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Publicity tweet:

Many feel globalization drives inequality, but which aspects of "superstar regions" impact whether NEIGHBORHOODS are mixed? We use overlapping geographies and combinatorial estimation to link creative class work, venture capital, housing growth, etc. to neighborhood diversity in income, education, and occupation.

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Rising Inequality and Neighborhood Mixing in US Metro Areas

Abstract: Superstar cities with high-paying creative-class jobs, venture capital, and innovation are thought to be more unequal. We analyze mixing in neighborhoods by income, education, and occupation, relating this intraurban measure with regional productivity indicators. Using non-overlapping census units and a machine-learning estimation technique which iterates over all combinations of economic, business, housing, and cultural indicators, we identify "ingredients" associated with economically and socially diverse neighborhoods. Broad support is not found that neighborhoods in superstar regions are less mixed; however, overrepresentation in creative occupations stymies mixing as does a combination of weak economic fundamentals with high shares of new housing.

Introduction

Rising income inequality in the US and globally has captured the attention of policymakers and researchers in recent years (Picketty 2014; Stiglitz 2012). In the US, the Gini coefficient measuring nationwide economic inequality rose from 0.403 in 1980 to 0.480 in 2014 (2014) while nearly all of income growth over the last several decades has gone to the very top – usually considered the top 1% - of the income distribution, with stagnant income for the middle-class.

Meanwhile, geographers and regional economists have long emphasized the interurban dimension of inequality. Porter (2003) distinguishes a region's economic activity by its involvement in local clusters – industries serving the region's population – and traded clusters – the true engines of contemporary growth involving industrial linkages across regions. While once convergence between poor and rich regions was the norm, beginning in the 1990s wage growth has been distributed to regions already better off, a shift linked to increasing regional integration and globalization (Berry and Glaeser 2005). Undergirding the growth in so-called "superstar cities" is a combination of venture capital, high tech jobs, human capital, and innovative capacity, which attracts knowledge workers and could further increase inequality. In short, the fastest growing places tend to be the most unequal.

Rather than linking regional productivity to regional inequality, this study links productivity indicators to an intraurban analogue of inequality – mixing – the extent to which non-like people live in close proximity. The increasingly popular notion of urban inversion posits a "back to the city" movement especially in large, prosperous metros led by young adults and retirees moving toward city centers and into higher density housing, reversing a decades-long trend of the suburbanization of the affluent (Ehrenhalt 2012). This is accompanied by the movement of tech jobs and headquarters to central cities in order to attract knowledge economy workers—both elements of global economic change which impact within-region spatial structure.

Decades of sociological research on concentrated disadvantage emphasizes that segregation in neighborhoods can damper life opportunities by creating spatial and network separation between rich and poor (see, e.g. Sampson 2013; Wilson 1987). As a region's land use patterns are largely determined by the location decisions of the wealthy, segregation within a city is an important component of increasing inequality and decreasing exposure to different social and economic groups. Glaeser, Resseger, and Tobio (2009) suggest that the wealthy may develop empathy for the poor through spatial proximity – which could translate into support for social welfare programs. Socioeconomic mixing, therefore, is thought to promote social and economic integration and increased opportunities for low-income residents. As evidence, a longitudinal city-level analysis found that the combination of city level inequality and economic segregation within the city's neighborhoods resulted in higher levels of crime (Hipp 2011), stressing the local dimension of inequality. A study of cities from 1970 to 2010 found that higher levels of inequality were associated with larger increases in crime rates and that this relationship strengthened over time (Hipp and Kane 2017).

While income inequality often dominates the discussion of social and economic transformation, wide-ranging scholarship has noted increasing divides in life chances, neighborhood choices, and spending habits that are class-based and occupation-based rather than purely income-based. Researchers of urban gentrification, for example, have emphasized that segregation by education level or by occupation type may be more reflective of these changes in cities (Freeman 2009). Segregation by these measures indicates less integrated regions overall where life opportunities, social organization, and socio-political attitudes can be narrower.

Florida (2017) discusses a number of these themes in *The New Urban Crisis*, building empirical research on metropolitan-level inequality and neighborhood segregation. He emphasizes how by most interurban and intraurban measures, a distinctive set of large, dense, high-tech, and booming metros are also the most unequal and unaffordable. In this paper, we extend his broad analysis of the connection between a metropolitan area's level of inequality and the spatial segregation experienced by its residents in its neighborhoods with two important methodological and conceptual contributions.

First, most prior research has measured segregation based on non-overlapping geographic units defined by statistical agencies – typically census tracts in the US – which do not account for the nearby environment. Hipp and Boessen (2013) propose using "egohoods" – census units plus those within a certain buffer distance – to more accurately characterize the surroundings of an individual in urban space. Clark, Anderson, Östh, and Malmberg (2015) use ego-centric measures and find the overlapping census unit approach to be an improved measure of neighborhood segregation and diversity. This paper considers "egohoods" of census block groups plus all other block groups within 1.5 miles.

Second, explanations for inequality in a region are nonlinear and combinatorial in nature. While a connection can be drawn between inequality and factors like growth, education, occupational share, and crime, these characteristics are not independent of each other and affect regions differently. Drawing linear associations in the form of correlations and ordinary least squares regression is largely unable to account for nonlinear moderating effects on parameter estimates; furthermore, interaction terms are cumbersome and difficult to interpret for all covariates in OLS. We use a promising alternative: the machine learning approach of Kernel Regularized Least Squares (KRLS) (Hainmueller and Hazlett 2014). KRLS provides estimates of the marginal effect of each independent variable at each data point in the covariate space and provides closed-form estimates of the pointwise partial derivatives. This allows for sharper estimation and importantly, the marginal effects can be regressed upon the model's other variables, allowing for the determination of which "ingredients" combine to impact inequality.

This study adds to the discussion of rising inequality across cities by connecting it to the level of mixing experienced by neighborhood residents with a new empirical approach which is more adept at considering regional inequality drivers including economic well-being, the business environment, housing characteristics, and demography.

Data, Hypotheses, and Method

This study's statistical analysis considers the 381 Metropolitan Statistical Areas (MSAs) in the United States in 2010. Unless otherwise noted, data come from the US Census American Community Survey (ACS) 5-year estimates for 2008-2012 (2014).

Dependent Variables

First, we use pySAL software to construct block group egohood measures, in effect replacing each block group characteristic with the average (or total) value of all block groups within 1.5 miles (Rey 2013). The actual size chosen for measuring the egohood is, of course, arbitrary to some degree. Hipp and Boessen's (2013) study of the localized process of neighborhood crime used egohoods measured at 0.25, 0.5, and 0.75 miles, while Hipp, Kane, and Kim (2017) use 2.5 and 5 miles to measure jobs-housing balance—a broader process more closely related to commuting. We argue the activity space of a neighborhood whereby a resident has some meaningful contact with others at schools, parks, stores, and local institutions lies somewhere in-between these thresholds. While the median block group population in US metros is 1,268, the median block group egohood is comprised of five block groups and contains 10,093 residents (see Appendix A). Consistent with Hipp and Boessen (2013) and given our use of categorically-derived variables, egohood populations are summed and are unweighted.

