The Role of Income in Environmental Justice: A National Analysis of Race, Housing Markets, and Air Pollution

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Abstract

Historically, evidence has shown that minority populations in the United States suffer a disproportionate burden of pollution compared to whites. This study examines whether this burden could be the result of income disparities between whites and minorities, acting through the housing market. We look at 324 Metropolitan Statistical Areas (MSA's) in the United States as defined by the Economic and Social Research Institute. Using demographic data from the 2000 Decennial Census and pollution data from the 1999 National Air Toxics Assessment, we compare the race-income correlation in each MSA for four races (white, black, Latino, and Asian) with the race-pollution correlation in those MSA's, while also looking at the role that pollution plays in the housing markets of these MSA's using a hedonic pricing model. We find that the race-pollution correlation is closely related to the race-income correlation, especially in MSA's where pollution plays an important role in determining prices in the housing market. These results hold across all four races, and suggest that income is a key driver behind the observed race-pollution correlation. We propose that any potential policy responses to environmental injustices should focus foremost on addressing the income disparity that exists between races.

JEL classification: Q53; Q56.

Keywords: Environmental Justice; Race; Pollution; Income; Market Dynamics.

I. Introduction

The Environmental Justice movement has been well documented since the controversial dumping of polychlorinated biphenyls (PCBs) in 1978 in Warren County, North Carolina. After a nationally visible protest and accusations that location selection for the landfill site was based on the demographics of the area, members of the House of Representatives commissioned further diligence on the matter. The US General Accounting Office (USGAO) surveyed the locations of hazardous waste landfills and how they relate to the racial and economic backgrounds of the surrounding residential communities in eight southern states. We discuss the findings of this study in Section II.

National awareness of the incident in Warren County put a spotlight on waste disposal facilities and polluting practices that can be harmful to the communities around them, as well as the governmental regulations that affect the placement of these facilities. Beginning with hazardous waste landfills, stories of similar situations began to surface throughout the country. Existing lead smelters in Texas and petrochemical refineries in Richmond, California are two examples of pollution sources in predominantly minority communities (Bullard, 1993).

Over the past few decades, many studies have shown that pollution sites are often surrounded by low-income communities and communities of color. The goal of our study is to delve deeper into factors that affect residential choices of the citizens in these communities. By looking at the relationships between three factors, namely race, income and pollution levels, and comparing them in cities across the country, we attempt to identify the drivers behind the correlation between race and pollution that has been found in previous literature. In particular, we assess whether residential mobility and the rational choice to live in areas of greater or less pollution can explain this correlation, and to identify effective policy solutions that prevent "environmental racism" (Bullard, 1993).

II. Literature Review

As mentioned above, the USGAO's report published in 1983 after the incident in Warren County was the first major study on the issue of environmental justice and is an often-referenced document. They found that, of the "four offsite hazardous waste landfills" in the eight southern states examined (Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee), three landfills were in communities that were a majority African-American. In addition, at least twenty-six percent of the population around all four sites was below the poverty level.

The USGAO also looked into the policies that govern the selection process for landfill locations. Originally, the process was a state responsibility, but the federal government passed regulations in January 1983 that required landfills to meet certain standards and required public participation in the process, except in the case of PCBs. The study used 1980 Census data to identify the racial and socioeconomic data for the regions surrounding the landfill sites. We use the Census in our study as well, in order to determine races and income levels down to the tract level (see Section IV).

The United Church of Christ Commission for Racial Justice, an active group in advocating for civil rights, employed Public Data Access, Inc. in order to develop a "comprehensive national analysis of the relationship between hazardous wastes and racial and ethnic communities" (United Church of Christ [UCC], 1987). The scale of this study, published in 1987, accomplished the goal of the UCC Commission for Racial Justice and came away with a few key findings. First, they found that race proved to be the most significant tested variable in the location of “commercial hazardous waste facilities” across the country. Additionally, “three out of five Black and Latino Americans lived in communities with uncontrolled toxic waste sites,” defined by the study as “closed or abandoned sites on the EPA’s list of which pose a present and potential threat to human health and the environment” (UCC, 1987).

Twenty years later, the United Church of Christ commissioned a follow up study (Bullard, Mohai, and Saha, 2007). The report used 2000 Census data and found that the racial disparities were even greater than previously reported. According to the study, race continued to be the strongest predictor of the location of hazardous wastes, stronger than socioeconomic factors like income and education. The study also opined on the improvement in method of analysis through a shift to “distance-based” approaches in the correlation studies (Bullard et al, 2007). In other words, study results were improved when researchers looked beyond the tract in which a point source was located and focused on the surrounding neighborhoods.

As awareness of the relationship between race and pollution has grown, several researchers have attempted to come up with explanations for the existence of this connection. Two primary theories have been proposed. The first, known as the “disproportionate siting” theory, states that facilities that house hazardous wastes or cause pollution are more likely to be built in areas with less political power to fight them. Traditionally, political power has been weakest in low-income, high racial minority areas. Thus, the theory concludes, the strong relationship between race and level of pollution is a direct result of the choice made by creators of these facilities to site them in areas with disproportionately large populations of racial minorities (Pastor, Sadd, and Hipp, 2001).

In contrast to the “disproportionate siting” theory is the “coming to the nuisance” theory. It has been referred to by other names as well, including “market dynamics,” “white flight,” and “minority move-in.” This theory proposes that the demographics of neighborhoods change after the creation of pollution-producing facilities. Based off of the idea that choices in a housing market include a variety of factors, it claims that particular populations accept pollution in a trade-off for lower housing prices, available jobs, and any number of other community characteristics. The relationship between race and pollution, therefore, according to the “coming to the nuisance” theory, is not the result of discriminatory siting of facilities, but rather the result of racial minorities being willing to accept pollution, and choosing to move near hazardous facilities after their construction (Been, 1994). Notably, the “coming to the nuisance” theory is dependent on the residential mobility hypothesis, which claims that individuals can and do choose to move toward or away from neighborhoods or houses due to their particular characteristics. For example, individuals may choose to move into an area after a new school is built, or may choose to move out of a house when the number of bedrooms is too small for their growing family. “White flight” and “minority move-in” both fall under the broader category of residential mobility. Studies have shown that rates of residential mobility tend to be fairly high in the United States, with up to 20% of residents moving in any given year (Chistensen and Levinson, 2003),

Vicki Been (1994) performed a study to assess the validity of these two differing theories. Been’s research looked at the demographics of communities at the time of siting of a “locally undesirable land use” (LULU), as well as how those demographics changed after construction, in order to determine whether the initial siting was disproportionate, or if market dynamics led minorities and low-income individuals to move to those neighborhoods afterward. The study found some evidence of siting disparities based on race and income, but that levels of poverty and percentages of racial minorities further increased after the sitings. Been therefore rejects the conclusions of the “disproportionate siting” theory, and claims that eliminating racism and classism in the siting process will not suffice to eliminate the prevalence of high pollution rates in low-income and racial minority communities (Been, 1994).

J.T. Hamilton (1995) looked specifically at the difference in area demographics between hazardous waste treatment, storage, and disposal facilities (TSDF’s) with plans to expand, and those with no plans to expand. The study found a significantly higher percentage of nonwhites near facilities that planned to expand. Hamilton concluded that the best explanation for this phenomenon was that minority communities were less likely to engage in collective action to oppose the placement of hazardous waste facilities in their neighborhoods, and that firms would preferentially choose to expand in those neighborhoods where opposition was low (Hamilton, 1995).

The results of both Been’s and Hamilton’s studies, as well as the general validity of both hypotheses, were called into question by a study performed in 1996 by Oakes, Anderton, and Anderson. Oakes et al. employed longitudinal data, at the census tract level, for all census tracts containing TSDF’s. Their results showed no indication of systemic bias in the siting of TSDF’s; rather, “that commercial TSDFs are, on average, sited in communities that are neither disproportionately poor nor minority communities” (Oakes et al, 1996). Similarly, they found no indication of significant changes in community demographics after a facility had been built.

Pastor, Sadd, and Hipp (2001) challenged the conclusions of previous studies by looking at pollution levels and minority populations in Los Angeles County. They compared the relative importance of “disproportionate siting” and “minority move-in” as factors that lead to high-pollution, racial minority communities, and found that "disproportionate siting" had a more significant impact. The study concludes that minority communities, which exhibit "political weakness," attract pollution-causing facilities, and that ethnic groups should work together to prevent construction of additional facilities in their neighborhoods.

The study most relevant to our research topic is that conducted by Depro, Timmins, and O'Neil (2012). Depro et al. question the conclusiveness of the results of previous studies, given that those studies ignored many economic factors that are relevant to housing markets. In particular, they show that the models used by previous studies are not actually able to identify minority move-in or other forms of residential mobility. Using data from Los Angeles County, they perform two analyses in an attempt to provide more economically robust results. The first is a tract-level analysis of demographic changes after the siting of a Toxic Release Inventory facility (TRI), incorporating housing model structure into a similar format to that used by previous researchers. Their second analysis looks at individual homebuyers who move into, out of, or within areas surrounding TRI sites. Using real estate transaction data, property crime rates, and school quality data, Depro et al assess the trade-offs made by homebuyers. The results of this study indicate the existence of a trade-off between exposure to pollution, school quality, crime levels, house size, and other consumption. More specifically, Latinos and low-income populations showed a willingness to accept pollution in exchange for other neighborhood features, while there was a strong indication of "white flight," and some indication that blacks and Asians tend to move away from polluted sites as well. These results provide evidence to support not only the residential mobility hypothesis in general, but also its applicability to pollution; in other words, Depro et al. showed that in Los Angeles, individuals can and do choose to move to or from sources of pollution when they are making their housing decisions.

III. Theory

The Depro, Timmins, and O'Neil study (2012) showed that an economic analysis of environmental justice issues can reveal market dynamics that were otherwise unidentified by traditional literature. However, the study relied on assumptions about homebuyers in its housing model; rather than simply regressing racial composition on pollution, as has traditionally been done in environmental justice, the researchers predicted how populations near TRI sites would change from 2000 to 2007 if pollution were not a factor in choosing where to live, and compared these predictions with the observed changes between the 2000 decennial census and the 2005-2009 American Community Survey (ACS). The predicted population changes were formed using an estimated utility function, based on data of community characteristics (school quality, property crime rates, house values, etc). Thus, inherent in the study's methodology were assumptions about the shape of individuals' preferences. Additionally, the study was limited to households in Los Angeles County between 1998 and 2008. Our study seeks to assess the strength of Depro et al.'s (2012) results without relying on these assumptions, and using data from across the United States. Since we do not use the estimated utility model or look at actual house purchases, our results do not directly show residential mobility in the way that Depro et al.'s do, but rather we look for indirect evidence of the same trends on a larger scale.

In order to do so, we examine three links in a hypothesized chain of causality: we predict that (1) other factors being equal, houses near pollution will have lower prices than houses not near pollution; (2) racial minority status will tend to be negatively correlated with income; (3) if – and only if – 1 and 2 hold, then areas with racial minorities will tend to be the areas with the highest levels of pollution, if residential mobility is the driver of the correlation between race and pollution. In other words, we predict that the correlation between race and pollution that has been found in environmental justice literature can be largely explained by the willingness of minority populations to live near pollution, if (1) being near pollution makes houses cheaper and (2) minority populations tend to have lower income levels.

We examine each of these links (1-3 above) for each Metropolitan Statistical Area (MSA) in the United States. Then, each MSA becomes one data point in our nationwide analysis. We hypothesize that for MSA's where there is a strong negative relationship between pollution and house value (link 1), and a strong correlation between race and income (link 2), there will also be a strong correlation between race and pollution, if the residential mobility theory is indeed correct in that individuals are willing and able to move according to neighborhood characteristics. Meanwhile, we predict that MSA's that show no significant relationship between pollution and house value, or between race and income, will not show a significant relationship between race and pollution if the residential mobility hypothesis is correct. Furthermore, we predict that in between these two extremes there is a spectrum: for any given MSA, the stronger its relationship between pollution and house value or between race and income, the greater the correlation between race and pollution.

To clarify our theory, let us look at the example of the two largest cities in the United States. Los Angeles is a city where race and income are closely related, with most minority individuals living in low-income neighborhoods; New York, on the other hand, does not have nearly as strong a relationship. There are many poor neighborhoods in New York that have large minority populations, but there are also many high-income minority neighborhoods. Our theory predicts, therefore, that as long as pollution negatively affects house prices in both cities, the poor minority neighborhoods in Los Angeles will tend to be the locations with the highest levels of pollution, while the wealthy white neighborhoods will have lower levels of pollution, resulting

in a strong correlation between race and pollution. In New York, on the other hand, we predict that the neighborhoods with highest pollution will have a variety of races present, while some minorities lived in unpolluted areas, resulting in a weak correlation between race and pollution. This phenomenon can be seen in the data: looking at the black population, Los Angeles has a very strong correlation between percent black and median household income
(r = -0.503) as well as a strong correlation between percent black and pollution-induced cancer risk (r = 0.208), while New York has much lower correlations (r = -0.291 and r = -0.012, respectively). Notably, the black-income correlation in New York is still strong, but it is much weaker than that in Los Angeles, which explains why the black-cancer risk correlation (a proxy for black-pollution) is likewise much weaker in New York than in Los Angeles.

The rationale behind our three-link theory outlined above is as follows. Pollution, like school quality, crime rates, and ability to live with people of the same race, is one of many factors that go into an individual's choice of where to live. If individuals are aware of pollution, therefore, and educated about its effects, then those with enough money will choose to move away from pollution (all else being equal), provided that proximity to pollution affects house prices. This will result in low-income populations living in high-pollution areas, accepting it in a trade-off in order to get as much as possible of other "goods" while staying within their limited budget constraints. Historically, low-income populations have tended to be comprised largely of minorities. Thus, minority populations end up living in areas with high levels of pollution, regardless of how the pollution is initially sited.

In order to conduct our analysis, we start by comparing pollution and housing data. Pollution is a crucial factor in the decision of where to live; just as it can be a "trade-off" in a decision, pollution can be a reason to relocate if one has the means. Our analysis of the role that pollution plays in the housing market consists of two different steps: first, we regress house value on pollution, controlling for MSA-specific effects; secondly, we introduce other hedonic variables so as to best approximate the true effect of pollution on house value. The initial variables used are median house value and level of pollution-caused risk of disease (cancer, respiratory, or neurological). Since both median house value and disease risk have a highly skewed distribution across census tracts, the natural log of each is taken. Determining the appropriate hedonic variables to introduce is an important step in our analysis. There are many confounding factors that likely are correlated with both pollution level and house value, which we attempt to account for by focusing on two main areas: community characteristics and house characteristics. The variables we ultimately use are the median number of rooms in houses in the tract, percent of houses in the tract with kitchens, and percent with plumbing facilities (house characteristics), percent of tract residents working in manufacturing, percent working in construction, and percent of tract area that is defined as urban (community characteristics).

Once we regress house value on pollution levels, we then categorize our data based on the results of this hedonic house price regression. We divide the 324 MSA's in the nation into thirds: the "most negative" grouping consists of MSA's in which pollution most affects the housing market, the "middle third" grouping consists of MSA's in which the effect of pollution on the housing market was smaller, and the "least negative" grouping consists of MSA's in which pollution had no effect (or a positive effect) on house value, according to our hedonic regression. We later perform statistical tests for differences between these categories, and also use the coefficients and t-statistics from the house price regression as interaction terms in subsequent regressions, as is explained in Section V.

Having categorized our data according to the role that pollution plays in each groupings' respective housing markets, we then look at the correlation between race and income, in order to give context to the degree of flexibility an individual has in housing choices as it relates to their ethnicity. There are a number of factors that could be correlated with both race and income, but unlike the relationship between pollution and house value, we are confident that a simple correlation suffices to identify the relationship. Furthermore, avoiding the use of a regression prevents the incorporation of more assumptions about causality into our analysis.

The next step is to examine the correlation between race and pollution, which is at the heart of much of the topical literature. At this point, we create scatter plots for each category of MSA, plotting the race-pollution correlation against the race-income correlation. This allows us to conduct two different analyses: (a) looking at the relationship between these two correlations of interest for each category -- that is, looking at how the race-income correlation informs the race-pollution correlation, given the role of pollution in housing markets -- and (b) looking at how the relationship between these two correlations of interest varies across MSA's categorized by the effect of pollution -- in other words, looking at how changes in the role of pollution in housing markets affects how the race-income correlation informs the race-pollution correlation.

Our theory predicts that the MSA's in which housing values are most strongly affected by pollution will show the strongest negative relationship between the two correlations of interest. To understand this relationship fully, the final portion of our study incorporates other variables as available. As before, each MSA constitutes one "data point," which we categorize according to a variety of characteristics: geographic region in the country, population, overall level of pollution, and income gap between the wealthy and the poor. The specific variables used are described in more detail in Section IV, below.

IV. Data Discussion

The main sources of data we use in our analysis are the 1999 National-Scale Air Toxics Assessment (NATA), and the Decennial Census data from 2000. Both of these data sets are publicly available at a highly detailed level. Although newer data is available from both the NATA and Census databases, we use the 1999 NATA study and the 2000 Decennial Census for four reasons: (1) unlike subsequent datasets, the 1999 NATA study and 2000 Census use identical definitions of census tract boundaries, (2) the 2010 Decennial Census does not include data on income or house values, (3) the US Census Bureau developed a new data collection method known as the American Community Survey (ACS), which does not have a full dataset available for the early 2000's, and (4) the EPA has not published a recent assessment that could be matched with the robust 2007-2011 ACS.

NATA is an assessment published by the Environmental Protection Agency (EPA) that provides risk levels for cancer and other non-cancer respiratory and neurological effects at the census tract level, based on "chronic exposure from outdoor sources" if they remain unchanged. In order to calculate these values, the EPA first collects emissions data in the form of the National Emissions Inventory. The EPA then uses air dispersion models to estimate ambient concentration of the emitted toxins, combines it with known natural sources of toxins, and checks the model's accuracy with available local monitoring devices. Ambient concentration is then converted to the more relevant exposure concentration, in other words the amount of the pollutants that people actually breathe. This number varies for individuals based on personal lifestyle, e.g. how much time is spent being active outside, but is a key metric in determining health risk. Based on the known health effects of the measured toxins, the EPA quantifies the risk for the defined community assuming lifetime exposure at the measured emissions levels at that time.

This analysis includes 177 known air toxins that are combined to yield the total risk levels of cancer, respiratory, and neurological effects from breathing in the local pollution. The measurements are expressed in the units of "*x* in a million," meaning that an additional *x* out of one million people above the normal cancer rate will develop cancer if the entire population is continuously exposed to the pollution levels. This metric is most appropriate for our scope of analysis. The information in the National Emissions Inventory is not gathered at the census tract level across the country. The EPA does make available the results of their dispersion modeling for each of the 177 pollutants for the census tracts. This is a viable option, but rather than going one pollutant at a time and by physical amount, the calculated risk parameters allow us to capture the impact of all emissions in a cleaner fashion.

The NATA analysis has been published four times, in 1996, 1999, 2002, and 2005. Each time that the EPA conducts the study, they change their methodology with the intention of improving it. Despite making the assessment more accurate, this approach prohibits the creation of a panel data set. It is disclosed on the EPA website that changes in risk or emission levels over time could be a result of either changing pollution conditions or improved estimation and modeling techniques, and, as a result, it is impossible to differentiate. Fortunately, our interest is not in the specific values of pollution levels at different times, but in how pollution relates to income and race in one time period; accordingly, the changes in methodology are not obstacles to our analysis.

Using this data as our primary measure of pollution means that we take a different approach than has been used in previous literature. Most of the sources outlined in Section II identify specific point sources, such as dumpsites or factories, and analyze the surrounding areas. This approach can cater to specific types of pollution and its effects on the nearby population. The NATA data focuses on concentrations of air pollution that people breathe; this, therefore, is irrespective of identified point sources or dumpsites that might, for example, contaminate groundwater aquifers or lead to exposure through ingestion of toxins. We use the NATA data in our analysis because we believe it allows us to take a broader approach, better aligned with the thesis of the paper, given that we conduct our analysis on a national scale.

The other component of the data used in the project is from the Census databases. We use data from the 2000 Decennial Census, which has very detailed information related to the three links that are of interest to us: pollution-house value, race-income, and race-pollution. The Census contains enormous amounts of data on income and general demographics, and the Census Public Use Microdata Sample (PUMS) contains information on housing characteristics such as number of houses with kitchen facilities and median number of rooms. Among the demographic and community-level variables explored are: population, racial composition, percent employment in manufacturing and construction, household income, house value, and income disparities between tracts in an MSA. Census data was downloaded from the Social Explorer database at the census tract level, organized by state and county. We downloaded data for the entire United States, and then matched it to the NATA data by census tract, according to its Federal Information Processing Standard (FIPS) code.

After matching Census and NATA data, our next step was to organize census tracts into MSA's. Initially, we attempted to do this using zipcode data accessed through the Housing and Urban Development (HUD) database. A United States Postal Service (USPS) dataset was used to organize census tracts into zipcodes, and a subsequent dataset was used to match zip codes to core-based statistical areas (CBSA's), a measure which includes both metropolitan and micropolitan statistical areas. We separated out the MSA's, but found that the resulting dataset had a few glaring flaws. First, the HUD crosswalk did not include the ten largest MSA's in the country, so we were missing some of the most important cities for our analysis. Secondly, the USPS definition of MSA's did not precisely match with the Census definition of MSA's, with roughly one out of every three being defined differently between the two. Lastly, there is neither a direct relationship between census tracts and zip codes, nor between zip codes and MSA's, such that we were only getting an approximation for which tracts were actually in each MSA.

The results of this methodology for the state of Texas can be found in the picture below (**Figure 1**). The MSA's in Texas are represented by the dark outlines while the census tracts in our dataset are shaded.

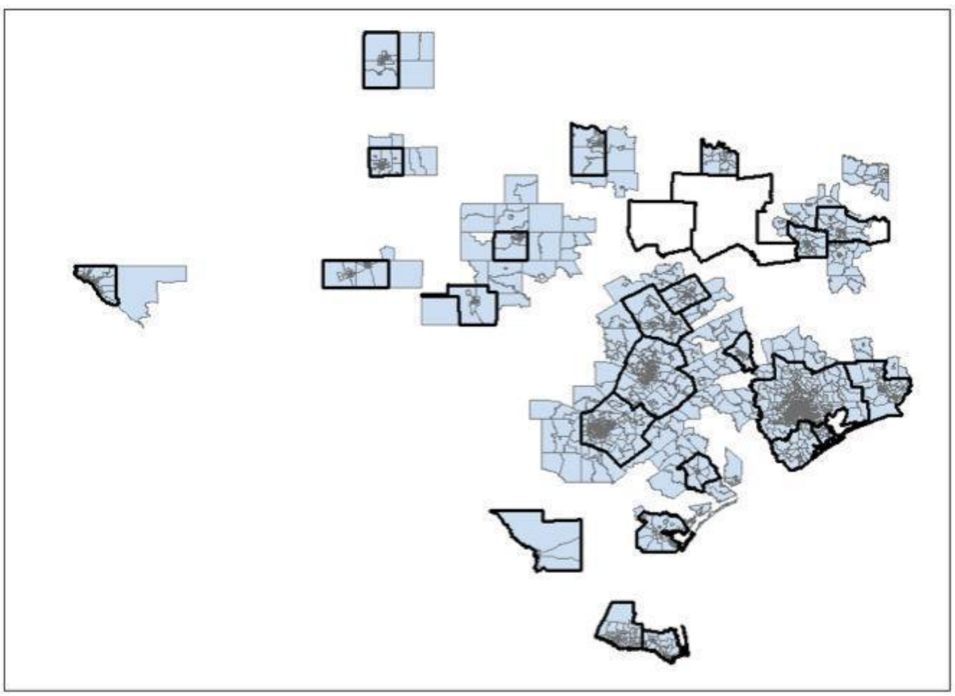

Figure 1: ArcGIS map of MSA data in Texas, according to initial crosswalk

This visual representation that we generated using ArcGIS software shows that this methodology needed further refining. In this map, Dallas and Fort Worth are empty outlines and, thus, not included in this initial dataset, since they were not included in the HUD crosswalk. It is also evident from the map below that our tract-level data bled over some of our MSA borders and in some cases there were missing tracts in the middle of MSA's. There was no reason to suspect a systematic bias in the inclusion or exclusion of tracts, but the dataset was clearly imperfect. The biggest risk was potentially double counting census tracts in neighboring MSA's.

We decided to pursue an alternative method of sorting our data into MSA's, which we were able to do using ArcGIS software and data downloaded from the Economic and Social Research Institute (ESRI). ESRI provides shapefiles of all the census tracts and MSA's in the nation, which we downloaded according to their 2000 Census definitions from the 2003 ESRI dataset. We then used ArcGIS to sort each census tract into an MSA if the centroid of its shape fell within the boundaries of that MSA. The resulting categorization provided us with a list of about 51,000 census tracts in 331 MSA's; of these 51,000 tracts, there was a discrepancy of only one single tract between the ESRI file and the NATA and Census data. Furthermore, visual analysis shows that there are very few tracts that are defined by ESRI as falling within an MSA's boundaries that are not included in our analysis. These can be seen in **Figure 2**; tracts that are included are shown in pink, while those that are excluded are shown in green.

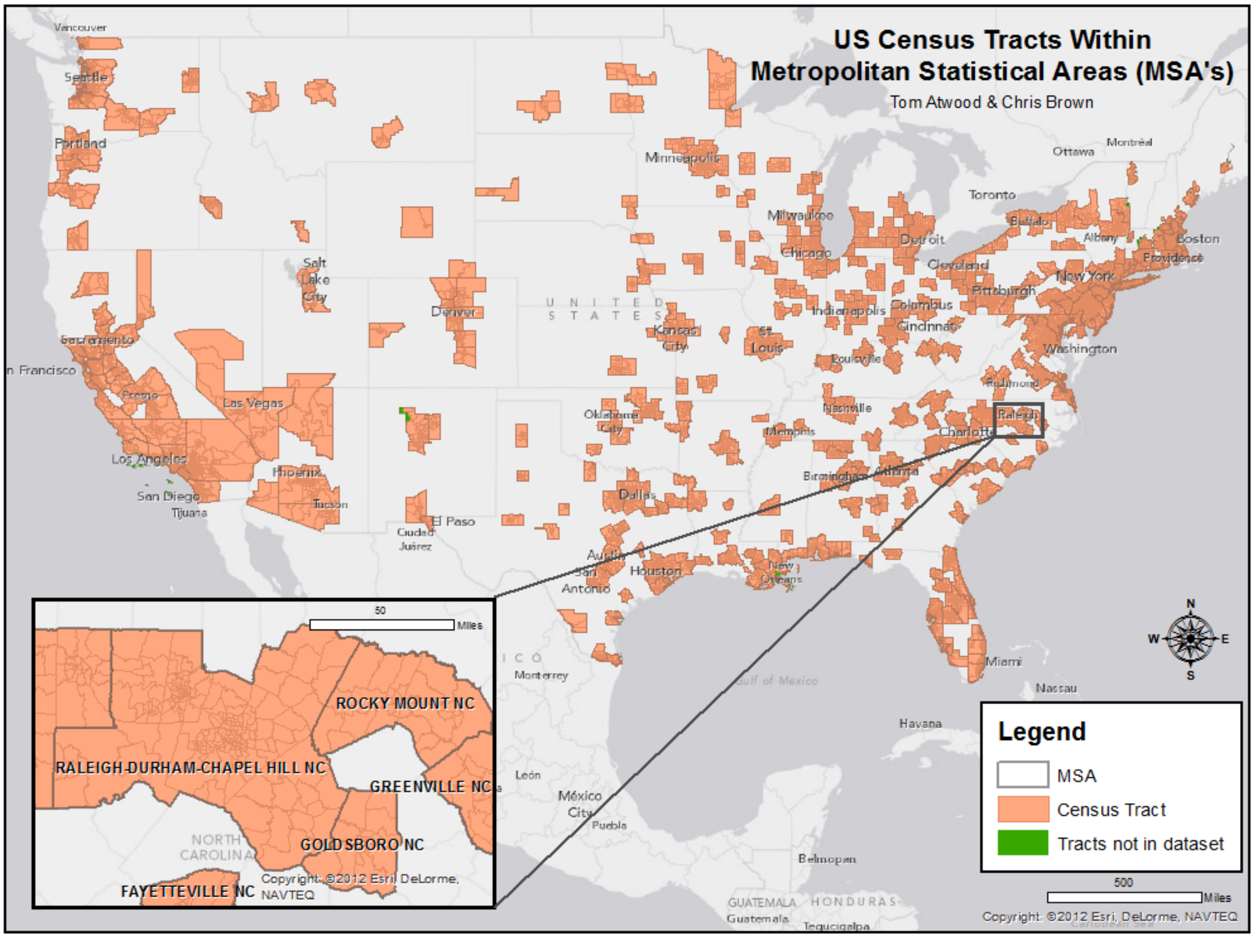

Figure 2: ArcGIS map of our updated dataset

There is a wide range of variables that we use in our analysis. For pollution, we use all three of the total risk levels calculated by the EPA (cancer, respiratory, and neurological). These risks are similar across areas, but not identical. **Figures 3, 4,** and **5**, on the following pages, show the relationships between the natural logs of these three risk types across census tracts. The correlations are above 0.7 for all three pairs, but there are some notable outliers, so we feel it worthwhile to look at each risk type independently.

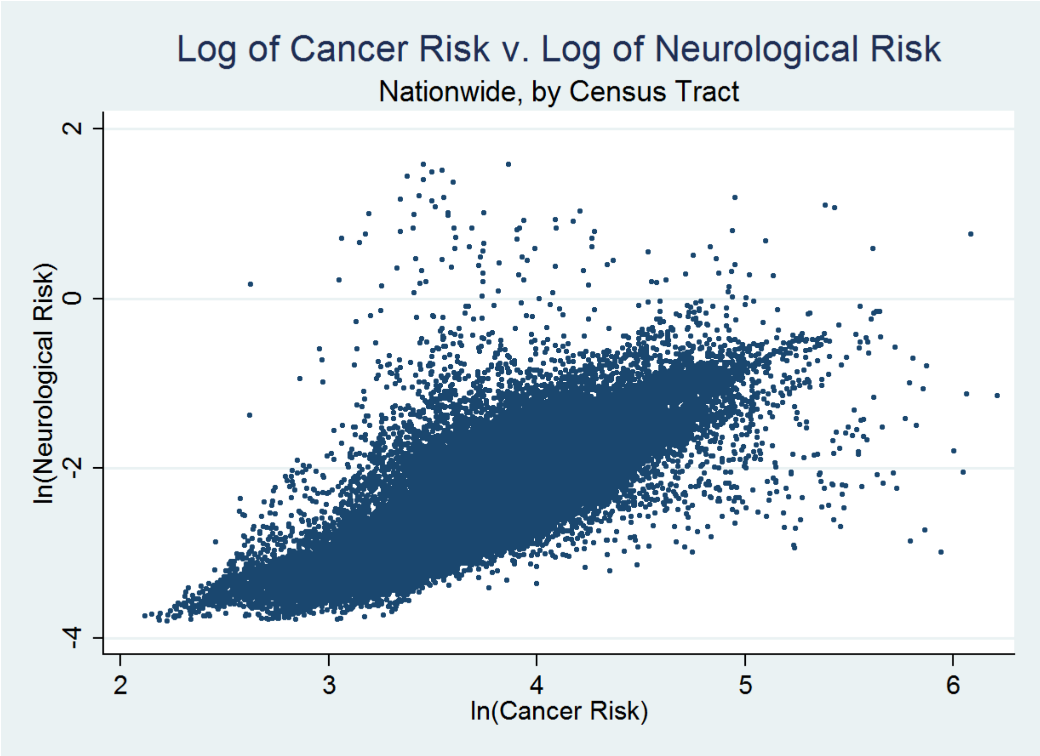

Figure 3: Correlation between ln(Cancer Risk) and ln(Neurological Risk) = 0.8013

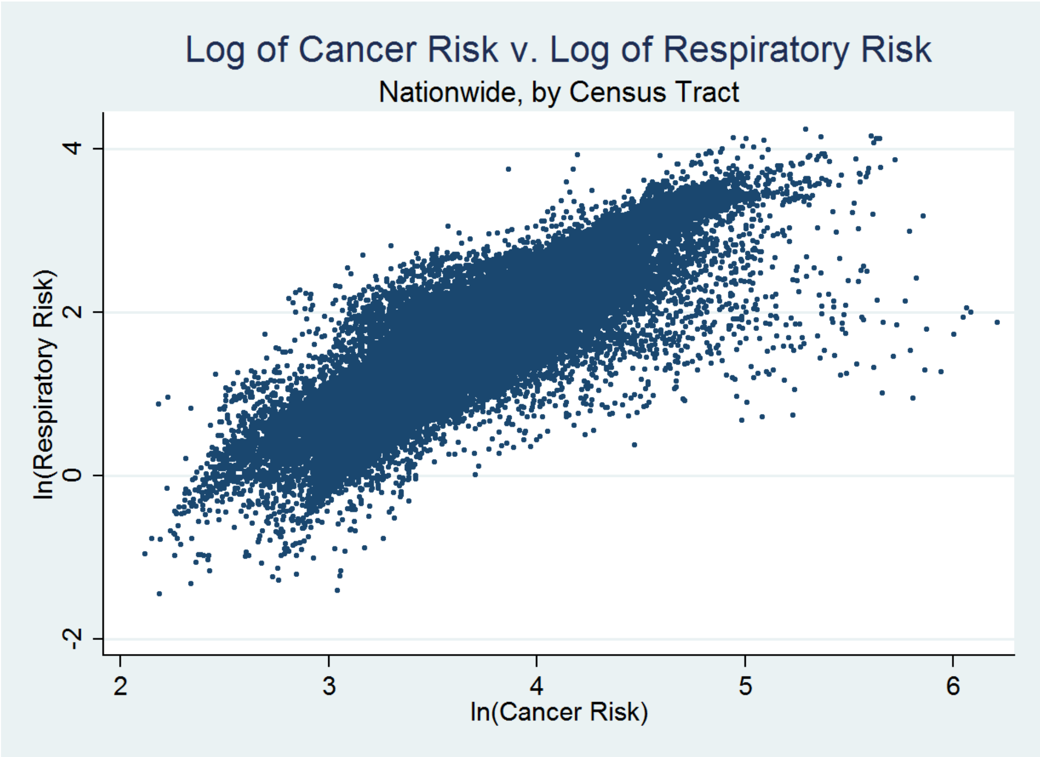

Figure 4: Correlation between ln(Cancer Risk) and ln(Respiratory Risk) = 0.8675

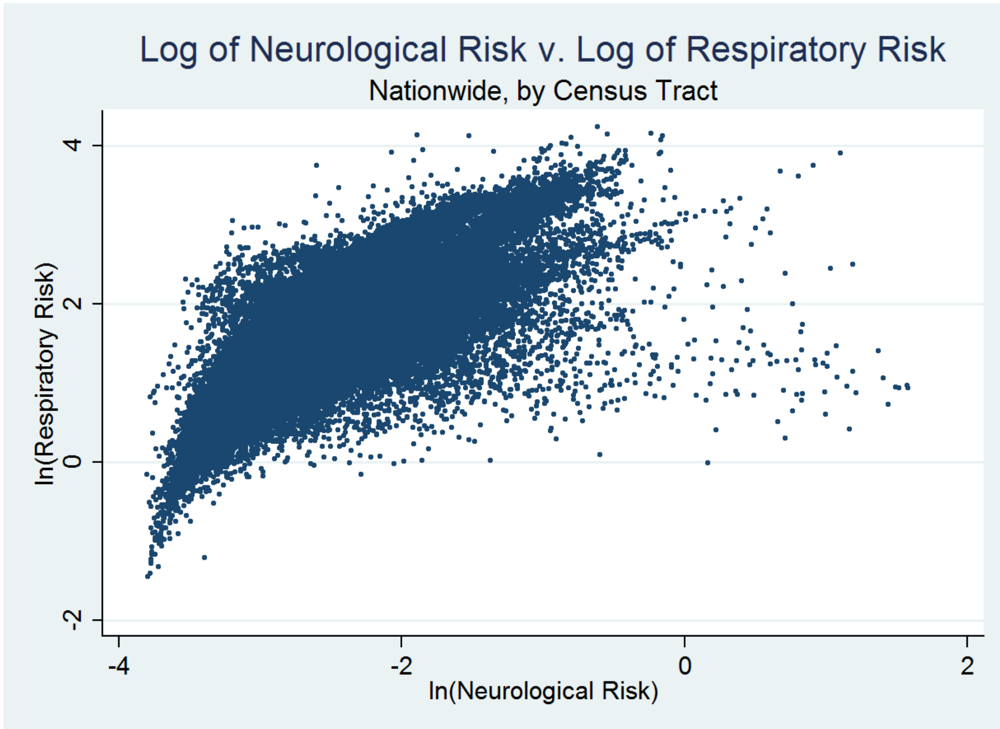

Figure 5: Correlation between ln(Neurological Risk) and ln(Respiratory Risk) = 0.7411

For house value, we use median house value for the census tract. Since this is self-reported, it may not be entirely reliable, but there is no reason to suspect a systematic bias. As previously mentioned, we use the natural log of median house value, since there is a strong positive skew to the distribution. Other housing characteristics we use are median number of rooms per house, percentage of houses with kitchens, and percentage of houses with plumbing.

For income, we use median household income. As with our variables for risk and house value, we take the natural log to adjust for the positive skew in the distribution.

For race, we look at four races individually: white, black, Latino, and Asian. Previous studies have shown that Latinos, blacks, and Asians may demonstrate widely different responses to pollution. As such, we do not risk losing sight of these individual dynamics by lumping minorities into a single "minority population" variable. Looking at each race individually makes our results more nuanced, ultimately providing us with more meaningful conclusions.

Notably, our data has some large outliers in a number of variables. A few census tracts have very large values for health risks, roughly one hundred tracts have zero population, and about 500 tracts have median house value reported as zero (presumably because there was no reported house value data for that tract). For this reason, we decided to systematically eliminate outliers so as to remove circumstances that might havinfluence our results.

We dropped any census tracts that reported a median income or a median house value of zero (623 tracts). It should also be noted that the US Census caps their measure of median house value at $1,000,001. However, this cap is only enacted in 89 tracts and we decided that, although the cap may prohibit completely capturing the effect of pollution on house value in these areas, they would still be beneficial in our analysis. We removed tracts that had a population less than 500 people (375 tracts). By definition census tracts are intended to have between 1,000 and 8,000 people in them, and we felt that tracts with low population totals have a higher potential to yield skewed demographic information that might affect our analysis, e.g. percent race in a tract. We cut any pollution risk values that were five standard deviations or more away from the mean (176 tracts). Here, we were not concerned about the measurement's accuracy and do believe that they still fit into the overall theory, but removed the tracts to prevent them from having too much influence in our linear nationwide analysis. Finally, we eliminated 7 MSA's that had fewer than 20 census tracts each due to concerns regarding insufficient information and data points for meaningful results (111 tracts). In the end, this reduced our data set from 51,316 tracts and 331 MSA's by 1,285 tracts and 7 MSA's to 50,031 tracts and 324 MSA's.

Our final data component, as mentioned in section III, is data at the MSA level used to test whether our results are identical for different types of cities. The first such variable is categorization by region of the country, into four regions (Northeast, Midwest, South, and West), which are subdivided into a total of nine divisions (New England, Mid Atlantic, West North Central, East North Central, South Atlantic, West South Central, East South Central, Mountain, and Pacific), as defined by the Census Bureau. **Figure 6**, below, shows how the country is organized into these regions and divisions. The second MSA variable we introduce into our analysis is population. We categorize those with populations greater than one million as "large" (61 MSA's), and those with populations smaller than 250,000 as "small" (143 MSA's).

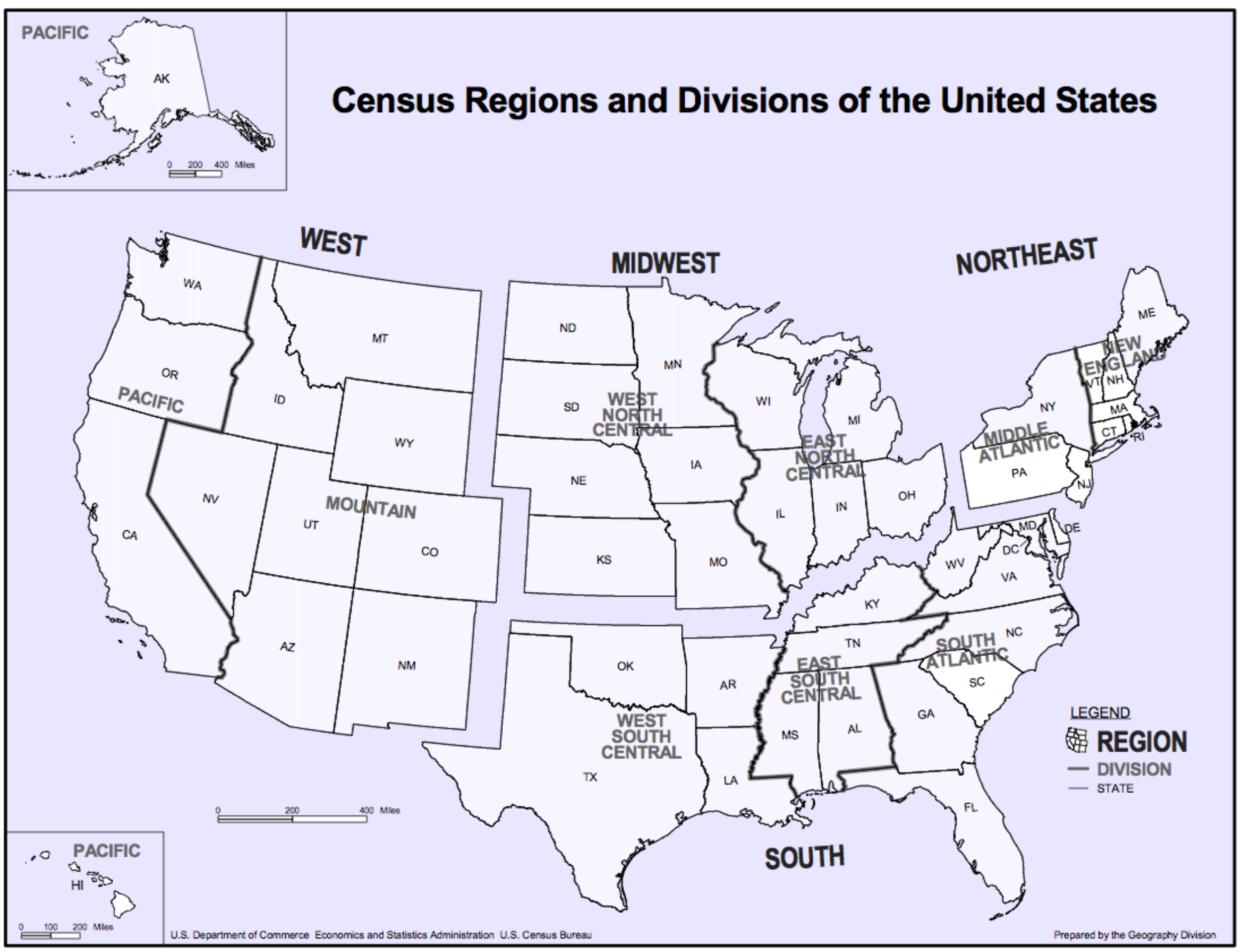

Figure 6: Census definitions of regions and divisions

In addition to looking at geographic region and population, we also analyze MSA's by their overall levels of pollution, in order to assess whether or not our results are strongest in areas of high pollution. We calculate the average level of cancer risk, neurological risk, and respiratory risk for each MSA across all tracts. For each type of risk, we not only use this raw average value, but also categorize each MSA as "high risk" (one of the 108 MSA's with highest levels of average risk), "moderate risk" (one of the 108 in the middle third), or "low risk" (one of the 108 with lowest average risk). Interestingly, some MSA's rank as "high risk" for one risk type, but "low risk" for one or both of the others.

The next MSA-specific variable we add is a measure of the income gap between the wealthy and the impoverished, as mentioned previously. For each MSA, we sort the tracts in that MSA by median income, and take the difference between the 95th and 5th percentiles. This gives us the range of the median incomes for the middle ninety percent of tracts, which we use as an estimate for the gap that exists between the rich and the poor in the MSA. As with average risk data, we supplement the raw values by sorting the MSA's into three categories depending on the size of the income gap. After initially dividing the country into three equal groups of 108 MSA's, we found that this did not accurately reflect the distribution of the data; there are a small number of MSA's with income gaps that are much higher than average, as well as a small number with very low income gaps, with a relatively flat distribution in between. Therefore, we define "large income gap" as the ten percent of MSA's with the largest income gap, "small income gap" for the ten percent of MSA's with the smallest income gap, and "medium income gap" for the eighty percent of MSA's in between. Finally, we calculate the median value of median household income across tracts in each MSA. This provides a point of reference to which to compare the income gap.

V. Empirical Specification

i. Hedonic Housing Price Regression

As discussed above, the first link in our causal chain is the effect that pollution has on housing markets, which we analyze by looking at the effect of health risk on house values. Our model is as follows:

$$V_i = \beta_1 R_i + \beta_2 H_i + \beta_3 N_i + \varepsilon \qquad \textbf{\textit{(1)}}$$

In Equation 1, V_i = natural log of median house value in census tract i, R_i = log of risk level in tract, H_i = house characteristics (median number of rooms per tract, percent of houses with kitchen facilities, and percent of houses with plumbing), N_i = neighborhood characteristics (percent of the tract that is characterized as "urban," percent of residents working in manufacturing, and percent working in construction), and ε = error term. Compared to economic literature of housing markets, this is a very simple model, with very few regressors. We do not doubt that there are more factors that affect the housing market. Data on many of these factors, such as crime rate by census tract, either does not exist or is not available publically at a nation level. Our goal, however, is not to determine a precise model for house value, but rather to provide an estimate for the relative effect of pollution on house prices in different cities; the exact coefficient is not of importance to our analysis so much as its relative size compared to the coefficient of other cities. We feel comfortable that our simple model is able to achieve this goal.

The regression is performed for all 324 MSA's. MSA's are then characterized by the slope coefficient of health risk (β_1): the 108 MSA's with the most negative values of β_1 are categorized as "most negative," the 108 MSA's with the least negative (or most positive) values of β_1 are categorized as "least negative," and the remaining 108 are categorized as "middle third." This same process is performed three times, once for each risk type.

In order to assess whether or not our model is accurately picking up the effect that pollution plays in the housing market, we run the regression in Equation 1 at a nationwide level for all tracts in our dataset, controlling for MSA-fixed effects:

$$V_i = \beta_1 R_i + \beta_2 H_i + \beta_3 N_i + \beta_4 MSA_1 + \ldots + \beta_{326} MSA_{323} + \varepsilon \qquad \textbf{(2)}$$

Here, V_i, R_i, H_i, N_i, and ε are all the same as in Equation 1, and MSA_1 through MSA_{323} are fixed effects for each MSA, omitting the final MSA to avoid collinearity.

ii. Regression of Race-Pollution Correlation on Race-Income Correlation

After categorizing MSA's by the effect that pollution has on the housing market, we look at the relationships between race and income, and race and pollution, for each MSA. For each of the four race types, we calculate the correlation between percent of that race and median household income, by census tract, for each MSA. We then calculate the correlation between percent of that race and pollution-related health risk, by census tract, for each MSA. The values of these correlations for each MSA can be seen in **Appendix A**. For each race and each risk type, in order to test our hypothesis that the strength of the race-pollution relationship is proportional to the strength of the race-income relationship, we create a scatter plot of these two correlations and created a best-fit line via a univariate regression. The equation for the regression is:

$$RP_j = \alpha_1 RI_j + \varepsilon \qquad \textbf{(3)}$$

In Equation 3, RP_j = race-health risk correlation for MSA j, RI_j = race-income correlation for MSA j, and ε = error term. This regression is run for all MSA's in the nation. It is then repeated for the categorized groups as described above, according to hedonic slope coefficients. For each race and risk type, we compare the slopes of the regression lines (α_1) between the "least negative," "middle third," and "most negative" groups of MSA's, in order to see whether the role of pollution in the housing market changes the strength of the relationship between the race-income correlation and the race-pollution correlation.

Finally, because simply running the regression in Equation 3 for separate categories of MSA does not tell us whether the differences between these groups are statistically significant, we run three additional regressions that introduce interaction terms into the equation. The first involves dummy variables for the hedonic slope coefficient categories, as follows:

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}MN_j + \alpha_3 RI_j{*}LN_j + \varepsilon \qquad \textbf{(4)}$$

In Equation 4, RP_j, RI_j, and ε are as in Equation 3 above. There are then two interaction terms between the race-income correlation for the MSA and two dummy variables: MN_j (equals 1 if MSA j is in the "most negative" category of MSA's, given its slope coefficient from the hedonic regression), and LN_j (equals 1 if MSA j is in the "least negative" category). Thus, the model allows for the effect of *RI* on *RP* in MSA j to depend on the categorization of MSA j in terms of the relative effect of pollution on house prices in that MSA. For example, in an MSA in the "most negative" category, where pollution strongly decreases house prices, the relationship between *RI* and *RP* is equal to $\alpha_1 + \alpha_2$. The "middle third" is the reference category; the effect of *RI* on *RP* for MSA's in this category is equal to α_1. We followed this model with two additional regressions:

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}\beta_{1j} + \varepsilon \qquad \textbf{(5)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}t\_stat\_for\_\beta_{1j} + \varepsilon \qquad \textbf{(6)}$$

In Equation 5, RP_j, RI_j, and ε are as in Equation 3 above, and $RI_j{*}\beta_{1j}$ is an interaction term between the race-income correlation for MSA j and the slope coefficient from the hedonic regression for MSA j. Like Equation 4, this model allows for the effect of *RI* on *RP* in MSA j to depend on the role of pollution in MSA j, but now, we allow the effect to vary continuously with the hedonic slope coefficients, rather than sorting data into three categories. In Equation 6, the race income correlation for MSA *j* is multiplied by the corresponding t-statistic from the hedonic regression, rather than the slope coefficient, to generate the interaction term. Equation 6 also allows for continuous variation of the interaction term and using the t-statistic allows us to control for the standard error associated with the data in each MSA. Equations 5 and 6 both explore the same phenomenon – the way in which the results from Equation 1 change the effect of *RI* on *RP* – but they do so using alternative measures: the coefficient itself, in Equation 5, and its t-statistic, in Equation 6. Naturally, the coefficients and their t-statistics are highly correlated, but their distributions are not identical, so we include both equations in our analysis as a robustness check to see if similar results hold for both.

iii. Supplemental Regressions

The models in Equations 3-6, above, allow us to examine the links of our causal chain as presented in our theory section: namely, the effect that the race-income correlation has on the race-pollution correlation, and how that relationship varies based on the role that pollution plays in the housing market. The following models are then added as supplemental regressions, to assess whether or not the results found from Equations 3-6 hold across all different types of MSA's. The supplemental regressions employ both the continuous and categorized approaches that are discussed in the previous subsection. As with the models described in the previous subsections, each of these regressions is run for each race and for each risk type, for a total of twelve times per regression. Our first specification is as follows:

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * South_j + \alpha_3 RI_j * West_j + \alpha_4 RI_j * Northeast_j + \varepsilon \qquad \textbf{(7)}$$

Equation 7 is used for a geographic region analysis. For each race type, *RP* is regressed on *RI* and three interaction terms equal to *RI* multiplied by a dummy variable that equals one if MSA *j* is in a region other than the Midwest. This equation allows us to understand how the relationship between *RI* and *RP* is impacted by the general location of an MSA. After running this regression, we run Wald tests for differences between each pair of coefficients, in order to assess whether the relationship varies between regions.

Our next three supplemental regressions all follow the same form:

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * LargePop_j + \alpha_3 RI_j * SmallPop_j + \varepsilon \qquad \textbf{(8)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * HighRisk_j + \alpha_3 RI_j * LowRisk_j + \varepsilon \qquad \textbf{(9)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * LargeGap_j + \alpha_3 RI_j * SmallGap_j + \varepsilon \qquad \textbf{(10)}$$

In Equations 8-10, *RP* is regressed on *RI* and two interaction terms, each equal to *RI* times a dummy variable. In Equation 8, *LargePop* equals 1 if the MSA has a population greater than one million, and *SmallPop* equals 1 if the MSA has a population less than 250,000. It should be noted that we perform this sort using MSA populations prior to dropping any tracts, lest we disrupt their true categorization. In Equation 9, *HighRisk* equals 1 if the MSA is in the top third in terms of average health risk (of the corresponding type, depending on the regression), and *LowRisk* equals 1 if the MSA is in the bottom third in terms of average health risk. In Equation 10, *LargeGap* equals 1 if the MSA is in the top 10% in the range of income gaps (see Section IV), and *SmallGap* equals 1 if the MSA is in the bottom 10% in the range of income gaps. These equations all involve dummy variable interaction terms, which we replace with continuous variable interaction terms in the following models:

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * AverageRisk_j + \varepsilon \qquad \textbf{(11)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * IncomeGap_j + \varepsilon \qquad \textbf{(12)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * MSA\_MedianIncome_j + \varepsilon \qquad \textbf{(13)}$$

$$RP_j = \alpha_1 RI_j + \alpha_2 RI_j * IncomeGap_j + \alpha_3 RI_j * MSA\_MedianIncome_j + \varepsilon \qquad \textbf{(14)}$$

Equations 11-14 are set up to measure the effect of continuous variation of the interaction terms on the *RI* and *RP* relationship like Equations 5 and 6. In Equation 11, the *RI* correlation in MSA *j* is multiplied by the average health risk for MSA *j*, calculated separately for each of the three types of health risk, to create the interaction term. In Equation 12 and 13, the income gap for MSA *j*, as defined in Section IV, and the MSA-wide median of median income levels in MSA *j* are multiplied by the *RI* correlation in MSA *j* to make the interaction term in their respective equations. In Equation 14, income gap and median income levels are used to form interaction terms in the same equation, in order to control for the effect of the median income level on how the income gap in MSA *j* affects the *RI* and *RP* relationship.

