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Abstract. This article provides a comparative assessment of three commonly used measures of area-level socio-economic status: Graham Social Deprivation Index (SDI), Neighborhood Atlas Area Deprivation Index (ADI), CDC Social Vulnerability Index (SVI). We assess their ability to predict a variety of health outcomes and compare them to two simpler measures, the Townsend Deprivation Index (TDI) and population percent in poverty (Poverty), at the county, zip-code, Census-tract, and Census-block-group levels. We do not know how hypothetical true area-SES would predict these outcomes. However, all measures appear valid, at zip-code, tract, and block-group levels, in that they predict health outcomes, controlling for age, gender, race/ethnicity, and comorbidities. Predictive power is comparable for SDI, SVI, and a standardized version of ADI, and superior to TDI, Poverty, or non-standardized ADI. Our preferred geographic level is Census tract if data is available, but zip-code is a reasonable substitute.

Contents

Introduction

Socio-economic status (SES) is well-known to be associated with a variety of mortality, health, and other life outcomes, and is treated as a central aspect of what are often called the Social Determinants of Health (SDoH). There is strong research and policy interest in having area-based SES measures that have been validated for different outcomes (e.g., Phillips et al., 2016; Kind and Buckingham, 2018), but no agreement on which measures to use, or which "domains" they should cover (e.g., income, education, housing). Many area-SES measures have been developed, principally using U.S. data. Trinidad et al. (2022), collect and classify 15 measures; Breslau et al. (2022) collect 22 measures, the union is 28 measures; additional measures have been proposed since (e.g., Dyer et al., 2023). However, there is little comparative assessment of which measure is preferable, at what geographic level, or for what outcomes.

We undertake such a comparative assessment here. We study three broad, commonly used measures: the Graham Social Deprivation Index (SDI) (Butler et al., 2013); the Neighborhood Atlas Area Deprivation Index (ADI) (Singh, 2003); and the Social Vulnerability Index (SVI) (Flanagan et al., 2011). Each of these measures covers the five most common SES domains discussed in the Trinidad et al. (2022) survey, for income, education, housing, household, and transportation. No other measure in the Trinidad survey covers all five of these domains. While we chose to study these measures independently from Trinidad, it is surely no accident that the three measures we chose are the first three listed in their Table comparing measures. We compare these measures to an earlier, simpler measure, still used today, the Townsend Deprivation Index (TDI) (Townsend, Phillimore and Beattie, 1988); and population percent with family income below the federal poverty line (Poverty). For ADI, we study a version that uses standardized elements (ADI_{std}). The Appendix summarizes other measures.

We compare these measures at the four geographic levels for which data is generally available: Census block-group; Census tract; 5-digit zip-code (with zip-codes mapped to Zip Code Tabulation Areas, or ZCTAs); and county. We assess the predictive power of each measure for the following outcomes: all-cause elderly mortality over 2000-2019; elderly diabetes prevalence in 2000 and 2019, elderly diabetes incidence over 2000-2005; and drug overdose mortality over 2017-2021; and elderly COVID-19 mortality. For the first three measures, we rely on national data for Medicare fee-for-service ("FFS") beneficiaries, For the drug overdose and COVID-19 outcomes, we use data from Illinois, Indiana, and Wisconsin.

This project is accompanied by a dataset, on Professor Black's website,[1] which contains the area-SES measures, for years and geographic levels much more extensive than those available from the SDI, SVI, and ADI websites.

New Contribution

Many area-SES measures have been developed for use with U.S. data, but little is known about which measures perform relatively better or worse; how broad multi-domain measures compare to simpler measures such as Poverty; and how these measures perform at different geographic levels. We provide guidance for researchers on which measure to use by comparing the performance of three commonly used measures, in predicting an array of health outcomes, at four geographic levels: Census block-group; Census tract; 5-digit zip-code (with zip-codes mapped to Zip Code Tabulation Areas, or ZCTAs); and county. We find that Census tract is the preferred geographic level if data is available, but zip-code level measures also perform well. We

[1] https://www.law.northwestern.edu/faculty/profiles/bernardblack/; click "datasets".

find that SDI, SVI, and ADI_{std} all perform similarly, with no clear preference ranking between then. All outperform TDI, Poverty, and non-standardized ADI.

Background

Conceptual Model of Area-SES Measures

We conceptualize an area-SES measure as a summary statistic for socio-economic disadvantage, which can predict health and other outcomes, controlling for individual measures such as age, gender, race/ethnicity, and current health status. An area-SES measure is likely to correlate with unmeasured individual attributes that predict health as well as area measures that predict health (e.g., air and noise pollution, access to healthy food). Predictive power may not be causal.

There is general agreement that SES is a complex, multidimensional construct, but no consensus on which domains an area-SES measure should cover, what weights to give to different domains as part of an overall measure, or how to capture particular domains. This lack of consensus may explain why so many measures exist. The Trinidad review of 15 measures finds that all measures include an income domain, and almost all include an education domain (13/15) and a housing domain (12/15). The next most common domains are household structure (8/15), transportation (5/15); race/ethnicity (4/15), health insurance (3/15); and language (2/15).

We view SES and race/ethnicity as separate factors that can predict health, and thus prefer an area-SES measure that does not directly include race/ethnicity. We believe racial/ethnic factors should be studied separately (as we do below) and not combined into a catch-all measure of area-SES. We note that minorities can have either worse or better health outcomes; for example, Asians and Hispanics have lower age-adjusted mortality than Whites. We understand that our preference is not universally shared. Of the measures we study, SVI includes a race element; SDI, ADI, and TDI do not.

As a summary measure of the power of an area-SES measure to predict outcomes, we use the gradient in logit marginal effects as one moves from high to low area-SES. We do not know truth, either for how to measure area-SES or the predictive power of an ideal measure. We hypothesized that an ideal measure would have generally monotonic marginal effects for most health outcomes as one moves from higher to lower area-SES, but recognize that this need not be true for all outcomes.

Prior Literature Comparing Area-SES Measures at Different Geographic Levels

Prior comparative assessment of the power of area-SES measures to predict individual-level outcomes is limited. We discuss in text the two prior studies that evaluate multiple outcomes at multiple geographic levels, and discuss narrower studies in the Appendix.

Pioneering work by the Public Health Disparities Geocoding project (Krieger et al., e.g., 2002, 2003, 2005) studied an array of health outcomes in Massachusetts and Rhode Island and an array of predictors. Krieger et al. (2003) report tract-level results but say they found “similar” results at block-group level and weaker results at zip-code level. The authors favor Poverty as an area-SES measure but say that they found similar SES gradients in unreported results for TDI and other composite measures.

Berkowitz et al. (2015) studied adults seen at a Massachusetts primary care network, and assessed several simple measures (Poverty, median household income, percent college, percent unemployed) plus two area-SES measures we do not study: the Neighborhood Deprivation Index (NDI, Messer et al., 2006) and an AHRQ measure (Bonito et al., 2008), at zip-code, tract, and block-group levels, for a number of health and healthcare use outcomes. They found similar predictive power for Poverty, median household income, and the area-SES measures, and similar power at zip-code, tract, and block-group levels.

Choice of Geographic Level

Which geographic level one should use to study area-SES is a nuanced question (Berkowitz et al., 2015). One problem is that little is known about the geographic level that best captures area factors that influence or predict individual health; this level can differ across factors. A second concern is measurement error. Data for the measures we study comes from 5-year American Community Survey (ACS) estimates. Narrower areas imply greater measurement error, which will bias regression estimates toward zero. Thus, even if a precise estimate for a narrower area would be preferable, a less precise estimate for a narrower area may not outperform a more precise estimate for a broader area. The zip-to-ZCTA mapping needed when using zip-code-level data also introduces error, but most populated zip-codes can be mapped 1:1 to ZCTAs, even if not every resident of the zip-code will be in the corresponding ZCTA.

A third concern is missing data. Smaller areas also have more missing data. SDI, SVI, and TDI have low missingness rates at all levels. ADI has much higher missingness (Table App-2). One can impute values from broader levels, but this introduces measurement error, and if missingness is high at the block-group level (as it is for ADI), the need for imputation reduces the potential value of the narrower level.

A final concern is practical, and concerns data availability. Our experience is that data providers will often provide zip-codes in otherwise de-identified datasets, but are reluctant to provide more granular data or may impose small-cell-size constraints. Public data sources that one wants to link for a particular project are often available only at zip-code or county level.

Given these competing considerations, we view the optimal geographic level to use for a specific project as an open, empirical question, on which this project can shed light by comparing performance at different levels.

Expected Uses of This Project

The important predictive power of area-SES for health outcomes suggests that an area-SES measure can be an important variable to control for when studying health outcomes. It would be feasible for researchers, when studying a specific outcome, to assess which area-SES measure has the strongest predictive power for that outcome, and use that measure. As we show below, for a given outcome and geographic level, that might be any of SDI, SVI, or ADI_{std}. Researchers can also construct their own custom measure.

We expect, however, that many researchers will prefer an "off the shelf" area-SES measure, plus some advice on which measure and geographic level to prefer. We provide evidence on these questions below. We also show that the coefficients on other covariates (we report results for race/ethnicity and gender) can change substantially if one controls for an area-SES measure, thus confirming the importance of controlling for area-SES.

Description of the Area-SES Measures

Table 1 indicates the elements of each area-SES measure. The table divides the elements into five domains for education; income/poverty; household composition; housing; and transportation (Trinidad et al., 2022, uses similar domains). SDI, SVI and ADI each include at least one element in each domain, but often use different elements. We briefly discuss each measure below; see Appendix for more details on each measure and replication.

Graham Social Deprivation Index (SDI)

SDI is the most parsimonious of the three main measures; it includes seven elements. It is built from nine initial elements. Each element is converted to a centile, factor analysis is performed on the centiles, and two elements with loadings below 0.60 (percent Black and high needs) are dropped. The retained elements are multiplied by factor score coefficients, summed, and transformed into overall centiles.

CDC Social Vulnerability Index (SVI)

SVI consists of 16 elements (15 through 2018), and is available at county and tract levels. Percentile ranks are computed for each element (reversing per-capita income); the ranks are summed and converted to an overall percentile score.

We also create SVI_{mod}, which excludes four elements that we believe should not be included in an area-SES measure: percent elderly, children, minority, and non-English speaking. In the Appendix, we explain these exclusions. The performance of SVI_{mod} is modestly better than SVI at zip-code level but performance is very similar at tract and block-group levels (Figure App-3). Given this similar performance, we focus in text on original SVI.

Area Deprivation Index (ADI)

ADI includes 17 elements, and is intended for use solely at block-group level. It is built using factor analysis, but uses non-standardized elements and factor loadings from Singh (2003), based on 1990 Census data at tract level. Non-standardized ADI (ADI_{orig}) is driven almost entirely by two elements, median home value and median family income (Petterson, 2023). Hannan et al. (2023) and Azar et al. (2023) report poor ADI_{orig} performance in areas with high housing costs; Powell, Sheehy and Kind (2023) respond.

We study a version that uses standardized elements (ADI_{std}) Also, on conceptual grounds, we prefer a further modified version that uses factor loadings that vary with geographic level and year, which we call ADI_{mod}. In practice, results for ADI_{std} and ADI_{mod} are very similar (see Figure App-2). We could not fully replicate reported ADI for 2020 and 2021. The Neighborhood Atlas researchers declined to cooperate with our replication effort. See Appendix for replication details.

Townsend Deprivation Index (TDI)

TDI is an early, simple index, developed in the United Kingdom in the 1980s, but the elements can be measured in the U.S.; TDI is still used today. It includes four elements, which are converted to a z-score and then summed. TDI does not include a direct poverty measure, likely because area-level poverty measures are not available in the U.K. (Gordon, 2003).

Gradients for Elements Across Area-SES Quintiles

Different elements measure different aspects of SES. However, sensible elements should show a gradient across area-SES quintiles, and often a monotonic gradient. For example, percentage without a high-school degree, or in poverty, should increase as high to low SES. We assess this expectation in Table App-3, using SDI quintiles, and find nearly universal monotonicity across all elements of all measures. This suggests that these elements are plausible as part of an overall area-SES measure. The exceptions, for SVI elements for percent elderly and children, are consistent with our choice to exclude these elements from SVI_{mod}.

Correlation Between Measures

Table 2 presents correlation coefficients for the area-SES measures and Poverty, at ZCTA and tract levels, in 2000 and 2020. See Table App-4 and Figure App-14 for other geographic levels and years. SDI and SVI correlate strongly at all geographic levels (generally above 0.9), in both 2000 and 2020. This suggests that they will have similar predictive power. ADI_{std} correlates strongly with Poverty in 2000, but this correlation weakens substantially by 2020, and is lower at narrower geographic levels. TDI generally has lower correlations with the other measures and Poverty. There is a general tendency for cross-measure correlations to be weaker in 2020 than in 2000, and for tract-level correlations to be higher than ZCTA-level correlations.

Data and Methods

Datasets

We summarize our datasets here, see Appendix for details, and Tables App-5 to App-8 for summary statistics.

Medicare FFS Beneficiaries 5% Random Sample. Our principal dataset, used for several outcomes, relies on a national 5% random sample of Medicare fee-for-service beneficiaries over 1999-2019. We use a one-year lookback to measure comorbidities. The dataset includes 1,366,366 beneficiaries aged 66+, including 61,745 aged exactly 66 as of January 1, 2000, whom we use to measure elderly mortality over time.

COVID-19 Elderly and Drug Overdose Mortality. We rely on individual death certificates for the State of Wisconsin, the State of Indiana, and Cook County, Illinois (Chicago and nearby suburbs) (together, "Three Midwest Areas") for 2020 through March 31, 2022, for 35,114 individual decedents, including 25,333 overdose decedents in Illinois and Indiana.

Census and American Community Survey (ACS). We obtain the elements of the area-SES measures from the 2000 Census and the American Community Survey (ACS) for 2010-2022. We studied performance at each geographic level without imputing missing data. We felt that imputation would compromise our effort to determine whether measure performance is stronger at tract or block-group level than at zip-code level.

Defining Quintiles and Five-Percentiles (Ventiles)

We report results for area-SES quintiles and five-percentiles, known as ventiles. The highest-numbered quintiles (5^{th}) and ventiles (20^{th}) reflect areas with the lowest SES. Figure App-13 provides selected results for centiles; centile estimates are much noisier than those for ventiles results.

Quintiles and ventiles are defined to have roughly equal numbers of geographic units. This produces similar numbers of *people* at tract and block-group levels, but not at zip-code and county levels. Table App-10 provides selected zip-code level results using population weights.

Outcome Measures

We summarize here our outcomes and regression methods; see Appendix for details. We use logistic regression and report marginal effects. The highest area-SES quintile or ventile is the omitted indicator variable in regressions.

All-Cause Elderly Mortality Over 2000-2019. All-cause mortality for Medicare FFS beneficiaries aged 66 as of January 1, 2000.

Diabetes Prevalence and Incidence. Diabetes prevalence in 2000 and 2019, and diabetes incidence over 2000-2005 for Medicare-FFS beneficiaries aged 66+ as of January 1, 2000.

COVID-19 Mortality for the Elderly (age 65+). Elderly COVID-19 mortality in the Three Midwest Areas, using the 2019 area-SES measures.

Drug Overdose Mortality Over 2017-2021. Drug overdose mortality for all persons over 2017-2021, in Illinois and Indiana.

Covariates

Our covariates, other than area-SES, are driven by data availability. We seek to use extensive covariates, including interactions, so that the coefficients on the area-SES indicator variables are measuring the predictive effect controlling for the individual characteristics available in our datasets. We generally use age (modeled as a cubic polynomial; which we verify is sufficient to capture reasonably well the nonlinear relationship between age and our outcomes, gender (female is the omitted indicator variable in our regressions), gender*(age cubic), race/ethnicity (White is the omitted indicator in regressions), gender*race/ethnicity, and dummy variables for the 17 Charlson comorbidities. See Appendix for details.

Measuring the Predictive Power of the Area-SES Measures

We use the coefficients on the area-SES indicator variables to measure the strength of the association between the area-SES measures and the outcomes. Assuming monotonicity is present, which is the case for most of the studied outcomes, we treat a larger coefficient magnitude as implying that an area-SES measure is providing a stronger signal of the unobserved true association between area-SES and an outcome. We also assessed the precision of the area-SES estimates, but found only modest variation between measures, so do not view precision as a useful comparative metric.

Comparing Area-SES Measures at Zip-Code Level

We first compare the predictive power of the area-SES measures and Poverty at the zip-code level. For race/ethnicity, marginal effects are averaged across both genders. We report quintile results in Table 3, and ventile results in Figure 1. In Table 3, column (1) reports marginal effects for racial/ethnic minorities and males, without controlling for area-SES. Column (2)-(6) report results controlling for area-SES and Poverty.

Elderly All-Cause Mortality

In Table 3, Panel A, we report results for all-cause elderly mortality over 2000-2019. Before adding area-SES quintiles, Blacks have higher mortality than Whites, but Hispanics and

Asians have lower mortality. We then add quintiles of the area-SES measures and Poverty. The Black mortality disadvantage shrinks and becomes statistically insignificant, while the Hispanic advantage increases and becomes similar to Asian. The marginal effects for the SES quintiles are monotonically increasing, with a quintile-5 coefficient for SDI, SVI and ADI_{std} similar to that for being male. TDI predicts more weakly than the other area-SES measures, and the coefficient on Black mortality does not shrink. Thus using a weaker area-SES measure can lead to different assessments of the predictive power of race/ethnicity for mortality, after controlling for area-SES.

In Figure 1, Panel A, we report marginal effects for ventiles. All four SES-measures have predictive power. However, TDI marginal effects are generally below SDI and ADI_{std}, with a puzzling dip for ventile-20 (lowest SES). SVI also generally has lower predictive power than SDI and ADI_{std}, with ventile-2 having lower mortality than the omitted ventile-1 (highest SES). Area-SES gradients are substantially larger if we do not control for comorbidities (Table App-18), but comparative assessment is similar.

Results using a Cox proportional-hazard survival model (Table App-17, Figure App-5) are broadly consistent with the logit results.

Diabetes Prevalence in 2000 and 2019

In Table 3, we report results for diabetes prevalence in 2000 (Panel B), and 2019 (Panel C), for Medicare-FFS beneficiaries aged 66+. Overall prevalence in 2000 averages 20.5% (Table App-7). All racial/ethnic minorities have substantially higher diabetes rates than Whites; rates are highest for Hispanics. Adding area-SES somewhat reduces the race/ethnicity coefficients, but these coefficients remain large. The marginal effects for the area-SES quintiles are monotonically increasing, but modest in magnitude, relative to those for Hispanics and Blacks. The marginal effects for SDI, SVI, and ADI_{std} are similar. TDI predicts diabetes prevalence less strongly than the other measures.

Figure 1, Panel B, provides a similar comparative picture. TDI has both the lowest coefficients and a low gradient for most of the SES spectrum. There is large nonlinearity in predictive power, with large gradients for the lowest-SES ventiles, especially ventile-20 versus ventile-19. We obtain similar results with versus without controlling for the Charlson comorbidities that are not potentially caused by diabetes (Table App-18).

In Table 3, Panel C, and Figure 1, Panel C, we study diabetes prevalence in 2019. Overall prevalence is higher, at 28.9% (Table App-7; compare CDC, 2020). The coefficients on race/ethnicity rise relative to 2000, especially for Asians. The overall predictive power of the area-SES measures is stronger and the jump for ventile-20 has vanished (except for TDI). The comparative analysis of the SES measures is similar: all measures, including Poverty, have monotonic gradients; SDI, ADI_{std}, and SVI have similar strength, and larger gradients than TDI.

Diabetes Incidence Over 2000-2005

In Table 3, Panel D, we report results for diabetes incidence over 2000-2005. All racial/ethnic minorities have substantially higher rates than Whites; highest for Hispanics. Controlling for area-SES measures only modestly reduces these coefficients. Only SVI shows monotonically increasing coefficients; the other area-SES measures and Poverty quintiles are often negative or near zero, before jumping for quintile-5.

In Figure 1, Panel D, we report marginal effects for ventiles. These show a mixed pattern, with near-zero coefficients for SDI, ADI_{std}, and TDI across much of the area-SES spectrum.

Elderly COVID-19 Mortality

In Table 3, Panel E, we report results for elderly COVID-19 mortality.[2] The coefficients on race/ethnicity categories decline modestly after controlling for SES, but remain large. This is consistent with area-SES explaining only a fraction of racial/ethnic disparities in elderly COVID-19 mortality (Barreto Parra et al., 2022), in contrast to the results for overall elderly mortality. The quintiles take economically meaningful coefficients, with magnitude monotonically increasing as SES falls, thus capturing a mortality risk separate from race/ethnicity, in sensible fashion.

For ADI_{std}, the gradient from quintile-1 to quintile-5 is larger than SDI, but with a a larger coefficient for quintile-2 but a lower gradient over quintiles 2-5. For SVI, the overall gradient from quintile-2 to quintile-5 is higher than for SDI or ADI_{std}, but with a slightly negative coefficient for quintile-2. For TDI, the gradient from quintile-1 to quintile-5 is well below the other measures.

In Figure 1, Panel E, all four measures have predictive power, but SVI generally has lower predictive power than SDI and ADI_{std}, with the oddity of lower COVID-19 mortality for ventile-2 than omitted ventile-1. The TDI marginal effects are weaker, and largely flat from ventile-9 on.

Drug Overdose Mortality

In Table 3, Panel F, we report results for all drug overdose mortality over 2017-2021. Whites have higher mortality rates than Blacks, Hispanics, and Asians. The White disadvantage increases after controlling for SES. Relative to the outcomes discussed above, which are limited to elderly persons, we see some important differences in the predictive power of the area-SES measures. SDI, SVI and TDI perform similarly. ADI_{std} has lower coefficients, with no meaningful

[2] Unruh et al. (2022) use SDI to study COVID-19 mortality in Cook County, Illinois. Sehgal et al. (2022) use county-level SVI as a covariate in a national study of the predictive power of Republican vote share for COVID-19 mortality.

gradient across quintiles 1-3. In Table App-14, we study both the original SVI measure, measured in 2020, and the 2020 version (SVI_{2020}); both perform similarly.

Ventiles (Figure 1, Panel F) present a somewhat different picture: SVI_{2020} and TDI generally have larger coefficients for middle-to-low area-SES levels, but SDI partly catches up for the lowest SES ventiles. However, we see some odd behavior for particular measures, including a large jump for TDI for ventile-20, and some bumps and dips for SVI_{2020}.

Medicare-FFS Spending

We also studied Medicare-FFS spending in 2000 and 2019 as additional outcomes. In contrast to the predictive power of area-SES measures for health outcomes, predictive power for spending was small, with no consistent pattern across SES quintiles. We therefore relegate these results in the Appendix.

Incremental R^2 as a Performance Measure

In Table App-20, we consider pseudo-R^2 as an alternative way to compare the performance of the area-SES measures. We compute the increase in pseudo-R^2 when each area-SES measure is added to a regression that includes our base covariates. Averaged across our outcomes, incremental pseudo-R^2 at zip-code level is 0.25% for SDI and ADI_{std}, and 0.23% for SVI, but only 0.19% for Poverty, 0.16% for ADI_{orig}, and 0.15% for TDI. This confirms the similar performance of SDI, ADI_{std}, and SVI, and weaker performance of Poverty and TDI.

Comparative Performance at Different Geographic Levels

Comparison of Zip-Code to Tract or Block-Group

In Table 4, we compare the performance of the area-SES measures at the other geographic levels, using the quintile-5 marginal effect as a summary measure of performance. See Appendix for full results at these levels. As was the case at zip-code level, no single area-SES measure performs best across outcomes and geographic levels.