We compute the degree of income mixing in each egohood based on the eleven discrete household income categories reported by the ACS. Numerous indices exist for capturing the degree of mixing in a small area. Florida (2017) uses group-specific dissimilarity indices measuring the separation between poor and non-poor, wealthy and non-wealthy, and an aggregated measure which combines the two. Reardon and Bischoff's (2011) rank-order information theory index captures the degree of mixing *relative* to the region overall. For each region, we use the mean of the block group egohoods' Gini coefficients because it is a single, ordered, continuous measure of mixing and considers mixing overall, not relative to the region. The regional mean therefore reflects the typical experience of a resident in a neighborhood of that metro—a high value indicating neighborhoods with a wide range of incomes.[i]

While at the regional or national levels a higher Gini value denotes inequality, at the neighborhood scale it reflects income mixing, or the extent to which a neighborhood area contains households with a wide range of incomes. This may be counterintuitive since typically a low value of Gini coefficient is considered "good." However, we prefer the Gini coefficient for categorizing neighborhood income mixing over a categorical approach using entropy since income is inherently a continuous measure.

We take the mean value across all block group egohoods in an MSA to capture the typical neighborhood experience. Since egohoods are overlapping analytical units, MSA-level variances were very small, suggesting that this form of spatial smoothing improves the robustness of the mean as a statistic to capture the MSA's "typical neighborhood experience." Our second outcome measure captures the level of education mixing in neighborhoods using the entropy across five educational categories from the ACS: no high school diploma, high school diploma, some college, bachelor's degree, and graduate degree. The entropy index is preferred as a categorical measure of the extent to which neighborhoods (or egohoods) are mixed across discrete educational categories. The third outcome measure is the level of occupational mixing in neighborhoods which is an entropy measure based on Florida's (2017) distinction between creative, service, and working class occupations (see Appendix B).

Economic Well-Being

The first set of independent variables captures the level of regional economic well-being. Numerous studies have related the level of wages or income to the level of inequality (Florida and Mellander 2014; Glaeser, Resseger, and Tobio 2009). We capture this using 1) *average household income* from the ACS and 2) MSA *GDP per capita* from the US Bureau of Economic Analysis. In addition we include *growth in household income over the previous decade* (2000-2010). Most prior research has generally associated income and growth with greater inequality region-wide, however our outcome measure of mixing at the neighborhood scale is conceptually the opposite of segregation measures. Thus we hypothesize an inverse relationship between mixing and these measures of income, productivity, and growth. Put differently, wealthy or growing regions will be less mixed. We also examine the effect of metro-level *unemployment* and the share of population with a *bachelor's degree or above*.

Business and Production

The second set of independent variables captures aspects of "superstar" or high-impact metros discussed in Florida (2017) which relate to the business environment and economic productivity. We do not hypothesize on the specific pathways whereby each indicator contributes or does not contribute to mixing, focusing principally on the interaction of independent variables facilitated by KRLS. One common measure of national and global integration is the *number of Fortune 1000 companies with headquarters locations* in a region which is provided by *ProximityOne (2017).* Another measure strongly implicated in rising inequality is the prevalence of start-up firms and venture capital investment, much of the activity of which is in the tech industry and historically is heavily concentrated in Silicon Valley and other highly innovative regions (Kenney 2000). We use a *logged measure of the total dollars of venture capital invested in that MSA from 2010-2015*. Following the perspective that invention and innovation are key components of the regional production function (Porter 2003), we include a logged count of patents issued to inventors in each MSA from the US Patent Office over 2010-2015. We also use the *percent of a region's employees working in creative industries* (Florida 2002). The final business variable used is the *percent of employees in an MSA who belong to a union* which is compiled by the Census' Current Population Survey. This indicator varies mostly based on state policy and industrial composition.

Housing

Given that the housing price bubble and the resulting foreclosure crisis could be considered causes and effects, respectively, of the Global Financial Crisis (Immergluck 2010, Martin 2011), and that housing unaffordability is a key characteristic of inequality as experienced in cities, we include several housing-related variables. *Average home value* is included from the ACS, as well as the *share of a region's homes built in the last ten years*. This measure is intended to capture booming MSAs like Phoenix, Las Vegas, Orlando, or Charlotte which saw continual in-migration, have home construction as a major part of their regional economy, and generally were hurt by the housing crash of 2006-2008. Contrastingly, we include the *percentage of households who have been in the same home one year* to capture in-migration and intraregional residential mobility, while the housing *occupancy rate* is used to provide a measure of housing market vibrancy.

Demographic/Cultural/Political

We included five measures capturing the demographic composition of the region. We capture the presence of retirement-age individuals (*65 and above*) as well as the youth share of the population (*aged 0 to 19*). To understand a region's racial/ethnic composition we include the *percent Black*, *percent Latino*, and a measure of *racial/ethnic heterogeneity* in the region based on a Herfindahl index of five groups (Asian, Black, Latino, White, and other race). Glaeser et al. (2009) finds a robust relationship between murder rate and region-wide inequality, thus we include the *violent crime rate* (per 1,000 persons) in an MSA by summing the Uniform Crime Report data for police agencies in the region. Following the contention from Florida (2017) that places with politically liberal attitudes tend to be more unequal, we include the *percentage who voted for President Obama* in 2012 (Rogers and Cage 2012). We also take into account the possibility that religious attitudes may impact the level of mixing and include a measure of a region's *percent religious adherents* from the American Religious Data Archive (ARDA). While city size is commonly associated with inequality (Baum-Snow and Pavan 2013), we omit this variable since the study includes numerous correlates to city size that may be more directly relevant to inequality on economic, policy, or cultural grounds.

Method – Kernel Regularized Least Squares

A limitation of regression models is that the base assumption of linearity between independent variables and the outcome measure, as well as a lack of interactions between covariates in the model. Although nonlinearization of independent variables is possible and interaction terms can be constructed, this can be cumbersome to parameterize. For this reason, an alternative approach that shows considerable promise is the machine learning approach of Kernel Regularized Least Squares (KRLS) models described in Hainmueller and Hazlett (2014) and implemented for Stata in Ferwerda, Hainmueller, and Hazlett (2013).

The KRLS approach provides estimates of the marginal effects of each independent variable at each data point in the covariate space (that is, the derivatives of this relationship) and provides closed-form estimates of the pointwise partial derivatives. The function minimizes squared loss, and prefers smoother functions by reducing complexity in the optimal solution, which minimizes over-fitting. The KRLS function nonparametrically estimates the relationship between all covariates and the outcome variable and their (nonparametric) interactions.

To detect nonlinearity and interactions, we regress the derivative estimates for each variable on each other variable one at a time and assessed the amount of variance explained. The R-square of these regressions captures the degree to which the effect of a measure on the outcome differs based on values of the explanatory variable (i.e., interaction effects). We used a cut-off $R^2 = 0.25$ and plotted relationships of substantive interest. Note that when derivatives are strongly related to other variables in the model (as captured by a high R^2), this implies interaction effects. We then plotted these interactions between the derivatives and a variable that exhibited a substantial relationship using Lowess regression to capture nonlinearities—which groups observations with similar covariate values (Cleveland 1979)—and we plot the predicted values from these in the figures.

