year=2000	0.026 ***	0.027				
	(0.003)	(0.015)				
Black			-0.013 **	-0.065 ***		
			(0.005)	(0.015)		
Model Specification						
Metro-Year Covariates		Yes				Yes
Group-Metro-Year Covariates		Yes		Yes		Yes
Metro-x-Group Fixed Effects	Yes	Yes				
Metro-x-Year Fixed Effects			Yes	Yes		
Group-x-Year Fixed Effects					Yes	Yes
Metro Fixed Effects					Yes	Yes
Adjusted R^2	0.879	0.933	0.691	0.770	0.822	0.883
N	644	644	488	488	644	644

Notes: Bootstrapped standard errors in parentheses. * p<.05; ** p<.01; *** p<.001. Sample includes observations from 100 largest metropolitan areas in 2000, excluding black observations from 39 metropolitan areas with fewer than 10,000 black families in 1970. Coefficients on covariates and fixed effects not shown. Metro-year covariates include metro population, unemployment rate, proportion under age 18, proportion over age 65, proportion with high school diploma, proportion foreign born, proportion female headed families, per capita income, proportions emplyed in manufacturing, construction, financial and real estate, professional and managerial jobs, and proportions of housing built within ten, five, and one years. Group-metro-year covariates include race-group-specific population, per capita income, proportion with high school diploma, proportion female headed families, and unemployment rate.

Table 4: Estimated Effects of Income Inequality on Income Segregation, 1970-2000, by Race Group and Decade

	By Race Group			By Decade			
	All Familes	White	Black	1970	1980	1990	2000
Gini Index	0.561 ***	0.450 ***	0.470 ***	0.624 *	0.649 *	0.688 ***	0.732 ***
	(0.085)	(0.110)	(0.124)	(0.268)	(0.276)	(0.194)	(0.153)
Year=1980	0.027 ***	0.028 *	0.065 ***				
	(0.007)	(0.014)	(0.018)				
Year=1990	0.025 *	0.024	0.095 ***				
	(0.012)	(0.018)	(0.029)				
Year=2000	0.012	0.016	0.087 *				
	(0.016)	(0.023)	(0.036)				
Black				-0.111 **	-0.036	-0.013	0.044
				(0.042)	(0.029)	(0.025)	(0.027)
Metro-Year Covariates	Yes	Yes	Yes				
Group-Metro-Year Covariates		Yes	Yes	Yes	Yes	Yes	Yes
Metro Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.959	0.956	0.921	0.689	0.789	0.821	0.866
N	400	400	244	161	161	161	161

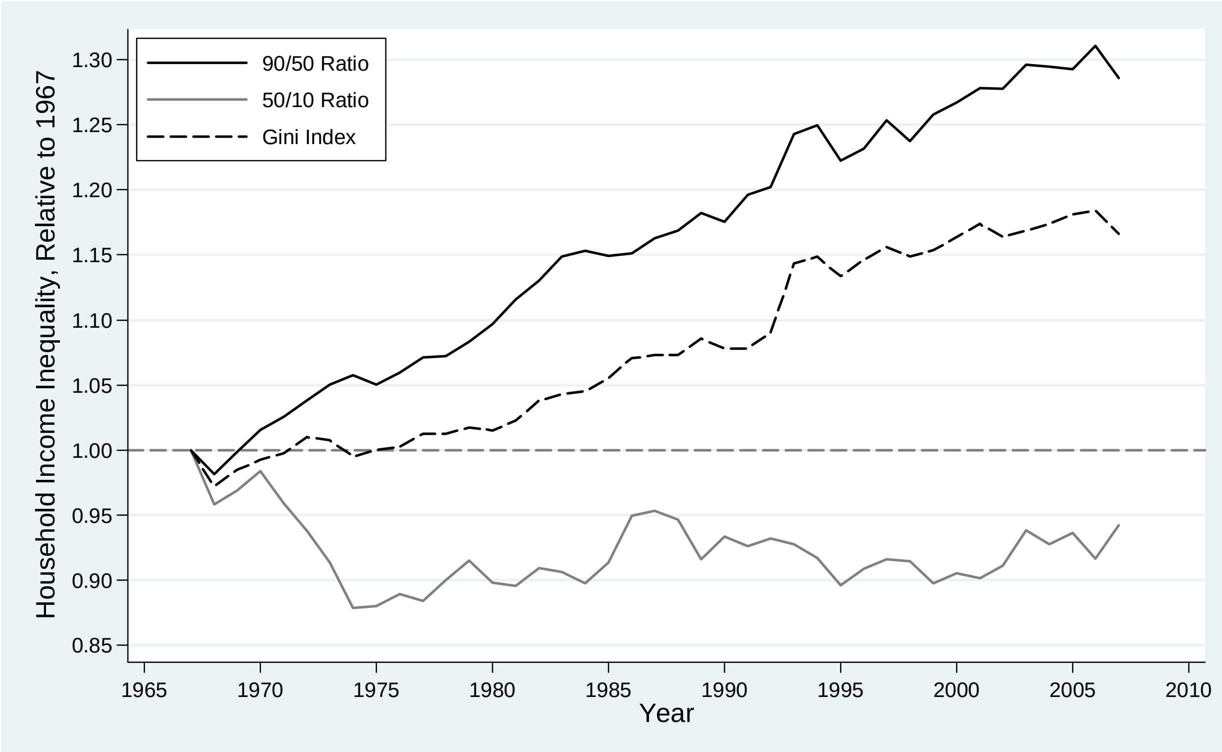
Notes: Bootstrapped standard errors in parentheses. * p<.05; ** p<.01; *** p<.001. Sample includes observations from 100 largest metropolitan areas in 2000, excluding black observations from 39 metropolitan areas with fewer than 10,000 black families in 1970. Coefficients on covariates and fixed effects not shown. Metro-year covariates include metro population, unemployment rate, proportion under age 18, proportion over age 65, proportion with high school diploma, proportion foreign born, proportion female headed families, per capita income, proportions emplyed in manufacturing, construction, financial and real estate, professional and managerial jobs, and proportions of housing built within ten, five, and one years. Group-metro-year covariates include race-group-specific population, per capita income, proportion with high school diploma, proportion female headed families, and unemployment rate.

Table 5: Estimated Effects of Income Inequality on Spatial Income Segregation, 100 Largest Metropolitan Areas, 1980-2000

Sample/ Years Included	Outcome (Radius) H(500m)	H(1000m)	H(2000m)	H(4000m)	H(diff)
1980-2000	0.377	0.355	0.411	0.414 *	-0.036
(N=300)	(0.247)	(0.213)	(0.214)	(0.194)	(0.089)
	0.915	0.894	0.874	0.852	0.909
1990-2000	0.396 *	0.401 *	0.385 ***	0.368 **	0.028
(N=200)	(0.185)	(0.160)	(0.114)	(0.140)	(0.112)
	0.940	0.942	0.942	0.940	0.890
1980	0.351 *	0.364 **	0.416 ***	0.366 **	-0.016
(N=100)	(0.169)	(0.133)	(0.109)	(0.133)	(0.076)
	0.629	0.621	0.585	0.586	0.235
1990	0.466 **	0.486 ***	0.497 ***	0.458 **	0.008
(N=100)	(0.147)	(0.139)	(0.137)	(0.152)	(0.062)
	0.563	0.550	0.504	0.444	0.462
2000	0.270	0.299 *	0.290	0.260 *	0.009
(N=100)	(0.148)	(0.119)	(0.155)	(0.117)	(0.065)
	0.385	0.388	0.377	0.369	0.268

Note: Bootstrapped standard errors in parentheses below estimated coefficient. * $p<.05$; ** $p<.01$; *** $p<.001$. Adjusted R^2 reported below standard error. Top two panels based on models that include metropolitan area and year fixed effects and the set of metro-by-year covariates described in the text. Bottom three panels based on models that include metro-year covariates but no fixed effects.