The choice between geographic levels, however, is clear. Tract is preferred. The coefficients for quintile-5 at tract level are generally well above those at zip-code level for outcomes with data available at both levels. Tract-level coefficients are generally similar to block-group coefficients, but can be higher or lower for specific outcomes.

Poorer Performance of County-Level Measures

Across the full range of outcomes, county-level measures performed much less well than measures at zip-code or narrower levels. First, for most health outcomes, the quintile-5 coefficient for each area-SES measure was often much smaller in magnitude at county level than at zip-code level (Table 4). Second, the area-SES coefficients were often non-monotonic across quintiles or ventiles (Table App-16). For several outcomes, coefficients are often negative (opposite from predicted) for middle quintiles 2-4. For some outcomes, we see sharp spikes or dips in coefficients for ventile-20 versus 19 (Figure App-12), which are either not present or less sharp for narrower geographic levels (Figure App-11).

County-level measures are crude for large, diverse urban counties. We hoped they might be meaningful for a national study that includes many smaller, more homogenous counties, but did not find this for most of the studied outcomes. The message for researchers: Use county-level measures with caution and confirm that they perform sensibly for your outcome(s).

Comparing the Area-SES Measures to the Poverty Measure

Prior research found that Poverty has predictive power comparable to TDI (Krieger et al., 2005) and NDI (Berkowitz et al., 2015). We therefore compared Poverty to the four studied area-SES measures. Using quintiles, Poverty performs better than TDI, but somewhat worse overall than the other area-SES measures (Table 3). Poverty had similar strength for some outcomes (elderly mortality, diabetes prevalence in 2000), but was weaker for others (COVID-19 mortality, diabetes prevalence in 2019).

We also went beyond a simple comparison of coefficients and ran horse-race regressions, which include an area-SES measure and Poverty in the same regression (Figure App-9 and App-10). Across outcomes, SDI, SVI, or ADI_{std} retain substantial power, and thus capture aspects that predict health outcomes, beyond Poverty alone. Conversely, Poverty has little predictive power, controlling for SDI, SVI, or ADI_{std}.

Recommendations for Practice

Limitations

We studied a limited number of area-SES measures, for a limited range of outcomes, principally for the elderly.

A principal use of an area-SES measure is to predict health outcomes, controlling for other patient-level information that may be available for a particular project. We used the patient covariates we had to control for patient-level demographics and other information. The predictive power of area-SES measures might change if one could include more person-level information. At the same time, we have no reason to think that moderate changes in available patient-level covariates would strongly affect the relative ranking of the area-SES measures.

The relative performance of the area-SES measures can differ across outcomes; we found some evidence for this for the outcomes we studied. However, given the basic similarity of the domains covered by each measure, we have no way of predicting in advance, for example, that measure A should be preferred for some outcomes and measure B for others.

We used several criteria to compare measures, including the gradient in the logit marginal effects as one moves from high to low-SES, coefficient monotonicity when moving from high to low-SES, overall R^2 from a regression that includes area-SES measure, incremental R^2 when an area-SES measure is added to a regression with patient-level covariates, and area under the receiver operating curve (ROC) (Table App-21), and found consistent results across these criteria. However, we do not know truth, either for how to measure area-SES or how a true area-SES measure would predict health outcomes. Thus, we cannot be sure, for example, that a monotonic measure is closer to truth than a non-monotonic measure for a particular outcome; or that a measure with a larger gradient is closer to truth than one with a smaller gradient.

We had national data, at all geographic levels, for several outcomes, but only for Medicare FFS beneficiaries. For COVID-19 and drug overdose mortality, our data was limited to three Midwestern states and to the zip-code and county levels.

The power of an area-SES measure to predict a particular outcome can change over time, as we saw for diabetes prevalence in 2000 versus 2019.

Subject to these limitations, we offer the suggestions below, as guides to good practice.

Choosing a Geographic Level

The best geographic level for studying the effects of area-SES on health outcomes, if data is available at all levels, is Census tract. Predictive power is generally higher than at zip-code level, and higher than or similar to block-group level. However, all measures predict, albeit somewhat less strongly, at zip-code level. Our results do not support use of county-level area-SES measures if data is available at narrower levels.

How Finely to Subdivide Area-SES

For studying the effects of area-SES on health outcomes, if sample size is sufficient, we prefer dividing SES fairly finely, perhaps into ventiles. However, if principal research interest lies in other predictors, and area-SES is simply a covariate, quintiles may be sufficient. We did not find additional value in using centiles instead of ventiles (Figure App-13).

Choosing an Area-SES Measure

In broad picture, our results confirm that there can be substantial value in controlling for area-SES when assessing the predictive power of other covariates. SDI, SVI, and ADI_{std} generally predict health outcomes more strongly than Poverty and TDI, judged by monotonicity and overall gradient, although not for all outcomes. However, across the studied outcomes and geographic levels, there was no clear winner among these three measures.

SDI and SVI correlate strongly with each other (Table 2) and are both good choices. If we had to choose a single measure across outcomes and geographic levels, we would prefer SDI. It is parsimonious, predicts well, uses elements that seem sensible to us, and is replicable.

SVI is also a reasonable choice. However, it is more complex and includes elements (percent elderly, children, minority, and non-English speaking), that led us to prefer an SVI_{mod} measure, without these elements, which performs somewhat better (Figure App-3).

ADI_{std} performed similarly to SDI or SVI, but overcontrols for Poverty and has far more missing values. The Neighborhood Atlas researchers did not cooperate with our replication, and oppose use of ADI at any level other than block-group, a level that is often not available to researchers. These factors count against ADI_{std}. We cannot recommend non-standardized ADI_{orig}. It performed acceptably for most outcomes (Figure App-2) but is not a true multi-domain measure and is problematic in some settings (Hannan et al., 2023; Petterson, 2023).

We concur with Rehkopf and Phillips (2023) that area-SES measures should be replicable. SDI, SVI, and TDI are; ADI is not (see Appendix for details). We also recommend that measure creators specify the exact ACS or other tables they use and make their replication code public.

Would another Area-SES Measure Perform Better?

Given the similar overall performance of SDI, SVI and ADI_{std}, other measures which capture the same principal domains will likely perform similarly. Of the other area-SES measures surveyed by Trinidad et al. (2022), none include all five domains captured by these measures; and only two include four of these domains. Thus, we have no *a priori* reason to expect that another measure would systematically outperform the measures we studied.

Conclusion

We compared the performance of three area-SES measures, SDI, SVI, and ADI (for which we studied and prefer a standardized version) for an array of health outcomes, at four geographic levels. All had substantial predictive power across outcomes. The both good and bad news is that there was no clear winner as between SDI, SVI, and ADI_{std}. Researchers can have comfort that any of the three will likely perform well for a particular outcome and research setting, although we recommend against using the publicly posted version of ADI.

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Table 1. Summary of elements used to build each area-SES measure

Table indicates which data elements are used in each SES measure. Red = removed in SVI_{mod}.

Data element	TDI	SDI	ADI	SVI	Element Description
Education					
did not complete high school [3]		x	x	x	% of population 25+ with less than 12 years education
low education (< 9 years)			x		% of population 25+ with less than 9 years education
Income/Poverty					
below poverty line[4]		x		x (thru 2019)	% of population with family income in the past 12 months below the poverty level
family poverty rate			x		% of families with income in the past 12 months below the poverty level
below 150% of poverty line			x	x (2020)	% of population with family income in the past 12 months below 150% of poverty level
median family income[5]			x		median family income
income disparity			x		log of (100 x ratio of number of households with < $10,000 income to number with income ≥ $50,000
per capita income				x (thru 2019)	mean income of population in the last year
housing cost > 30% of household income				x (2020)	Household housing cost > 30% of household income in last 12 months
no health insurance				x (2020)	% of uninsured in the total civilian, non-institutionalized population
occupational composition			x		% Employed population aged 16+ employed in white-collar occupations
unemployed	x		x	x	% of civilian population 16+ unemployed
non-employed 16-64		x			% of population aged 16-64 unemployed or not in the labor force.
Household Composition					
single parent		x	x	x	% of households with single parent
disabled				x	% of population age 5+ not in an institution with a disability
elderly				x	% of population 65 and over
children				x	% of population 17 and below
minority				x	All persons except non-Hispanic White
non-English speaking				x	% of population 5 and over who speak English less than "well"
Housing					
crowded households	x	x	x	x	% of households with more than one person per room
renter occupied units[6]	x	x	x		% of occupied housing units not owner occupied
median home value			x		Median home value
median gross rent			x		Median gross rent
median mortgage			x		We use "selected monthly owner costs" for owners with a mortgage.
no plumbing			x		% of housing units lacking plumbing facilities
no telephone[7]			x (thru		% of housing units with no access to telephone

[3] ADI uses a measure for *did* complete HS = (1 – did not completer HS). This is substantively equivalent; it leads to the opposite sign on this element within the ADI approach.

[4] In 2020, SVI replaced percent below poverty with percent below 150% of poverty line.

[5] ADI as reported on the ADI website uses median *household* income instead of the stated element of median *family* income. See Petterson (2023) and Appendix Part III.

[6] ADI uses a substantively equivalent measure for owner occupied units = (1 – renter occupied units.

[7] Replaced beginning in 2020 with % of households with no internet connection.

Data element	TDI	SDI	ADI	SVI	Element Description
			2019)		
no internet[8]			x (2020)	x (2020)	% of households with no internet connection
multi-unit				x	% of housing units with 10 or more units in structure
mobile homes				x	% of housing units that are mobile homes
group quarters				x	% of persons in group quarters
Transportation					
no vehicle	x	x	x	x	% of households with no vehicle available

[8] New ADI and SVI element beginning 2020; for ADI replaces % of households with no telephone. The ADI website does not state what factor score coefficient is used for this new element. Our educated guess is that they use the coefficient from Singh (2003) for no telephone.

Table 2. ZCTA and Tract-Level Correlations Between Area-SES Measures

Table shows Pearson correlation coefficients between Area-SES measures and Poverty in 2000 (left-hand columns, based on 2000 Census)) and 2020 (right-hand columns, based on 2020 ACS), at ZCTA and Census Tract levels.

	2000 Census				2020 ACS			
	TDI	SDI	ADI_{std}	SVI	TDI	SDI	ADI_{std}	SVI
ZCTA level								
SDI	0.688	1			0.617	1		
ADI_{std}	0.567	0.767	1		0.485	0.712	1	
SVI	0.637	0.903	0.635	1	0.562	0.881	0.586	1
% below poverty	0.597	0.795	0.770	0.639	0.466	0.677	0.670	0.533
Tract level								
SDI	0.816	1			0.770	1		
ADI_{std}	0.726	0.874	1		0.589	0.847	1	
SVI	0.752	0.950	0.850	1	0.688	0.914	0.806	1
% below poverty	0.778	0.833	0.840	0.759	0.630	0.796	0.749	0.689

Table 3. Marginal Effect of Area-SES Measures at Zip-Code Level

Table shows marginal effects, from logit regressions, of area-SES and poverty quintiles measured at ZCTA level, and mapped to zip-codes. Highest SES (quintile-1) is omitted. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes prevalence in 2019. **Panel D.** Diabetes incidence over 2000-2005. **Panel E.** COVID-19 mortality. **Panel F.** Drug Overdose Mortality over 2017-2021. See text section "Covariates" for covariates. Marginal effects for race/ethnicity are averaged across both genders. * = statistically significant at the 1% level or better, using heteroskedasticity-robust standard errors.

Panel A. All-Cause Elderly Mortality over 2000-2019

	(1)	(2)	(3)	(4)	(5)	(6)
Area-SES Measure	**none**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2		0.0289*	0.0394*	0.0206*	0.0352*	0.0360*
Quintile 3		0.0506*	0.0637*	0.0439*	0.0534*	0.0554*
Quintile 4		0.0740*	0.0927*	0.0686*	0.0639*	0.0819*
Quintile 5		0.1016*	0.1034*	0.1002*	0.0765*	0.0982*
Race/ethnicity						
Black	0.0389*	0.0050	0.0075	0.0072	0.0212*	0.0098
Hispanic	-0.0830*	-0.1175*	-0.1150*	-0.1160*	-0.1025*	-0.1135*
Asian	-0.1094*	-0.1222*	-0.1057*	-0.1232*	-0.1243*	-0.1147*
Other	0.0012	-0.0128	-0.0087	-0.0127	-0.0088	-0.0103
Male	0.1040*	0.1045*	0.1042*	0.1046*	0.1046*	0.1039*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,745	61,185	61,067	61,185	61,189	61,188

Panel B. Diabetes Prevalence in 2000

Area-SES Measure	**none**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2		0.0097*	0.0156*	0.0109*	0.0093*	0.0062*
Quintile 3		0.0146*	0.0187*	0.0177*	0.0108*	0.0090*
Quintile 4		0.0186*	0.0238*	0.0242*	0.0112*	0.0132*
Quintile 5		0.0358*	0.0390*	0.0366*	0.0245*	0.0308*
Race/ethnicity						
Black	0.1483*	0.1310*	0.1320*	0.1339*	0.1390*	0.1339*
Hispanic	0.1869*	0.1680*	0.1679*	0.1711*	0.1744*	0.1704*
Asian	0.0729*	0.0654*	0.0723*	0.0665*	0.0644*	0.0693*
Other	0.0795*	0.0714*	0.0727*	0.0723*	0.0739*	0.0725*
Male	0.0178*	0.0182*	0.0179*	0.0182*	0.0182*	0.0180*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,366,366	1,355,314	1,347,454	1,355,345	1,355,352	1,355,418

Panel C. Diabetes Prevalence in 2019

Area-SES Measure	**none**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2		0.0179*	0.0230*	0.0087*	0.0154*	0.0189*
Quintile 3		0.0342*	0.0433*	0.0291*	0.0256*	0.0334*
Quintile 4		0.0534*	0.0593*	0.0526*	0.0345*	0.0531*
Quintile 5		0.0824*	0.0764*	0.0831*	0.0554*	0.0646*
Race/ethnicity						
Black	0.1892*	0.1623*	0.1666*	0.1630*	0.1735*	0.1719*
Hispanic	0.2039*	0.1782*	0.1837*	0.1786*	0.1877*	0.1908*
Asian	0.1685*	0.1601*	0.1743*	0.1596*	0.1563*	0.1709*
Other	0.0595*	0.0564*	0.0608*	0.0568*	0.0548*	0.0589*
Male	0.0578*	0.0583*	0.0581*	0.0584*	0.0584*	0.0580*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,318,438	1,315,649	1,253,280	1,315,092	1,315,375	1,315,832

Panel D. Diabetes Incidence over 2000-2005

Area-SES Measure	none	SDI	ADI$_{std}$	SVI	TDI	Poverty
Quintile 2		-0.0008	-0.0140*	0.0052*	*-0.0043*	-0.0072*
Quintile 3		-0.0061*	-0.0119*	0.0069*	-0.0057*	-0.0098*
Quintile 4		0.0024	-0.0018	0.0103*	-0.0055*	-0.0040*
Quintile 5		0.0313*	0.0211*	0.0348*	0.0290*	0.0195*
Race/ethnicity						
Black	0.0993*	0.0796*	0.0871*	0.0821*	0.0816*	0.0870*
Hispanic	0.1621*	0.1582*	0.1638*	0.1609*	0.1562*	0.1658*
Asian	0.0981*	0.0955*	0.0997*	0.0966*	0.0872*	0.1010*
Other	0.0240*	0.0288*	0.0318*	0.0292*	0.0274*	0.0320*
Male	0.0072*	0.0082*	0.0080*	0.0083*	0.0083*	0.0080*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	881,170	860,248	854,556	860,266	860,269	860,302

Panel E. COVID-19 Mortality

Area-SES Measure	none	SDI	ADI$_{std}$	SVI	TDI	Poverty
Quintile 2		0.0018*	0.0037*	-0.0003	0.0010*	0.0027*
Quintile 3		0.0029*	0.0042*	0.0016*	0.0026*	0.0031*
Quintile 4		0.0038*	0.0052*	0.0033*	0.0026*	0.0045*
Quintile 5		0.0058*	0.0070*	0.0053*	0.0028*	0.0036*
Race/ethnicity						
Black	0.0085*	0.0048*	0.0053*	0.0047*	0.0067*	0.0064*
Hispanic	0.0122*	0.0082*	0.0087*	0.0082*	0.0098*	0.0096*
Asian	0.0022*	0.0005	0.0014*	0.0004	0.0007	*0.0010*
Other	0.0129*	0.0124*	0.0127*	0.0125*	0.0125*	0.0125*
Male	0.0063*	0.0063*	0.0063*	0.0063*	0.0063*	0.0063*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,874,779	2,812,475	2,812,475	2,874,779	2,874,779	2,874,779

Panel F. Drug Overdose Mortality over 2017-2021, in Indiana and Illinois

Area-SES Measure	none	SDI	ADI$_{std}$	SVI$_{2020}$	TDI	Poverty
Quintile 2		0.0030*	0.0004	0.0062*	0.0033*	0.0030*
Quintile 3		0.0048*	-0.0033*	0.0119*	0.0070*	0.0039*
Quintile 4		0.0077*	0.0046*	0.0156*	0.0155*	0.0116*
Quintile 5		0.0256*	0.0175*	0.0303*	0.0289*	0.0244*
Race/ethnicity						
Black	-0.0005	-0.0100*	-0.0063*	-0.0103*	-0.0114*	-0.0086*
Hispanic	-0.0161*	-0.0228*	-0.0207*	-0.0234*	-0.0237*	-0.0193*
Asian	-0.0377*	-0.0402*	-0.0396*	-0.0409*	-0.0415*	-0.0386*
Other	-0.0039	-0.0077	-0.0055	-0.0092	-0.0098	-0.0065
Male	0.0121*	0.0124*	0.0125*	0.0124*	0.0123*	0.0123*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Observations	446,309	446,249	436,509	446,202	446,202	446,309

Table 4. Comparison of Quintile-5 Coefficients Across Geographic Levels

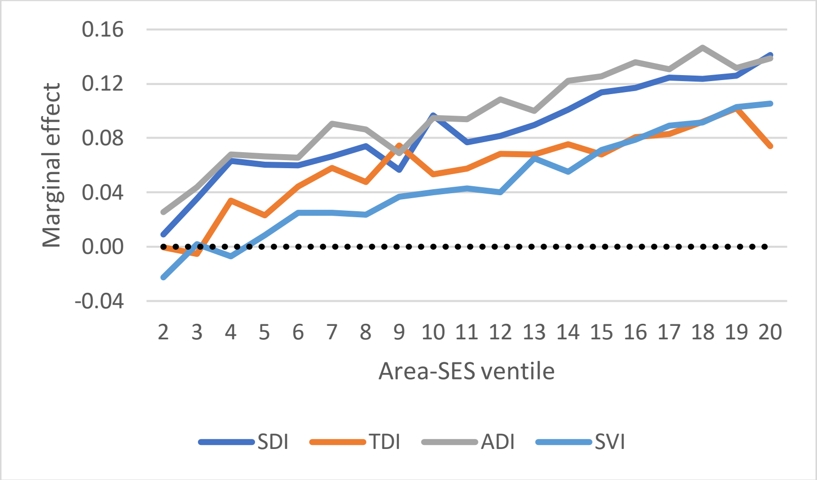
Table shows coefficients for area-SES quintile-5, from regressions similar to Table 3, at indicated geographic levels. SVI for Drug Overdose Mortality over 2017-2021 is SVI_{2020}.

Outcome	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
All-Cause Mortality					
County	.0409	.0562	.0445	.0112	.0479
Zip-code	.1016	.1034	.1002	.0765	.0982
Tract	.1339	.1485	.1277	.0976	.1245
Block Group	.1290	.1339	.1062	.0991	.1105
Diabetes Prevalence in 2000					
County	.0204	.0344	.0168	.0008	.0212
Zip-code	.0358	.0390	.0366	.0245	.0308
Tract	.0524	.0509	.0463	.0436	.0374
Block Group	.0539	.0497	.0496	.0457	.0381
Diabetes Prevalence in 2019					
County	.0517	.0524	.0477	.0630	.0500
Zip-code	.0824	.0764	.0831	.0554	.0646
Diabetes Incidence over 2000-2005					
County	.0470	.0361	.0483	.0198	.0304
Zip-code	.0313	.0211	.0348	.0290	.0195
Tract	.0489	.0247	.0369	.0563	.0252
Block Group	.0466	.0262	.0399	.0536	.0268
COVID-19 Mortality					
County	.0018	-.0011	-	.0025	.0036
Zip-code	.0058	.0070	.0053	.0028	.0036
Drug Overdose Mortality over 2017-2021					
County	-.0178	-.0572	-.0580	.1048	-.0137
Zip-code	.0256	.0175	.0303	.0289	.0244

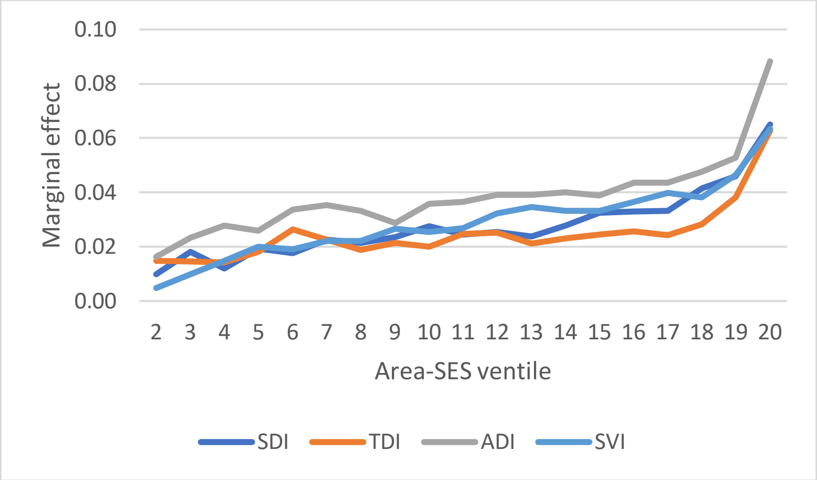
Figure 1. Marginal Effects for Ventiles at Zip-Code Level

Figure shows marginal effects from logit regression of ventiles of SDI, ADI, SVI, and TDI for indicated outcomes at zip-code level. Highest SES (ventile-1) is omitted. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes prevalence in 2019. **Panel D.** Diabetes incidence over 2000-2005. **Panel E.** COVID-19 mortality. **Panel F.** Drug Overdose Mortality over 2017-2021. Covariates are same as Table 3. **All panels.** ADI is ADI_{std}.