Results and Discussion

Descriptive Statistics

Table 1 provides top ten, bottom ten, and mean statistics across MSAs for our three outcome measures: neighborhood income mixing, educational mixing, and occupational mixing. Appendix C provides further comparison between these three measures at the MSA, block group, and egohood level and suggests that mixing is more attenuated at the neighborhood than regional scale, but correlations between mixing measures are low enough to merit three separate analyses. Florida's tract-level findings using a dissimilarity index concluded that the most segregated metros by income were Rustbelt metros like Cleveland, Milwaukee, and Detroit. New York was just outside the top ten, while other superstar cities and tech hubs generally had lower levels of income segregation. In contrast, we measure the extent to which an MSA's typical neighborhood is comprised of a variety of income levels (mixing). The most mixed tended to be mid-sized, poorer areas in the South and Texas such as Greenville, NC, Brownsville, TX, McAllen, TX, and New Orleans, LA. While income mixing is not significantly correlated with city size, it is inversely correlated with MSA median income (r=-0.414) and strongly correlated with the share of households earning below $20,000/yr (r=0.770). This is somewhat expected since unlike Florida's dissimilarity index, the mean of the Gini would be sensitive to the region's income distribution. Glaeser et al.'s (2009) study found that in 2000, Brownsville and McAllen ranked #2 and #3 in metro-level Gini (inequality). However, the experience of the typical resident of these cities is that they are spatially proximate to a wider array of households by income, illustrating the distinction between metropolitan and neighborhood measures.

<< Table 1 about here >>

In contrast, the places with the most segregated neighborhoods by income – where the typical experience would not likely be spatial proximity to households of a different income – consisted of two metros each from Alaska and Utah, Washington, DC, and Sheboygan, WI. These are typically higher income metros overall, but not universally. Sheboygan actually had the lowest overall income inequality in Glaser's study (using 2006 data); however, its neighborhoods are amongst the least mixed by income while it ranks #113/381 in median income.

We find the lowest levels of educational mixing to be in smaller metro areas in Appalachia, the South, and California's central valley. In contrast, the areas where the typical experience in a neighborhood is one of mixing amongst educational groups includes large metros such as New York, Miami, and San Jose (with San Francisco and Boston at #12 and #13) as well as a number of college towns – Columbia, MO, Athens, GA, New Haven, CT, and Charlottesville, VA. As was the case with income mixing, neighborhood educational mixing is sensitive to the MSA's college education share ($r = 0.730$); for example Lake Havasu City-Kingman, AZ has the second-lowest college education share (11.9%) and Dalton, GA has the fifth-lowest (12.6%). The results for our five-category education mixing measure differ from Florida's educational segregation index that only combined two dissimilarity indices: the segregation of high-school dropouts from everyone else, and the segregation of college graduates from everyone else. In contrast to our results, his top ten included Los Angeles, Houston, Chicago, and San Francisco.

Finally, whereas Florida's top ten by occupational segregation is almost exclusively comprised of high-end, tech-heavy large metros, our neighborhood-oriented measure of overall occupational mixing is very different. The ten most mixed are almost all small-to-medium metro areas in the Midwest. The ten metros where occupational categories are most segregated are comparable in size but with the exception of the lowest two – Atlantic City and Carbondale – are in the Sunbelt. Occupational mixing is not highly correlated with city size, median income, or college education; rather it is most highly correlated with an MSA's share of service workers ($r = -0.743$). Occupational mixing, in this sense, is a function of both neighborhood occupational composition and whether a region's economic base extends beyond services.

Using neighborhood-level egohoods to mirror an individual's experience within a city does not support the claim that large, dense, knowledge-based metros are more segregated. Myriad aspects of land use pattern and development history have led to the manner in which the well-off and the less well-off end up in proximate neighborhoods such as redlining, the timing of property booms and development, the recentness of migration and home construction, the distribution of natural amenities, the distribution of jobs, and whether the region's central city declined or remained vibrant.

Neighborhood Income Mixing Results

Main Effects

The main effects of metro-level factors on all three types of mixing are found in Table 2. Average coefficient estimates are shown as well as the estimate at the 25th, 50th, and 75th

percentile of the covariate's distribution with the outcome measure capturing the average neighborhood's level of mixing in each MSA irrespective of that MSA's marginal distribution. A region's average household income is inversely related to the average level of income mixing in its neighborhoods. There is no effect for the fairly similar per-capita GDP measure, highlighting that these two measures are distinct conceptually. However, metros with growing average income experience greater levels of neighborhood income mixing. College education rates, but also higher unemployment rates in a region are each positively related to levels of neighborhood income mixing.

<< Table 2 about here >>

In terms of business-related variables, more Fortune 1000 companies and a higher rate of patenting are related to greater neighborhood income mixing, suggesting that these two indicators of economic productivity and global integration have a relation with neighborhood-level factors. However, the share of the population in a creative class occupation and the union membership rate each have a stronger, inverse relationship with neighborhood income mixing. Since these measures typically indicate a high share in one particular occupation type (creative or working-class), this result indicates that occupational polarization across a metro is associated with neighborhoods that are more homogenous by income.

While we might expect higher average home values in a metropolitan area to be related to more stratification across neighborhoods by income (by virtue of segregated, high-priced neighborhoods), there is no relationship between average home value and neighborhood income mixing. However, the housing occupancy rate has an inverse relationship with neighborhood income mixing: higher average vacancy indicates higher neighborhood income mixing. So too does the percentage of homes in the city that were built in the previous 10 years – a higher proportion of new housing across the region is associated with lower neighborhood income mixing.

While the share of senior citizens in a region bears no relationship with neighborhood income mixing, metros with a higher share of children exhibit lower levels of neighborhood income mixing. This could be due to families with children (more specifically, metros with high levels of families with children) seeking more stable or homogenous suburban neighborhoods, which could be reflected through lower neighborhood income mixing. Additionally, greater levels of religious affiliation are associated with greater neighborhood income mixing. A higher share of Black or Latino population in a region is related to more neighborhood income mixing. However, a lower level of racial/ethnic mixing is associated with more mixed income neighborhoods, suggesting that while minority-heavy regions tend to have neighborhoods that are more mixed by income, metros with a blend of White, Black, Asian, and Latino residents actually are associated with more homogenous neighborhoods by income.

KRLS/Lowess Effects

Up to now we have focused exclusively on the main effects of our model. However, KRLS analysis allows for nonlinear interaction effects, while Lowess plots show how parameter estimates vary across the covariate space. Figures 1-3 show derivative estimates against the variables themselves where $R^2 > 0.25$. Table 3 summarizes main effects and uses arrows as well as union and intersect notation to approximate the shape of the Lowess plot, indicating the nonlinear effects of the "moderating" variable on a parameter estimate.