The last step in our analysis is to combine the previously specified interaction terms, via the following equation:

$$\begin{gathered} RP_j = \alpha_1 RI_j + \alpha_2 RI_j * \beta_{1j} + \alpha_3 RI_j * IncomeGap_j + \alpha_4 RI_j * MSA\_MedianIncome_j + \\ \alpha_5 RI_j * AverageRisk_j + \alpha_6 RI_j * LargePop_j + \alpha_7 RI_j * SmallPop_j + \\ \alpha_8 RI_j * South_j + \alpha_9 RI_j * West_j + \alpha_{10} RI_j * Northeast_j + \varepsilon \qquad \textbf{(15)} \end{gathered}$$

Equation 15 expands on the approach of Equation 14 to see how all of the controls relate to one another. Here we use interaction terms that vary continuously with the size of the hedonic slope coefficient, income gap, median income, and average risk, and dummy interaction terms for regions and MSA size classifications.

Values of all the variables used in our supplemental regressions are listed by MSA in **Appendix B**.

VI. Results

i. Hedonic Housing Price Regression

The results of running the regression in Equation 1 ($V_i = \beta_1 R_i + \beta_2 H_i + \beta_3 N_i + \varepsilon$) for all MSA's are as follows. For all three risk types, the majority of the MSA's have a negative coefficient for β_1. The sign and significance of the slope-coefficient for the MSA's in each of these models can be seen in **Table 1**. Additionally, the slope-coefficient and t-statistic for each MSA can be seen in **Appendix C**.

Hedonic Regressions for Each MSA: LN(Median House Value) on LN(Risk), House Characteristics, and Neighborhood Characteristics			
Sign & Significance of Risk Coefficient	**(1) Model with Cancer Risk**	**(2) Model with Neurological Risk**	**(3) Model with Respiratory Risk**
Significant Negative	77	88	66
Insignificant Negative	137	112	120
Insignificant Positive	79	94	96
Significant Positive	31	30	42
Total	*324*	*324*	*324*

Table 1: Sign and significance of slope coefficients for risk in hedonic regression

The results of the nationwide regression as specified in Equation 2 ($V_i = \beta_1 R_i + \beta_2 H_i + \beta_3 N_i + \beta_4 MSA_1 + \ldots + \beta_{326} MSA_{323} + \varepsilon$) are shown in **Table 2**:

Nationwide Hedonic Regression: LN(Median House Value) on LN(Risk), House Characteristics, and Neighborhood Characteristics, with MSA-Fixed Effects			
Variable	**(1) Model with Cancer Risk**	**(2) Model with Neurological Risk**	**(3) Model with Respiratory Risk**
LN (Cancer Risk)	-0.0333*** (-5.00)		
LN (Neurological Risk)		-0.0472*** (-8.75)	
LN (Respiratory Risk)			0.0147*** (2.99)
Median Number of Rooms	0.185*** (106.29)	0.182*** (102.53)	0.189*** (110.09)
Percent with Kitchen Facilities	-0.00286** (-2.26)	-0.00305** (-2.42)	-0.00264** (-2.09)
Pecent with Plumbing	0.0441*** (27.76)	0.0440*** (27.70)	0.0444*** (27.99)
Percent in Urban Area	-0.00240*** (-29.59)	-0.00225*** (-27.96)	-0.00271*** (-33.15)
Percent Working in Manufacturing	-0.0132*** (-41.02)	-0.0131*** (-40.90)	-0.0130*** (-40.36)
Percent Working in Construction	-0.0248*** (-47.35)	-0.0250*** (-47.72)	-0.0245*** (-46.85)
Constant	6.832*** (51.46)	6.661*** (52.07)	6.634*** (51.74)
Adjusted R-squared	*0.643*	*0.644*	*0.643*
N	*50031*	*50031*	*50031*
** = p<0.10, ** = p<0.05, *** = p<0.01*			

Table 2: Results of nationwide hedonic price regression

The slope coefficients for both cancer and neurological risk are negative and strongly significant, as we expected, showing a negative effect of health risk on house value. The coefficient for respiratory risk is slightly positive and significant. This suggests that there are omitted variables that are causing a bias in our results, and we are not seeing the true effect that pollution has on the housing market. Nonetheless, we are at least able to assess the relative importance of pollution in housing markets between MSA's. Our control variables (house characteristics and neighborhood characteristics) are significant across all risk types, and largely look as we expected, with the exception of kitchen facilities, which has a negative sign. This can likely be explained by the fact that almost all of the tracts in our dataset had 100% with kitchen facilities, so a few outlying tracts could easily cause a false negative in the sign.

ii. Regression of Race-Pollution on Race-Income

With four race types and three risk types, we ran the regression in Equation 3 ($RP_j = \alpha_1 RI_j + \varepsilon$) twelve times. The consolidated regression results and corresponding twelve scatter plots are shown below (**Table 3; Figures 7 - 18**):

Regression of Race-Health Risk Correlation on Race-Income Correlation												
	(1) White-HealthRisk on White-Income			(2) Black-HealthRisk on Black-Income			(3) Latino-HealthRisk on Latino-Income			(4) Asian-HealthRisk on Asian-Income		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.405*** (-5.50)	-0.437*** (-5.40)	-0.324*** (-3.92)	-0.610*** (-11.79)	-0.573*** (-10.31)	-0.543*** (-9.64)	-0.519*** (-11.32)	-0.564*** (-11.69)	-0.472*** (-9.47)	-0.409*** (-12.71)	-0.437*** (-13.03)	-0.347*** (-9.80)
Constant	-0.152*** (-3.29)	-0.129** (-2.55)	-0.194*** (-3.74)	0.0353 (1.26)	0.0536* (1.78)	0.0656** (2.15)	0.0548** (2.50)	0.0496** (2.15)	0.0817*** (3.42)	0.215*** (21.37)	0.201*** (19.14)	0.238*** (21.47)
Adj. R-sq.	0.083	0.080	0.043	0.299	0.246	0.221	0.282	0.296	0.215	0.332	0.343	0.227
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 3: Univariate regressions of race-health risk on race-income

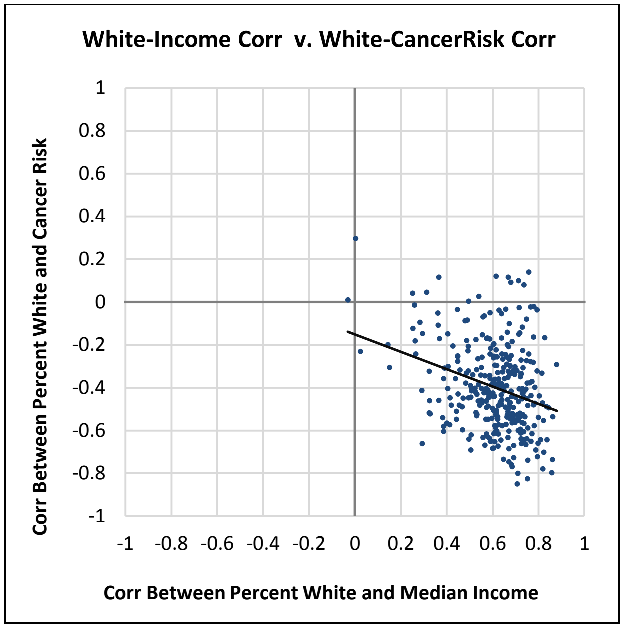

Figure 7

*RP = (-0.405)*RI + (-0.152)*

Slope t-stat: -5.50

Intercept t-stat: -3.29

Correlation: 0.293

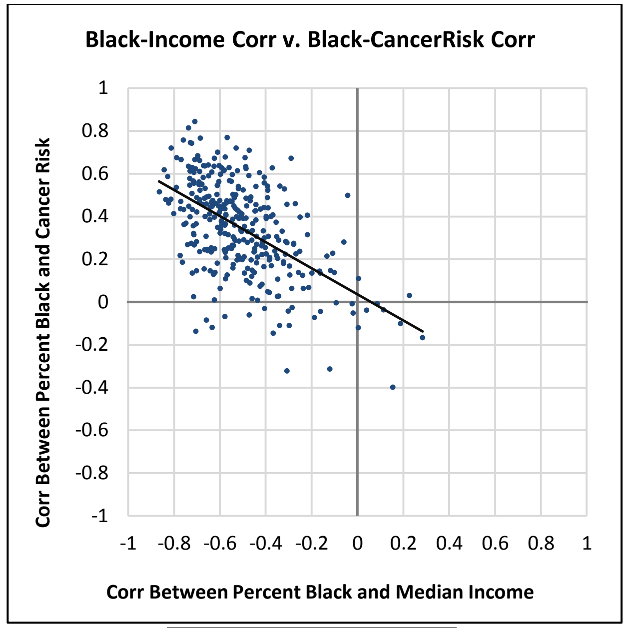

Figure 8

*RP = (-0.610)*RI + (0.0353)*

Race-Income t-stat: -11.79

Intercept t-stat: 1.26

Correlation: 0.549

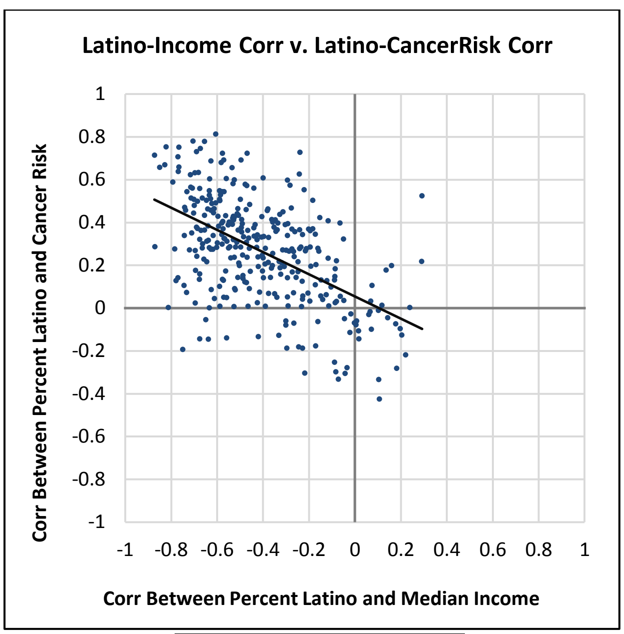

Figure 9

*RP = (-0.519)*RI + (0.0548)*

Race-Income t-stat: -11.32

Intercept t-stat: 2.50

Correlation: 0.534

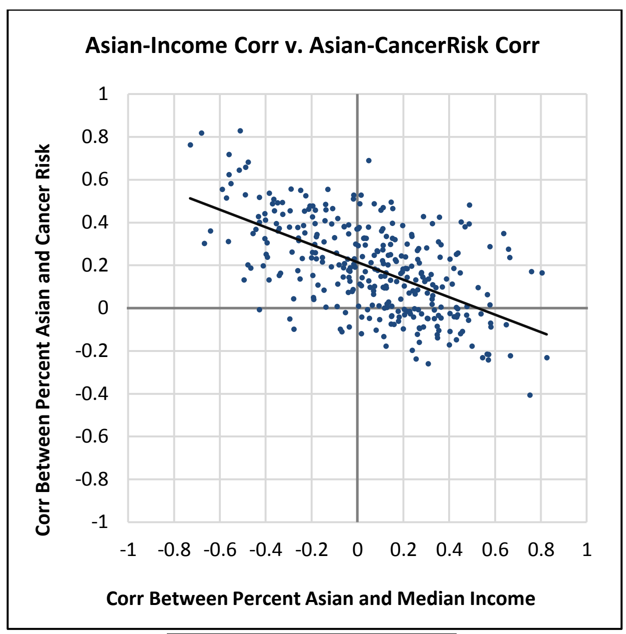

Figure 10

*RP = (-0.409)*RI + (0.215)*

Race-Income t-stat: -12.71

Intercept t-stat: 21.37

Correlation: 0.578

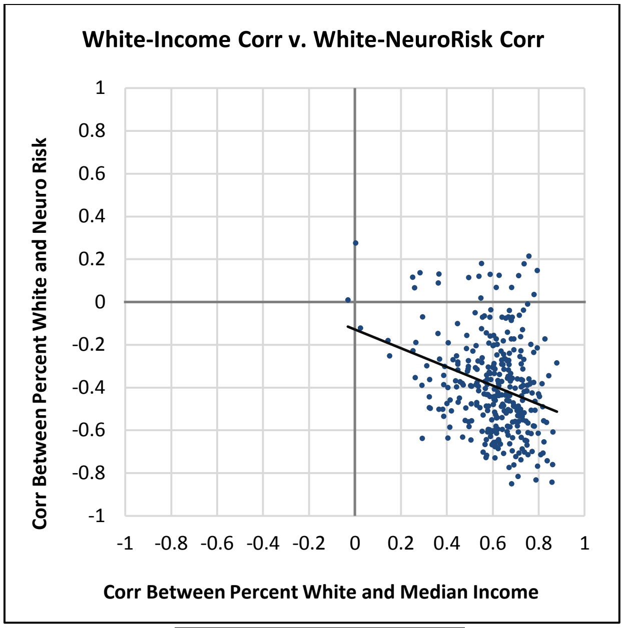

Figure 11

*RP = (-0.437)*RI + (-0.129)*

Race-Income t-stat: -5.40

Intercept t-stat: -2.55

Correlation: 0.288

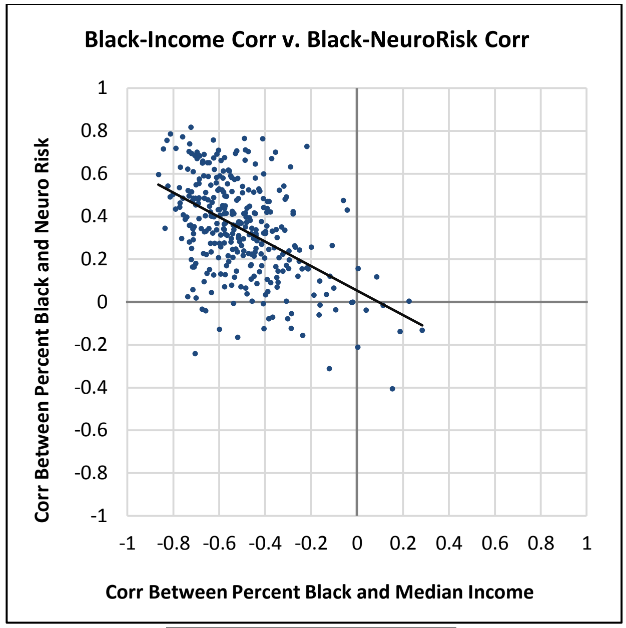

Figure 12

*RP = (-0.573)*RI + (0.0536)*

Race-Income t-stat: -10.31

Intercept t-stat: 1.78

Correlation: 0.498

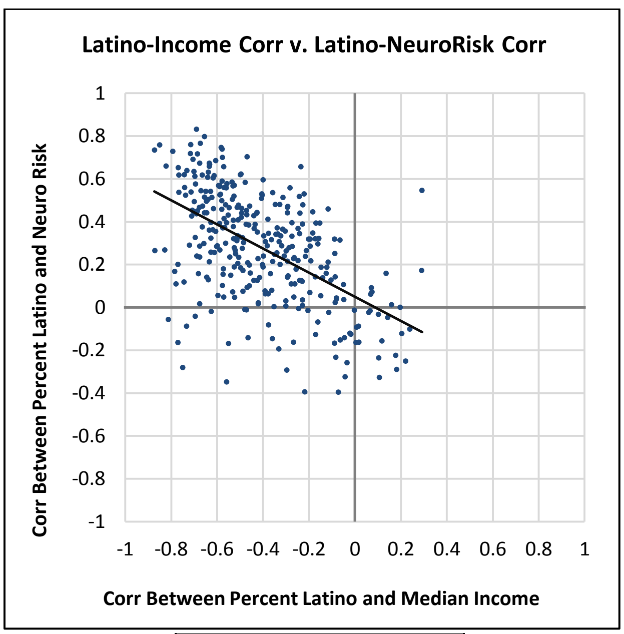

Figure 13

*RP = (-0.564)*RI + (0.0496)*

Race-Income t-stat: -11.69

Intercept t-stat: 2.15

Correlation: 0.546

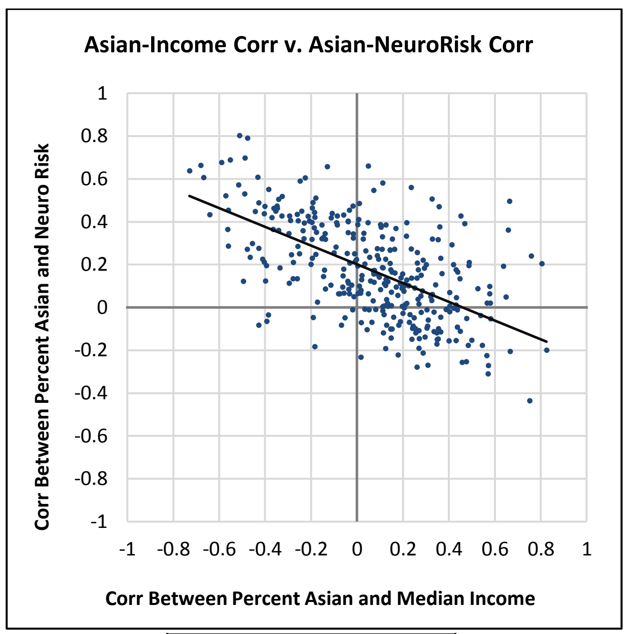

Figure 14

*RP = (-0.437)*RI + (0.201)*

Race-Income t-stat: -13.03

Intercept t-stat: 19.14

Correlation: 0.587

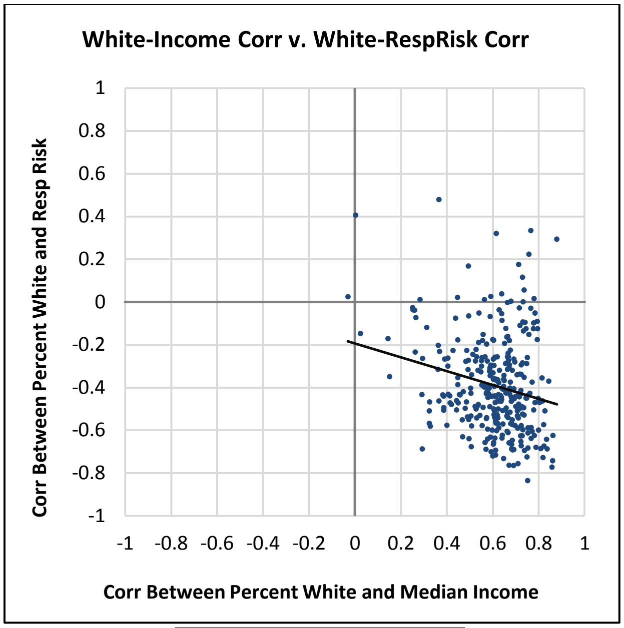

Figure 15

*RP = (-0.324)*RI + (-0.194)*

Race-Income t-stat: -3.92

Intercept t-stat: -3.74

Correlation: 0.212

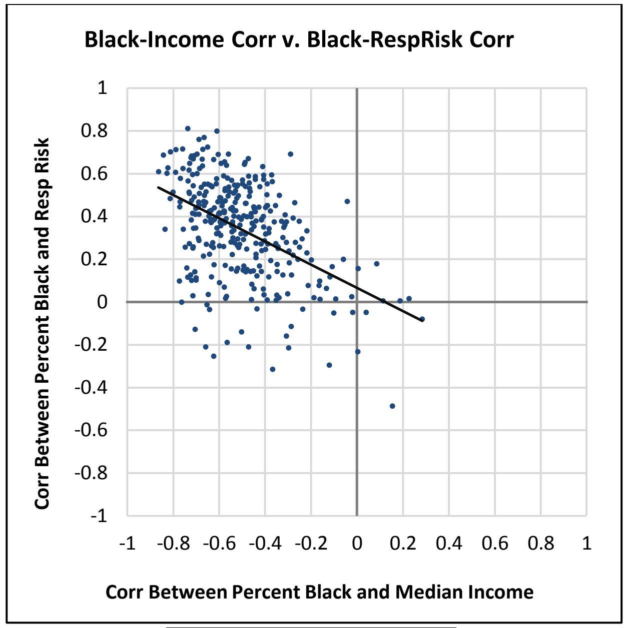

Figure 16

*RP = (-0.543)*RI + (0.0656)*

Race-Income t-stat: -9.64

Intercept t-stat: 2.15

Correlation: 0.473

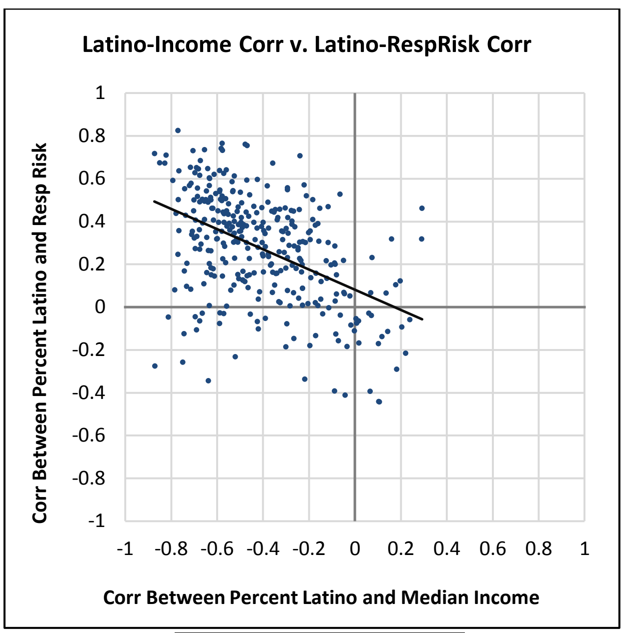

Figure 17

*RP = (-0.472)*RI + (0.0817)*

Race-Income t-stat: -9.47

Intercept t-stat: 3.42

Correlation: 0.467

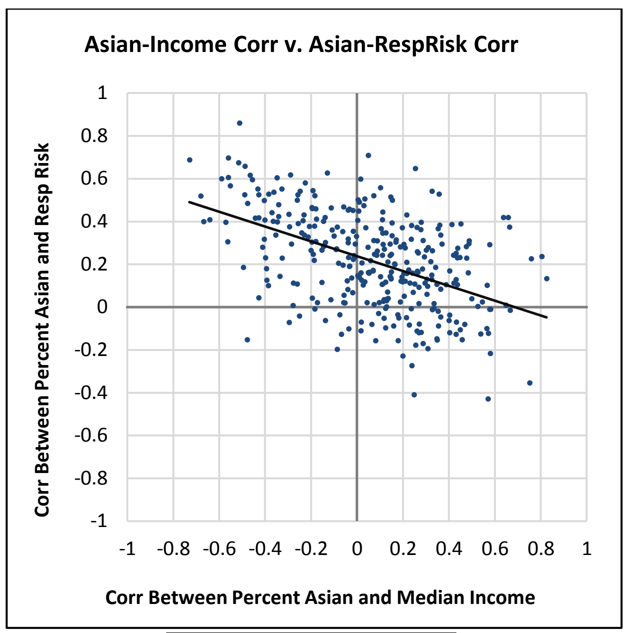

Figure 18

*RP = (-0.347)*RI + (0.238)*

Race-Income t-stat: -9.80

Intercept t-stat: 21.47

Correlation: 0.48

Overall, the consolidated results from Equation 3 (**Table 3)** show strong negative and significant relationships at the 1% level for all race and risk type combinations. These values are depicted by negatively sloped regression lines in all twelve of the scatter plots. For the black and Latino populations, as the race-income correlation approaches negative one (i.e. living in an area with a high percentage of minorities is highly correlated with low income levels), the race-health risk correlation approaches positive one (i.e. living in an area with a high percentage of minorities is highly correlated with living in a polluted area). For the white population, as the race-income correlation approaches positive one (i.e. living in an area with a high percent white is highly correlated with high income), the race-health risk correlation approaches negative one (i.e. living in an area with a high percent white is highly correlated with living in an unpolluted area). The Asian population, meanwhile, shows behavior somewhere between that exhibited by the white population and that exhibited by the Latino and black populations: the race-income correlations vary between approximately -0.8 and 0.8, and the race-health risk correlations correspondingly vary between roughly 0.8 and -0.4. For all four races, we see the same negative slope, supporting our hypothesis that as the percent of a race becomes more highly correlated with poverty (or wealth), it also becomes more highly correlated with pollution (or lack thereof).

Notably, these scatter plots show that the relationship between the race-income correlation and race-health risk correlation is weakest for the white population. The adjusted R-squared values of the univariate regression between these correlations are below 0.09 for all three risk types. The percent white-income correlation is positive for almost all MSA's, but the percent white-health risk correlations have a much wider distribution, resulting in a poor linear fit. Some MSA's may have very low minority populations at the MSA level or an uneven distribution of minority populations at the tract level, in which cases neither the race-income correlation nor the race-health risk correlation would be very informative, since most of the population is the same race. The regression in Equation 3 was repeated using only MSA's that had a white population less than 95% of the total (310 MSA's), and the race income coefficients were virtually unchanged while the R-squared values decreased. This result would indicate that the distribution may not be due to raw demographic percentages; however, it should be noted that variations of percentage white and percentage of a minority are inherently different. For example, in a typical MSA, a 10-percentage-point difference in percent white between two census tracts may only be 10-20% of the overall level (assuming a population that is 50-90% white), while a 10-percentage- point difference in percent of a particular minority may be as much as 100-1,000% of the overall level (assuming a population that is 1-10% of each minority group). Thus, in some MSA's, it may be the case that there is insufficient variation in percent white between tracts to obtain a meaningful correlation between percent white and health risk. Another explanation could be that health risk in these MSA's is highly correlated with industry, traffic, or some other unobserved variable. As a result, wealthy whites may be choosing to live in these areas, despite the pollution, resulting in data points in the upper right portion of the graphs, where there is a high white-income correlation but also a positive white-health risk correlation.

To test the other aspect of our hypothesis, that the race-pollution relationship is also dependent on the effect of pollution on house values, we repeat the regression in Equation 3 for each race and risk type, on the three categories of MSA's as we previously defined with respect to their hedonic regression slope coefficients ("most negative," "middle third," and "least negative"). We also produce three additional scatter plots for each race and risk type to visually represent the segmentation; the plots for Latinos and cancer risk are shown below as examples, (**Figures 19 - 22**), and the others can be seen in **Appendix D**.

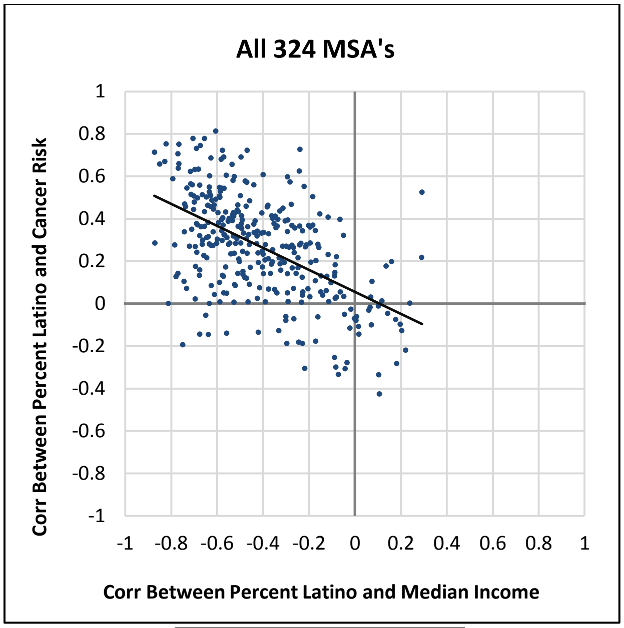

Figure 19

*RP = (-0.519)*RI + (0.0548)*

Race-Income t-stat: -11.32

Intercept t-stat: 2.50

Correlation: 0.534

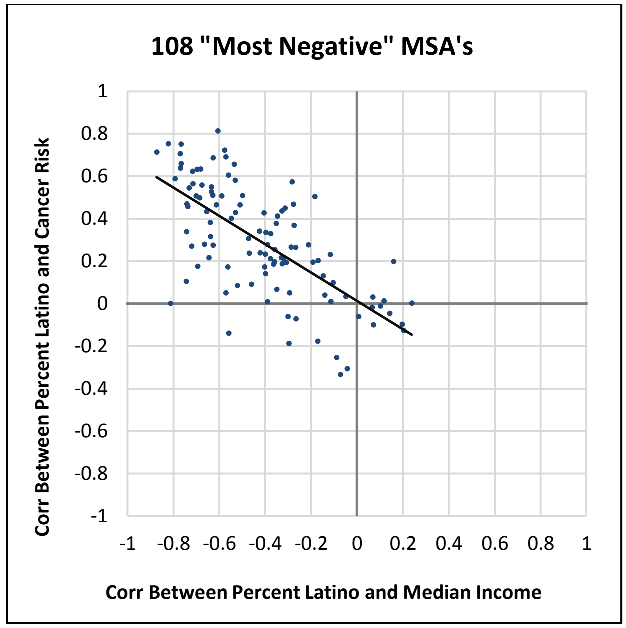

Figure 20

*RP = (-0.667)*RI + (0.0129)*

Race-Income t-stat: -9.72

Intercept t-stat: 0.38

Correlation: 0.686

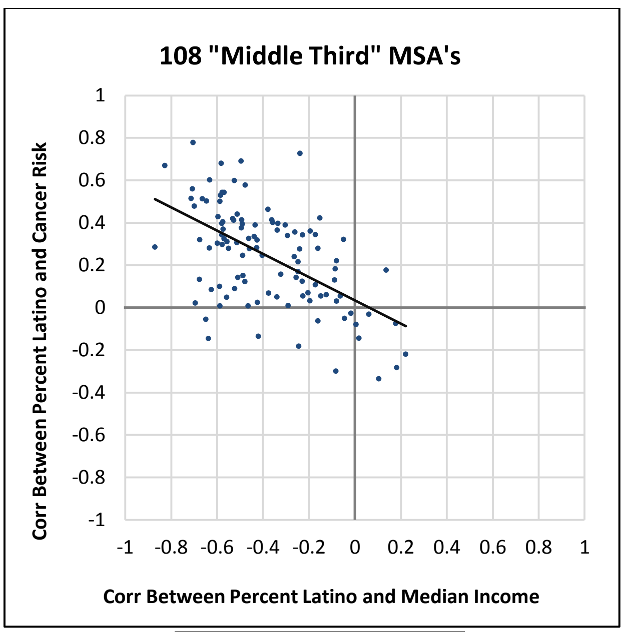

Figure 21

*RP = (-0.547)*RI + (0.0341)*

Race-Income t-stat: -6.90

Intercept t-stat: 0.95

Correlation: 0.557

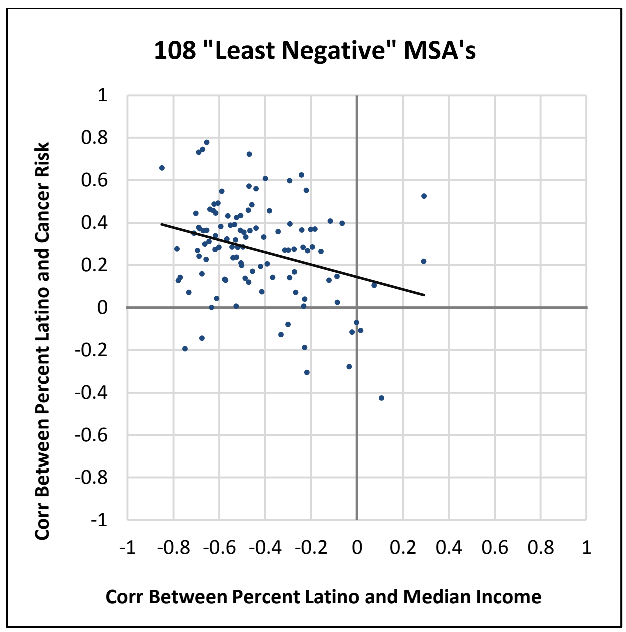

Figure 22

*RP = (-0.291)*RI + (0.144)*

Race-Income t-stat: -3.26

Intercept t-stat: 3.27

Correlation: 0.302

In these four graphs, and generally for each race and risk type, it can be clearly seen that the slope is steepest and the correlation is highest for the "most negative" third, while the relationships weaken in the "middle third" and are weakest in the "least negative" third. For a quantitative version of these graphs, the tables below show a side-by-side comparison of the regression results (**Tables 4 - 6**).

Single-Variate Regression by MSA Categories: Correlation between Race and Cancer Risk on Correlation between Race and Income, according to categorization by hedonic regression coefficients

	(1) White-CancerRisk Corr. on White-Income Corr.			(2) Black-CancerRisk Corr. on Black-Income Corr.			(3) Latino-CancerRisk Corr. on Latino-Income Corr.			(4) Asian-CancerRisk Corr. on Asian-Income Corr.		
	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative
Race-Income Correlation	-0.713*** (-5.44)	-0.470*** (-3.61)	-0.0642 (-0.53)	-0.721*** (-9.98)	-0.518*** (-4.40)	-0.490*** (-5.17)	-0.667*** (-9.72)	-0.547*** (-6.90)	-0.291*** (-3.26)	-0.447*** (-8.46)	-0.414*** (-7.55)	-0.327*** (-5.56)
Constant	0.0228 (0.26)	-0.123 (-1.56)	-0.322*** (-4.35)	-0.0161 (-0.38)	0.0982 (1.54)	0.0653 (1.40)	0.0129 (0.38)	0.0341 (0.95)	0.144*** (3.27)	0.178*** (10.07)	0.228*** (13.86)	0.240*** (13.51)
Adj. R-sq.	0.211	0.101	-0.007	0.479	0.146	0.194	0.466	0.304	0.083	0.397	0.344	0.218
N	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*

** = p<0.10, ** = p<0.05, *** = p<0.01*

Table 4: Model using cancer risk

Single-Variate Regression by MSA Categories: Correlation between Race and Neurological Risk on Correlation between Race and Income, according to categorization by hedonic regression coefficients

	(1) White-NeurologicalRisk Corr. on White-Income Corr.			(2) Black-NeurologicalRisk Corr. on Black-Income Corr.			(3) Latino-NeurologicalRisk Corr. on Latino-Income Corr.			(4) Asian-NeurologicalRisk Corr. on Asian-Income Corr.		
	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative
Race-Income Correlation	-0.662*** (-5.06)	-0.383** (-2.40)	-0.249** (-2.03)	-0.668*** (-7.98)	-0.397*** (-3.68)	-0.550*** (-5.46)	-0.807*** (-12.42)	-0.542*** (-6.17)	-0.333*** (-3.85)	-0.585*** (-10.21)	-0.354*** (-6.36)	-0.367*** (-6.32)
Constant	-0.0629 (-0.75)	-0.117 (-1.18)	-0.209*** (-2.80)	0.0426 (0.88)	0.133** (2.24)	0.0361 (0.73)	0.00884 (0.28)	0.0242 (0.59)	0.120*** (2.87)	0.181*** (10.21)	0.190*** (11.16)	0.244*** (13.00)
Adj. R-sq.	0.187	0.042	0.028	0.369	0.105	0.212	0.589	0.258	0.115	0.491	0.269	0.267
N	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*

** = p<0.10, ** = p<0.05, *** = p<0.01*

Table 5: Model using neurological risk

Single-Variate Regression by MSA Categories: Correlation between Race and Respiratory Risk on Correlation between Race and Income, according to categorization by hedonic regression coefficients												
	(1) White-RespiratoryRisk Corr. on White-Income Corr.			(2) Black-RespiratoryRisk Corr. on Black-Income Corr.			(3) Latino-RespiratoryRisk Corr. on Latino-Income Corr.			(4) Asian-RespiratoryRisk Corr. on Asian-Income Corr.		
	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative	Most Negative	Middle Third	Least Negative
Race-Income Correlation	-0.826*** (-5.58)	-0.110 (-0.78)	-0.0628 (-0.48)	-0.738*** (-7.03)	-0.440*** (-4.81)	-0.440*** (-4.32)	-0.725*** (-8.85)	-0.456*** (-5.23)	-0.201** (-2.39)	-0.424*** (-6.54)	-0.332*** (-5.23)	-0.276*** (-5.11)
Constant	0.0816 (0.86)	-0.324*** (-3.66)	-0.307*** (-3.83)	-0.0212 (-0.34)	0.130*** (2.66)	0.0757 (1.48)	-0.000407 (-0.01)	0.0993** (2.33)	0.168*** (4.15)	0.196*** (10.50)	0.232*** (11.73)	0.289*** (15.91)
Adj. R-sq.	0.220	-0.004	-0.007	0.311	0.171	0.142	0.420	0.198	0.042	0.281	0.198	0.190
N	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*	*108*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 6: Model using respiratory risk

Overall, these results support both of our hypotheses. First, the negative coefficients of race-income in all of the regressions show that as the race-income correlation becomes stronger (approaches -1 for minorities, or approaches 1 for whites), the race-health risk correlation likewise becomes stronger (approaches 1 for minorities, -1 for whites). Additionally, the fact that the coefficients are generally largest in the “most negative” MSA’s and smallest in the “least negative” MSA’s shows that the impact of the race-income relationship on the race-pollution relationship increases when the role of pollution in the housing market increases. There are a few exceptions; notably the black-neurological risk regression in **Table 5** has a slope-coefficient for the “least negative” MSA’s that is steeper than for the “middle third” by about 0.15.

After running the regression in Equations 3 for all races, risk types, and categories of MSA by hedonic slope coefficients, we decided to rerun the models, excluding MSA’s that had extremely low percentages of each respective minority. However, after experimenting with these cuts, we found no significant changes in results from Equation 3. Consequently, we decided to keep the dataset whole, rather than imposing arbitrary cutoffs.

Table 7 below shows the results of the regression in Equation 4 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}MN_j + \alpha_3 RI_j{*}LN_j + \varepsilon$), which sought to confirm statistically the impact of the housing market that is demonstrated in the graphs and tables above.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms Between Race-Income Correlation and Hedonic Slope Coefficient Dummies ("Most Negative" and "Least Negative" Hedonic Coefficients)												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.405*** (-5.04)	-0.336*** (-4.04)	-0.294*** (-3.42)	-0.616*** (-10.25)	-0.517*** (-8.35)	-0.535*** (-8.34)	-0.504*** (-8.38)	-0.495*** (-8.40)	-0.487*** (-8.06)	-0.410*** (-7.23)	-0.359*** (-6.28)	-0.338*** (-5.61)
"Most Negative" Hedonic Coefficients Interaction Term	-0.0322 (-0.77)	-0.198*** (-4.49)	-0.0934** (-2.03)	-0.0116 (-0.26)	-0.117** (-2.48)	-0.0470 (-0.97)	-0.0881 (-1.48)	-0.239*** (-3.99)	-0.0919 (-1.46)	-0.0770 (-1.01)	-0.258*** (-3.19)	-0.138 (-1.57)
"Least Negative" Hedonic Coefficients Interaction Term	0.0897** (2.09)	-0.0111 (-0.25)	0.0702 (1.49)	0.0851* (1.75)	0.0170 (0.33)	0.0938* (1.79)	0.0578 (0.97)	0.0384 (0.64)	0.132** (2.13)	0.0939 (1.18)	0.00663 (0.08)	0.0736 (0.90)
Constant	-0.163*** (-3.54)	-0.146*** (-2.99)	-0.206*** (-4.04)	0.0429 (1.51)	0.0633** (2.11)	0.0752** (2.47)	0.0571*** (2.61)	0.0503** (2.26)	0.0822*** (3.49)	0.217*** (21.54)	0.206*** (19.82)	0.241*** (21.74)
Adj. R-sq.	0.103	0.143	0.072	0.305	0.262	0.235	0.293	0.344	0.240	0.338	0.367	0.237
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 7: Model using interaction terms with dummy variables for hedonic slope coefficient categories

For all races and risk types, the coefficient on the interaction term with the “most negative third” dummy variable is negative, and for eleven of the twelve, the coefficient on the interaction term with the “least negative third” dummy variable is positive. This provides evidence that, as shown in the graphs and tables above, the relationship between the race-income correlation and the race-health risk correlation is stronger (more negative) in MSA’s where pollution has a more negative impact on house prices. In five of the twelve regressions, the “most negative third” interaction term is statistically significant, and the “least negative third” interaction term is significant in four of the twelve.

There are a few interesting cases to note. The only instance where the coefficient for the interaction term in the "least negative third" is negative (white-neurological risk), and thus contrary to our hypothesis, is not significant. Second, the puzzling relationship in **Table 5** that was mentioned above, between the middle and least negative thirds for black-neurological risk, is shown to be insignificant according to the results in **Table 7**. Finally, the coefficient for the "least negative" interaction term for black-respiratory risk indicates that there is a significant difference between the middle and the least negative thirds of black-respiratory risk in the direction that we expect (less negative); however, when looking at the results in **Table 6**, the race-income correlation coefficients between categories are identical to three decimal places.

Table 8, on the next page, shows the results of the regression in Equation 5 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j * \beta_{1j} + \varepsilon$), which interacts *RI* with the hedonic slope coefficient directly. Included in the table are the marginal effects of the race-income correlation on the race-pollution correlation, evaluated at the first, second, and third quartiles of the hedonic slope coefficient.

For all races and risk types, the slope coefficient for the race-income correlation is significant at the one-percent level and negative, as expected. Furthermore, for all races and risk types, the coefficient for the interaction term is positive, and it is significant for eleven of the twelve regressions. This indicates that as the hedonic pollution coefficient becomes more negative (i.e. pollution plays a stronger negative role in the housing market), the impact of the race-income correlation on the race-pollution correlation becomes more negative (greater in absolute value). In addition to this statistical significance, it can also be seen that the marginal effect of *RI* on *RP* increases as the hedonic slope coefficient becomes more negative. The most pronounced change can be seen in the Asian-health risk specification, in which the marginal effect changes by 0.1341 (35% of its value) when the hedonic slope coefficient is moved from its

75th percentile to its 25th percentile. This fits with our "causal chain" theory that the housing market is ultimately driving much the of the race-pollution relationship that has been found in previous literature.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Term Between Race-Income Correlation and Hedonic Slope Coefficient												
	(1) White-HealthRisk on White-Income and Interaction Term			(2) Black-HealthRisk on Black-Income and Interaction Term			(3) Latino-HealthRisk on Latino-Income and Interaction Term			(4) Asian-HealthRisk on Asian-Income and Interaction Term		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.366*** (-4.89)	-0.373*** (-4.64)	-0.279*** (-3.37)	-0.585*** (-10.82)	-0.526*** (-9.19)	-0.509*** (-8.84)	-0.499*** (-10.73)	-0.525*** (-11.11)	-0.453*** (-9.10)	-0.377*** (-11.29)	-0.404*** (-11.84)	-0.333*** (-9.42)
Interaction Term	0.106** (2.51)	0.255*** (4.26)	0.205*** (3.23)	0.0737 (1.58)	0.194*** (2.99)	0.162** (2.43)	0.130** (2.20)	0.401*** (4.98)	0.261*** (2.92)	0.224*** (3.07)	0.389*** (3.73)	0.285*** (2.82)
Constant	-0.166*** (-3.60)	-0.151*** (-3.04)	-0.211*** (-4.12)	0.0417 (1.48)	0.0651** (2.17)	0.0747** (2.45)	0.0554** (2.54)	0.0473** (2.12)	0.0824*** (3.49)	0.219*** (21.85)	0.206*** (19.83)	0.241*** (21.87)
Marginal Effect of RI on RP												
At 25th Percentile of Hedonic Slope Coefficient	-0.3997	-0.4411	-0.3242	-0.6087	-0.5782	-0.5446	-0.5405	-0.6322	-0.5099	-0.4489	-0.5081	-0.3954
At 50th Percentile of Hedonic Slope Coefficient	-0.3765	-0.3874	-0.2856	-0.5925	-0.5372	-0.5141	-0.5119	-0.5478	-0.4608	-0.3997	-0.4262	-0.3418
At 75th Percentile of Hedonic Slope Coefficient	-0.3564	-0.3532	-0.2543	-0.5785	-0.5112	-0.4894	-0.4871	-0.4942	-0.4210	-0.3572	-0.3740	-0.2984
Adj. R-sq.	0.098	0.127	0.070	0.302	0.264	0.233	0.291	0.344	0.233	0.349	0.369	0.244
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 8: Model using an interaction term with the hedonic slope coefficient

In **Table 9**, on the next page, we show the output of Equation 6 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j * t\_stat\_for\_\beta_{1j} + \varepsilon$), which uses the hedonic price regression t-statistics rather than the hedonic beta coefficients. Again, the marginal effects of *RI* on *RP* are shown, evaluated at the 25th, 50th, and 75th percentiles of the hedonic t-statistic. The results here are even stronger than those in **Table 8**. The race-income correlation coefficient is negative and significant at the one-percent level for all twelve race and risk types, just like in **Table 8**. The interaction coefficient similarly is positive and significant for all twelve combinations, and is significant at the one-percent level in ten out of twelve cases. This indicates that as the t-statistic becomes more negative, the impact of the race-income correlation on the race-pollution correlation becomes more negative and thus stronger. With regard to marginal effects, the largest change can again be seen in the Asian-neurological risk specification, although all race and risk-type combinations exhibit economically substantial changes in marginal effects when the t-statistic is allowed to vary across its interquartile range.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Term Between Race-Income Correlation and Hedonic T-Statistic												
	(1) White-HealthRisk on White-Income and Interaction Term			(2) Black-HealthRisk on Black-Income and Interaction Term			(3) Latino-HealthRisk on Latino-Income and Interaction Term			(4) Asian-HealthRisk on Asian-Income and Interaction Term		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.372*** (-5.08)	-0.402*** (-5.05)	-0.301*** (-3.67)	-0.573*** (-10.81)	-0.537*** (-9.49)	-0.509*** (-9.00)	-0.504*** (-10.93)	-0.537*** (-11.40)	-0.463*** (-9.34)	-0.382*** (-11.42)	-0.407*** (-11.97)	-0.340*** (-9.60)
Interaction Term	0.0240*** (3.49)	0.0266*** (3.92)	0.0234*** (3.19)	0.0217*** (2.77)	0.0215*** (2.76)	0.0267*** (3.21)	0.0224** (2.10)	0.0437*** (4.63)	0.0266** (2.55)	0.0417*** (2.67)	0.0526*** (3.60)	0.0345** (2.03)
Constant	-0.161*** (-3.55)	-0.137*** (-2.76)	-0.202*** (-3.95)	0.0441 (1.58)	0.0611** (2.04)	0.0748** (2.48)	0.0553** (2.53)	0.0472** (2.11)	0.0821*** (3.46)	0.217*** (21.71)	0.204*** (19.71)	0.239*** (21.64)
Marginal Effect of RI on RP												
At 25th Percentile of Hedonic T-Statistic	-0.4163	-0.4593	-0.3373	-0.6133	-0.5833	-0.5504	-0.5458	-0.6310	-0.5043	-0.4592	-0.5198	-0.3934
At 50th Percentile of Hedonic T-Statistic	-0.3889	-0.4167	-0.3071	-0.5884	-0.5490	-0.5160	-0.5202	-0.5610	-0.4701	-0.4114	-0.4356	-0.3490
At 75th Percentile of Hedonic T-Statistic	-0.3562	-0.3859	-0.2787	-0.5587	-0.5241	-0.4837	-0.4896	-0.5103	-0.4380	-0.3545	-0.3746	-0.3073
Adj. R-sq.	0.114	0.119	0.069	0.313	0.261	0.243	0.290	0.338	0.228	0.344	0.367	0.235
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 9: Model using an interaction term with the t-statistic from the hedonic regression

iii. Supplemental Regressions

Finally, the results from our supplemental regressions are shown below. **Table 10** shows the results of the regional regressions from Equation 7 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}South_j + \alpha_3 RI_j{*}West_j + \alpha_4 RI_j{*}Northeast_j + \varepsilon$). **Table 11** shows the p-values for a series of tests that were conducted to test for differences between the coefficients. Each value represents that likelihood that the two coefficients are equal. All pairings of coefficients were tested, so each region can be compared to each of the others. Stars indicate significance, and the coloration of the squares indicate which coefficient is greater; squares are white if the first coefficient listed in the pair is greater (i.e. less negative), while gray squares indicate that the second coefficient listed in the pair is greater.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms Between Race-Income Correlation and Region Dummies (South, West, and Northeast)												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.440*** (-5.53)	-0.453*** (-5.20)	-0.414*** (-4.69)	-0.626*** (-10.04)	-0.578*** (-8.88)	-0.609*** (-9.06)	-0.567*** (-9.43)	-0.568*** (-9.00)	-0.567*** (-8.70)	-0.467*** (-7.60)	-0.523*** (-8.20)	-0.336*** (-4.96)
South Region Interaction Term	0.0844* (1.95)	0.0975** (2.06)	0.163*** (3.39)	0.0555 (1.18)	0.0606 (1.23)	0.130** (2.55)	0.110* (1.66)	0.117* (1.69)	0.171** (2.40)	0.147* (1.79)	0.184** (2.17)	0.0611 (0.68)
West Region Interaction Term	0.199*** (3.74)	0.0969* (1.66)	0.255*** (4.32)	-0.0123 (-0.17)	-0.178** (-2.42)	0.0166 (0.22)	0.230*** (3.59)	0.158** (2.34)	0.300*** (4.31)	0.0566 (0.56)	0.159 (1.51)	-0.0883 (-0.79)
Northeast Region Interaction Term	-0.0693 (-1.35)	-0.163*** (-2.90)	-0.0413 (-0.72)	-0.0647 (-1.16)	-0.162*** (-2.79)	-0.0247 (-0.41)	-0.123* (-1.92)	-0.206*** (-3.07)	-0.0720 (-1.04)	-0.0385 (-0.39)	-0.0554 (-0.55)	-0.110 (-1.02)
Constant	-0.165*** (-3.67)	-0.135*** (-2.75)	-0.201*** (-4.04)	0.0317 (1.10)	0.0356 (1.18)	0.0578* (1.86)	0.0572*** (2.71)	0.0551** (2.49)	0.0830*** (3.63)	0.207*** (19.18)	0.191*** (17.13)	0.231*** (19.43)
Adj. R-sq.	0.147	0.152	0.128	0.306	0.293	0.241	0.345	0.360	0.287	0.336	0.355	0.229
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 10: Regressions categorized by geographic region

P-Values of Tests for Statistical Differences Between Regression Coefficients From Regression of Race-Health Risk Corr. on Race-Income Corr. and Interaction Terms Between Race-Income Corr. and Region Dummies												
	(1) White-HealthRisk on White-Income			(2) Black-HealthRisk on Black-Income			(3) Latino-HealthRisk on Latino-Income			(4) Asian-HealthRisk on Asian-Income		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
South v. West	0.0184**	0.9898	0.0870*	0.3108	0.0007***	0.1177	0.0674*	0.5597	0.0726*	0.3577	0.8023	0.1660
South v. Northeast	0.0009***	< 0.0001***	0.0001***	0.0170**	0.0001***	0.0046***	0.0005***	0.0001***	0.0007***	0.0500*	0.0145**	0.0997*
West v. Northeast	< 0.0001***	0.0001***	< 0.0001***	0.4734	0.8343	0.6007	< 0.0001***	< 0.0001***	< 0.0001***	0.3941	0.0645*	0.8594
Midwest v. South	0.0526*	0.0404**	0.0008***	0.2403	0.2201	0.0114**	0.0972*	0.0913*	0.0172**	0.0745*	0.0306**	0.4992
Midwest v. West	0.0002***	0.0974*	< 0.0001***	0.8615	0.0162**	0.8277	0.0004***	0.0199**	< 0.0001***	0.5786	0.1329	0.4321
Midwest v. Northeast	0.1785	0.0040***	0.4693	0.2461	0.0057***	0.6813	0.0555*	0.0024***	0.3003	0.6945	0.5861	0.3086
	** = p<0.10, ** = p<0.05, *** = p<0.01*											

White boxes indicate tests where the second coefficient listed is more negative than the first coefficient (e.g. in the South v. Northeast comparison in the White-Cancer Risk model, the Northeast coefficient is more negative (significant at the 1% level)). Gray boxes indicate tests where the first coefficient is more negative (e.g. in the South v. West comparison in the White-Cancer Risk model, the South coefficient is more negative (significant at the 5% level)).

Table 11: P-values for tests of differences between regional coefficients

In **Table 10**, the coefficient on the interaction term is negative for all four races in the Northeast, and it is significant in three of the four, suggesting that the effect of the race-income correlation on the race-pollution correlation is stronger (more negative) in Northeastern MSA's than in the Midwest. This is further supported by the results in **Table 11**, which shows that the coefficient on the Northeast-interaction term is significantly more negative than the coefficient on the South-interaction term in every specification, and than the West and Midwest in many. Results for the other three regions are less conclusive, but the coefficient on the interaction terms for the South and West regions seem to be less negative than those for the Midwest. Our results indicate that the relationship between the correlations of interest is weaker in the South and on the West Coast than in the Midwest, which is weaker than in the Northeast. The nuances of the differences between regions are not explored in this analysis, nor the dynamics that give rise to such differences, but are recommended for future study.

Table 12, below, shows the results of the regression in Equations 8 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j * LargePop_j + \alpha_3 RI_j * SmallPop_j + \varepsilon$).