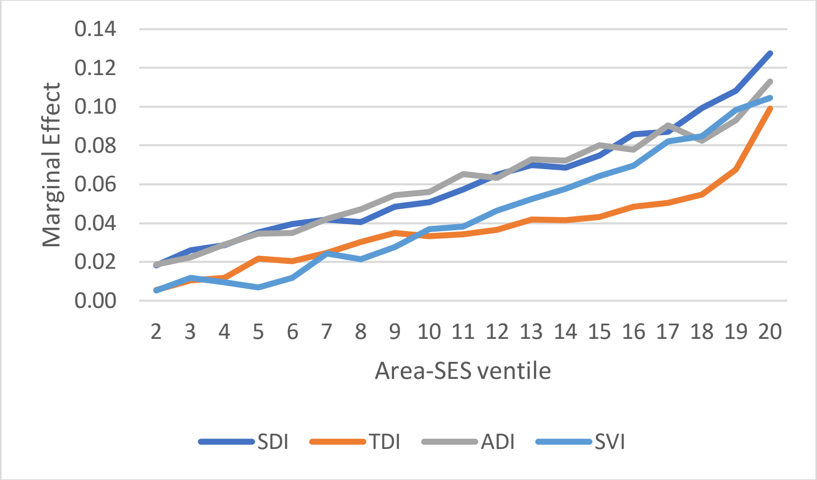
Panel. A. All-Cause Elderly Mortality Over 2000-2019



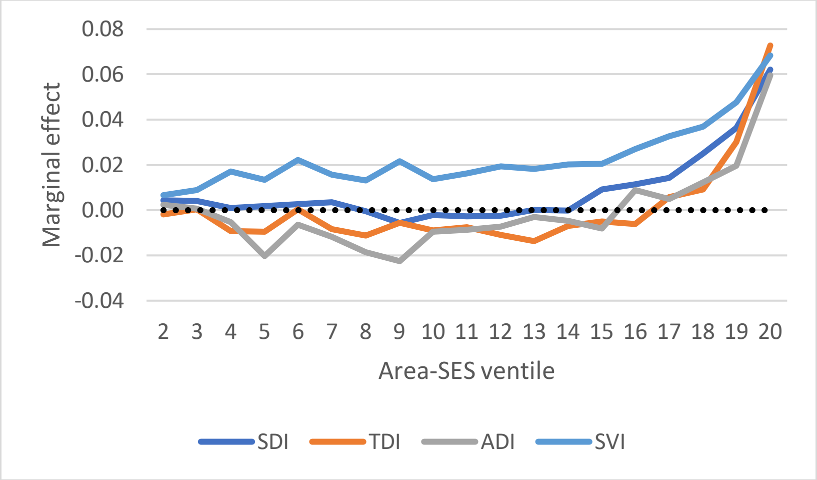
Panel B. Diabetes Prevalence in 2000



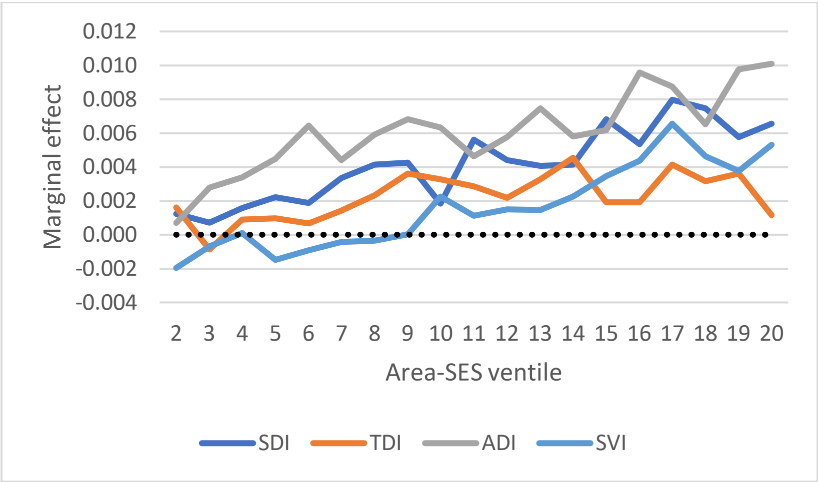
Panel C. Diabetes Prevalence in 2019



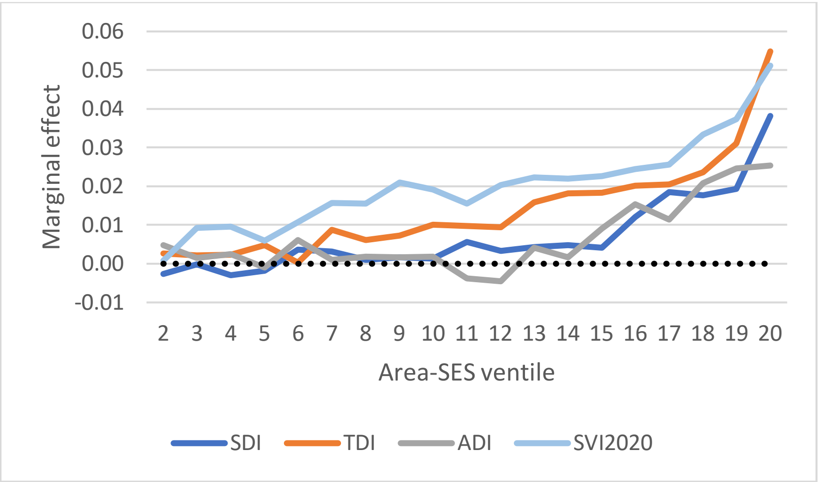
Panel D. Diabetes Incidence over 2000-2005



Panel. E. COVID-19 Mortality



Panel F. Drug Overdose Mortality over 2017-2021



Appendix for

A Comparative Assessment of Measures of Area-Level Socio-Economic Status

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Appendix for

A Comparative Assessment of Measures of Area-Level Socio-Economic Status

Lorenzo Franchi, Natalia Barreto, Anna Chorniy, Benjamin W. Weston, John Meurer, Jeff Whittle, Ronald T. Ackermann, and Bernard Black

Abstract: This Appendix provides additional documentation and results for Franchi et al. (2023), *A Comparative Assessment of Measures of Area-Level Socio-Economic Status,* https://ssrn.com/abstract=4547382.

Contents

The datasets and do files to create the area-SES measures studied in this project are available from Professor Black's website at https://www.law.northwestern.edu/faculty/profiles/bernardblack/; click on "datasets".

I. Additional Literature Review and Discussion

A. Uses of SDI, SVI, ADI, and TDI in the Medical and Health Outcomes Literatures

We list here selected recent uses of SDI,[1] SVI,[2] ADI,[3] and TDI,[4] in addition to those cited in the text, with no claim to have provided a complete list. The surveys by Breslau et al. (2022) and Trinidad et al. (2022) contain additional citations.

B. Additional Comparative Analyses

We discuss here a number of additional comparative analyses of area-SES measures, that were narrower than the Krieger et al. and Berkowitz et al. comparisons discussed in the text. We relegated discussion of these studies to this Appendix for space reasons.

Crawford and Schold (2019) study the predictive value of ADI_{orig}, Poverty, median household income and several other single-item measures in 8 states at zip-code level for mortality, length of stay, in-hospital costs, and 30-day readmission rates, for a broad set of major surgeries. They did not find a clear ranking of predictors. Even when gradients existed, they were sometimes small and not always monotonic.

Ghirimoldi et al. (2021) study the predictive value for hospital readmission after colorectal surgery at a single safety-net hospital of ADI_{orig}, the Distressed Communities Index, and insurance status. They find that ADI_{orig} has predictive power, controlling for individual-level characteristics, but the other two measures do not.

Michaels et al. (2021) compare the predictive value of ADI_{orig} and the Distressed Communities Index, at a single hospital for several post-surgery outcomes: any complication within 30 days, 30-day readmission, 30-day mortality, 10-year mortality and hospitalization cost. ADI predicted significantly higher complication rates, higher cost, but not the other outcomes. The Distressed Communities Index was not a significant predictor for any of these outcomes.

[1] Selected studies relying on SDI include Liaw et al. (2018); Bevan et al. (2020, 2022); Cottrell et al., (2020a, 2020b); Patel et al. (2020); Griggs et al. (2022); Lucas et al., (2021); Green et al. (2022); Bazemore et al. (2016).

[2] Selected studies relying on SVI (at county level unless otherwise specified) include Diaz et al. (2020); Gay et al. (2016); An and Ziang (2015); Flanagan et al. (2018, 2021); Fletcher et al. (2020); Ramesh et al. (2022); li et al. (2022); Sharpe and Rickless (2021); Troppy et al. (2021); Barry et al. (2021); Hughes et al. (2021); Rickless et al. (2023); Dasgupta et al. (2020); Adams et al. (2020); Wolkin et al. (2015).

[3] Selected studies using ADI include Durfey et al. (2019); Kind et al. (2014); Kind and Buckingham (2018); Carmichael et al. (2020); Knighton et al. (2013); Michaels et al (2021); Hu et al. (2018, 2021); Mora et al. (2020) Sheehy et al. (2020) Rahman, Meyers, and Wright (2020); Powell et al. (2020); Jencks et al. (2019), Crawford and Scholl (2019).

[4] TDI was developed in the U.K. but uses elements that can be measured using U.S. data. Selected recent uses of TDI (2010 or later) include Cathorall et al. (2015); Furmanchuk et al. (2021); Galiatsatos et al. (2020); Lopez-de-Fede et al. (2016); Rice et al. (2014).

Carmichael et al. (2020) is a narrow study of the predictive value of crude versions (split into high versus low values) of the ADI_{orig}, SVI, the Community Needs Index, and Distressed Communities Index, each measured at a single geographic level, but not the same level across measures (block-group or zip-code, depending on the measure) for a single outcome (the likelihood that a cholecystectomy (gall-bladder removal) is emergency versus planned, at a single university hospital. They found similar predictive value for ADI_{orig} and SVI, and positive but lower predictive value for the other measures.

Yu et al. (2014) find similar predictive value for a composite SES measure used by Krieger et al. (2002, 2003) and Yost et al. (2006) at tract level as predictors of cancer incidence for a number of common cancers. However, Krieger et al. find that Poverty performs as well as TDI and their own composite measure.

Lopez-de-Fede et al. (2016) develop a Small Area Deprivation Index (SADI) at ZCTA level, and compare it to TDI, Poverty, and two measures of access to health care providers, as predictors of two closely related outcomes (existence of a comorbidity; existence of two or more comorbidities) for Medicaid recipients in South Carolina. They find superior performance for SADI. However, they constructed SADI from elements that were strongly correlated with the outcomes. Thus, their finding that SADI predicted these outcomes better than competing measures was driven by index construction, and does not imply good performance for other outcomes.

Dyer et al. (2023) construct a highly complex "structural racism index," and report that it has higher R^2 than ADI (ADI_{orig}, one infers), SDI, SVI and the Child Opportunity Index in predicting several Census-tract-level area health outcomes. Unlike this project and the other comparisons above, they use their measure to predict area-level rather than individual-level outcomes.

C. Summary of Selected Additional Area-SES Measures

1. Measures Replicable Using ACS data.

We summarize briefly here a number of additional area-SES measures that might be considered as competitors to the four we study. We list only measures applicable to the general population that can be built using ACS data, and that do not include health outcomes in constructing the index. We discuss area-SES measures; measures of the "social determinants of health" have often somewhat different, broader domains.[5]

Allik et al. (2020) discuss some of the judgments that enter into creation of an area-SES measure. Lian, Struthers, and Liu (2016) argue, from a construct validity perspective, that the optimal elements of an area-SES measure will depend on geographic level. Kolak (2020) suggests that a multidimensional index, derived from a larger number of elements, may capture the concept of SES better than a single measure. Breslau et al. (2022) list the elements included in each measure.

[5] See, e.g., Baker et al., 2021); Braveman and Gottlieb, 2014 Breslau et al. (2022); U.S. Department of Health and Human Services, Healthy People 2030 project, at https://health.gov/healthypeople/priority-areas/social-determinants-health.

1. *Neighborhood Deprivation Index (NDI)*, developed by Messer et al. (2006). Uses 8 elements. Should be replicable for 2000; uses only ACS and Decennial Census.[6] Should be largely replicable using ACS for other years.[7] Built at tract level. Berkowitz et al. (2015) report similar performance for NDI, Poverty, and the AHRQ Measure.[8]

2. *AHRQ Measure*. Developed by the RTI consulting group for the Agency for Healthcare Research and Quality (Bonito et al., 2008). Uses 7 elements. Should be replicable, uses only ACS. Built at block-group level for 2000. Berkowitz et al. (2015) report similar performance for NDI, Poverty, and the AHRQ Measure.[9]

3. *Community Needs Index*. Developed by Roth and Barsi (2005). Uses 9 elements. Should be replicable, uses only ACS. Built at zip-code level.[10] Built using domains quintiles, so has only 21 possible values.

4. *(Palmetto) Small Area Deprivation Index*. Developed by Lopez-de-Fede et al. (2016) (available at ZCTA level). Uses 3 elements. Should be replicable, uses only ACS.[11] Developed to predict chronic disease among publicly insured Medicaid recipients in South Carolina. Built at ZCTA level.

5. *Distressed Communities Index* (available at zip-code and county level). Developed by Economic Innovation Group (2020). Uses 7 elements. Should be replicable; uses only ACS and the Census Bureau Business Patterns dataset, which is available on the Census website.[12] Available only for 2020.[13] Does not appear to be competitive with other indices. Ghirimoldi et al. (2021) find that ADI_{orig} at block-group level performs better than at zip-code level Distressed Communities Index in predicting hospital readmissions. Michaels et al. (2021) find that ADI_{orig} at block-group level outperforms zip-code level Distressed Communities Index in predicting post-surgery outcomes and cost.

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[6] No online dataset, but relies only on ACS variables and Messer et al. (2006) indicate the specific ACS and Census variables used and the methodology used to construct the index.

[7] No online dataset. Of the 20 elements in this index, 19 are from ACS and replicable, but one is specific to the 2000 Decennial Census: % of people living in the same house since 1995. The closest substitute for other years is from ACS Table B07001, which includes the element "Geographical mobility in the past year for current residence in US," which provides a count of people who did not change residence over a 1-year span, from which one can compute percent.

[8] Also used by, e.g., O'Campo et al. (2007); Schempf et al. (2011); Laraia et al. (2012); Akwo et al. (2018); Andrews et al. (2020); .Kramer et al. (2013); Silver, Trong, and Ostvar (2020); Ma et al. (2015); Powell et al. (2014); Walker et al. (2020).

[9] No online dataset, but Bonito et al. (2008) indicate the elements and methodology used to construct the index. Also used by Putnam et al. (2016).

[10] No online dataset, but Roth and Barsi (2005) indicate the elements and methodology used to construct the index.

[11] There is no online dataset, but this measure relies only on ACS variables, and Lopez-de-Fede et al. (2016) indicate the elements and methodology used to construct the index.

[12] **Source**: https://www.census.gov/data/developers/data-sets/cbp-nonemp-zbp/zbp-api.html.

[13] **Source**: https://eig.org/distressed-communities/get-the-data/dci-academic-dataset/. Data is for 2020 and costs $500 to download. Should be replicable; Economic Innovation Group (2020) indicate the elements and methodology used to construct the index.

2. Additional measures, using elements not available from ACS

We also summarize two additional measures, that draw from a broad array of sources, beyond the ACS.

6. *Child Opportunity Index* (COI, available at tract level).[14] Developed by Acevedo-Garcia et al. (2015), updated by Noelke et al. (2020). Not replicable. Available only for 2010 and 2015. Intended to measure child educational and other opportunities. Complex, 29-element index, that relies on the 2010 Census, the ACS, and 11 other sources, some for COI elements, others for outcomes used to compute weights. Some elements are non-public; others are assigned zero weight after a weighting exercise, but the creators do not specify which ones. Elements are assigned weights through a complex process, not reproducible from their technical documentation.

7. *Structural Racism Index* (SREI, available at tract level). Developed by Dyer et al. (2023). Not realistically replicable. Available only for 2019. Intended to quantify disparities in the distribution of neighborhood resources that shape ethno-racial health inequities. Highly complex index, includes 49 measures drawn from ACS and 10 other sources, so very difficult for users to replicate.

Table App-4, Panel B, includes selected correlation coefficients between the area-SES measures studied here, Poverty, and the last two measures (COI and SREI). The correlations for both measures with SDI, SVI, and ADI_{std} are generally strong, ranging from 0.852 to 0.879 for COI in 2015; and from 0.798 to 0.888 for SREI in 2019. This suggests that both measures should have predictive strength comparable to the measures we study.

Given the strong correlation between the measures we study and these two measures, it is not clear that the substantial effort needed to construct them for other years and geographic levels would be worthwhile.

D. Comparisons of Individual SES to Area-SES Measures

Research that studies both individual and area-SES, and seeks to estimating the separate effects of each, is rare. The usual challenge is finding a dataset that includes both. Exceptions (using U.S. data unless otherwise indicated) include Subramanian et al. (2005); Moss et al. (2021); Ingleby et al. (2020) (UK data); Buajitti. Chiodo, and Rosella (2020). At the level of individual elements, the correlations between individual and area measures are often modest (e.g., Christine et al., 2017).

E. Monotonicity

We would expect a good area-SES measure to have predictive power for most health outcomes that is monotonic across the SES spectrum. However, there is no reason to expect predictive power to be linear. There may be outcomes for which area-SES has predictive value primarily for part of the SES spectrum. Moody, Darden and Pigozzi (2017), who study child blood

[14] **Source**: https://www.diversitydatakids.org/child-opportunity-index. The website provides zip-code estimates, but these are built using a crosswalk from track to zip-code, rather than build directly at the zip-code or ZCTA level.

lead levels in Detroit, provide an example. There may be outcomes for which the gradient in predictive power of an area-SES measure is much stronger at the very bottom (or top) of the SES distribution than elsewhere. Diabetes prevalence in 2000, discussed below, provides an example. There may also be outcomes for which higher area-SES predicts worse outcomes. Yu et al. (2014) provide an example, involving lung cancer incidence rates, which presumably relate to smoking uptake rates decades earlier.

F. Prediction versus Causation

The association between area-SES and health outcomes is likely to be causal, in part, but only in part. Part of the reason that area-SES is associated with individual SES, which is usually not directly measured. Causation can run from both individual and area-SES to health and from health to individual and area-SES. The extensive literature includes, e.g., Deaton (2003); Evans and Snyder (2006); Krieger et al. (2005); Ludwig et al. (2011).

II. Available Data, Correlations, and Domains for Area-SES Measures

A. Geographic Levels

We construct SDI, SVI, ADI, and TDI, and measure Poverty, using ACS data at the Census block group, Census tract, ZCTA, and county levels. We map the ZCTA level measures to zip codes using standard crosswalks, see details below.

Census tracts are chosen to have relatively homogeneous populations.[15] Tract size averages 4,500 persons (in 2020); the Census Bureau splits tracts if population would otherwise exceed 8,000. Block groups are geographically compact subdivisions of tracts which average around 1,500 persons. Most but not all Census tracts are inside a single ZCTA. Most populated ZCTAs can be mapped 1:1 to zip codes, although not every resident of a ZCTA will live in the corresponding zip code.

We construct the following area-SES measures. For additional details, see Professor Black's website (go to https://www.law.northwestern.edu/faculty/profiles/bernardblack/; click on "datasets").

B. Available Area-SES Measures and Years

For SVI, we provide both the original measure (SVI) and a modified version (SVI_{mod}), where we drop some elements (percent children, percent elderly, percent non-English speakers, percent minority). In the table below, SVI_{2020} refers to the 2020 CDC version of SVI, which changes some elements. We report both SVI and SVI_{2020} for 2020-2021. $SVI_{2020, mod}$ starts with the SVI_{2020} variables, and then drops the same four as for SVI_{mod}.

For ADI, we provide:

a standardized version (ADI_{std}), that uses standardized elements, to which we apply the Singh (2003) factor loadings;

[15] Source: https://catalog.data.gov/dataset/census-tracts-20101.

a modified version (ADI_{mod}), with standardized elements and factor loadings that are specific to each year and geographic level;

a *non-standardized* version of ADI (ADI_{orig}), that uses non-standardized raw elements, Singh (2003) factor loadings, and uses Median Family Income (the variable indicated in Singh (2003) and on the ADI website), instead of Median Household Income (the variable actually used to construct the ADI reported on the ADI website), except for 2015-2016, where only Median Household Income is available;

For block-group level 2013-2021, we also provide a non-standardized version of ADI ($ADI_{orig, mhi}$) where we use Median Household Income for all years. This is the closest match to non-standardized ADI as reported on the ADI website.

If one is going to use ADI, we recommend using either ADI_{std} or ADI_{mod}.

Summary of Area-SES Measures that We Construct

Measure	Description
SDI	Graham Social Deprivation Index
SVI	CDC Social Vulnerability Index, using the SVI elements used through 2018, not reflecting the change in elements in 2020
SVI_{mod}	Modified version of SVI, which excludes the SVI elements for percent children, percent elderly, percent non-English speakers, and percent minority
SVI_{2020}	2020 CDC Social Vulnerability Index
$SVI_{2020,mod}$	Modified version of SVI_{2020}, which excludes the SVI elements for percent children, percent elderly, percent non-English speakers, and percent minority
ADI_{std}	Area Deprivation Index version, built using standardized elements
ADI_{mod}	Modified version of ADI_{std}, using factor loadings computed for each year and geographic level
ADI_{orig}	Area Deprivation Index, built using non-standardized elements. Differs slightly from the ADI measure as reported on the ADI website; see discussion below of why we could not fully replicate ADI.
$ADI_{orig, mhi}$	Area Deprivation Index, built using non-standardized elements and Median Household Income instead of Median Family income. Median Household Income is the measure that ADI actually uses, even though the ADI website and documentation says they use Median Family Income
TDI	Townsend Deprivation Index
Poverty	Percent of population with family income below 100% of the federal poverty limit

Data needed to construct the area-SES measures is generally available for the indicated years and geographic levels:

Geographic level	Years available
County	2000, 2010-2021
ZCTA and zip-code	2000, 2011-2021
Census tract	2000, 2010-2021
Census block group	2000, 2013-2021

Data Missingness and Imputation

We worked hard to reduce data missingness. When an element was not available, we looked for and generally found an acceptable substitute at the same geographic level. These efforts result in over 99% coverage at all geographic levels for SDI, SVI, and TDI. Missingness is a larger issue for ADI, especially at block-group level; imputation is needed.

We did not impute area-SES values that were initially missing. There are two natural ways to conduct imputation. The first is downward imputation from a broader geographic level to a narrower geographic level that is entirely embedded in the broader level (for example, from tract to block-group) or that is mostly embedded in the broader level (for example, from ZCTA to tract, or from county to ZCTA) when a value is missing at the narrower geographic level. One can either impute just the missing element(s) and then compute the area-SES measure, or impute the value of the area-SES measure. The second uses data from the non-missing elements for the area with missing data, plus data from areas with complete data, to predict the value of the missing element. We did not compare different imputation approaches.

Reported ADI uses downward imputation to the block-group level, apparently of the full measure, not only the missing elements. The other measures have very few missing values; the SVI and SDI websites do not discuss imputation to lower levels.[16]

Reported Area-SES Measures

The data available from Professor Black's website includes the original measures, as downloaded from the SDI, SVI, and ADI websites. These are the only measures, geographic levels, and years available from the original websites. There is no TDI website. ADI is reported at block-group level. SVI is reported at county and tract levels. SDI is reported at county, ZCTA, and tract levels.

Measure	**Description**
$ADI_{rep\text{-}v4.01}$	ADI for 2020-2021, version 4.01. This is the version that was available on the ADI website as of October 26, 2023
$ADI_{rep\text{-}v4}$	ADI for 2020-2021, version 4.0. This version is no longer available from the ADI website; it has since been replaced with v.4.01.
$ADI_{rep\text{-}v3.2}$	ADI for 2020, version v.3.2, downloaded from the ADI website in 2022. No longer available from the ADI website.
$ADI_{rep\text{-}v3.1}$	ADI for 2015 and 2019. The 2019 ADI is no longer available from the ADI website.
SVI_{rep}	SVI as reported for years 2000, 2010, 2014, 2016, 2018
$SVI_{rep,2020}$	SVI as reported for 2020
SDI_{rep}	Graham Social Deprivation Index reported on Graham Center website for 2012 and 2015-2019.