<< Table 3 about here >>

<< Figure 1 about here >>

<< Figure 2 about here >>

<< Figure 3 about here >>

Although per-capita GDP exhibited no significant main effect, a context with a higher share of Black population and a moderate-level of racial/ethnic mixing results in a positive effect of per-capita GDP on income mixing (Figures 1A and 1B, respectively). While metro-level average incomes had a negative relationship with neighborhood income mixing, this was strongest with a moderate-level of senior citizens (Figure 1C). Put differently, metro-level incomes did not have as significant a negative effect on neighborhood income mixing in the presence of very many or very few senior citizens in a region. While regions with growing average income exhibited more neighborhood income mixing, this is tempered when a high proportion of the region's workers are creative class (1E). This important finding which suggests that while metro growth may have a positive effect on neighborhood income mixing, it is tempered when employment is too highly concentrated in creative class occupations. Furthermore, while overall there is an inverse relationship between creative class share and neighborhood income mixing, higher GDP/capita tends to strengthen the effect of creative class polarization (1F).

A number of highly fitting Lowess curves are found for the impact of new housing on neighborhood income mixing – which has a negative main effect Figures 1G through 1J. Four other regional variables individually strengthen this negative effect: lower average household incomes, lower patent counts, a lower share of creative class employment, and a lower share of Obama voters. These results suggest a relationship between rapid housing construction in a region and neighborhood homogeneity by income, which is strengthened in lower-income, less creative, less inventive, and Republican-leaning metros.

Additionally, moderate average household income augments the positive effect of Black population on neighborhood income mixing - a relationship that breaks down in very wealthy or poor regions (1O). While on its own the violent crime rate has no effect on a region's level of neighborhood income mixing, combined with low levels of new housing, there is a positive effect (1Q). In addition, more new housing mitigates the positive relationship between unemployment and neighborhood income mixing (1D). A related phenomenon might be the impact of housing tenure. While there is essentially no main effect, a lower college education rate and a lower share of creative class workers each combine with long housing tenure to decrease neighborhood income mixing (1K-1L). Put differently, regions with a lot of people who stay put in their homes are associated with lower neighborhood income mixing, but only in regions with low levels of college education or creative class work. Finally, while the percent who voted for Obama in 2012 has no effect on its own, in highly unionized regions Obama support is strongly related to neighborhood income mixing, but in non-unionized regions Obama support is strongly negatively related to neighborhood income mixing (1P).

Neighborhood Educational Mixing Results

Main Effects

Overall, a region's per-capita GDP as well as growth in average household income each have an inverse relationship with neighborhood-level educational mixing; the relationship with growth is stronger. A region's unionization rate is strongly negatively associated with neighborhood mixing by education. However, regions with higher home values, with a high share of long-tenured residents, and with a low proportion of child population (i.e. fewer families with children) also have higher levels of neighborhood educational mixing. While more Latino population and higher racial/ethnic mixing is associated with educational mixing in neighborhoods, a region's Black population is inversely related. The percentage who voted for President Obama in 2012 and religious affiliation also have positive relationships with educational mixing.

KRLS/Lowess

Several factors mitigate these relationships. While regional college education share is associated with greater educational mixing this relationship is greatest at a moderate-level of household income, GDP/capita, and Obama voters (2A-2C). At the extremes of these three distributions, the relationship between college education rates and neighborhood educational mixing weakens.

While regional creative class share has a positive, but insignificant main effect on educational mixing in neighborhoods, it has a positive or negative relationship depending on the distribution of three other variables. In regions with a low share of senior citizens or few long-tenured householders, creative class share has a negative relationship with neighborhood educational mixing (2E-2F). Additionally, higher college education rates also result in a negative impact for creative class share on educational mixing: high education and creative class result in lower mixing (2G). This appears consistent with the notion of highly educated creative class, often tech-oriented employees who tend to be younger and are more likely to move, either within or across regions. Given these mitigating factors – but not alone – a creative class economy may result in neighborhoods which are less mixed by education level. The marginal effect of patenting is similarly affected by college education share: only in highly educated regions is does a high amount of patent activity associate with lower educational mixing (patents and creative class share are positively correlated, r=0.508). Finally, while the presence of more

Latinos has a positive relationship with neighborhood educational mixing, this is lessened by high racial/ethnic mixing in the region.

Neighborhood Occupational Mixing Results

Main Effects

Results show that occupational mixing in neighborhoods is positively associated with both GDP/capita and average household income but inversely related to growth in household income, suggesting that more prosperous regions – but not growing regions – exhibit local mixing by occupation type. In addition, unemployment and college education rates in a region have an inverse effect on neighborhood occupational mixing. A higher share of creative class workers is associated with more mixing, but the number of Fortune 1000 headquarters has an inverse relationship with neighborhood occupational mixing.

Housing occupancy rates, long-tenured householders, and the share of new homes each have a positive relationship with neighborhood occupational mixing, though no relationship was seen for average home value in a region. While the share of senior citizens was immaterial, the proportion of children had a positive relationship with occupational mixing in neighborhoods. While we did not expect either age category to have much of an effect given that these are non-working age individuals, a higher share of families in a region (population age 0-19) appears associated with mixing. Lower shares of Black and Latino population – and lower racial/ethnic mixing in a region – are each associated with more occupational mixing. Religious affiliation has a positive relationship with occupational mixing while the violent crime rate has an inverse relationship with occupational mixing.

KRLS/Lowess

We detect several mitigating effects for the relationships between these measures and occupational mixing. While new housing's impact on income and educational mixing was strongly related to other factors, it has a more straightforward relationship with occupational mixing: generally positive, but declining in regions with a high share of Latinos (Figure 3E). The positive effects of GDP and household income for occupational mixing are heavily influenced by other conditions. Only at moderate-levels of household income did GDP have a positive relationship – it was close to zero in very high or very low income metros (3A). The same could be said for the joint effect of household income and patenting: at very high or low levels of patenting, household income did not have a strong positive relationship with neighborhood occupational mixing (3B). Also at very high levels of venture capital investment, higher average incomes are actually associated with lower neighborhood occupational mixing (3C).

The level of racial/ethnic mixing in a region has several mitigating effects. While highly religious metros are associated with more occupational mixing, this effect is tempered and actually negative in cases of high racial/ethnic mixing (3I). While higher home values have no main effect on occupational mixing, their relationship with occupational mixing is positive in racially homogeneous metros, but negative in racially mixed metros (3D). Finally while a region's Latino share is inversely related to neighborhood occupational mixing, this effect is augmented further in racially/ethnically mixed metros (3G). Lastly while support for Obama in 2012 was not related to neighborhood occupational mixing on average, this effect depends on religious affiliation: in religious areas, Obama support is associated with more mixing, while in less religious areas, Obama support is associated with less neighborhood occupational mixing.