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms Between Race-Income Correlation and MSA Population Dummies (Large Population and Small Population)												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.377*** (-4.85)	-0.432*** (-5.04)	-0.307*** (-3.52)	-0.579*** (-9.90)	-0.574*** (-9.14)	-0.509*** (-8.00)	-0.457*** (-8.38)	-0.494*** (-8.61)	-0.414*** (-6.96)	-0.383*** (-7.09)	-0.442*** (-7.90)	-0.419*** (-7.09)
Large Population Interaction Term	-0.0760 (-1.49)	-0.0543 (-0.97)	-0.114** (-1.99)	0.0368 (0.62)	0.0913 (1.44)	0.0304 (0.47)	-0.0728 (-0.99)	-0.129* (-1.67)	-0.128 (-1.60)	-0.160 (-1.33)	-0.219* (-1.76)	-0.0555 (-0.42)
Small Population Interaction Term	-0.0467 (-1.23)	-0.0117 (-0.28)	-0.0338 (-0.80)	-0.0459 (-1.11)	0.00372 (0.08)	-0.0494 (-1.10)	-0.106** (-2.05)	-0.115** (-2.10)	-0.0920 (-1.63)	-0.0241 (-0.35)	0.0384 (0.54)	0.132* (1.77)
Constant	-0.148*** (-3.17)	-0.123** (-2.40)	-0.182*** (-3.49)	0.0438 (1.53)	0.0621** (2.02)	0.0738** (2.37)	0.0552** (2.50)	0.0481** (2.08)	0.0796*** (3.32)	0.217*** (21.10)	0.205*** (19.23)	0.242*** (21.46)
Adj. R-sq.	0.085	0.077	0.048	0.300	0.246	0.222	0.287	0.303	0.220	0.332	0.348	0.233
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 12: Population analysis

In contrast to our previous results, this regression does not have any significant trends that clearly hold across all races and risk types. There is weak evidence that the relationship between the correlations of interest is increased in MSA's with populations over one million, but it is only significant in three of the twelve models, and at the five percent level, only in one. Of the three models that show significance of small populations (less than 250,000 residents), two have a negative sign (Latino-cancer risk and Latino-neurological risk) while one is positive (Asian-respiratory risk). Many of the models have negative signs on both the large and small population interaction terms; at first glance, this seems contradictory, but in theory it is possible that the relationship between *RI* and *RP* is weakest in mid-sized cities (populations between 250,000 and 1,000,000), which is what the results for those models indicate. On the whole, given the differences between models, it seems safe to conclude that population does not play an essential role in determining how *RI* informs *RP*, and that our results hold for MSA's of all sizes.

Tables 13 and 14, on the next page, show the results of Equation 9 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}HighRisk_j + \alpha_3 RI_j{*}LowRisk_j + \varepsilon$) and Equation 11 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}AverageRisk_j + \varepsilon$), respectively.

As with the results of the population analysis, there are no universal trends with respect to average health risk. In both tables, there is evidence that higher neurological risk weakens the relationship between the correlations of interest, for all races except Asian. It is unclear what would cause this, except that the distribution of neurological risk had a very strong positive skew, so it may be that a few MSA's with high risk levels is creating a bias in the data. Otherwise, with varied signs, only occasional significance, and relatively small marginal effects, it does not seem that average risk has any consistently important effect on the relationship between race-income and race-pollution.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms Between Race-Income Correlation and Average Health Risk Dummies (High Avg. Risk and Low Avg. Risk)												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.362*** (-4.55)	-0.492*** (-6.00)	-0.319*** (-3.65)	-0.594*** (-10.06)	-0.582*** (-9.97)	-0.528*** (-8.64)	-0.479*** (-8.38)	-0.689*** (-11.85)	-0.495*** (-7.52)	-0.384*** (-6.75)	-0.442*** (-8.05)	-0.353*** (-5.75)
High Avg. Risk Interaction Term	-0.0769* (-1.81)	0.165*** (3.66)	-0.00819 (-0.17)	-0.0167 (-0.35)	0.124** (2.56)	0.0321 (0.63)	-0.0607 (-1.05)	0.262*** (4.31)	0.0175 (0.26)	-0.136 (-1.60)	-0.0343 (-0.40)	-0.0538 (-0.58)
Low Avg. Risk Interaction Term	-0.0436 (-1.03)	0.0586 (1.29)	-0.00931 (-0.20)	-0.0275 (-0.60)	-0.0601 (-1.24)	-0.0481 (-0.98)	-0.0566 (-0.95)	0.137** (2.28)	0.0392 (0.61)	0.0161 (0.22)	0.0339 (0.44)	0.0416 (0.52)
Constant	-0.154*** (-3.33)	-0.141*** (-2.82)	-0.193*** (-3.70)	0.0363 (1.28)	0.0598** (2.01)	0.0700** (2.28)	0.0552** (2.51)	0.0551** (2.44)	0.0808*** (3.36)	0.216*** (21.50)	0.202*** (19.09)	0.239*** (21.43)
Adj. R-sq.	0.087	0.112	0.037	0.296	0.272	0.223	0.281	0.330	0.211	0.336	0.341	0.225
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 13: Average health risk analysis with dummy interaction variables

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Term Between Race-Income Correlation and Average Risk												
	(1) White-HealthRisk on White-Income and Interaction Term			(2) Black-HealthRisk on Black-Income and Interaction Term			(3) Latino-HealthRisk on Latino-Income and Interaction Term			(4) Asian-HealthRisk on Asian-Income and Interaction Term		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.370*** (-4.29)	-0.500*** (-5.93)	-0.341*** (-3.99)	-0.628*** (-8.40)	-0.632*** (-9.98)	-0.616*** (-10.11)	-0.509*** (-6.18)	-0.666*** (-11.03)	-0.488*** (-8.21)	-0.105 (-0.94)	-0.449*** (-6.51)	-0.254*** (-3.76)
Interaction Term	-0.00111 (-0.78)	0.880** (2.45)	0.00502 (0.81)	0.000575 (0.32)	0.874* (1.91)	0.0245*** (2.95)	-0.000291 (-0.15)	1.214*** (2.76)	0.00400 (0.49)	-0.00947*** (-2.83)	0.157 (0.20)	-0.0258 (-1.61)
Constant	-0.149*** (-3.23)	-0.137*** (-2.72)	-0.197*** (-3.79)	0.0367 (1.29)	0.0610** (2.02)	0.0814*** (2.66)	0.0547** (2.49)	0.0520** (2.27)	0.0823*** (3.43)	0.217*** (21.74)	0.201*** (19.10)	0.240*** (21.53)
Marginal Effect of RI on RP												
At 25th Percentile of Average Risk	-0.3997	-0.4526	-0.3284	-0.6125	-0.5850	-0.5567	-0.5162	-0.6008	-0.4784	-0.3542	-0.4408	-0.3166
At 50th Percentile of Average Risk	-0.4069	-0.4403	-0.3231	-0.6088	-0.5727	-0.5309	-0.5181	-0.5838	-0.4742	-0.4150	-0.4386	-0.3438
At 75th Percentile of Average Risk	-0.4154	-0.4166	-0.3135	-0.6044	-0.5492	-0.4841	-0.5203	-0.5511	-0.4666	-0.4875	-0.4344	-0.3931
Adj. R-sq.	0.082	0.094	0.041	0.297	0.252	0.240	0.280	0.310	0.213	0.346	0.341	0.231
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 14: Average health risk analysis with continuous interaction variable

Tables 15 and 16 show the results of Equation 10 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}LargeGap_j + \alpha_3 RI_j{*}SmallGap_j + \varepsilon$) and Equation 12 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}IncomeGap_j + \varepsilon$), respectively.

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms Between Race-Income Correlation and Income Gap Dummies (Large Income Gap and Small Income Gap)												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.403*** (-5.41)	-0.436*** (-5.35)	-0.322*** (-3.86)	-0.606*** (-11.47)	-0.568*** (-10.00)	-0.536*** (-9.33)	-0.526*** (-11.12)	-0.560*** (-11.26)	-0.484*** (-9.40)	-0.437*** (-12.62)	-0.456*** (-12.65)	-0.356*** (-9.22)
Large Income Gap Interaction Term	-0.0258 (-0.43)	-0.118* (-1.81)	-0.0431 (-0.64)	0.0536 (0.77)	-0.0174 (-0.23)	0.0629 (0.83)	0.0349 (0.46)	-0.0927 (-1.16)	0.0459 (0.55)	-0.0937 (-0.82)	-0.185 (-1.55)	-0.146 (-1.15)
Small Income Gap Interaction Term	-0.0127 (-0.21)	0.0103 (0.16)	-0.00507 (-0.08)	-0.0302 (-0.48)	-0.0299 (-0.44)	-0.0460 (-0.67)	0.0509 (0.52)	0.0680 (0.67)	0.0873 (0.83)	0.362*** (3.56)	0.346*** (3.26)	0.210* (1.85)
Constant	-0.151*** (-3.26)	-0.123** (-2.44)	-0.192*** (-3.69)	0.0385 (1.36)	0.0539* (1.77)	0.0696** (2.26)	0.0547** (2.48)	0.0488** (2.11)	0.0814*** (3.40)	0.209*** (20.91)	0.196*** (18.73)	0.235*** (21.00)
Adj. R-sq.	0.078	0.084	0.038	0.297	0.242	0.220	0.279	0.296	0.213	0.356	0.367	0.235
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 15: Income gap analysis with dummy interaction variables

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Term Between Race-Income Correlation and 95%-5% Income Gap												
	(1) White-HealthRisk on White-Income and Interaction Term			(2) Black-HealthRisk on Black-Income and Interaction Term			(3) Latino-HealthRisk on Latino-Income and Interaction Term			(4) Asian-HealthRisk on Asian-Income and Interaction Term		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.400*** (-4.61)	-0.340*** (-3.59)	-0.304*** (-3.13)	-0.683*** (-9.68)	-0.582*** (-7.65)	-0.656*** (-8.58)	-0.549*** (-6.88)	-0.448*** (-5.37)	-0.498*** (-5.74)	-0.260*** (-2.65)	-0.167 (-1.65)	-0.165 (-1.54)
Interaction Term	-1.26E-7 (-0.12)	-2.29E-6* (-1.96)	-4.74E-7 (-0.40)	1.78E-6 (1.50)	2.11E-7 (0.16)	2.79E-6** (2.17)	6.44E-7 (0.46)	-2.48E-6* (-1.69)	5.53E-7 (0.36)	-3.40E-6 (-1.61)	-6.16E-6*** (-2.82)	-4.13E-6* (-1.78)
Constant	-0.151*** (-3.27)	-0.123** (-2.44)	-0.192*** (-3.71)	0.0408 (1.44)	0.0543* (1.78)	0.0741** (2.42)	0.0552** (2.51)	0.0483** (2.09)	0.0819*** (3.42)	0.215*** (21.42)	0.201*** (19.34)	0.238*** (21.54)
Marginal Effect of RI on RP												
At 25th Percentile of Income Gap	-0.4046	-0.4210	-0.3208	-0.6195	-0.5744	-0.5570	-0.5259	-0.5363	-0.4784	-0.3801	-0.3852	-0.3118
At 50th Percentile of Income Gap	-0.4058	-0.4420	-0.3251	-0.6032	-0.5725	-0.5315	-0.5200	-0.5590	-0.4734	-0.4113	-0.4415	-0.3497
At 75th Percentile of Income Gap	-0.4070	-0.4655	-0.3300	-0.5849	-0.5703	-0.5028	-0.5134	-0.5845	-0.4677	-0.4463	-0.5048	-0.3922
Adj. R-sq.	0.080	0.088	0.040	0.302	0.243	0.230	0.281	0.300	0.213	0.335	0.357	0.232
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 16: Income gap analysis with continuous interaction variable

The results of the dummy-interaction analysis are largely insignificant, but there are a few coefficients that are statistically significant: the significant positive signs on the small income-gap interaction term in all three Asian models and the significant negative sign on the large income-gap interaction term in the white-neurological model provide some evidence that as income gap increases, the *RI*-*RP* relationship strengthens (becomes more negative). This is supported by a number of the results in **Table 16**, although not all. Four of the interaction terms have significant negative signs, while only one has a significant positive sign. Interestingly, although the marginal effect of *RI* on *RP* changes considerably as income gap varies in the Asian-neurological specification, none of the other models show notable change in the marginal effects. Combined with the inconsistency in signs of the coefficients, this lack of economically relevant marginal effects suggests that, despite the few instances of statistical significance, income gap between the rich and the poor may not play any real role in determining how *RI* is related to *RP*.

The results of the income-gap analysis are put into context by the results of Equations 13 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}MSA\_MedianIncome_j + \varepsilon$) and 14 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}IncomeGap_j + \alpha_3 RI_j{*}MSA\_MedianIncome_j + \varepsilon$), which use median income. These results are shown in **Table 17 and Table 18**, respectively:

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Term Between Race-Income Correlation and Overall MSA Median Income												
	(1) White-HealthRisk on White-Income and Interaction Term			(2) Black-HealthRisk on Black-Income and Interaction Term			(3) Latino-HealthRisk on Latino-Income and Interaction Term			(4) Asian-HealthRisk on Asian-Income and Interaction Term		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.219** (-2.13)	-0.0871 (-0.79)	-0.111 (-0.96)	-0.574*** (-5.59)	-0.376*** (-3.43)	-0.565*** (-5.06)	-0.389*** (-3.35)	-0.271** (-2.25)	-0.339*** (-2.69)	-0.216 (-1.52)	-0.0668 (-0.45)	-0.0539 (-0.35)
Interaction Term	-5.16E-6** (-2.57)	-9.69E-6*** (-4.48)	-5.90E-6** (-2.62)	-9.70E-7 (-0.42)	-5.19E-6** (-2.09)	5.84E-7 (0.23)	-3.05E-6 (-1.22)	-6.87E-6*** (-2.63)	-3.13E-6 (-1.15)	-4.78E-6 (-1.39)	-9.16E-6** (-2.58)	-7.24E-6* (-1.93)
Constant	-0.138*** (-2.99)	-0.102** (-2.07)	-0.177*** (-3.44)	0.0339 (1.20)	0.0461 (1.53)	0.0664** (2.16)	0.0550** (2.51)	0.0499** (2.18)	0.0818*** (3.42)	0.212*** (20.44)	0.194*** (18.12)	0.233*** (20.47)
Marginal Effect of RI on RP												
At 25th Percentile of Median Income	-0.4000	-0.4267	-0.3178	-0.6075	-0.5582	-0.5445	-0.4958	-0.5122	-0.4487	-0.3831	-0.3877	-0.3077
At 50th Percentile of Median Income	-0.4239	-0.4717	-0.3451	-0.6120	-0.5823	-0.5418	-0.5099	-0.5441	-0.4632	-0.4053	-0.4302	-0.3413
At 75th Percentile of Median Income	-0.4511	-0.5227	-0.3762	-0.6172	-0.6096	-0.5387	-0.5260	-0.5802	-0.4797	-0.4304	-0.4784	-0.3794
Adj. R-sq.	0.099	0.132	0.06	0.297	0.254	0.219	0.283	0.309	0.216	0.334	0.355	0.234
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 17: Median income analysis with continuous interaction variable

Regression of Race-Health Risk Correlation on Race-Income Correlation and Two Interaction Terms: Race-Income Correlation * Income Gap, and Race-Income Correlation * MSA Median Income												
	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Coefficients & t-Statistics												
Race-Income Correlation	-0.196* (-1.91)	-0.0702 (-0.63)	-0.0892 (-0.77)	-0.518*** (-4.98)	-0.321*** (-2.89)	-0.497*** (-4.41)	-0.353*** (-3.02)	-0.265** (-2.17)	-0.304** (-2.39)	-0.221 (-1.55)	-0.0760 (-0.52)	-0.0582 (-0.37)
First Interaction Term (RaceIncome*IncomeGap)	3.63E-6** (2.44)	2.68E-6* (1.67)	3.48E-6** (2.08)	4.37E-6*** (2.59)	4.31E-6** (2.39)	5.28E-6*** (2.89)	4.03E-6** (1.98)	6.78E-7 (0.32)	3.90E-6* (1.76)	-2.63E-6 (-0.89)	-4.31E-6 (-1.40)	-1.96E-6 (-0.60)
Second Interaction Term (RaceIncome*MedianIncome)	-1.01E-5*** (-3.55)	-1.33E-5*** (-4.35)	-1.06E-5*** (-3.33)	-7.10E-6** (-2.15)	-1.12E-5*** (-3.18)	-6.83E-6* (-1.90)	-8.30E-6** (-2.29)	-7.75E-6** (-2.03)	-8.22E-6** (-2.08)	-1.78E-6 (-0.37)	-4.25E-6 (-0.85)	-5.01E-6 (-0.95)
Constant	-0.134*** (-2.92)	-0.0993** (-2.01)	-0.173*** (-3.38)	0.0384 (1.36)	0.0505* (1.68)	0.0718** (2.35)	0.0574*** (2.62)	0.0503** (2.19)	0.0841*** (3.53)	0.214*** (20.10)	0.198*** (17.99)	0.234*** (20.05)
Marginal Effect of RI on RP												
At 25th Percentiles of IncomeGap & MedianIncome	-0.4202	-0.4417	-0.3372	-0.6119	-0.5624	-0.5497	-0.5012	-0.5131	-0.4539	-0.3770	-0.3778	-0.3031
At 50th Percentiles of IncomeGap & MedianIncome	-0.4336	-0.4789	-0.3545	-0.6048	-0.5752	-0.5331	-0.5028	-0.5429	-0.4563	-0.4094	-0.4370	-0.3443
At 75th Percentiles of IncomeGap & MedianIncome	-0.4493	-0.5214	-0.3745	-0.5973	-0.5901	-0.5147	-0.5051	-0.5767	-0.4595	-0.4459	-0.5037	-0.3909
Adj. R-sq.	0.112	0.136	0.069	0.31	0.264	0.237	0.29	0.307	0.221	0.333	0.357	0.232
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*
** = p<0.10, ** = p<0.05, *** = p<0.01*												

Table 18: Income gap and median income analysis with continuous interaction variables

Between the two tables, the coefficients on the median income interaction terms are negative for all race and risk type combinations except one, and are significant for 16 out of 24. This provides strong evidence that as median income increases, *RI* has a stronger (more negative) effect on *RP*. This is an intriguing result; one might expect that the relationship between the correlations of interest would be strongest in the poorest MSA's, but it seems that the opposite is true. Also of note is that in **Table 18**, the signs on the income-gap interaction terms are positive for 9 of the 12 and significant for 8 of those 9, in sharp contrast to the results seen in **Tables 15-16**. The discrepancy between these outcomes can be explained by the fact that income-gap and MSA-level median income are correlated. Without controlling for median income, there is an omitted variable bias, leading to the results seen in **Tables 15-16**; when we include the median income interaction term in Equation 14, we remove this bias, and reveal the true impact that income-gap has on the relationship between *RI* and *RP*. Specifically, we can see that as income-gap increases, the effect of *RI* on *RP* becomes less pronounced.

At this point in the analysis, there is varied evidence of particular MSA-level characteristics influencing the relationship between the correlations of interest. We run one final regression to assess whether controlling for these characteristics simultaneously changes how they perform. **Table 19** shows the results of Equation 15 ($RP_j = \alpha_1 RI_j + \alpha_2 RI_j{*}\beta_{1j} + \alpha_3 RI_j{*}IncomeGap_j + \alpha_4 RI_j{*}MSA\_MedianIncome_j + \alpha_5 RI_j{*}AverageRisk_k + \alpha_6 RI_j{*}LargePop_j + \alpha_7 RI_j{*}SmallPop_j + \alpha_8 RI_j{*}South_j + \alpha_9 RI_j{*}West_j + \alpha_{10} RI_j{*}Northeast_j + \varepsilon$).

Regression of Race-Health Risk Correlation on Race-Income Correlation and Interaction Terms with Nine Other Variables

	(1) White-HealthRisk on White-Income and Interaction Terms			(2) Black-HealthRisk on Black-Income and Interaction Terms			(3) Latino-HealthRisk on Latino-Income and Interaction Terms			(4) Asian-HealthRisk on Asian-Income and Interaction Terms		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Race-Income Correlation	-0.143 (-0.97)	-0.127 (-0.86)	-0.266* (-1.81)	-0.560*** (-3.37)	-0.521*** (-3.24)	-0.734*** (-4.63)	-0.353** (-2.09)	-0.276* (-1.75)	-0.496*** (-3.04)	-0.0708 (-0.29)	-0.292 (-1.28)	-0.271 (-1.17)
Hedonic Slope Coefficient Interaction Term	0.0898** (2.17)	0.245*** (4.21)	0.176*** (2.85)	0.0734 (1.56)	0.205*** (3.19)	0.166** (2.49)	0.0822 (1.40)	0.384*** (4.87)	0.183** (2.05)	0.215*** (2.90)	0.355*** (3.27)	0.257** (2.45)
Income Gap Interaction Term	4.46E-6*** (2.54)	1.93E-6 (1.05)	3.63E-6* (1.87)	2.97E-6 (1.46)	1.66E-6 (0.80)	2.50E-6 (1.15)	3.43E-6* (1.57)	-9.45E-7 (-0.43)	2.90E-6 (1.20)	-2.56E-6 (-0.72)	-3.59E-6 (-0.98)	6.59E-7 (0.17)
MSA Median Income Interaction Term	-9.49E-6*** (-2.93)	-1.01E-5*** (-2.92)	-7.62E-6** (-2.14)	-2.82E-6 (-0.70)	-3.60E-6 (-0.87)	1.15E-7 (0.03)	-4.49E-6 (-1.15)	-3.39E-6 (-0.86)	-3.41E-6 (-0.81)	5.64E-6 (1.00)	-7.31E-7 (-0.12)	-3.50E-6 (-0.55)
Average Risk Interaction Term	-0.00174 (-0.96)	0.953** (2.57)	0.0120 (1.58)	-0.000535 (-0.23)	1.094** (2.35)	0.0256** (2.30)	-0.00235 (-0.94)	0.983** (2.12)	0.00745 (0.72)	-0.0118** (-2.50)	0.523 (0.65)	0.00411 (0.17)
Large Population Interaction Term	-0.102* (-1.84)	-0.0916 (-1.59)	-0.195*** (-3.18)	-0.00538 (-0.08)	0.0370 (0.56)	-0.0864 (-1.24)	-0.114 (-1.43)	-0.185** (-2.38)	-0.236*** (-2.71)	-0.0458 (-0.35)	-0.200 (-1.52)	-0.0624 (-0.41)
Small Population Interaction Term	-0.0442 (-1.07)	-0.0273 (-0.65)	0.00380 (0.08)	-0.0373 (-0.78)	-0.000651 (-0.01)	0.0101 (0.20)	-0.112* (-2.00)	-0.149*** (-2.73)	-0.0635 (-1.07)	-0.149* (-1.82)	-0.0225 (-0.29)	0.111 (1.27)
South Region Interaction Term	0.0262 (0.56)	0.0262 (0.52)	0.113** (2.20)	0.0361 (0.69)	0.0331 (0.61)	0.103* (1.83)	0.0755 (1.06)	0.0545 (0.75)	0.153** (1.99)	0.106 (1.16)	0.114 (1.18)	0.0187 (0.18)
West Region Interaction Term	0.184*** (3.42)	0.0238 (0.41)	0.212*** (3.52)	-0.0318 (-0.44)	-0.243*** (-3.27)	-0.0499 (-0.65)	0.200*** (2.92)	0.0282 (0.40)	0.258*** (3.48)	0.0267 (0.26)	0.112 (1.06)	-0.123 (-1.06)
Northeast Region Interaction Term	-0.0512 (-0.98)	-0.137** (-2.47)	-0.0609 (-1.03)	-0.0782 (-1.35)	-0.159*** (-2.68)	-0.101 (-1.59)	-0.138** (-2.05)	-0.230*** (-3.43)	-0.103 (-1.39)	-0.00142 (-0.01)	-0.00203 (-0.02)	-0.0667 (-0.57)
Constant	-0.155*** (-3.42)	-0.133*** (-2.76)	-0.188*** (-3.78)	0.0452 (1.54)	0.0557* (1.85)	0.0797** (2.55)	0.0575*** (2.72)	0.0529** (2.49)	0.0806*** (3.53)	0.216*** (19.55)	0.202*** (17.59)	0.238*** (19.25)
Adj. R-sq.	0.177	0.224	0.172	0.309	0.322	0.273	0.353	0.420	0.302	0.359	0.377	0.240
N	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*	*324*

** = p<0.10, ** = p<0.05, *** = p<0.01*

Table 19: Multivariate analysis including nine interaction terms

There are a few particular things to note from these results. First, although the coefficient on the race-income correlation is no longer significant for all models, this is not problematic; there are no MSA's for which all the interaction terms will equal or even approach zero, so the coefficient on the race-income correlation alone is no longer very meaningful, since it will always be modified by the interaction terms. Secondly, the interaction terms all perform similarly to how they did independently, with no major changes. There is still evidence that the relationship between the correlations of interest is strengthened (made more negative) by: making the hedonic slope coefficient more negative, decreasing the income gap, increasing the

MSA-level median income, decreasing the average neurological risk, increasing the population, or moving into the Northeast region. Lastly, despite the introduction of nine controls, the constants are remarkably similar to what they were in the initial regressions described by Equation 3 ($RP_j = \alpha_1 RI_j + \varepsilon$). This is explored further in the next subsection.

iv. Siting Analysis

Despite the overwhelming evidence for the importance of income, our results may also indicate the existence of disproportionate siting based on race alone, independent of income. In the scatter plots and regressions of race-pollution on race-income, there are sizable intercepts for almost every race. The constants from our regressions of the race-health risk correlations on the race-income correlations, specifically from Equation 3 and Equation 15, are listed in **Table 20**, on the following page. We use these two equations to demonstrate the similarity between the constants with no controls (Equation 3) and with nine controls (Equation 15). These values indicate that in MSA's where there is no correlation between race and income, there is still a correlation between race and pollution. As might be expected, the constants are negative for whites and positive for all minority groups, and are significantly different from zero for all race and risk types except in the black-cancer risk model. More specifically, the constants are reasonably similar between black and Latino populations, falling between 0.045 and 0.082 for all health risk types, while the Asian population has very positive constants for all risk types, each greater than 0.200 and significant at the 1% level. Although no MSA's exist where the race-income correlation is exactly zero, the constants (or intercepts) indicate the hypothetical race-health risk correlations based on the nationwide trend.

Constants from Univariate Regression and Multivariate Nine-Interaction Term Regression												
	(1) White-HealthRisk on White-Income			(2) Black-HealthRisk on Black-Income			(3) Latino-HealthRisk on Latino-Income			(4) Asian-HealthRisk on Asian-Income		
	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk	Cancer Risk	Neuro. Risk	Resp. Risk
Constant from Univariate Regression	-0.152*** (-3.29)	-0.129** (-2.55)	-0.194*** (-3.74)	0.0353 (1.26)	0.0536* (1.78)	0.0656** (2.15)	0.0548** (2.50)	0.0496** (2.15)	0.0817*** (3.42)	0.215*** (21.37)	0.201*** (19.14)	0.238*** (21.47)
Constant from Nine-Interaction Term Regression	-0.155*** (-3.43)	-0.133*** (-2.78)	-0.189*** (-3.80)	0.0453 (1.54)	0.0559* (1.85)	0.0797** (2.55)	0.0577*** (2.74)	0.0530** (2.50)	0.0806*** (3.53)	0.216*** (19.54)	0.203*** (17.61)	0.238*** (19.28)
* = p<0.10, ** = p<0.05, *** = p<0.01												

Table 20: Constants from Equation 3 and Equation 15

In order to examine how this theory relates to actual MSA's in our dataset, we identify 33 unique MSA's (34 total) where the race-income correlation fell between -0.025 and 0.025 for any race. **Table 21**, found in **Appendix E**, lists the qualifying MSA's with corresponding race-health risk correlations and demographic statistics.

There are a few identifiable trends in **Table 21**. First, Asian is the race that most frequently has a race-income correlation near zero, composing over 60% of the total entries. As identified at the beginning of Section VI, subsection ii, in the Asian scatter plot and supported by the values in **Table 20**, the distribution of MSA data points range from -0.8 to 0.8 and are centered on the y-axis (where the race-income correlation equals zero) while other minorities are concentrated where the race-income correlation is negative. A potential explanation for this is that Asians make up a lower percentage of the population relative to other minorities (4.4% compared to 13.2% for black, 66.0% for white, and 14.2% for Latino) and thus fluctuations in percent Asian between census tracts lead to relatively large fluctuations in MSA-level correlations, creating a wider range than that seen in the other race groups. Additionally, there is not nearly as strong of a historical relationship between poverty and percent Asian as there is between poverty and percent Latino or percent black. Second, **Table 21** has a disproportionate number of MSA's that fall into our "small population" category (with populations less than 250,000). Of the 324 MSA's across the country, 44.1% are less than 250,000 while 48.5% of the MSA's in **Table 21** are in the same category. 26 of the 33 MSA's have populations at, or under, 502,141 (78.8%), also a higher rate than the national rate of 68.5%, suggesting that smaller MSA's are somewhat less likely to have a strong race-income correlation. Lastly, despite the positive and significant constants for the Latino population in **Table 20**, all of the race-health risk correlations are negative for Latinos in this range of race-income correlations shown in **Table 21**. This calls into question whether the theoretical "intercepts" of our regressions show the actual trend that exists when race and income are not correlated. For blacks, three of the four MSA's identified have negative race-health risk correlations; while all weak, these again suggest that one should be careful not to read too much into the constants from the regressions.

VII. Conclusion

i. Summary of Findings

The demonstrated results strongly support our initial hypotheses. Beginning with the hedonic regression, our prediction that pollution would decrease house value was supported by the fact that the majority of the MSA's had a negative coefficient for the effect of health risk on house value for all three risk types. There are still some positive values for this coefficient, and since it is hard to imagine a rational person paying more to increase pollution and health risks, these results must be understood from a relative standpoint. As mentioned previously, this demonstrates that our simple regression omits variables that bias the effect of pollution on house values, but we do not suspect that bias is systematic.

Our scatter plots, correlations, and regressions nearly all support the conclusion that the race-pollution correlation is intrinsically tied to the race-income correlation. This conclusion is further strengthened by the evidence that the relationship between these correlations is stronger in MSA's where pollution has a stronger effect on the housing market. Together, our results provide strong evidence of the market fundamentals underlying the residential mobility hypothesis. The fact that our results hold up across races and risk types suggests that ultimately, income may be more important than race in determining the burden of pollution that one faces.

Our attempts to identify MSA-specific characteristics that impact our results met limited success, with many of our supplemental regressions proving inconclusive. Nonetheless, there is some evidence that the relationship between the correlations of interest is strongest in MSA's with over one million residents, the Northeast, MSA's with small income gaps, MSA's with high median income, and MSA's with lower neurological risk.

In addition to strong evidence for the residential mobility hypothesis, our results also suggest that disproportionate siting may exist. This evidence is nebulous, however, rendered particularly difficult to interpret due to the lack of unifying characteristics among MSA's with low race-income correlations. The relevant variables are all interconnected, with the correlations of interested dependent not only on income and pollution, but overall percent minority, MSA population, cultural norms, local industries, and availability of jobs and housing, among others. As a result, it is difficult to pinpoint any piece of data as direct evidence of disproportionate siting. Taken in the context of our other results, we can see that there is much variation in the relationship between race and pollution that disproportionate siting does not seem to explain, and which is better understood through the lens of market dynamics.

ii. Policy Implications

Our results provide some important policy implications. While we cannot rule out disproportionate siting as a factor in causing environmental injustice, the race-income correlation ultimately can explain much of the variation in the race-pollution correlation across all races. In other words, the unequal level of pollution that is found in minority communities can be traced largely to the fact that their lower incomes give minorities less power in the housing market. This means that if a policymaker were to seek to eliminate racial disparities in levels of pollution, addressing disproportionate siting alone would fail to do so. We recommend, therefore, that any environmental justice policy solutions should first address the race-income correlation. As long as minorities have lower incomes than whites, and as long as housing markets capitalize pollution into housing prices, whites will continue to have a greater power to move away from pollution in the housing market. Alternatively, an intervention could attempt to increase the power of minority individuals in the housing market, such as by subsidizing housing for minorities in neighborhoods with low levels of pollution.

Our supplemental regressions provide some direction in terms of where policy interventions should be focused in order to be most effective. The relationship between the correlations of interest is strongest in MSA's with over million people, high median income, a relatively small gap between the rich and the poor, and in the Northeast. Therefore, if the race-income correlation could be lessened in an MSA that meets these criteria, one would expect that the race-pollution correlation would likewise decrease by a proportionately high amount. Interventions in the South or the West, or targeted at MSA's with high levels of neurological risk, are less likely to be as effective.

It is worthy to note that, inasmuch as market dynamics are able to explain a large portion of the race-pollution relationship, an argument can be made that no policy interventions are needed. In other words, if minority individuals are choosing to live near pollution through the housing market in a trade-off for other goods, then unequal burdens of pollution need not necessarily be seen as a problematic outcome. However, of particular concern with regard to this is the issue of information – it may be that those who choose to live near pollution are not fully aware of its health effects.

We recommend, therefore, that education be considered as a major component of environmental justice efforts. Our results show that there are some MSA's in which particular populations are positively correlated with both higher income and higher pollution; in these cases, this means that the wealthy are choosing to live near pollution. It is possible that these situations are the results of rational choices in which pollution is accepted along with favorable characteristics. We cannot rule out the possibility, though, that the individuals who choose to live near pollution in these cases are simply unaware of the associate health risks. It would be beneficial to inform the broader population, particularly minorities and low-income populations, which are most likely to live in polluted areas, about the health risks posed by pollution. If this were done, any pollution disparities that persisted would be the result of an informed choice. The fact that our results support the residential mobility hypothesis and suggest that market forces largely drive race-pollution correlations could be taken as an implication that no corrective action is required; for this to be the case, it must first be made sure that all parties are educated about the health risks of pollution and are not unwittingly exposing themselves to environmental hazards.

iii. Recommendations for Future Research

This study provides a broad picture of the important role that income plays in creating pollution disparities between races across the United States. There are many nuanced aspects of this role to which we allude throughout our analysis but do not examine in detail, and which are recommended as areas of future research. First, as mentioned in Section VI, we find evidence of regional differences in the way that the race-income correlation affects the race-health risk correlation. There are a wide number of potential explanations for this, including differences in culture, demographics, industry, and historical norms. Performing a more in-depth analysis for each region independently would afford a clearer view of the particular relationship that exists in each. Our results indicate that the relationship between correlations is strongest in the Northeast, making it a logical choice for the first such analysis.

Similar to the above, a future study could examine how results differ between MSA's with different racial compositions. In our current analysis, an MSA that is composed equally of all race types would be treated the same as an MSA that is 99% white. We tried running our regressions with the most outlying MSA's excluded (less than 1% for each minority type, or more than 95% white), and found no significant differences, but it would be interesting to examine the differences between races in more detail. A study could look at how the relationship between the race-income and race-pollution correlations varies by percentage of each race type in the MSA, as well as by overall minority population in the MSA. It would be particularly intriguing to see if the relationships for one race type vary as percent composition of other races changes: for example, how the relationship between the Latino-income and Latino-pollution correlations compare between an MSA that is predominantly white and an MSA that is predominantly black. There are a variety of paths such an analysis could take, all of which would lend greater clarity to the relationship between the correlations of interest.

Another area for further research which was beyond the scope of our analysis is the toxicological difference between the types of pollution-related health risk. For a number of our regressions, the results varied between risk types, suggesting that there may be important differences between the ways they influence housing markets. It is foreseeable that for a particular risk type and the pollutants associated with it, there may be connections to certain industries or manufacturing practices that cause it to play a more important role in some areas than in others. An analysis of each risk type and its distribution could shed light on specific market dynamics that bring about the differences we see in our results.

Fourth, while we attempt to examine the role of disproportionate siting by looking at regression constants and MSA's with race-income correlations near zero, we recognize that this is a limited analysis, and does not provide conclusive results. Further exploration into the role of disproportionate siting on a national level would help to establish a conclusive comparison of the relative importance of siting and market dynamics. While our results strongly show the importance of income acting through the housing market, the evidence we find for disproportionate siting is far less clear, so it is difficult to make comparisons between the two.

One particular avenue for a future study to take would be to apply Depro, Timmins, and O'Neil's (2012) methodology to cities other than Los Angeles. As explained in Section II, Depro et al. use real estate transaction data to examine demographic changes around toxic waste sites. Their methods allow for a direct assessment of the role residential mobility by comparing how community composition by race changes over time. Depro et al. found strong evidence that market dynamics are responsible for pollution disparities by race in Los Angeles; our national analysis suggests that similar outcomes are likely in other cities as well.

Lastly, we recommend that as data becomes available, our analysis be repeated with more recent demographic information and pollution risk levels. In the thirteen years since the Decennial Census, the demographics of the United States have changed dramatically, especially with regard to the Latino population. Similarly, it is unlikely that pollution levels have stayed unchanged. At present, the most recent publically available NATA data is from 2005, and the most recent census data is from the 2011 American Community Survey (ACS). Once 2008 NATA data becomes available, this could be paired with the 2006-2010 ACS five-year estimates and used to repeat our study. Applying our methodology to a more recent dataset would provide important insight into whether the results we find still hold.

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Appendix A - Correlation Values

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
ABILENE TX	126,555	-0.509	0.338	0.373	0.360	-0.664	0.299	0.473	0.392	0.288	-0.088	-0.213	-0.171	0.722	-0.349	-0.502	-0.430
AKRON OH	694,960	-0.534	0.288	0.116	0.278	-0.378	0.213	0.064	0.248	-0.033	0.172	0.064	0.190	0.551	-0.305	-0.125	-0.300
ALBANY GA	120,822	-0.748	0.368	0.387	0.257	0.117	0.013	-0.156	-0.138	0.421	-0.041	-0.004	0.111	0.750	-0.378	-0.389	-0.259
ALBANY-SCHENECTADY-TROY NY	875,583	-0.524	0.613	0.706	0.540	-0.490	0.247	0.326	0.127	0.029	0.327	0.346	0.473	0.574	-0.617	-0.717	-0.540
ALBUQUERQUE NM	709,780	-0.315	0.223	0.336	0.360	-0.526	0.238	0.190	0.344	0.263	0.085	0.207	0.167	0.672	-0.100	-0.040	-0.180
ALEXANDRIA LA	126,337	-0.771	0.471	0.462	0.468	0.181	-0.282	-0.289	-0.291	-0.010	0.191	0.250	0.230	0.784	-0.472	-0.464	-0.470
ALLENTOWN-BETHLEHEM-EASTON PA	637,958	-0.556	0.472	0.612	0.515	-0.623	0.488	0.514	0.462	0.154	0.464	0.320	0.498	0.622	-0.547	-0.594	-0.541
ALTOONA PA	129,144	-0.651	0.641	0.651	0.724	-0.590	0.508	0.565	0.539	0.403	-0.026	-0.020	-0.038	0.612	-0.606	-0.656	-0.692
AMARILLO TX	217,858	-0.385	0.197	0.246	0.324	-0.573	0.129	0.180	0.299	-0.053	-0.022	-0.048	0.019	0.669	-0.208	-0.272	-0.418
ANCHORAGE AK	254,889	-0.642	0.146	0.152	-0.035	-0.771	0.142	0.201	0.246	-0.465	0.186	0.234	0.616	0.815	-0.333	-0.382	-0.355
ANN ARBOR MI	578,736	-0.392	0.523	0.437	0.552	-0.425	0.025	0.127	-0.068	-0.194	0.476	0.465	0.460	0.497	-0.640	-0.583	-0.639
ANNISTON AL	112,249	-0.713	0.555	0.609	0.544	0.069	0.032	0.062	0.067	0.255	-0.238	-0.119	-0.178	0.711	-0.553	-0.608	-0.542
APPLETON-OSHKOSH-NEENAH WI	358,365	-0.093	-0.003	-0.037	0.015	-0.391	0.206	0.077	0.343	-0.455	0.348	0.299	0.595	0.295	-0.147	-0.069	-0.263
ASHEVILLE NC	225,965	-0.443	0.540	0.579	0.587	-0.241	0.366	0.344	0.303	-0.018	0.509	0.473	0.451	0.469	-0.597	-0.632	-0.631
ATHENS GA	153,444	-0.393	0.541	0.356	0.451	-0.050	0.322	0.107	0.218	-0.229	0.351	0.394	0.336	0.387	-0.604	-0.387	-0.494
ATLANTA GA	4,112,198	-0.593	0.379	0.258	0.312	-0.158	0.265	0.323	0.307	0.144	0.249	0.268	0.294	0.624	-0.485	-0.380	-0.433
ATLANTIC-CAPE MAY NJ	344,726	-0.545	0.387	0.516	0.328	-0.390	0.278	0.307	0.282	-0.086	0.418	0.426	0.373	0.581	-0.486	-0.596	-0.435
AUBURN-OPELIKA AL	115,092	-0.237	0.064	-0.156	-0.034	-0.087	0.147	0.251	0.285	-0.394	0.304	0.194	0.178	0.284	-0.095	0.137	0.012
AUGUSTA-AIKEN GA-SC	477,441	-0.714	0.315	0.485	0.258	0.004	-0.079	-0.163	-0.055	0.578	0.287	0.064	0.291	0.696	-0.337	-0.490	-0.281
AUSTIN-SAN MARCOS TX	1,249,763	-0.376	0.169	0.090	0.193	-0.577	0.134	0.102	0.144	0.047	0.377	0.396	0.279	0.620	-0.256	-0.199	-0.256
BAKERSFIELD CA	661,645	-0.308	0.278	0.171	0.279	-0.634	0.001	0.213	0.007	0.215	-0.016	0.333	-0.050	0.639	-0.054	-0.271	-0.055
BALTIMORE MD	2,535,548	-0.603	0.418	0.207	0.322	-0.048	0.035	0.037	0.068	0.270	-0.096	-0.145	-0.080	0.601	-0.424	-0.204	-0.331
BANGOR ME	88,095	-0.772	0.435	0.443	0.445	-0.696	0.633	0.612	0.628	-0.495	0.131	0.122	0.185	0.804	-0.438	-0.441	-0.470
BARNSTABLE-YARMOUTH MA	159,282	-0.668	0.485	0.590	0.470	-0.701	0.507	0.634	0.500	-0.371	0.487	0.419	0.440	0.664	-0.527	-0.581	-0.517
BATON ROUGE LA	602,894	-0.732	0.547	0.496	0.514	0.143	-0.046	-0.047	-0.114	0.034	0.169	0.202	0.118	0.736	-0.567	-0.518	-0.529
BEAUMONT-PORT ARTHUR TX	385,090	-0.765	0.187	0.296	-0.001	-0.228	0.344	0.389	0.088	-0.056	0.208	0.067	0.054	0.766	-0.278	-0.378	-0.029
BELLINGHAM WA	166,814	-0.559	0.568	0.189	0.538	-0.046	-0.050	-0.141	0.062	-0.560	0.622	0.287	0.696	0.260	-0.014	0.066	-0.038
BENTON HARBOR MI	162,453	-0.742	0.269	0.398	0.160	-0.073	-0.333	-0.395	-0.157	0.228	-0.016	-0.069	-0.085	0.758	-0.243	-0.360	-0.152
BERGEN-PASSAIC NJ	1,373,167	-0.437	0.008	0.087	-0.032	-0.658	0.227	0.299	0.109	0.103	0.457	0.387	0.557	0.676	-0.300	-0.371	-0.224
BILLINGS MT	129,352	-0.610	0.701	0.691	0.800	-0.571	0.692	0.658	0.625	0.565	-0.216	-0.224	-0.101	0.648	-0.735	-0.708	-0.731

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
BILOXI-GULFPORT-PASCAGOULA MS	363,988	-0.547	0.469	0.297	0.154	-0.230	0.125	0.123	0.198	-0.173	0.107	0.024	0.020	0.600	-0.497	-0.305	-0.175
BINGHAMTON NY	252,320	-0.673	0.582	0.650	0.636	-0.633	0.603	0.668	0.600	-0.154	0.235	0.385	0.266	0.597	-0.544	-0.667	-0.598
BIRMINGHAM AL	921,106	-0.665	0.532	0.329	0.551	-0.114	0.010	-0.023	-0.004	0.119	0.148	0.111	0.271	0.678	-0.546	-0.334	-0.570
BISMARCK ND	94,719	-0.043	0.499	0.430	0.471	0.290	0.218	0.172	0.318	0.144	0.297	0.269	0.240	0.150	-0.306	-0.252	-0.349
BLOOMINGTON IN	120,563	-0.612	0.546	0.583	0.577	-0.583	0.680	0.747	0.741	-0.348	0.359	0.463	0.397	0.610	-0.577	-0.677	-0.636
BLOOMINGTON-NORMAL IL	150,433	-0.498	0.524	0.510	0.570	-0.153	0.422	0.395	0.461	0.203	0.103	0.076	0.157	0.327	-0.523	-0.497	-0.581
BOISE CITY ID	432,345	-0.218	0.407	0.159	0.333	-0.589	0.101	0.393	-0.077	0.133	0.201	0.019	0.069	0.639	-0.167	-0.434	0.038
BOSTON MA-NH	3,389,340	-0.418	0.262	0.225	0.272	-0.520	0.284	0.251	0.309	-0.186	0.393	0.443	0.377	0.576	-0.410	-0.384	-0.423
BOULDER-LONGMONT CO	291,288	-0.320	0.528	0.542	0.350	-0.459	0.091	0.101	0.150	-0.213	0.461	0.426	0.326	0.554	-0.257	-0.261	-0.259
BRAZORIA TX	241,767	-0.121	-0.313	-0.312	-0.295	-0.606	0.492	0.355	0.352	0.658	0.274	0.361	0.418	0.514	-0.340	-0.229	-0.245
BREMERTON WA	231,969	-0.219	0.314	0.728	0.230	-0.235	0.285	0.658	0.217	-0.232	0.453	0.320	0.430	0.405	-0.404	-0.637	-0.300
BRIDGEPORT CT	459,479	-0.622	0.139	0.620	0.440	-0.676	0.159	0.674	0.491	-0.277	-0.100	0.211	0.111	0.714	-0.150	-0.707	-0.500
BROCKTON MA	255,459	-0.843	0.618	0.715	0.688	-0.851	0.658	0.760	0.673	-0.349	0.491	0.473	0.604	0.837	-0.643	-0.743	-0.686
BROWNSVILLE-HARLINGEN-SAN BENITO TX	326,245	0.004	0.110	0.156	0.156	-0.745	0.105	0.118	-0.125	0.566	0.062	0.020	0.101	0.730	-0.117	-0.129	0.116
BRYAN-COLLEGE STATION TX	152,415	-0.252	0.237	0.191	0.378	-0.268	0.264	0.228	0.449	-0.195	0.152	0.230	0.041	0.387	-0.358	-0.343	-0.506
BUFFALO-NIAGARA FALLS NY	1,170,111	-0.542	0.176	0.247	0.362	-0.399	0.142	0.240	0.164	0.150	-0.037	0.009	0.246	0.605	-0.195	-0.288	-0.358
BURLINGTON VT	165,626	-0.673	0.638	0.658	0.714	-0.470	0.723	0.703	0.754	-0.516	0.643	0.572	0.674	0.749	-0.638	-0.669	-0.724
CANTON-MASSILLON OH	406,934	-0.603	0.638	0.710	0.411	-0.347	0.412	0.481	0.456	0.477	0.007	-0.051	0.227	0.609	-0.652	-0.730	-0.439
CEDAR RAPIDS IA	191,701	-0.575	0.109	0.496	0.521	-0.578	0.298	0.739	0.765	-0.192	0.049	0.489	0.544	0.578	-0.168	-0.607	-0.640
CHAMPAIGN-URBANA IL	179,669	-0.383	0.209	0.471	0.344	-0.634	0.549	0.658	0.604	-0.365	0.508	0.364	0.400	0.571	-0.462	-0.644	-0.545
CHARLESTON WV	251,662	-0.429	0.605	0.529	0.443	-0.088	0.131	0.319	0.206	0.649	-0.079	0.048	0.008	0.387	-0.580	-0.534	-0.440
CHARLESTON-NORTH CHARLESTON SC	547,154	-0.757	0.363	0.408	0.341	-0.104	0.098	0.127	0.197	0.150	0.008	0.071	0.164	0.772	-0.372	-0.425	-0.374
CHARLOTTE-GASTONIA-ROCK HILL NC-SC	1,499,293	-0.570	0.474	0.415	0.390	-0.257	0.142	0.179	0.180	0.153	0.325	0.166	0.333	0.573	-0.491	-0.433	-0.422
CHARLOTTESVILLE VA	159,576	-0.517	0.285	0.300	0.266	-0.293	0.394	0.472	0.418	-0.256	0.316	0.404	0.389	0.637	-0.434	-0.488	-0.445
CHATTANOOGA TN-GA	465,161	-0.598	0.597	0.433	0.489	-0.304	0.389	0.357	0.462	0.204	-0.007	0.098	0.292	0.605	-0.615	-0.456	-0.527
CHICAGO IL	8,272,768	-0.519	0.200	0.357	0.158	-0.294	0.141	0.217	0.231	0.112	0.096	-0.016	0.107	0.706	-0.320	-0.508	-0.339
CHICO-PARADISE CA	203,171	-0.568	0.770	0.494	0.639	-0.227	0.056	0.480	0.306	-0.561	0.717	0.454	0.606	0.495	-0.448	-0.560	-0.549
CINCINNATI OH-KY-IN	1,646,395	-0.531	0.502	0.358	0.466	-0.215	0.267	0.238	0.301	0.195	0.169	0.089	0.140	0.531	-0.525	-0.375	-0.488
CLARKSVILLE-HOPKINSVILLE TN-KY	207,033	-0.698	0.681	0.670	0.600	0.015	-0.107	-0.087	-0.065	0.449	-0.120	-0.111	-0.107	0.618	-0.603	-0.598	-0.539
CLEVELAND-LORAIN-ELYRIA OH	2,250,871	-0.506	0.329	0.072	0.319	-0.287	0.266	0.279	0.288	0.049	0.127	0.064	0.161	0.572	-0.404	-0.145	-0.401
COLORADO SPRINGS CO	516,929	-0.464	0.196	0.169	0.143	-0.711	0.351	0.426	0.339	0.135	0.028	0.006	0.040	0.610	-0.295	-0.313	-0.258
COLUMBIA MO	135,454	-0.593	0.627	0.661	0.648	-0.526	0.599	0.570	0.612	-0.385	0.537	0.552	0.528	0.672	-0.746	-0.773	-0.764
COLUMBIA SC	541,891	-0.621	0.461	0.275	0.388	-0.148	0.055	0.055	0.037	-0.032	0.188	0.206	0.191	0.638	-0.477	-0.291	-0.402

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COLUMBUS GA-AL	274,624	-0.599	0.064	-0.128	0.091	-0.003	-0.069	-0.013	-0.111	0.581	-0.072	0.020	-0.217	0.589	-0.050	0.130	-0.068
COLUMBUS OH	1,540,157	-0.469	0.088	0.316	0.494	-0.291	0.010	0.148	0.344	0.052	-0.048	-0.011	0.158	0.489	-0.084	-0.324	-0.537
CORPUS CHRISTI TX	371,078	-0.309	0.456	0.491	0.375	-0.689	0.242	0.240	0.330	0.571	-0.243	-0.311	-0.430	0.762	-0.378	-0.384	-0.427
CUMBERLAND MD-WV	102,008	-0.118	0.147	0.121	0.117	-0.086	0.025	0.023	0.028	0.302	0.280	0.200	0.266	0.144	-0.199	-0.181	-0.172
DALLAS TX	3,519,176	-0.408	0.165	-0.009	0.061	-0.485	0.333	0.303	0.385	0.252	0.065	0.091	0.107	0.648	-0.396	-0.244	-0.361
DANBURY CT	217,980	-0.323	0.188	0.224	0.301	-0.594	0.382	0.570	0.396	-0.590	0.553	0.676	0.599	0.596	-0.386	-0.550	-0.441
DANVILLE VA	110,156	-0.865	0.515	0.596	0.610	0.238	0.003	-0.102	-0.059	0.287	0.427	0.220	0.310	0.862	-0.535	-0.608	-0.625
DAVENPORT-MOLINE-ROCK ISLAND IA-IL	359,062	-0.546	0.265	0.078	0.357	-0.467	0.363	0.208	0.274	-0.080	0.200	0.063	0.204	0.681	-0.416	-0.173	-0.445
DAYTONA BEACH FL	485,327	-0.542	0.305	0.320	0.375	0.017	-0.144	-0.161	-0.169	-0.044	0.229	0.252	0.121	0.535	-0.265	-0.276	-0.319
DAYTON-SPRINGFIELD OH	950,558	-0.495	0.212	0.296	0.293	-0.172	0.345	0.321	0.382	0.431	0.002	0.012	0.127	0.493	-0.228	-0.313	-0.316
DECATUR AL	145,867	-0.530	0.720	0.695	0.520	-0.428	0.283	0.440	0.441	0.369	0.098	0.158	0.295	0.623	-0.673	-0.686	-0.501
DECATUR IL	114,706	-0.824	0.462	0.543	0.628	-0.606	0.813	0.686	0.530	0.335	-0.050	-0.113	-0.007	0.835	-0.487	-0.562	-0.642
DENVER CO	2,109,282	-0.296	0.168	0.238	0.238	-0.564	0.432	0.479	0.506	-0.024	0.077	0.105	0.136	0.608	-0.441	-0.515	-0.539
DES MOINES IA	456,022	-0.521	0.530	0.579	0.546	-0.580	0.343	0.458	0.353	-0.488	0.657	0.698	0.657	0.626	-0.573	-0.650	-0.588
DETROIT MI	4,441,551	-0.536	0.360	0.339	0.336	-0.170	0.203	0.395	0.158	0.305	0.070	-0.011	0.130	0.562	-0.423	-0.430	-0.396
DOTHAN AL	137,916	-0.725	0.275	0.360	0.126	-0.035	-0.278	-0.258	-0.184	0.244	-0.042	-0.088	0.067	0.731	-0.225	-0.314	-0.094
DOVER DE	126,697	-0.289	0.672	0.631	0.691	-0.315	0.271	0.366	0.315	0.010	0.487	0.485	0.490	0.293	-0.661	-0.638	-0.688
DUBUQUE IA	89,143	-0.714	0.607	0.290	0.669	-0.677	0.558	0.286	0.616	0.188	0.042	-0.066	0.023	0.671	-0.603	-0.292	-0.659
DULUTH-SUPERIOR MN-WI	242,414	-0.520	0.540	-0.166	0.295	-0.359	0.198	-0.146	0.068	-0.184	0.259	-0.183	-0.009	0.551	-0.458	0.181	-0.275
DUTCHESS COUNTY NY	280,150	-0.707	0.623	0.686	0.142	-0.496	0.691	0.622	0.396	0.280	0.166	0.150	0.395	0.692	-0.727	-0.761	-0.267
EAU CLAIRE WI	148,337	-0.488	0.634	0.663	0.653	-0.294	0.597	0.467	0.547	-0.177	0.343	0.351	0.411	0.324	-0.518	-0.494	-0.567
EL PASO TX	679,622	0.283	-0.166	-0.132	-0.080	-0.734	0.073	-0.087	0.096	0.577	0.014	0.098	-0.011	0.794	-0.036	0.147	-0.091
ELKHART-GOSHEN IN	182,791	-0.702	0.146	0.180	0.438	-0.779	0.127	0.110	0.438	0.224	0.070	0.100	0.173	0.827	-0.167	-0.173	-0.509
ELMIRA NY	91,070	-0.686	0.766	0.682	0.624	-0.434	0.390	0.389	0.314	0.365	0.003	-0.114	0.084	0.685	-0.769	-0.696	-0.646
ERIE PA	279,296	-0.578	0.320	0.414	0.426	-0.640	0.383	0.504	0.490	0.113	0.207	0.185	0.293	0.611	-0.360	-0.460	-0.471
EUGENE-SPRINGFIELD OR	322,959	-0.412	0.332	0.764	0.633	-0.507	0.433	0.477	0.384	-0.342	0.152	0.505	0.478	0.612	-0.394	-0.674	-0.557
EVANSVILLE-HENDERSON IN-KY	296,195	-0.498	0.391	0.540	0.553	-0.463	0.327	0.386	0.425	0.304	-0.048	-0.097	0.059	0.508	-0.403	-0.556	-0.580
FARGO-MOORHEAD ND-MN	174,367	-0.491	0.676	0.764	0.644	-0.301	-0.079	0.031	0.181	-0.342	0.372	0.360	0.422	0.641	-0.457	-0.540	-0.636
FAYETTEVILLE NC	302,963	-0.665	0.399	0.486	0.499	0.221	-0.219	-0.251	-0.216	0.401	-0.173	-0.156	-0.064	0.627	-0.359	-0.437	-0.463
FAYETTEVILLE-SPRINGDALE-ROGERS AR	311,121	-0.582	0.244	0.342	0.260	-0.242	0.626	0.517	0.455	-0.431	0.426	0.608	0.551	0.505	-0.690	-0.645	-0.534
FITCHBURG-LEOMINSTER MA	140,448	-0.659	0.458	0.512	0.466	-0.696	0.269	0.327	0.273	-0.563	0.311	0.364	0.304	0.724	-0.337	-0.397	-0.338
FLAGSTAFF AZ-UT	122,366	-0.339	0.542	0.522	0.499	-0.184	0.370	0.348	0.409	0.049	0.689	0.661	0.708	0.366	0.116	0.130	0.480
FLINT MI	436,141	-0.638	0.467	0.547	0.387	-0.376	0.330	0.346	0.368	0.326	0.017	0.060	0.149	0.668	-0.500	-0.583	-0.426