Figure 1: Trends in Household Income Inequality, 1967-2007



Note: The two solid lines show the trends in the ratio of household incomes at two percentiles of the income distribution. All trends are divided by their value in 1967 in order to put the trends on a common scale. *Source*: Authors' calculations from http://www.census.gov/hhes/www/income/histinc/p60no231_tablea3.pdf.

Figure 2: Comparison of Stylized Income Distributions

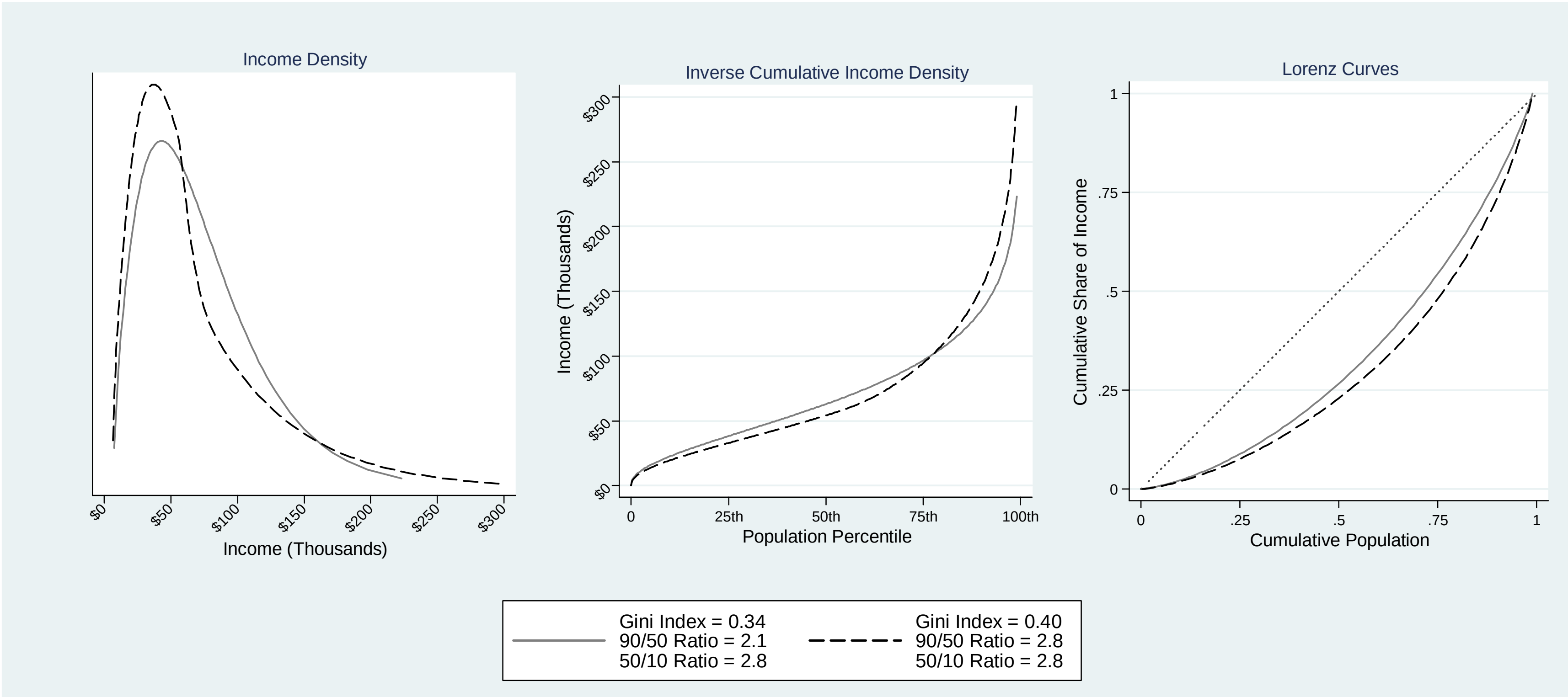
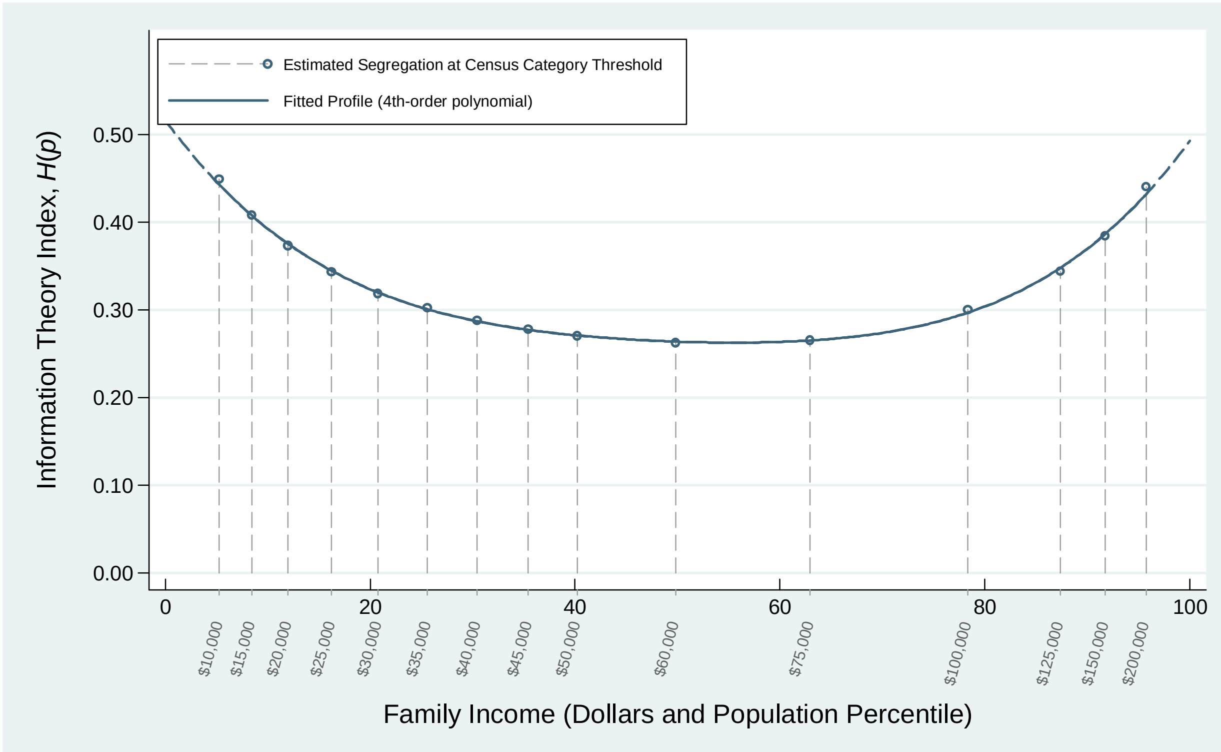
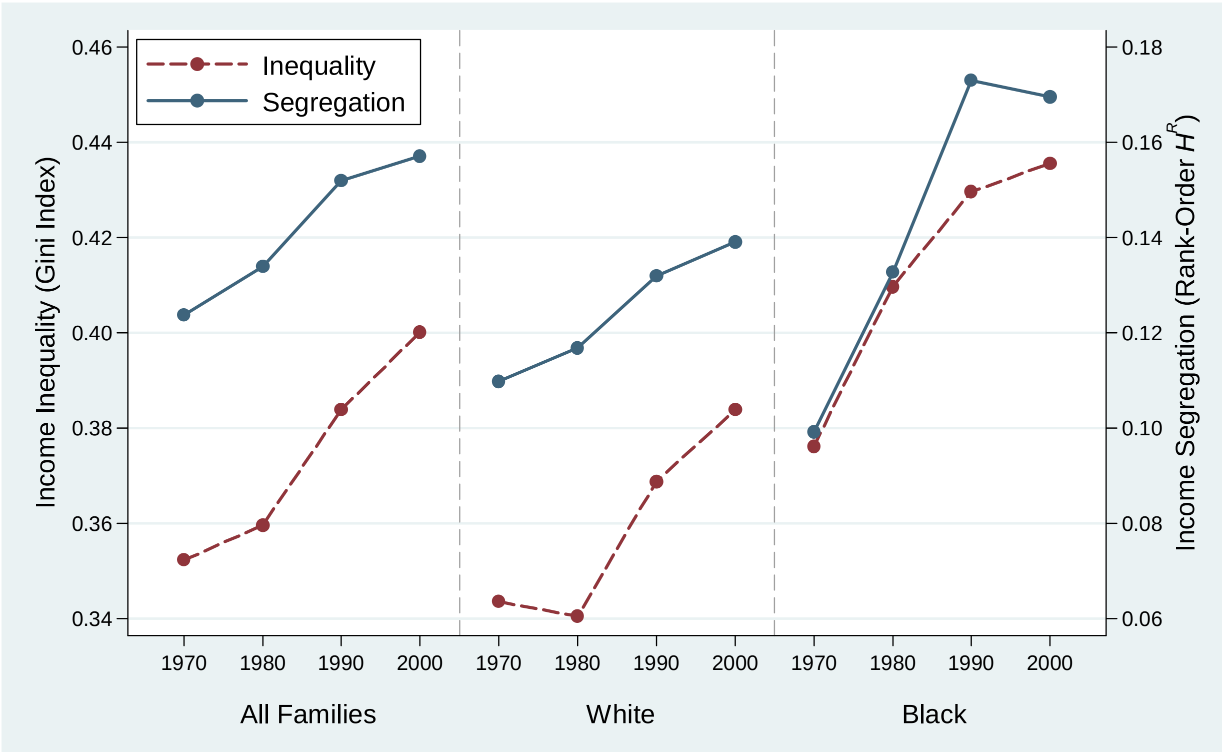