Conclusions

This study contributes to the increasingly apparent issue of income inequality in US metropolitan areas by linking often-cited inequality drivers with a related, but different outcome measure: neighborhood mixing. We make two methodological contributions: first, to take an egocentric approach of overlapping census block groups to more accurately capture an individual's surroundings in urban space, and second, to use combinatorial estimation which allows for the identification of "ingredients" which combine to impact spatial inequality. Specifically, we link differences (or, mixing) in income, educational attainment, and occupation type – the lived experience of being near others in a neighborhood – to regional drivers related to economic well-being, business and production, housing, and demographic characteristics.

While Florida (2017) suggests that large, dense, knowledge-based metro regions are more segregated, we find different patterns at the neighborhood scale. Poorer, higher poverty metros, many in the South and in Texas, tend to have neighborhoods that are actually more mixed by income while "superstar" regions have neither the most mixed or most segregated neighborhoods. Larger regions and college towns do tend to have higher levels of educational mixing in their neighborhoods, and regions with a higher share of service workers have more homogenous neighborhoods (see Appendix D for a brief comparison of some key metros).

Despite these differences from Florida's findings, KRLS allows for the emergence of a major point regarding the relationship between occupation type and creative class. When a metro's occupational blend is more polarized, its neighborhoods tend to be more homogenous by income. Residents sort by myriad factors but broad distinctions between creative, service, and working-class occupations appear to show strong effects. In addition, while income growth is a strong predictor of income mixing, it is tempered when employment is too highly concentrated in creative class occupations – consistent with the concern of inequality in “superstar” cities. Certain other factors appear to also combine with a metro’s creative class share to make neighborhoods more homogenous by education level: fewer seniors, shorter housing tenure, and higher college educated share. This is somewhat consistent with the notion of highly educated, younger, mobile, tech-oriented creative class worker; results hint at the possibility that this phenomenon may lead to greater sorting into neighborhoods by education level. So, while superstar cities may not be as consistently unequal, similar combinations of factors may lead to neighborhood segregation.

A region’s share of new housing – built within the previous ten years – also shows a number of mitigating effects on neighborhood mixing. Given this study’s timeframe this corresponds to housing built during the 2000s; much of it in the lead-up to the global financial crisis. More new housing in a region meant lower income mixing overall, a result which is consistent with homogenous city areas with a similarly aged and priced housing stock. However this negative relationship was strongly augmented by regions with lower incomes, less inventive activity, less creative class, and less support for Obama. While this is speculative, these factors appear to suggest a component of neighborhood segregation in fast-growing cities that were hit hard by the financial crisis. There appears to be a paradoxically similar relationship between long-tenured householdership and income-based segregation; however, this relationship existed only in regions with low education levels and less creative class work.

An additional point can be made regarding racial and ethnic composition: more black or Latino residents in a region generally led to more neighborhood mixing by income, but less neighborhood mixing by occupation. Metros with a more even racial/ethnic mix, on the other hand, are associated with income segregation. A region’s history of redlining or race-based spatial separation is one key element of historical development trajectory omitted from empirical treatment in this paper. While new housing share does capture one dimension of local land use pattern, myriad idiosyncratic factors have led to the way in which the privileged and less privileged have sorted across urban neighborhoods, including development timing, home construction trends, central city vibrancy, and the prevalence of stable, wealthy enclaves. This paper's cross-sectional analysis using 2008-2012 data also coincides with a time of urban transition—demographically as millennials age into homeownership, the economy moves beyond the Global Financial Crisis, and many urban downtowns are revitalized. Future research on urban neighborhood dynamics would benefit from a longitudinal approach beyond the scope of this paper.

The combinatorial effects of region-level covariates on mixing measures are particularly tricky to analyze case-by-case or through more intuitive, bivariate relationships—a strength of KRLS despite the reality that some of the uncovered relationships may be undertheorized or defy clear explanation. These findings demonstrate that while implicating "superstar" cities in the crisis of inequality is insufficient, there are strong connections between this large-scale problem and the level of exposure in neighborhoods that individuals have to others who are not like them.

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[i] We generated rank order information theory indices (*H)* for income and education and re-ranour model. The correlation between *H* and our measure was r = 0.091 for income mixing and r = -0.071 for educational mixing, indicating these measures are conceptually distinct—likely due to the fact that H is region-relative whereas our measure is one of central tendency. Furthermore, interpretation of H becomes more complex while using block group egohoods, which already condition values based on neighbors and would merit additional research.

Tables and Figures

TABLE 1: TOP AND BOTTOM 10 METRO AREAS BY NEIGHBORHOOD MIXING

INCOME MIXING BY NEIGHBORHOOD* (2010)		
Rank	Metropolitan Statistical Area (MSA)	Gini Coefficient
1	Greenville, NC	0.461
2	Brownsville-Harlingen, TX	0.455
3	Morgantown, WV	0.451
4	McAllen-Edinburg-Mission, TX	0.450
5	Athens-Clarke County, GA	0.448
6	College Station-Bryan, TX	0.446
7	Corvallis, OR	0.445
8	Bloomington, IN	0.440
9	New Orleans-Metairie, LA	0.438
10	El Centro, CA	0.438
	Mean Value across all MSAs	0.399
372	Cheyenne, WY	0.3643
373	Anchorage, AK	0.3639
374	Sheboygan, WI	0.3631
375	Norwich-New London, CT	0.3618
376	Provo-Orem, UT	0.3588
377	Columbus, IN	0.3580
378	Fairbanks, AK	0.3564
379	Washington-Arlington-Alexandria, DC-VA-MD-WV	0.3550
380	California-Lexington Park, MD	0.3506
381	Ogden-Clearfield, UT	0.3484

*Measured by Gini Coefficient; high values are most mixed within a neighborhood

EDUCATION LEVEL MIXING BY NEIGHBORHOOD* (2010)		
Rank	Metropolitan Statistical Area (MSA)	Entropy
1	Columbia, MO	0.929
2	New York-Newark-Jersey City, NY-NJ-PA	0.925
3	Napa, CA	0.924
4	Santa Fe, NM	0.922
5	Miami-Fort Lauderdale-West Palm Beach, FL	0.921
6	Athens-Clarke County, GA	0.921
7	San Jose-Sunnyvale-Santa Clara, CA	0.920
8	New Haven-Milford, CT	0.920
9	Charlottesville, VA	0.919
10	Missoula, MT	0.918
	Mean Value across all MSAs	0.871
372	Hinesville, GA	0.814
373	Lake Havasu City-Kingman, AZ	0.814
374	Mansfield, OH	0.812
375	Jacksonville, NC	0.812
376	Visalia-Porterville, CA	0.810
377	Lima, OH	0.809
378	Dalton, GA	0.808
379	Weirton-Steubenville, WV-OH	0.807
380	Altoona, PA	0.800
381	Madera, CA	0.798