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
FLORENCE AL	142,950	-0.658	0.491	0.331	0.516	-0.274	0.276	0.333	0.402	0.352	0.309	0.316	0.365	0.667	-0.511	-0.348	-0.540
FLORENCE SC	125,761	-0.721	0.135	0.250	0.100	-0.218	-0.305	-0.394	-0.337	0.637	0.347	0.192	0.419	0.719	-0.144	-0.255	-0.110
FORT COLLINS-LOVELAND CO	251,494	-0.460	0.016	0.223	0.011	-0.510	0.465	0.335	0.303	-0.074	-0.100	0.063	-0.036	0.577	-0.425	-0.361	-0.275
FORT LAUDERDALE FL	1,623,018	-0.451	0.234	0.299	0.146	0.159	0.198	0.013	0.318	0.476	-0.033	-0.253	0.282	0.391	-0.308	-0.301	-0.267
FORT MYERS-CAPE CORAL FL	440,371	-0.352	0.306	0.339	0.008	-0.358	0.255	0.215	0.163	0.074	0.101	0.118	0.011	0.438	-0.358	-0.368	-0.075
FORT PIERCE-PORT ST. LUCIE FL	310,224	-0.623	0.250	0.398	0.174	-0.327	0.188	0.202	0.020	0.118	0.093	0.008	0.034	0.661	-0.290	-0.424	-0.164
FORT SMITH AR-OK	207,290	-0.407	0.584	0.442	0.594	-0.472	0.572	0.434	0.594	-0.140	0.483	0.345	0.418	0.589	-0.242	-0.159	-0.345
FORT WALTON BEACH FL	168,685	-0.578	0.436	0.364	0.417	-0.266	-0.072	0.048	-0.147	-0.086	0.111	0.385	-0.198	0.567	-0.343	-0.371	-0.256
FORT WAYNE IN	502,141	-0.479	0.330	0.038	0.398	-0.532	0.420	0.073	0.539	0.016	0.528	0.067	0.597	0.523	-0.403	-0.051	-0.489
FORT WORTH-ARLINGTON TX	1,702,625	-0.389	0.308	0.049	0.272	-0.461	0.279	0.198	0.227	0.072	0.246	0.157	0.311	0.583	-0.445	-0.193	-0.394
FRESNO CA	922,516	-0.369	0.407	0.331	0.563	-0.676	0.321	0.236	0.270	-0.147	0.309	0.327	0.399	0.779	-0.480	-0.377	-0.505
GADSDEN AL	103,459	-0.638	0.253	0.274	0.546	-0.425	0.342	0.352	0.596	0.348	-0.124	-0.119	0.105	0.644	-0.266	-0.292	-0.571
GAINESVILLE FL	217,955	-0.449	0.238	0.120	0.353	-0.283	0.573	0.559	0.005	-0.058	0.379	0.432	0.020	0.552	-0.404	-0.284	-0.387
GALVESTON-TEXAS CITY TX	246,379	-0.624	0.010	0.126	-0.253	-0.521	0.085	0.267	-0.232	0.125	-0.178	-0.193	-0.098	0.766	-0.023	-0.198	0.335
GARY IN	631,362	-0.688	0.610	0.554	0.410	-0.294	0.051	0.442	0.557	0.571	-0.218	-0.272	-0.124	0.771	-0.614	-0.698	-0.605
GLENS FALLS NY	118,117	0.039	-0.037	-0.038	-0.049	0.061	-0.031	-0.023	-0.029	0.165	0.224	0.161	0.199	-0.031	0.010	0.010	0.025
GOLDSBORO NC	113,329	-0.789	0.675	0.718	0.713	0.107	-0.425	-0.326	-0.444	0.293	0.123	0.183	0.234	0.809	-0.643	-0.714	-0.685
GRAND FORKS ND-MN	97,478	-0.134	0.215	0.036	0.063	-0.245	-0.181	-0.005	0.042	-0.208	0.476	0.403	0.377	0.448	-0.254	-0.290	-0.353
GRAND JUNCTION CO	116,255	-0.717	0.357	0.473	0.415	-0.602	0.284	0.284	0.318	-0.130	0.553	0.657	0.626	0.649	-0.305	-0.315	-0.343
GRAND RAPIDS-MUSKEGON-HOLLAND MI	1,088,514	-0.574	0.207	0.128	0.172	-0.358	0.402	0.537	0.672	0.109	0.221	0.272	0.105	0.639	-0.382	-0.372	-0.456
GREAT FALLS MT	80,357	-0.162	-0.045	-0.014	0.012	-0.422	0.238	0.228	0.279	0.017	0.104	0.080	0.160	0.730	-0.425	-0.459	-0.524
GREELEY CO	180,936	-0.626	0.635	0.758	0.255	-0.627	0.457	0.398	0.263	-0.186	0.298	0.371	0.217	0.655	-0.491	-0.435	-0.288
GREEN BAY WI	226,778	-0.802	0.413	0.503	0.513	-0.645	0.216	0.442	0.325	-0.641	0.359	0.432	0.407	0.689	-0.320	-0.472	-0.411
GREENSBORO--WINSTON-SALEM--HIGH POINT NC	1,251,509	-0.562	0.253	0.216	0.496	-0.488	0.152	0.075	0.167	0.004	0.370	0.387	0.405	0.619	-0.297	-0.247	-0.526
GREENVILLE NC	133,798	-0.582	0.618	0.514	0.590	-0.063	0.055	-0.152	-0.038	0.169	0.218	0.369	0.303	0.578	-0.628	-0.508	-0.594
GREENVILLE-SPARTANBURG-ANDERSON SC	962,441	-0.578	0.365	0.437	0.371	-0.202	0.368	0.319	0.348	0.217	0.143	0.128	0.157	0.582	-0.425	-0.487	-0.428
HAGERSTOWN MD	131,923	-0.674	0.457	-0.034	0.667	-0.551	0.280	-0.168	0.482	0.149	-0.040	-0.143	0.130	0.682	-0.441	0.068	-0.666
HAMILTON-MIDDLETOWN OH	332,807	-0.385	0.044	-0.078	0.117	-0.353	0.378	0.003	0.444	0.484	-0.058	-0.178	0.159	0.363	-0.108	0.089	-0.203
HARRISBURG-LEBANON-CARLISLE PA	629,401	-0.487	0.485	0.351	0.461	-0.514	0.307	0.312	0.320	0.110	0.370	0.186	0.407	0.528	-0.516	-0.387	-0.500
HARTFORD CT	1,183,803	-0.517	0.391	0.484	0.497	-0.665	0.513	0.618	0.503	0.020	0.141	0.130	0.125	0.728	-0.563	-0.687	-0.626
HATTIESBURG MS	111,674	-0.721	0.432	0.514	0.474	-0.328	0.437	0.481	0.457	-0.092	0.256	0.282	0.269	0.728	-0.452	-0.535	-0.493
HICKORY-MORGANTON-LENOIR NC	341,851	-0.487	0.392	0.417	0.318	-0.299	0.270	0.264	0.367	-0.191	0.040	-0.047	0.246	0.504	-0.391	-0.392	-0.404
HONOLULU HI	867,885	-0.285	-0.026	-0.054	0.127	-0.332	-0.127	-0.194	0.025	0.163	0.319	0.271	0.201	0.024	-0.230	-0.121	-0.148

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
HOUMA LA	194,477	-0.538	0.487	-0.007	0.509	-0.018	-0.027	-0.125	-0.085	0.018	-0.043	-0.071	-0.071	0.615	-0.392	0.069	-0.361
HOUSTON TX	4,177,646	-0.425	0.073	0.141	0.169	-0.509	0.364	0.409	0.468	0.239	-0.198	-0.149	-0.275	0.697	-0.303	-0.403	-0.444
HUNTINGTON-ASHLAND WV-KY-OH	315,538	-0.344	0.027	0.144	0.250	-0.126	0.062	0.159	0.217	0.004	0.009	0.066	0.500	0.361	-0.051	-0.147	-0.314
HUNTSVILLE AL	342,376	-0.505	0.411	0.368	0.387	-0.318	0.211	0.287	0.355	0.438	0.256	0.165	0.275	0.505	-0.444	-0.393	-0.426
INDIANAPOLIS IN	1,607,486	-0.461	0.290	0.174	0.414	-0.339	0.366	0.371	0.408	0.306	-0.050	-0.088	0.096	0.485	-0.332	-0.218	-0.468
IOWA CITY IA	111,006	-0.405	-0.030	-0.125	0.034	-0.466	0.008	-0.141	0.091	-0.428	-0.007	-0.083	0.043	0.496	0.003	0.115	-0.066
JACKSON MI	158,422	-0.644	0.385	0.651	0.423	-0.686	0.498	0.716	0.556	0.335	-0.009	-0.021	0.015	0.701	-0.444	-0.724	-0.489
JACKSON MS	440,801	-0.692	0.549	0.482	0.443	-0.161	-0.063	-0.068	0.007	0.499	-0.179	-0.153	0.037	0.693	-0.552	-0.485	-0.452
JACKSON TN	107,377	-0.722	0.508	0.199	0.384	-0.183	0.504	0.446	0.501	0.663	0.235	0.496	0.373	0.722	-0.534	-0.227	-0.414
JACKSONVILLE FL	1,100,491	-0.585	0.614	0.580	0.379	0.066	-0.017	-0.015	-0.394	0.249	-0.003	-0.048	-0.411	0.586	-0.636	-0.597	-0.324
JACKSONVILLE NC	150,355	-0.612	0.182	0.337	0.319	-0.273	0.168	0.285	0.195	0.326	0.395	0.506	0.541	0.615	-0.223	-0.403	-0.366
JAMESTOWN NY	139,750	-0.646	0.412	0.343	0.401	-0.627	0.275	0.324	0.184	-0.016	0.204	0.324	0.223	0.736	-0.417	-0.419	-0.352
JANESVILLE-BELOIT WI	152,307	-0.485	0.101	0.065	0.141	-0.480	0.122	-0.010	0.119	-0.404	0.323	0.212	0.317	0.556	-0.153	-0.071	-0.180
JERSEY CITY NJ	608,975	-0.307	-0.322	0.004	-0.160	-0.441	0.560	0.126	0.471	0.114	-0.134	-0.119	0.027	0.685	-0.184	-0.072	-0.319
JOHNSON CITY-KINGSPORT-BRISTOL TN-VA	480,091	-0.444	0.427	0.233	0.422	-0.263	0.357	0.109	0.375	0.146	0.494	0.175	0.513	0.443	-0.510	-0.251	-0.505
JOHNSTOWN PA	232,621	-0.440	0.183	0.251	0.208	-0.147	0.131	0.188	0.119	0.388	0.135	-0.009	0.104	0.427	-0.205	-0.270	-0.226
JOPLIN MO	157,322	-0.423	0.435	0.518	0.539	-0.294	0.339	0.141	0.077	-0.016	0.527	0.344	0.354	0.507	-0.415	-0.394	-0.340
KALAMAZOO-BATTLE CREEK MI	452,851	-0.541	0.265	0.208	0.300	-0.421	-0.135	0.018	-0.102	0.112	0.293	0.004	0.345	0.606	-0.253	-0.201	-0.297
KANKAKEE IL	103,833	-0.701	0.420	0.018	0.113	-0.470	0.237	0.093	0.146	0.329	0.108	0.319	0.262	0.734	-0.440	-0.038	-0.135
KANSAS CITY MO-KS	1,776,062	-0.528	0.399	0.247	0.427	-0.336	0.398	0.344	0.418	0.059	0.211	0.124	0.216	0.623	-0.535	-0.367	-0.569
KENOSHA WI	149,577	-0.773	0.218	0.535	0.098	-0.743	0.339	0.619	0.168	0.262	-0.124	-0.280	-0.113	0.777	-0.282	-0.579	-0.125
KILLEEN-TEMPLE TX	312,952	-0.516	0.207	0.311	0.256	-0.702	0.444	0.448	0.450	0.110	0.272	0.330	0.241	0.622	-0.329	-0.423	-0.364
KNOXVILLE TN	687,249	-0.440	0.270	0.320	0.379	-0.248	0.216	0.369	0.266	0.038	0.325	0.263	0.371	0.457	-0.317	-0.372	-0.434
KOKOMO IN	101,541	-0.494	0.354	0.239	0.403	-0.828	0.670	0.268	0.672	0.236	0.196	0.560	0.316	0.531	-0.431	-0.314	-0.488
LA CROSSE WI-MN	126,838	-0.689	0.236	0.487	0.288	-0.656	0.364	0.515	0.409	-0.443	0.367	0.448	0.415	0.612	-0.393	-0.527	-0.443
LAFAYETTE IN	182,821	-0.472	0.709	0.524	0.588	-0.404	0.246	0.524	0.302	-0.393	0.238	-0.065	0.124	0.602	-0.442	-0.300	-0.361
LAFAYETTE LA	385,647	-0.669	0.155	0.226	0.215	0.292	0.525	0.547	0.461	0.112	0.469	0.581	0.443	0.663	-0.199	-0.276	-0.256
LAKE CHARLES LA	183,577	-0.715	0.025	0.058	0.029	0.136	0.177	0.160	0.066	0.081	-0.103	-0.010	-0.158	0.716	-0.026	-0.062	-0.028
LAKELAND-WINTER HAVEN FL	483,924	-0.493	0.136	0.413	0.169	-0.267	0.071	-0.162	0.066	0.526	0.096	0.087	0.002	0.573	-0.169	-0.341	-0.197
LANCASTER PA	470,658	-0.710	0.666	0.164	0.685	-0.681	0.633	0.158	0.645	-0.058	0.380	0.179	0.467	0.692	-0.670	-0.172	-0.690
LANSING-EAST LANSING MI	447,728	-0.443	0.455	0.646	0.573	-0.613	0.465	0.615	0.619	-0.201	0.233	0.202	0.264	0.571	-0.547	-0.727	-0.689
LAREDO TX	193,117	-0.213	0.069	0.155	0.078	-0.871	0.286	0.266	-0.275	0.825	-0.232	-0.200	0.133	0.879	-0.291	-0.286	0.294
LAS CRUCES NM	174,682	0.187	-0.101	-0.139	0.005	-0.664	0.280	0.376	-0.029	0.269	-0.161	-0.191	0.016	0.732	-0.307	-0.390	0.001

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
LAS VEGAS NV-AZ	1,563,282	-0.250	0.396	0.243	0.256	-0.474	0.459	0.388	0.444	0.269	0.211	0.016	0.093	0.442	-0.548	-0.396	-0.461
LAWRENCE KS	99,962	-0.447	0.426	0.416	0.437	-0.588	0.502	0.525	0.547	-0.404	0.441	0.437	0.497	0.543	-0.481	-0.494	-0.530
LAWRENCE MA-NH	396,230	-0.724	0.742	0.818	0.676	-0.690	0.731	0.832	0.651	0.262	0.269	0.138	0.371	0.683	-0.760	-0.850	-0.687
LAWTON OK	114,996	-0.348	0.107	0.070	0.143	-0.494	0.413	0.463	0.487	0.448	0.164	0.134	0.232	0.487	-0.180	-0.156	-0.227
LEWISTON-AUBURN ME	87,692	-0.813	0.720	0.785	0.702	-0.586	0.529	0.528	0.503	-0.041	0.073	0.122	0.081	0.857	-0.797	-0.843	-0.772
LEXINGTON KY	479,198	-0.393	0.488	0.419	0.502	-0.195	0.361	0.287	0.356	-0.009	0.298	0.214	0.294	0.400	-0.566	-0.474	-0.576
LIMA OH	155,084	-0.737	0.814	0.024	0.811	-0.772	0.707	-0.163	0.825	0.242	0.080	-0.099	0.158	0.752	-0.825	-0.009	-0.835
LINCOLN NE	250,291	-0.593	0.356	0.131	0.357	-0.574	0.370	0.155	0.443	-0.398	0.250	0.124	0.229	0.645	-0.397	-0.182	-0.409
LITTLE ROCK-NORTH LITTLE ROCK AR	583,845	-0.689	0.480	0.485	0.761	-0.241	0.277	0.126	0.226	0.327	0.057	0.060	-0.012	0.690	-0.493	-0.487	-0.765
LONGVIEW-MARSHALL TX	208,780	-0.703	0.282	0.455	0.347	-0.579	0.544	0.590	0.518	0.487	0.392	0.195	0.295	0.745	-0.407	-0.557	-0.449
LOS ANGELES-LONG BEACH CA	9,510,491	-0.239	0.124	0.155	0.296	-0.616	0.445	0.461	0.406	0.129	0.019	0.037	0.029	0.686	-0.521	-0.561	-0.574
LOUISVILLE KY-IN	1,025,598	-0.512	0.399	0.283	0.270	-0.172	0.108	0.142	0.020	0.125	0.103	0.103	-0.006	0.525	-0.419	-0.308	-0.275
LOWELL MA-NH	301,686	-0.828	0.587	0.756	0.602	-0.793	0.588	0.729	0.591	-0.552	0.580	0.689	0.566	0.787	-0.691	-0.833	-0.680
LUBBOCK TX	242,628	-0.407	0.299	0.323	0.351	-0.655	0.433	0.442	0.494	-0.038	0.346	0.400	0.317	0.730	-0.526	-0.551	-0.598
LYNCHBURG VA	214,911	-0.635	0.607	0.235	0.428	-0.277	0.467	0.109	0.451	0.153	0.396	-0.100	0.392	0.636	-0.645	-0.229	-0.464
MACON GA	322,549	-0.815	0.480	0.491	0.484	0.103	-0.335	-0.235	-0.441	0.538	-0.027	-0.039	-0.126	0.818	-0.471	-0.490	-0.462
MADISON WI	426,526	-0.457	0.367	0.003	0.368	-0.473	0.307	-0.010	0.302	-0.386	0.131	-0.036	0.100	0.549	-0.341	0.019	-0.327
MANCHESTER NH	198,378	-0.759	0.758	0.773	0.716	-0.656	0.778	0.797	0.735	-0.489	0.529	0.530	0.524	0.710	-0.799	-0.815	-0.757
MANSFIELD OH	175,818	-0.533	0.438	0.573	0.547	-0.635	0.527	0.674	0.567	0.403	0.227	0.069	0.169	0.554	-0.470	-0.606	-0.578
MCALLEN-EDINBURG-MISSION TX	569,463	0.114	-0.037	-0.016	0.005	-0.813	0.002	-0.056	-0.046	0.806	0.164	0.205	0.235	0.779	-0.022	0.035	0.016
MEDFORD-ASHLAND OR	181,269	-0.667	0.636	0.690	0.769	-0.641	0.463	0.609	0.646	-0.143	0.407	0.174	0.286	0.687	-0.534	-0.634	-0.691
MELBOURNE-TITUSVILLE-PALM BAY FL	470,480	-0.521	0.218	0.234	0.264	-0.171	-0.177	-0.127	-0.133	0.200	-0.098	-0.028	-0.229	0.527	-0.175	-0.204	-0.221
MEMPHIS TN-AR-MS	1,135,614	-0.704	0.366	0.485	0.410	-0.087	0.184	0.143	0.200	0.192	0.242	0.139	0.120	0.715	-0.406	-0.517	-0.444
MERCED CA	210,554	-0.355	0.373	0.700	0.451	-0.626	0.086	-0.019	0.151	-0.290	0.556	0.406	0.617	0.691	-0.328	-0.224	-0.406
MIAMI FL	2,230,391	-0.368	-0.146	-0.071	-0.314	-0.066	0.397	0.314	0.527	0.309	-0.261	-0.269	-0.195	0.668	-0.323	-0.318	-0.256
MIDDLESEX-SOMERSET-HUNTERDON NJ	1,169,641	-0.323	0.180	0.144	0.127	-0.548	0.402	0.466	0.390	0.134	0.247	0.120	0.210	0.454	-0.482	-0.449	-0.433
MILWAUKEE-WAUKESHA WI	1,500,736	-0.578	0.360	0.338	0.422	-0.313	0.450	0.514	0.352	-0.180	0.332	0.248	0.306	0.697	-0.563	-0.558	-0.579
MINNEAPOLIS-ST. PAUL MN-WI	2,968,806	-0.524	0.430	0.477	0.485	-0.495	0.377	0.422	0.417	-0.402	0.411	0.471	0.406	0.614	-0.525	-0.581	-0.566
MOBILE AL	540,258	-0.790	0.537	0.434	0.606	0.203	-0.127	-0.122	-0.094	0.064	0.013	-0.070	-0.082	0.799	-0.539	-0.429	-0.599
MODESTO CA	446,997	-0.314	0.283	0.481	0.407	-0.525	0.424	0.279	0.400	-0.039	0.176	0.403	0.300	0.537	-0.463	-0.395	-0.479
MONMOUTH-OCEAN NJ	1,119,457	-0.340	-0.109	0.207	0.021	-0.349	0.067	0.248	0.102	0.412	0.112	0.293	0.385	0.313	0.047	-0.298	-0.119
MONROE LA	147,250	-0.678	0.551	0.344	0.536	-0.193	0.195	0.217	0.137	0.189	0.161	0.111	0.280	0.685	-0.564	-0.356	-0.551
MONTGOMERY AL	333,055	-0.730	0.399	0.359	0.273	0.197	-0.097	0.001	0.121	0.343	0.095	0.105	0.185	0.730	-0.404	-0.366	-0.284

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
MUNCIE IN	118,769	-0.362	0.238	0.253	0.374	-0.511	0.143	0.206	0.152	-0.279	0.042	0.134	0.008	0.448	-0.252	-0.280	-0.387
MYRTLE BEACH SC	196,629	-0.706	-0.136	-0.241	-0.128	-0.403	0.173	0.200	0.248	0.357	0.424	0.471	0.527	0.736	0.080	0.179	0.057
NAPLES FL	251,377	-0.448	0.251	0.215	0.062	-0.558	-0.139	-0.347	0.004	0.076	0.182	0.173	0.246	0.628	-0.038	0.125	-0.037
NASHUA NH	184,626	-0.625	0.672	0.674	0.666	-0.673	0.745	0.766	0.684	0.070	0.079	0.031	0.168	0.567	-0.669	-0.666	-0.657
NASHVILLE TN	1,231,311	-0.546	0.596	0.582	0.570	-0.264	0.240	0.232	0.286	0.020	0.240	0.149	0.206	0.590	-0.651	-0.628	-0.631
NASSAU-SUFFOLK NY	2,717,784	-0.295	0.127	0.197	0.183	-0.415	0.074	0.140	0.071	0.216	0.299	0.396	0.429	0.369	-0.171	-0.267	-0.230
NEW BEDFORD MA	170,033	-0.600	0.475	0.529	0.417	-0.737	0.457	0.524	0.428	0.043	-0.008	-0.104	0.020	0.649	-0.415	-0.509	-0.367
NEW HAVEN-MERIDEN CT	542,149	-0.569	0.126	0.170	0.026	-0.650	-0.055	0.542	0.501	-0.115	0.192	0.104	0.033	0.747	-0.080	-0.416	-0.288
NEW LONDON-NORWICH CT-RI	293,566	-0.560	0.629	0.618	0.692	-0.560	0.605	0.558	0.641	-0.100	0.328	0.255	0.331	0.592	-0.650	-0.610	-0.700
NEW ORLEANS LA	1,334,701	-0.653	0.240	0.134	-0.013	0.075	0.105	0.073	0.231	0.117	-0.001	-0.034	-0.054	0.664	-0.258	-0.141	-0.002
NEW YORK NY	9,295,264	-0.302	-0.042	-0.079	0.039	-0.498	0.286	0.184	0.356	0.011	0.112	0.100	0.139	0.588	-0.172	-0.070	-0.308
NEWARK NJ	2,032,989	-0.586	0.448	0.450	0.466	-0.459	0.484	0.473	0.524	0.349	-0.139	-0.150	-0.155	0.724	-0.639	-0.634	-0.672
NEWBURGH NY-PA	387,669	-0.409	0.442	0.483	0.400	-0.400	0.608	0.595	0.396	0.431	0.251	0.176	0.250	0.413	-0.572	-0.585	-0.439
NORFOLK-VIRGINIA BEACH-NEWPORT NEWS VA-NC	1,560,331	-0.715	0.321	0.342	0.252	-0.080	0.031	0.039	0.151	0.265	-0.009	0.038	0.163	0.724	-0.334	-0.362	-0.294
OAKLAND CA	2,392,557	-0.544	0.503	0.411	0.442	-0.487	0.138	0.172	0.124	0.088	0.175	0.275	0.261	0.619	-0.532	-0.541	-0.530
OCALA FL	258,916	-0.503	0.199	0.265	-0.140	-0.196	0.032	0.070	-0.180	0.468	0.380	0.391	-0.082	0.494	-0.206	-0.275	0.168
ODESSA-MIDLAND TX	237,132	-0.403	0.255	0.206	0.287	-0.785	0.276	0.168	0.080	0.545	-0.232	-0.178	0.023	0.794	-0.322	-0.214	-0.176
OKLAHOMA CITY OK	1,083,346	-0.344	0.290	0.092	0.258	-0.408	0.332	0.509	0.376	-0.014	0.230	0.050	0.239	0.585	-0.420	-0.328	-0.402
OLYMPIA WA	207,355	-0.102	0.138	0.064	-0.052	-0.455	0.171	0.161	-0.033	-0.109	0.465	0.438	0.360	0.266	-0.242	-0.190	-0.072
OMAHA NE-IA	716,998	-0.436	0.211	0.287	0.122	-0.381	0.456	0.287	0.566	0.085	0.267	0.156	0.241	0.568	-0.418	-0.405	-0.386
ORANGE COUNTY CA	2,846,289	-0.377	0.400	0.421	0.426	-0.629	0.511	0.542	0.512	-0.037	0.142	0.113	0.231	0.642	-0.578	-0.595	-0.623
ORLANDO FL	1,644,561	-0.441	0.307	0.311	0.224	-0.229	0.041	0.009	0.087	0.285	0.144	0.078	0.178	0.494	-0.322	-0.301	-0.272
OWENSBORO KY	91,545	-0.688	0.662	0.390	0.455	-0.563	0.173	0.300	0.207	0.437	-0.032	-0.011	0.103	0.726	-0.662	-0.439	-0.488
PANAMA CITY FL	148,217	-0.573	0.463	0.371	0.017	-0.089	-0.254	-0.166	-0.392	-0.251	0.136	0.251	-0.043	0.591	-0.430	-0.363	0.027
PENSACOLA FL	404,044	-0.737	0.634	0.621	0.115	0.102	-0.012	-0.031	-0.171	0.027	0.325	0.319	0.102	0.745	-0.665	-0.648	-0.125
PEORIA-PEKIN IL	347,387	-0.716	0.565	0.164	0.596	-0.596	0.428	0.057	0.449	0.209	0.239	0.013	0.276	0.721	-0.594	-0.163	-0.626
PHILADELPHIA PA-NJ	5,100,931	-0.539	0.449	0.360	0.426	-0.330	0.217	0.307	0.258	-0.061	0.188	0.147	0.195	0.604	-0.506	-0.444	-0.500
PHOENIX-MESA AZ	3,251,876	-0.329	0.332	0.351	0.377	-0.590	0.548	0.570	0.638	0.279	-0.027	-0.023	-0.118	0.616	-0.507	-0.542	-0.601
PINE BLUFF AR	84,278	-0.730	0.613	0.280	0.507	-0.043	-0.306	-0.324	-0.412	0.431	-0.149	-0.154	-0.128	0.734	-0.606	-0.268	-0.494
PITTSBURGH PA	2,358,695	-0.416	0.281	0.170	0.388	-0.161	0.279	0.297	0.389	0.170	0.123	0.095	0.313	0.405	-0.301	-0.190	-0.431
PITTSFIELD MA	83,095	-0.469	0.473	0.448	0.532	-0.577	0.723	0.701	0.732	-0.512	0.827	0.802	0.860	0.600	-0.683	-0.663	-0.721
POCATELLO ID	75,565	-0.579	-0.068	0.276	0.070	-0.677	0.133	0.467	0.361	-0.180	0.230	0.511	0.458	0.251	0.041	0.116	-0.025
PORTLAND ME	242,323	-0.649	0.590	0.477	0.551	-0.706	0.779	0.692	0.731	-0.428	0.400	0.276	0.417	0.667	-0.633	-0.503	-0.611

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
PORTLAND-VANCOUVER OR-WA	1,918,009	-0.278	0.274	0.422	0.392	-0.421	0.194	0.022	0.037	-0.002	0.369	0.224	0.330	0.471	-0.449	-0.388	-0.420
PORTSMOUTH-ROCHESTER NH-ME	237,559	-0.279	0.270	0.412	0.218	-0.344	0.358	0.341	0.156	-0.335	0.162	0.184	0.142	0.448	-0.277	-0.317	-0.177
PROVIDENCE-FALL RIVER-WARWICK RI-MA	1,184,995	-0.551	0.564	0.590	0.435	-0.570	0.543	0.560	0.395	-0.354	0.394	0.450	0.336	0.625	-0.616	-0.643	-0.463
PROVO-OREM UT	368,536	-0.466	0.491	0.381	0.517	-0.709	0.561	0.454	0.353	-0.327	0.493	0.426	0.551	0.711	-0.600	-0.486	-0.430
PUEBLO CO	141,472	-0.461	0.120	0.107	0.398	-0.721	0.271	0.291	0.568	0.354	-0.106	-0.099	-0.089	0.724	-0.272	-0.290	-0.578
PUNTA GORDA FL	141,627	0.153	-0.399	-0.406	-0.486	-0.300	-0.061	0.006	-0.185	0.269	-0.094	-0.108	-0.120	0.003	0.297	0.276	0.406
RACINE WI	188,831	-0.701	0.488	0.548	0.102	-0.715	0.564	0.761	0.083	-0.068	-0.111	-0.084	-0.128	0.740	-0.535	-0.646	-0.096
RALEIGH-DURHAM-CHAPEL HILL NC	1,187,941	-0.599	0.322	0.275	0.262	-0.439	0.336	0.368	0.159	0.310	0.136	-0.059	0.278	0.629	-0.400	-0.339	-0.319
RAPID CITY SD	88,565	-0.567	0.250	0.312	-0.189	-0.690	0.377	0.437	-0.107	-0.478	0.201	0.271	-0.153	0.795	-0.723	-0.768	-0.125
READING PA	373,638	-0.729	0.745	0.740	0.649	-0.822	0.753	0.660	0.710	-0.184	0.457	0.421	0.519	0.819	-0.779	-0.706	-0.727
REDDING CA	163,256	-0.373	0.627	0.671	0.594	-0.505	0.210	0.234	0.133	-0.248	0.549	0.591	0.540	0.677	-0.470	-0.509	-0.374
RENO NV	339,486	-0.648	0.494	0.587	0.035	-0.732	0.544	0.640	0.204	-0.326	0.437	0.518	0.229	0.785	-0.398	-0.507	-0.052
RICHLAND-KENNEWICK-PASCO WA	191,822	-0.416	0.222	0.376	0.384	-0.676	-0.144	0.017	-0.065	0.420	0.185	0.200	0.242	0.679	0.092	-0.078	0.003
RICHMOND-PETERSBURG VA	996,512	-0.629	0.129	0.322	0.277	-0.232	0.007	0.125	0.164	0.071	0.064	0.172	0.171	0.664	-0.140	-0.357	-0.315
RIVERSIDE-SAN BERNARDINO CA	3,254,612	-0.109	0.228	0.264	0.166	-0.440	0.375	0.428	0.396	0.364	0.296	0.230	0.336	0.365	-0.459	-0.501	-0.463
ROANOKE VA	235,932	-0.611	0.350	0.367	0.347	-0.379	0.463	0.412	0.489	0.216	0.184	0.018	0.209	0.627	-0.380	-0.391	-0.378
ROCHESTER MN	124,277	-0.417	0.082	0.271	0.143	-0.340	0.050	0.254	0.157	-0.240	0.232	0.450	0.347	0.405	-0.148	-0.401	-0.262
ROCHESTER NY	1,098,201	-0.614	0.504	0.557	0.553	-0.579	0.397	0.498	0.497	0.088	0.265	0.242	0.309	0.662	-0.537	-0.606	-0.604
ROCKFORD IL	371,236	-0.578	0.233	0.072	0.374	-0.524	0.090	0.047	0.228	0.034	0.295	-0.008	0.504	0.657	-0.245	-0.075	-0.426
ROCKY MOUNT NC	143,026	-0.625	0.398	0.488	0.384	-0.083	-0.298	-0.233	-0.126	0.488	0.481	0.210	0.308	0.648	-0.392	-0.485	-0.393
SACRAMENTO CA	1,635,453	-0.451	0.138	0.514	0.445	-0.559	0.049	0.396	0.450	-0.089	0.006	0.396	0.271	0.481	-0.088	-0.553	-0.497
SAGINAW-BAY CITY-MIDLAND MI	403,070	-0.583	0.455	0.613	0.422	-0.639	0.316	0.631	0.264	0.437	-0.003	-0.092	0.230	0.633	-0.468	-0.665	-0.437
SALEM OR	347,214	-0.460	0.149	0.319	0.337	-0.528	0.412	0.321	0.303	-0.033	0.125	0.454	0.456	0.607	-0.441	-0.408	-0.394
SALINAS CA	401,762	-0.165	0.145	-0.061	0.077	-0.527	0.007	0.520	0.103	0.103	0.147	0.083	0.141	0.559	-0.070	-0.528	-0.151
SALT LAKE CITY-OGDEN UT	1,333,914	-0.479	0.157	0.440	0.152	-0.619	0.274	0.362	0.462	-0.196	0.259	0.397	0.302	0.644	-0.326	-0.477	-0.507
SAN ANGELO TX	104,010	-0.516	0.420	0.374	0.398	-0.767	0.659	0.619	0.636	0.178	-0.015	0.056	-0.037	0.823	-0.701	-0.655	-0.673
SAN ANTONIO TX	1,592,383	-0.163	0.135	0.098	0.098	-0.714	0.514	0.539	0.579	0.348	-0.086	-0.171	-0.149	0.781	-0.577	-0.581	-0.625
SAN DIEGO CA	2,805,382	-0.349	0.204	0.301	0.176	-0.568	0.324	0.373	0.283	0.093	0.010	0.225	-0.030	0.530	-0.315	-0.470	-0.256
SAN FRANCISCO CA	1,728,846	-0.354	0.217	0.165	0.272	-0.368	0.143	0.157	0.196	-0.285	0.261	0.246	0.293	0.588	-0.356	-0.334	-0.442
SAN JOSE CA	1,682,585	-0.481	0.280	0.372	0.248	-0.634	0.281	0.361	0.203	0.125	0.164	0.225	0.115	0.483	-0.378	-0.496	-0.278
SAN LUIS OBISPO-ATASCADERO- PASO ROBLES CA	246,681	-0.020	-0.051	0.000	-0.049	-0.140	0.040	0.139	-0.032	-0.571	0.514	0.522	0.395	0.253	-0.123	-0.229	-0.036
SANTA BARBARA-SANTA MARIA-LOMPOC CA	396,736	-0.188	-0.072	0.032	0.020	-0.618	0.338	0.605	0.179	-0.258	0.327	0.285	0.525	0.667	-0.352	-0.622	-0.240
SANTA CRUZ-WATSONVILLE CA	255,602	-0.472	-0.060	0.227	-0.209	-0.612	0.044	0.257	0.144	-0.295	-0.051	0.114	-0.072	0.657	-0.034	-0.268	-0.123

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
SANTA FE NM	147,635	0.227	0.031	0.004	0.016	-0.646	0.312	0.141	0.162	0.403	-0.109	0.006	-0.120	0.641	-0.242	-0.070	-0.085
SANTA ROSA CA	458,614	-0.407	0.556	0.599	0.573	-0.398	0.335	0.334	0.357	0.073	0.486	0.546	0.520	0.414	-0.447	-0.458	-0.472
SARASOTA-BRADENTON FL	582,662	-0.392	0.048	0.106	0.009	-0.391	0.008	0.064	-0.054	0.159	-0.077	-0.045	-0.089	0.447	-0.034	-0.101	0.021
SAVANNAH GA	293,000	-0.721	0.629	0.695	0.683	0.008	-0.061	-0.093	-0.076	0.179	-0.062	-0.223	-0.158	0.738	-0.642	-0.702	-0.694
SCRANTON--WILKES-BARRE--HAZLETON PA	624,776	-0.200	0.136	0.257	0.197	-0.323	0.158	0.334	0.170	0.144	0.129	0.205	0.143	0.263	-0.181	-0.354	-0.234
SEATTLE-BELLEVUE-EVERETT WA	2,400,714	-0.399	0.400	0.320	0.442	-0.545	0.286	0.235	0.359	-0.196	0.426	0.318	0.465	0.467	-0.489	-0.381	-0.551
SHARON PA	120,293	-0.657	0.245	0.223	0.270	-0.117	0.232	0.212	0.301	0.182	-0.042	-0.083	-0.052	0.673	-0.268	-0.240	-0.294
SHEBOYGAN WI	112,646	0.002	-0.120	-0.211	-0.232	-0.767	0.752	0.537	0.357	-0.680	0.817	0.663	0.519	0.671	-0.685	-0.463	-0.308
SHERMAN-DENISON TX	110,595	-0.688	0.523	0.575	0.508	-0.552	0.389	0.432	0.432	-0.038	0.389	0.349	0.452	0.707	-0.526	-0.579	-0.532
SHREVEPORT-BOSSIER CITY LA	392,302	-0.758	0.432	0.485	0.625	0.072	-0.099	0.092	-0.040	0.433	-0.043	0.046	-0.072	0.767	-0.437	-0.505	-0.638
SIOUX CITY IA-NE	124,130	-0.690	0.469	0.688	0.468	-0.694	0.176	0.577	0.405	-0.667	0.302	0.607	0.398	0.747	-0.274	-0.650	-0.450
SIOUX FALLS SD	172,412	-0.575	0.406	0.449	0.531	-0.686	0.372	0.451	0.517	-0.362	0.453	0.463	0.536	0.661	-0.390	-0.460	-0.533
SOUTH BEND IN	265,559	-0.588	0.442	0.523	0.450	-0.405	0.427	0.531	0.464	0.352	-0.036	-0.147	-0.020	0.616	-0.517	-0.614	-0.538
SPOKANE WA	424,156	-0.497	0.290	0.217	0.149	-0.540	0.235	0.150	0.078	-0.261	0.174	0.134	0.107	0.652	-0.357	-0.264	-0.194
SPRINGFIELD IL	201,437	-0.660	0.308	0.403	0.378	-0.534	0.391	0.505	0.374	0.199	0.182	0.157	0.117	0.673	-0.337	-0.437	-0.403
SPRINGFIELD MA	581,243	-0.441	0.269	0.338	0.274	-0.716	0.623	0.719	0.653	-0.036	-0.090	0.084	-0.103	0.754	-0.589	-0.713	-0.613
SPRINGFIELD MO	325,721	-0.536	0.293	0.414	0.402	-0.570	0.325	0.416	0.436	-0.062	0.144	0.096	0.353	0.588	-0.343	-0.442	-0.490
ST. CLOUD MN	167,392	-0.487	0.625	0.711	0.541	-0.204	0.070	-0.013	0.016	-0.477	0.680	0.791	0.483	0.558	-0.633	-0.703	-0.493
ST. JOSEPH MO	102,490	-0.470	0.485	0.394	0.557	-0.239	0.727	0.441	0.706	0.296	0.129	-0.138	0.111	0.506	-0.621	-0.477	-0.677
ST. LOUIS MO-IL	2,603,607	-0.605	0.563	0.431	0.691	-0.081	0.221	0.045	0.060	0.231	-0.027	-0.034	0.112	0.612	-0.587	-0.441	-0.715
STAMFORD-NORWALK CT	353,556	-0.642	0.443	0.448	0.224	-0.699	0.479	0.495	0.322	-0.261	0.376	0.434	0.498	0.719	-0.520	-0.535	-0.337
STATE COLLEGE PA	135,758	-0.023	-0.009	-0.002	0.025	-0.221	0.553	0.529	0.571	-0.428	0.517	0.489	0.524	0.291	-0.412	-0.390	-0.433
STEUBENVILLE-WEIRTON OH-WV	132,008	-0.710	0.844	0.353	0.491	-0.211	0.277	0.266	0.519	0.278	0.160	0.054	0.361	0.707	-0.849	-0.359	-0.509
STOCKTON-LODI CA	563,598	-0.269	0.225	0.257	0.279	-0.628	0.687	0.258	0.500	-0.137	0.003	0.086	-0.064	0.580	-0.548	-0.304	-0.406
SUMTER SC	104,646	-0.837	0.479	0.345	0.341	0.177	-0.075	-0.224	0.104	0.667	-0.223	-0.206	-0.016	0.843	-0.494	-0.344	-0.369
SYRACUSE NY	732,117	-0.483	0.449	0.397	0.461	-0.513	0.441	0.467	0.446	-0.235	0.385	0.359	0.403	0.531	-0.531	-0.482	-0.542
TACOMA WA	700,820	-0.639	0.233	0.422	0.376	-0.599	0.304	0.289	0.319	-0.411	0.196	0.224	0.279	0.675	-0.296	-0.396	-0.403
TALLAHASSEE FL	284,539	-0.634	-0.119	0.044	0.263	-0.229	-0.187	0.035	0.009	0.236	0.344	0.273	-0.009	0.668	0.116	-0.069	-0.273
TAMPA-ST. PETERSBURG-CLEARWATER FL	2,362,853	-0.399	0.391	0.330	0.246	-0.117	0.407	0.460	0.469	0.210	0.185	0.110	0.120	0.382	-0.540	-0.502	-0.435
TERRE HAUTE IN	149,192	-0.565	0.314	0.553	0.580	-0.479	0.578	0.583	0.761	-0.146	0.083	0.144	0.282	0.602	-0.371	-0.601	-0.664
TEXARKANA TX-TEXARKANA AR	129,749	-0.770	0.667	0.630	0.578	-0.023	-0.115	-0.120	0.052	0.453	0.402	0.427	0.388	0.767	-0.651	-0.615	-0.586
TOLEDO OH	618,203	-0.607	0.450	0.523	0.470	-0.364	0.187	0.316	0.201	0.128	0.003	-0.083	0.001	0.675	-0.491	-0.584	-0.514
TOPEKA KS	169,871	-0.632	0.474	0.467	0.539	-0.529	0.429	0.408	0.426	0.206	-0.031	-0.003	0.049	0.708	-0.547	-0.532	-0.590

MSA	Population	Black Income	Black Cancer	Black Neur	Black Resp	Latino Income	Latino Cancer	Latino Neur	Latino Resp	Asian Income	Asian Cancer	Asian Neur	Asian Resp	White Income	White Cancer	White Neur	White Resp
TRENTON NJ	350,761	-0.636	0.448	0.402	0.372	-0.530	0.581	0.568	0.544	0.752	-0.408	-0.436	-0.355	0.659	-0.571	-0.520	-0.495
TUCSON AZ	843,746	-0.350	0.027	0.114	0.032	-0.490	0.394	0.275	0.372	0.097	-0.054	0.141	0.020	0.604	-0.260	-0.157	-0.179
TULSA OK	803,235	-0.398	0.225	0.034	0.318	-0.362	0.414	0.081	0.448	0.196	0.385	0.006	0.371	0.591	-0.216	-0.036	-0.296
TUSCALOOSA AL	164,875	-0.594	0.374	0.313	0.486	-0.248	0.170	0.219	0.277	0.055	0.096	0.235	0.162	0.607	-0.387	-0.334	-0.507
TYLER TX	174,706	-0.713	0.267	0.320	0.345	-0.536	0.656	0.586	0.585	0.364	-0.047	-0.045	-0.047	0.822	-0.554	-0.556	-0.574
UTICA-ROME NY	299,896	-0.390	0.441	0.471	0.451	-0.274	0.369	0.396	0.387	-0.295	0.454	0.427	0.374	0.420	-0.482	-0.508	-0.480
VALLEJO-FAIRFIELD-NAPA CA	518,821	-0.272	0.459	0.263	0.464	-0.589	0.009	0.268	-0.027	0.238	0.335	0.137	0.381	0.325	-0.461	-0.363	-0.467
VENTURA CA	748,801	-0.298	-0.109	0.156	-0.215	-0.638	-0.146	0.129	-0.345	0.262	0.227	0.257	0.258	0.615	0.121	-0.173	0.321
VICTORIA TX	84,088	-0.697	0.684	0.701	0.692	-0.873	0.713	0.735	0.717	0.582	-0.090	-0.053	-0.011	0.861	-0.736	-0.761	-0.742
VINELAND-MILLVILLE-BRIDGETON NJ	146,438	-0.660	-0.084	-0.040	-0.210	-0.529	0.319	0.377	0.339	0.321	0.157	0.050	0.211	0.779	-0.164	-0.235	-0.098
VISALIA-TULARE-PORTERVILLE CA	368,021	-0.060	0.280	0.475	0.200	-0.750	-0.194	-0.280	-0.258	0.003	0.291	0.194	0.146	0.757	0.140	0.215	0.224
WACO TX	213,517	-0.596	0.338	0.406	0.375	-0.493	0.356	0.441	0.329	-0.297	0.377	0.345	0.433	0.712	-0.465	-0.558	-0.478
WASHINGTON DC-MD-VA-WV	4,923,153	-0.549	0.250	0.280	0.280	-0.196	0.285	0.320	0.315	0.266	0.277	0.175	0.253	0.580	-0.411	-0.432	-0.446
WATERBURY CT	228,984	-0.691	0.561	0.461	0.298	-0.769	0.638	0.653	0.501	-0.019	0.086	-0.011	0.066	0.797	-0.660	-0.614	-0.450
WATERLOO-CEDAR FALLS IA	128,012	-0.543	0.159	0.425	0.222	-0.558	0.312	0.578	0.377	0.017	-0.121	-0.233	-0.111	0.602	-0.200	-0.479	-0.267
WAUSAU WI	125,834	-0.575	0.409	0.318	0.473	-0.576	0.405	0.371	0.226	-0.730	0.763	0.638	0.687	0.754	-0.739	-0.610	-0.682
WEST PALM BEACH-BOCA RATON FL	1,130,260	-0.459	0.334	0.344	0.083	-0.308	0.194	0.241	0.254	0.146	-0.075	-0.100	0.137	0.539	-0.385	-0.414	-0.189
WHEELING WV-OH	153,172	-0.443	0.384	0.413	0.422	-0.123	0.128	0.188	0.135	0.105	0.360	0.374	0.366	0.449	-0.430	-0.468	-0.471
WICHITA FALLS TX	140,518	-0.526	0.196	0.144	0.144	-0.646	0.503	0.496	0.542	0.008	0.377	0.411	0.449	0.749	-0.451	-0.416	-0.439
WICHITA KS	545,220	-0.416	0.273	0.270	0.240	-0.426	0.319	0.444	0.368	-0.138	0.458	0.317	0.302	0.572	-0.462	-0.486	-0.429
WILLIAMSPORT PA	120,044	-0.732	0.578	0.703	0.617	-0.499	0.508	0.620	0.537	0.126	0.334	0.386	0.346	0.723	-0.612	-0.738	-0.653
WILMINGTON NC	228,748	-0.635	0.449	0.402	0.118	-0.473	0.119	0.453	0.379	0.253	0.131	-0.100	0.647	0.665	-0.456	-0.439	-0.160
WILMINGTON-NEWARK DE-MD	586,216	-0.576	0.679	0.676	0.656	-0.400	0.234	0.190	0.238	0.458	-0.110	-0.256	-0.153	0.604	-0.682	-0.657	-0.657
WORCESTER MA-CT	508,982	-0.598	0.432	0.590	0.413	-0.671	0.363	0.546	0.294	-0.226	0.525	0.604	0.579	0.674	-0.476	-0.663	-0.431
YAKIMA WA	222,581	-0.474	0.592	0.704	0.671	-0.696	0.023	-0.041	-0.046	0.125	0.093	0.131	0.035	0.713	0.099	0.124	0.175
YOLO CA	161,404	-0.257	0.138	0.121	0.199	-0.296	-0.188	-0.293	-0.078	-0.153	0.215	0.320	0.115	0.539	0.027	0.121	-0.052
YORK PA	381,751	-0.736	0.448	0.522	0.566	-0.742	0.470	0.560	0.553	-0.112	0.393	0.417	0.462	0.753	-0.483	-0.566	-0.588
YOUNGSTOWN-WARREN OH	594,746	-0.666	0.244	0.095	0.451	-0.376	0.068	-0.082	0.235	0.325	0.041	0.033	0.128	0.680	-0.249	-0.085	-0.465
YUBA CITY CA	139,149	-0.287	0.063	-0.123	-0.115	-0.503	0.198	0.330	0.354	0.360	0.237	0.376	0.383	0.324	-0.324	-0.443	-0.509
YUMA AZ	160,026	0.086	-0.009	0.117	0.179	-0.572	0.050	0.049	-0.030	0.759	0.170	0.240	0.225	0.563	-0.064	-0.065	0.011

Note: The color scales are such that in each column red is negative, blue is positive, and white is zero.