Figure 3: Family Income Segregation Profile, Chicago Metropolitan Area, 2000



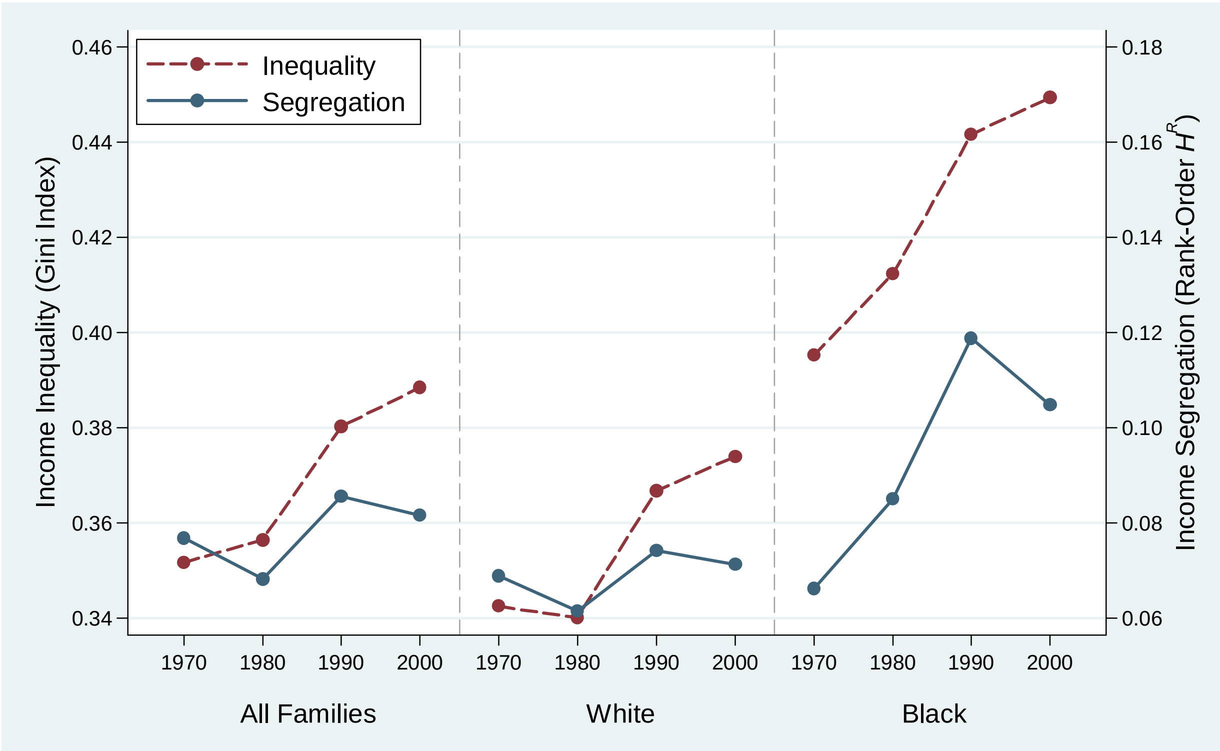
Note: Figure indicates estimated between-tract segregation between families with incomes above and at-or-below each percentile of the metropolitan-wide family income distribution. Segregation levels at each threshold are averages of segregation levels computed from 50 random subsamples of 10,000 families from the metropolitan area.