*Measured by Entropy; high values are most mixed

OCCUPATION TYPE MIXING BY NEIGHBORHOOD* (2010		
Rank	Metropolitan Statistical Area (MSA)	Entropy
1	Wausau, WI	0.942
2	Sheboygan, WI	0.935
3	Columbus, IN	0.927
4	Appleton, WI	0.927
5	Fargo, ND-MN	0.924
6	Racine, WI	0.924
7	Bismarck, ND	0.923
8	Chambersburg-Waynesboro, PA	0.922
9	Cedar Rapids, IA	0.921
10	Fond du Lac, WI	0.921
	Mean Value across all MSAs	0.869
372	Lake Havasu City-Kingman, AZ	0.801
373	Brownsville-Harlingen, TX	0.798
374	Brunswick, GA	0.798
375	Laredo, TX	0.797
376	Jacksonville, NC	0.791
377	McAllen-Edinburg-Mission, TX	0.791
378	Sierra Vista-Douglas, AZ	0.789
379	Sebring, FL	0.787
380	Atlantic City-Hammonton, NJ	0.785
381	Carbondale-Marion, IL	0.784

*Measured by Entropy; high values are most mixed

Table 2. KRLS models of average income mixing, education mixing, and occupation mixing in 381 SMSAs

	Average income mixing					Average education mixing					Average occupation mixing				
Economic Well-Being	Avg (t-value)		P25	P50	P75	Avg (t-value)		P25	P50	P75	Avg (t-value)		P25	P50	P75
GDP per capita	0.009		-0.090	-0.006	0.079	-0.111	†	-0.223	-0.110	0.005	0.276	**	0.164	0.279	0.391
	(0.24)					-(1.89)					(4.17)				
Average household income	-0.001	**	-0.001	-0.001	-0.001	0.000		0.000	0.000	0.000	0.001	**	0.000	0.001	0.001
	-(23.53)					(0.31)					(7.50)				
Percent with a bachelor's degree	1.103	**	0.800	1.117	1.438	1.989	**	1.395	2.121	2.658	-0.766	**	-1.016	-0.790	-0.575
	(16.57)					(20.51)					-(7.59)				
Unemployment rate	1.500	**	0.899	1.557	2.139	0.023		-0.586	-0.027	0.530	-0.672	*	-1.106	-0.648	-0.207
	(8.83)					(0.09)					-(2.27)				
Change in average household income, 2000-10	39.961	**	17.001	40.572	61.617	-12.845	†	-26.727	-14.011	0.654	-39.201	**	-56.384	-40.569	-23.216
	(8.46)					-(1.73)					-(4.60)				
Business and Production															
Venture capital rate (logged)	-0.045		-0.153	-0.038	0.063	-0.076		-0.205	-0.055	0.068	0.069		-0.082	0.081	0.202
	-(1.32)					-(1.35)					(0.98)				
Fortune 1000 headquarters	0.108	†	0.001	0.084	0.203	-0.128		-0.208	-0.123	-0.047	-0.141	†	-0.202	-0.136	-0.083
	(1.85)					-(1.57)					-(1.74)				
Number of patents (logged) 2010-15	0.587	*	-0.131	0.581	1.249	0.321		-0.609	0.442	1.324	-0.122		-0.665	-0.109	0.489
	(2.37)					(0.83)					-(0.28)				
Percent employees in creative industries	-0.261	**	-0.534	-0.255	0.001	0.120		-0.126	0.143	0.396	0.533	**	0.300	0.532	0.765
	-(3.69)					(1.09)					(4.33)				
Percent union employees	-10.841	*	-27.092	-11.334	5.206	-44.263	**	-68.712	-43.751	-16.450	-8.491		-25.765	-5.771	15.016
	-(2.34)					-(5.92)					-(0.95)				
Housing															
Average housing sales price	0.006		-0.054	0.005	0.066	0.054	*	-0.022	0.050	0.131	0.014		-0.050	0.020	0.091
	(0.40)					(2.27)					(0.50)				
Percent new housing units in last 10 years	-0.063	†	-0.226	-0.044	0.119	-0.028		-0.161	-0.017	0.099	0.196	**	0.043	0.195	0.359
	-(1.82)					-(0.50)					(3.07)				
Percent occupied units	-0.305	**	-0.578	-0.296	-0.034	-0.035		-0.317	-0.067	0.263	1.134	**	0.906	1.167	1.457
	-(4.09)					-(0.31)					(8.90)				
Percent in same house 5 years ago	0.123		-0.191	0.146	0.485	0.255	†	-0.349	0.196	0.776	1.322	**	0.792	1.311	1.781
	(1.25)					(1.67)					(7.52)				

Demographic, Cultural, and Political															
Percent aged 65 and up	0.165		-0.121	0.121	0.487	-0.100		-0.514	-0.094	0.303	0.092		-0.050	0.136	0.316
	(1.22)					-(0.52)					(0.47)				
Percent aged 0 to 19	-1.526	**	-2.103	-1.579	-1.051	-1.239	**	-1.624	-1.245	-0.865	1.548	**	0.878	1.586	2.217
	-(9.19)					-(5.13)					(6.09)				
Percent black	0.270	**	0.110	0.267	0.434	-0.148	**	-0.312	-0.140	0.018	-0.500	**	-0.682	-0.529	-0.321
	(7.01)					-(2.66)					-(8.44)				
Percent Latino	0.180	**	0.099	0.170	0.244	0.200	**	0.057	0.209	0.367	-0.108	**	-0.223	-0.096	0.022
	(6.66)					(5.30)					-(2.74)				
Racial/ethnic heterogeneity	-0.067	*	-0.141	-0.062	0.004	0.128	**	0.017	0.132	0.237	-0.158	**	-0.265	-0.158	-0.058
	-(2.45)					(3.15)					-(3.52)				
Percent voted for Obama in 2008	-0.028		-0.126	-0.029	0.060	0.116	*	0.016	0.122	0.231	-0.067		-0.172	-0.082	0.024
	-(0.85)					(2.30)					-(1.17)				
Percent religious adherents	0.101	**	-0.031	0.106	0.232	0.138	**	-0.020	0.115	0.282	0.135	*	-0.013	0.134	0.258
	(3.70)					(3.15)					(2.55)				
Violent crime rate	0.003		-0.005	0.004	0.012	0.002		-0.005	0.001	0.010	-0.017	**	-0.025	-0.018	-0.011
	(1.58)					(0.67)					-(4.53)				
N	381					381					381				
R-square	0.940					0.894					0.842				
† p<0.10, * p<0.05, ** p<0.01															

TABLE 3: SUMMARY OF NONLINEAR EFFECTS IN KRLS REGRESSION

Category	Variable	Main Effect* (Income)	Which metro-area factors impact neighborhood income mixing?**	Main Effect* (Education)	Which metro-area factors impact neighborhood education mixing?**	Main Effect* (Occupation)	Which metro-area factors impact neighborhood occupation mixing?**
Economic Well-Being	GDP/capita	0	↑% Black	-		+	∩ Avg. HH Income
			∩ Racial/Ethnic Mixing				
	Average HH Income	-	U % > Age 65	0		+	∩ Patent count
							↓ Venture Capital
	% with B.A.	+		+	∩ Avg. HH Income	-	
					∩ GDP/capita		
					∩ % Obama voters		
	Unemployment	+	↓ % New Homes	0		-	
	Growth in Avg. HH Inc.	+	↓% Creative Class	-		-	
Business and Production	Venture Capital	0		0		0	
	Fortune 500 HQs	+		0		-	
	Patent Count	+		0	↓% w/B.A.	0	
	% Creative Class	-	↓ GDP/capita	0	↑ % > Age 65	+	
					↑ % Long Tenure		
					↓% w/B.A.		
	Unionization Rate	-		-	↑ Racial/Ethnic mixing	0	