Appendix B - MSA Characteristics for Supplemental Regressions

MSA	Region	Population	Income Gap	Median Income	Avg. Cancer Risk	Avg. Neuro. Risk	Avg. Resp. Risk
ABILENE TX	S	126,555	40,614	31,782	24.81480	0.04546	1.65001
AKRON OH	MW	694,960	55,115	42,350	36.00324	0.07501	5.49646
ALBANY GA	S	120,822	39,836	35,084	23.82946	0.05610	2.75794
ALBANY-SCHENECTADY-TROY NY	NE	875,583	47,916	43,191	43.05917	0.07343	8.28775
ALBUQUERQUE NM	W	709,780	51,966	37,860	38.53612	0.05623	3.37416
ALEXANDRIA LA	S	126,337	33,044	28,747	27.07610	0.06079	3.21255
ALLENTOWN-BETHLEHEM-EASTON PA	NE	637,958	47,172	41,114	36.13332	0.07310	4.31033
ALTOONA PA	NE	129,144	29,871	33,929	28.57544	0.05121	2.20707
AMARILLO TX	S	217,858	43,809	32,168	23.86925	0.04127	1.44272
ANCHORAGE AK	W	254,889	66,778	54,765	38.82125	0.06314	2.43967
ANN ARBOR MI	MW	578,736	70,241	59,217	36.74023	0.06494	4.35836
ANNISTON AL	S	112,249	31,340	31,549	27.38652	0.05555	3.35260
APPLETON-OSHKOSH-NEENAH WI	MW	358,365	32,253	46,619	30.73300	0.06371	2.30320
ASHEVILLE NC	S	225,965	33,049	34,860	32.44133	0.06678	4.51398
ATHENS GA	S	153,444	40,089	35,919	23.70532	0.05367	3.66666
ATLANTA GA	S	4,112,198	76,086	48,142	47.32357	0.09942	9.79826
ATLANTIC-CAPE MAY NJ	NE	344,726	40,338	43,635	27.57706	0.05449	2.89377
AUBURN-OPELIKA AL	S	115,092	48,915	28,932	26.25368	0.07118	3.76736
AUGUSTA-AIKEN GA-SC	S	477,441	54,135	36,735	29.85074	0.09513	4.42090
AUSTIN-SAN MARCOS TX	S	1,249,763	77,594	46,664	36.83996	0.07478	4.88494
BAKERSFIELD CA	W	661,645	57,697	35,854	50.90418	0.14929	12.07210
BALTIMORE MD	S	2,535,548	70,290	47,817	47.95060	0.14015	7.78225
BANGOR ME	NE	88,095	30,420	35,023	22.86241	0.04729	1.74101
BARNSTABLE-YARMOUTH MA	NE	159,282	43,672	49,069	24.25108	0.04541	2.31885
BATON ROUGE LA	S	602,894	48,743	38,239	40.57669	0.07883	5.55129
BEAUMONT-PORT ARTHUR TX	S	385,090	36,982	35,867	38.02261	0.10484	6.72614
BELLINGHAM WA	W	166,814	30,962	42,122	25.64698	0.06821	2.09548
BENTON HARBOR MI	MW	162,453	44,477	38,894	27.82022	0.05441	2.36250
BERGEN-PASSAIC NJ	NE	1,373,167	85,519	59,357	57.62679	0.13153	13.11108
BILLINGS MT	W	129,352	41,435	38,229	23.57757	0.04142	1.53615
BILOXI-GULFPORT-PASCAGOULA MS	S	363,988	29,236	35,639	26.79777	0.05892	4.65262
BINGHAMTON NY	NE	252,320	37,794	37,122	36.16143	0.05540	3.95962
BIRMINGHAM AL	S	921,106	65,946	37,525	44.16740	0.16040	6.00350
BISMARCK ND	MW	94,719	24,935	41,269	21.31701	0.04297	1.41148
BLOOMINGTON IN	MW	120,563	37,532	37,553	27.92504	0.06381	2.43907
BLOOMINGTON-NORMAL IL	MW	150,433	53,882	45,998	28.55926	0.05335	2.22083
BOISE CITY ID	W	432,345	43,643	41,830	54.75052	0.28962	4.10304
BOSTON MA-NH	NE	3,389,340	74,581	55,116	45.72141	0.07997	7.17385
BOULDER-LONGMONT CO	W	291,288	64,943	59,876	30.44329	0.04910	2.70265
BRAZORIA TX	S	241,767	39,006	43,452	30.25055	0.05135	4.96249
BREMERTON WA	W	231,969	52,870	49,656	37.01428	0.05765	4.54177
BRIDGEPORT CT	NE	459,479	81,458	55,486	46.02493	0.06784	5.87259

MSA	Region	Population	Income Gap	Median Income	Avg. Cancer Risk	Avg. Neuro. Risk	Avg. Resp. Risk
BROCKTON MA	NE	255,459	42,255	56,224	41.52881	0.07842	6.73976
BROWNSVILLE-HARLINGEN-SAN BENITO TX	S	326,245	33,936	24,897	27.41339	0.04856	1.72192
BRYAN-COLLEGE STATION TX	S	152,415	42,515	27,650	28.16005	0.05552	2.53891
BUFFALO-NIAGARA FALLS NY	NE	1,170,111	45,265	37,381	56.12148	0.09075	7.54750
BURLINGTON VT	NE	165,626	42,533	47,534	30.94425	0.05780	3.03645
CANTON-MASSILLON OH	MW	406,934	34,558	38,176	34.27048	0.07838	3.37268
CEDAR RAPIDS IA	MW	191,701	41,849	45,824	32.62748	0.05414	2.35387
CHAMPAIGN-URBANA IL	MW	179,669	57,717	38,059	26.66884	0.04713	1.46420
CHARLESTON WV	S	251,662	34,513	32,917	41.52985	0.06747	3.53955
CHARLESTON-NORTH CHARLESTON SC	S	547,154	50,181	35,990	31.19898	0.06682	3.44524
CHARLOTTE-GASTONIA-ROCK HILL NC-SC	S	1,499,293	57,461	42,399	39.29879	0.09418	6.51266
CHARLOTTESVILLE VA	S	159,576	47,671	43,598	23.00615	0.04918	2.10639
CHATTANOOGA TN-GA	S	465,161	50,277	36,447	57.10688	0.10150	6.89562
CHICAGO IL	MW	8,272,768	77,118	48,512	59.43071	0.14507	8.18710
CHICO-PARADISE CA	W	203,171	30,198	32,345	31.82844	0.11420	4.29535
CINCINNATI OH-KY-IN	MW	1,646,395	65,203	42,054	49.13696	0.12222	7.24711
CLARKSVILLE-HOPKINSVILLE TN-KY	S	207,033	28,190	36,837	25.86032	0.05243	2.75739
CLEVELAND-LORAIN-ELYRIA OH	MW	2,250,871	58,616	41,628	39.43561	0.12162	4.29150
COLORADO SPRINGS CO	W	516,929	55,821	45,000	31.42394	0.04570	2.12025
COLUMBIA MO	MW	135,454	45,044	40,261	23.81642	0.04448	1.54094
COLUMBIA SC	S	541,891	52,830	37,993	34.99371	0.07464	5.25249
COLUMBUS GA-AL	S	274,624	49,930	31,858	32.21692	0.15700	5.45524
COLUMBUS OH	MW	1,540,157	65,196	42,750	47.34131	0.10846	4.92131
CORPUS CHRISTI TX	S	371,078	46,561	34,849	30.08066	0.05644	2.11586
CUMBERLAND MD-WV	S	102,008	20,461	31,900	22.08049	0.04442	2.09962
DALLAS TX	S	3,519,176	78,714	45,058	44.49593	0.10064	7.08695
DANBURY CT	NE	217,980	74,149	76,202	37.92586	0.06099	6.61527
DANVILLE VA	S	110,156	26,874	32,159	19.24281	0.04578	1.87844
DAVENPORT-MOLINE-ROCK ISLAND IA-IL	MW	359,062	40,688	39,689	45.13182	0.09762	2.70650
DAYTONA BEACH FL	S	485,327	30,873	35,583	34.66045	0.06104	10.02820
DAYTON-SPRINGFIELD OH	MW	950,558	47,100	40,625	41.47107	0.07525	4.18375
DECATUR AL	S	145,867	34,163	36,146	43.29144	0.07676	3.06326
DECATUR IL	MW	114,706	45,516	41,136	30.02343	0.08539	1.58377
DENVER CO	W	2,109,282	66,602	52,047	39.14418	0.06488	4.01671
DES MOINES IA	MW	456,022	45,903	46,106	28.49678	0.05401	2.60458
DETROIT MI	MW	4,441,551	77,926	48,090	55.74016	0.10333	6.97196
DOTHAN AL	S	137,916	32,450	32,964	21.23130	0.06086	2.74203
DOVER DE	S	126,697	23,836	39,918	20.86050	0.04440	2.33686
DUBUQUE IA	MW	89,143	30,128	38,525	24.17241	0.05083	1.64305
DULUTH-SUPERIOR MN-WI	MW	242,414	35,133	35,429	26.32420	0.08794	2.26433
DUTCHESS COUNTY NY	NE	280,150	57,250	54,102	36.50373	0.07225	8.19017
EAU CLAIRE WI	MW	148,337	35,412	40,330	25.58719	0.08635	1.89910
EL PASO TX	S	679,622	39,361	27,445	36.12801	0.09520	2.76860
ELKHART-GOSHEN IN	MW	182,791	38,900	43,933	39.06366	0.09117	2.88877
ELMIRA NY	NE	91,070	38,855	33,723	36.46160	0.06534	5.07613

MSA	Region	Population	Income Gap	Median Income	Avg. Cancer Risk	Avg. Neuro. Risk	Avg. Resp. Risk
ERIE PA	NE	279,296	36,014	36,908	32.06694	0.10423	2.12799
EUGENE-SPRINGFIELD OR	W	322,959	37,815	38,897	44.28499	0.10945	3.64400
EVANSVILLE-HENDERSON IN-KY	MW	296,195	42,975	36,483	43.06178	0.07423	3.82241
FARGO-MOORHEAD ND-MN	MW	174,367	37,049	38,021	22.73201	0.04956	1.33144
FAYETTEVILLE NC	S	302,963	38,610	37,154	36.05265	0.06908	4.13058
FAYETTEVILLE-SPRINGDALE-ROGERS AR	S	311,121	32,626	36,753	26.59451	0.04753	2.53578
FITCHBURG-LEOMINSTER MA	NE	140,448	43,326	44,226	33.24570	0.05256	3.32449
FLAGSTAFF AZ-UT	W	122,366	34,910	37,500	21.82792	0.04024	4.82424
FLINT MI	MW	436,141	47,357	42,112	38.37916	0.06618	3.97215
FLORENCE AL	S	142,950	34,919	30,182	24.58594	0.22136	2.70200
FLORENCE SC	S	125,761	37,246	34,472	22.47512	0.05828	2.55954
FORT COLLINS-LOVELAND CO	W	251,494	49,092	50,006	24.16606	0.03700	1.33976
FORT LAUDERDALE FL	S	1,623,018	63,894	41,810	44.23332	0.07363	11.02269
FORT MYERS-CAPE CORAL FL	S	440,371	41,810	40,122	32.26067	0.05392	7.12561
FORT PIERCE-PORT ST. LUCIE FL	S	310,224	43,520	37,239	24.16795	0.04448	3.10395
FORT SMITH AR-OK	S	207,290	33,661	32,280	20.84559	0.05134	2.20843
FORT WALTON BEACH FL	S	168,685	47,704	40,899	26.45816	0.04073	7.45949
FORT WAYNE IN	MW	502,141	41,887	41,634	28.57924	0.10421	2.66744
FORT WORTH-ARLINGTON TX	S	1,702,625	62,989	43,179	37.75136	0.08909	5.02289
FRESNO CA	W	922,516	52,764	33,289	38.92040	0.14896	3.96952
GADSDEN AL	S	103,459	26,138	26,900	32.44477	0.08104	3.21538
GAINESVILLE FL	S	217,955	50,329	32,648	28.66160	0.05102	8.45544
GALVESTON-TEXAS CITY TX	S	246,379	56,823	33,824	39.37820	0.05911	4.11667
GARY IN	MW	631,362	50,015	42,254	61.79428	0.20294	4.96997
GLENS FALLS NY	NE	118,117	25,262	38,284	23.08549	0.04258	3.40006
GOLDSBORO NC	S	113,329	27,358	31,547	23.95101	0.06192	2.73810
GRAND FORKS ND-MN	MW	97,478	37,573	35,943	17.00595	0.03357	0.72158
GRAND JUNCTION CO	W	116,255	36,779	34,187	23.02454	0.03814	1.53212
GRAND RAPIDS-MUSKEGON-HOLLAND MI	MW	1,088,514	48,740	45,587	35.08370	0.07538	3.47425
GREAT FALLS MT	W	80,357	31,328	32,470	20.94091	0.03594	1.02105
GREELEY CO	W	180,936	46,517	42,672	23.80738	0.03948	1.48046
GREEN BAY WI	MW	226,778	39,760	48,520	36.54524	0.06697	2.95412
GREENSBORO--WINSTON-SALEM--HIGH POINT NC	S	1,251,509	48,906	40,037	39.87549	0.11738	4.47880
GREENVILLE NC	S	133,798	27,379	32,262	24.60723	0.04871	2.38589
GREENVILLE-SPARTANBURG-ANDERSON SC	S	962,441	41,803	36,537	31.68698	0.06126	4.24503
HAGERSTOWN MD	S	131,923	36,749	44,316	31.73360	0.09993	2.64426
HAMILTON-MIDDLETOWN OH	MW	332,807	59,056	44,362	37.75739	0.13265	4.64711
HARRISBURG-LEBANON-CARLISLE PA	NE	629,401	41,683	42,008	36.95043	0.08446	5.21689
HARTFORD CT	NE	1,183,803	65,137	51,792	41.28120	0.07705	6.16097
HATTIESBURG MS	S	111,674	32,574	26,341	28.98256	0.07232	2.98262
HICKORY-MORGANTON-LENOIR NC	S	341,851	22,648	37,750	33.56365	0.10119	3.57026
HONOLULU HI	W	867,885	60,090	54,909	34.98983	0.05171	2.43983
HOUMA LA	S	194,477	22,846	34,102	19.75027	0.06342	1.74650
HOUSTON TX	S	4,177,646	75,142	41,940	61.01730	0.11746	12.17377
HUNTINGTON-ASHLAND WV-KY-OH	S	315,538	23,525	28,507	46.92562	0.24228	2.76108

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HUNTSVILLE AL	S	342,376	64,962	40,100	29.00542	0.05509	3.04286
INDIANAPOLIS IN	MW	1,607,486	55,346	42,929	43.90588	0.09057	4.24011
IOWA CITY IA	MW	111,006	51,554	42,674	30.48595	0.06630	2.73882
JACKSON MI	MW	158,422	45,193	42,440	35.16383	0.06690	3.02676
JACKSON MS	S	440,801	54,447	36,795	40.60592	0.09837	4.43270
JACKSON TN	S	107,377	48,132	33,958	23.64720	0.06320	2.26300
JACKSONVILLE FL	S	1,100,491	56,581	40,159	40.73418	0.07161	6.90629
JACKSONVILLE NC	S	150,355	29,542	32,302	21.07997	0.04024	1.75233
JAMESTOWN NY	NE	139,750	26,517	34,811	26.68649	0.04840	2.47096
JANESVILLE-BELOIT WI	MW	152,307	47,223	43,322	32.97477	0.31440	2.96435
JERSEY CITY NJ	NE	608,975	43,146	39,113	91.33573	0.23020	23.87066
JOHNSON CITY-KINGSPORT-BRISTOL TN-VA	S	480,091	24,815	30,542	26.24074	0.06948	3.47659
JOHNSTOWN PA	NE	232,621	21,964	30,406	23.17236	0.05378	1.68133
JOPLIN MO	MW	157,322	19,227	32,697	24.89146	0.04415	1.63739
KALAMAZOO-BATTLE CREEK MI	MW	452,851	41,184	40,724	33.34663	0.07675	3.24291
KANKAKEE IL	MW	103,833	35,283	40,691	23.29263	0.05421	1.53702
KANSAS CITY MO-KS	MW	1,776,062	62,811	43,450	39.04031	0.08846	4.91804
KENOSHA WI	MW	149,577	44,526	47,810	32.61882	0.06228	3.59955
KILLEEN-TEMPLE TX	S	312,952	32,691	36,392	23.72170	0.04493	1.79979
KNOXVILLE TN	S	687,249	49,789	35,109	35.85397	0.08301	4.72280
KOKOMO IN	MW	101,541	40,004	43,958	30.03814	0.09669	2.45825
LA CROSSE WI-MN	MW	126,838	37,226	42,730	21.48203	0.05391	1.19248
LAFAYETTE IN	MW	182,821	43,229	39,321	37.77092	0.23024	2.43978
LAFAYETTE LA	S	385,647	38,929	30,024	24.31458	0.05281	2.86839
LAKE CHARLES LA	S	183,577	34,033	36,008	31.94636	0.06590	3.53372
LAKELAND-WINTER HAVEN FL	S	483,924	31,836	34,714	31.05936	0.04881	4.39177
LANCASTER PA	NE	470,658	34,145	45,940	42.52137	0.15847	5.17706
LANSING-EAST LANSING MI	MW	447,728	48,415	45,339	43.26617	0.06663	3.38681
LAREDO TX	S	193,117	38,754	24,104	29.95286	0.05930	2.48537
LAS CRUCES NM	W	174,682	29,562	27,532	24.79057	0.05830	2.03705
LAS VEGAS NV-AZ	W	1,563,282	55,292	46,037	35.53859	0.06513	4.82718
LAWRENCE KS	MW	99,962	46,582	40,617	24.71949	0.04724	2.21519
LAWRENCE MA-NH	NE	396,230	86,702	56,285	43.37666	0.07661	6.21848
LAWTON OK	S	114,996	33,474	34,807	24.90926	0.04627	1.96815
LEWISTON-AUBURN ME	NE	87,692	35,908	38,784	26.27944	0.06223	2.51984
LEXINGTON KY	S	479,198	55,738	37,460	30.18897	0.06227	3.08367
LIMA OH	MW	155,084	33,933	40,025	29.06854	0.10544	2.83465
LINCOLN NE	MW	250,291	53,999	42,839	32.04246	0.07140	2.40269
LITTLE ROCK-NORTH LITTLE ROCK AR	S	583,845	41,481	38,037	38.21836	0.08671	3.66854
LONGVIEW-MARSHALL TX	S	208,780	29,408	33,865	22.87124	0.16731	3.15636
LOS ANGELES-LONG BEACH CA	W	9,510,491	73,180	41,906	92.88636	0.29551	22.29655
LOUISVILLE KY-IN	S	1,025,598	62,108	39,697	43.70244	0.09930	9.09586
LOWELL MA-NH	NE	301,686	69,281	60,838	49.66583	0.08170	6.95427
LUBBOCK TX	S	242,628	37,992	31,698	27.68511	0.04807	1.66083
LYNCHBURG VA	S	214,911	35,637	35,872	19.93910	0.08214	1.99272

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MACON GA	S	322,549	48,001	32,550	25.30489	0.05678	3.75887
MADISON WI	MW	426,526	51,028	53,284	37.19210	0.08980	3.37334
MANCHESTER NH	NE	198,378	50,629	51,823	49.31162	0.08480	5.55327
MANSFIELD OH	MW	175,818	30,149	37,766	21.72416	0.04200	1.44195
MCALLEN-EDINBURG-MISSION TX	S	569,463	31,322	23,386	27.11597	0.04856	2.27280
MEDFORD-ASHLAND OR	W	181,269	33,211	37,326	55.71839	0.27063	6.35478
MELBOURNE-TITUSVILLE-PALM BAY FL	S	470,480	38,773	39,539	30.64945	0.05245	5.20811
MEMPHIS TN-AR-MS	S	1,135,614	66,139	38,005	38.72757	0.08707	5.39826
MERCED CA	W	210,554	33,199	34,397	28.37633	0.16368	3.59710
MIAMI FL	S	2,230,391	57,049	34,406	52.49904	0.09226	12.40012
MIDDLESEX-SOMERSET-HUNTERDON NJ	NE	1,169,641	70,579	66,022	40.77396	0.08514	7.05885
MILWAUKEE-WAUKESHA WI	MW	1,500,736	60,888	41,595	46.87978	0.10706	5.06157
MINNEAPOLIS-ST. PAUL MN-WI	MW	2,968,806	62,378	53,242	50.62125	0.07978	5.71995
MOBILE AL	S	540,258	44,939	33,058	30.43298	0.06341	3.55828
MODESTO CA	W	446,997	35,551	39,964	67.54130	0.19623	5.46910
MONMOUTH-OCEAN NJ	NE	1,119,457	74,241	57,557	38.06273	0.06378	5.05725
MONROE LA	S	147,250	41,012	31,660	27.55109	0.06225	2.97691
MONTGOMERY AL	S	333,055	50,459	34,943	33.34813	0.06017	3.65352
MUNCIE IN	MW	118,769	45,680	27,177	30.98334	0.06802	2.71825
MYRTLE BEACH SC	S	196,629	21,563	36,322	21.49768	0.04180	2.09277
NAPLES FL	S	251,377	47,428	48,314	32.13635	0.05347	12.61060
NASHUA NH	NE	184,626	72,706	62,517	44.97719	0.07557	4.61455
NASHVILLE TN	S	1,231,311	64,321	43,114	38.51429	0.07554	5.14446
NASSAU-SUFFOLK NY	NE	2,717,784	68,482	69,038	52.04561	0.07556	10.33359
NEW BEDFORD MA	NE	170,033	50,019	34,872	36.34769	0.06627	4.31736
NEW HAVEN-MERIDEN CT	NE	542,149	66,544	50,174	53.80570	0.06800	5.05422
NEW LONDON-NORWICH CT-RI	NE	293,566	40,485	52,181	28.18961	0.05677	3.21597
NEW ORLEANS LA	S	1,334,701	52,280	32,839	40.48334	0.08368	5.69659
NEW YORK NY	NE	9,295,264	69,475	40,833	93.57481	0.19894	22.66254
NEWARK NJ	NE	2,032,989	91,803	54,827	48.94532	0.10861	10.68174
NEWBURGH NY-PA	NE	387,669	54,552	53,678	34.47649	0.05977	6.61217
NORFOLK-VIRGINIA BEACH-NEWPORT NEWS VA-NC	S	1,560,331	53,189	40,304	33.22952	0.06431	2.93930
OAKLAND CA	W	2,392,557	86,350	56,867	55.58915	0.18398	10.14910
OCALA FL	S	258,916	24,088	31,176	26.17764	0.04951	7.82740
ODESSA-MIDLAND TX	S	237,132	40,452	35,139	28.32827	0.04843	2.31728
OKLAHOMA CITY OK	S	1,083,346	47,207	34,023	32.97266	0.06539	3.42483
OLYMPIA WA	W	207,355	41,141	47,655	32.25500	0.05480	3.01413
OMAHA NE-IA	MW	716,998	59,071	44,462	31.32468	0.07327	2.83957
ORANGE COUNTY CA	W	2,846,289	75,200	59,519	77.96212	0.27155	16.70726
ORLANDO FL	S	1,644,561	53,955	40,722	40.27629	0.07514	8.87918
OWENSBORO KY	S	91,545	40,884	37,540	35.41460	0.07541	2.71163
PANAMA CITY FL	S	148,217	36,246	36,139	27.68515	0.05634	8.67594
PENSACOLA FL	S	404,044	36,875	34,625	32.62587	0.06173	7.38675
PEORIA-PEKIN IL	MW	347,387	45,513	44,692	30.79823	0.26180	2.55498
PHILADELPHIA PA-NJ	NE	5,100,931	71,261	48,886	47.12617	0.10397	7.48545

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PHOENIX-MESA AZ	W	3,251,876	61,924	44,861	44.48168	0.07650	7.52720
PINE BLUFF AR	S	84,278	33,819	31,047	21.38090	0.06406	1.61249
PITTSBURGH PA	NE	2,358,695	47,753	35,931	58.16369	0.09745	5.00601
PITTSFIELD MA	NE	83,095	30,008	41,556	25.55316	0.05127	3.27819
POCATELLO ID	W	75,565	37,296	35,174	56.77618	0.20603	2.20561
PORTLAND ME	NE	242,323	45,546	44,916	34.14755	0.08565	3.44541
PORTLAND-VANCOUVER OR-WA	W	1,918,009	44,701	46,104	80.48161	0.34713	9.61819
PORTSMOUTH-ROCHESTER NH-ME	NE	237,559	33,412	48,076	30.47019	0.05181	2.85284
PROVIDENCE-FALL RIVER-WARWICK RI-MA	NE	1,184,995	50,033	41,389	39.20247	0.06906	4.85963
PROVO-OREM UT	W	368,536	43,196	48,571	32.09616	0.06598	2.67971
PUEBLO CO	W	141,472	40,731	32,361	30.74318	0.08832	2.05713
PUNTA GORDA FL	S	141,627	22,650	36,798	24.18381	0.04636	3.94275
RACINE WI	MW	188,831	50,381	45,915	29.44760	0.06600	2.68729
RALEIGH-DURHAM-CHAPEL HILL NC	S	1,187,941	66,281	46,506	34.53883	0.07561	4.62454
RAPID CITY SD	MW	88,565	36,103	35,900	20.85617	0.03667	2.73459
READING PA	NE	373,638	37,746	43,663	43.83267	0.14405	4.28731
REDDING CA	W	163,256	33,933	32,694	25.76590	0.09352	3.53752
RENO NV	W	339,486	55,540	50,890	33.56506	0.06097	8.89510
RICHLAND-KENNEWICK-PASCO WA	W	191,822	48,619	41,573	25.37325	0.04591	2.18916
RICHMOND-PETERSBURG VA	S	996,512	59,169	44,041	57.32199	0.07518	4.17006
RIVERSIDE-SAN BERNARDINO CA	W	3,254,612	56,702	40,436	43.62001	0.17993	6.52136
ROANOKE VA	S	235,932	42,187	36,399	28.34895	0.07404	3.40150
ROCHESTER MN	MW	124,277	68,826	54,865	23.75587	0.03834	1.24804
ROCHESTER NY	NE	1,098,201	53,161	41,447	44.48773	0.07206	7.85063
ROCKFORD IL	MW	371,236	51,672	42,607	32.45698	0.08913	2.95212
ROCKY MOUNT NC	S	143,026	28,177	34,078	27.14193	0.10804	2.13985
SACRAMENTO CA	W	1,635,453	60,000	47,102	48.82302	0.18779	6.03485
SAGINAW-BAY CITY-MIDLAND MI	MW	403,070	48,269	40,344	36.36281	0.08017	3.04350
SALEM OR	W	347,214	25,677	42,286	59.21820	0.15752	5.72912
SALINAS CA	W	401,762	45,050	46,675	33.00946	0.13046	3.64896
SALT LAKE CITY-OGDEN UT	W	1,333,914	57,856	50,747	44.99505	0.12914	6.06915
SAN ANGELO TX	S	104,010	28,079	31,987	23.14612	0.04454	1.64266
SAN ANTONIO TX	S	1,592,383	57,281	34,633	42.24426	0.08271	5.52569
SAN DIEGO CA	W	2,805,382	66,719	47,139	60.63936	0.29998	10.29380
SAN FRANCISCO CA	W	1,728,846	80,434	65,303	55.51452	0.17927	9.68743
SAN JOSE CA	W	1,682,585	87,641	75,728	51.66640	0.18992	8.41455
SAN LUIS OBISPO-ATASCADERO- PASO ROBLES CA	W	246,681	36,438	43,144	27.75071	0.15258	4.69962
SANTA BARBARA-SANTA MARIA-LOMPOC CA	W	396,736	56,787	46,291	35.47179	0.15603	4.22839
SANTA CRUZ-WATSONVILLE CA	W	255,602	50,344	55,006	33.27409	0.13130	4.15241
SANTA FE NM	W	147,635	51,920	41,660	23.51872	0.04204	2.13980
SANTA ROSA CA	W	458,614	35,426	52,111	35.58552	0.14385	4.72564
SARASOTA-BRADENTON FL	S	582,662	43,326	41,612	28.67097	0.04809	3.42376
SAVANNAH GA	S	293,000	50,614	33,820	32.83365	0.11869	4.58672
SCRANTON--WILKES-BARRE--HAZLETON PA	NE	624,776	30,765	32,828	33.19489	0.05835	3.37304
SEATTLE-BELLEVUE-EVERETT WA	W	2,400,714	55,665	54,904	60.62365	0.08428	7.51868

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SHARON PA	NE	120,293	35,502	35,600	26.03100	0.08321	1.96575
SHEBOYGAN WI	MW	112,646	38,570	48,216	26.11217	0.06428	1.67324
SHERMAN-DENISON TX	S	110,595	27,050	37,303	23.70580	0.05157	2.51848
SHREVEPORT-BOSSIER CITY LA	S	392,302	40,999	30,585	34.50334	0.07226	3.38677
SIOUX CITY IA-NE	MW	124,130	35,695	37,554	22.41472	0.05499	1.37813
SIOUX FALLS SD	MW	172,412	37,882	43,179	24.64749	0.04678	1.76862
SOUTH BEND IN	MW	265,559	52,672	35,993	36.61947	0.07999	3.59663
SPOKANE WA	W	424,156	44,626	37,065	33.19599	0.06138	3.41443
SPRINGFIELD IL	MW	201,437	54,599	44,429	25.06618	0.04308	1.71169
SPRINGFIELD MA	NE	581,243	49,590	39,684	37.88930	0.07001	5.72357
SPRINGFIELD MO	MW	325,721	43,973	34,341	29.58472	0.05581	2.09359
ST. CLOUD MN	MW	167,392	32,069	40,908	21.67330	0.04286	1.27500
ST. JOSEPH MO	MW	102,490	31,096	34,167	24.91246	0.05320	2.13530
ST. LOUIS MO-IL	MW	2,603,607	61,690	42,485	59.33337	0.11971	7.47440
STAMFORD-NORWALK CT	NE	353,556	163,827	82,914	42.71680	0.07510	8.20454
STATE COLLEGE PA	NE	135,758	49,948	38,700	26.49585	0.05307	2.12468
STEUBENVILLE-WEIRTON OH-WV	MW	132,008	29,487	32,150	73.64226	0.12172	1.96232
STOCKTON-LODI CA	W	563,598	45,510	41,059	70.71051	0.16156	6.11553
SUMTER SC	S	104,646	24,581	30,377	25.63053	0.07906	3.00206
SYRACUSE NY	NE	732,117	49,405	39,739	39.53477	0.06917	6.08129
TACOMA WA	W	700,820	46,538	46,292	47.90292	0.06021	4.89440
TALLAHASSEE FL	S	284,539	60,060	34,281	30.62198	0.05419	11.53178
TAMPA-ST. PETERSBURG-CLEARWATER FL	S	2,362,853	45,883	36,033	42.70090	0.07609	7.09190
TERRE HAUTE IN	MW	149,192	32,332	35,193	32.60030	0.05680	2.22950
TEXARKANA TX-TEXARKANA AR	S	129,749	28,132	31,446	20.75589	0.05297	2.83056
TOLEDO OH	MW	618,203	47,703	40,056	36.10739	0.07683	3.81243
TOPEKA KS	MW	169,871	44,527	38,663	31.27492	0.05797	3.06683
TRENTON NJ	NE	350,761	75,197	58,071	45.22052	0.09785	7.28760
TUCSON AZ	W	843,746	56,027	37,237	30.36313	0.04842	3.47637
TULSA OK	S	803,235	50,663	37,739	37.35971	0.08482	4.34198
TUSCALOOSA AL	S	164,875	47,314	36,803	33.71557	0.08057	3.86633
TYLER TX	S	174,706	36,728	37,058	24.79339	0.04967	2.07860
UTICA-ROME NY	NE	299,896	35,498	35,882	33.28989	0.05427	3.86219
VALLEJO-FAIRFIELD-NAPA CA	W	518,821	47,414	51,209	34.86392	0.11375	4.89851
VENTURA CA	W	748,801	69,965	57,846	44.19630	0.17572	7.74197
VICTORIA TX	S	84,088	24,980	35,109	23.44851	0.04854	1.93690
VINELAND-MILLVILLE-BRIDGETON NJ	NE	146,438	33,811	39,441	25.84840	0.05997	2.98942
VISALIA-TULARE-PORTERVILLE CA	W	368,021	26,683	32,778	34.27069	0.21852	5.65835
WACO TX	S	213,517	42,624	34,271	26.25872	0.05061	2.11466
WASHINGTON DC-MD-VA-WV	S	4,923,153	90,395	61,628	41.77554	0.08050	5.92531
WATERBURY CT	NE	228,984	52,154	46,517	38.65049	0.06188	4.40821
WATERLOO-CEDAR FALLS IA	MW	128,012	41,058	37,619	26.37047	0.05200	2.00716
WAUSAU WI	MW	125,834	29,665	45,282	24.63326	0.06757	1.34768
WEST PALM BEACH-BOCA RATON FL	S	1,130,260	71,266	45,066	36.32019	0.06121	7.32477
WHEELING WV-OH	S	153,172	29,337	29,894	31.90038	0.05355	2.01518

MSA	Region	Population	Income Gap	Median Income	Avg. Cancer Risk	Avg. Neuro. Risk	Avg. Resp. Risk
WICHITA FALLS TX	S	140,518	34,732	32,439	23.03915	0.04280	1.35345
WICHITA KS	MW	545,220	57,535	41,657	34.06285	0.05152	2.10079
WILLIAMSPORT PA	NE	120,044	27,666	36,202	24.84264	0.04837	1.87140
WILMINGTON NC	S	228,748	49,803	36,349	34.15923	0.06375	4.23070
WILMINGTON-NEWARK DE-MD	S	586,216	60,682	49,583	40.07223	0.09825	5.12117
WORCESTER MA-CT	NE	508,982	52,362	48,627	32.06531	0.05123	3.28760
YAKIMA WA	W	222,581	40,186	33,017	23.84521	0.04444	1.56633
YOLO CA	W	161,404	46,225	43,323	34.48988	0.42199	5.65331
YORK PA	NE	381,751	37,242	45,313	47.34357	0.12145	5.37460
YOUNGSTOWN-WARREN OH	MW	594,746	35,865	34,806	33.55153	0.16360	2.65401
YUBA CITY CA	W	139,149	30,190	36,057	26.84266	0.12661	5.35076
YUMA AZ	W	160,026	27,931	31,494	22.90336	0.04830	2.46979

Appendix C - MSA Hedonic Regression Coefficients

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
ABILENE TX	126,555	0.190	0.340	0.177	0.450	0.170	0.730
AKRON OH	694,960	-0.767	-5.070	-0.549	-5.090	-0.464	-4.410
ALBANY GA	120,822	-0.336	-2.030	-0.409	-1.430	-0.024	-0.060
ALBANY-SCHENECTADY-TROY NY	875,583	-0.113	-1.750	-0.134	-2.120	0.044	0.920
ALBUQUERQUE NM	709,780	0.129	1.830	-0.020	-0.180	-0.034	-0.450
ALEXANDRIA LA	126,337	-0.122	-0.480	-0.030	-0.140	-0.065	-0.330
ALLENTOWN-BETHLEHEM-EASTON PA	637,958	0.076	0.740	-0.117	-1.220	-0.021	-0.270
ALTOONA PA	129,144	-0.640	-1.920	-1.007	-4.660	-0.728	-3.710
AMARILLO TX	217,858	0.507	1.240	0.156	0.620	0.092	0.420
ANCHORAGE AK	254,889	0.256	1.820	0.263	2.040	0.243	2.030
ANN ARBOR MI	578,736	-0.019	-0.140	0.017	0.110	0.087	0.980
ANNISTON AL	112,249	-0.286	-1.050	-0.113	-0.570	-0.063	-0.330
APPLETON-OSHKOSH-NEENAH WI	358,365	0.067	0.640	-0.089	-1.130	0.054	0.610
ASHEVILLE NC	225,965	0.208	0.860	0.250	1.010	0.255	1.160
ATHENS GA	153,444	-0.161	-0.390	0.991	2.070	0.547	1.110
ATLANTA GA	4,112,198	0.263	3.490	0.494	6.780	0.295	3.790
ATLANTIC-CAPE MAY NJ	344,726	-0.888	-3.590	-0.949	-4.020	-0.504	-3.970
AUBURN-OPELIKA AL	115,092	1.912	1.800	0.414	0.700	1.073	1.600
AUGUSTA-AIKEN GA-SC	477,441	-0.040	-0.270	-0.034	-0.320	0.156	0.940
AUSTIN-SAN MARCOS TX	1,249,763	0.568	7.390	0.596	7.170	0.369	6.850
BAKERSFIELD CA	661,645	0.324	4.260	0.350	7.020	0.156	5.510
BALTIMORE MD	2,535,548	-0.568	-10.210	-0.243	-5.430	-0.350	-7.740
BANGOR ME	88,095	-0.254	-1.180	-0.156	-0.850	-0.031	-0.190
BARNSTABLE-YARMOUTH MA	159,282	-0.863	-1.770	-0.032	-0.080	-0.645	-2.380
BATON ROUGE LA	602,894	-0.384	-2.830	-0.399	-2.590	-0.391	-3.340
BEAUMONT-PORT ARTHUR TX	385,090	-0.077	-0.680	-0.069	-0.730	0.007	0.050
BELLINGHAM WA	166,814	-0.211	-0.980	-0.066	-0.780	0.001	0.010
BENTON HARBOR MI	162,453	-0.325	-0.910	0.194	0.960	0.028	0.180
BERGEN-PASSAIC NJ	1,373,167	0.203	2.660	0.090	1.490	0.205	3.550
BILLINGS MT	129,352	-0.306	-1.050	-0.334	-1.470	-0.039	-0.270
BILOXI-GULFPORT-PASCAGOULA MS	363,988	-0.179	-1.400	0.007	0.070	-0.009	-0.150
BINGHAMTON NY	252,320	-0.056	-0.780	-0.074	-0.540	-0.005	-0.050
BIRMINGHAM AL	921,106	-0.420	-3.560	-0.068	-1.100	-0.426	-3.190
BISMARCK ND	94,719	0.992	1.580	0.425	0.800	0.362	1.020
BLOOMINGTON IN	120,563	-0.066	-0.220	-0.106	-0.470	-0.055	-0.280
BLOOMINGTON-NORMAL IL	150,433	-0.057	-0.160	0.064	0.320	0.061	0.390
BOISE CITY ID	432,345	-0.077	-0.980	-0.088	-1.430	-0.011	-0.200
BOSTON MA-NH	3,389,340	0.334	4.250	0.353	5.910	0.112	2.090
BOULDER-LONGMONT CO	291,288	-0.599	-1.660	-0.133	-0.550	-0.276	-1.810
BRAZORIA TX	241,767	0.399	2.330	0.442	2.820	0.349	2.950

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
BREMERTON WA	231,969	0.490	1.320	-0.338	-1.050	0.735	2.290
BRIDGEPORT CT	459,479	0.213	1.500	-0.085	-0.550	-0.132	-0.910
BROCKTON MA	255,459	0.175	0.710	-0.031	-0.200	0.004	0.020
BROWNSVILLE-HARLINGEN-SAN BENITO TX	326,245	-0.407	-1.360	-0.209	-1.580	-0.130	-1.400
BRYAN-COLLEGE STATION TX	152,415	-0.339	-1.010	-0.104	-0.390	-0.245	-1.160
BUFFALO-NIAGARA FALLS NY	1,170,111	-0.280	-3.670	-0.328	-5.590	-0.227	-3.600
BURLINGTON VT	165,626	0.148	1.260	0.245	1.970	0.237	2.540
CANTON-MASSILLON OH	406,934	-0.303	-2.710	-0.511	-5.420	-0.128	-1.230
CEDAR RAPIDS IA	191,701	-0.190	-2.250	-0.227	-1.640	-0.154	-1.230
CHAMPAIGN-URBANA IL	179,669	-0.918	-2.840	-0.804	-4.080	-0.775	-3.300
CHARLESTON WV	251,662	-0.215	-2.110	0.094	0.620	0.006	0.040
CHARLESTON-NORTH CHARLESTON SC	547,154	-0.313	-1.090	-0.487	-2.670	-0.796	-4.390
CHARLOTTE-GASTONIA-ROCK HILL NC-SC	1,499,293	-0.087	-1.130	0.032	0.500	-0.053	-0.990
CHARLOTTESVILLE VA	159,576	0.163	0.490	0.207	0.480	0.281	0.950
CHATTANOOGA TN-GA	465,161	-0.201	-3.280	0.075	0.910	-0.045	-0.470
CHICAGO IL	8,272,768	0.327	8.600	-0.019	-0.660	0.242	8.370
CHICO-PARADISE CA	203,171	-0.049	-0.350	0.003	0.030	-0.062	-0.560
CINCINNATI OH-KY-IN	1,646,395	0.148	2.420	0.068	1.280	0.079	1.460
CLARKSVILLE-HOPKINSVILLE TN-KY	207,033	0.327	1.320	0.387	1.820	0.437	2.360
CLEVELAND-LORAIN-ELYRIA OH	2,250,871	-0.269	-4.440	-0.170	-6.030	-0.140	-3.160
COLORADO SPRINGS CO	516,929	0.016	0.080	0.310	1.920	0.132	1.280
COLUMBIA MO	135,454	0.000	0.000	-0.213	-0.720	-0.136	-0.580
COLUMBIA SC	541,891	-0.092	-0.600	0.010	0.090	-0.055	-0.430
COLUMBUS GA-AL	274,624	0.327	2.010	0.020	0.250	0.324	1.490
COLUMBUS OH	1,540,157	-0.113	-2.560	-0.239	-5.330	-0.269	-4.220
CORPUS CHRISTI TX	371,078	0.032	0.240	-0.003	-0.030	-0.023	-0.240
CUMBERLAND MD-WV	102,008	0.117	0.430	0.078	0.270	0.317	1.300
DALLAS TX	3,519,176	0.232	3.350	0.248	4.640	0.270	6.020
DANBURY CT	217,980	0.256	1.190	0.355	1.290	0.183	1.030
DANVILLE VA	110,156	-0.465	-2.570	-0.378	-2.130	-0.351	-2.500
DAVENPORT-MOLINE-ROCK ISLAND IA-IL	359,062	0.077	0.870	0.097	1.260	0.099	1.010
DAYTONA BEACH FL	485,327	-0.229	-1.270	-0.072	-0.460	-0.404	-1.650
DAYTON-SPRINGFIELD OH	950,558	-0.105	-1.720	-0.040	-0.500	-0.017	-0.260
DECATUR AL	145,867	-0.115	-1.470	-0.142	-1.130	-0.041	-0.270
DECATUR IL	114,706	-0.819	-2.330	-0.719	-4.090	-0.640	-2.140
DENVER CO	2,109,282	0.127	1.670	0.092	1.200	0.038	0.650
DES MOINES IA	456,022	-0.149	-1.940	-0.287	-3.290	-0.133	-2.230
DETROIT MI	4,441,551	-0.593	-9.840	-0.684	-15.130	-0.250	-5.540
DOTHAN AL	137,916	0.074	0.330	-0.042	-0.320	0.215	1.100
DOVER DE	126,697	1.228	2.710	0.370	1.290	0.166	0.780
DUBUQUE IA	89,143	-0.698	-1.640	0.014	0.070	-0.243	-1.370
DULUTH-SUPERIOR MN-WI	242,414	-0.330	-1.730	-0.094	-2.570	-0.303	-4.420
DUTCHESS COUNTY NY	280,150	-0.147	-0.740	-0.466	-2.850	0.313	2.770
EAU CLAIRE WI	148,337	0.368	1.210	-0.058	-0.410	0.194	1.170
EL PASO TX	679,622	0.107	1.080	0.124	3.010	0.018	0.270
ELKHART-GOSHEN IN	182,791	0.043	0.540	0.003	0.040	-0.030	-0.200

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
ELMIRA NY	91,070	-0.189	-0.560	-0.517	-1.500	0.238	0.820
ERIE PA	279,296	-0.656	-3.230	-0.275	-3.580	-0.376	-2.530
EUGENE-SPRINGFIELD OR	322,959	0.182	2.320	0.249	4.560	0.304	4.220
EVANSVILLE-HENDERSON IN-KY	296,195	-0.189	-1.670	-0.582	-4.250	-0.333	-2.780
FARGO-MOORHEAD ND-MN	174,367	0.133	0.230	-0.149	-0.580	0.227	0.780
FAYETTEVILLE NC	302,963	-0.193	-0.950	-0.093	-0.690	-0.050	-0.340
FAYETTEVILLE-SPRINGDALE-ROGERS AR	311,121	0.362	1.360	0.356	1.330	0.178	1.010
FITCHBURG-LEOMINSTER MA	140,448	0.278	0.810	0.115	0.590	0.326	1.620
FLAGSTAFF AZ-UT	122,366	0.416	1.090	0.162	0.380	0.304	2.150
FLINT MI	436,141	-0.488	-1.350	-0.609	-2.400	0.028	0.110
FLORENCE AL	142,950	0.041	0.140	-0.044	-0.330	-0.127	-0.340
FLORENCE SC	125,761	0.021	0.040	-0.380	-1.640	0.060	0.240
FORT COLLINS-LOVELAND CO	251,494	-0.741	-1.310	-0.232	-0.720	-0.145	-0.710
FORT LAUDERDALE FL	1,623,018	-0.593	-3.930	-0.316	-2.590	-0.372	-6.450
FORT MYERS-CAPE CORAL FL	440,371	-0.780	-2.160	-0.556	-2.310	0.091	0.490
FORT PIERCE-PORT ST. LUCIE FL	310,224	-1.533	-2.160	-0.811	-1.650	-0.112	-0.290
FORT SMITH AR-OK	207,290	0.091	0.680	0.011	0.100	-0.087	-0.860
FORT WALTON BEACH FL	168,685	-0.971	-2.900	-0.812	-2.900	-0.324	-2.890
FORT WAYNE IN	502,141	-0.186	-1.620	0.012	0.200	-0.197	-1.710
FORT WORTH-ARLINGTON TX	1,702,625	-0.022	-0.230	0.090	1.410	0.012	0.190
FRESNO CA	922,516	-0.193	-2.740	-0.144	-2.270	-0.202	-4.180
GADSDEN AL	103,459	-0.328	-2.690	-0.259	-2.850	-0.179	-0.890
GAINESVILLE FL	217,955	-0.801	-1.070	-0.262	-0.730	-0.450	-1.000
GALVESTON-TEXAS CITY TX	246,379	-0.315	-1.850	-0.309	-1.640	-0.019	-0.140
GARY IN	631,362	-0.382	-5.570	-0.205	-2.940	-0.151	-1.620
GLENS FALLS NY	118,117	0.008	0.040	0.068	0.350	0.128	1.580
GOLDSBORO NC	113,329	0.829	1.600	0.049	0.070	0.626	1.570
GRAND FORKS ND-MN	97,478	-0.007	-0.030	0.637	1.820	0.271	1.130
GRAND JUNCTION CO	116,255	0.131	0.400	0.145	0.730	0.168	1.070
GRAND RAPIDS-MUSKEGON-HOLLAND MI	1,088,514	-0.102	-1.110	0.044	0.720	-0.002	-0.040
GREAT FALLS MT	80,357	-0.858	-2.470	-0.646	-2.980	-0.431	-2.780
GREELEY CO	180,936	0.483	1.410	0.251	1.070	0.156	1.740
GREEN BAY WI	226,778	-0.521	-2.850	-0.350	-2.640	-0.410	-3.270
GREENSBORO--WINSTON-SALEM--HIGH POINT NC	1,251,509	-0.053	-1.050	-0.040	-1.140	-0.142	-1.770
GREENVILLE NC	133,798	-0.067	-0.200	-0.277	-1.440	-0.260	-1.220
GREENVILLE-SPARTANBURG-ANDERSON SC	962,441	0.078	0.920	0.003	0.030	0.151	1.810
HAGERSTOWN MD	131,923	-0.234	-1.300	0.019	0.430	-0.373	-1.950
HAMILTON-MIDDLETOWN OH	332,807	-0.318	-1.870	-0.045	-0.730	-0.143	-1.270
HARRISBURG-LEBANON-CARLISLE PA	629,401	-0.211	-1.650	-0.262	-2.640	-0.003	-0.030
HARTFORD CT	1,183,803	-0.035	-0.520	-0.176	-2.570	-0.076	-1.500
HATTIESBURG MS	111,674	-0.251	-1.060	-0.463	-1.700	-0.334	-1.200
HICKORY-MORGANTON-LENOIR NC	341,851	0.034	0.560	0.037	0.680	0.168	3.550
HONOLULU HI	867,885	0.049	0.270	0.110	1.240	-0.081	-1.360
HOUMA LA	194,477	-0.099	-0.610	0.002	0.030	0.045	0.730
HOUSTON TX	4,177,646	0.131	2.490	0.199	3.830	0.010	0.240
HUNTINGTON-ASHLAND WV-KY-OH	315,538	-0.049	-0.860	-0.035	-0.860	0.065	0.460

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
HUNTSVILLE AL	342,376	-0.332	-1.250	-0.258	-1.420	-0.115	-0.730
INDIANAPOLIS IN	1,607,486	-0.217	-3.750	-0.251	-4.770	-0.174	-2.740
IOWA CITY IA	111,006	-0.009	-0.040	0.074	0.530	-0.059	-0.330
JACKSON MI	158,422	-0.416	-1.430	-0.993	-5.870	-0.297	-1.480
JACKSON MS	440,801	-0.176	-1.310	-0.217	-1.890	0.033	0.220
JACKSON TN	107,377	-0.298	-1.330	-0.102	-0.540	-0.129	-0.690
JACKSONVILLE FL	1,100,491	-0.604	-6.350	-0.444	-4.350	-0.558	-3.870
JACKSONVILLE NC	150,355	0.437	0.710	0.250	0.500	0.068	0.230
JAMESTOWN NY	139,750	-0.337	-1.710	-0.384	-2.640	-0.124	-1.190
JANESVILLE-BELOIT WI	152,307	-0.026	-0.090	0.103	0.610	0.083	0.310
JERSEY CITY NJ	608,975	0.759	3.940	0.108	1.050	0.591	2.330
JOHNSON CITY-KINGSPORT-BRISTOL TN-VA	480,091	-0.025	-0.340	-0.015	-0.300	0.068	1.180
JOHNSTOWN PA	232,621	-0.538	-1.850	-0.435	-2.830	-0.295	-1.190
JOPLIN MO	157,322	-0.061	-0.340	-0.572	-2.160	-0.290	-1.630
KALAMAZOO-BATTLE CREEK MI	452,851	-0.071	-0.520	-0.090	-1.180	-0.042	-0.400
KANKAKEE IL	103,833	-0.583	-1.320	0.163	0.720	0.142	0.600
KANSAS CITY MO-KS	1,776,062	-0.203	-2.840	-0.335	-6.300	-0.175	-3.240
KENOSHA WI	149,577	-0.306	-1.000	-0.556	-2.530	-0.071	-0.220
KILLEEN-TEMPLE TX	312,952	0.170	1.160	0.154	1.070	0.111	0.970
KNOXVILLE TN	687,249	-0.061	-0.690	-0.171	-2.190	-0.112	-1.370
KOKOMO IN	101,541	-0.099	-0.650	0.107	1.200	0.011	0.070
LA CROSSE WI-MN	126,838	0.241	2.000	-0.053	-0.570	0.224	2.200
LAFAYETTE IN	182,821	-0.021	-0.150	-0.021	-0.490	-0.190	-1.220
LAFAYETTE LA	385,647	0.405	1.880	0.645	2.900	0.290	1.930
LAKE CHARLES LA	183,577	-0.188	-1.060	-0.065	-0.350	-0.092	-0.650
LAKELAND-WINTER HAVEN FL	483,924	0.089	0.560	0.025	0.160	0.262	1.680
LANCASTER PA	470,658	-0.516	-3.300	-0.062	-1.110	-0.401	-2.920
LANSING-EAST LANSING MI	447,728	-0.343	-3.950	-0.567	-5.240	-0.439	-4.410
LAREDO TX	193,117	-0.177	-0.470	0.031	0.150	0.130	0.650
LAS CRUCES NM	174,682	-0.474	-1.310	-0.218	-1.400	-0.020	-0.080
LAS VEGAS NV-AZ	1,563,282	0.089	1.280	-0.086	-1.670	-0.049	-1.620
LAWRENCE KS	99,962	-0.192	-0.310	-0.239	-0.610	0.029	0.090
LAWRENCE MA-NH	396,230	0.256	1.210	0.144	0.830	0.318	2.430
LAWTON OK	114,996	-0.039	-0.160	-0.045	-0.290	-0.025	-0.180
LEWISTON-AUBURN ME	87,692	-0.147	-0.820	-0.001	0.000	-0.126	-0.970
LEXINGTON KY	479,198	-0.105	-1.010	-0.124	-1.020	-0.093	-0.850
LIMA OH	155,084	-0.677	-6.600	0.111	1.100	-0.557	-6.190
LINCOLN NE	250,291	-0.031	-0.140	-0.049	-0.500	0.059	0.590
LITTLE ROCK-NORTH LITTLE ROCK AR	583,845	-0.075	-0.910	-0.039	-0.460	-0.292	-3.600
LONGVIEW-MARSHALL TX	208,780	-0.196	-0.920	-0.072	-0.920	-0.059	-0.430
LOS ANGELES-LONG BEACH CA	9,510,491	0.192	4.720	0.261	8.220	0.279	12.030
LOUISVILLE KY-IN	1,025,598	-0.248	-3.450	-0.166	-2.710	-0.163	-3.470
LOWELL MA-NH	301,686	-0.534	-3.680	-0.393	-4.850	-0.380	-3.950
LUBBOCK TX	242,628	-0.322	-1.030	-0.246	-1.240	-0.281	-1.750
LYNCHBURG VA	214,911	-0.744	-2.600	-0.509	-5.770	-0.436	-1.580
MACON GA	322,549	-0.217	-1.190	-0.482	-2.050	-0.273	-1.530

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
MADISON WI	426,526	-0.395	-1.820	-0.052	-0.660	-0.261	-2.320
MANCHESTER NH	198,378	0.214	1.640	0.199	1.620	0.140	0.960
MANSFIELD OH	175,818	-0.296	-0.840	-0.570	-2.400	-0.260	-1.580
MCALLEN-EDINBURG-MISSION TX	569,463	-0.278	-0.940	-0.070	-0.410	-0.039	-0.220
MEDFORD-ASHLAND OR	181,269	0.157	0.680	-0.099	-1.080	-0.058	-0.480
MELBOURNE-TITUSVILLE-PALM BAY FL	470,480	-0.563	-1.860	-0.299	-1.410	-0.490	-3.550
MEMPHIS TN-AR-MS	1,135,614	0.011	0.100	-0.315	-2.830	-0.003	-0.030
MERCED CA	210,554	-0.036	-0.170	0.083	0.900	0.019	0.200
MIAMI FL	2,230,391	0.728	4.610	0.605	5.910	0.054	0.660
MIDDLESEX-SOMERSET-HUNTERDON NJ	1,169,641	-0.317	-3.960	-0.310	-4.550	-0.220	-4.340
MILWAUKEE-WAUKESHA WI	1,500,736	-0.895	-8.790	-0.643	-9.060	-0.781	-8.880
MINNEAPOLIS-ST. PAUL MN-WI	2,968,806	-0.155	-4.810	-0.191	-4.650	-0.111	-3.920
MOBILE AL	540,258	-0.515	-2.700	-0.340	-2.430	-0.378	-2.040
MODESTO CA	446,997	0.045	0.670	0.050	0.570	-0.046	-0.760
MONMOUTH-OCEAN NJ	1,119,457	-1.370	-5.080	0.153	1.170	-0.071	-0.890
MONROE LA	147,250	-0.317	-0.750	0.032	0.110	-0.108	-0.340
MONTGOMERY AL	333,055	-0.379	-3.040	-0.062	-0.280	-0.148	-0.750
MUNCIE IN	118,769	-0.164	-0.690	-0.304	-1.420	-0.138	-0.590
MYRTLE BEACH SC	196,629	-1.100	-2.670	-0.874	-2.520	-0.540	-2.250
NAPLES FL	251,377	-0.766	-1.780	-0.031	-0.110	-0.924	-3.200
NASHUA NH	184,626	0.353	1.320	0.366	1.920	0.175	0.820
NASHVILLE TN	1,231,311	-0.181	-2.590	-0.202	-2.620	-0.143	-2.680
NASSAU-SUFFOLK NY	2,717,784	0.117	2.170	0.236	4.750	0.183	4.420
NEW BEDFORD MA	170,033	-0.602	-2.750	-0.411	-3.330	-0.293	-2.120
NEW HAVEN-MERIDEN CT	542,149	-0.140	-2.050	0.194	1.380	0.071	0.440
NEW LONDON-NORWICH CT-RI	293,566	-0.370	-1.260	-0.192	-1.010	-0.218	-1.090
NEW ORLEANS LA	1,334,701	0.249	3.800	0.204	3.210	0.163	4.590
NEW YORK NY	9,295,264	0.154	3.210	0.278	7.560	0.188	3.790
NEWARK NJ	2,032,989	0.142	2.460	0.058	1.170	0.102	2.940
NEWBURGH NY-PA	387,669	0.062	0.510	0.098	0.630	0.118	1.820
NORFOLK-VIRGINIA BEACH-NEWPORT NEWS VA-NC	1,560,331	-0.214	-3.550	-0.196	-3.040	-0.087	-1.490
OAKLAND CA	2,392,557	0.076	1.100	0.155	3.120	0.136	2.960
OCALA FL	258,916	-0.012	-0.020	0.014	0.040	-0.302	-1.130
ODESSA-MIDLAND TX	237,132	0.067	0.160	0.070	0.230	0.176	0.980
OKLAHOMA CITY OK	1,083,346	0.128	1.630	0.045	0.670	0.117	2.450
OLYMPIA WA	207,355	0.103	0.420	0.175	0.900	0.209	1.530
OMAHA NE-IA	716,998	0.064	0.500	-0.212	-2.130	0.244	1.960
ORANGE COUNTY CA	2,846,289	-0.332	-5.650	-0.364	-8.060	-0.192	-5.070
ORLANDO FL	1,644,561	0.294	4.140	0.272	4.010	0.296	3.570
OWENSBORO KY	91,545	-1.233	-3.770	-0.384	-1.570	-1.155	-3.710
PANAMA CITY FL	148,217	-1.043	-2.570	-0.450	-3.180	-0.320	-1.340
PENSACOLA FL	404,044	-0.553	-4.320	-0.440	-3.960	-0.364	-2.450
PEORIA-PEKIN IL	347,387	-0.223	-1.450	-0.041	-0.600	-0.181	-1.330
PHILADELPHIA PA-NJ	5,100,931	-0.948	-17.450	-0.674	-16.580	-0.712	-17.170
PHOENIX-MESA AZ	3,251,876	0.041	0.750	-0.112	-2.450	0.017	0.590
PINE BLUFF AR	84,278	-1.398	-2.020	-0.092	-0.240	-0.561	-0.860