Figure 4: Trends in Family Income Inequality and Income Segregation, 1970-2000, by Race, 100 Largest Metropolitan Areas



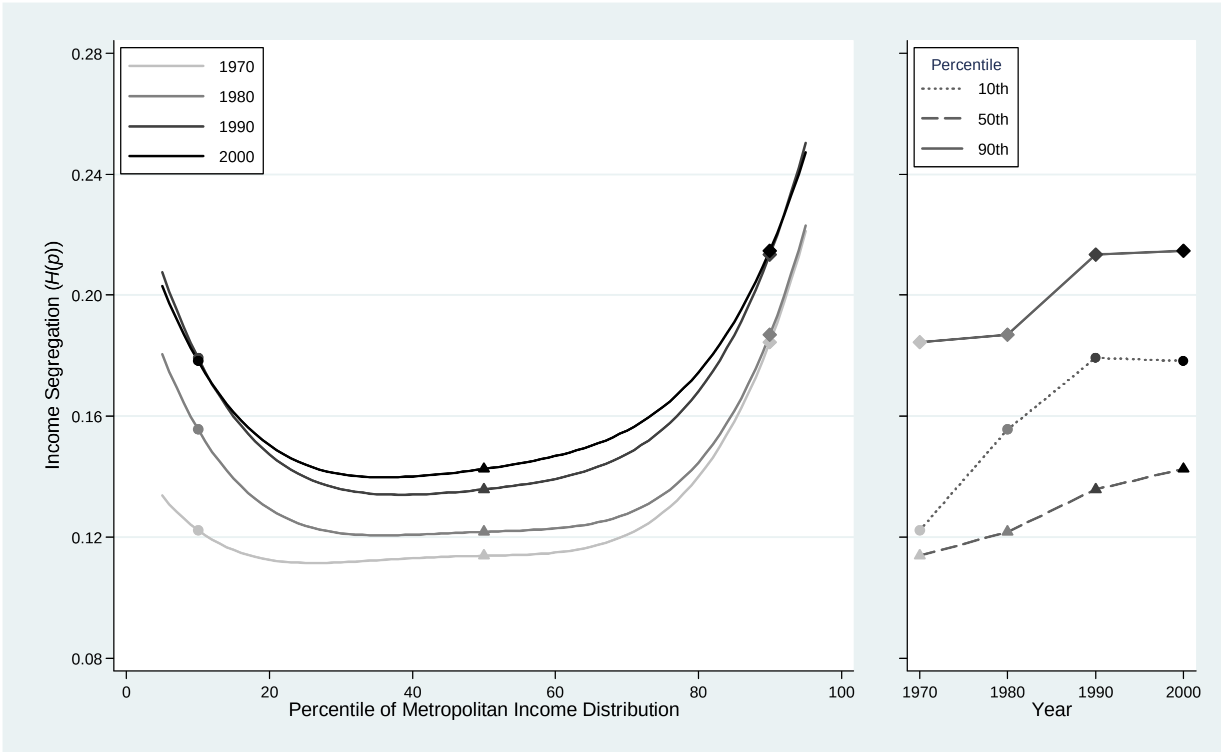
Note: Black trends based on 61 metropolitan areas with at least 10,000 black families in each census year, 1970-2000.

Figure 5: Trends in Family Income Inequality and Income Segregation, 1970-2000, by Race, Small Metropolitan Areas



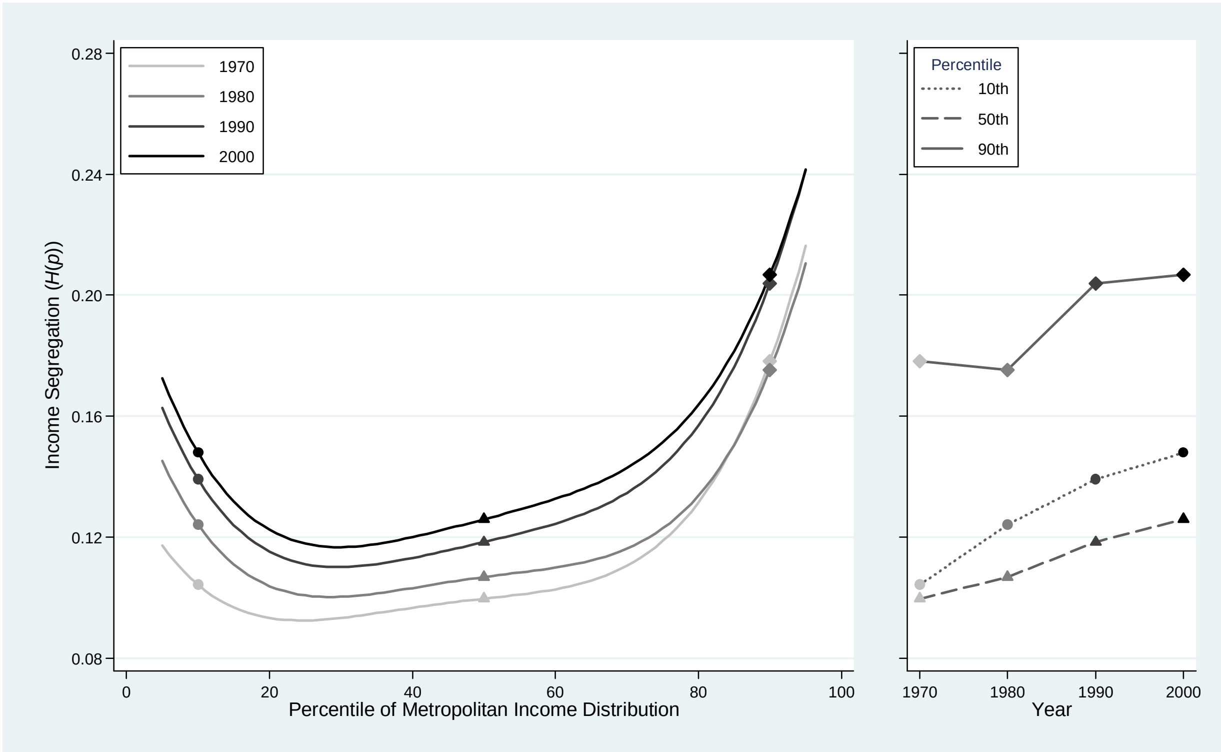
Note: Samples for each panel of the figure include all metropolitan areas with at least 10,000 families of the respective group in each year, 1970-2000, excluding 100 largest metropolitan areas. Trends for all families based on 179 metropolitan areas; trends for white families based on 176 metropolitan areas; trends for black families based on 15 metropolitan areas.

Figure 6: Trends in Average Metropolitan Area Income Segregation, by Income Percentile, All Families, 100 Largest Metropolitan Areas, 1970-2000



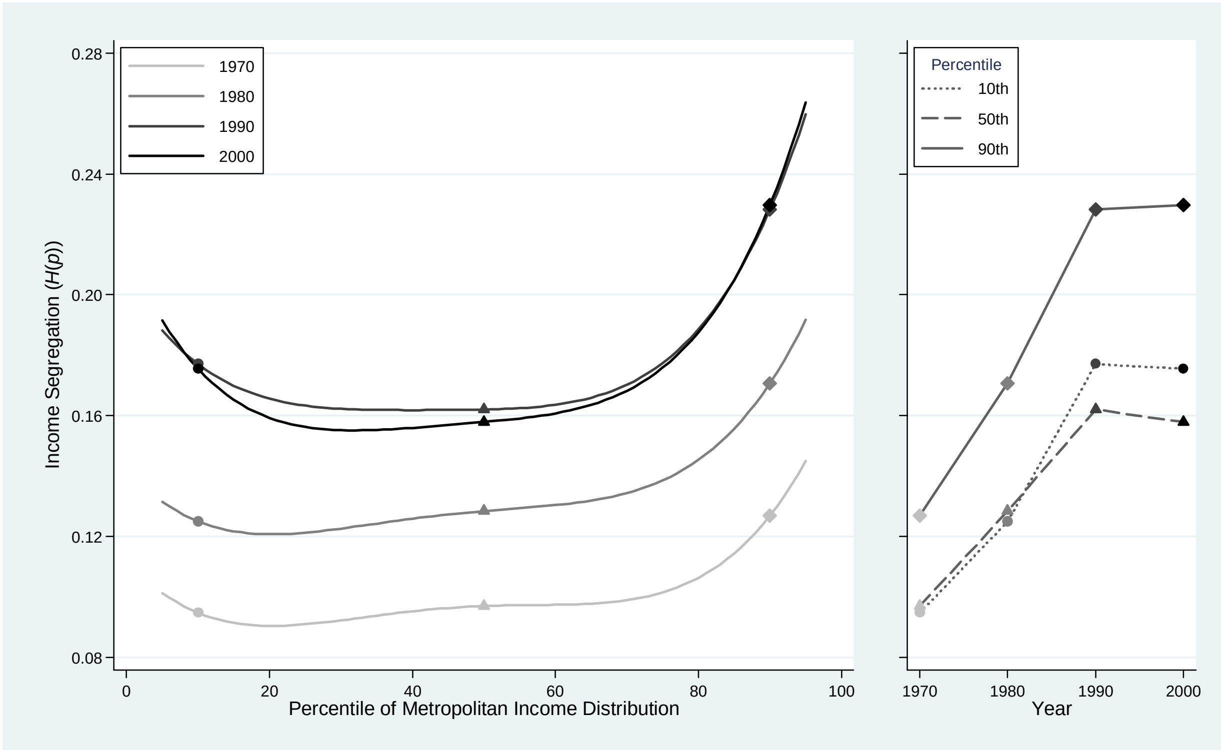
Note: Left panel of figure indicates estimated average between-tract segregation (as measured by the information theory index, *H*) between families with incomes at-or-above and below each percentile of the metropolitan-wide family income distribution. Right panel shows trends for between-tract segregation at three specific percentiles.