B. Correlations Between Area-SES Measures

Table App-4, Panel A, supplements text Table 2, and reports a broader set of correlations between area-SES measures and Poverty. Panel B reports correlations between our area-SES measures and Poverty and two other measures, COI and SREI.

[16] The Graham SDI imputes SDI values from block-group and tract level upwards to construct values for Primary Care Service Areas. Butler et al. (2012).

C. Domains and Comparison of Domain Weights Across Measures

We divide the area-SES measures into five domains covering education; income/poverty; household composition; housing; and transportation. The Trinidad et al. (2022) overview of area-SES measures uses the same five principal domains, plus three others used in only a few measures: race-ethnicity (included only in SVI; we place it in the household composition domain); language (included only in SVI, we place it in the household composition domain); and insurance (included in SVI_{2020}; we place it in the income/poverty domain).

In Table App-4, Panel C, we report for each SES measure the number of elements in each of the domains listed in Table 1 (education; income/poverty; household composition; housing; transportation; and other) and the weight that each domain receives as part of the overall measure. The discussion below focuses on SDI, SVI, and ADI_{std}. We obtain the weights as follows:

> SDI: We rescale the factor score coefficients to sum to 1. Then, we calculate the domain weight by summing the rescaled factor score coefficients within each domain. We used SDI tract-level factor score coefficients for 2020.
>
> ADI_{std}: We compute domain weights in a manner similar to SDI, except that we first reverse the sign on negative factor score coefficients (for elements where higher values predict less deprivation). We use Singh's 2003 factor score coefficients, which are the coefficients used in ADI for all years.
>
> ADI_{mod}: Similar to ADI_{std}, except we use tract-level factor score coefficients from 2020.
>
> TDI relies on four normalized elements, weighted equally, so each element has 25% weight.
>
> SVI uses centiles for each element, weighted equally, so the domain weights is the fraction of elements in a particular domain.

As Panel C indicates, the weights given to a specific domain can differ greatly across indices. For example, the weights on the household domain range from 3% for ADI_{mod} to 40% for SVI. The weights on income/poverty vary from 18.75% for SVI_{2020} to 50% for ADI_{mod}. Yet as we saw in the text, the performance of these three measures is similar notwithstanding differences in elements and large differences in domain weights.

III. SDI: Details and Replication

SDI is built using factor analysis applied to 9 initial elements. Two elements, percent Black and percent "high needs," are discarded after factor analysis due to factor loadings less than 0.60.

SDI values are available from the Graham Institute website, for 2012 and 2015-2019 at tract, ZCTA, county, and primary care service area levels. The same elements are retained across years, even though some factor loadings can be modestly below 0.60 for some years or geographic levels. The SDI creators were aware of the TDI elements and included similar elements, with some variations. For instance, SDI uses percent *non*-employed instead of the TDI element of percent *un*employed, because the non-employment rate correlated more strongly with the other SDI elements.

We compared our constructed SDI to the reported SDI values for 2012 and 2019 at tract level. We were able to closely replicate the downloaded values, with Pearson correlation coefficients at tract level of 0.9924 in 2012 and 0.9981 in 2019.[17]

IV. SVI: Details, Modified SVI, and Replication

SVI was developed by the Centers for Disease Control and Prevention (Flanagan et al., 2011). It was originally developed as a measure to assess need for disaster relief, but has since been often used as an area-SES measure as well. It is reported biannually.

A. Replication of SVI

SVI values for 2000, 2010, 2014, 2016, 2018, and 2020 are available from CDC.[18] CDC posts SVI, and several "themes" (similar but not identical to our domains) as percentile ranks score on a 0-1 scale, to 4 decimals. We measured the correlation between our SVI centile measure and reported SVI (call this SVI_{rep}), and found very high perfect correlation (0.997 or higher) for 2014, 2016, 2018, and 2020.

We obtained lower correlation of 0.973 for 2000. This reflects an error in SVI_{rep}. We replicated the raw values for the SVI elements, as reported on the CDC website, and confirmed that the reported percentiles for some elements are not consistent with the raw element values.

B. Original versus Modified SVI

We created a modified SVI (SVI_{mod}) that excludes four elements that we believe are not appropriate elements of an area-SES measures: percent elderly, percent children, percent minority, and percent non-English speaking. Our reasoning for preferring SVI_{mod} over SVI, and a similarly modified version of SVI_{2020} over the original version, is as follows.

Percent elderly and percent children could be sensible measures for the original SVI use, as a guide to need for disaster relief, but we do not view them as sensible SES measures from a conceptual level. For percent elderly, the SDI developers found, and we confirm, that this element loads opposite to the overall SDI measure - areas with higher percent elderly are richer, not poorer (Butler et al., 2012). See Table App-3. Percent children loads nonmonotonically across SDI quintiles in 2000, and is relatively flat in 2020 (Table App-3). Note too that the income and household domain elements will already capture the tendency for large families to be poorer.

A more controversial choice we make for SVI_{mod} is to also exclude percent minority and percent non-English speaking. We believe that minority status is better handled as a separate potential dimension of need, rather than bundled into an overall SES measure. Trinidad et al. (2022) report that most area-SES measures do not include a race/ethnicity element, and explain that use of race/ethnicity in an area-SES measure is controversial. We note that, as a general matter, Blacks are often in worse health than Whites, while Hispanics and Asians are in better

[17] Source: https://www.graham-center.org/rgc/maps-data-tools/sdi/social-deprivation-index.html, For several elements, we had initial questions about the differences between the element definitions in Butler et al. (2012) and the definitions stated on the SDI website. We were able to reconcile these discrepancies through discussion with the SDI developers; the developers have since corrected the website definitions.

[18] Source: https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html.

health than Whites (see Table 4 on all-cause elderly mortality). Asians are also often relatively high-income. Thus, the logic of combining these groups into percent minority is unclear.

We prefer to also exclude percent non-English speaking because this element is related to minority status, especially Hispanic and Asian.[19]

Our preference for measuring racial/ethnic status separately from SES begs the question of what one should do if one has a dataset where race/ethnicity is not coded, or is not coded reliably. Given background knowledge that when predicting health measures, percent Black may predict very differently than percent Hispanic or percent Asian, we still would not prefer the original SVI. It might make sense to add separate covariates for percent Black, percent Hispanic, and percent Asian.

C. Differences Between SVI and SVI_{mod}: Correlations and Domain Weights

Our modifications to SVI result in the elements of SVI_{mod} being very similar to the SDI elements (Table 1). All of the elements we would remove are in the household domain; the modification reduces the high weight that SVI places on this domain (see Table App-4, Panel C), and brings the domain weights closer to SDI. These modifications increase the already high correlation between SDI and SVI at county and ZCTA levels, but turn out to only slightly affect correlations at tract and block-group levels (Table App-4, Panel A).

D. Comparison of Performance of SVI and SVI_{mod}

SVI and SVI_{mod} correlate highly (Table App-4, Panel A). Comparative performance is similar, as one would expect given the high correlations.

In Figure App-3, we compare the predictive power of ventile estimates of SVI and SVI_{mod} at different geographic levels. SVI_{mod} tends to have bigger coefficients than SVI at zip-code level. Differences in coefficients between SVI and SVI_{mod} are smaller at narrower geographic levels.

For drug overdose deaths, we also report results for SVI_{2020} and $SVI_{2020,mod}$ (Table App-14). The coefficients for both measures are similar to each other and to the pre-2020 measures.

V. ADI: Replication and Comparison of ADI measures

A. Overview

The ADI includes 17 elements. It is intended for use solely at block-group level; the ADI website states that "other geographic units . . . will not be valid."[20] The Neighborhood Atlas website reports ADI values for 2015, 2020, and 2021. ADI uses factor analysis of the 17 elements, but oddly (i) uses non-standardized elements; and (ii) relies on loadings for each element from Singh (2003), who computes tract-level loadings using 1990 Census data. Lack of standardization

[19] The correlation at ZCTA level between percent minority and percent non-English speaking is 0.556 in 2000 and 0.521 in 2020.

[20] Source: https://www.neighborhoodatlas.medicine.wisc.edu/ (last visited July 15, 2023). Available years are 2015, 2020, and 2021. A fuller quote: "Census Block Group is considered the closest approximation to a "neighborhood". As such, . . . other geographic units (including 5-digit zip-codes, ZCTA, and others) will not be valid."

is not apparent from the ADI website or published work by the ADI developers. We were unaware of it until it was highlighted by Hannan et al. (2023) and Petterson (2023). Use of stale factor loadings is also not apparent from the ADI website. [21]

As Petterson (2023) shows, non-standardized ADI (ADI_{orig}) is an index driven by two elements, median home value and median family income, rather than a true multi-component index. ADI_{orig} has very low values for Cronbach's alpha, a standard measure of construct validity for a multi-item measure (Figure App-15). We study a version that uses the ADI factor loadings, applied to standardized elements (mean 0, standard deviation 1); we call this ADI_{std}. We prefer, however, a modified, standardized version (ADI_{mod}) that uses factor loadings computed for each geographic level and year, which we call ADI_{mod}. We prefer ADI_{mod}, because updated factor loadings, computed at the same geographic level as the measure, have stronger theoretical justification. In practice, ADI_{std} and ADI_{mod} have similar predictive power (Figure App-2). This reflects the time-persistence of area-SES levels (Niles et al., 2015) and implies that precise loadings have little effect on predictive power.

ADI as reported on the ADI website (ADI_{rep}) could not be replicated for 2020 and 2021. The Neighborhood Atlas researchers declined to cooperate with our replication effort. The ADI_{orig} values that we computed are close to the reported values for 2015, but not for 2020 and 2021.

Hannan et al. (2023) and Azar et al. (2023) report poor performance of ADI_{orig} in areas with high housing costs; Powell, Sheehy and Kind (2023) respond. Petterson (2023) criticizes lack of standardization.

B. Comparison of ADI_{orig} and ADI_{std}

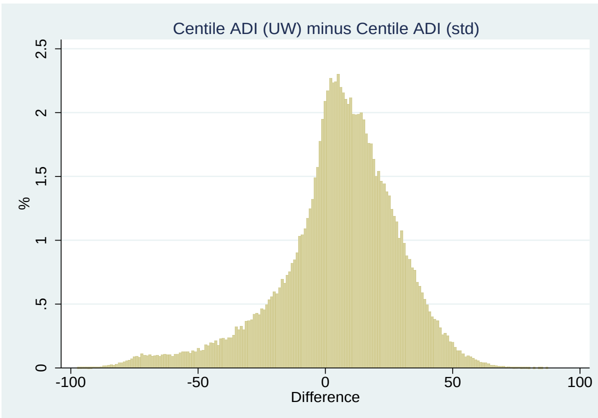
As Petterson (2023) documents, non-standardized ADI_{orig} is basically a two-element measure, for which the elements are median home value and median *household* income. There are very large differences between ADI_{orig} and ADI_{std}. Figure ADI-1, Panel A, provides a histogram showing the differences between the two versions for 2020. For this graph, we use ADI_{orig} as currently reported on the ADI website. This is based on code they call version 4; see discussion below of the differences between different ADI code versions. Manifestly, there are large differences between the original and standardized versions.

[21] A recent article by Neighborhood Atlas researchers, Hunt et al. (2021), at e2502, refers to Kind et al. (2014) and Kind and Buckingham (2018), which use the original Singh factor loadings, as containing "complete methods for construction of ADI."

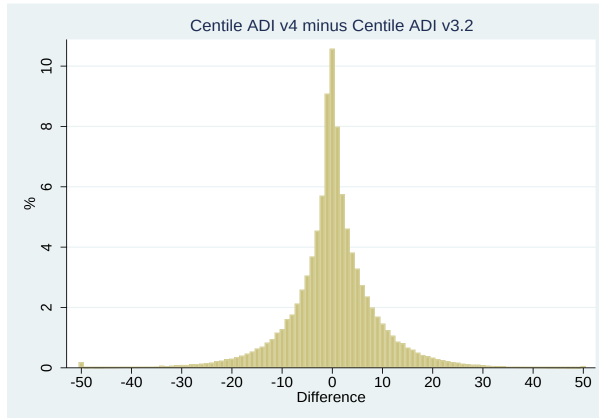
Figure ADI-1

Figure provides histograms of the differences between $ADI_{rep\text{-}v4}$ and ADI_{std} (Panel A), and between $ADI_{rep\text{-}v4}$ and $ADI_{rep\text{-}v3.2}$ (Panel B). For Panel B, differences of 50+ points are shown as vertical bars at the left and right edges of the graph (only visible on the left-hand edge).

Panel A. $ADI_{rep\text{-}v4}$ minus ADI_{std} for 2020



Panel B. $ADI_{rep\text{-}v4}$ minus $ADI_{rep\text{-}v3.2}$ for 2020



C. Comparison of ADI_{orig} to reported ADI

Even after we realized that the reported ADI is not standardized, replication was challenging, made harder because the ADI creators did not cooperate with our replication effort.

ADI is reported as centile values, but not raw values, by the University of Wisconsin, Center for Health Disparities Research, at block-group level and 9-digit zip-code level, for 2015, 2019, 2020, and 2021.[22] We compared our constructed ADI measures (ADI_{orig}, ADI_{std}, and ADI_{mod}) centiles for 2015 and 2020 at block-group level, for block-groups for which we have no missing values, to the reported values (ADI_{rep}). For 2015, replication was almost perfect, with a Pearson correlation coefficient between our centiles for ADI_{orig} to the reported centiles for ADI_{rep} of r = 0.9970. If we recompile their centiles, the correlation becomes 0.9998.[23] In 2015, their variable median *family* income is not available at block-group level, so we substituted median *household* income, which was available. Median household income must be the variable they use across years, as reported by Petterson (2023), who replicated ADI for 2020.[24] With this substitution (call this version $ADI_{orig,mhi}$) we can achieve near-perfect correlation with ADI_{rep} in 2019 (r = 0.9973), and strong correlation between ADI_{orig} and ADI_{rep} without this substitution (r = 0.9885).

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[22] Source**:** https://www.neighborhoodatlas.medicine.wisc.edu. This website contains data for 2015, 2020, and 2021. It previously reported 2019 values, which we downloaded while they were available.

[23] We use Stata command "xtile newvarname=oldvarname, nq(100)" to recompile the ADI reported centile values for the block-groups with no missing data. Since Stata only has reported centile values (1 ~ 100) to work with, it will move some block-groups from the reported centiles to adjacent centiles, so that the recompiled centiles have equal numbers of block-groups.

[24] Petterson replicated ADI for 2020 created using ADI code version 3.2 (which we call $ADI_{rep\text{-}v3.2}$). He would presumably have failed, as we did, to closely replicate ADI for 2020 created using ADI code version 4 (which we call $ADI_{rep\text{-}v4}$).

However, even after substituting median household income for median family income, we could not closely replicate the 2020 and 2021 versions of the $ADI_{rep\text{-}v4}$, with correlations of 0.9339 for 2020 and 0.9353 for 2021. Eventually, after substantial effort, we believe we understand why. The ADI creators initially posted ADI for 2020 created using a code they called version 3.2.[25] They later substituted a different version using code they called version 4.0, and explained that this was a minor change:

> Construction of the version 4.0 ADI has minor standard shrinkage statistical updates included to mitigate the effect of year-to-year sampling variations in block-group level component estimates within American Community Survey (ACS) data. This results in very little actual change in ADI ranking but buffers from known and future expected variation in ACS source data.

This statement notwithstanding, there are large differences between the v3.2 and v4.0 versions of ADI for 2020 (call these $ADI_{rep\text{-}v3.2}$ and $ADI_{rep\text{-}v4}$). We had downloaded $ADI_{rep\text{-}v3.2}$ before it was removed from the ADI website. If we replace median family income with median household income and compare our $ADI_{orig,mhi}$ for 2020 to $ADI_{rep\text{-}v3.2}$, replication succeeds ($r = 0.9903$). However, the correlation between their versions - between $ADI_{rep\text{-}v3.2}$ and $ADI_{rep\text{-}v4}$ - is only $r = 0.9448$. This explains why we could not replicate $ADI_{rep\text{-}v4}$.

Figure ADI-1, Panel B provides a histogram of the differences between their two versions. Differences of 50+ points are shown as vertical bars at the left and right edges of the graph (only visible on the left-hand edge). Many values differ by 10 points or more, a fair number by 20 or more, and a few by 50 or more.

In September 2023, after we conducted this analysis, the ADI purveyors removed the data prepared using version 4.0 from their website and replaced it with version 4.01, with no explanation of the differences between the two versions. The correlation between version 3.2 and version 4.01 is much higher than that between version 3.2 and 4.0, and suggests that there was a coding mistake in version 4.0, which was corrected in version 4.01. Version 4.01 is still not standardized and, although correlation with version 3.2 is higher, is still not replicable because the "sampling shrinkage" procedure is not stated and, as for prior versions, their code is not posted.

D. Performance of ADI_{orig}

Given the large differences between ADI_{orig} and ADI_{std} shown in Figure ADI-1, we expected to find substantial differences in performance between the two measures. To our surprise, the differences for most of our outcomes were limited. In Figure App-2, we compare the predictive power of ventile estimates of ADI_{orig}, ADI_{std}, and ADI_{mod} at block-group levels. We discuss zip-code level results; the Figure includes results at other geographic levels, which are consistent with the zip-code level results.

For COVID-19 mortality, all-cause elderly mortality, and diabetes prevalence in 2019, there are only small differences between ADI_{orig} and ADI_{std}. For diabetes prevalence in 2000 and incidence over 2000-2005, there is a sharp upward tilt in coefficients for ventiles 19-20, across area-SES measures (Figure 1), which is not captured by ADI_{orig}. And for drug-overdose mortality, ADI_{orig} has no predictive power, in contrast to ADI_{std} and the other area-SES measures.

[25] Neither this nor their other code versions is publicly available.

That results are similar for ADI_{orig} and ADI_{std} for some outcomes says much about the relative insensitivity of predictive power to how an area-SES measure is constructed, for at least some outcomes. Still, there is no good reason to use ADI_{orig}, which is not truly a multi-domain measure and performs either similarly to ADI_{std}, or worse, depending on the outcome.

E. Comparison of ADI_{std} and ADI_{mod}

At the zip-code level, ADI_{std} and ADI_{mod} generally perform similarly. Differences tend to be larger at broader geographic levels: county level coefficients for ADI_{std} and ADI_{mod} differ more than those at narrower levels. However, trends across ventiles are similar.

F. ADI_{mod} is Highly Correlated with Poverty

Of the 15 ADI measures, 6 are within the income/poverty domain. Six more are within the housing domain; of these several relate closely to income (median home value, median gross rent, median monthly mortgage). This heavy weight on poverty-related measures is unique to ADI_{std} among the measures we study. It leads to ADI_{std} correlating highly with Poverty, and ADI_{mod} even more so. See Table App-4. In effect, ADI_{std} and ADI_{mod} are less multi-domain than they seem on the surface, due to the heavy weighting of income and poverty measures.

VI. Data and Methods

We discuss here our datasets and regression methods. See Table App-5 to Table App-8 for summary statistics.

A. Datasets

Medicare FFS Beneficiaries: 5% Random Sample

For several outcomes, we rely on a national 5% random sample of Medicare fee-for-service beneficiaries over 1999-2019 (50 states plus D.C. and Puerto Rico); principally on the 1,366,366 beneficiaries aged 66+ as of January 1, 2000, and the 61,745 beneficiaries aged exactly 66 as of January 1, 2000, with at least one claim in 1999. These data include all Medicare Part A (hospital) and B (outpatient and provider) claims as well as age, gender, race/ethnicity, 9-digit residence zip-code through 2014 (which we map to block-group and tract), 5-digit zip-code for 2015 on, and county SSA code. We use a one-year lookback to measure comorbidities; thus when studying diabetes prevalence in 2000 and 2019, we measure comorbidities using claims from 1999 and 2018.

COVID-19 Elderly Mortality Sample

To study COVID-19 mortality at zip-code level, we rely on individual death certificates for the State of Wisconsin, the State of Indiana, and Cook County, Illinois (Chicago and nearby suburbs) (together, "Three Midwest Areas,") for 2020 through March 31, 2022, including age, gender, race/ethnicity, and residence zip-code. These three areas have different and diverse demographics and a combined population of around 18 million, including around 45,000 COVID decedents. Table App-2 provides summary statistics for this dataset.[26] To study COVID-19 mortality at county level, we rely on individual death certificates for 2020 for the entire U.S. from the National Center for Health Statistics, including age, gender, race/ethnicity, and residence county (zip-code is not available).

Drug Overdose Deaths over 2017-2021 Sample

To study drug overdose mortality in Indiana and Illinois over 2017-2021, we rely on individual-level datasets from each state's vital records department. Drug overdose mortality is measured based on ICD-10 codes X40-X44 (unintentional), X60-X64 (suicide), X85 (homicide), and Y10-Y14 (undetermined).

Census and American Community Survey (ACS)

We obtain the elements of the area-SES measures at all four geographic levels from the 2000 Census and the American Community Survey (ACS) for 2010-2021 (block-group data available starting 2013, ZCTA data starting 2011). Data for the area-SES measures is essentially complete at county and ZCTA levels, but is sometimes missing at tract level, and more often missing at block-group level. We studied performance at each level using the available data, without imputing missing data downward from the next broader level, we felt that imputation would compromise our effort to determine whether measure performance is stronger at tract or block-group level.[27] We rely on crosswalks between geographic levels and datasets; see Appendix for details.

B. Choice of Covariates

The aim of this project is to assess the comparative strength of area-SES measures to predict health outcomes, controlling for individual level covariates, especially demographic information, available in the datasets we relied on. We sought to use a reasonably comprehensive set of covariates, so that we would be measuring the power of an area-SES measure in addition to individual-level information, rather than simply the association of an area-SES measure with the individual information that is often available in health datasets, while also being mindful of the potential cost, in reduced degrees of freedom, of including too many covariates, or doing so in too flexible a form.

For all outcomes, we obtain demographics from the Medicare FFS dataset and mortality datasets from which we obtain health outcomes. We used ICD-9/ICD-10 codes to define comorbidities.

All logistic models include gender (in the logistic regressions, we include a dummy variable for Male, with Female as the omitted category); a categorical variable for race/ethnicity. For the Medicare datasets, we use the following categories, which are the only ones available: Black, White, Asian, and Hispanic, and Other. We include dummy variables for each, with White as the omitted category. The mortality datasets include separate variables for race and ethnicity; we use these to define categories of Black (whether Hispanic or not), Hispanic (non-

[26] For more details on this dataset and how we measure COVID-19 mortality, see Barreto-Parra et al. (2022).

[27] Exception: For the revised 2020 SVI at block-group level, we impute tract-level data for housing cost burden, which is not available from ACS at the block-group level.

Black), Asian (non-Hispanic), White (non-Hispanic), and Other (non-Hispanic), and again use White as the omitted category in regressions.

For all-cause elderly mortality over 2000-2019, the sample is people aged 66 as of January 1, 2000, so the regression model does not include age. For the other outcomes, we capture age using a cubic polynomial, which we determined to be sufficiently flexible to to capture the non-linear relationship between our outcomes and patient or decedent age. For outcomes limited to the elderly, we measure age relative to 65.

We allow for gender effects to be heterogeneous with age and race/ethnicity by including gender directly and also interacting gender (in regressions, the male dummy variable) with the cubic polynomial for age with race/ethnicity.

For drug overdose mortality over 2017-2021, we also include an Illinois dummy variable (Indiana is omitted), to account for differences in drug overdose rates between the three Midwest areas.