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
PITTSBURGH PA	2,358,695	-0.073	-1.760	0.009	0.200	0.098	2.250
PITTSFIELD MA	83,095	-0.973	-2.180	-0.487	-2.060	-0.428	-1.720
POCATELLO ID	75,565	-0.094	-1.490	-0.154	-1.190	-0.261	-1.390
PORTLAND ME	242,323	0.001	0.000	-0.006	-0.040	0.037	0.240
PORTLAND-VANCOUVER OR-WA	1,918,009	0.084	2.010	0.092	3.450	0.093	2.520
PORTSMOUTH-ROCHESTER NH-ME	237,559	0.356	2.040	0.605	3.330	0.396	3.650
PROVIDENCE-FALL RIVER-WARWICK RI-MA	1,184,995	-0.027	-0.390	0.059	0.860	0.007	0.130
PROVO-OREM UT	368,536	-0.037	-0.310	-0.020	-0.400	-0.112	-1.360
PUEBLO CO	141,472	-0.306	-2.500	-0.133	-1.950	-0.114	-0.630
PUNTA GORDA FL	141,627	-1.317	-0.850	-1.465	-1.130	-0.171	-0.220
RACINE WI	188,831	-1.467	-3.130	-0.744	-4.660	-0.283	-0.600
RALEIGH-DURHAM-CHAPEL HILL NC	1,187,941	-0.079	-0.720	-0.051	-0.620	0.212	2.000
RAPID CITY SD	88,565	0.705	1.450	0.509	1.120	0.296	2.200
READING PA	373,638	-0.848	-5.480	-0.481	-6.070	-0.885	-5.260
REDDING CA	163,256	0.081	0.560	0.064	0.880	0.119	1.820
RENO NV	339,486	-0.276	-0.640	-0.216	-0.870	0.141	1.000
RICHLAND-KENNEWICK-PASCO WA	191,822	0.020	0.120	0.018	0.120	0.069	0.810
RICHMOND-PETERSBURG VA	996,512	0.076	2.080	0.095	1.190	0.082	1.310
RIVERSIDE-SAN BERNARDINO CA	3,254,612	0.395	5.910	0.116	2.850	0.196	6.260
ROANOKE VA	235,932	-0.198	-0.830	-0.099	-0.430	-0.232	-0.950
ROCHESTER MN	124,277	-0.033	-0.090	-0.295	-0.860	-0.009	-0.040
ROCHESTER NY	1,098,201	-0.054	-0.770	-0.229	-3.320	-0.026	-0.570
ROCKFORD IL	371,236	-0.130	-1.170	-0.150	-2.250	-0.011	-0.120
ROCKY MOUNT NC	143,026	-0.153	-1.130	-0.061	-1.060	0.072	0.410
SACRAMENTO CA	1,635,453	-0.104	-2.090	-0.249	-5.020	-0.195	-3.450
SAGINAW-BAY CITY-MIDLAND MI	403,070	-0.462	-4.530	-0.397	-5.830	-0.198	-1.650
SALEM OR	347,214	-0.040	-0.620	-0.083	-1.280	-0.105	-1.340
SALINAS CA	401,762	0.030	0.100	-0.418	-3.580	0.018	0.110
SALT LAKE CITY-OGDEN UT	1,333,914	0.104	1.790	0.039	1.480	-0.012	-0.320
SAN ANGELO TX	104,010	-1.071	-1.560	-0.674	-1.710	-0.467	-1.590
SAN ANTONIO TX	1,592,383	-0.152	-2.090	-0.057	-0.750	-0.103	-2.030
SAN DIEGO CA	2,805,382	0.212	2.120	-0.028	-0.430	0.165	2.950
SAN FRANCISCO CA	1,728,846	0.036	0.380	0.153	2.060	-0.075	-0.950
SAN JOSE CA	1,682,585	-0.026	-0.160	-0.317	-2.470	-0.114	-1.260
SAN LUIS OBISPO-ATASCADERO- PASO ROBLES CA	246,681	-0.252	-0.710	0.003	0.030	-0.298	-2.030
SANTA BARBARA-SANTA MARIA-LOMPOC CA	396,736	0.427	0.840	-0.439	-2.080	0.188	0.830
SANTA CRUZ-WATSONVILLE CA	255,602	0.078	0.290	0.051	0.320	0.007	0.050
SANTA FE NM	147,635	0.409	1.490	0.355	1.350	0.301	2.280
SANTA ROSA CA	458,614	-0.295	-1.710	-0.096	-0.990	-0.136	-1.250
SARASOTA-BRADENTON FL	582,662	-0.592	-2.560	-0.566	-3.090	-0.681	-5.010
SAVANNAH GA	293,000	-0.810	-2.690	-0.830	-4.380	-0.896	-3.340
SCRANTON--WILKES-BARRE--HAZLETON PA	624,776	-0.057	-0.750	-0.174	-2.360	-0.011	-0.190
SEATTLE-BELLEVUE-EVERETT WA	2,400,714	0.197	5.370	0.197	5.650	0.129	5.060
SHARON PA	120,293	-0.398	-1.350	-0.016	-0.120	-0.202	-1.290
SHEBOYGAN WI	112,646	-0.251	-1.180	0.026	0.190	0.185	1.110
SHERMAN-DENISON TX	110,595	0.445	1.130	0.079	0.270	0.297	1.340

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
SHREVEPORT-BOSSIER CITY LA	392,302	-0.264	-2.470	-0.241	-1.870	-0.321	-2.770
SIOUX CITY IA-NE	124,130	-0.338	-1.220	-0.111	-0.520	0.083	0.460
SIOUX FALLS SD	172,412	0.114	0.410	0.036	0.110	0.124	0.550
SOUTH BEND IN	265,559	-0.976	-2.590	-0.679	-4.870	-0.644	-3.730
SPOKANE WA	424,156	0.215	1.730	0.203	2.360	0.224	3.510
SPRINGFIELD IL	201,437	0.296	0.920	0.376	0.830	0.047	0.180
SPRINGFIELD MA	581,243	-0.459	-3.000	-0.419	-3.260	-0.371	-3.090
SPRINGFIELD MO	325,721	-0.196	-3.090	-0.230	-2.610	-0.267	-3.200
ST. CLOUD MN	167,392	-0.054	-0.240	-0.045	-0.220	0.034	0.260
ST. JOSEPH MO	102,490	-0.037	-0.160	-0.413	-1.260	-0.136	-0.390
ST. LOUIS MO-IL	2,603,607	-0.182	-4.030	-0.217	-4.700	-0.062	-1.380
STAMFORD-NORWALK CT	353,556	-0.134	-0.460	-0.125	-0.740	0.386	1.990
STATE COLLEGE PA	135,758	0.347	1.100	0.224	1.340	0.296	2.040
STEUBENVILLE-WEIRTON OH-WV	132,008	-0.279	-2.860	-0.133	-1.140	-0.390	-1.200
STOCKTON-LODI CA	563,598	-0.306	-3.610	0.289	2.240	0.017	0.130
SUMTER SC	104,646	-0.061	-0.150	0.213	2.160	-0.383	-1.080
SYRACUSE NY	732,117	-0.045	-0.800	-0.040	-0.710	-0.030	-0.740
TACOMA WA	700,820	-0.034	-0.340	-0.026	-0.260	-0.009	-0.100
TALLAHASSEE FL	284,539	0.366	1.490	0.492	1.750	-0.225	-1.210
TAMPA-ST. PETERSBURG-CLEARWATER FL	2,362,853	0.025	0.390	-0.064	-1.250	-0.038	-0.830
TERRE HAUTE IN	149,192	-0.137	-1.080	-0.341	-1.920	-0.206	-1.010
TEXARKANA TX-TEXARKANA AR	129,749	0.143	0.190	0.297	0.690	0.205	0.730
TOLEDO OH	618,203	-0.753	-6.040	-0.928	-8.280	-0.697	-6.880
TOPEKA KS	169,871	-0.330	-0.950	-0.393	-1.530	-0.400	-1.770
TRENTON NJ	350,761	-1.258	-2.290	-0.946	-2.990	-1.544	-3.190
TUCSON AZ	843,746	-0.199	-1.090	-0.019	-0.150	0.084	1.070
TULSA OK	803,235	-0.034	-0.470	-0.036	-0.710	0.002	0.040
TUSCALOOSA AL	164,875	-0.168	-0.790	-0.118	-0.650	-0.211	-0.860
TYLER TX	174,706	-1.187	-3.090	-0.951	-4.060	-0.677	-2.710
UTICA-ROME NY	299,896	-0.343	-3.380	-0.454	-4.300	-0.202	-2.490
VALLEJO-FAIRFIELD-NAPA CA	518,821	-0.120	-0.710	-0.016	-0.130	-0.016	-0.150
VENTURA CA	748,801	-0.249	-1.200	-0.379	-3.310	-0.143	-1.520
VICTORIA TX	84,088	-0.429	-0.550	-0.232	-0.480	-0.157	-0.320
VINELAND-MILLVILLE-BRIDGETON NJ	146,438	0.829	2.090	0.254	1.160	0.604	3.490
VISALIA-TULARE-PORTERVILLE CA	368,021	0.092	0.700	-0.054	-0.930	-0.248	-3.040
WACO TX	213,517	0.374	0.940	0.068	0.270	0.156	0.820
WASHINGTON DC-MD-VA-WV	4,923,153	0.323	7.010	0.339	6.740	0.295	8.030
WATERBURY CT	228,984	-0.527	-2.640	-0.341	-2.330	-0.016	-0.110
WATERLOO-CEDAR FALLS IA	128,012	-0.223	-0.430	-0.685	-2.240	-0.026	-0.090
WAUSAU WI	125,834	-0.043	-0.180	0.030	0.370	0.176	0.930
WEST PALM BEACH-BOCA RATON FL	1,130,260	-0.461	-2.150	-0.259	-1.870	-0.650	-5.800
WHEELING WV-OH	153,172	0.263	0.850	0.261	0.770	0.040	0.190
WICHITA FALLS TX	140,518	-0.066	-0.200	0.029	0.090	0.151	0.570
WICHITA KS	545,220	-0.083	-0.980	-0.034	-0.250	0.014	0.180
WILLIAMSPORT PA	120,044	-0.301	-1.220	-0.343	-2.080	-0.153	-1.270
WILMINGTON NC	228,748	0.292	0.960	0.111	0.400	0.058	0.300

MSA	Population	CR Beta	CR t-stat	NR Beta	NR t-stat	RR Beta	RR t-stat
WILMINGTON-NEWARK DE-MD	586,216	-0.361	-3.360	-0.294	-4.440	-0.251	-2.660
WORCESTER MA-CT	508,982	0.349	1.770	0.002	0.010	0.364	3.450
YAKIMA WA	222,581	-0.030	-0.110	0.051	0.430	0.125	1.380
YOLO CA	161,404	-0.277	-0.590	0.114	0.630	-0.118	-0.490
YORK PA	381,751	-0.287	-2.730	-0.221	-2.930	-0.413	-4.150
YOUNGSTOWN-WARREN OH	594,746	-0.126	-0.590	-0.042	-0.760	-0.538	-2.850
YUBA CITY CA	139,149	1.337	3.380	0.508	2.430	0.428	1.880
YUMA AZ	160,026	-0.338	-0.770	-0.208	-1.050	0.103	0.750

Note: The color scales are such that in each column red is negative, blue is positive, and white is zero.