Figure 7: Trends in Average Metropolitan Area Income Segregation, by Income Percentile, White Families, 100 Largest Metropolitan Areas, 1970-2000



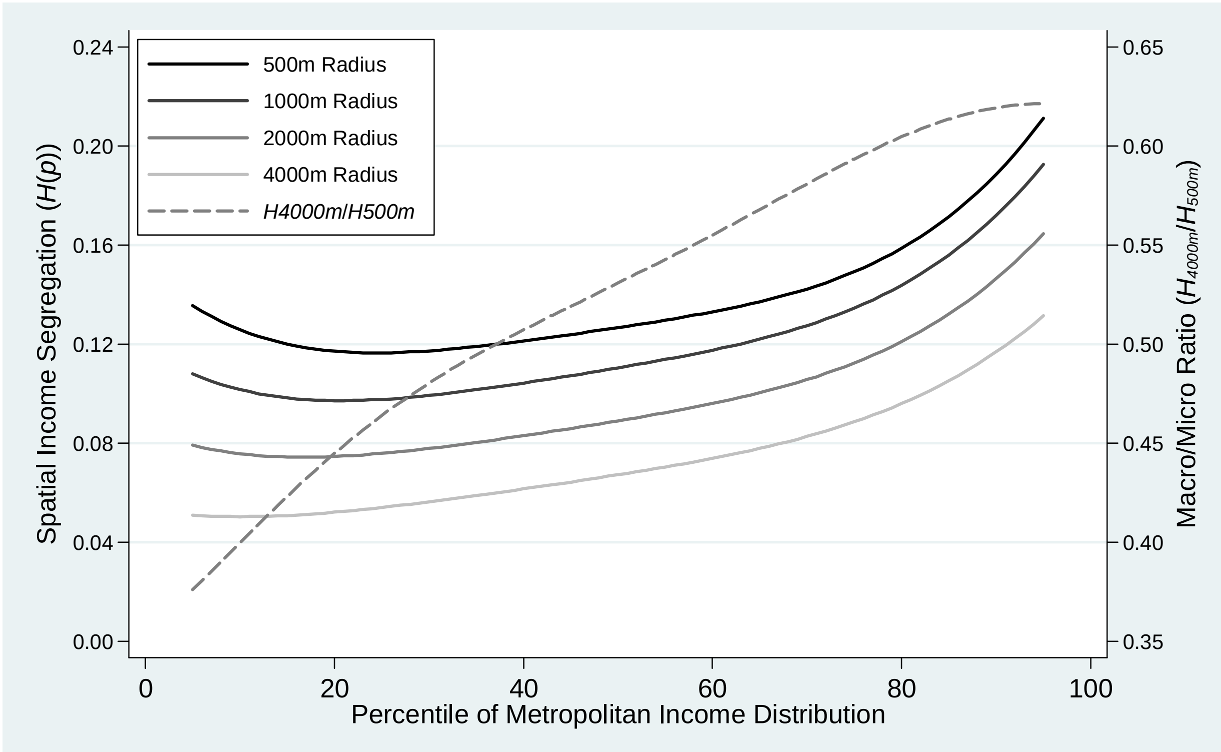
Note: Left panel of figure indicates estimated average between-tract segregation (as measured by the information theory index, *H*) between white families with incomes at-or-above and below each percentile of the metropolitan-wide family income distribution. Right panel shows trends for between-tract segregation at three specific percentiles.

Figure 8: Trends in Average Metropolitan Area Income Segregation, by Income Percentile, Black Families, 61 Largest Metropolitan Areas with at least 10,000 Black Families, 1970-2000



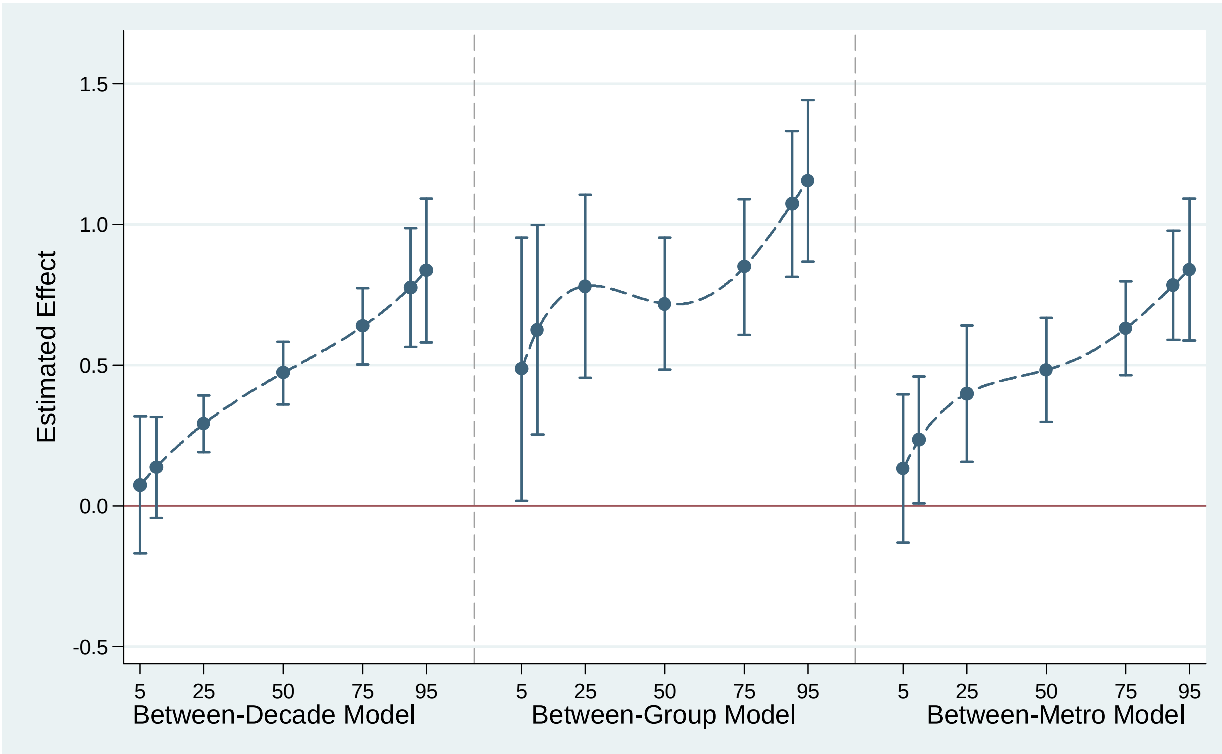
Note: Left panel of figure indicates estimated average between-tract segregation (as measured by the information theory index, *H*) between black families with incomes at-or-above and below each percentile of the metropolitan-wide family income distribution. Right panel shows trends for between-tract segregation at three specific percentiles.