For the area-SES measures, we opted for fitting quintiles and ventiles, to allow for a nonlinear relationship between the area-SES measures and health outcomes. Our judgment, after also considering deciles as intermediate between quintiles and ventiles, is that quintiles will often be sufficient to capture SES marginal effects when SES is used primarily as a regression covariate but is not the focus of the analysis. Using area-SES deciles would also be a reasonable choice. Ventiles allow capture of finer differences in the predictive power of the area-SES categories across the full range of SES levels, but require more regressors (nineteen, versus four for quintiles), which will lead to greater noise in coefficient estimates. We also evaluated centiles but found that using these fine divisions led to noisy estimates for individual centiles.

C. Outcome Measures

Our outcomes are binary, so we estimate them using logistic regression, and then convert the logit coefficients to marginal effects. All models use heteroskedasticity-consistent standard errors.

COVID-19 Mortality for the Elderly (age 65+)

We study COVID-19 mortality for the elderly at zip-code level in the Three Midwest Areas, using the 2019 area-SES measures.[28] The outcome measure is a dummy variable for death due to COVID-19. The sample is 35,114 COVID-19 decedents aged 65+ (roughly 77% of all COVID-19 decedents) plus a synthetic population of non-decedents, based on our Medicare-FFS sample for 2018, grossed up (using frequency weights in regressions) to match population counts derived from ACS data for 2019. We run a logit regression on this sample of COVID-19 mortality from March 1, 2020, through March 31, 2022, using eqn. (1).

$$Mortality_i =^{logit} \alpha + SES_i * \beta + X_i' \gamma + \epsilon_i \qquad (1)$$

[28] We lack the data needed to study the tract and block-group levels, and have too few counties to make county-level analysis sensible. We study the elderly population because for the non-elderly, we can obtain data from the ACS on SES or on race/ethnicity, but not on both at the same time. See Table App-5 for summary statistics.

Here i indexes individuals, SES_i is an area-SES measure, $\boldsymbol{X}_i$ is a covariate matrix, ϵ_i is the error term. In some specifications, we include Poverty as an additional predictor variable.

All-Cause Elderly Mortality Over 2000-2019

We study all-cause mortality for Medicare FFS beneficiaries aged 66 as of January 1, 2000, using the 2000 area-SES measures.[29] We use both a logit model similar to eqn. (1), where the outcome is mortality by year-end 2019, and a Cox proportional-hazard model, using the same covariates. The outcome is death at time *t*, measured in quarters of a year.

$$Cox\ Model\colon\ S_i(t|X_i) = S_0(t)^{\exp\{SES_i * \beta + X_i'\gamma\}} \qquad (2)$$

Here i indexes individual Medicare beneficiaries; $\boldsymbol{X}_i$ is a vector of covariates and $\boldsymbol{\beta}$ is a vector of the associated coefficients. The covariates are the same as for the logit model.

Diabetes Prevalence in 2000 and 2019; Diabetes Incidence over 2000-2005

We use all Medicare-FFS beneficiaries aged 66+ as of January 1, 2000, and 2019, to study diabetes prevalence, measured using the ICD-9 and ICD-10 diagnosis codes that enter the Charlson comorbidity code list of diabetes, applied to Medicare claims for the prior year. We also use the 2000 sample to study diabetes incidence over 2000-2005 for beneficiaries who survive through 2005.[30] We use dummy variables for Charlson comorbidities that are not caused by diabetes, with and without controlling for Poverty. We use a logit model, similar to eqn. (1), where the outcome is a dummy variable for whether the beneficiary had diabetes.

Drug Overdose Mortality Over 2017-2021

The health outcomes above are limited to the elderly. We also study drug overdose mortality for all persons over 2017-2021, in Illinois and Indiana, using the 2020 area-SES measures.[31]

VII. Measuring and Modeling the COVID Mortality Rate

To estimate the mortality rate (Covid-MR) due to COVID-19 as a function of age, gender, race/ethnicity, and SES, we need both a numerator (number of COVID-19 decedents) and a denominator (population), by age, gender, race/ethnicity, and SES (proxied by SDI quintile). We obtain the numerator for the Three Midwest Areas (Indiana, Wisconsin, and Cook County, Illinois) by age, gender, and race/ethnicity directly from mortality records for these areas.

Constructing an appropriate denominator requires more work. We obtain the denominator by combining information from the Medicare Beneficiary Summary File for 2019, ACS data for 2020 (5-year averages over 2016-2020). We start with population estimates from the 2020 ACS. These estimates are broken down by age ranges, gender, race/ethnicity, and are available at county

[29] See Table App-6 for summary statistics.

[30] See Table App-7 for summary statistics.

[31] See Table App-8 for summary statistics.

and state levels, but not at lower geographic levels.[32] We collapse the available race and ethnicity categories into Black, non-Hispanic White, non-Black Hispanic, Asian, and other. The available age ranges in ACS are: 0-4; 5-9; 10-14; 15-17; 18-19; 20; 21; 22-24; 25-29; 30-34; 35-39; 40-44; 45-49; 50-54; 55-59; 60-61; 62-64; 65-66; 67-69; 70-74; 75-79; 80-84; and 85+. Note that ACS provides only a single count for persons age 85+.

Within each ACS age group we use the annual survival probabilities from the National Center for Health Statistics (NCHS) by age and gender for 2018 (latest available year) (for example, there is roughly a 0.96 probability that a male aged 75 will survive to age 76), to divide the ACS population for the age group (in this example, ages 75-79), by gender, race/ethnicity, and location, into an estimated number of persons age 75, 76, 77, 78, and 79, and thus estimate population in 2020 by age, gender, race/ethnicity, and location POP_{agrl}^{ACS}.[33] We proceed similarly for other age groups.

We also have counts of Medicare fee-for-service (FFS) beneficiaries in 2019 included in our 5% random sample, at zip-code level, with information on age, gender, and race/ethnicity. We combine the ACS and Medicare data to construct a zip-code level synthetic elderly population by year of age, gender, race/ethnicity, and area-SES, within each of the Three Midwest Areas, as follows. Let *a* represent year of age, *g* represent gender, *r* represent race/ethnicity, *l* represent location (Cook County, Wisconsin, or Indiana), *D* represent an area-SES quintile, and *z* represent zip-code. We count the number of Medicare FFS beneficiaries by age, gender, race/ethnicity, and zip-code in 2019, n_{agrz}. We sum these counts across all zip-codes that fall within each area-SES quintile, within each location:

$$n_{agrDl} = \sum_{z \in l,D} n_{agrz}$$

We then use this data to compute multipliers, which we round to the nearest whole number, and use the multipliers to gross up our 5% sample of Medicare beneficiaries, to make it representative of the overall alive population:

$$m_{agrl} = \frac{POP_{agrl}^{ACS}}{\sum_T n_{agrDl}} \times (1 - \ Covid\ MR_{agrl}) \qquad (3)$$

We apply the factor (1 - Covid MR_{agrl}) because, for the mortality estimate below, we will combine this synthetic population of *alive* persons, estimated from the Medicare data, with COVID decedents, to obtain a population of all persons who would have been alive, but for the COVID pandemic.

The multiplier varies by age, gender, race/ethnicity, and location, for several reasons. First, as Medicare beneficiaries die, our dataset is refreshed, to bring it to 5% of the current number of beneficiaries. The newly added beneficiaries are principally newly eligible people aged 65. This results in our Medicare sample generally overweighting younger beneficiaries relative to the

[32] Source https://www.census.gov/programs-surveys/acs/data/race-aian.html. For the available geographic areas, see https://api.census.gov/data/2015/acs/acs5/spt/geography.html. Although data is potentially available at the Census tract level, which could be rolled up to the ZCTA level, in practice there are many missing values at the tract level.

[33] See the system of equations (9) below for age 85+; we follow the same approach for other age ranges.

overall elderly population. Second, Medicare does an imperfect job of capturing race/ethnicity. The multiplier lets us adjust the race/ethnicity proportions in our Medicare sample to make them more population representative. This implicitly assumes that persons identified as Asian in the Medicare sample are representative of all Asians in the population, and similarly for other race/ethnicity groups.

We use this multiplier to gross up our Medicare sample to approximate the number of elderly persons in the population:

$$POP_{agrDl} = n_{agrDl} \times m_{agrl}$$

These estimates are by year of age, but can be rolled up to age groups, and to cover all three locations, as needed for a particular estimate. Figure App-1 shows how the multipliers for each area (averaged across race/ethnicity) vary by age, separately for women (left-hand graph) and men (right-hand graph).

VIII. Crosswalks and Mapping Medicare Counties to Census Counties

A. Crosswalks

We use the following crosswalks between geographic levels and datasets.

9-digit zip to Census block-group and Census tract. We map 9-digit zip-codes, available in our Medicare data through 2014, to block-groups, using a mapping from the University of Wisconsin group that builds the ADI, available for 2015, 2019, 2020, and 2021; we use the 2015 version.[34] Block groups are embedded in tracts; the block-group number includes the tract number.

ZCTA to zip-code. Most ZCTAs map 1:1 to populated zip-codes. We use crosswalks from the American Academy of Family Physicians website.[35] Approximately 98% of the beneficiaries in our Medicare-FFS sample in 2000 live in zip-codes that can be mapped to ZCTAs.

SSA to FIPS county codes. Our Medicare FFS dataset uses Social Security Administration (SSA) county identifiers for beneficiaries for 1999-2014; starting in 2015, it also includes FIPS (Federal Information Processing System) codes. We obtain area-SES measures from Census and ACS, which use FIPS codes. Thus, when applying the area-SES measures to Medicare FFS beneficiaries prior to 2015 at county level, we need to map SSA county codes to FIPS codes. We use 2003 and 2018 crosswalks from the National Bureau of Economic Research (NBER).[36] For each data year, we use the NBER crosswalk that is closest in time to our data.

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[34] In 2000, we can map 1,008,752 (61%) of the Medicare-FFS beneficiaries to tracts with Census measures available; and 1,008,259 (61%) to block-groups with Census measures available. We have no reason to expect bias in our results due to incomplete mapping of beneficiaries to tracts or block-groups. The 2019 crosswalk is no longer available on the ADI website.

[35] Source: https://udsmapper.org/zip-code-to-zcta-crosswalk. We use a 2019 crosswalk to study diabetes prevalence in 2019 and a 2020 crosswalk to study drug overdoses.

[36] Source: https://www.nber.org/research/data/ssa-federal-information-processing-series-fips-state-and-county-crosswalk. The 2018 crosswalk was the most recent available when we carried out this mapping.

B. Mapping Medicare to ACS Counties in 2000

We use the 2003 NBER SSA-to-FIPS crosswalk, which is the earliest available. After correcting the Medicare data, which has two SSA codes for Los Angeles County, we can map 98.3% Medicare beneficiaries to counties with area-SES measures. For counties, we can map 3,219 of 3,235; the remainder are all small.

Loss of sample arises principally because the Medicare FFS Master Beneficiary Summary File (MBSF), which contains the SSA county identifiers, includes 221 SSA codes that appear to be entry errors - they do not correspond to actual counties in the official SSA list.

IX. Measuring Comorbidities

For outcomes that rely on the Medicare FFS sample, we control for comorbidities using individual dummies for each of the 17 conditions included in the Charlson comorbidity measure (Charlson, 1986) . We identify the presence of a comorbidity based on the presence of an ICD code during the year preceding the outcome.[37] When studying diabetes prevalence and incidence, we use comorbidities which, in the judgment of Dr. Meurer, who has expertise in diabetes, are generally not seen as outcomes of diabetes, though they may share obesity as a risk factor.[38]

In Table App-18 we compare results including, versus not including, these comorbidities. For all-cause mortality, the area-SES gradients are substantially larger if we exclude comorbidities; for example, the coefficient for SDI for quintile 5 is 0.1330 versus 0.1016 with comorbidities. However, the relative gradients across different area-SES measures are similar. For diabetes prevalence, including versus excluding comorbidities makes little difference in the coefficients on the area-SES measures.

X. Centiles of the Area-SES Measures

We evaluated whether there was significant additional value in using centiles rather than ventiles for datasets large enough to make use of centiles plausible. In Figure App-13, we compare ventile to centile estimates for SDI, ADI_{std}, and SVI, at zip-code level, for all-cause elderly mortality and diabetes prevalence in 2000. All three outcomes use the Medicare population age 66+ as of January 1, 2000, from our 5% random sample - around 1.7 million people.

For all-cause elderly mortality (Panel A), the centile estimates were much noisier than the ventile estimates, but with similar overall gradients. This suggests limited value in using the centile estimates. However, some oddities emerged. In logit regressions with centiles, the first (highest income) *centile* is omitted. In contrast, with ventiles, the first (highest income) *ventile* is omitted. The coefficients for the second centile had sometimes surprisingly large magnitudes, which varied substantially between measures and between geographic levels. For SDI, for

[37] The Charlson comorbidities are cerebrovascular disease; myocardial infarction; congestive heart failure; peripheral vascular disease; dementia; peptic ulcer disease; diabetes without complications; diabetes with complications; hemiplegia; renal disease; chronic pulmonary disease; rheumatic disease; mild liver disease; moderate or severe liver disease; malignancy including lymphoma and leukemia; metastatic cancer; and aids/HIV.

[38] The Charlson comorbidities we use when studying diabetes prevalence are chronic pulmonary disease; rheumatic disease; mild liver disease; moderate or severe liver disease; malignancy including lymphoma and leukemia; metastatic cancer; and aids/HIV.

example, the second centile estimates at zip, tract, and block-group levels were (-0.05, 0.01, 0.00); for SVI the estimates were (+0.05, 0.12, and 0.03). The large swings between geographic levels and between measures may be driven by small numbers of decedents in each centile. We conclude that the centile estimates are not reliable, even with a reasonably large sample (61,745 beneficiaries aged 66 in 2000, at zip-level).

For diabetes prevalence in 2000, we had a much larger sample of 1,366,366 beneficiaries (at zip-code level), of whom 280,405 had diabetes. For this sample, the centile estimates were generally closer to the ventile estimates. However, ADI_{std} measure tilted up very sharply for the very lowest centiles, while the other two measures did not. We lack a good explanation for the very sharp tilt, given a modest gradient across all other centiles, or for the differences between measures. Here too, these results suggest caution in using centile estimates.

There may be other datasets and outcomes for which centile estimates would perform better, but for the outcomes we studied in these datasets, we prefer the ventiles.

XI. Changes Over Time in Correlations Between Area-SES Measures

Table 2 shows that the Pearson correlation coefficients between area-SES measures are generally lower in 2020 than in 2000, especially at narrower geographic levels. Table App-4 provides additional correlation coefficients. In Figure App-14, we show annual correlations over 2012-2020. There is a general tendency for the correlations between TDI and the other measures to fall over this time period, and to be lowest for TDI-vs-ADI_{std}. The highest correlations are for SDI and SVI, generally around 0.90 at all geographic levels. Given these correlations, one would expect these two measures to produce similar results. The next highest correlations are between SDI and ADI_{std}, which are generally above 0.75. Other pairwise correlations are lower, sometimes substantially so, and leave more room for different measures to have different predictive power.

XII. Defining Quintiles and Ventiles Based on Population

In the text, we define quintiles and ventiles to have approximately equal numbers of geographic units, rather than equal numbers of people. This choice does not matter much for Census tracts and block-groups, which are defined to have populations within a narrow range. However, it can matter for ZCTAs (which we map to zip-codes) and counties. In Table App-9, Panel A, we show, for each SES measure, the population within each ZCTA quintile. Panel B is similar, except shows population within each ventile. Panel C shows the population within each county quintile.[39]

At the ZCTA level, SDI, TDI and SVI all have much higher populations in quintile 5; ADI_{std} has the highest population in quintile 1. The gradients in population are even sharper at county level for TDI and ADI_{std}, but flatten for SVI (Table App-9, Panel C). A natural question, given the differences in population across quintiles weighted by number of ZCTAs, is how our results would change if we instead weighted the ZCTAs so that quintiles or ventiles had roughly equal numbers of people. We explore that question in Table App-10, using all-cause mortality, diabetes prevalence in 2019, and diabetes incidence over 2000-2005 as outcomes.

[39] Because of the poor performance of area-SES measures, measured at the county level, we did not study 5-percentiles at the county level.

For all-cause mortality (Panel A), compared to text Table 3, Panel B, ADI_{std} strengthens, SDI has a similar gradient, but SVI and TDI weaken. For diabetes prevalence in 2019 (Panel B), compared to text Table 3, Panel C, the coefficients on the area-SES measures increase. For diabetes incidence over 2000-2005 (Panel C), compared to text Table 3, Panel E, ADI_{std} is similar; the other measures strengthen. This analysis suggests that there can sometimes be a modest advantage to using population weighting with zip-code level data, but improved predictive power is not seen for all area-SES measures or all outcomes.

XIII. Comparative Performance of Area-SES Measures at Narrower Geographic Levels

In Table App-11, App-12, and App-13, we report marginal effects for area-SES quintiles at Census tract and block-group-levels for the outcomes available at these geographic levels: all-cause elderly mortality, diabetes prevalence in 2000, and diabetes incidence over 2000-2005. TDI has lower coefficients at zip-code level for several elderly health outcomes (COVID-19 mortality, all-cause mortality, diabetes prevalence), but catches up to SVI at tract and block-group levels for diabetes prevalence, and to SDI for diabetes incidence. SVI performs relatively better at zip-code than at smaller levels. The somewhat higher quintile-5 coefficients for SVI relative to SDI or ADI_{std}, when predicting all-cause mortality and diabetes prevalence at zip-code level, do not persist at tract or block-group level.

XIV. County-Level Results

In Table-App 14, we report the predictive power of quintiles of the county-level SES measures for the studied health outcomes. As discussed in the text: (i) county-level coefficients are often (although not always) well below those at zip-code level; (ii) coefficients are often non-monotonic in the middle quintiles (diabetes prevalence in 2019 is an exception). TDI performs especially poorly at county level, except for diabetes prevalence in 2019.

XV. National County-Level Analysis of COVID-19 Mortality in 2020

Our zip-code level data on COVID-19 Mortality is limited to the Three Midwest Areas. We supplement this analysis with national data on COVID-19 mortality, limited to the county level in 2020, in Appendix Figure App-12, Panel A and Panel B. The coefficients on SES ventiles vary widely, with no apparent gradient. This supports the conclusion from the Three Midwest Areas that county level SES is not a useful predictor of COVID-19 mortality.

XVI. Comparing the Area-SES Measures to the Poverty Measure

Prior research found that Poverty (percent of population with income below the federal poverty level) has predictive power comparable to TDI (Krieger et al., 2005) and NDI (Berkowitz et al., 2015). We therefore compared the predictive power of Poverty to the four studied area-SES measures (Figure App-8). We also went beyond a simple comparison of coefficients and ran horse-race regressions. How do the area-SES measures perform, controlling for Poverty, and vice-versa? In the left-hand graphs of Figure App-9, we report ventile graphs for the area-SES measures at zip-code level, controlling for Poverty. The right-hand graphs show results for Poverty, controlling for each area-SES measure.

Across most outcomes, TDI has very little predictive power after controlling for Poverty. Overdose mortality is an exception.

SDI, ADI_{std}, and SVI generally retain predictive power, controlling for Poverty, but their power differed somewhat by outcome. For COVID-19 mortality (Figure App-9, Panel A), ADI_{std} appears to outperform the other measures, but this is deceptive. ADI includes six poverty measures, versus three for SVI and two for SDI. This appears to overcontrol for Poverty. This can be seen in the right-hand graph, where controlling for ADI_{std}, higher Poverty predicts *lower* COVID-19 mortality. For elderly all-cause mortality (Figure App-9, Panel B), ADI_{std} and SDI predict strongly after controlling for Poverty, but SVI predicts weakly. For diabetes prevalence in 2000 and 2019 (Figure App-9, Panel C and D), all three measures predict well. For diabetes incidence (Figure App-9, Panel E), SDI and ADI_{std} have similar gradients, but SVI is non-monotonic, reaching a minimum for ventile 5. For overdose mortality (Figure App-9, Panel F), SDI and SVI predict overdose mortality with similar strength and gradients, but ADIstd predicts negatively, especially for middle ventiles.

Overall, SDI, ADI_{std}, and SVI retain substantial power, controlling for Poverty. This provides evidence that the other measures capture aspects of SES that predict health outcomes, beyond Poverty alone. However, ADI_{std} tends to overcontrol for Poverty, leading to the odd result, across several outcomes, that for people with similar ADI_{std} levels, greater Poverty predicts better health outcomes.

In the right hand graphs, we report coefficients for Poverty ventiles, controlling for each of the area-SES measures. Poverty generally performs poorly controlling for SDI, SVI, or ADI_{std}, although often respectably controlling for TDI.

Figure App-10 is similar to Figure App-9, but is at tract level, and is limited to the three outcomes available at tract level: all-cause elderly mortality, diabetes prevalence in 2000, and diabetes incidence over 2000-2005. Results are consistent with those at zip-code level. For all three outcomes, ADI_{std}, SDI, and SVI all have predictive power, while TDI has almost no predictive power.

XVII. Additional Analyses for Overdose Deaths

We conducted several additional analyses for drug overdose deaths. First, in unreported results for all drug overdose deaths, we limited the sample to decedents ages 12+.[40] Results were almost unchanged from those reported. Second, we studied overdose deaths involving natural or synthetic opioids ICD-10 codes T40.0-40.4 and T40.6). These accounted for 74.7% of all overdose deaths. See Table App-19 for results, which are similar to those reported in the text. This table also shows results separately for all persons and for ages 12+.

XVIII. Results for Medicare Spending

In addition to the health outcomes reported in the text, we also examined a spending outcome: Medicare-FFS spending per beneficiary. We define Medicare spending as the sum of Medicare Part A and Part B spending in 2000 and 2019 for all beneficiaries aged 66+ as of January

[40] Drug Overdose deaths for individuals aged 0-11 are 36, of which 21 are opioid-related deaths. Total deaths for overdose are 25,333, of which 18,919 are opioid-related.

1, 2000, and as of January 1, 2019, in the 5% national random sample, using the 2000 and 2019 area-SES measures. We report amounts in 2000$.[41]. Since Medicare uses administratively set prices, Medicare FFS spending is, in effect, a measure of healthcare utilization.

We use the same base covariates as for other outcomes, plus Charlson comorbidities measured in 1999 and 2018.[42] We use the OLS analogue to the logit regression in Appendix equation (1):

$$Spending_i =^{OLS} \alpha + \beta * SES_i + \gamma_{i_i} * X_i + \epsilon_i \qquad (4)$$

We relegated these results to this Appendix after finding that the predictive power of area-SES measures is generally small relative to the sample mean and often non-monotonic, especially after controlling for patient comorbidities. See Table App-15 for zip-code level results. Predictive power is also small in 2000 at Census tract and block-group level (results not reported). At the same time, there is a large jump in coefficients for quintile 5 versus quintile 4, which is seen across area-SES measures, but not for Poverty. The quintile coefficients, and the observed jump from quintile 4 to quintile 5, are substantially larger if we do not control for comorbidities.

The modest predictive power of area-SES measures for Medicare spending in 2000 and 2019 is reinforced by the ventile graphs (Figure App-6). At the zip-code level, the ventile estimates for SDI, SVI, and TDI are basically flat through ventile 17 in both years, before tilting up for the lowest-SES ventiles, more strongly for TDI. ADI_{std} takes a negative coefficient across all ventiles for both years, relative to the omitted Ventile 1.