Appendix D – Hedonic Slope Coefficient Categorized Graphs

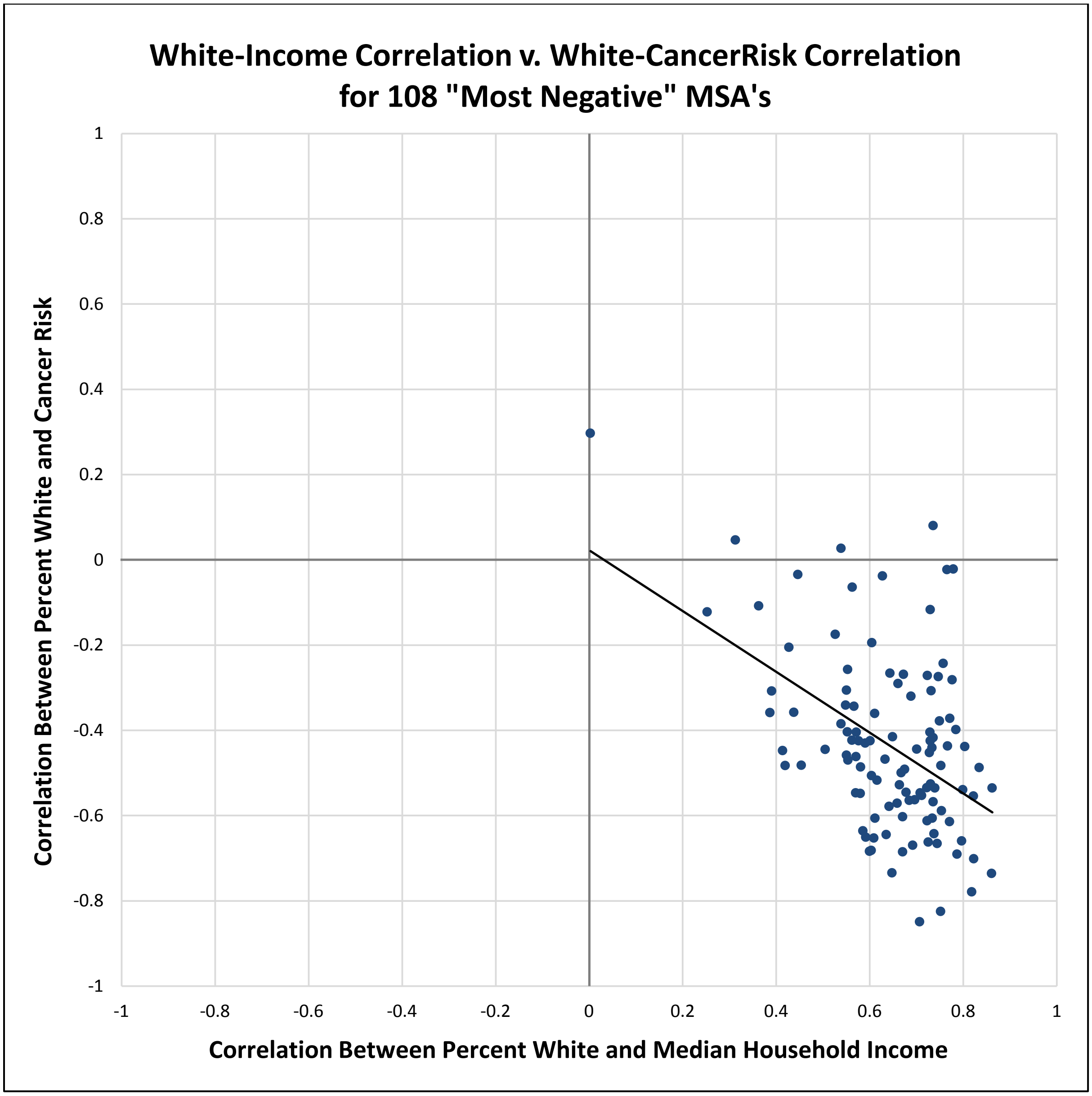

Figure A1

*RP = (-0.713)*RI + (0.0228)*

Race-Income Beta: -0.713

Race-Income t-stat: -5.44

Intercept: 0.0228

Intercept t-stat: 0.26

Correlation: 0.467

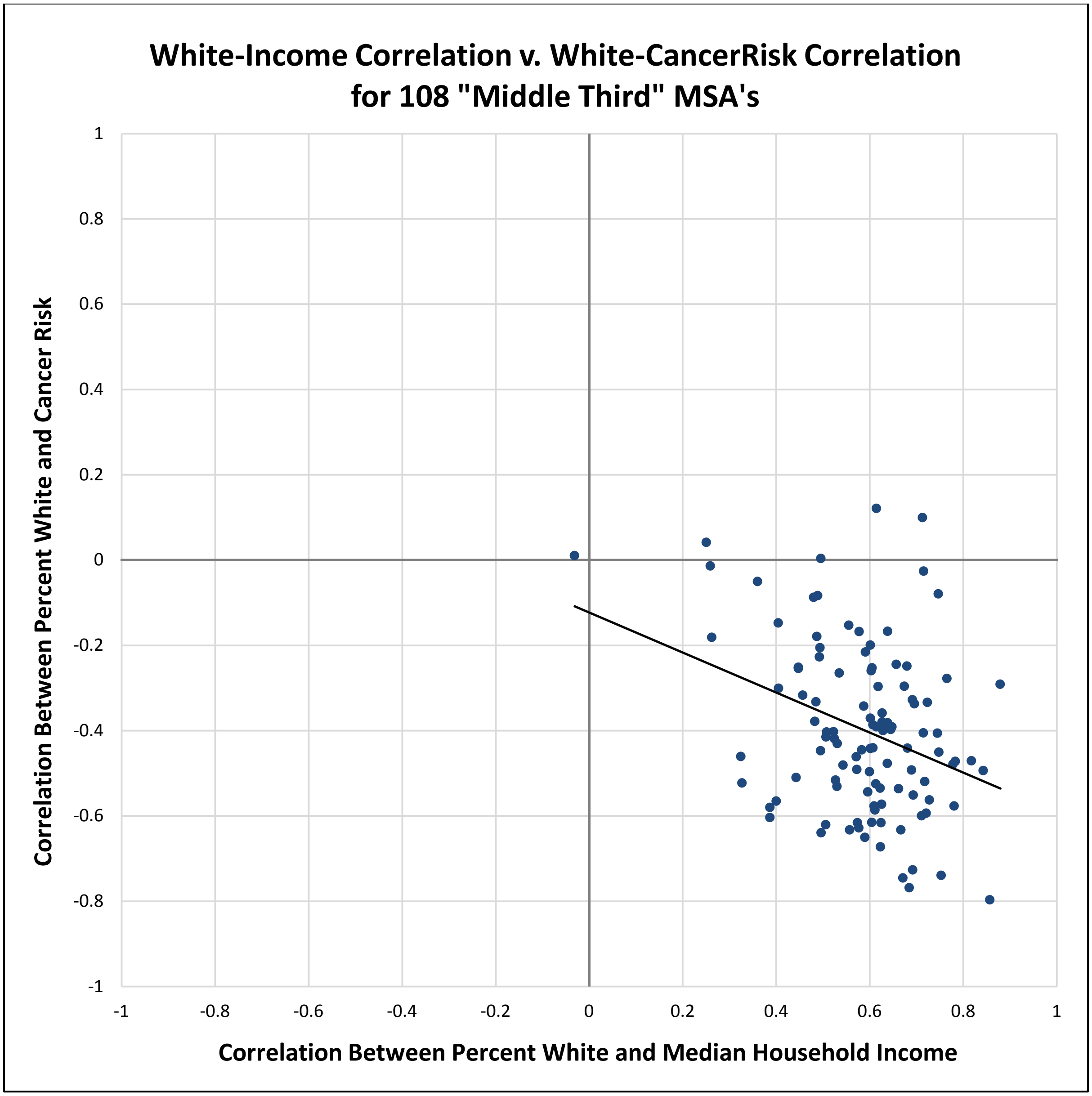

Figure A2

*RP = (-0.470)*RI + (-0.123)*

Race-Income Beta: -0.470

Race-Income t-stat: -3.61

Intercept: -0.123

Intercept t-stat: -1.56

Correlation: 0.332

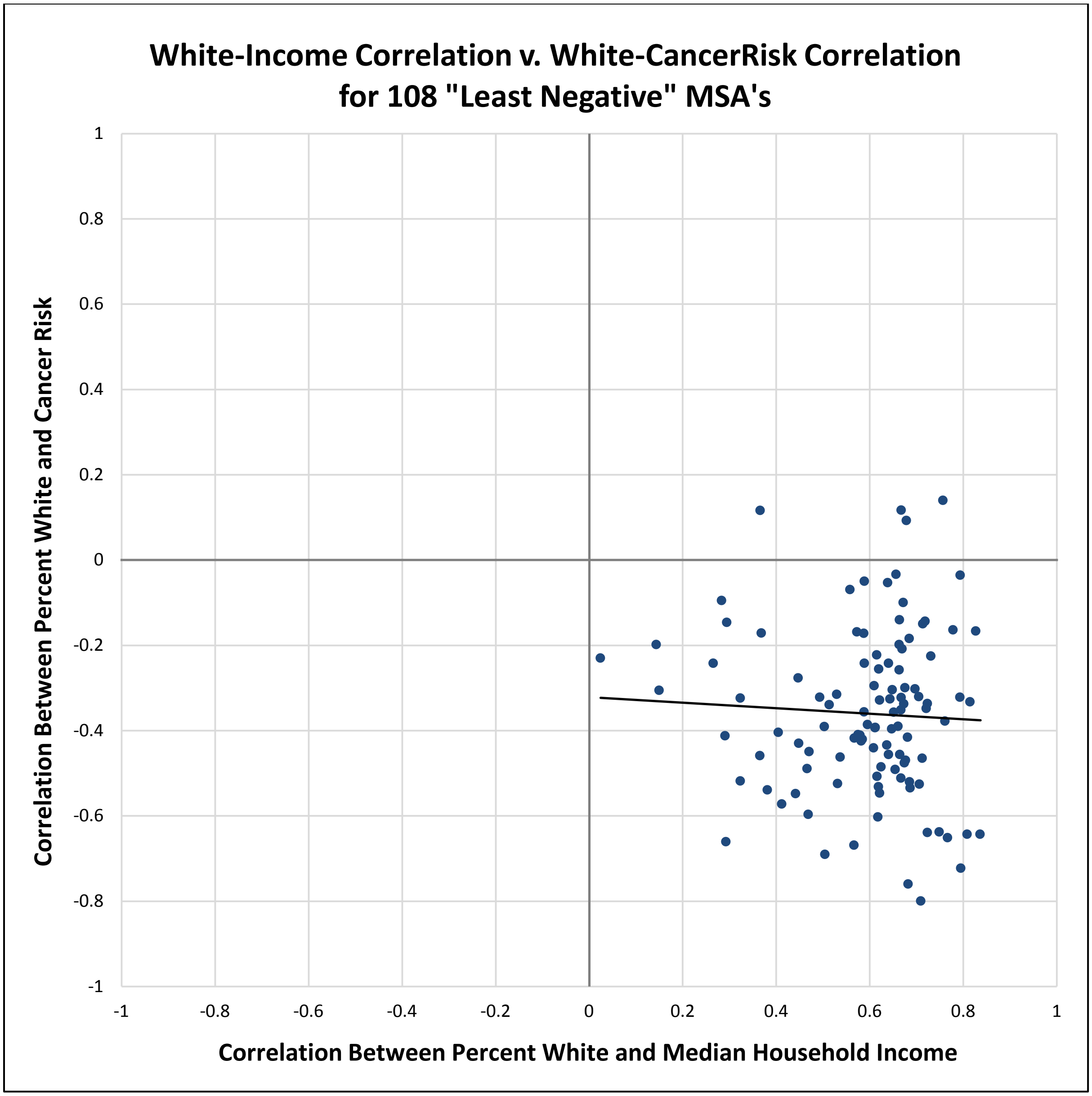

Figure A3

*RP = (-0.0642)*RI + (-0.322)*

Race-Income Beta: -0.0642

Race-Income t-stat: -0.53

Intercept: -0.322

Intercept t-stat: -4.35

Correlation: 0.055

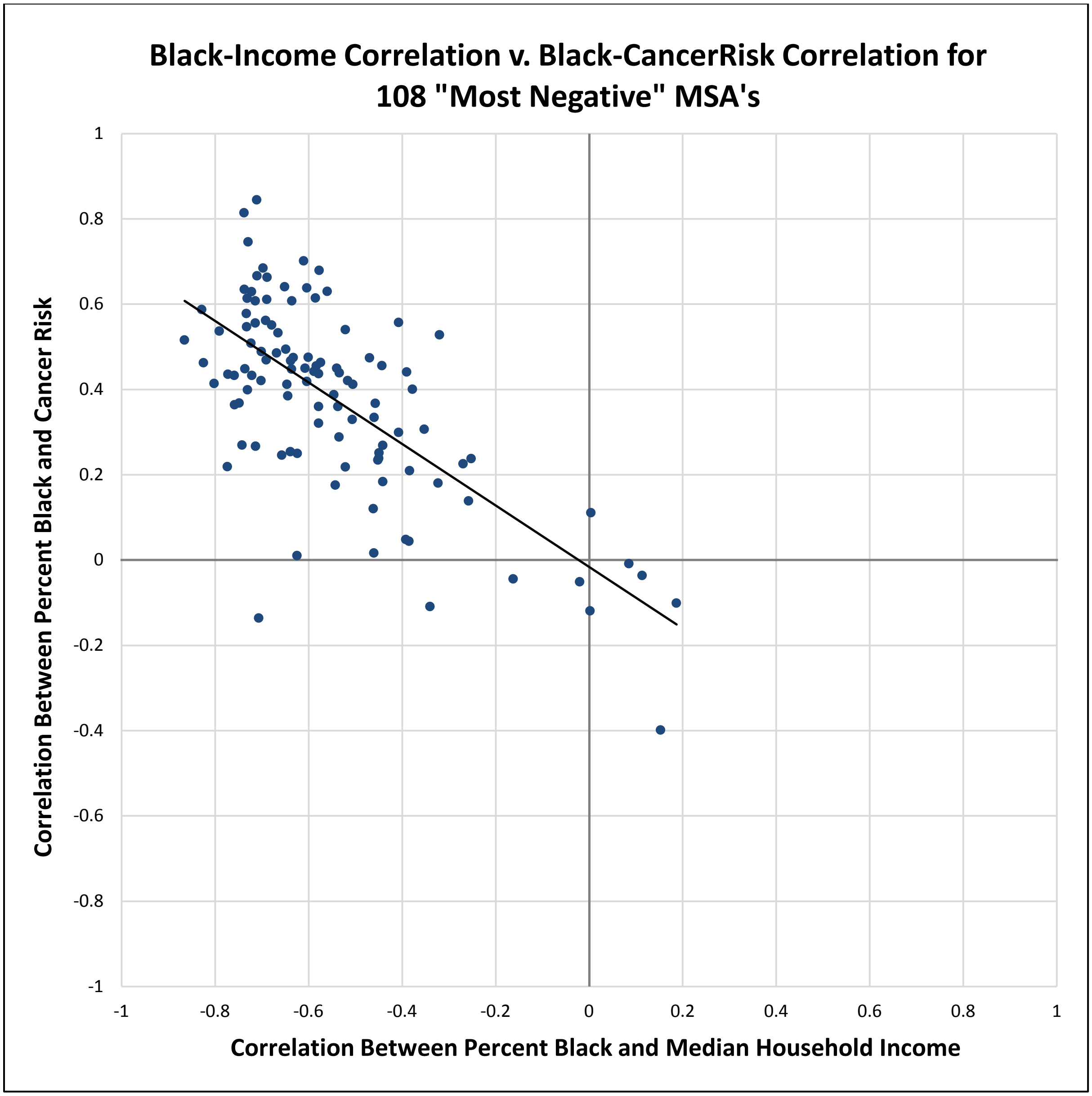

Figure A4

*RP = (-0.721)*RI + (-0.0161)*

Race-Income Beta: -0.721

Race-Income t-stat: -9.98

Intercept: -0.0161

Intercept t-stat: -0.38

Correlation: 0.696

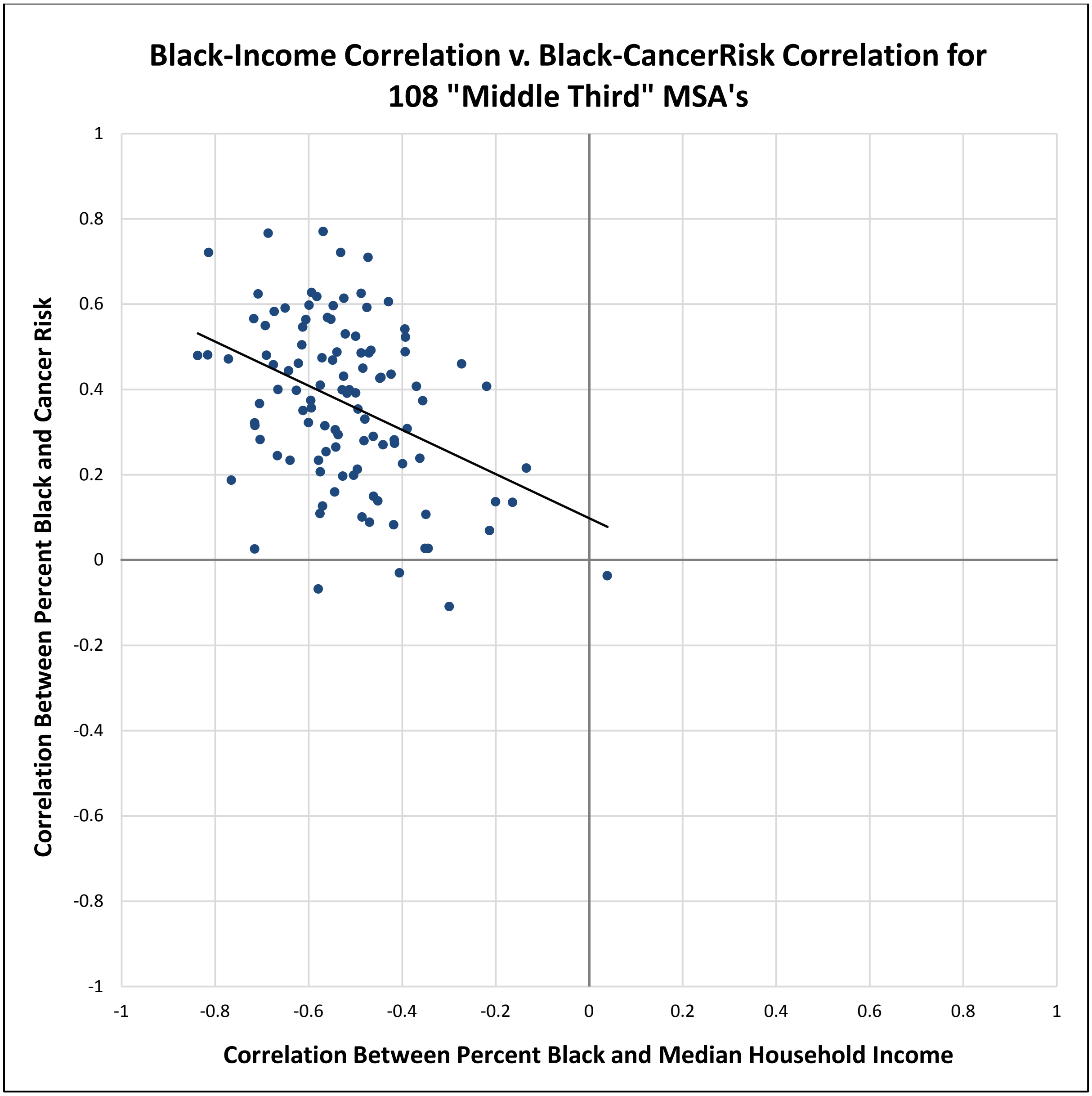

Figure A5

*RP = (-0.518)*RI + (0.0982)*

Race-Income Beta: -0.518

Race-Income t-stat: -4.40

Intercept: 0.0982

Intercept t-stat: 1.54

Correlation: 0.392

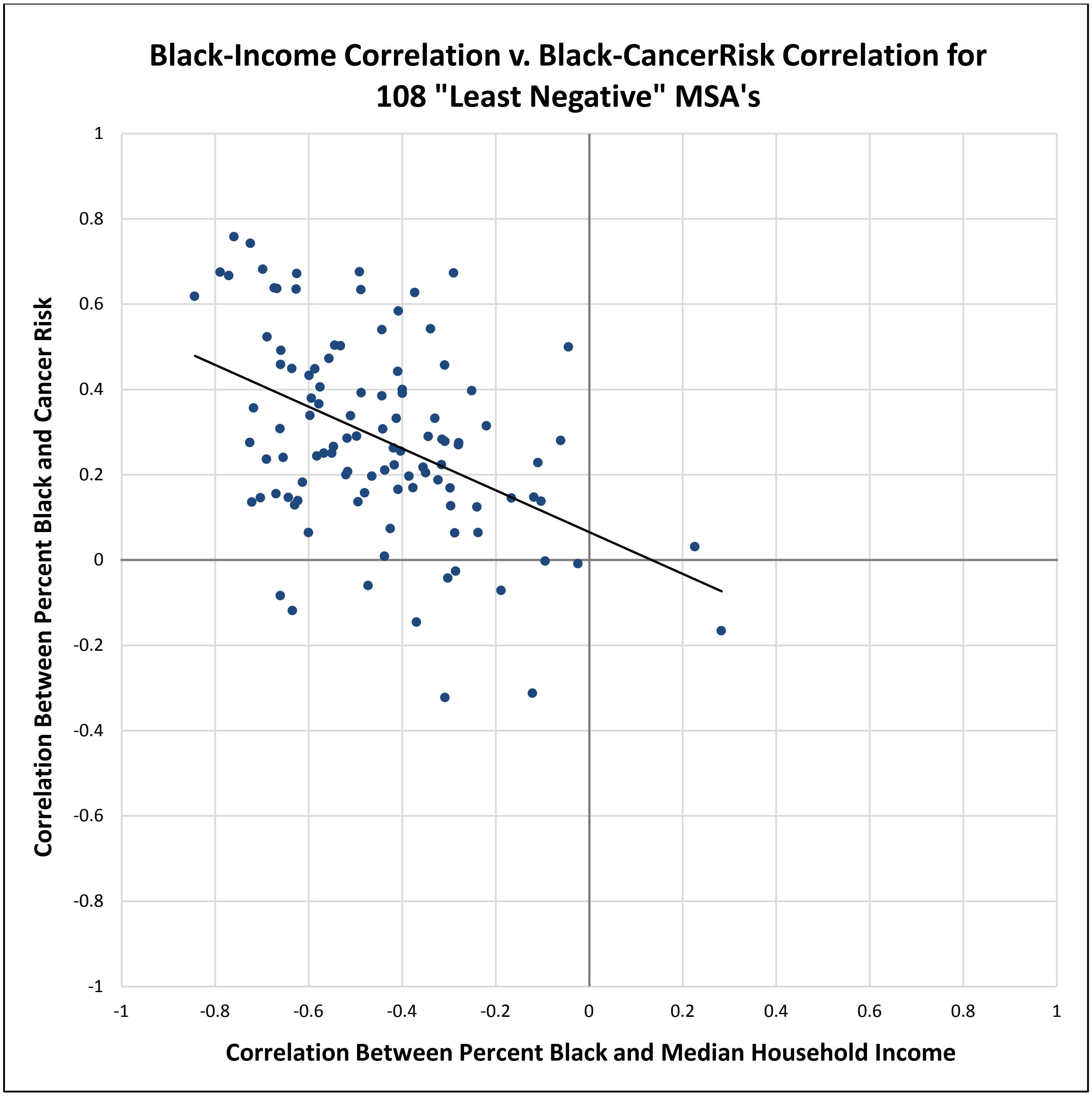

Figure A6

*RP = (-0.490)*RI + (0.0653)*

Race-Income Beta: -0.490

Race-Income t-stat: -5.17

Intercept: 0.0653

Intercept t-stat: 1.40

Correlation: 0.448

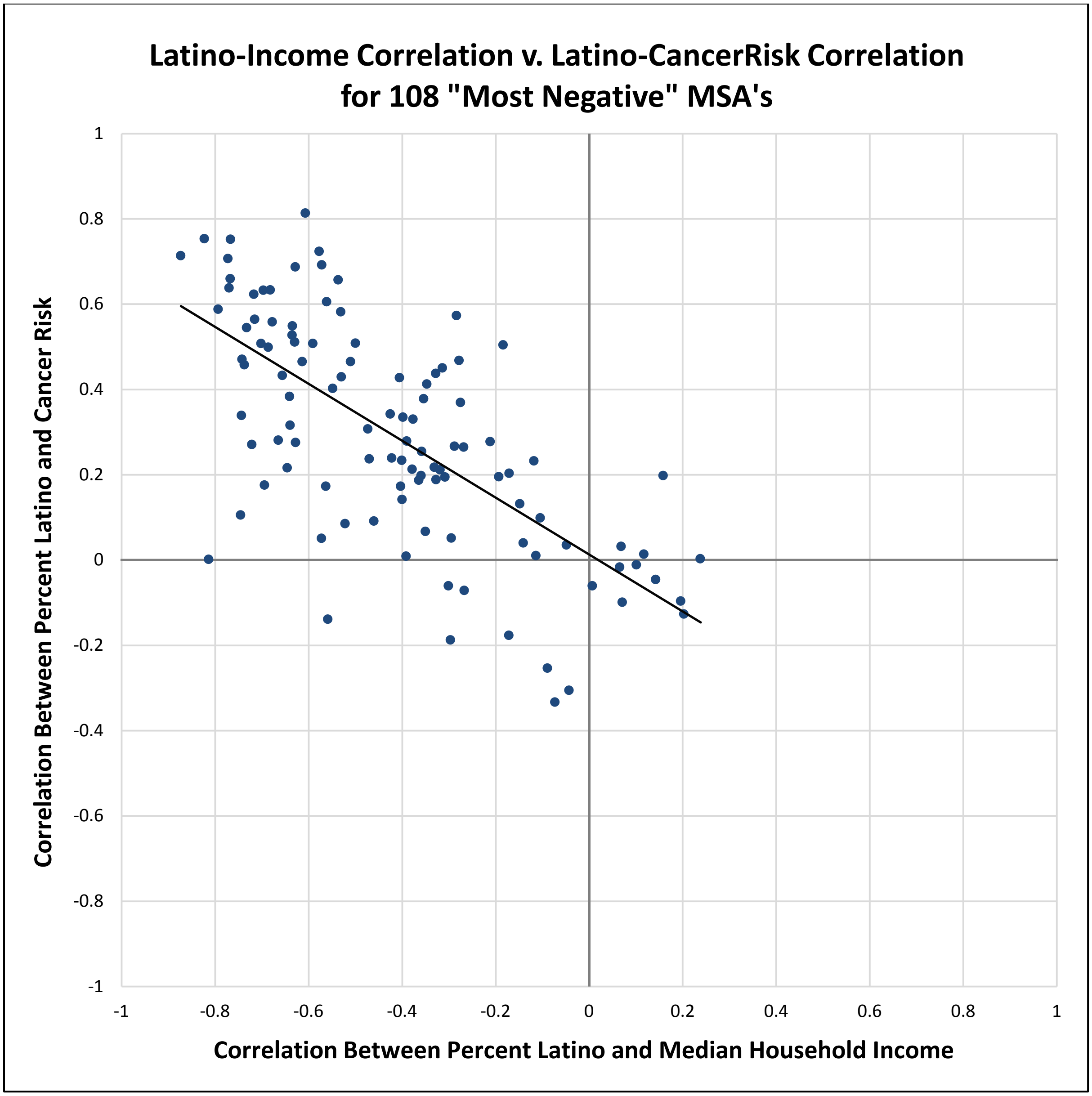

Figure A7

*RP = (-0.667)*RI + (0.0129)*

Race-Income Beta: -0.667

Race-Income t-stat: -9.72

Intercept: 0.0129

Intercept t-stat: 0.38

Correlation: 0.686

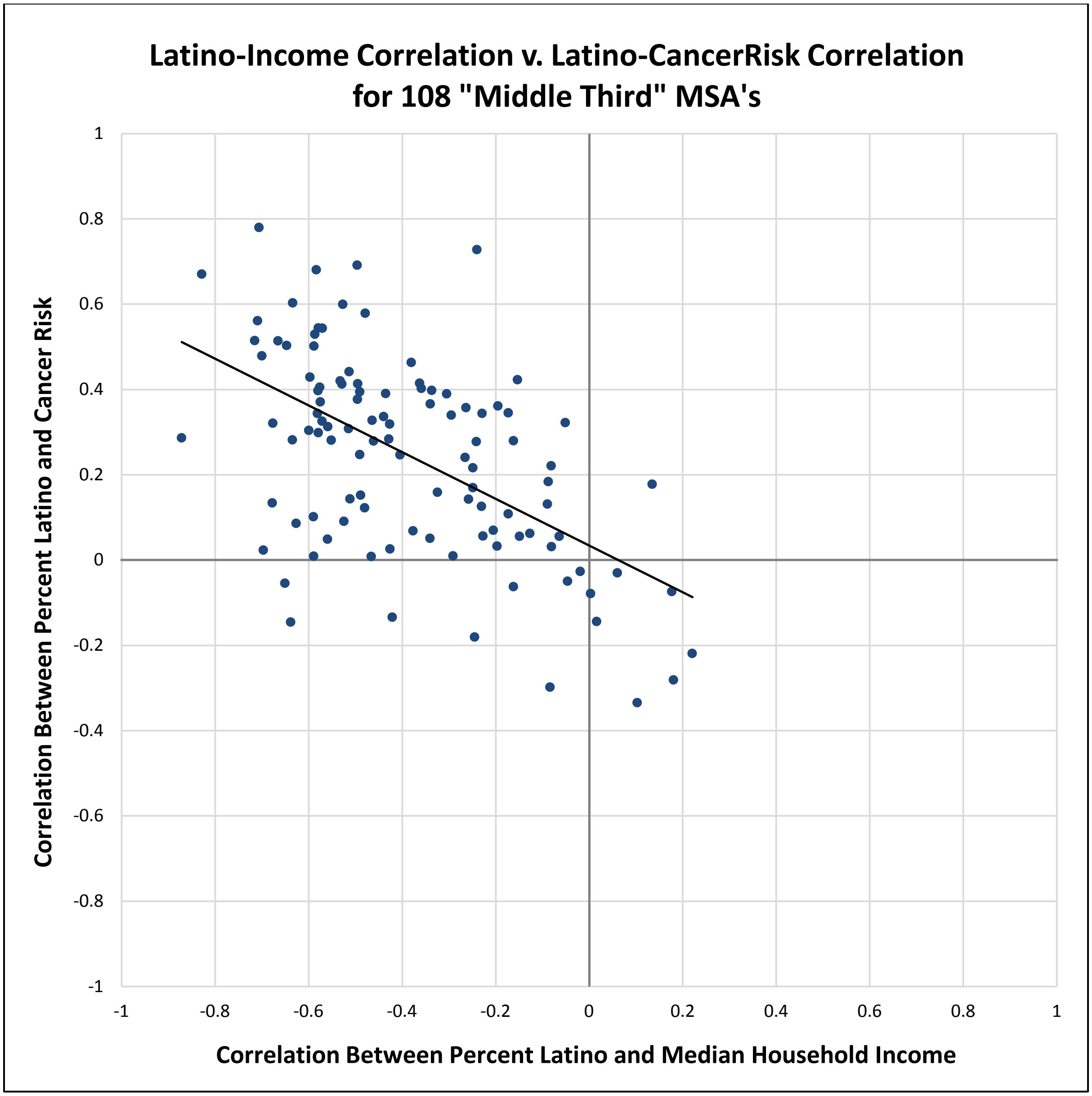

Figure A8

*RP = (-0.547)*RI + (0.0341)*

Race-Income Beta: -0.547

Race-Income t-stat: -6.90

Intercept: 0.0341

Intercept t-stat: 0.95

Correlation: 0.557

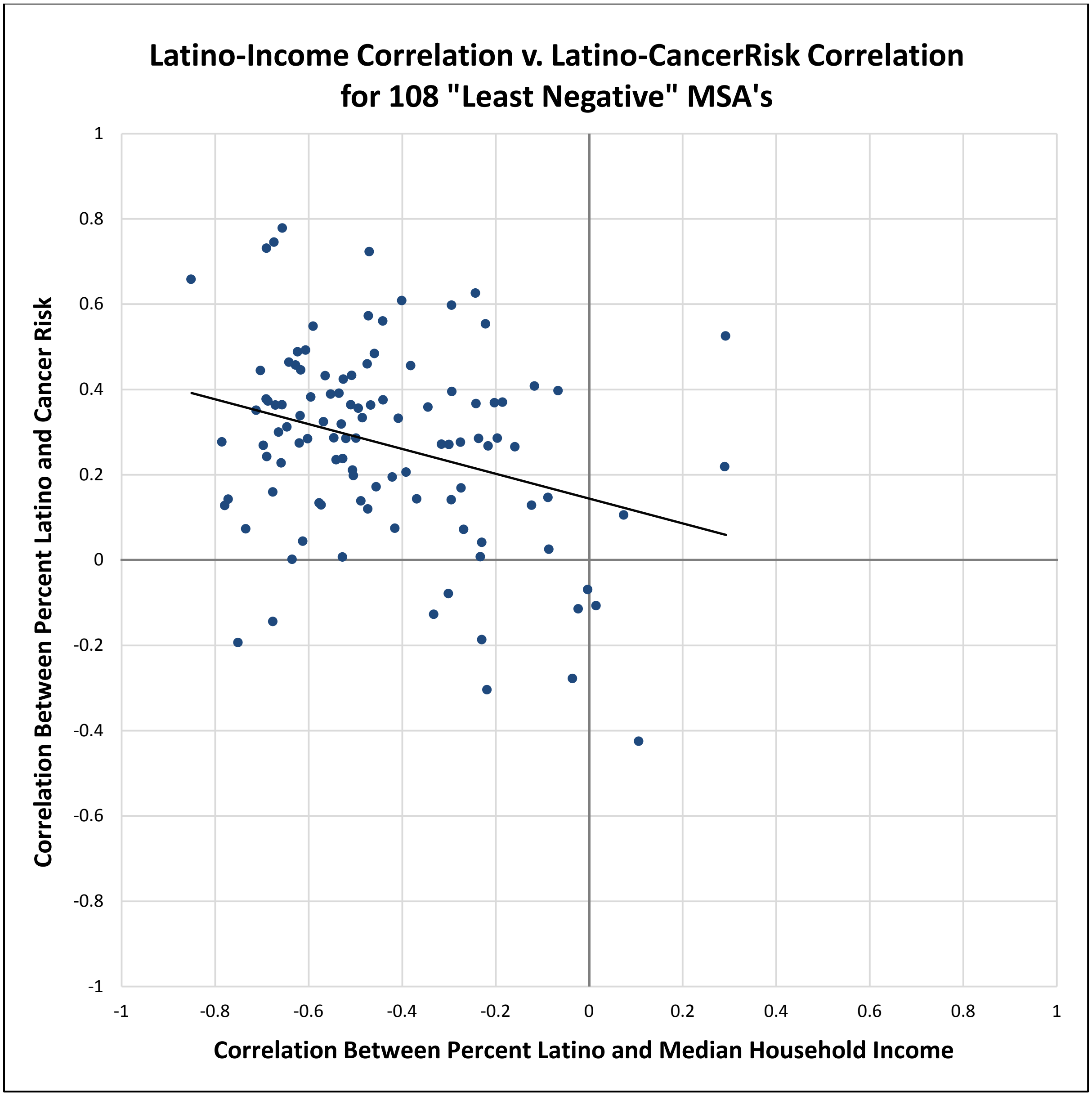

Figure A9

*RP = (-0.291)*RI + (0.144)*

Race-Income Beta: -0.291

Race-Income t-stat: -3.26

Intercept: 0.144

Intercept t-stat: 3.27

Correlation: 0.302

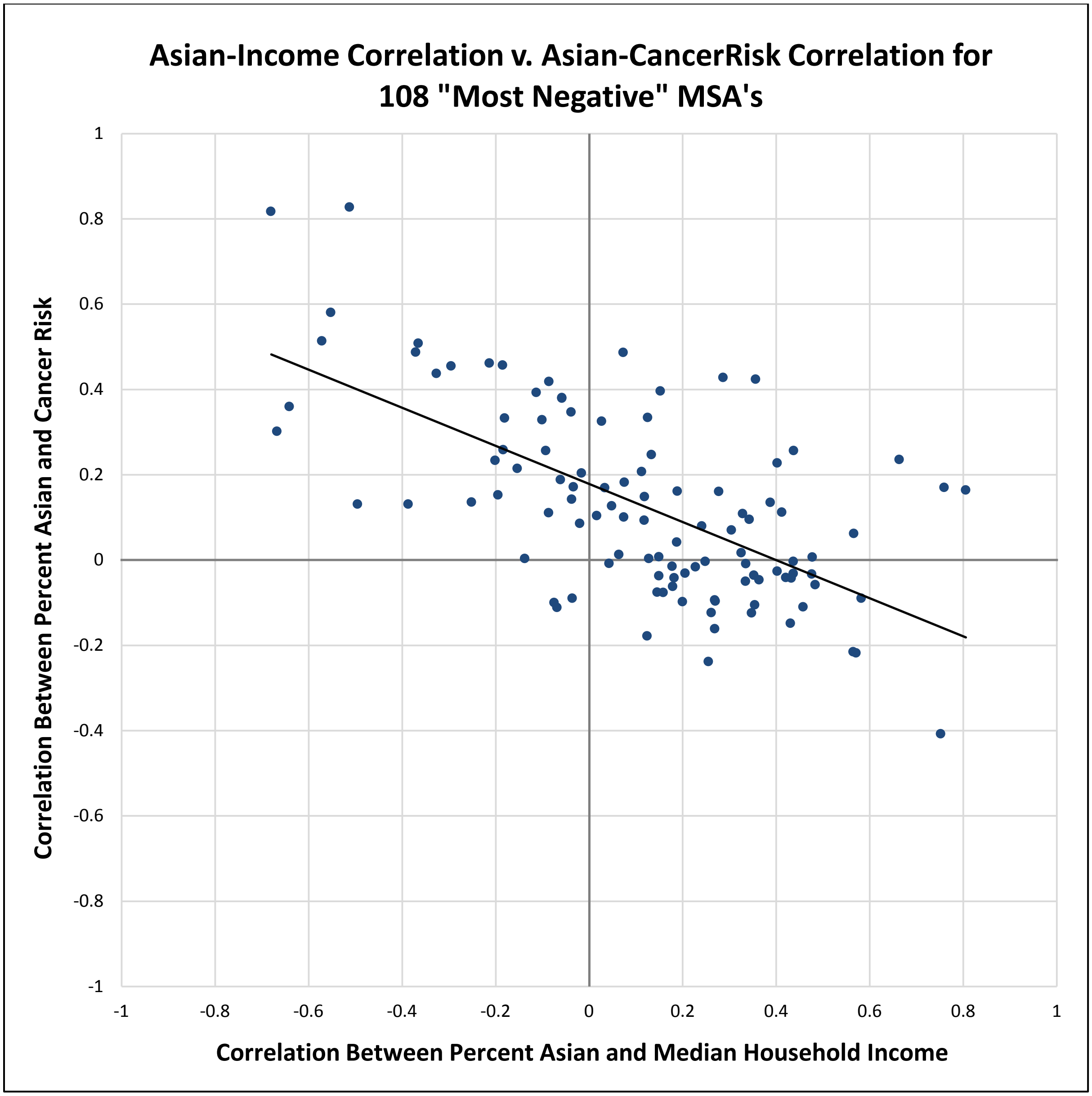

Figure A10

*RP = (-0.447)*RI + (0.178)*

Race-Income Beta: -0.447

Race-Income t-stat: -8.46

Intercept: 0.178

Intercept t-stat: 10.07

Correlation: 0.635

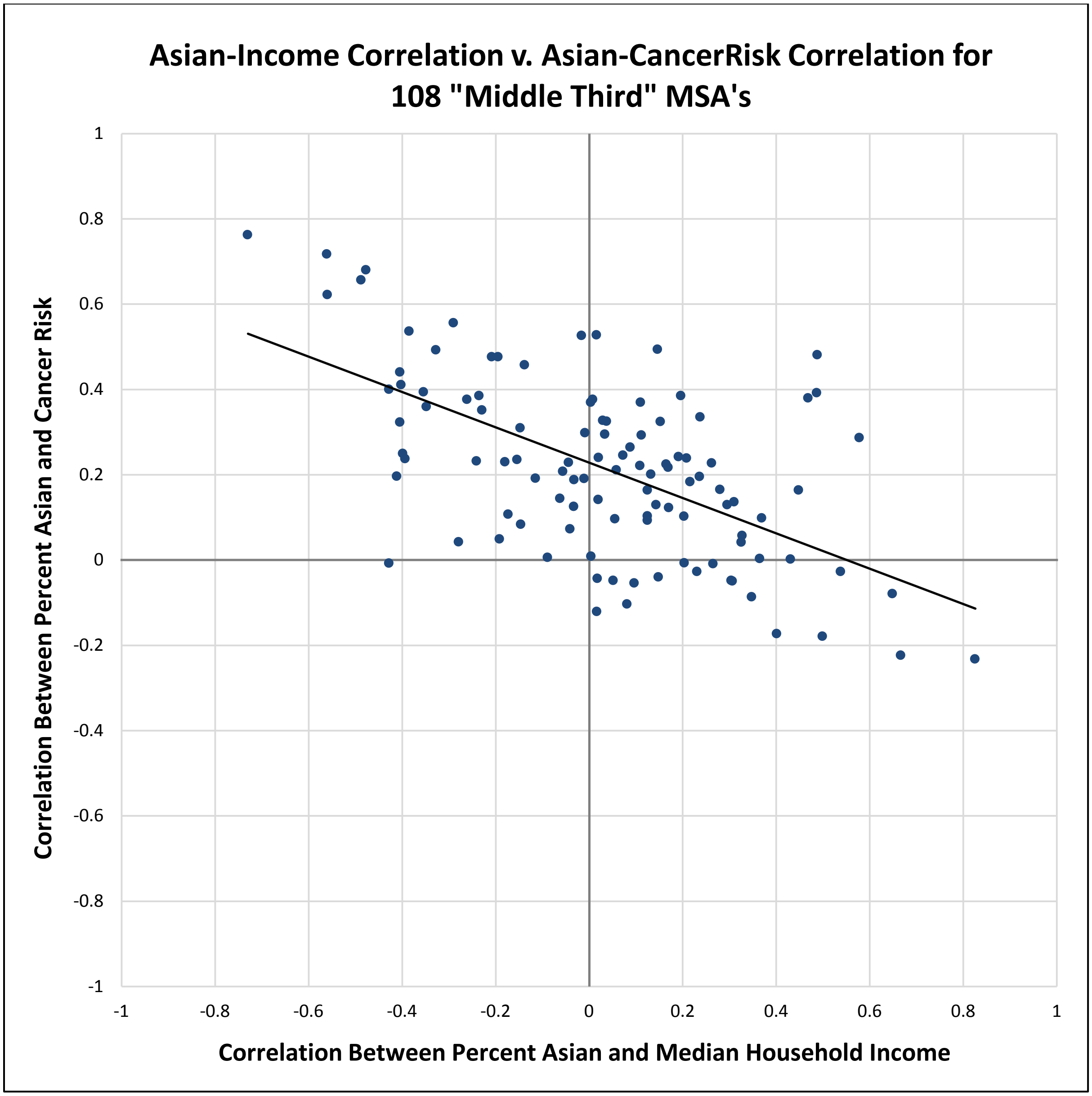

Figure A11

*RP = (-0.414)*RI + (0.228)*

Race-Income Beta: -0.414

Race-Income t-stat: -7.55

Intercept: 0.228

Intercept t-stat: 13.86

Correlation: 0.592

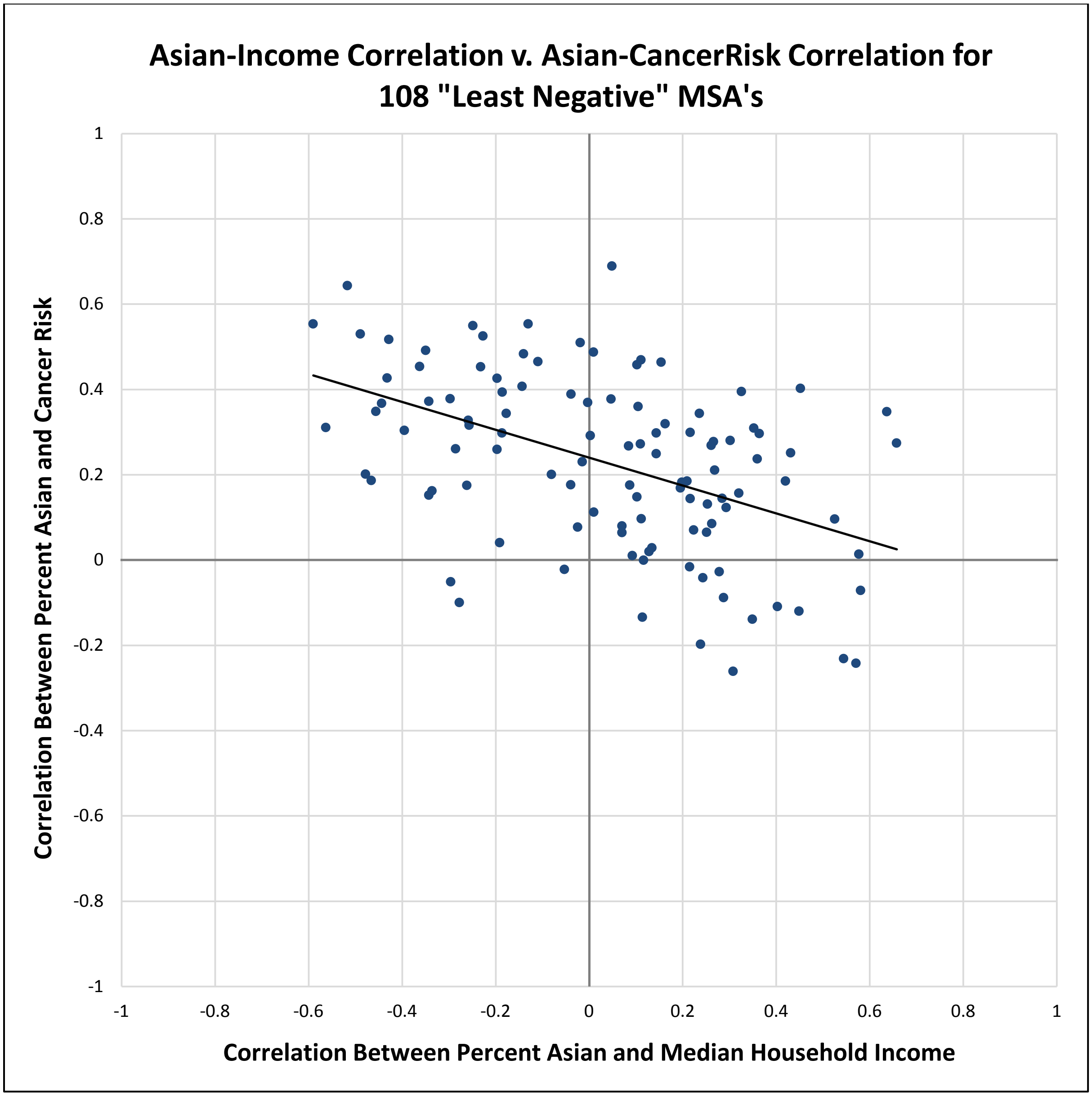

Figure A12

*RP = (-0.327)*RI + (0.240)*

Race-Income Beta: -0.327

Race-Income t-stat: -5.56

Intercept: 0.240

Intercept t-stat: 13.51

Correlation: 0.475

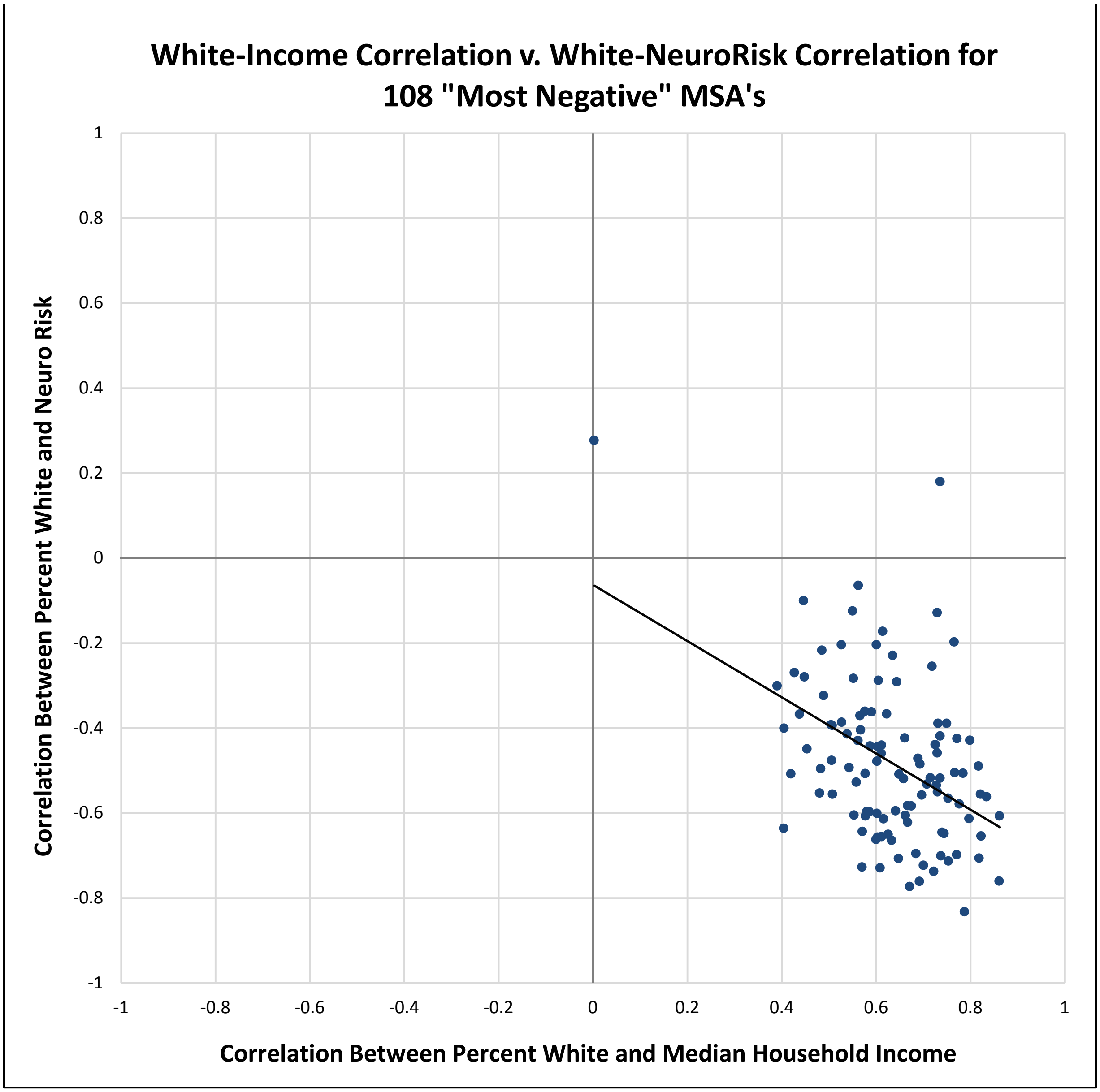

Figure A13

*RP = (-0.662)*RI + (-0.0629)*

Race-Income Beta: -0.662

Race-Income t-stat: -5.06

Intercept: -0.0629

Intercept t-stat: -0.75

Correlation: 0.442

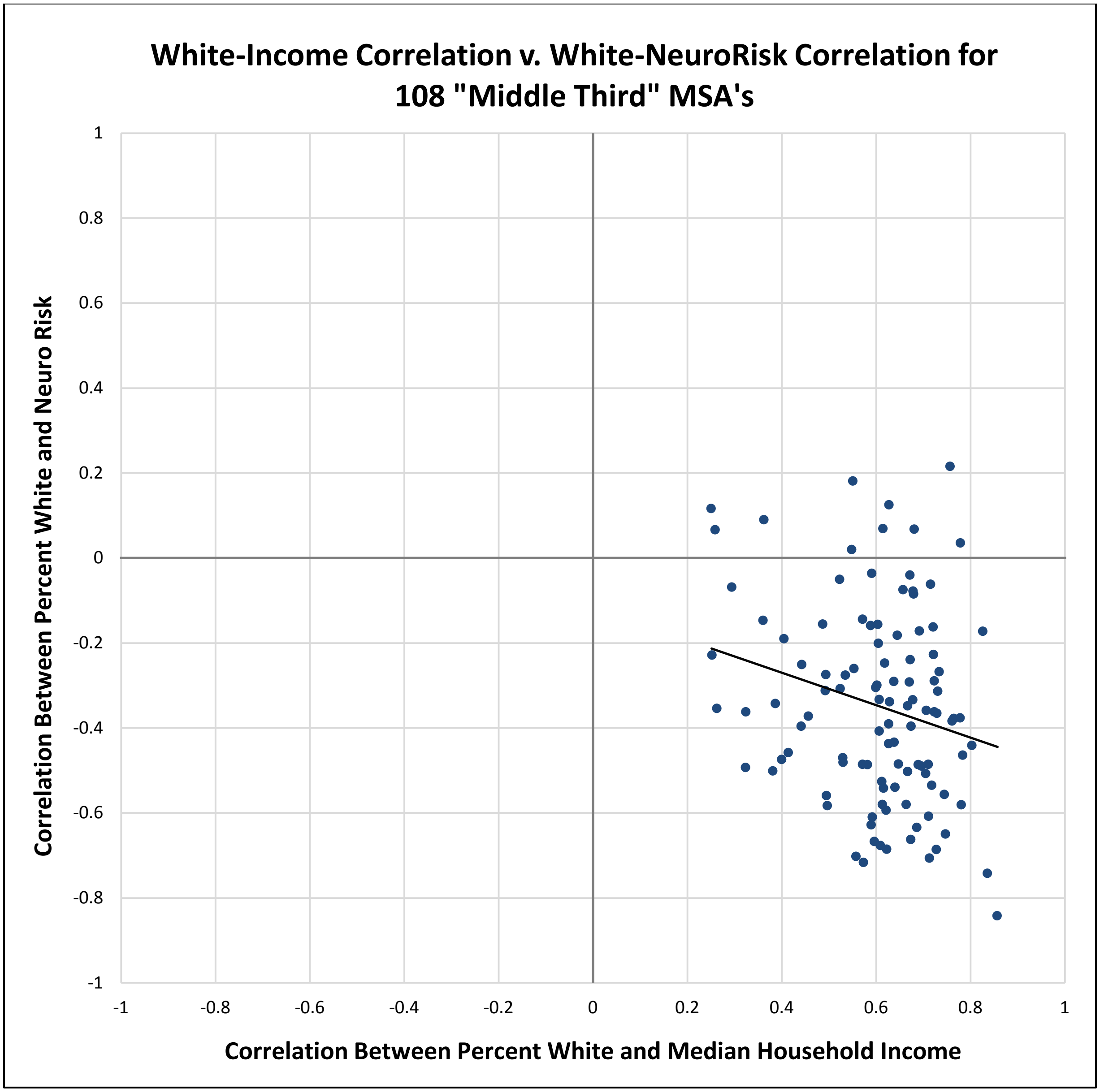

Figure A14

*RP = (-0.383)*RI + (-0.117)*

Race-Income Beta: -0.383

Race-Income t-stat: -2.40

Intercept: -0.117

Intercept t-stat: -1.18

Correlation: 0.226

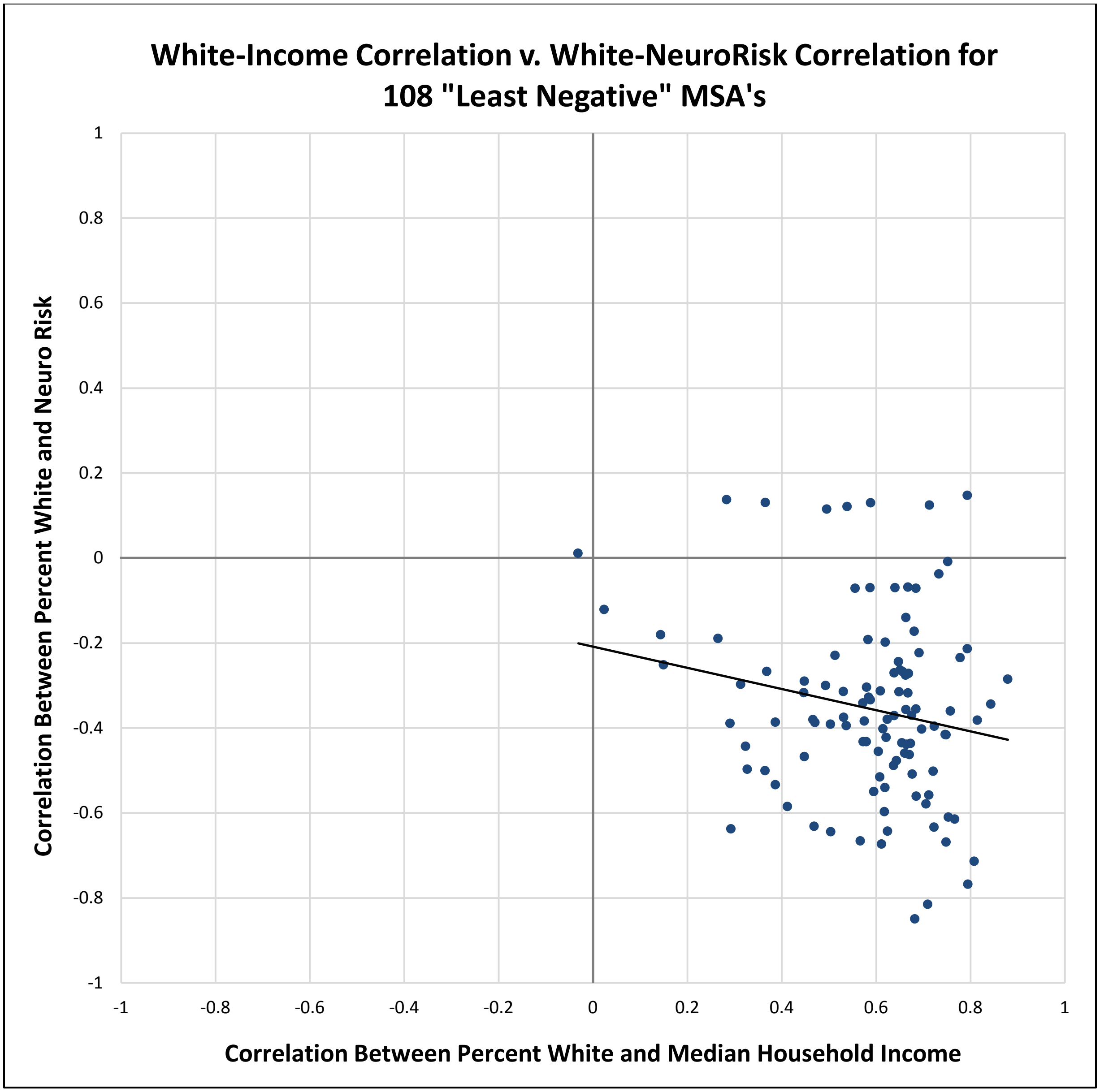

Figure A15

*RP = (-0.249)*RI + (-0.209)*

Race-Income Beta: -0.249

Race-Income t-stat: -2.03

Intercept: -0.209

Intercept t-stat: -2.80

Correlation: 0.192

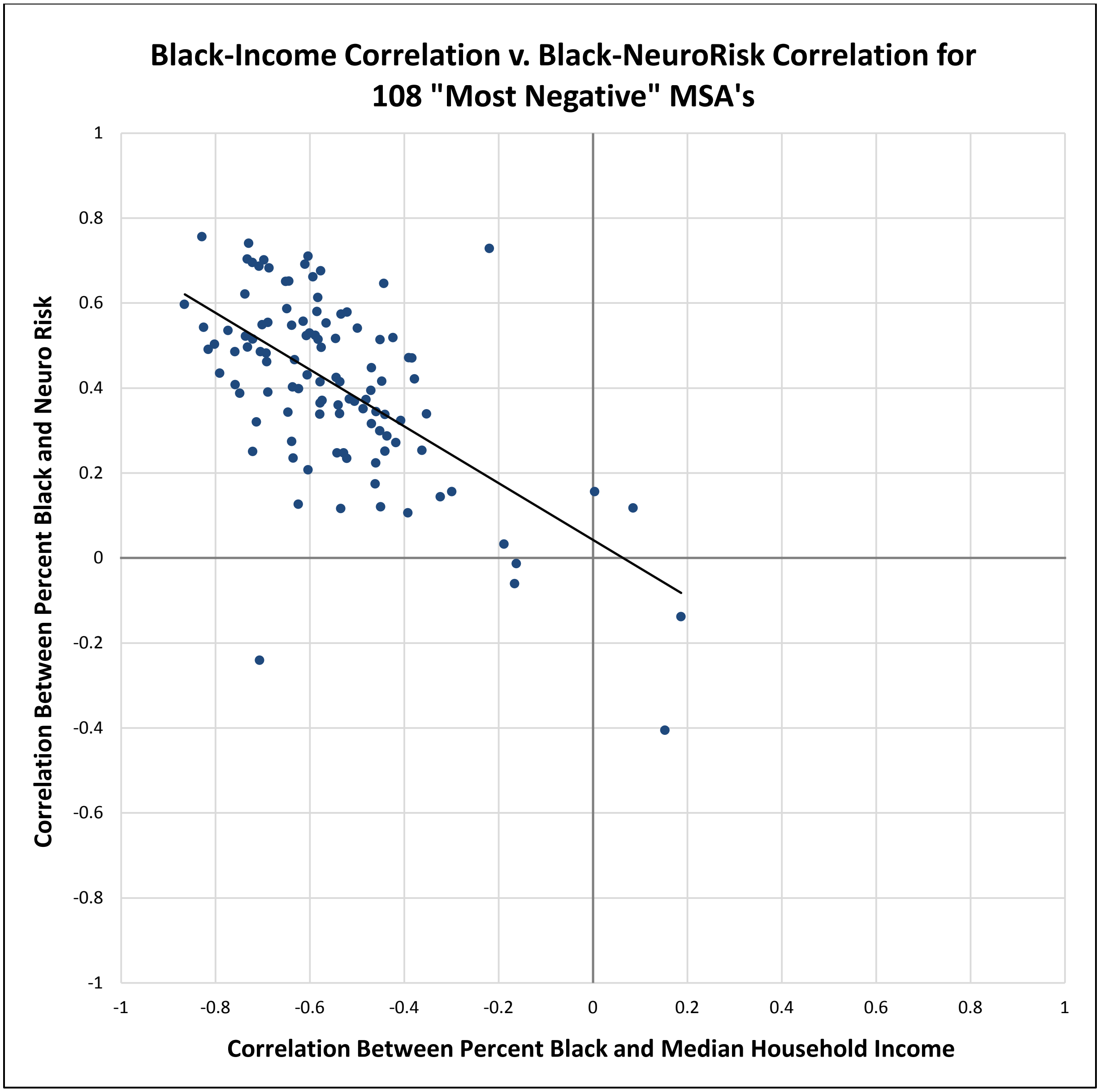

Figure A16

*RP = (-0.668)*RI + (0.0426)*

Race-Income Beta: -0.668

Race-Income t-stat: -7.98

Intercept: 0.0426

Intercept t-stat: 0.88

Correlation: 0.612

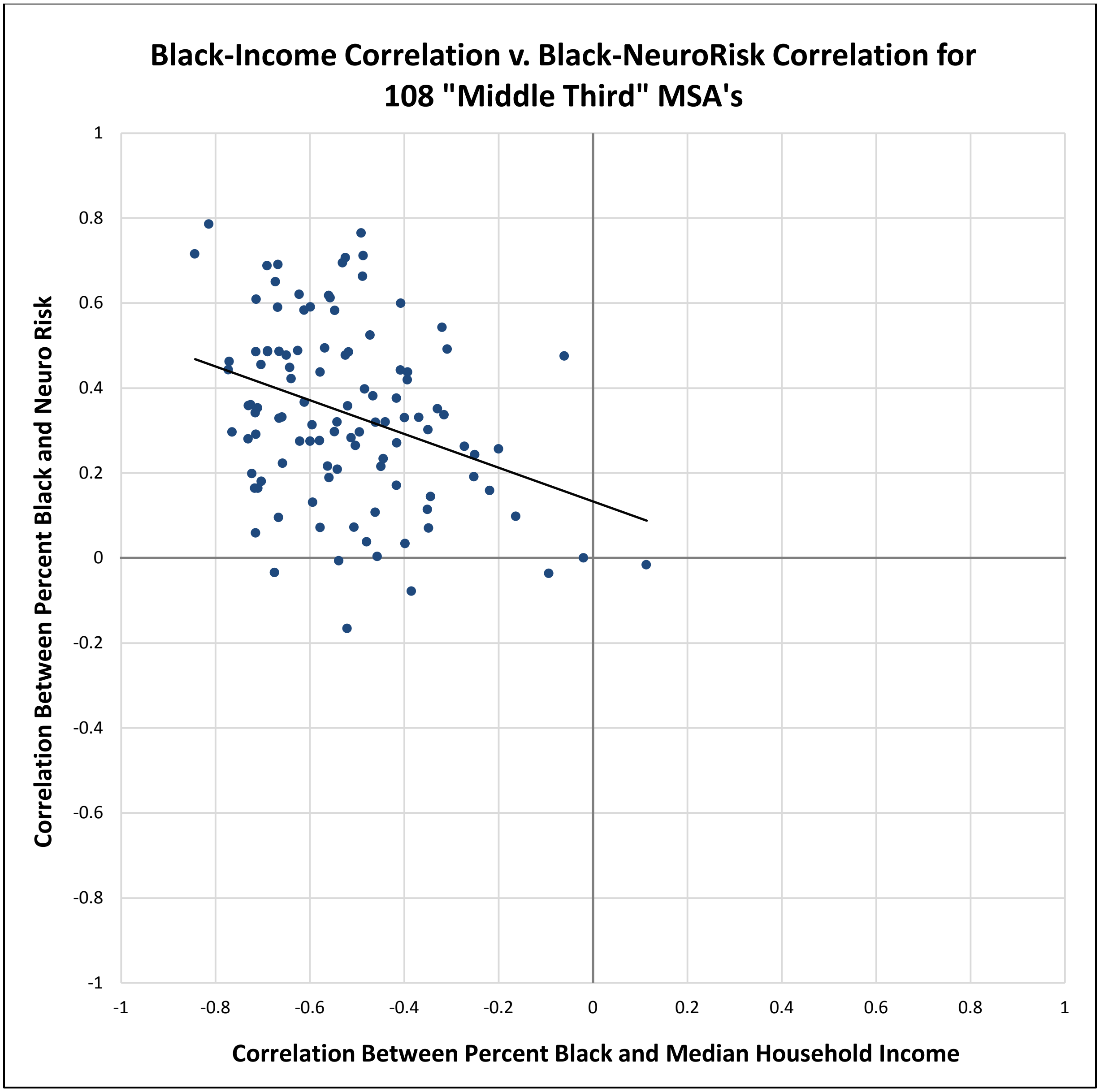

Figure A17

*RP = (-0.397)*RI + (0.133)*

Race-Income Beta: -0.397

Race-Income t-stat: -3.68

Intercept: 0.133

Intercept t-stat: 2.24

Correlation: 0.336

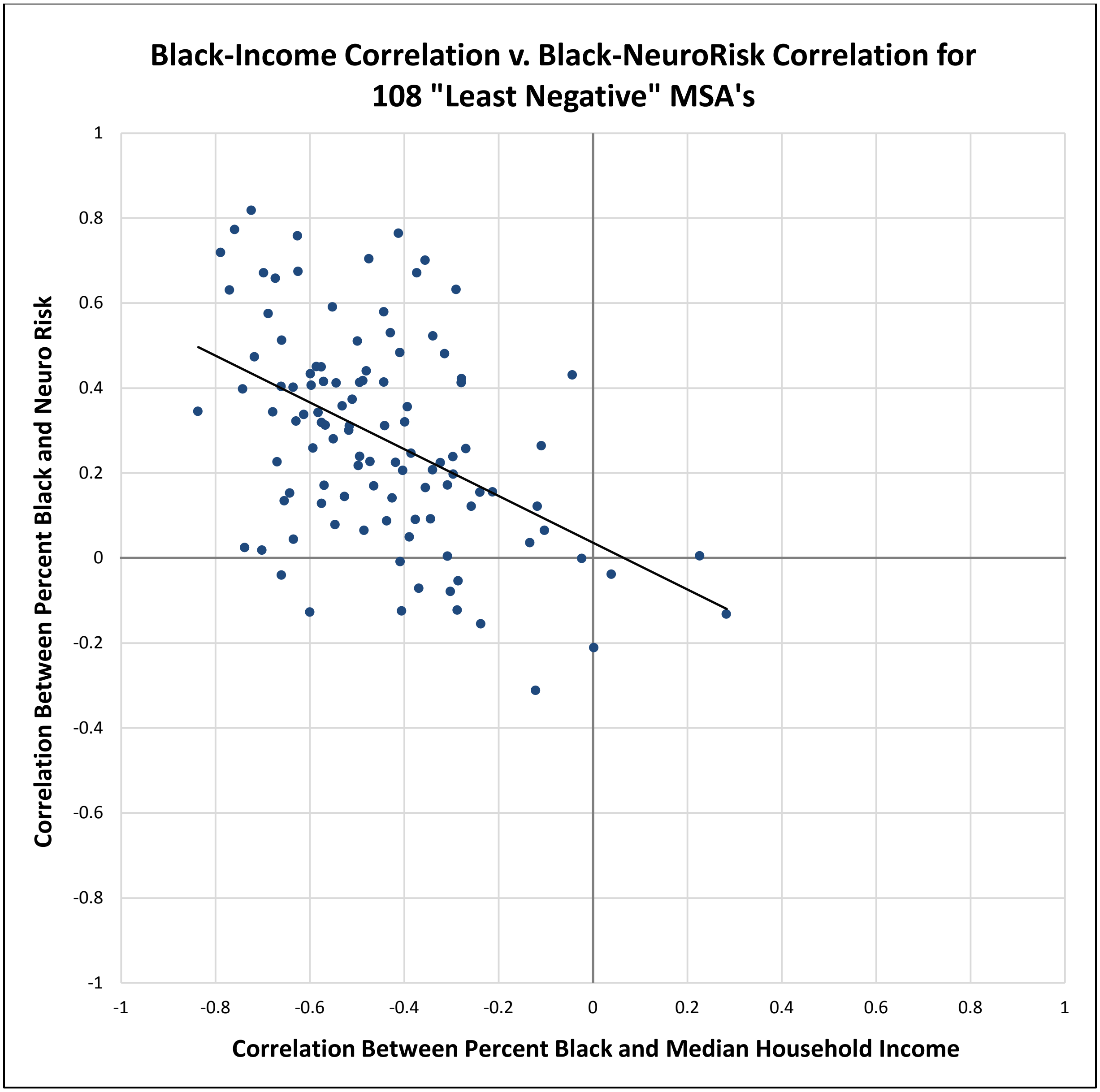

Figure A18

*RP = (-0.550)*RI + (0.0361)*

Race-Income Beta: -0.550

Race-Income t-stat: -5.46

Intercept: 0.0361

Intercept t-stat: 0.73

Correlation: 0.469

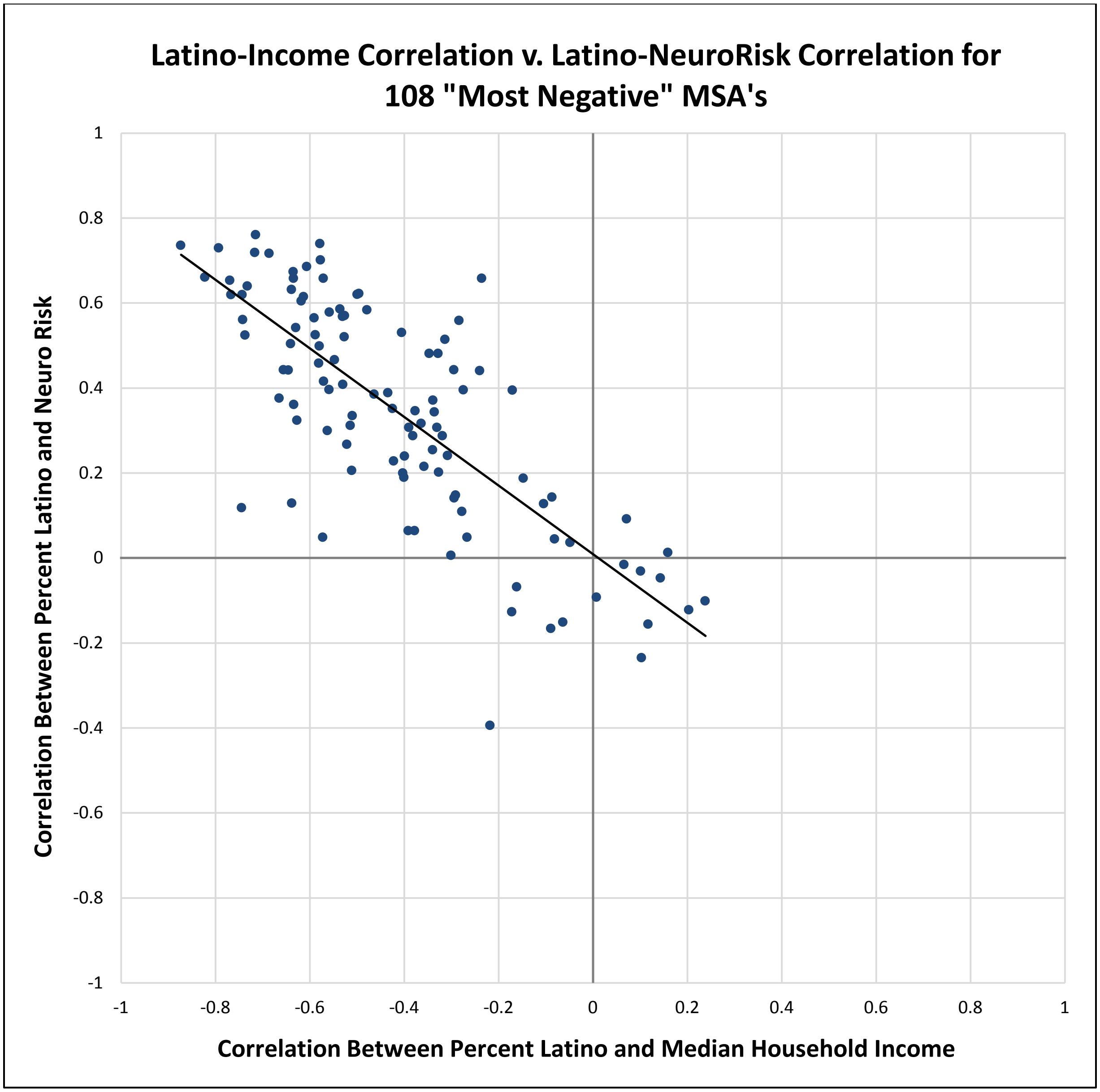

Figure A19

*RP = (-0.807)*RI + (0.00884)*

Race-Income Beta: -0.807

Race-Income t-stat: -12.42

Intercept: 0.00884

Intercept t-stat: 0.28

Correlation: 0.77

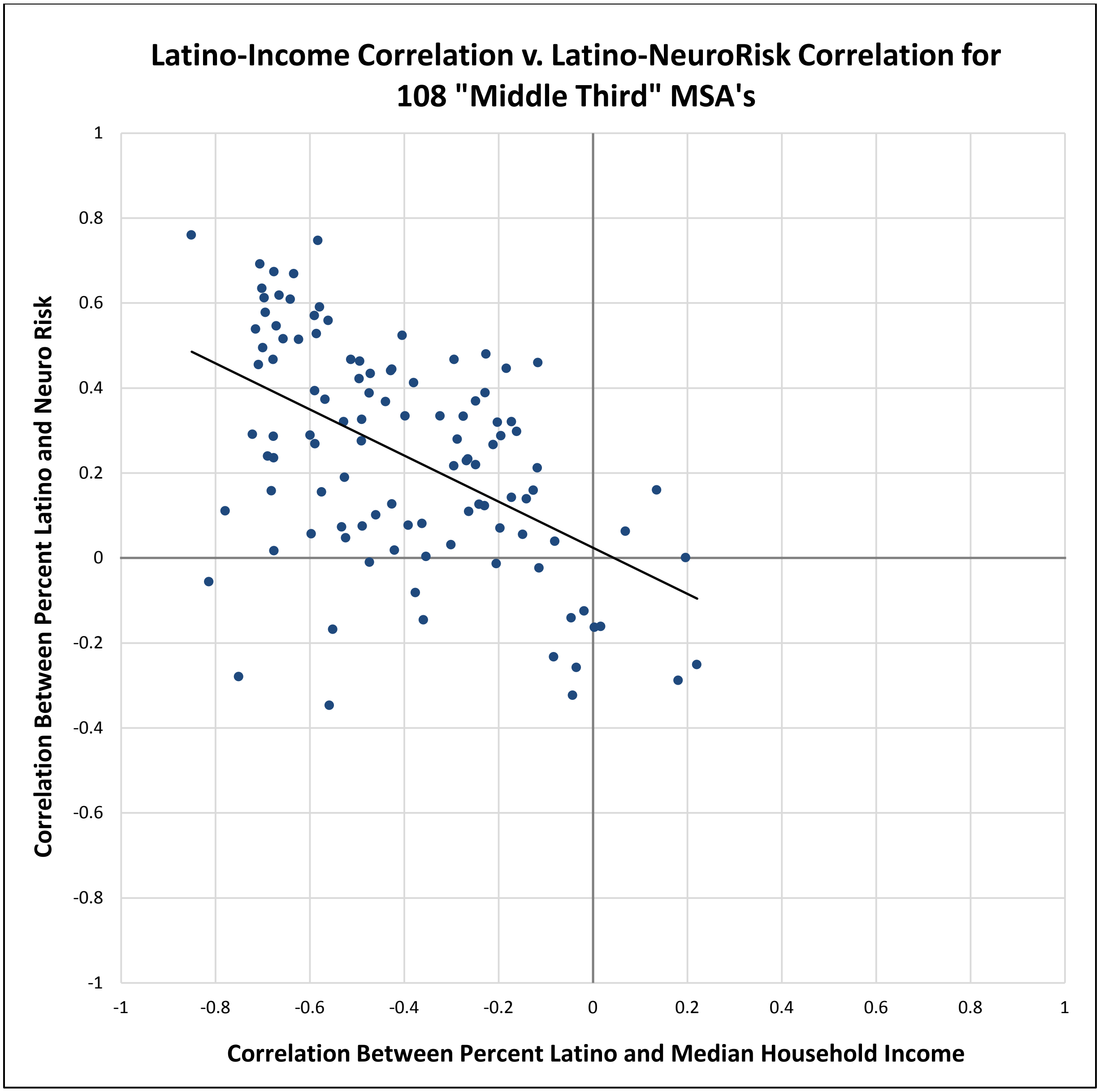

Figure A20

*RP = (-0.542)*RI + (0.0242)*

Race-Income Beta: -0.542

Race-Income t-stat: -6.17

Intercept: 0.0242

Intercept t-stat: 0.59

Correlation: 0.515

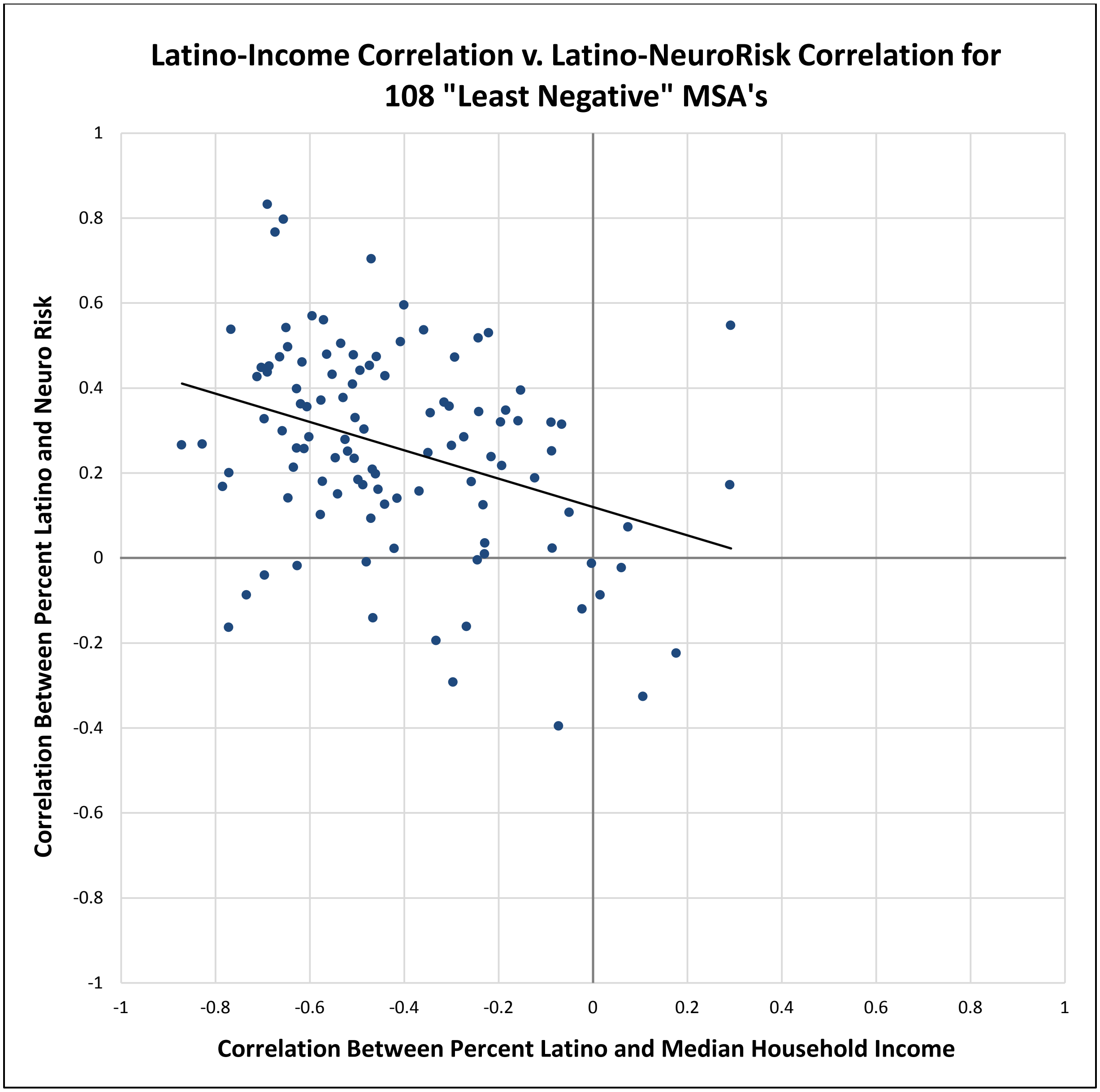

Figure A21

*RP = (-0.333)*RI + (0.120)*

Race-Income Beta: -0.333

Race-Income t-stat: -3.85

Intercept: 0.120

Intercept t-stat: 2.87

Correlation: 0.351

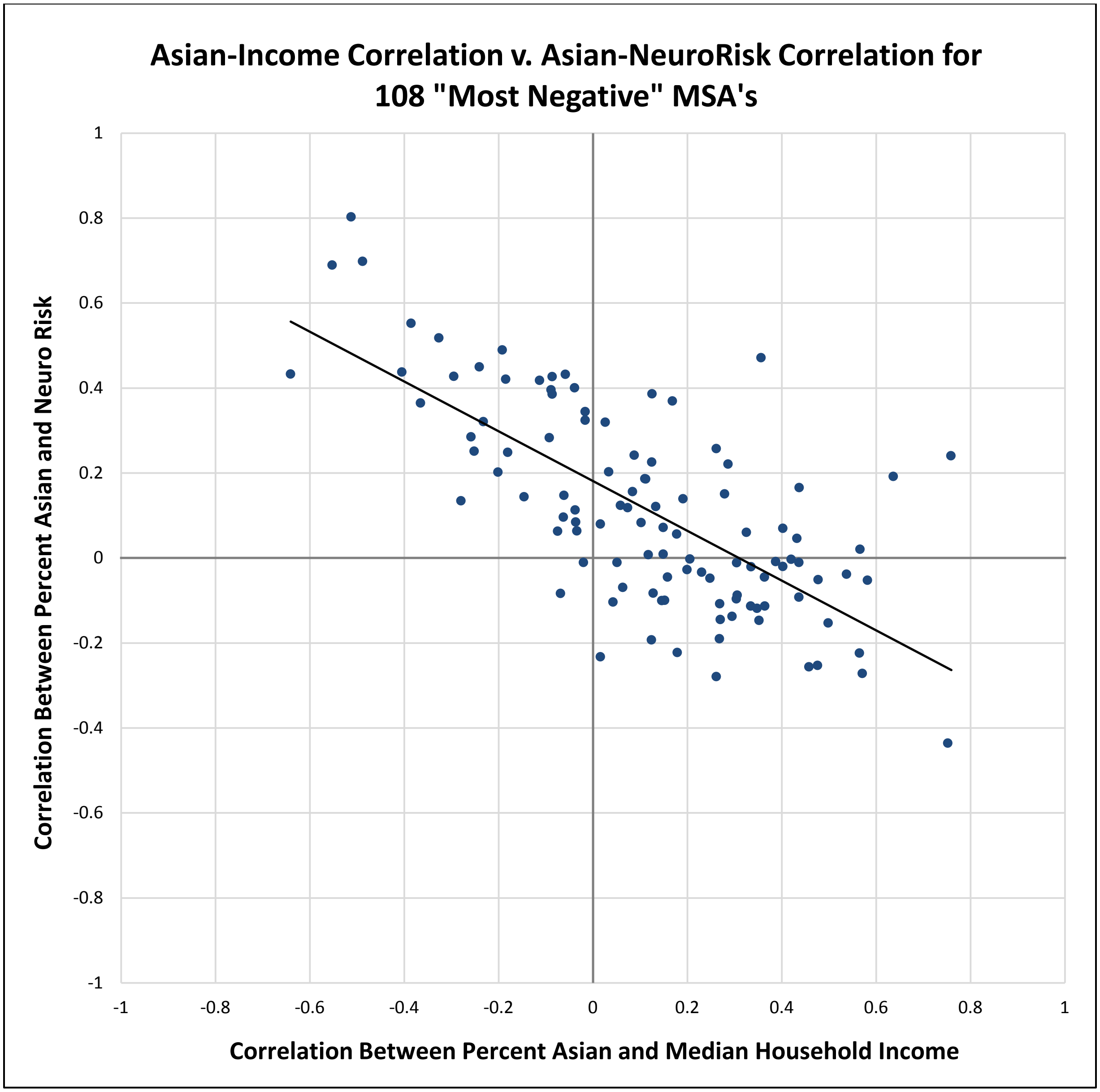

Figure A22

*RP = (-0.585)*RI + (0.181)*

Race-Income Beta: -0.585

Race-Income t-stat: -10.21

Intercept: 0.181

Intercept t-stat: 10.21

Correlation: 0.704

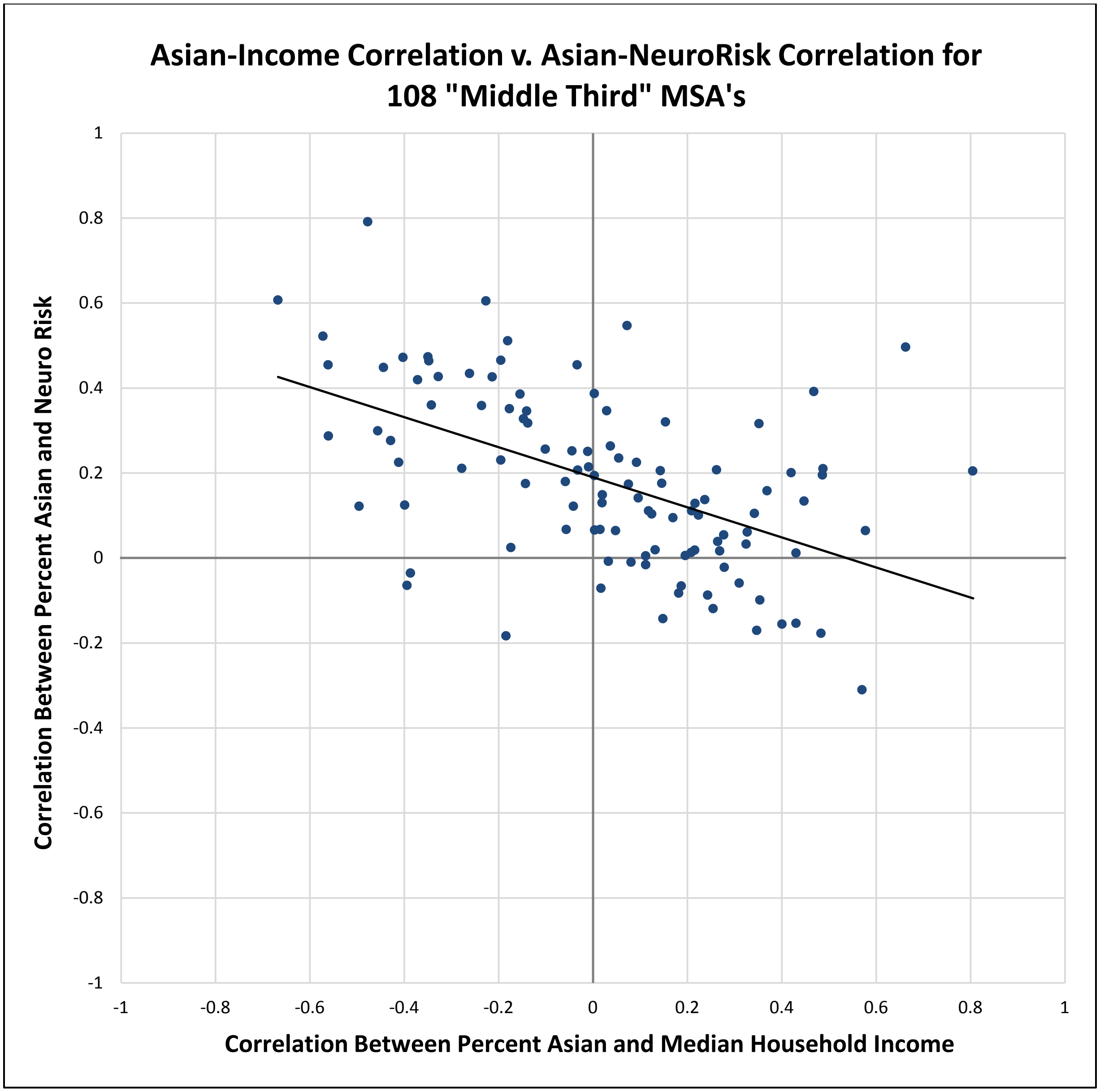

Figure A23

*RP = (-0.354)*RI + (0.190)*

Race-Income Beta: -0.354

Race-Income t-stat: -6.36

Intercept: 0.190

Intercept t-stat: 11.16

Correlation: 0.525

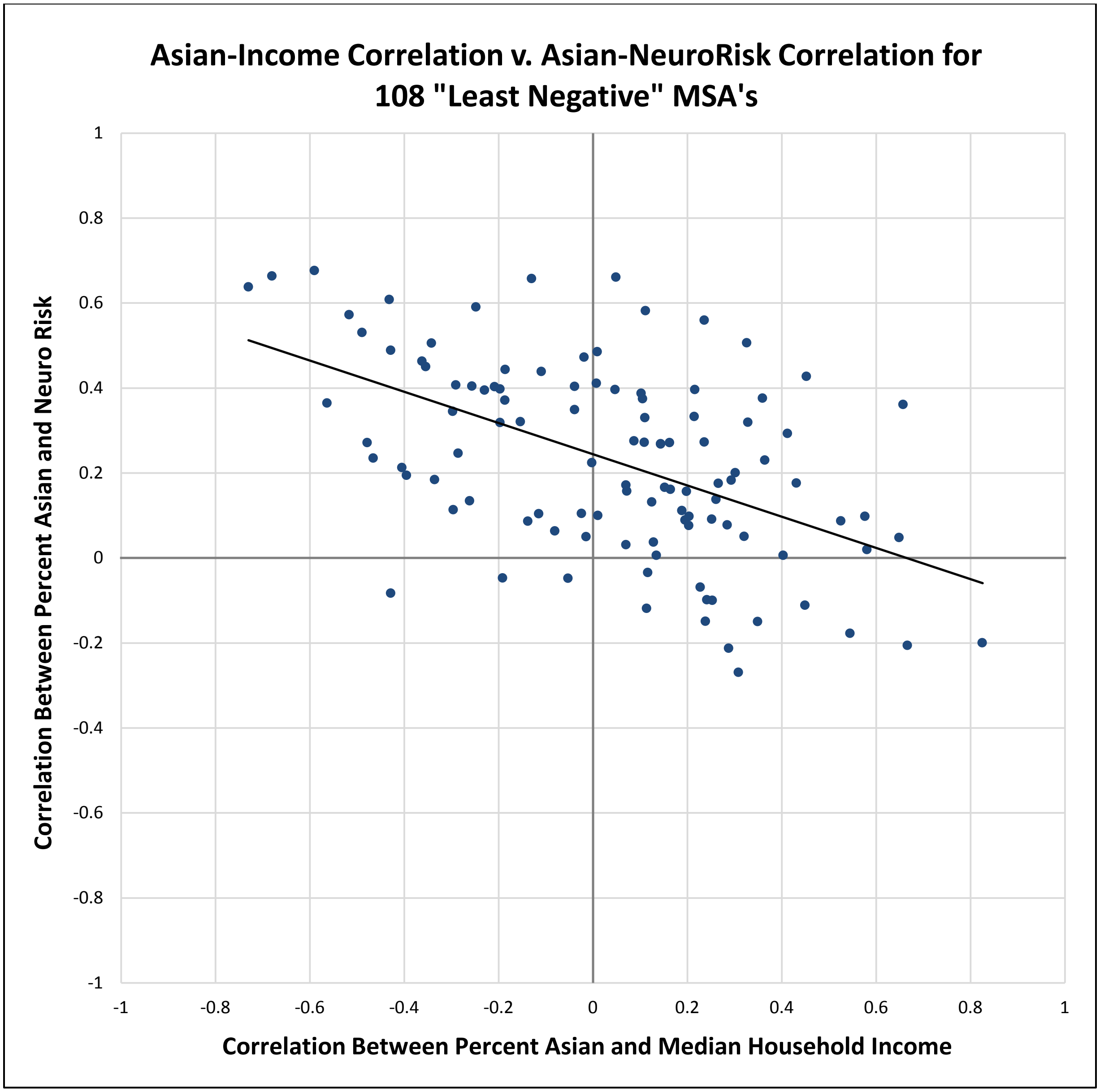

Figure A24

*RP = (-0.367)*RI + (0.244)*

Race-Income Beta: -0.367

Race-Income t-stat: -6.32

Intercept: 0.244

Intercept t-stat: 13.00

Correlation: 0.523

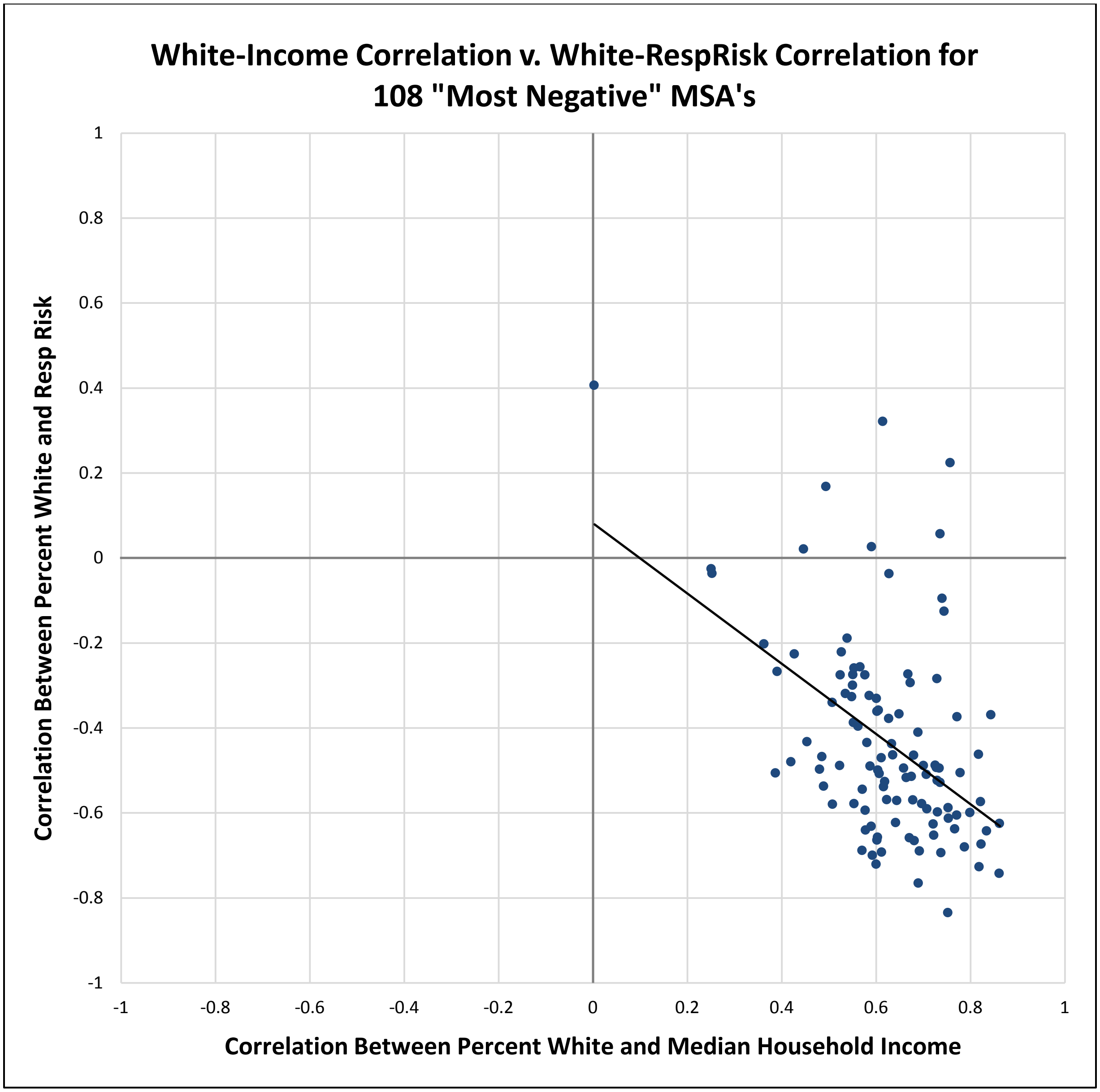

Figure A25

*RP = (-0.826)*RI + (0.0816)*

Race-Income Beta: -0.826

Race-Income t-stat: -5.58

Intercept: 0.0816

Intercept t-stat: 0.86

Correlation: 0.476

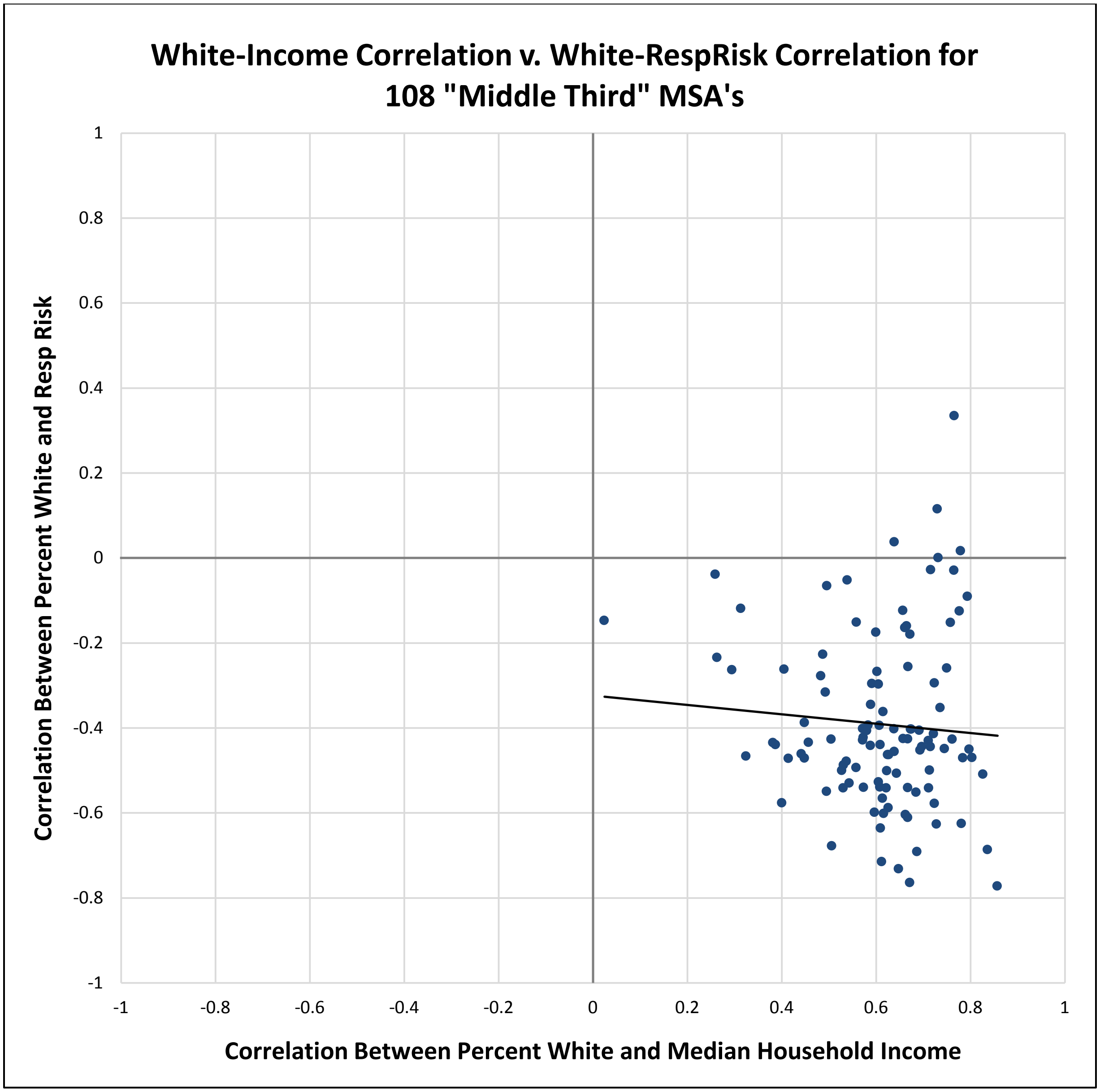

Figure A26

*RP = (-0.110)*RI + (-0.324)*

Race-Income Beta: -0.110

Race-Income t-stat: -0.78

Intercept: -0.324

Intercept t-stat: -3.66