Housing	Average Home Value	0		+		0	↓ Racial/Ethnic Mix
	% New Homes (<10yrs)	-	↓ Avg. HH Income	0		+	↓ % Latino
			↓ Patent Count				
			↓ Creative Class				
			↓ % Obama Voters				
	Occupancy Rate	-				+	
	% Long tenure (>10yrs)	0	↓ % w/B.A.	+	↑ % w/B.A.	+	
			↓ % Creative Class		↑ Creative Class		
Demographic,	% > Age 65	0	↑ % Obama Voters	0	↑ Avg. HH Inc.	0	
Cultural, and			↑ Creative Class		↑ % Latino		
Political	% < Age 19	-		-		+	∩ % > Age 65
	% Black	+	∩ Avg. HH Income	-		-	
	% Latino	+		+	↓ Racial/Ethnic Mixing	-	↓ Racial/Ethnic Mixing
	Racial/Ethnic Mixing	-		+		-	
	% Obama voters (2008)	0	↑ Unionization	+		0	↑ % Religious Affiliated
	% Religious Affiliated	+		+		+	↓ Racial/Ethnic Mixing
	Violent Crime Rate	0	↑w/o New Housing	0		-	

* Summarizes the direction of the main effect from Table 2: positive and significant (p<0.10 or better), negative and significant (p<0.10 or better), or not significant (0)

**Mitigating factor which affects main effect. Arrow, U or ∩ indicates direction of effect which can be seen in Figures 2-4.

Figure 1

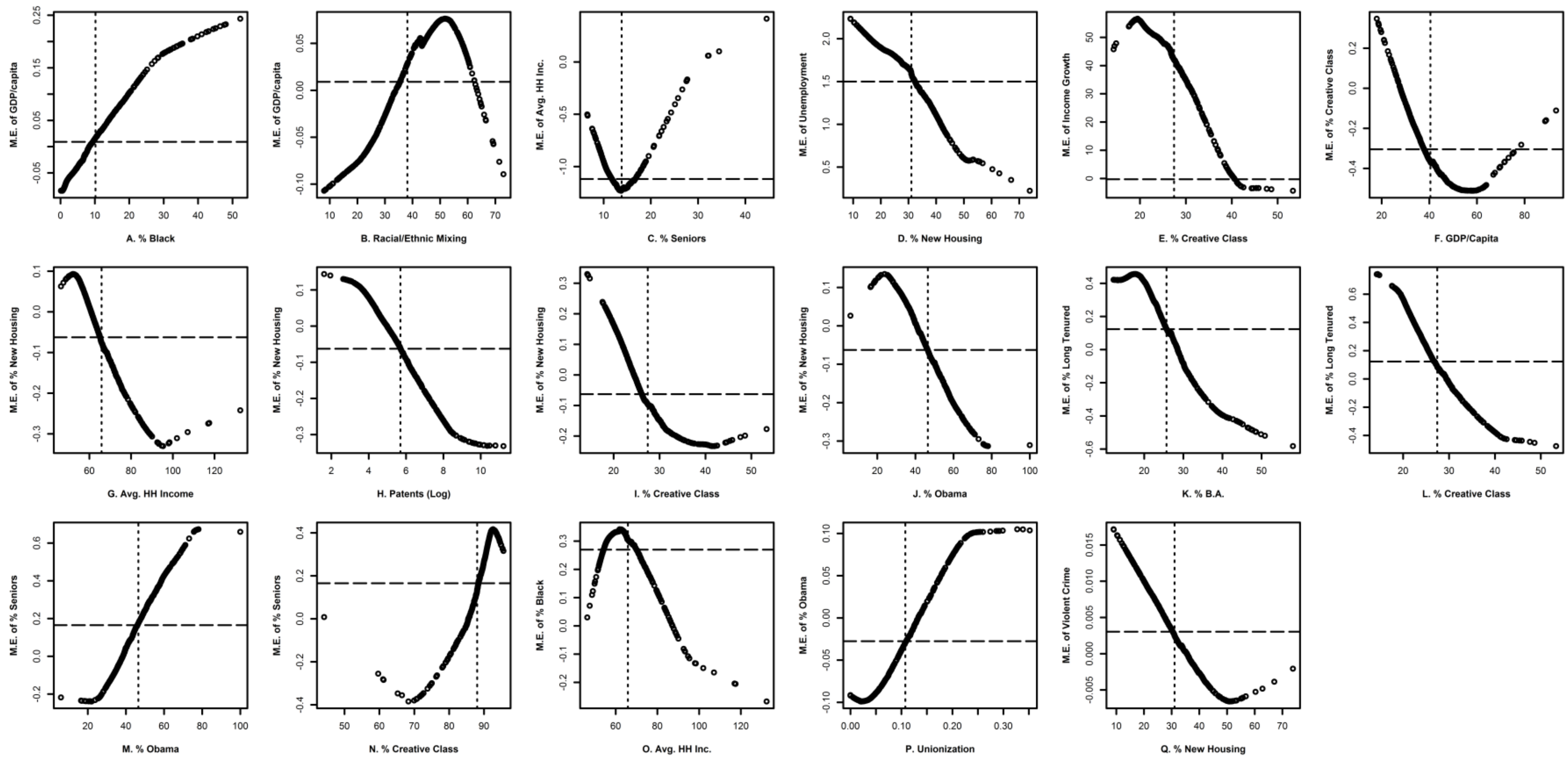

M.E. of GDP/capita
A. % Black
M.E. of GDP/capita
B. Racial/Ethnic Mixing
M.E. of Avg. HH Inc.
C. % Seniors
M.E. of Unemployment
D. % New Housing
M.E. of Income Growth
E. % Creative Class
M.E. of % Creative Class
F. GDP/Capita
M.E. of % New Housing
G. Avg. HH Income
M.E. of % New Housing
H. Patents (Log)
M.E. of % New Housing
I. % Creative Class
M.E. of % New Housing
J. % Obama
M.E. of % Long Tenured
K. % B.A.
M.E. of % Long Tenured
L. % Creative Class
M.E. of % Seniors
M. % Obama
M.E. of % Seniors
N. % Creative Class
M.E. of % Black
O. Avg. HH Inc.
M.E. of % Obama
P. Unionization
M.E. of Violent Crime
Q. % New Housing