XIX. Construct Validity (Cronbach's Alpha)

Cronbach's alpha is a measure of the internal consistency of a multielement measure, often called construct validity. It measures the correlation between the elements of the measure. Cronbach's alpha depends on the number of elements, the average correlation among them, and the average variance:

$$\alpha = \frac{N * \bar{c}}{\bar{v} + (N-1)\bar{c}}$$

Here N is equal to the number of items, $\bar{c}$ is the average covariance among the elements and $\bar{v}$ is the average variance of the elements. Cronbach's alpha also increases with the average inter-element correlation, holding the number of items constant. Alpha will be low if the average inter-element correlation is low, or the average variance is high,. For a measure designed to use a broad set of elements, rather than many highly similar elements, one rule of thumb from psychology is that α values above 0.7 are considered strong, and values above 0.6 are respectable (Kline, 2000).

[41] We apply a discount rate of approximately 1.48 (CPI July 2022/CPI July 2000) to the amounts of 2019. We use the Consumer Price Index data for all urban consumers, sourced from the website of the Federal Reserve Bank of St. Louis. Link to the data: https://fred.stlouisfed.org/series/CPIAUCSL.

[42] We also include state FE based on prior research, associated with the Dartmouth Atlas project, which we confirm with our data, showing large geographic variation in Medicare-FFS spending per beneficiary, which varies in 2000 from $2,738 in Puerto Rico, and roughly $4,000 in many states, to $7,161 in D.C.

Nunnally and Bernstein (1994) recommend higher values of 0.7-0.8 for applied psychometric research.

Figure App-15 shows Cronbach's α values for each area-SES measure for 2000 and by year for 2011-2021, at tract and ZCTA levels. Values are generally higher at tract level, and fall moderately over 2011-2021. The values are strong for SDI, SVI, and ADI_{std}. They are less satisfactory for TDI, but this reflects the small number of elements rather than low inter-element correlation. The much lower values for ADI_{orig}, around 0.2, are far below normal standards for measure reliability. The low values reflect the failure to standardize elements, and the high variance of the two elements that dominate the non-standardized index.

XX. Absolute and Incremental Pseudo-R^2

A simple measure of the performance of area-SES measures, sometimes used in other studies (e.g., Butler et al., 2012) is R^2 (or for the binary outcomes we study, estimated using logit, pseudo-R^2). We did not use pseudo-R^2 in the analysis in text because it is a crude measure that cannot easily capture modest differences in predictive value, or aspects of measure reliability such as monotonicity. Also, for an outcome where individual outcomes are hard to predict, R^2 will be low, but the information added by an area-SES measure can still be important.

We report results in Table App-20 for pseudo-R^2 for our outcomes, at zip-code and tract levels, both for the area-SES measures used alone, and for incremental pseudo-$R^{2,}$ in which we add an area-SES measure to the other covariates in our regressions and measure the increase in pseudo-R^2. We view incremental pseudo-R^2 as a better fit for our research question, which is about the predictive power of an area-SES measure, when added to other, often available, individual-level covariates. The bottom rows of this table provide averages across outcomes for both the measures used alone and for incremental pseudo-R^2.

At the zip-code level, we can study all six outcomes. There are individual outcomes, for which each of SDI, SVI, and ADI_{std} has higher pseudo-R^2 used alone, and for which each has higher incremental pseudo-R^2. Averaged across outcomes, incremental pseudo-R^2 is 0.25% for SDI, ADI_{std}, and SVI_{mod}, and slightly lower at 0.23% for SVI, but meaningfully lower for Poverty (0.19%), with TDI having the lowest incremental power (0.15%). Thus, the signal from pseudo-R^2 is consistent with SDI, ADI_{std}, and SVI_{mod} all being good measures, with similar predictive power.

At the tract level we can study only three outcomes, all-cause elderly mortality, diabetes prevalence in 2000, and diabetes incidence over 2000-2005. The average predictive power of ADI_{std} is now higher than the other measures, at 0.32% versus 0.26% for SDI and 0.28% for SVI_{mod}. However, this is driven by our not having available, at tract level, the outcome on which ADI_{std} performed much worse than the other measures.

At both levels, both the individual covariates we have available and the area-SES measures contribute importantly to overall pseudo R^2. Compare Basu and Narayanaswamy (2019), who include a broad array of both individual health measures and area-SES elements in a random forest prediction model, and find that individual and area measures contribute importantly to prediction of poorly controlled diabetes.

XXI. Area Under the ROC Curve

Another measure of regression goodness of fit is Area under the Receiver Operating Characteristics, or ROC, Curve (henceforth, AUC). For a binary outcome, AUC is the percentage of correctly predicted outcomes. In Table App-21, we report AUC percentages when predicting our outcomes using area-SES alone, and the increase in AUC when we add area-SES measures to our base set of covariates.

Consistent with the low-pseudo R^2 values in Table App-20, area-SES alone predicts only moderately better than random chance, and area-SES, when added to our other covariates, only slightly improves prediction. SDI, SVI, and ADI_{std} all have higher raw and incremental AUC values than Poverty, with TDI again having the least predictive value.

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Table App-1. Summary of ACS-5-year and 2000 Census Tables used to build each area-SES Measure

Table is an expanded version of text Table 1, which indicates which ACS and 2000 Census tables contain the data for each element, used in each area-SES measure. The ACS tables generally allow us to build the area-SES measures at county and tract levels from 2010-2021; ZCTA level from 2011-2021, and block-group level from 2013-2021. We were able to build the individual area-SES measures for all years. Footnotes indicate cases where we used a different ACS data table for a specific geographic level or specific year because the ACS table did not contain the element. **Red** = removed in modified SVI measure. Blue = measure used in SVI_{2020} only. The ACS elements are 5-year averages. Number in the SVI columns indicates the SVI "theme" to which each SVI element belongs.[43] Source for 2000 Census data: https://data2.nhgis.org/; Source for ACS data: https://data.census.gov/.

Data element	TDI	SDI	ADI	SVI	SVI_{2020}	ACS	2000 Census
Education							
did not complete high school (< 12 years)		x		1	1	B15003[44,45]	P037
low education (< 9 years)			x			B15003	P037
high education (12+ years)[46]			x			B15003	P037
Income/Poverty[47]							
below federal poverty line		x		1		B17021	P087
family poverty rate			x			B17010	P090
below 150% of poverty line			x		1	C17002[48]	P088
median family income			x			B19113[49]	P077
income disparity			x			B19001	P052
per capita income				1		B19301	P082
no health insurance					1	B27010	-
occupational composition			x			C24010	P050

[43] SVI is computed by starting with percentile range of the elements, summing them within each of four "themes"; converting the theme scores to percentiles; summing those percentiles, and then computing an overall percentile. The SVI themes are (1) socio-economic status; (2) household composition; (3) minority status; and (4) housing and transportation.

[44] Table B15003, which covers population aged 25+, is not available at ZCTA level in 2011; we substitute it with Table B15001, which contains age and gender breakdowns for persons aged 18+. Age categories are 18-24, 25-34, 35-44, 45-64, 65+.

[45] In 2010 and 2011, Table B15003 is not available at the county level as a 5-year average. We substitute Table B15003 with Table B15001.

[46] Equals 1 – (did not complete HS)).

[47] All poverty-related tables are limited to persons for whom poverty status is known.

[48] For 2015-2018, Table C17002 is not available at the county level. We substitute it with Table B17026 "Ratio of income to poverty level of families in the past 12 months", and which is for "families" rather than "households."

[49] Table B19113 (median family income) is not available at block-group level for 2015-2016. We use Table B19013 (median household income). Consistent with Petterson (2023), we achieve close replication of reported ADI_{rep} to ADI_{orig} if we use median household income instead of median family income for all years, even when median family income (the element ADI says it uses) is available at the block-group level.

Data element	TDI	SDI	ADI	SVI	SVI_{2020}	ACS	2000 Census
unemployed 16+	x		x	1	1	B23025[50]	P043
non-employed 16-64[51]		x				B23025	PCT035[52]
Household Composition							
single parent		x	x	2	2	B11005	P010
Disabled [53]				2	2	B18101[54,55]	P042
Elderly [56]				2	2	B01001	P008
Children [57]				2	2	B01001	P008
minority[58]				3	3	B03002	P007
non-English speaking				3	2	B16004	P019
Housing							
crowded households	x	x	x	4	4	B25014	H020
renter occupied units[59]	x	x				B25014	H007
owner occupied units			x			B25014	H007

[50] Table B23025 is not available at the tract level for 2010. We substitute it with Table B23001 "Sex by age by employment status for the population 16 years and over".

[51] ACS does not have a non-employed variable, so we proceed as follows, and then confirm that we can then replicate the SDI for 2015 posted on the Graham website. Population aged 16+ is divided into labor force and not in the labor force, labor force is then divided into civilian labor force and armed forces, civilian labor force is further split into employed and unemployed. Percentage unemployed is defined as unemployed/civilian labor force. We define percentage non-employed as (unemployed + not in the labor force)/(civilian labor force + not in the labor force).

[52] Table PCT035 is not available at block-group level. We use Table P043 "Sex by employment status for the population 16 years and over".

[53] Omitted in 2010 and 2011 because the disability measure is not available from ACS. The original SVI omits this variable in 2010 for this reason. Disabled is measured for ages 5+ in 2000, and for all ages for 2012 on.

[54] Table B18101 provides estimates of disability for the entire population by age groups (under 5, 5-17, 18-34, 35-64, 65-74, 75+), is not available for 2010-2011 and we could not find a good substitute. Thus, we did not compute SVI at any level for these years.

[55] Table B18101 is not available at the block-group level. We substitute Table C21007, which uses a different denominator – it provides % disabled for population aged 18+ (for persons for whom poverty status is determined), and compute disability for persons aged 18+.

[56] Butler et al. (2013), at 543, considered this measure, but found that at the Census tract level, it was negative associated with other deprivation measures.

[57] It is not apparent to us that the proportion of children in the population is a sensible measure of social deprivation. Butler et al. (2013), at 543, considered a measure of high-needs population consisting of the percent of the population under age 5, or female between 15-44. This measure dropped out of their final index due to a factor loading below their cutoff.

[58] Used only in SVI, defined there all persons except non-Hispanic White. Defined using ACS as total of: Black or African American alone + American Indian and Alaska Native alone + Asian alone + Native Hawaiian and other Pacific Islander alone + some other race alone + two or more race + Hispanic (white alone). Butler et al. (2013) considered percent Black as a measure, but this measure dropped out of their final index due to a factor loading below their cutoff.

[59] Equals 1 – (owner-occupied units).

Data element	TDI	SDI	ADI	SVI	SVI2020	ACS	2000 Census
median home value			x			B25077	H085
median gross rent			x			B25064	H063
median monthly mortgage			x			B25088	H091
housing cost burden					1	B25106[60]	-
no plumbing			x			B25049	H048
no telephone (ADI thru 2019)[61]			x			B25043	H043
no internet connection (ADI from 2020)			x			B28003	-
multi-unit buildings				4	4	B25032	H030
mobile homes				4	4	B25032	H030
group quarters				4	4	B09019[62]	P009
Transportation							
no vehicle	x	x	x	4	4	B25044	H044

[60] Table B25106 is not available at the block-group level, and there is no good substitute. We assign the tract level values from Table B25106 to all block-groups in each tract.

[61] Beginning in 2020, ADI replaced the element for no telephone with the element for no internet connection. ACS has Table B28003 for "Presence of a computer and type of Internet subscription in household". This table is available at the tract level from 2013, with 5-year estimates beginning in 2017. For Block group and ZCTA, this table is available from 2017. In computing ADI for 2020, we use the factor loading for no telephone. The ADI website does not explain what loading the ADI developers used, but ADI otherwise uses factor loadings from Singh (2003), and it would be odd to update the loading for one element but not for the other elements.

[62] The same data for group quarters is available from Tables B26001 and B09019 for years and levels where both are available. However (i) Table B09019 is not available for 2010-2011; and (ii) Table B26001 is not available at block-group level. We use Table B09019 where available, and B26001 otherwise.

Table App-2. Area-SES Measure Completeness in American Community Survey and 2000 Census

Based on 50 states plus DC plus Puerto Rico. **Panel A.** Number of missing values for each measure in 2000 and 2020. "All measures missing" is based on the measures studied. Note that many *zip-codes* have zero population (e.g., PO Box; big office building); but these will not map to ZCTAs. For block-group level, we did not determine whether any block-groups have zero population, but it would be odd for Census to divide an empty Census tract into block-groups. **Panel B.** Table indicates principal elements for which ADI has largest number of missing values at block-group level in 2020. None of these elements are used in the other three area-SES measures.

Panel A. Number of missing values

	2000 Census				2020 ACS			
	County	**ZCTA**	**Tract**	**Block Group**	**County**	**ZCTA**	**Tract**	**Block Group**
Total records	3,219	33,178	66,304	211,267	3,221	33,120	85,395	242,335
Net (populated)	3,219	31,951	65,904	209,462	3,221	32,750	84,522	240,096
Missing values								
TDI	0	105	145	397	0	437	264	732
SDI	0	116	149	338	0	264	252	641
ADI_{std}, ADI_{orig}, ADI_{mod}	2	1,462	1,539	19,493	18	8,151	12,594	130,624
SVI, SVI_{mod}	0	110	150	420	0	637	301	898
SVI_{2020}, $SVI_{mod,2020}$					0	444	268	751
% in poverty	0	47	78	213	0	210	199	506
All measures missing	0	47	78	213	0	210	199	506
All measures exist	3,217	30,488	64,364	190,689	3,203	24,599	71,928	109,472

Panel B. Sources of missing data for ADI in 2020

ADI element	**No. of missing values**
Income disparity	66,593
Median gross rent	62,141
Median mortgage	33,519
Median family income	25,380
Median home value	21,316

Table App-3. Summary, by SDI Quintile, of Elements used to build area-SES Measures at ZCTA level

Table indicates means for SDI quintiles of data elements used to build each area-SES measure. Red = removed in SVI_{mod}. Blue: new elements of SVI_{2020}. Table entries are 5-year averages.

Data elements	**2000**					**2020**				
SDI Quintiles	1	2	3	4	5	1	2	3	4	5
Education										
did not complete HS (%)	10.51	15.25	18.93	24.23	33.48	4.37	7.63	10.32	14.10	21.29
low education (< 9 years) (%)	3.42	5.42	6.85	9.35	14.70	1.38	2.45	3.61	5.17	8.98
high education (12+ years) (%)	89.49	84.75	81.07	75.77	66.52	95.63	92.37	89.68	85.90	78.71
Income/Poverty										
below poverty (%)	3.79	7.53	11.12	15.53	26.49	4.22	8.29	12.23	16.79	25.34
family poverty rate (%)	2.51	5.28	8.02	11.50	21.73	2.38	5.28	8.10	11.76	20.38
below 150% of poverty line (%)	9.04	15.31	20.71	26.85	40.33	10.42	15.74	21.07	27.30	38.24
median family income	66,000	52,158	46,341	40,897	32,445	102,518	86,812	77,307	67,040	52,651
income disparity	1.94	2.79	3.28	3.72	4.46	1.24	1.73	2.11	2.51	3.17
per capita income	27,267	21,778	19,687	17,210	14,337	43,206	36,392	32,450	27,979	22,341
no health insurance (%)						4.75	6.37	8.02	10.08	13.23
occupational composition (%)	63.47	56.81	53.59	50.50	49.01	62.41	58.12	54.68	51.28	47.40
unemployed 16+ (%)	3.07	4.29	5.11	6.58	11.15	3.32	4.17	4.92	5.93	8.56
non-employed 16-64 (%)	16.26	20.50	24.14	29.40	40.31	39.44	41.05	43.43	46.25	49.39
Household										
single parent (%)	4.81	6.21	7.05	8.25	12.44	8.71	11.85	13.97	16.84	24.38
disabled (%)	14.63	17.58	19.94	22.42	26.09	12.84	14.04	15.74	17.36	17.69
elderly (%)	13.12	14.90	14.89	14.46	12.61	23.38	21.15	20.62	19.25	15.97
children (%)	25.39	24.38	24.02	24.26	25.88	19.26	20.26	20.38	21.10	23.65
minority (%)	7.41	9.73	12.62	19.16	50.19	11.20	14.22	18.38	24.86	50.77
non-English speaking (%)	0.77	1.11	1.37	2.01	6.32	0.52	0.86	1.24	1.85	5.96
Housing										
crowded households (%)	1.22	2.21	3.03	4.16	9.99	0.83	1.47	2.06	2.71	5.72
renter occupied units (%)	16.41	22.71	26.03	28.49	43.35	13.85	20.99	25.41	29.62	41.22
owner occupied units (%)	83.59	77.29	73.97	71.51	56.65	86.15	79.01	74.59	70.38	58.78
median home value	157,349	117,458	99,789	86,513	80,946	287,217	236,718	208,944	175,414	157,587
median gross rent	629	544	504	462	444	1,150	1,020	948	875	831
median monthly mortgage	1,182	966	875	809	804	1,713	1,515	1,408	1,290	1,238
no plumbing (%)	0.48	0.66	0.87	1.23	2.46	0.38	0.50	0.61	0.78	1.61
multi-unit (%)	3.58	5.48	6.67	6.30	15.38	2.12	4.34	5.85	6.11	9.29
mobile homes (%)	6.01	10.26	13.83	16.93	12.92	6.07	8.32	11.28	14.26	13.49
group quarters (%)	1.17	1.68	2.33	3.20	5.62	1.50	1.58	2.11	2.69	3.44
housing cost burden (%)	-	-	-	-	-	16.19	19.76	21.71	24.07	29.67
Transport										
no vehicle (%)	2.72	4.61	6.54	8.50	19.95	1.93	3.54	5.14	6.93	13.44
Other										
no telephone (%)	1.04	1.83	2.75	4.25	7.44	0.00	0.00	0.00	0.00	0.00
no internet (%)	-	-	-	-	-	6.52	7.26	8.46	9.52	11.88

Table App-4. Correlations and Domain Weights

Panel A. Pearson correlation coefficients between Area-SES measures and Poverty in 2000 (left-hand columns, based on 2000 Census) and 2020 (right-hand columns, based on 2020 ACS). Table is similar to Table 2, but with all the SES-Measures, and for all geographic levels. **Panel B.** Pearson correlation coefficients for centiles of reversed Child Opportunity Index (COI) (for 2010 and 2015) and Structural Racism Index (SREI) (for 2019) at tract level versus centiles of SDI, SVI, ADI$_{std}$, TDI, and Poverty. Years reported are the only ones available from the websites for these indices. **Panel C**. Number of elements for each measure in each domain; and weights that each measure assigns to each domain at tract level in 2020, using domains in Table App-1. Top part of table shows number of elements in each domain; bottom part shows fractional weights assigned to each domain by each measure. Fractional weights may not sum to exactly 100% due to rounding. Weights for other years and geographic levels will be the same for TDI, SVI, and ADI$_{std}$, but somewhat different for SDI and ADI$_{mod}$ because factor loadings vary by geographic level and year.

Panel A. Correlations between Area-SES Measures and Poverty for 2000 and 2020

	2000 Census							**2020 ACS**								
	TDI	SDI	ADI$_{std}$	ADI$_{mod}$	ADI$_{orig}$	SVI	SVI$_{mod}$	TDI	SDI	ADI$_{std}$	ADI$_{mod}$	ADI$_{orig}$	SVI	SVI$_{mod}$	SVI$_{2020}$	SVI$_{mod,2020}$
County level																
SDI	0.691	1						0.673	1							
ADI$_{std}$	0.641	0.784	1					0.532	0.792	1						
ADI$_{mod}$	0.635	0.788	0.977	1				0.505	0.815	0.919	1					
ADI$_{orig}$	0.104	0.472	0.678	0.718	1			0.036	0.424	0.657	0.742	1				
SVI	0.651	0.945	0.755	0.745	0.453	1		0.643	0.934	0.747	0.762	0.408	1			
SVI$_{mod}$	0.607	0.963	0.754	0.755	0.490	0.969	1	0.617	0.934	0.738	0.780	0.458	0.966	1		
SVI$_{2020}$								0.648	0.903	0.677	0.671	0.307	0.976	0.926	1	
SVI$_{mod,2020}$								0.633	0.915	0.670	0.689	0.350	0.955	0.969	0.969	1
Poverty	0.745	0.799	0.885	0.929	0.508	0.734	0.730	0.582	0.809	0.758	0.890	0.476	0.716	0.731	0.642	0.658
ZCTA level																
SDI	0.688	1						0.617	1							
ADI$_{std}$	0.567	0.767	1					0.485	0.712	1						
ADI$_{mod}$	0.570	0.829	0.952	1				0.580	0.851	0.879	1					
ADI$_{orig}$	0.110	0.459	0.691	0.740	1			-0.011	0.280	0.699	0.518	1				
SVI	0.637	0.903	0.635	0.688	0.363	1		0.562	0.881	0.586	0.725	0.214	1			
SVI$_{mod}$	0.625	0.932	0.683	0.751	0.442	0.973	1	0.569	0.911	0.632	0.780	0.291	0.968	1		
SVI$_{2020}$								0.549	0.861	0.546	0.679	0.165	0.984	0.943	1	
SVI$_{mod, 2020}$								0.562	0.893	0.588	0.732	0.230	0.960	0.976	0.974	1
Poverty	0.597	0.795	0.770	0.846	0.437	0.639	0.680	0.466	0.677	0.670	0.849	0.316	0.533	0.589	0.477	0.525
Tract level																
SDI	0.816	1						0.770	1							
ADI$_{std}$	0.726	0.874	1					0.589	0.847	1						
ADI$_{mod}$	0.769	0.912	0.979	1				0.628	0.882	0.961	1					
ADI$_{orig}$	0.229	0.514	0.701	0.670	1			0.057	0.392	0.649	0.668	1				
SVI	0.752	0.950	0.850	0.877	0.527	1		0.688	0.914	0.806	0.835	0.409	1			
SVI$_{mod}$	0.732	0.952	0.861	0.892	0.583	0.981	1	0.676	0.919	0.812	0.852	0.480	0.968	1		
SVI$_{2020}$								0.704	0.914	0.790	0.817	0.374	0.986	0.950	1	
SVI$_{mod,2020}$								0.699	0.923	0.799	0.835	0.438	0.959	0.981	0.973	1
Poverty	0.778	0.833	0.840	0.904	0.451	0.759	0.767	0.630	0.796	0.749	0.843	0.425	0.689	0.717	0.663	0.689

	2000 Census							**2020 ACS**								
	TDI	SDI	ADI_{std}	ADI_{mod}	ADI_{orig}	SVI	SVI_{mod}	TDI	SDI	ADI_{std}	ADI_{mod}	ADI_{orig}	SVI	SVI_{mod}	SVI_{2020}	$SVI_{mod,2020}$
Block Group level																
SDI	0.807	1						0.750	1							
ADI_{std}	0.710	0.867	1					0.484	0.773	1						
ADI_{mod}	0.755	0.909	0.972	1				0.532	0.818	0.946	1					
ADI_{orig}	0.220	0.490	0.675	0.657	1			0.015	0.312	0.643	0.678	1				
SVI	0.752	0.932	0.818	0.852	0.485	1		0.663	0.877	0.704	0.659	0.311	1			
SVI_{mod}	0.734	0.934	0.826	0.865	0.539	0.976	1	0.659	0.890	0.712	0.730	0.394	0.961	1		
SVI_{2020}								0.678	0.872	0.688	0.711	0.273	0.983	0.938	1	
$SVI_{mod,2020}$								0.680	0.887	0.699	0.735	0.347	0.947	0.976	0.965	1
Poverty	0.738	0.813	0.806	0.874	0.422	0.728	0.735	0.553	0.758	0.662	0.767	0.350	0.612	0.638	0.580	0.602

Panel B. Selected correlations between COI and SREI and Area-SES Measures

	SDI	ADI_{std}	ADI_{mod}	ADI_{orig}	SVI	SVI_{mod}	TDI	Poverty
COI, 2010	0.877	0.842	0.888	0.589	-	-	0.744	0.810
COI, 2015	0.879	0.860	0.906	0.704	0.852	0.874	0.728	0.833
SREI, 2019	0.798	0.888	0.921	0.815	0.803	0.839	0.558	0.792

Panel C. Number of Elements in Each Domain and Domain Weights at Tract Level in 2020

Domain	**Education**	**Income/Poverty**	**Household**	**Housing**	**Transport**	**Total**
Elements						
SDI	1	2	1	2	1	7
SVI	1	3	6	4	1	15
SVI_{2020}	1	3	6	5	1	16
SVI_{mod}	1	3	2	4	1	11
$SVI_{2020,mod}$	1	3	2	5	1	12
ADI	2	6	1	6	1	17
TDI	0	1	0	2	1	4
Weights						
SDI	20.64%	31.63%	9.60%	25.69%	12.43%	100%
ADI_{std}	13.33%	41.09%	5.27%	28.80%	11.52%	100%
ADI_{mod}	18.50%	50.07%	3.05%	23.11%	5.27%	100%
SVI	6.67%	20.00%	40.00%	26.67%	6.67%	100%
SVI_{2020}	6.25%	18.75%	37.50%	31.25%	16.67%	100%
SVI_{mod}	9.09%	27.27%	18.18%	36.36%	9.09%	100%
TDI	0.00%	25.00%	0.00%	50.00%	25.00%	100%

Table App-5. Summary Statistics for COVID-19 Mortality for the Three Midwest Areas

Table shows for the three Midwest areas, for adult COVID-19 decedents in the Three Midwest Areas, overall and for indicated subsamples: population, COVID-19 deaths, and COVID-19 mortality rate (Covid MR), over March 1, 2020, through March 31, 2022.