Correlation: 0.077

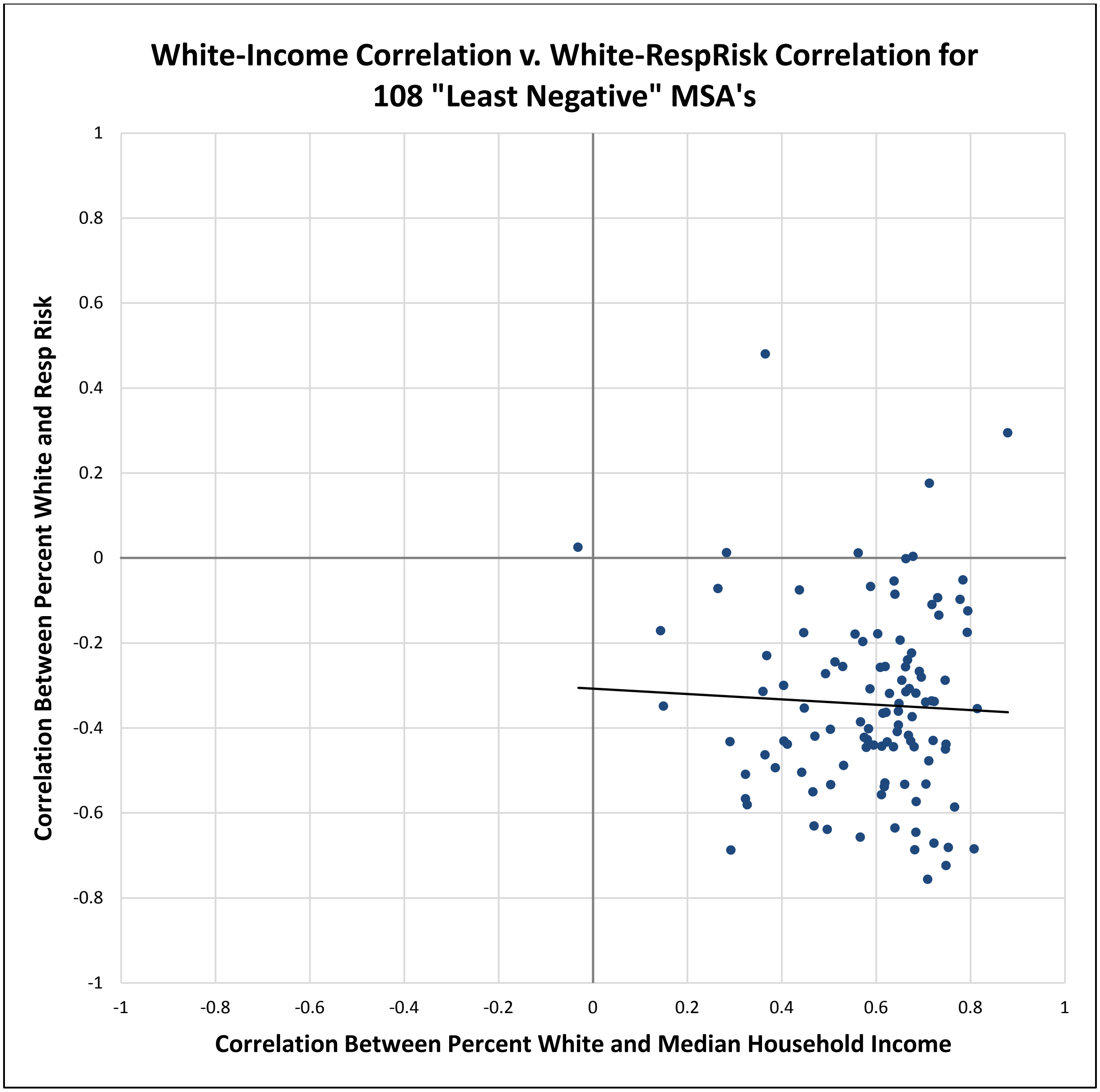

Figure A27

*RP = (-0.0628)*RI + (-0.307)*

Race-Income Beta: -0.0628

Race-Income t-stat: -0.48

Intercept: -0.307

Intercept t-stat: -3.83

Correlation: 0.045

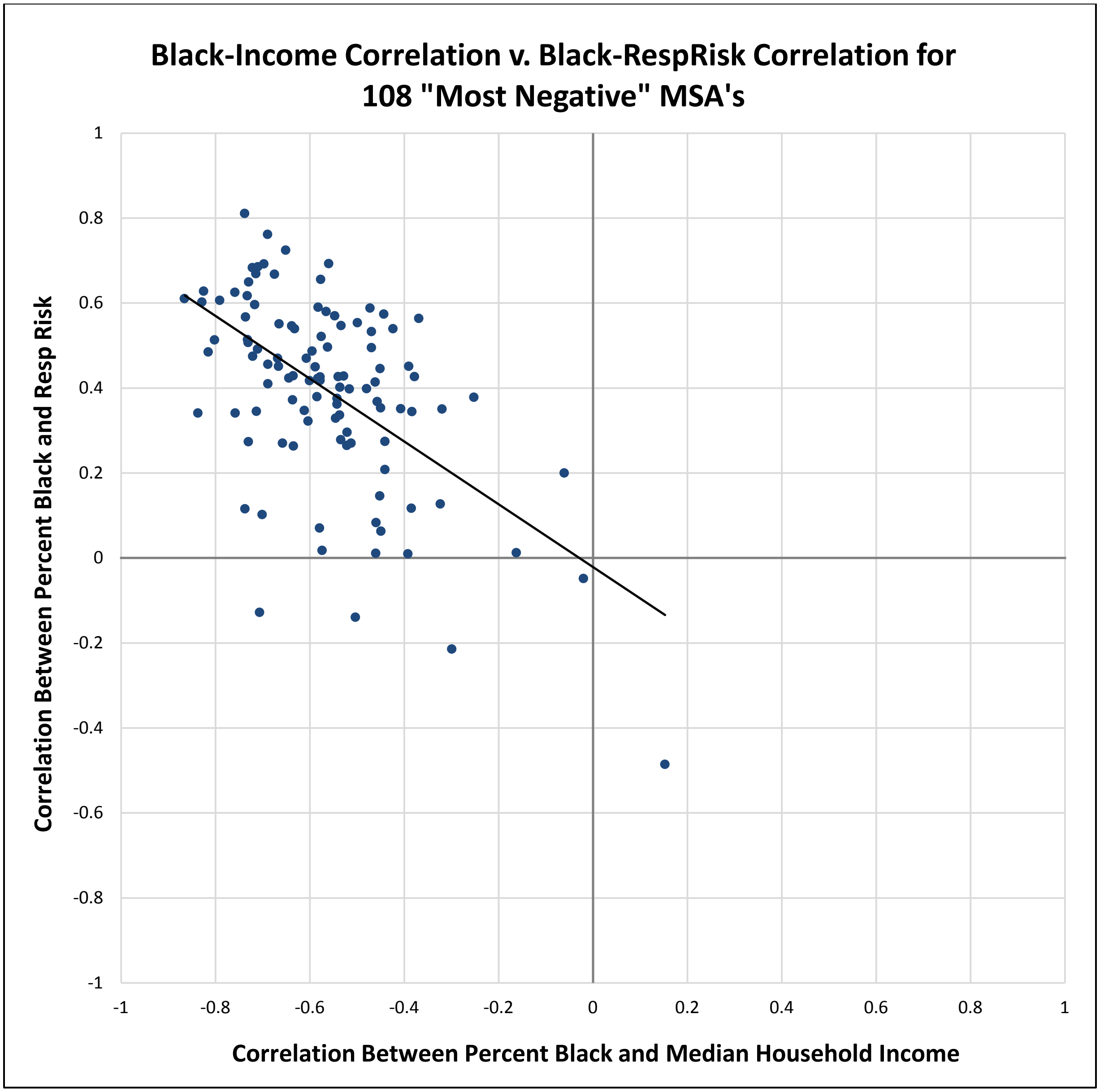

Figure A28

*RP = (-0.738)*RI + (-0.0212)*

Race-Income Beta: -0.738

Race-Income t-stat: -7.03

Intercept: -0.0212

Intercept t-stat: -0.34

Correlation: 0.564

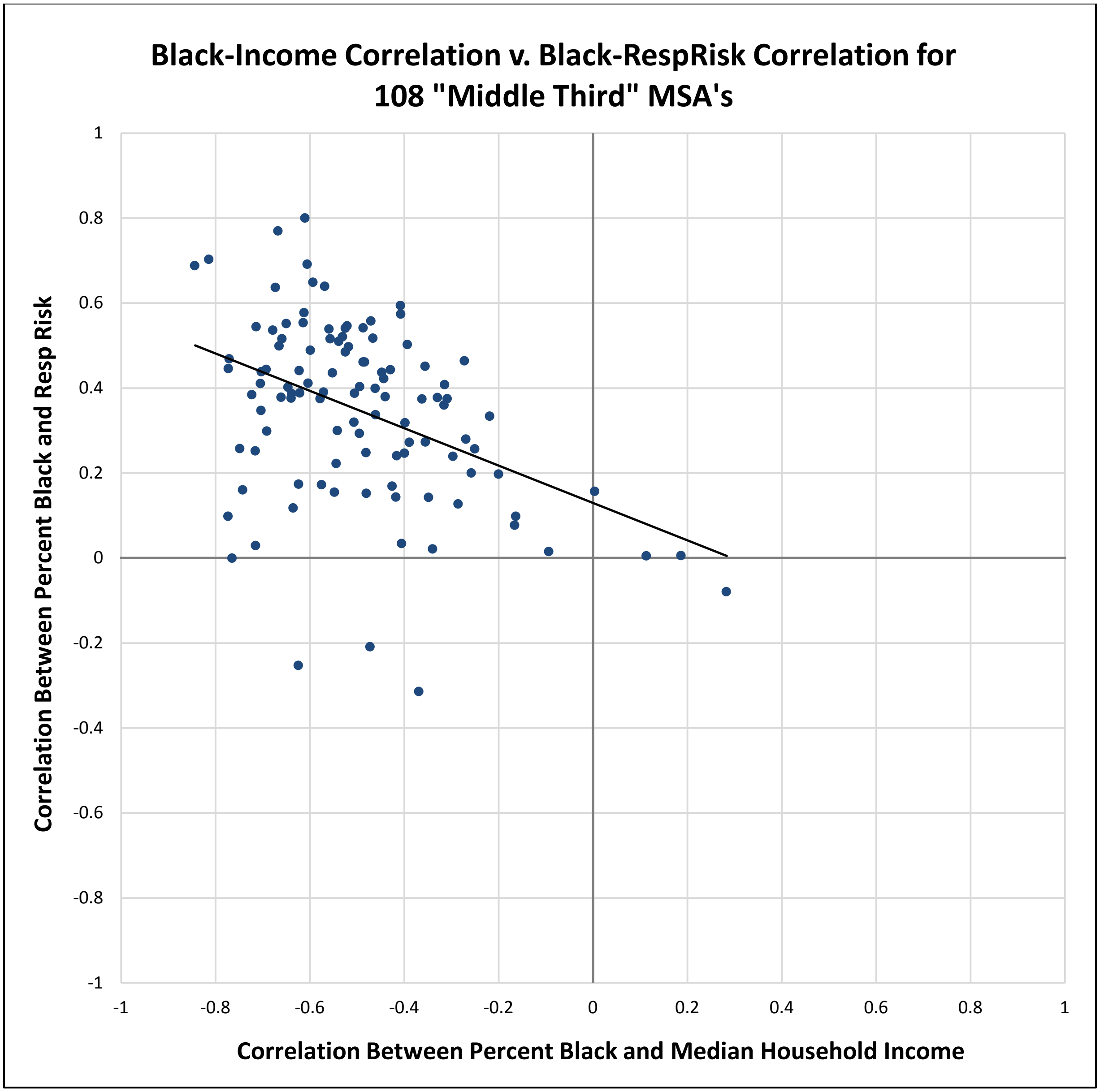

Figure A29

*RP = (-0.440)*RI + (0.130)*

Race-Income Beta: -0.440

Race-Income t-stat: -4.81

Intercept: 0.130

Intercept t-stat: 2.66

Correlation: 0.423

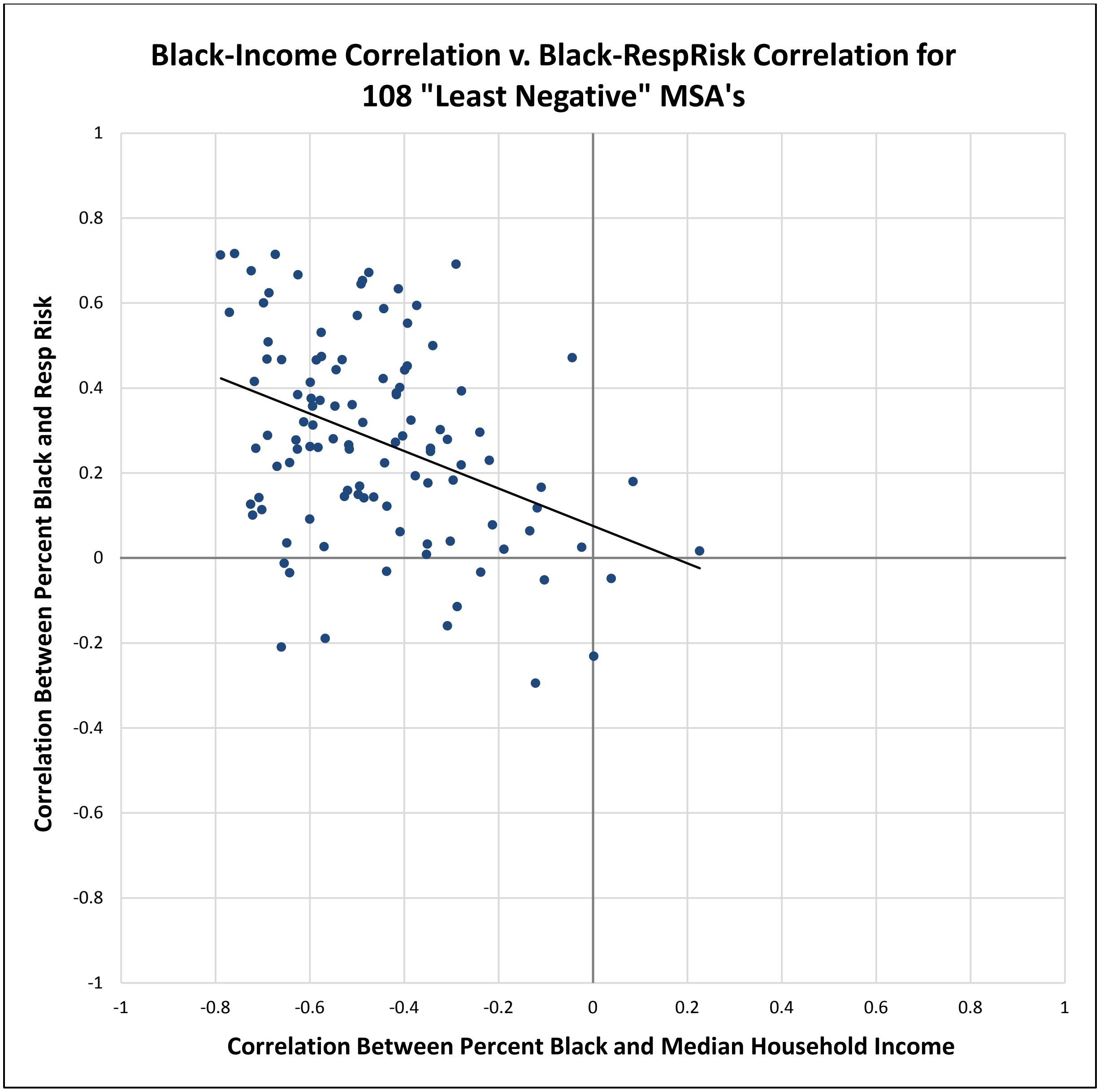

Figure A30

*RP = (-0.440)*RI + (0.0757)*

Race-Income Beta: -0.440

Race-Income t-stat: -4.32

Intercept: 0.0757

Intercept t-stat: 1.48

Correlation: 0.387

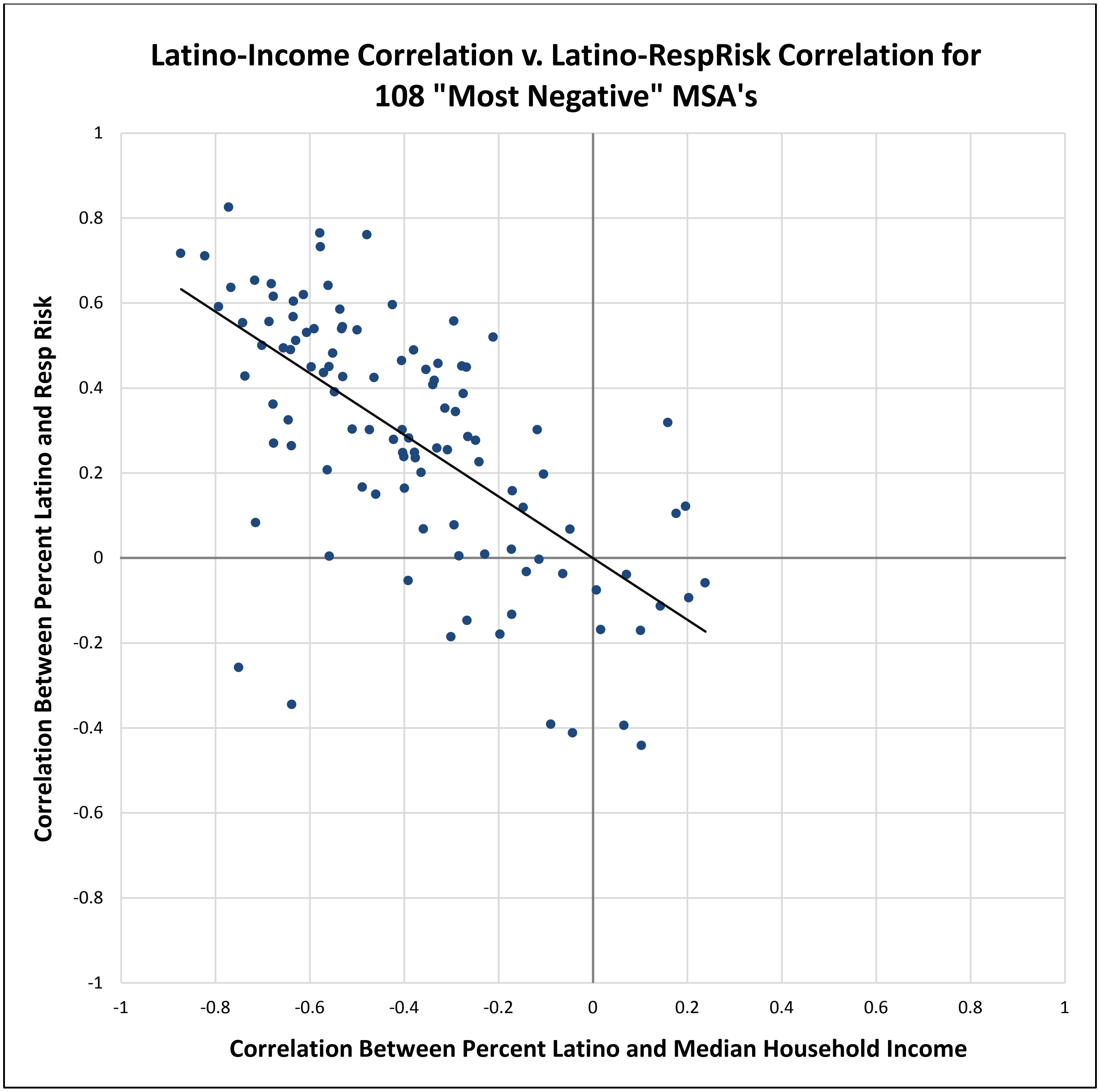

Figure A31

*RP = (-0.725)*RI + (-0.0004)*

Race-Income Beta: -0.725

Race-Income t-stat: -8.85

Intercept: -0.000407

Intercept t-stat: -0.01

Correlation: 0.652

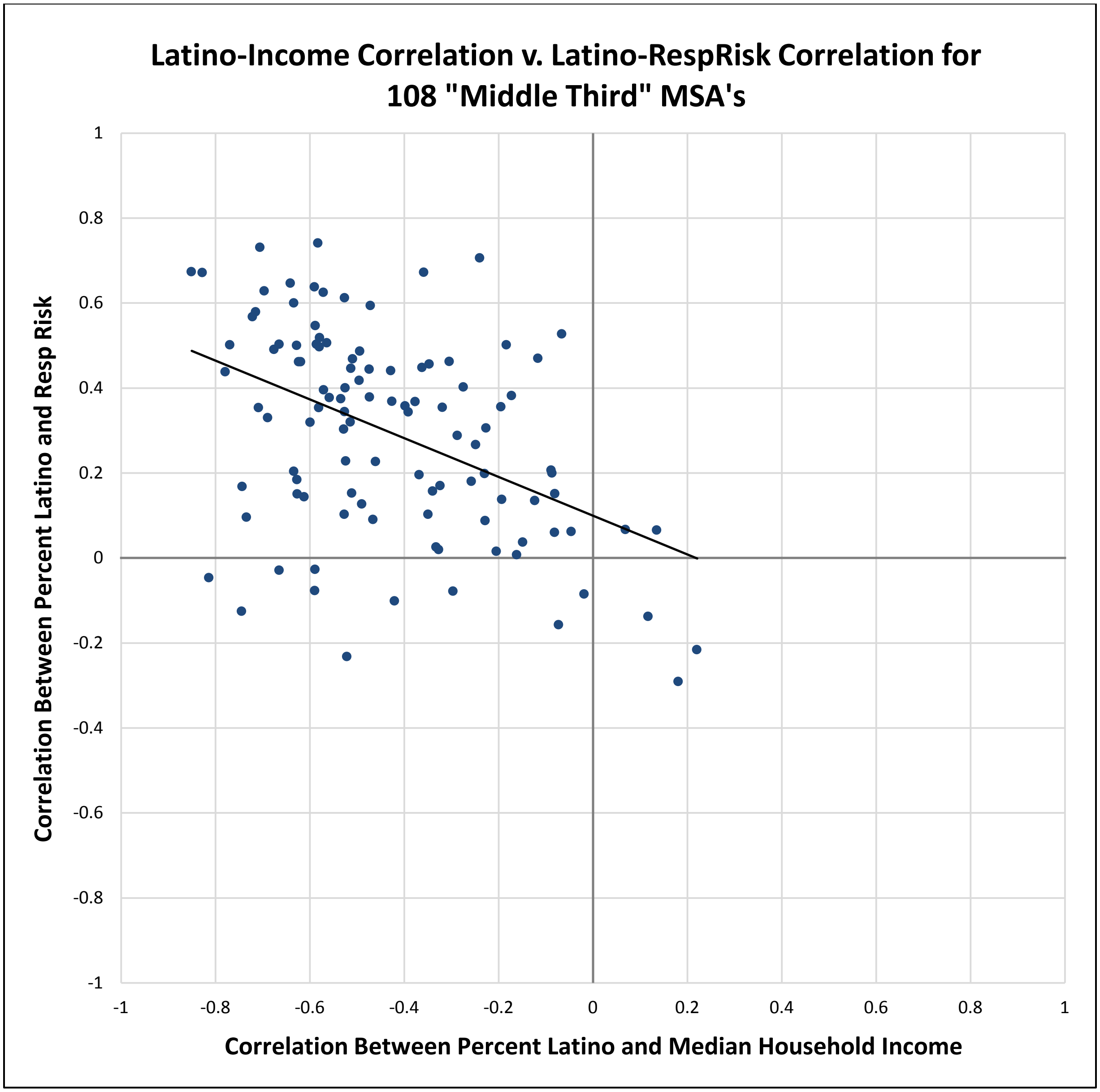

Figure A32

*RP = (-0.456)*RI + (0.0993)*

Race-Income Beta: -0.456

Race-Income t-stat: -5.23

Intercept: 0.0993

Intercept t-stat: 2.33

Correlation: 0.453

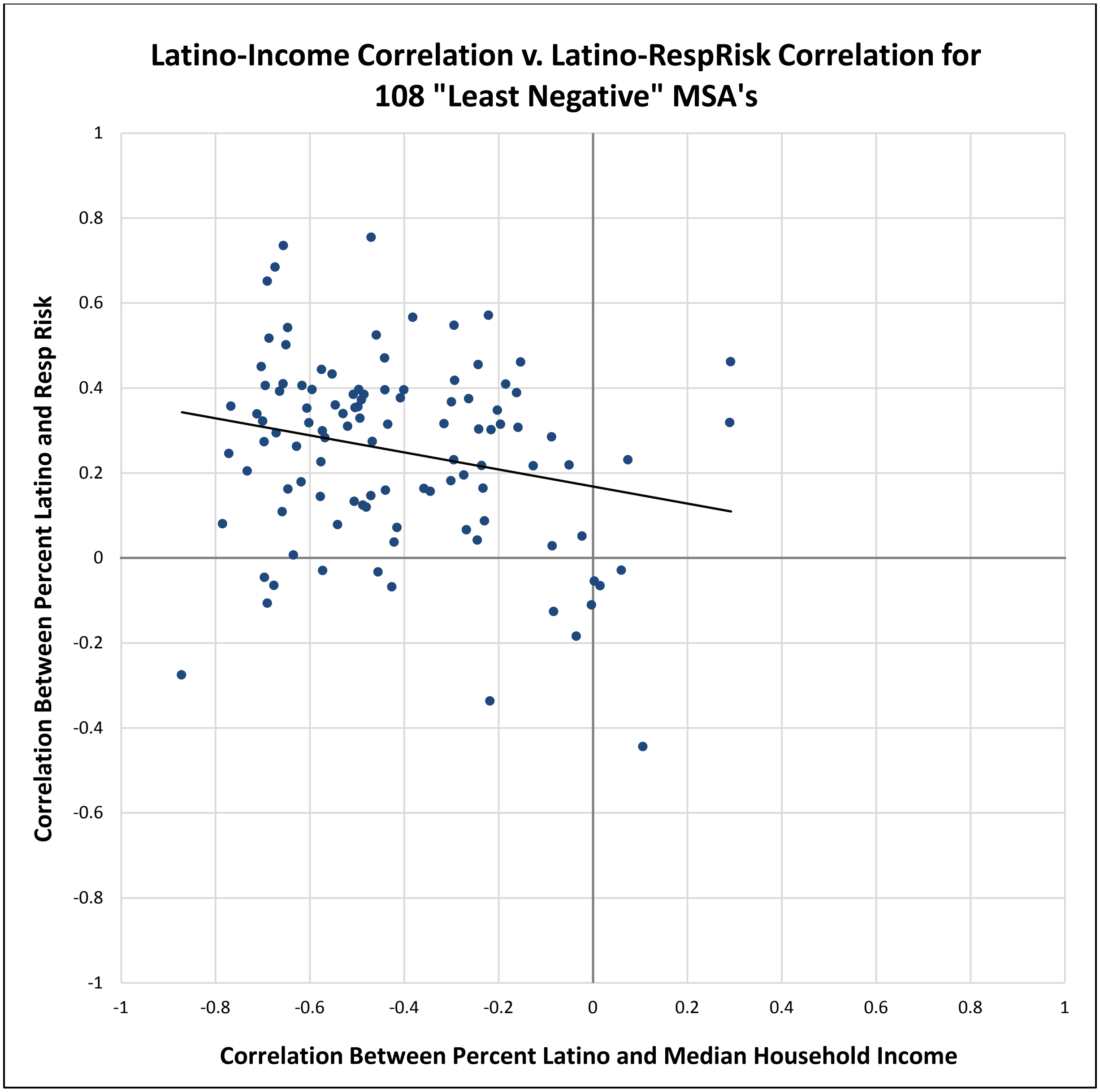

Figure A33

*RP = (-0.201)*RI + (0.168)*

Race-Income Beta: -0.201

Race-Income t-stat: -2.39

Intercept: 0.168

Intercept t-stat: 4.15

Correlation: 0.226

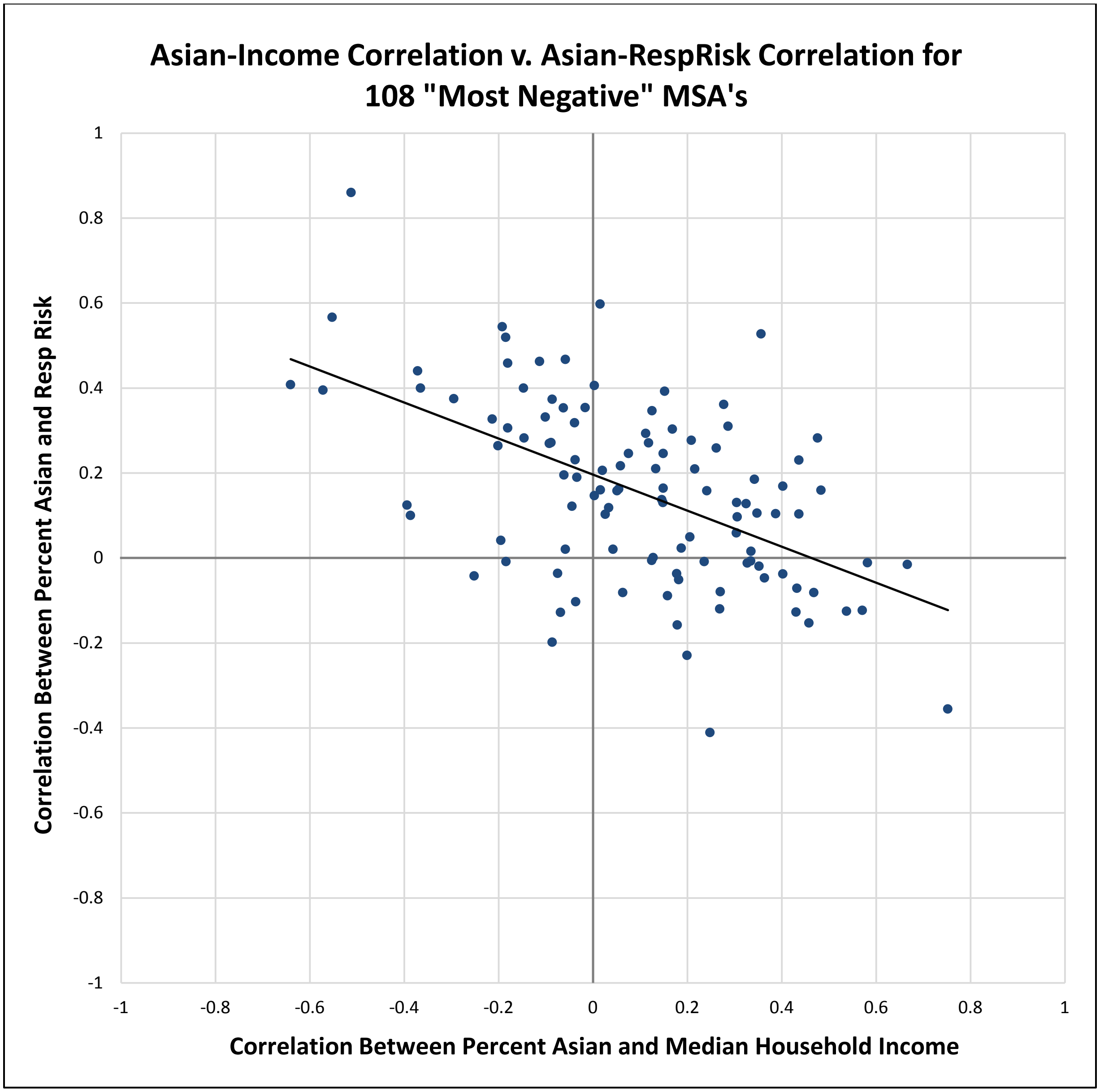

Figure A34

*RP = (-0.424)*RI + (0.196)*

Race-Income Beta: -0.424

Race-Income t-stat: -6.54

Intercept: 0.196

Intercept t-stat: 10.50

Correlation: 0.537

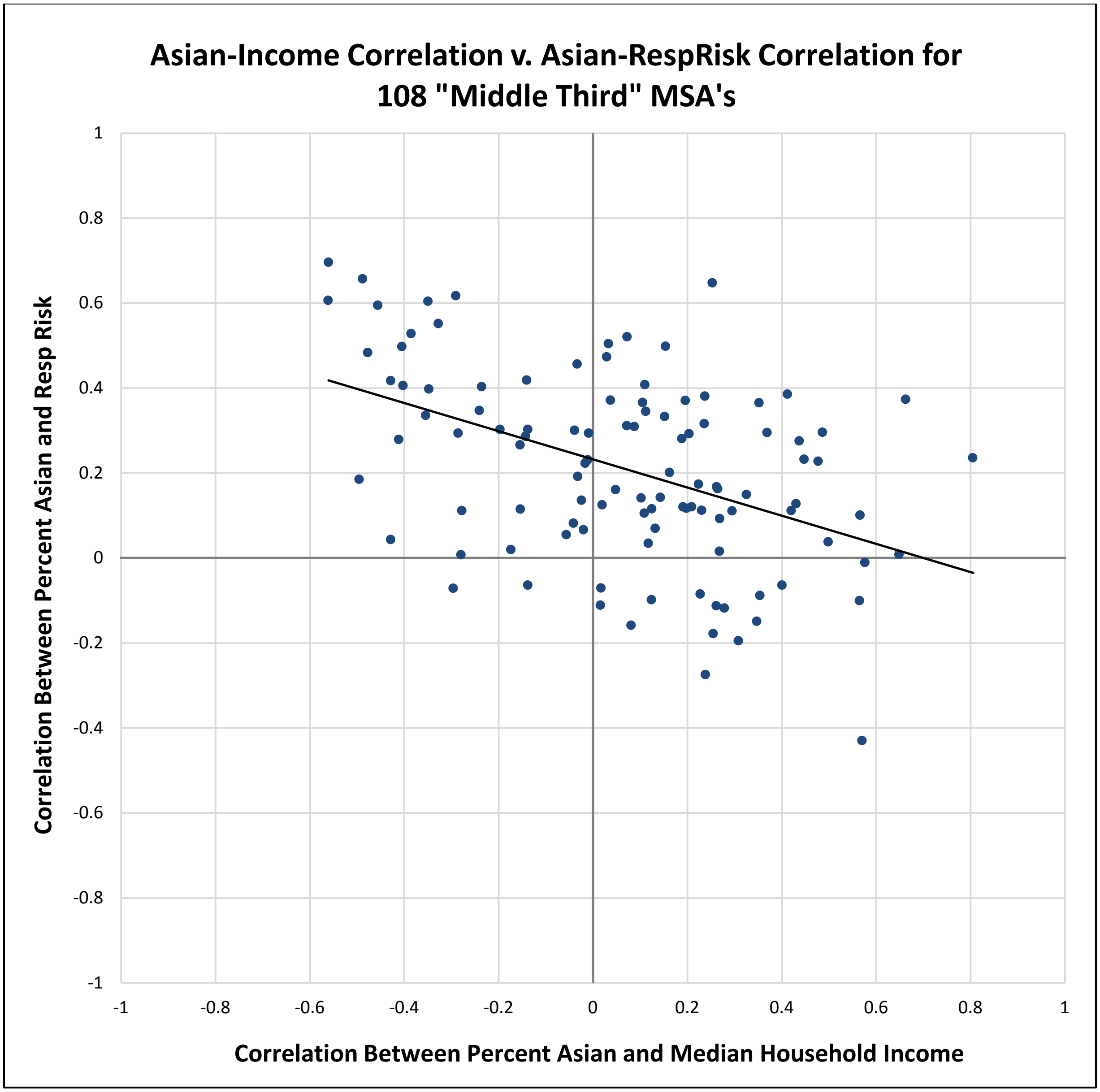

Figure A35

*RP = (-0.332)*RI + (0.232)*

Race-Income Beta: -0.332

Race-Income t-stat: -5.23

Intercept: 0.232

Intercept t-stat: 11.73

Correlation: 0.453

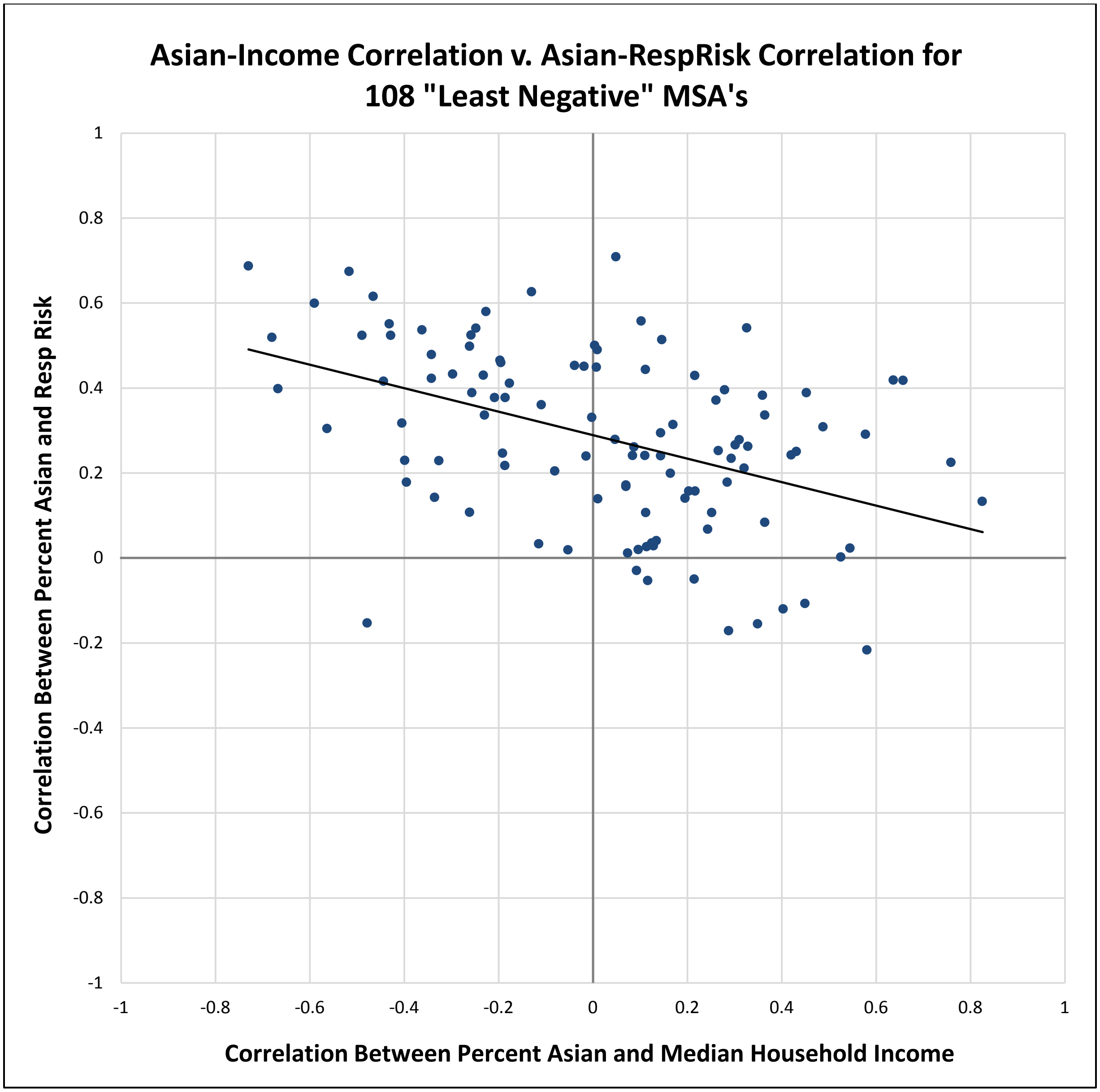

Figure A36

*RP = (-0.276)*RI + (0.289)*

Race-Income Beta: -0.276

Race-Income t-stat: -5.11

Intercept: 0.289

Intercept t-stat: 15.91

Correlation: 0.445

Appendix E - Disproportionate Siting Analysis

MSA Name	Race	Population	Race-Income Corr.	Race-Cancer Corr.	Race-Neuro. Corr.	Race-Resp. Corr.	Percent Race	CR Beta	NR Beta	RR Beta
NEW YORK NY	Asian	9,295,264	0.011	0.112	0.100	0.139	9.18%	0.154	0.278	0.188
DENVER CO	Asian	2,109,282	-0.024	0.077	0.105	0.136	2.98%	0.127	0.092	0.038
PORTLAND-VANCOUVER OR-WA	Asian	1,918,009	-0.002	0.369	0.224	0.330	4.59%	0.084	0.092	0.093
GREENSBORO--WINSTON-SALEM--HIGH POINT NC	Asian	1,251,509	0.004	0.370	0.387	0.405	1.35%	-0.053	-0.040	-0.142
NASHVILLE TN	Asian	1,231,311	0.020	0.240	0.149	0.206	1.58%	-0.181	-0.202	-0.143
HARTFORD CT	Asian	1,183,803	0.020	0.141	0.130	0.125	2.23%	-0.035	-0.176	-0.076
OKLAHOMA CITY OK	Asian	1,083,346	-0.014	0.230	0.050	0.239	2.52%	0.128	0.045	0.117
FORT WAYNE IN	Asian	502,141	0.016	0.528	0.067	0.597	1.02%	-0.186	0.012	-0.197
LEXINGTON KY	Asian	479,198	-0.009	0.298	0.214	0.294	1.56%	-0.105	-0.124	-0.093
VISALIA-TULARE-PORTERVILLE CA	Asian	368,021	0.003	0.291	0.194	0.146	3.27%	0.092	-0.054	-0.248
HUNTINGTON-ASHLAND WV-KY-OH	Asian	315,538	0.004	0.009	0.066	0.500	0.37%	-0.049	-0.035	0.065
WATERBURY CT	Asian	228,984	-0.019	0.086	-0.011	0.066	1.34%	-0.527	-0.341	-0.016
ASHEVILLE NC	Asian	225,965	-0.018	0.509	0.473	0.451	0.63%	0.208	0.250	0.255
HOUMA LA	Asian	194,477	0.018	-0.043	-0.071	-0.071	0.74%	-0.099	0.002	0.045
JOPLIN MO	Asian	157,322	-0.016	0.527	0.344	0.354	0.57%	-0.061	-0.572	-0.290
WICHITA FALLS TX	Asian	140,518	0.008	0.377	0.411	0.449	1.73%	-0.066	0.029	0.151
JAMESTOWN NY	Asian	139,750	-0.016	0.204	0.324	0.223	0.36%	-0.337	-0.384	-0.124
WATERLOO-CEDAR FALLS IA	Asian	128,012	0.017	-0.121	-0.233	-0.111	0.98%	-0.223	-0.685	-0.026
DOVER DE	Asian	126,697	0.010	0.487	0.485	0.490	1.69%	1.228	0.370	0.166
ALEXANDRIA LA	Asian	126,337	-0.010	0.191	0.250	0.230	0.86%	-0.122	-0.030	-0.065
GREAT FALLS MT	Asian	80,357	0.017	0.104	0.080	0.160	0.81%	-0.858	-0.646	-0.431
BROWNSVILLE-HARLINGEN-SAN BENITO TX	Black	326,245	0.004	0.110	0.156	0.156	0.48%	-0.407	-0.209	-0.130
SAN LUIS OBISPO-ATASCADERO- PASO ROBLES CA	Black	246,681	-0.020	-0.051	0.000	-0.049	2.03%	-0.252	0.003	-0.298
STATE COLLEGE PA	Black	135,758	-0.023	-0.009	-0.002	0.025	2.24%	0.347	0.224	0.296
SHEBOYGAN WI	Black	112,646	0.002	-0.120	-0.211	-0.232	1.09%	-0.251	0.026	0.185
DAYTONA BEACH FL	Latino	485,327	0.017	-0.144	-0.161	-0.169	6.50%	-0.229	-0.072	-0.404
AUGUSTA-AIKEN GA-SC	Latino	477,441	0.004	-0.079	-0.163	-0.055	2.44%	-0.040	-0.034	0.156
SAVANNAH GA	Latino	293,000	0.008	-0.061	-0.093	-0.076	2.18%	-0.810	-0.830	-0.896
COLUMBUS GA-AL	Latino	274,624	-0.003	-0.069	-0.013	-0.111	4.04%	0.327	0.020	0.324
CLARKSVILLE-HOPKINSVILLE TN-KY	Latino	207,033	0.015	-0.107	-0.087	-0.065	5.05%	0.327	0.387	0.437
HOUMA LA	Latino	194,477	-0.018	-0.027	-0.125	-0.085	1.50%	-0.099	0.002	0.045
TEXARKANA TX-TEXARKANA AR	Latino	129,749	-0.023	-0.115	-0.120	0.052	3.57%	0.143	0.297	0.205
HONOLULU HI	White	867,885	0.024	-0.230	-0.121	-0.148	18.76%	0.049	0.110	-0.081
PUNTA GORDA FL	White	141,627	0.003	0.297	0.276	0.406	90.42%	-1.317	-1.465	-0.171

Note: The color scales are such that in each column red is negative, blue is positive, and white is zero.

Table 21: MSA's with a Race-Income Correlation between -0.025 and 0.025