Figure 9: Average Metropolitan Area Spatial Household Income Segregation, by Income Percentile and Local Environment Radius, 100 Largest Metropolitan Areas, 2000



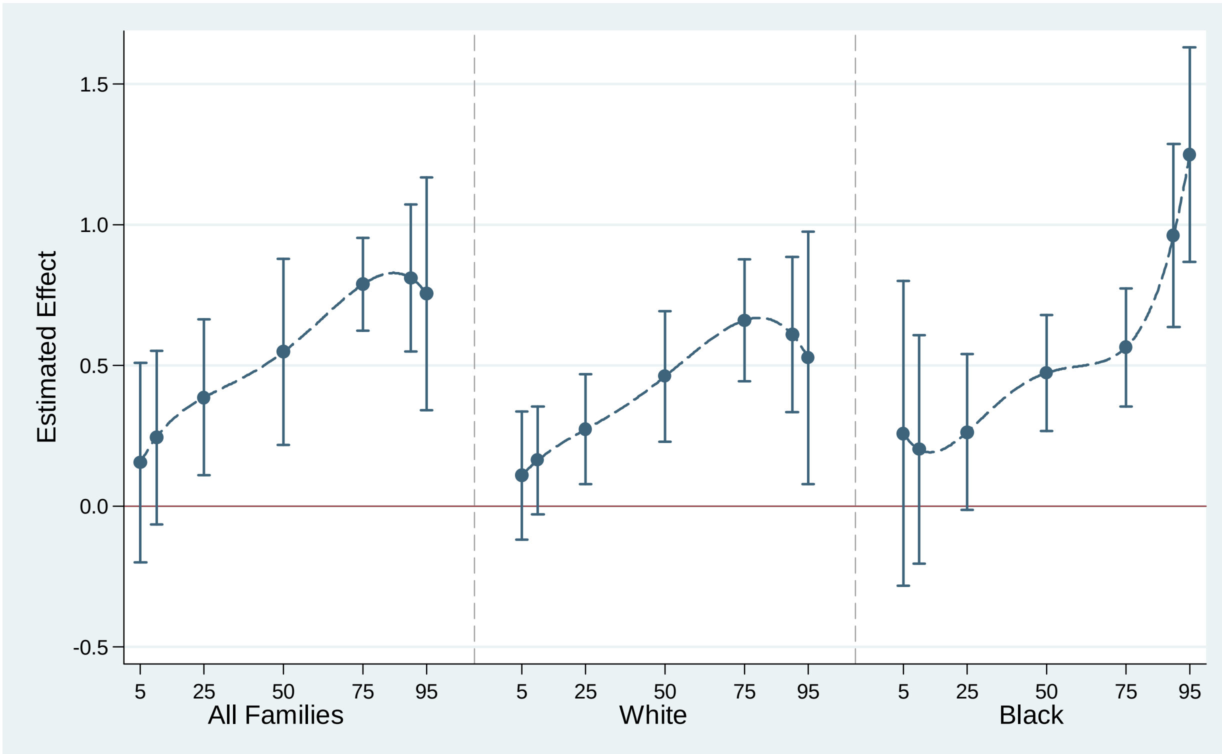
Note: Solid lines indicate estimated average between-tract segregation (as measured by the spatial information theory index, *H*, using four different local environment radii) between families with incomes above and at-or-below each percentile of the metropolitan-wide family income distribution. Dashed line indicates ratio of segregation using a 4000m radius to that using a 500m radius.

Figure 10: Estimated Effects of Family Income Inequality on Income Segregation, by Percentile of Income Distribution and Model, 100 Largest Metropolitan Areas, 1970-2000



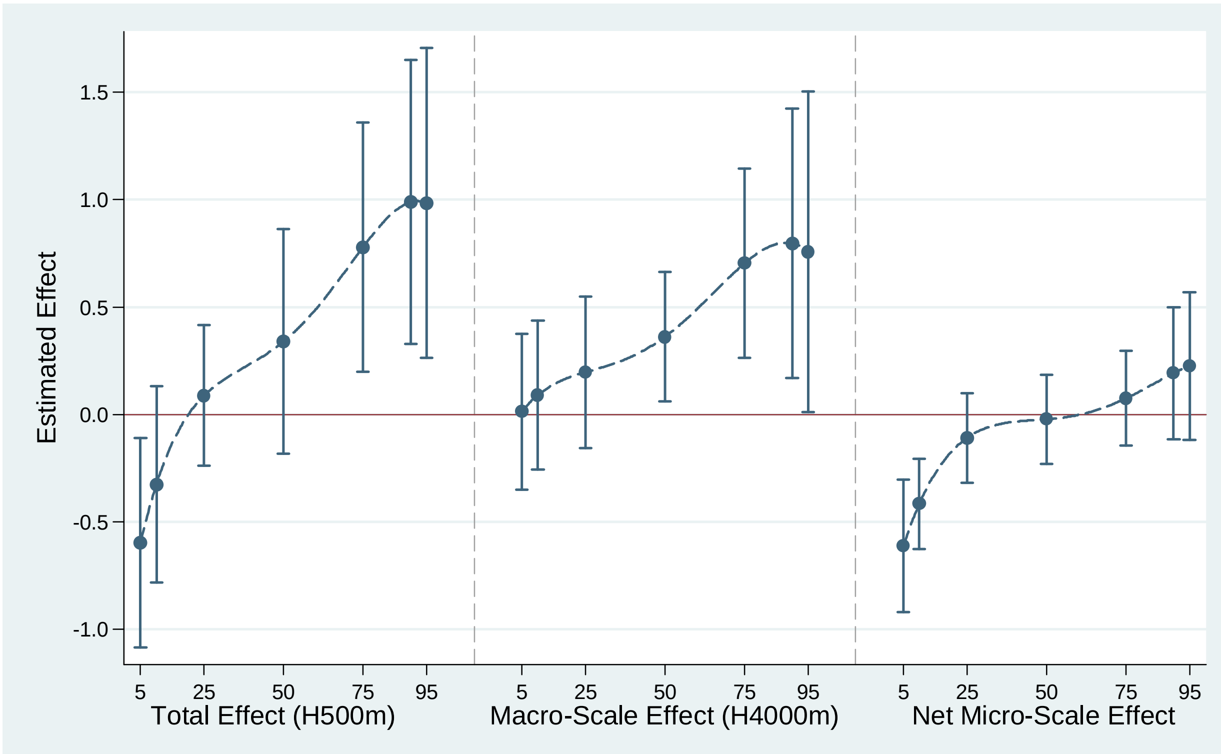
Note: Bars indicate 95% confidence interval for estimates. Model specifications and samples are identical to those of Model 2 (between-decade model), Model 4 (between-group model), and Model 6 (between-metro model) in Table 3 above.