Age	Population	COVID Deaths	Covid MR (%)
By age			
0-14	3,289,596	30	0.001%
15-19	1,146,655	38	0.003%
20-24	1,203,896	60	0.005%
25-29	1,257,532	143	0.01%
30-34	1,199,947	263	0.02%
35-39	1,120,811	371	0.03%
40-44	1,109,286	635	0.06%
45-49	1,124,173	1,026	0.09%
50-54	1,102,190	1,548	0.14%
55-59	1,189,886	2,406	0.20%
60-64	1,137,719	3,754	0.33%
65-69	848,090	4,646	0.55%
70-74	775,234	5,521	0.71%
75-79	441,488	5,988	1.36%
80-84	352,125	5,983	1.70%
85-89	222,197	5,917	2.66%
90-94	113,236	4,634	4.09%
95+	38,146	2,425	6.36%
All ages	**17,672,208**	**45,388**	0.26%
Adults (18+)	**13,466,779**	**45,320**	0.34%
Elderly (65+)	**2,790,516**	**35,114**	1.26%
By gender			
Men	8,699,348	24,845	0.29%
Women	8,972,859	20,543	0.23%
By race/ethnicity			
White	12,103,469	33,027	0.27%
Black	2,201,856	6,868	0.31%
Hispanic	2,190,946	4,054	0.19%
Asian	707,966	857	0.12%
Other	467,970	582	0.12%

Table App-6. Summary Statistics for All-Cause Elderly Mortality

Table shows the Medicare FFS sample over 2000-2019, for beneficiaries aged 66 as of January 1, 2000, overall and for indicated subsamples: Medicare FFS population, deaths, and mortality rate (MR).

	Medicare FFS Population	**Deaths**	**MR (%)**
By gender			
Men	37,268	19,708	52.88%
Women	24,477	15,754	64.36%
Total	61,745	35,462	57.43%
By race/ethnicity			
White	51,590	29,408	57.00%
Black	5,130	3,352	65.34%
Hispanic	3,381	1,843	54.51%
Asian	1,015	482	47.49%
Other	629	377	59.94%

Table App-7. Summary Statistics for Medicare FFS Sample and Diabetes Prevalence in 2000 and 2019

Table shows, for the indicated subsamples and years, the number of Medicare-FFS beneficiaries age 66+ in the national 5% random sample, and the number and percentage with diabetes based on the Charlson comorbidities for diabetes in the preceding year, in 2000 and 2019.

	2000			**2019**		
	Beneficiaries	**With Diabetes**	**Diabetes %**	**Beneficiaries**	**With Diabetes**	**Diabetes %**
By age						
66-69	263,831	52.704	19.98%	328,184	84,687	25.80%
70-74	350,739	75,165	21.43%	353,363	102,510	29.01%
75-79	321,531	70,056	21.79%	249,991	78,708	31.48%
80-84	225,673	46,517	20.61%	179,323	57,275	31.94%
85-89	133,055	24,986	18.78%	120,659	36,081	29.90%
90-94	55,248	8,775	15.85%	64,317	17,163	26.69%
95+	16,289	2,202	13.52%	22,601	4,985	22.06%
All Elderly (66+)	**1,366,366**	**280,405**	**20.52%**	**1,318,438**	**381,409**	**28.93%**
By gender						
Men	455,016	99,831	21.94%	537,319	172,975	32.19%
Women	911,350	180,574	19.81%	781,119	208,434	26.68%
By race/ethnicity						
White	1,181,711	218,909	18.53%	1,089,398	284,693	26.13%
Black	95,401	31,805	33.34%	87,711	39,303	44.81%
Hispanic	57,282	21,402	37.36%	61,851	28,598	46.24%
Asian	20,709	5,382	25.99%	38,225	16,201	42.38%
Other	11,263	2,907	25.81%	41,253	12,614	30.58%

Table App-8. Summary Statistics for Drug Overdose Mortality over 2017-2021, in Illinois and Indiana

Table shows the number of decedents for drug overdose in Illinois and Indiana, for years 2017-2021, overall and for indicated subsamples. Population is 2020 ACS population.

	Population	Overdose deaths	Overdose deaths %	Opioids deaths	Opioids/Overdose %
By age					
0-11	2,886,327	36	0.001%	21	58.33%
12-19	2,056,605	355	0.02%	231	65.07%
20-24	1,317,124	1,558	0.12%	1,272	81.64%
25-29	1,349,632	2,754	0.20%	2,293	83.26%
30-34	1,291,306	3,046	0.24%	2,454	80.56%
35-39	1,237,850	3,235	0.26%	2,515	77.74%
40-44	1,225,087	2,853	0.23%	2,136	74.87%
45-49	1,250,659	2,794	0.22%	2,051	73.41%
50-54	1,226,348	2,827	0.23%	1,998	70.68%
55-59	1,293,376	2,813	0.22%	1,990	70.74%
60-64	1,236,896	1,701	0.14%	1,186	69.72%
65-69	920,640	861	0.09%	559	64.92%
70-74	841,695	260	0.03%	139	53.46%
75-79	484,544	117	0.02%	46	39.32%
80-84	386,635	56	0.01%	20	35.71%
85-89	241,846	42	0.02%	5	11.90%
90-94	123,428	21	0.02%	2	9.52%
95+	41,626	4	0.01%	1	25.00%
Total	19,411,624	25,333	0.13%	18,919	74.68%
By gender					
Female	9,864,856	7,836	0.08%	5,559	70.94%
Male	9,546,768	17,497	0.18%	13,360	76.36%
By race/ethnicity					
White	12,990,848	17,301	0.13%	12,567	72.64%
Black	2,428,274	5,950	0.25%	4,735	79.58%
Hispanic	2,664,256	1,888	0.07%	1,506	79.77%
Asian	868,046	150	0.02%	80	53.33%
Other	460,200	44	0.01%	31	70.45%

Table App-9. Population by SES Quintile and Ventile at ZCTA and County Levels

Table indicates total population by SES quintile and ventile for 2000 (using Census data) and 2020 (using ACS data), for the indicated area-SES measures, for ZCTAs and counties. The quintiles and ventiles include equal numbers of geographic units but can differ in population. At the Census tract and block-group level, populations are similar across quintiles and ventiles (results not shown). Which zip-code is in which quintile or ventile differs across area-SES measure. Population differs across area-SES measures due to differing numbers of missing values. **Panel A.** Quintiles at ZCTA level. **Panel B.** Ventiles at ZCTA level. **Panel C.** Quintiles at county level.

	2000				**2020**			
	SDI	**TDI**	**ADI$_{std}$**	**SVI**	**SDI**	**TDI**	**ADI$_{std}$**	**SVI**
Panel A. Area-SES Quintiles at ZCTA Level (1 = highest SES)								
1	49,327,817	31,175,746	92,678,994	25,403,918	33,813,791	20,389,308	94,379,419	12,238,102
2	47,306,842	35,988,495	53,245,596	45,794,904	54,491,829	45,851,441	58,726,725	47,051,626
3	47,246,055	46,798,898	43,098,471	51,809,207	61,722,492	65,056,233	50,845,142	66,116,415
4	55,289,704	66,876,030	42,585,517	62,391,433	72,295,738	87,633,261	52,015,300	83,428,716
5	85,952,361	104,285,567	52,131,955	99,723,372	107,137,815	110,515,596	63,139,698	120,599,569
Total	**285,122,779**	**285,124,736**	**283,740,533**	**285,122,834**	**329,461,665**	**329,445,839**	**319,106,284**	**329,434,428**
Panel B. Area-SES Ventiles at ZCTA Level (1 = highest SES)								
1	11,888,595	5,890,913	25,416,206	2,264,019	3,367,422	1,241,152	25,318,938	1,523,236
2	13,138,990	8,597,230	25,416,759	5,007,674	8,691,705	4,301,496	25,914,348	3,217,401
3	12,565,718	8,662,632	22,947,068	8,336,000	10,647,265	6,468,414	22,743,682	5,263,068
4	11,734,514	8,024,971	18,898,961	9,796,225	11,107,399	8,378,246	20,402,451	7,587,123
5	12,191,131	8,192,433	14,984,017	10,809,865	13,727,198	10,119,369	16,306,324	10,358,874
6	12,045,538	9,448,328	14,004,755	11,228,237	13,311,915	11,214,177	16,039,188	13,584,917
7	10,991,765	8,889,253	12,515,481	11,834,233	13,901,944	11,946,180	13,952,502	14,752,096
8	12,078,408	9,458,481	11,741,343	11,922,569	13,550,772	12,571,715	12,428,711	14,774,863
9	10,972,008	10,318,744	11,071,165	13,241,539	14,486,475	13,859,287	13,453,129	15,458,075
10	11,363,229	10,679,538	10,948,986	12,566,844	14,233,824	16,000,432	12,578,500	15,677,944
11	12,415,963	12,452,726	10,560,026	12,508,578	16,476,332	17,082,848	11,961,165	16,550,024
12	12,494,855	13,347,890	10,518,294	13,492,246	16,525,861	18,113,666	12,852,348	17,784,720
13	12,376,683	14,358,053	9,765,914	14,835,447	17,091,929	19,911,446	12,695,030	18,303,851
14	12,859,508	15,189,246	10,631,250	14,553,894	17,599,673	20,912,547	12,958,831	19,485,052
15	14,868,089	17,357,235	10,629,475	16,172,453	18,483,017	22,518,990	13,077,753	19,497,849
16	15,185,424	19,971,496	11,558,878	16,829,639	19,121,119	24,290,278	13,283,686	21,398,561
17	15,198,810	19,945,228	10,826,626	18,401,224	20,085,166	26,349,732	13,208,435	23,061,614
18	16,952,836	22,543,486	12,185,111	19,824,014	24,810,320	25,632,416	14,426,907	26,623,768
19	21,744,714	29,325,513	13,570,008	26,213,558	28,348,716	30,284,620	15,897,137	30,807,971
20	32,056,001	32,471,340	15,550,210	35,284,576	33,893,613	28,248,828	19,607,219	33,723,770
Total	**285,122,779**	**285,124,736**	**283,740,533**	**285,122,834**	**329,461,665**	**329,445,839**	**319,106,284**	**329,434,777**

	2000				2020			
	SDI	**TDI**	**ADI_{std}**	**SVI**	**SDI**	**TDI**	**ADI_{std}**	**SVI**
Panel C. Area-SES Quintiles at County Level (1 = highest SES)								
1	51,268,238	27,011,596	125,921,535	41,953,219	49,972,921	23,118,795	133,702,148	43,828,092
2	52,467,976	31,209,631	55,700,861	56,276,829	65,542,024	39,368,177	71,850,840	72,455,890
3	63,879,655	37,697,554	40,624,633	65,597,925	68,424,858	51,856,597	55,434,049	86,349,051
4	59,649,574	56,683,227	39,445,173	66,598,012	77,910,123	64,952,292	45,682,010	85,476,357
5	57,965,073	132,628,508	23,538,100	54,804,531	67,975,024	150,529,089	23,104,905	41,715,560
Total	**285,230,516**	**285,230,516**	**285,230,302**	**285,230,516**	**329,824,950**	**329,824,950**	**329,773,952**	**329,824,950**

Table App-10. Predictive Power of SES Measures at Zip-Code Level with Quintiles Based on Population

Table reports marginal effects of population-weighted area-SES quintiles for selected zip-code-level outcomes. Area-SES quintiles are defined to have roughly equal number of *people*, rather than equal number of *zip-codes* (as in the text). **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2019. **Panel C.** Diabetes incidence over 2000-2005. Covariates same as Table 3, Panel E. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

Panel A. All-Cause Elderly Mortality over 2000-2019

	(1)	(2)	(3)	(4)	(5)
Area-SES Measure	**SDI**	**ADI**$_{std}$	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0306*	0.0477*	0.0298*	0.0359*	0.0354*
Quintile 3	0.0558*	0.0708*	0.0572*	0.0474*	0.0534*
Quintile 4	0.0865*	0.1062*	0.0821*	0.0603*	0.0812*
Quintile 5	0.0992*	0.1245*	0.0951*	0.0627*	0.0995*
Race/ethnicity					
Black	0.0049	0.0067	0.0064	0.0208*	0.0098
Hispanic	-0.1178*	-0.1150*	-0.1170*	-0.1032*	-0.1139*
Asian	-0.1220*	-0.1026*	-0.1231*	-0.1250*	-0.1152*
Other	-0.0124	-0.0080	-0.0121	-0.0086	-0.0100
Male	0.1045*	0.1040*	0.1046*	0.1046*	0.1039*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	61,185	61,076	61,185	61,189	61,188

Panel B. Diabetes Prevalence 2019

Area-SES Measure	**SDI**	**ADI**$_{std}$	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0200*	0.0219*	0.0232*	0.0155*	0.0174*
Quintile 3	0.0394*	0.0445*	0.0455*	0.0240*	0.0323*
Quintile 4	0.0616*	0.0661*	0.0656*	0.0306*	0.0494*
Quintile 5	0.0872*	0.0822*	0.0864*	0.0603*	0.0613*
Race/ethnicity					
Black	0.1595*	0.1669*	0.1606*	0.1705*	0.1718*
Hispanic	0.1752*	0.1837*	0.1758*	0.1840*	0.1907*
Asian	0.1586*	0.1754*	0.1593*	0.1531*	0.1708*
Other	0.0558*	0.0610*	0.0561*	0.0534*	0.0588*
Male	0.0584*	0.0580*	0.0583*	0.0584*	0.0580*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	1,315,649	1,253,280	1,315,092	1,315,375	1,315,832

Panel C. Diabetes Incidence over 2000- 2005

Area-SES Measure	**SDI**	**ADI**$_{std}$	**SVI**	**TDI**	**Poverty**
Quintile 2	-0.0018	-0.0084*	0.0018	-0.0044*	-0.0036*
Quintile 3	*-0.0035*	-0.0160*	0.0048*	-0.0040*	-0.0100*
Quintile 4	0.0120*	-0.0053*	0.0190*	0.0098*	-0.0029*
Quintile 5	0.0454*	0.0182*	0.0442*	0.0572*	0.0216*
Race/ethnicity					
Black	0.0738*	0.0873*	0.0769*	0.0739*	0.0866*
Hispanic	0.1501*	0.1645*	0.1527*	0.1399*	0.1653*
Asian	0.0939*	0.0995*	0.0955*	0.0786*	0.1009*
Other	0.0268*	0.0319*	0.0277*	0.0229*	0.0317*
Male	0.0082*	0.0081*	0.0083*	0.0081*	0.0080*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	860,248	854,556	860,266	860,269	860,302

Table App-11. Area-SES Quintiles at Tract and Block Group Levels: All-Cause Elderly Mortality over 2000-2019

Table shows marginal effects for quintiles of area-SES measures and Poverty, measured in 2000 at tract and block-group levels, for mortality over 2000-2019 among persons aged 66 as of January 1, 2000, included in national 5% random sample of Medicare FFS beneficiaries. Covariates are same as Table 3, Panel B. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

Geographic Level	**Tract**					**Block Group**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0487*	0.0419*	0.0328*	0.0424*	0.0429*	0.0472*	0.0390*	0.0344*	0.0466*	0.0297*
Quintile 3	0.0765*	0.0763*	0.0668*	0.0708*	0.0719*	0.0686*	0.0804*	0.0657*	0.0687*	0.0618*
Quintile 4	0.1093*	0.1112*	0.1093*	0.0843*	0.0975*	0.1078*	0.1174*	0.0996*	0.0862*	0.0931*
Quintile 5	0.1339*	0.1485*	0.1277*	0.0976*	0.1245*	0.1290*	0.1339*	0.1062*	0.0991*	0.1105*
Race/ethnicity										
Black	-0.0111	-0.0081	-0.0109	0.0073	-0.0021	-0.0018	-0.0006	0.0058	0.0130	0.0072
Hispanic	-0.1299*	-0.1300*	-0.1316*	-0.1153*	-0.1210*	-0.1212*	-0.1203*	-0.1145*	-0.1102*	-0.1118*
Asian	-0.1327*	-0.1145*	-0.1356*	-0.1381*	-0.1217*	-0.1417*	-0.1196*	-0.1440*	-0.1467*	-0.1318*
Other	-0.0385	-0.0291	-0.0400*	-0.0387	-0.0332	-0.0326	-0.0291	-0.0359	-0.0322	-0.0293
Male	0.1033*	0.1031*	0.1035*	0.1037*	0.1030*	0.1055*	0.1059*	0.1054*	0.1053*	0.1045*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,643	40.486	40,643	40,643	40,643	37,751	35,193	37,737	37,810	37,790

Table App-12. Area-SES Quintiles at Tract and Block Group Levels: Diabetes Prevalence in 2000

Table shows marginal effects of quintiles of area-SES measures and Poverty, measured at tract and block-group levels, for diabetes prevalence in 2000, for national 5% random sample of Medicare FFS beneficiaries aged 66+. Covariates are same as Table 3, Panel C. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better. *Note:* Results for diabetes prevalence in 2019 are not available at tract and block-group level, because the Medicare data includes only 5-digit zip-code from 2014 on.

Geographic Level	**Tract**					**Block Group**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0149*	0.0220*	0.0157*	0.0069*	0.0112*	0.0145*	0.0192*	0.0192*	0.0119*	0.0073*
Quintile 3	0.0209*	0.0269*	0.0232*	0.0122*	0.0130*	0.0247*	0.0297*	0.0269*	0.0168*	0.0150*
Quintile 4	0.0311*	0.0361*	0.0295*	0.0186*	0.0210*	0.0353*	0.0381*	0.0328*	0.0233*	0.0193*
Quintile 5	0.0524*	0.0509*	0.0463*	0.0436*	0.0374*	0.0539*	0.0497*	0.0496*	0.0457*	0.0381*
Race/ethnicity										
Black	0.1210*	0.1267*	0.1260*	0.1277*	0.1298*	0.1221*	0.1268*	0.1268*	0.1284*	0.1303*
Hispanic	0.1607*	0.1675*	0.1649*	0.1630*	0.1705*	0.1630*	0.1665*	0.1657*	0.1653*	0.1714*
Asian	0.0621*	0.0704*	0.0632*	0.0578*	0.0681*	0.0628*	0.0693*	0.0623*	0.0587*	0.0680*
Other	0.0696*	0.0745*	0.0704*	0.0698*	0.0730*	0.0695*	0.0729*	0.0695*	0.0696*	0.0729*
Male	0.0181*	0.0175*	0.0180*	0.0180*	0.0177*	0.0181*	0.0164*	0.0179*	0.0180*	0.0175*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	907,866	896,588	907,830	907,835	907,874	843,093	778,355	843,047	843,063	843,155

Table App-13. Area-SES Quintiles at Tract and Block Group Levels: Diabetes Incidence over 2000-2005

Table shows marginal effects of area-SES and poverty quintiles, measured at tract level and block-group levels, for diabetes incidence over 2000-2005 among persons aged 66+ as of January 1, 2000, included in national 5% random sample of Medicare FFS beneficiaries. Covariates are same as in text Table 3, Panel E. **Panel A.** Tract level. **Panel B.** Block group level. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better.