Figure 2

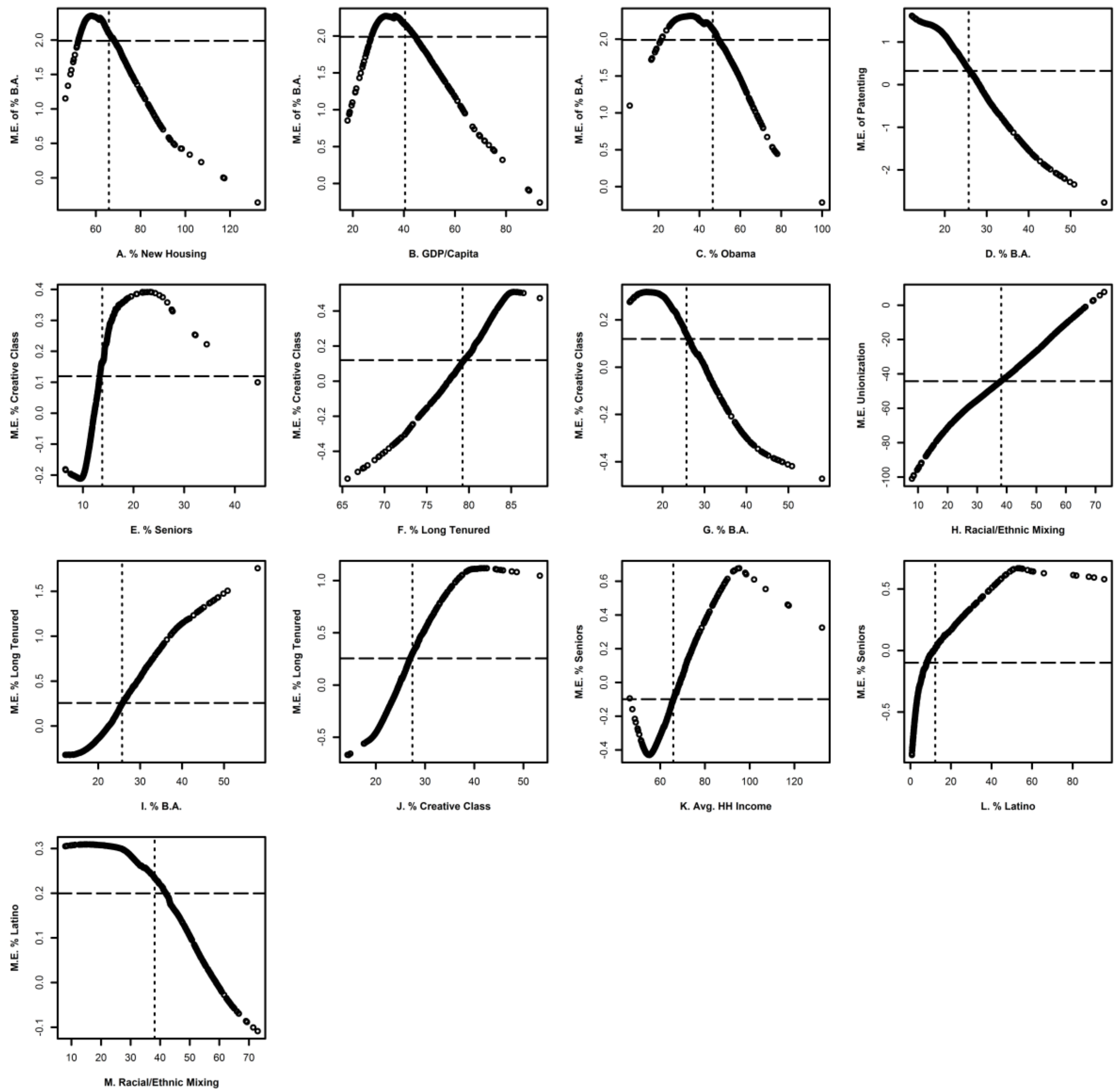
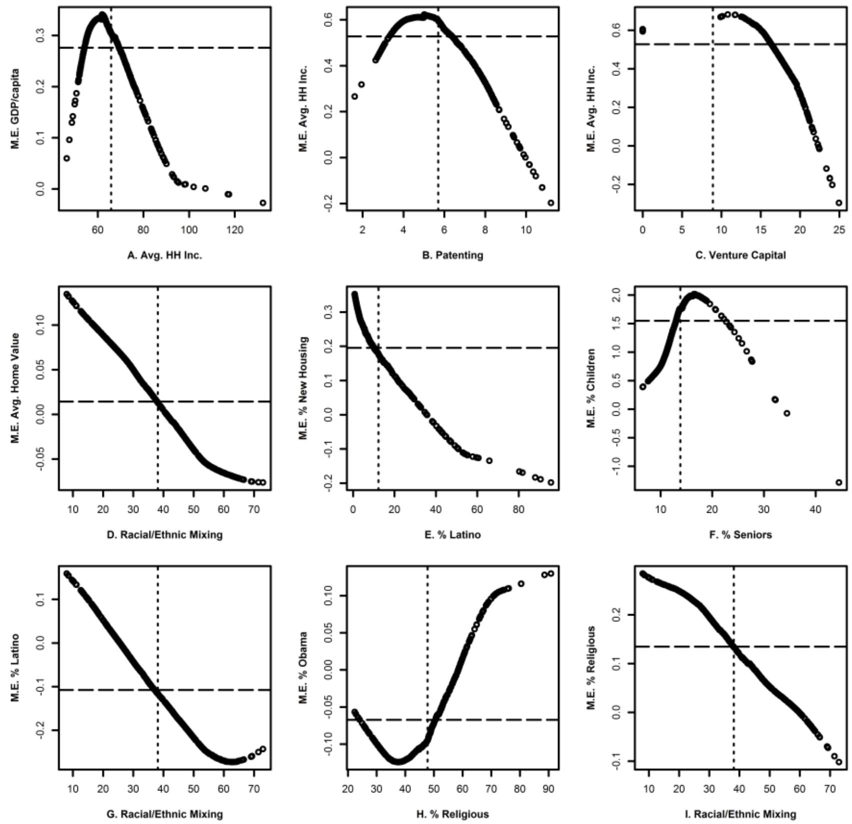

A. % New Housing
M.E. of % B.A.
B. GDP/Capita
M.E. of % B.A.
C. % Obama
M.E. of % B.A.
D. % B.A.
M.E. of Patenting
E. % Seniors
M.E. % Creative Class
F. % Long Tenured
M.E. % Creative Class
G. % B.A.
M.E. % Creative Class
H. Racial/Ethnic Mixing
M.E. Unionization
I. % B.A.
M.E. % Long Tenured
J. % Creative Class
M.E. % Long Tenured
K. Avg. HH Income
M.E. % Seniors
L. % Latino
M.E. % Seniors
M. Racial/Ethnic Mixing
M.E. % Latino

Figure 3



M.E. GDP/capita
A. Avg. HH Inc.
M.E. Avg. HH Inc.
B. Patenting
M.E. Avg. HH Inc.
C. Venture Capital
M.E. Avg. Home Value
D. Racial/Ethnic Mixing
M.E. % New Housing
E. % Latino
M.E. % Children
F. % Seniors
M.E. % Latino
G. Racial/Ethnic Mixing
M.E. % Obama
H. % Religious
M.E. % Religious
I. Racial/Ethnic Mixing