Figure 11: Estimated Effects of Family Income Inequality on Income Segregation, by Percentile of Income Distribution and Race, 100 Largest Metropolitan Areas, 1970-2000



Note: Bars indicate 95% confidence interval for estimates. Model specifications and samples are identical to those of Columns 1-3 of Table 4.

Figure 12: Estimated Effects of Income Inequality on Spatial Household Income Segregation, by Local Environment Radius and Percentile of Income Distribution, 100 Largest Metropolitan Areas, 1980-2000



Note: Bars indicate 95% confidence interval for estimates. Model specifications and samples are identical to those of Column 1 of Table 4. Left panel shows estimates from models where outcome variable is the spatial information theory index $\widetilde{H}(p)$ using a 500m radius and computed at the specified percentiles. Middle panel shows estimates where outcome variable is the same, but using a 4000m radius. Right panel shows the estimates from models where the outcome is the net-micro segregation—the difference between $\widetilde{H}_{500m}(p)$ and $\widetilde{H}_{4000m}(p)$.

Appendix

Appendix Section 1: Computing Income Segregation

Practical Issues in Computing the Rank-Order Information Theory Index (H^R)

To compute H^R from Equation (3), we need to know the function $H(p)$ over the domain $(0,1)$. In practice, however (given Census data, for example), we can compute $H(p)$ for only a finite number of values of p, corresponding to the income category thresholds that the Census uses to report incomes. For example, in the 2000 Census, income was reported in 16 categories ("less than \$10,000," "\$10,000-\$15,000," "\$15,000-\$20,000," and so on, up to "\$150,000-\$200,000", and "greater than \$200,000"). These allow us to compute $H(p)$ at 15 distinct values of p (those corresponding to $F(10{,}000)$, $F(15{,}000)$,…, $F(200{,}000)$ in this case). Within each census tract, the Census provides counts (estimates, really, based on a 1-in-6 sample) of the number of families with incomes below each of these income thresholds. For each of the thresholds, we can compute p, the proportion of the population with incomes below the threshold and $H(p)$, the information theory index of segregation between those below the thresholds and those at or above the threshold. Following Reardon et al. (2006), we then approximate the function $H(p)$ over the range $(0,1)$ by fitting an m-th order polynomial to the values, weighting each point by the square of $E(p)$:

$$H(p) = \beta_0 + \beta_1 p + \beta_2 p^2 + \cdots + \beta_m p^m + \epsilon_p, \quad \epsilon_p \sim N\left(0, \frac{\sigma^2}{E(p)^2}\right) \tag{A1}$$

We use a fourth-order polynomial here, but our results are insensitive to the choice of any higher-order polynomial. If $\hat{\beta}_k$ is the estimated k-th coefficient from this model, then Reardon et al. (2006) show that equation (3) will evaluate to

$$\widehat{H}^R = \hat{\beta}_0 + \frac{1}{2}\hat{\beta}_1 + \cdots + \left[\frac{2}{(m+2)^2} + 2\sum_{n=0}^{m} \frac{(-1)^{m-n}({}_mC_n)}{(m-n+2)^2}\right]\hat{\beta}_m, \tag{A2}$$

where $({}_mC_n) \equiv \frac{m!}{n!(m-n)!}$ denotes the binomial coefficient (the number of distinct combinations of n

elements from a set of size m). While this looks messy, in practice, the procedure is straightforward: 1) for each income threshold k reported by the Census, we compute p_k, the proportion of the relevant population below threshold k; 2) we compute $H(p_k)$, the information theory index of segregation between those above and below the income threshold k, for each threshold k; 3) we fit a polynomial regression model through the points $(p_k, H(p_k))$; and 4) we use the estimated coefficients from the model to compute an estimate of H^R from Equation (A2).

Once we have estimated the function $H(p)$ from Equation (A1), we can also compute estimated values of segregation at any desired threshold. Suppose, for example, we wish to estimate the segregation between families in the top 10 percent of the income distribution and all others. Even if there is not an income threshold in the Census data that corresponds exactly to the 90th percentile, we can estimate $H(.9)$ from the fitted polynomial (Equation 4). For example, even though there is no income threshold in Chicago that corresponds exactly to the 90th income percentile, we can compute the estimated value of $\widehat{H}(.9) = 0.370$ from the estimated parameters of the fitted $H(p)$ profile in Figure 3. This will enable us to compute and compare the segregation levels of well-defined income groups even when the Census does not provide the exact information needed.

Correcting Small Sample Bias in Income Segregation Measures

One complication with comparing income segregation levels across metropolitan areas and racial groups is that evenness measures of income segregation are biased upwards in small populations (specifically, when the population is relatively small compared to the number of tracts). This bias results from the fact that income segregation measures (including the rank-order information theory index) are generally ratios of average within-unit (e.g., tracts) income variation to total population income variation. When the number of households in a unit is small (either because the population is small or because of sampling), estimates of within-unit variation will be biased downwards. The bias can be substantial. When we take a random sample of 10,000 households from a metropolitan area and compare income segregation among the sample to income segregation among the total population, the sample estimates are considerably higher. Given that Census family income data are based on 1-in-6 samples, this has implications for comparing income segregation across metropolitan areas, years, and groups that vary in population size.

To ensure that our comparisons of the levels of segregation among metropolitan areas, race groups, and decades are not biased by differences in population size, we adjust the estimated segregation levels for population size. For each of the 644 cases in our analysis, we draw 50 random samples (without replacement) of 10,000 families of the specified racial group (or from the total population) and compute H^R from each sample. The mean of these 50 estimates provides a population-size-adjusted estimate of income segregation for each group-metro-year case. This procedure eliminates bias due to different population sizes, by ensuring that each of the estimates of H^R are based on the same size sample. The resulting estimates are comparable across race groups, metropolitan areas, and years, regardless of population size.

Appendix Section 2: Data and Sample

Data Comparability Issues

Metropolitan boundaries and definitions: Metropolitan boundaries change over time. We use consistent metropolitan area definitions across census years to ensure comparability of the results over time. We use the OMB 2003 metropolitan area definitions, the first definitions based on the 2000 census.

Census confidentiality procedures: The Census employs certain measures to ensure confidentiality that affect the reporting of race-specific income distributions. More specifically, the Census suppresses data within certain geographic units when they determine that the population numbers for certain groups are small enough to threaten the privacy rights of individuals or families. For instance, if there are only a handful of black families in a census tract, the Census would not release the income data for black families in that tract because it may be possible to identify individual families. In 1980 the Census also employed complimentary suppression, which can lead to the suppression of other groups besides the small sub-group to avoid inferences through subtraction. We do not adjust our analyses for suppression, but because we only include in our race-specific analyses metropolitan areas with greater than 10,000 families in that race group, the problem is minimized.

Income: Total income is defined by the Census as the sum of the amounts reported separately for wage or salary income; net self-employment income; interest, dividends, or net rental or royalty income or income from estates and trusts; social security or railroad retirement income; Supplemental Security Income (SSI); public assistance or welfare payments; retirement, survivor, or disability pensions; and all other income.

We use family income data from the 1970-2000 Censuses. We obtain tract-level family income data by race for 1970, 1980, and 2000 from the Geolytics Neighborhood Change Database CDs (GeoLytics, 2004) as well as the 1990 data from the National Historical Geographic Information System's online data extract system (Minnesota Population Center, 2004). This was necessary because family income by race was not available in the STF3 files in 1990, the files available in the Geolytics CDs. Instead, the 1990 family income by race was in the STF4a files.

The census reports income for families and households. We use family income because the data is available by race for all four census years. Families are residential units that include two or more people related by blood or marriage. Households are all residential units, including those that contain one person. Thus, family income only includes those related by blood or marriage whereas household income includes the incomes of all people living in a household. In compiling statistics on family income, the incomes of all members 15 years old and over related to the householder are summed and treated as a single amount. Although family income is generally higher on average than household income because many households only contain one person, the use of household or family income yields similar results in the regression analyses.

The Census also changes the number of income categories used in each decennial Census. For the total population there are 15 income bins in 1970, 17 in 1980, 25 in 1990, and 16 in 2000. The income-by-race bins are the same except for in 1980 when there are only 9 income bins by race. Our approach to measuring income segregation is insensitive to these differences.

Gini Index: The Gini index is computed from Census data using a procedure described in detail in Nielsen and Alderson (1997).

Data Sources for, and Construction of, Covariates

Total Population (by race): 1970-2000 obtained from National Historical Geographic Information System (NHGIS).

Unemployment (by race): 1970 obtained from NHGIS; 1980-2000 obtained from Geolytics. We collapsed unemployment by gender and then calculate the percent of the population that is unemployed. This measure includes persons 16 years of age and older in the civilian employment force who are not employed.

Age: 1970 obtained from NHGIS; 1980-2000 obtained from Geolytics. We calculate the percent of the population that is less than 18 and the percent of the population older than 65. In 1970, the under-18 category is actually under-19.

Education (by race): 1970-2000 obtained from NHGIS. We calculate the percent of the population with at least a high school degree for the population 25 years and older.

Per Capita Income (by race): 1970-2000 obtained from NHGIS. In 1970 there was no specific variable for per capita income so we constructed the measure using the aggregate individual income variable.

Foreign born: 1970-2000 obtained from Geolytics. We calculate the percent of the population that was born outside of the United States.

Occupational industries: 1970-1990 obtained from NHGIS; 2000 obtained from Geolytics. We calculate the percent of the population that is employed in the following occupational industries: Manufacturing, Construction, FIRE (finance, insurance, and real estate), and Professional/Managerial (information, FIRE, education, health, other professional, and public administration). This measure includes persons 16 years of age and older in the civilian employment force.

Family structure (by race): 1970 obtained from NHGIS; 1980-2000 obtained from Geolytics. We calculate the percent of families that are headed by females. We also calculate the total number of families.

Residential mobility: 1970-2000 obtained from Geolytics. We calculate the percent of the population that resides in the same house as they did 5 years before as well as the percent of the population that resides in a different house in the same county. These measures includes persons 5 years of age and older.

New housing construction: 1970 obtained from NHGIS; 1980-2000 obtained from Geolytics. We calculate the percent of housing (occupied + vacant) that was built 10, 5, and 1 year before the census year.

Appendix Section 3: Appendix Tables

Table A1: Trends in Family Income Segregation, by Race and Income Percentile, 100 Largest Metropolitan Areas, 1970-2000

Group and Percentile		Year			
	1970	1980	1990	2000	Change
Black					
5th	0.101	0.132	0.188	0.192	0.091
10th	0.095	0.125	0.177	0.176	0.081
25th	0.091	0.121	0.163	0.156	0.065
50th	0.097	0.128	0.162	0.158	0.061
75th	0.102	0.139	0.177	0.176	0.074
90th	0.127	0.171	0.228	0.230	0.103
95th	0.145	0.192	0.260	0.264	0.119
White					
5th	0.117	0.145	0.163	0.173	0.056
10th	0.104	0.124	0.139	0.148	0.044
25th	0.093	0.101	0.111	0.118	0.025
50th	0.100	0.107	0.118	0.126	0.026
75th	0.119	0.123	0.144	0.151	0.032
90th	0.178	0.175	0.204	0.207	0.029
95th	0.216	0.210	0.242	0.241	0.025
All					
5th	0.134	0.180	0.208	0.203	0.069
10th	0.122	0.156	0.179	0.178	0.056
25th	0.112	0.124	0.140	0.144	0.032
50th	0.114	0.122	0.136	0.143	0.029
75th	0.128	0.134	0.156	0.163	0.035
90th	0.184	0.187	0.213	0.215	0.031
95th	0.221	0.223	0.250	0.247	0.026

Notes: Segregation measures indicate segregation (*H*) of families with incomes above the specified income percentile from those with incomes below the percentile. Sample Includes 100 largest metropolitan areas (according to 2000 population). For Blacks, sample includes 61 of 100 metropolitan areas with at least 10,000 Black families in each census 1970-2000.

Table A2: Estimated Effects of Income Inequality on Income Segregation at Various Percentiles of Income Distribution, 100 Largest Metropolitan Areas, Various Specifications, 1970-2000

	Percentile of Income Distribution						
Model	5th	10th	25th	50th	75th	90th	95th
Model 2	0.076	0.138	0.292 ***	0.474 ***	0.639 ***	0.778 ***	0.837 ***
(N=644)	(0.124)	(0.091)	(0.051)	(0.057)	(0.069)	(0.108)	(0.130)
Model 4	0.486 *	0.626 ***	0.782 ***	0.719 ***	0.849 ***	1.074 ***	1.156 ***
(N=488)	(0.239)	(0.190)	(0.166)	(0.120)	(0.123)	(0.132)	(0.147)
Model 6	0.133	0.235	0.400 **	0.484 ***	0.631 ***	0.785 ***	0.840 ***
(N=644)	(0.135)	(0.115)	(0.124)	(0.094)	(0.085)	(0.099)	(0.129)
All Families	0.155	0.244	0.387 **	0.550 **	0.789 ***	0.811 ***	0.756 ***
(N=400)	(0.181)	(0.158)	(0.142)	(0.169)	(0.084)	(0.133)	(0.211)
White	0.110	0.164	0.273 **	0.462 ***	0.661 ***	0.611 ***	0.527 *
(N=400)	(0.116)	(0.098)	(0.100)	(0.118)	(0.110)	(0.141)	(0.229)
Black	0.259	0.202	0.263	0.474 ***	0.565 ***	0.962 ***	1.250 ***
(N=244)	(0.276)	(0.207)	(0.141)	(0.106)	(0.107)	(0.166)	(0.194)

Notes: Coefficients are estimated effects of income inequality on income segregation at specified percentile of income distribution. Bootstrapped standard errors in parentheses. * p<.05; ** p<.01; *** p<.001. Estimates from Models 2, 4, and 6 use sample and corrresponding model specifications from table 3 above. Estimates for all families use sample of 100 largest metropolitan areas and specification from Table 4 above; estimates for white and black families use sample of 100 largest metropolitan areas with at least 10,000 families of specified group (100 metropolitan areas for white models; 61 metropolitan areas for black models) and use specification from Table 4 above.