Panel A. Tract level

Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0017	-0.0011	0.0033	-0.0068*	-0.0007
Quintile 3	0.0051*	-0.0085*	0.0047*	-0.0004	-0.0052*
Quintile 4	0.0165*	0.0017	0.0172*	0.0137*	0.0018
Quintile 5	0.0489*	0.0247*	0.0369*	0.0563*	0.0252*
Race/ethnicity					
Black	0.0725*	0.0858*	0.0797*	0.0716*	0.0854*
Hispanic	0.1433*	0.1561*	0.1500*	0.1361*	0.1576*
Asian	0.0947*	0.1018*	0.0969*	0.0840*	0.1017*
Other	0.0287*	0.0323*	0.0302*	0.0247*	0.0335*
Male	0.0088*	0.0083*	0.0087*	0.0088*	0.0085*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	578,619	570,365	578,612	578,616	578,624

Panel B. Block group level

Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0077*	-0.0001	0.0097*	0.0001	0.0019
Quintile 3	0.0084*	-0.0035	0.0097*	0.0058*	0.0004
Quintile 4	0.0223*	0.0077*	0.0184*	0.0152*	0.0066*
Quintile 5	0.0466*	0.0262*	0.0399*	0.0536*	0.0268*
Race/ethnicity					
Black	0.0761*	0.0862*	0.0814*	0.0750*	0.0860*
Hispanic	0.1466*	0.1582*	0.1498*	0.1402*	0.1572*
Asian	0.0966*	0.1037*	0.0971*	0.0876*	0.1021*
Other	0.0283*	0.0297*	0.0288*	0.0247*	0.0321*
Male	0.0090*	0.0073*	0.0088*	0.0090*	0.0086*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	536,861	492,745	536,831	536,839	536,909

Table App-14. Drug Overdose Mortality over 2017-2021: Comparing SVI Measures

Table compares marginal effects for SVI, SVI_{mod}, SVI_{2020}, and $SVI_{mod,2020}$, measured in 2020 at zip-code level, for drug overdose mortality over 2017-2021 in Indiana and Illinois. Covariates are same as Table 3, Panel F. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

	(1)	(2)	(3)	(4)
Area-SES Measure	**SVI**	**SVI_{mod}**	**SVI_{2020}**	**$SVI_{mod,2020}$**
Quintile 2	0.0049*	0.0083*	0.0062*	0.0069*
Quintile 3	0.0122*	0.0095*	0.0119*	0.0095*
Quintile 4	0.0114*	0.0123*	0.0156*	0.0117*
Quintile 5	0.0274*	0.0264*	0.0303*	0.0289*
Race/ethnicity				
Black	-0.0091*	-0.0081*	-0.0103*	-0.0100*
Hispanic	-0.0222*	-0.0210*	-0.0234*	-0.0228*
Asian	-0.0397*	-0.0389*	-0.0409*	-0.0401*
Other	-0.0075	-0.0065	-0.0092	-0.0079
Male	0.0124*	0.0124*	0.0124*	0.0124*
Other Covariates	Yes	Yes	Yes	Yes
Observations	446,200	446,200	446,202	446,202

Table App-15. Medicare-FFS Spending in 2000 and 2019: Zip-Code Level

Table shows marginal effects of quintiles of area-SES measures and Poverty at zip-code level, for Medicare-FFS spending in 2000 and 2019, for beneficiaries aged 66+ as of January 1, 2000, or January 1, 2019, respectively, included in national 5% random sample of Medicare FFS beneficiaries. Covariates are cubic in (age-65), gender (female is omitted), male*(age cubic), race/ethnicity, male*(race/ethnicity), dummies for selected Charlson comorbidities, and constant term (coefficients are suppressed except as indicated). Marginal effects for race/ethnicity are averaged across both genders. **Panel A.** Medicare Spending in 2000. **Panel B.** Medicare Spending in 2019. **Both panels.** Amounts in 2000$. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

Panel A. Medicare Spending in 2000

Comorbidities	**No**					**Yes**				
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	*-67*	-455*	122*	-128*	-136*	-125**	-391*	9	-164*	-130*
Quintile 3	-128 *	-516*	48	-163*	-283*	-198*	-512*	-119*	-243*	-296*
Quintile 4	-98*	-314*	122*	*-87*	-160*	-317*	-510*	-166*	-223*	-306*
Quintile 5	502*	56	517*	792*	210*	-77*	-386*	*-71*	273*	-203*
Race/ethnicity										
Black	1343*	1535*	1415*	1242*	1496*	192*	311*	220*	33	261*
Hispanic	105	268*	184*	-101	259*	-584*	-481*	-549*	-801*	-514*
Asian	-660*	-590*	-623*	-922*	-565*	-405*	-421*	-388*	-587*	-380*
Other	*304*	372*	*322*	222	360*	-25	4	-19	-112	-3
Male	347*	346*	347*	352*	343*	-318*	-314*	-318*	-314*	-318*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,373,354	1,365,337	1,373,386	1,373,392	1,373,458	1,373,354	1,365,337	1,373,386	1,373,392	1,373,458

Panel B. Medicare Spending in 2019

Comorbidities	**No**					**Yes**				
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**Poverty**
Quintile 2	56	-156*	221*	135*	60	-145*	-372*	*97*	-35	-141*
Quintile 3	94*	-128*	334*	173*	2	-240*	-538*	2	-113*	-370*
Quintile 4	174*	49	459*	227*	116*	-424*	-585*	-144*	-184*	-489*
Quintile 5	561*	349*	733*	736*	272*	-461*	-569*	-305*	-2	-570*
Race/ethnicity										
Black	1007*	1095*	1021*	971*	1119*	-349*	-329*	-350*	-488*	-336*
Hispanic	14	36	24.9337	-38.2398	*140*	-515*	-538*	-515*	-647*	-525*
Asian	-1573*	-1554*	-1571*	-1682*	-1512*	-1210*	-1329*	-1209*	-1265*	-1263*
Other	-309*	-372*	-303*	-361*	-280*	31	-79	32	-3	21
Male	254*	242*	254*	255*	259*	-568*	-574*	-572*	-576*	-566*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,342,404	1,278,748	1,341,834	1,342,124	1,342,591	1,342,404	1,278,748	1,341,834	1,342,124	1,342,591

Table App-16. Predictive Effects of Area-SES Quintiles at County Level

Table shows marginal effects of area-SES and poverty quintiles, measured at county level in 2020, for indicated outcomes. Covariates are same as in text Table 3. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better; italics = significant at 5% level.

Outcome	**COVID-19 Mortality**					**COVID-19 Mortality**				
Sample	**IN&WI**					**National**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**
Quintile 2	-0.0004*	-0.0002	-0.0001	0.0003	-0.0001	0.0000	0.0005*	0.0002*	0.0008*	-0.0002*
Quintile 3	0.0011*	0.0009*	0.0020*	0.0016*	0.0020*	-0.0002*	0.0005*	0.0002*	0.0010*	-0.0001*
Quintile 4	0.0031*	0.0010*	0.0023*	0.0027*	0.0022*	0.0010*	0.0010*	0.0004*	0.0019*	0.0011*
Quintile 5	0.0018*	-0.0011*	-	0.0025*	0.0036*	-0.0000	-0.0002*	0.0003*	0.0009*	*0.0001*
Race/ethnicity										
Black	0.0035*	0.0045*	0.0035*	0.0037*	0.0036*	0.0044*	0.0044*	0.0044*	0.0045*	0.0044*
Hispanic	0.0033*	0.0040*	0.0034*	0.0034*	0.0036*	0.0020*	0.0021*	0.0019*	0.0021*	0.0019*
Asian	0.0022*	0.0025*	0.0022*	0.0020*	0.0022*	-0.0013*	-0.0012*	-0.0013*	-0.0012*	-0.0012*
Other	-0.0044*	-0.0043*	-0.0044*	-0.0044*	-0.0044*	-0.0035*	-0.0035*	-0.0035*	-0.0034*	-0.0035*
Male	0.0031*	0.0030*	0.0031*	0.0031*	0.0031*	0.0024*	0.0024*	0.0024*	0.0024*	0.0024*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,982,741	1,982,741	1,982,741	1,982,741	1,982,741	53,542,600	53,473,621	53,542,600	53,542,600	53,542,600

Outcome	**All-cause mortality**					**Diabetes prevalence 2000**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**
Quintile 2	0.0286*	0.0236*	0.0225*	0.0136	0.0304*	-0.0102*	0.0065*	-0.0042*	0.0041*	-0.0001
Quintile 3	0.0399*	0.0400*	0.0364*	0.0302*	0.0371*	-0.0013	0.0122*	-0.0017	-0.0039*	-0.0053*
Quintile 4	0.0534*	0.0556*	0.0377*	0.0297*	0.0494*	-0.0052*	0.0083*	-0.0010	*-0.0031*	0.0052*
Quintile 5	0.0409*	0.0562*	0.0445*	0.0112	0.0479*	0.0204*	0.0344*	0.0168*	0.0008	0.0212*
Race/ethnicity										
Black	0.0299*	0.0284*	0.0298*	0.0395*	0.0291*	0.1395*	0.1417*	0.1416*	0.1476*	0.1423*
Hispanic	-0.0917*	-0.1008*	-0.0953*	-0.0790*	-0.0967*	0.1764*	0.1774*	0.1809*	0.1929*	0.1809*
Asian	-0.1149*	-0.1065*	-0.1158*	-0.1052*	-0.1125*	0.0672*	0.0747*	0.0696*	0.0715*	0.0716*
Other	-0.0043	-0.0033	-0.0052	0.0005	-0.0039	0.0761*	0.0764*	0.0771*	0.0803*	0.0770*
Male	0.1039*	0.1038*	0.1038*	0.1037*	0.1038*	0.0178*	0.0176*	0.0177*	0.0177*	0.0177*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,356	61,356	61,356	61,356	61,356	1,357,461	1,357,460	1,357,461	1,357,461	1,357,461

Outcome	**Diabetes prevalence in 2019**					**Overdose mortality 2017-2021**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**	**SDI**	**ADI$_{std}$**	**SVI$_{2020}$**	**TDI**	**Poverty**
Quintile 2	0.0099*	0.0111*	0.0070*	0.0211*	0.0092*	-0.0056*	*-0.0049*	0.0169*	-0.0061*	-0.0374*
Quintile 3	0.0341*	0.0314*	0.0204*	0.0318*	0.0188*	-0.0143*	-0.0203*	0.0151*	0.0215*	0.0166*
Quintile 4	0.0502*	0.0427*	0.0297*	0.0435*	0.0319*	0.0542*	-0.0571*	0.0819*	0.0212*	0.0237*
Quintile 5	0.0517*	0.0524*	0.0477*	0.0630*	0.0500*	*-0.0178*	-0.0572*	-0.0580*	0.1048*	-0.0137*
Race/ethnicity										
Black	0.1817*	0.1871*	0.1808*	0.1814*	0.1140*	-0.0270*	-0.0153*	-0.0281*	-0.0297*	-0.0208*
Hispanic	0.1926*	0.2064*	0.1972*	0.1964*	0.1066*	-0.0483*	-0.0412*	-0.0502*	-0.0501*	-0.0419*
Asian	0.1724*	0.1793*	0.1722*	0.1768*	0.1092*	-0.0918*	-0.0871*	-0.0929*	-0.0967*	-0.0873*
Other	0.0598*	0.0617*	0.0592*	0.0607*	0.0864*	-0.0634*	-0.0516*	-0.0658*	-0.0724*	-0.0532*
Male	0.0578*	0.0577*	0.0580*	0.0577*	0.0253*	0.0205*	0.0197*	0.0207*	0.0214*	0.0198*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,311,862	1,311,862	1,315,370	1,311,862	1,315,370	143,910	143,910	143,910	143,910	143,910

Outcome	**Diabetes incidence over 2000-2005**				
	(1)	(2)	(3)	(4)	(5)
Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**Poverty**
Quintile 2	-0.0148*	-0.0125*	-0.0014	0.0018	-0.0052*
Quintile 3	-0.0054*	-0.0013	0.0069*	-0.0140*	-0.0116*
Quintile 4	-0.0083*	0.0049*	0.0132*	-0.0005	0.0091*
Quintile 5	0.0488*	0.0373*	0.0503*	0.0201*	0.0318*
Race/ethnicity					
Black	0.0783*	0.0895*	0.0798*	0.0866*	0.0867*
Hispanic	0.1427*	0.1571*	0.1485*	0.1612*	0.1587*
Asian	0.0920*	0.1012*	0.0952*	0.0897*	0.1013*
Other	0.0262*	0.0304*	0.0271*	0.0301*	0.0304*
Male	0.0083*	0.0082*	0.0082*	0.0082*	0.0082*
Other Covariates	Yes	Yes	Yes	Yes	Yes
Observations	862,319	862,318	862,319	862,319	862,319

Table App-17. Cox Survival Model for Elderly All-Cause Mortality: Area-SES Quintiles at Zip-Code and Tract Levels

Table shows hazard ratios from Cox survival model for effects of quintiles of area-SES measures, measured at zip-code level (left-hand columns) and tract level (right-hand columns), on survival over 2000-2019. Covariates and sample are same as in text Table 3, Panel B. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

Geographic Level	**Zip-code**				**Tract**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI**	**TDI**	**SDI**	**ADI_{std}**	**SVI**	**TDI**
Quintile 2	1.1027*	1.1481*	1.0844*	1.1185*	1.1779*	1.1542*	1.1153*	1.1340*
Quintile 3	1.1799*	1.2236*	1.1687*	1.1878*	1.2666*	1.2861*	1.2371*	1.2539*
Quintile 4	1.2645*	1.3465*	1.2639*	1.2264*	1.4187*	1.4122*	1.4137*	1.3054*
Quintile 5	1.3708*	1.3778*	1.3824*	1.2781*	1.5080*	1.5779*	1.4796*	1.3395*
Race/ethnicity								
Black	0.9648	0.9724	0.9699	1.0084	0.9041*	0.9116*	0.9046*	0.9552
Hispanic	0.6568*	0.6581*	0.6598*	0.6866*	0.6442*	0.6436*	0.6418*	0.6758*
Asian	0.6358*	0.6688*	0.6355*	0.6323*	0.6119*	0.6478*	0.6062*	0.6028*
Other	0.9428	0.9534	0.9484	0.9644	0.8962	0.9231	0.8836	0.8934
Male	1.3455*	1.3444*	1.3461*	1.3444*	1.3485*	1.3477*	1.3488*	1.3470*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,185	61,076	61,185	61,189	40,643	40,486	40,643	40,643

Table App-18. Predictive Effects of Area-SES Quintiles at Zip-Code Level with and without Comorbidities

Table shows marginal effects of quintiles of area-SES measures at zip-code level for indicated outcomes, either without (left-hand regressions) or with (right-hand regressions) controls for Charlson comorbidities. Right hand columns are same as text Table 3, for the indicated outcomes. Sample, specification, and covariates are otherwise same as in text Table 3. **Panel A.** All-cause mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes prevalence in 2019. **Panel D.** Diabetes incidence over 2000-2005**.** We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better, *italics* = statistically significant at the 5% level.

Panel A. All-cause mortality over 2000-2019

Comorbidities	**No**				**Yes**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**
Quintile 2	0.0348*	0.0461*	0.0290*	0.0432*	0.0289*	0.0394*	0.0206*	0.0352*
Quintile 3	0.0601*	0.0759*	0.0570*	0.0650*	0.0506*	0.0637*	0.0439*	0.0534*
Quintile 4	0.0915*	0.1122*	0.0900*	0.0778*	0.0740*	0.0927*	0.0686*	0.0639*
Quintile 5	0.1330*	0.1325*	0.1326*	0.1038*	0.1016*	0.1034*	0.1002*	0.0765*
Race/ethnicity								
Black	0.0459*	0.0507*	0.0500*	0.0656*	0.0050	0.0075	0.0072	0.0212*
Hispanic	-0.0724*	-0.0686*	-0.0688*	-0.0537*	-0.1175*	-0.1150*	-0.1160*	-0.1025*
Asian	-0.1140*	-0.0927*	-0.1147*	-0.1188*	-0.1222*	-0.1057*	-0.1232*	-0.1243*
Other	0.0107	0.0160	0.0113	0.0159	-0.0128	-0.0087	-0.0127	-0.0088
Male	0.1172*	0.1166*	0.1173*	0.1172*	0.1045*	0.1042*	0.1046*	0.1046*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	61,185	61,076	61,185	61,189	61,185	61,076	61,185	61,189

Panel B. Diabetes Prevalence in 2000

Area-SES Measure	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**	**SDI**	**ADI$_{std}$**	**SVI**	**TDI**
Quintile 2	0.0101*	0.0155*	0.0112*	0.0095*	0.0097*	0.0156*	0.0109*	0.0093*
Quintile 3	0.0150*	0.0188*	0.0183*	0.0112*	0.0146*	0.0187*	0.0177*	0.0108*
Quintile 4	0.0194*	0.0244*	0.0250*	0.0118*	0.0186*	0.0238*	0.0242*	0.0112*
Quintile 5	0.0374*	0.0403*	0.0382*	0.0259*	0.0358*	0.0390*	0.0366*	0.0245*
Race/ethnicity								
Black	0.1295*	0.1306*	0.1324*	0.1376*	0.1310*	0.1320*	0.1339*	0.1390*
Hispanic	0.1688*	0.1689*	0.1720*	0.1754*	0.1680*	0.1679*	0.1711*	0.1744*
Asian	0.0649*	0.0721*	0.0660*	0.0638*	0.0654*	0.0723*	0.0665*	0.0644*
Other	0.0711*	0.0725*	0.0720*	0.0737*	0.0714*	0.0727*	0.0723*	0.0739*
Male	0.0200*	0.0197*	0.0200*	0.0199*	0.0182*	0.0179*	0.0182*	0.0182*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,355,314	1,347,454	1,355,345	1,355,352	1,355,314	1,347,454	1,355,345	1,355,352

Panel C. Diabetes prevalence in 2019

Area-SES Measure	SDI	ADI_{std}	SVI	TDI	SDI	ADI_{std}	SVI	TDI
Quintile 2	0.0189*	0.0242*	0.0088*	0.0162*	0.0179*	0.0230*	0.0087*	0.0154*
Quintile 3	0.0360*	0.0455*	0.0304*	0.0272*	0.0342*	0.0433*	0.0291*	0.0256*
Quintile 4	0.0563*	0.0627*	0.0551*	0.0367*	0.0534*	0.0593*	0.0526*	0.0345*
Quintile 5	0.0869*	0.0805*	0.0874*	0.0582*	0.0824*	0.0764*	0.0831*	0.0554*
Race/ethnicity								
Black	0.1615*	0.1661*	0.1623*	0.1734*	0.1623*	0.1666*	0.1630*	0.1735*
Hispanic	0.1754*	0.1811*	0.1758*	0.1855*	0.1782*	0.1837*	0.1786*	0.1877*
Asian	0.1553*	0.1701*	0.1548*	0.1513*	0.1601*	0.1743*	0.1596*	0.1563*
Other	0.0536*	0.0582*	0.0540*	0.0519*	0.0564*	0.0608*	0.0568*	0.0548*
Male	0.0575*	0.0574*	0.0576*	0.0575*	0.0583*	0.0581*	0.0584*	0.0584*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,315,649	1,253,280	1,315,092	1,315,375	1,315,649	1,253,280	1,315,092	1,315,375

Panel D. Diabetes incidence over 2000-2005

Area-SES Measure	SDI	ADI_{std}	SVI	TDI	SDI	ADI_{std}	SVI	TDI
Quintile 2	-0.0004	-0.0142*	0.0055*	*-0.0041*	-0.0008	-0.0140*	0.0052*	*-0.0043*
Quintile 3	-0.0057*	-0.0118*	0.0075*	-0.0053*	-0.0061*	-0.0119*	0.0069*	-0.0057*
Quintile 4	*0.0031*	-0.0013	0.0112*	-0.0051*	0.0024	-0.0018	0.0103*	-0.0055*
Quintile 5	0.0325*	0.0219*	0.0362*	0.0298*	0.0313*	0.0211*	0.0348*	0.0290*
Race/ethnicity								
Black	0.0760*	0.0836*	0.0786*	0.0783*	0.0796*	0.0871*	0.0821*	0.0816*
Hispanic	0.1564*	0.1621*	0.1591*	0.1546*	0.1582*	0.1638*	0.1609*	0.1562*
Asian	0.0945*	0.0989*	0.0957*	0.0863*	0.0955*	0.0997*	0.0966*	0.0872*
Other	0.0266*	0.0297*	0.0270*	0.0253*	0.0288*	0.0318*	0.0292*	0.0274*
Male	0.0083*	0.0081*	0.0084*	0.0083*	0.0082*	0.0080*	0.0083*	0.0083*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	860,248	854,556	860,266	860,269	860,248	854,556	860,266	860,269

Table App-19. Zip-Code Level: Opioid-Related Overdose Mortality, 2017-2021, in Illinois and Indiana

Table is similar to text Table 3, Panel F, but outcome is opioid-related overdose mortality, instead of all overdose mortality. Reported results also consider a subsample with people aged 12+. Covariates are same as Table 3, Panel F. Marginal effects for race/ethnicity are averaged across both genders. We use heteroskedasticity-robust standard errors. * = statistically significant at the 1% level or better. Observations are of population groups defined by age (in years)*zip-code*gender*race/ethnicity.

Sample	**All ages**				**Ages 12+**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Area-SES Measure	**SDI**	**ADI_{std}**	**SVI_{2020}**	**TDI**	**SDI**	**ADI_{std}**	**SVI_{2020}**	**TDI**
Quintile 2	*0.0024*	-0.0013	0.0048*	*0.0024*	*0.0024*	-0.0013	0.0048*	*0.0025*
Quintile 3	0.0017	-0.0060*	0.0092*	0.0032*	0.0017	-0.0061*	0.0093*	0.0033*
Quintile 4	0.0031*	0.0000	0.0104*	0.0106*	0.0031*	0.0000	0.0105*	0.0107*
Quintile 5	0.0194*	0.0132*	0.0240*	0.0232*	0.0197*	0.0134*	0.0244*	0.0235*
Race/ethnicity								
Black	-0.0058*	-0.0030*	-0.0062*	-0.0075*	-0.0059*	-0.0031*	-0.0063*	-0.0077*
Hispanic	-0.0161*	-0.0147*	-0.0166*	-0.0171*	-0.0163*	-0.0149*	-0.0168*	-0.0174*
Asian	-0.0338*	-0.0335*	-0.0343*	-0.0349*	-0.0342*	-0.0339*	-0.0347*	-0.0354*
Other	-0.0084	-0.0070	-0.0096	-0.0103	-0.0085	-0.0071	-0.0097	-0.0105
Male	0.0114*	0.0115*	0.0114*	0.0113*	0.0115*	0.0116*	0.0115*	0.0114*
Other Covariates	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	446,202	446,202	446,202	446,202	439,755	439,755	439,755	439,755

Table App-20. Pseudo-R^2 and Incremental Pseudo R^2

Table shows pseudo-R^2 at zip-code and tract level for the indicated outcomes and area-SES measures. Incremental pseudo-R^2 is increase in pseudo-R^2 when areas-SES measure is added to regression with the other covariates used for each measure, which generally include age, gender, race/ethnicity, sometimes comorbidities, and selected interactions (e.g., male*age). Covariates are same as in text Table 3. Negative incremental pseudo-R^2 values are shown with shaded cells. **Panel A.** Zip-code level. **Panel B.** Tract level.

Panel A. Zip-code level

Outcome	**Model**	**SDI**	**ADI_{std}**	**ADI_{mod}**	**ADI_{orig}**	**SVI**	**SVI_{mod}**	**TDI**	**Poverty**
COVID-19 Mortality	Area-SES measure alone	0.42%	0.50%	0.49%	0.36%	0.46%	0.49%	0.22%	0.26%
	Incremental Pseudo-R^2	0.18%	0.31%	0.30%	0.29%	0.21%	0.25%	0.05%	0.12%
All-cause Elderly Mortality over 2000-2019	Area-SES measure alone	0.59%	0.71%	0.75%	0.68%	0.56%	0.64%	0.28%	0.55%
	Incremental Pseudo-R^2	0.38%	0.47%	0.48%	0.47%	0.35%	0.40%	0.18%	0.35%
Diabetes Prevalence in 2000	Area-SES measure alone	0.54%	0.55%	0.54%	0.22%	0.47%	0.49%	0.38%	0.48%
	Incremental Pseudo-R^2	0.07%	0.09%	0.09%	0.05%	0.07%	0.08%	0.03%	0.05%
Diabetes Prevalence in 2019	Area-SES measure alone	0.78%	0.67%	0.65%	0.26%	0.78%	0.73%	0.48%	0.46%
	Incremental Pseudo-R^2	0.30%	0.30%	0.29%	0.18%	0.31%	0.32%	0.09%	0.17%
Diabetes Incidence over 2000-2005	Area-SES measure alone	0.32%	0.34%	0.25%	0.24%	0.08%	0.29%	0.27%	0.21%
	Incremental Pseudo-R^2	0.08%	0.10%	0.06%	0.05%	0.04%	0.07%	0.07%	0.04%
Drug Overdose Mortality	Area-SES measure alone	1.49%	0.86%	0.94%	0.09%	1.38%	1.29%	1.36%	1.21%
	Incremental Pseudo-R^2	0.50%	0.20%	0.20%	-0.10%	0.40%	0.40%	0.50%	0.40%
Average across outcomes	**Area-SES measure alone**	**0.69%**	**0.61%**	**0.60%**	**0.31%**	**0.62%**	**0.66%**	**0.50%**	**0.53%**
Average across outcomes	**Incremental Pseudo-R^2**	**0.25%**	**0.25%**	**0.24%**	**0.16%**	**0.23%**	**0.25%**	**0.15%**	**0.19%**

Panel B. Tract level

Outcome	**Model**	**SDI**	**ADI_{std}**	**ADI_{mod}**	**ADI_{orig}**	**SVI**	**SVI_{mod}**	**TDI**	**Poverty**
All-cause Elderly Mortality over 2000-2019	Area-SES measure alone	0.90%	1.05%	1.05%	0.96%	0.89%	0.99%	0.53%	0.78%
	Incremental Pseudo-R^2	0.58%	0.70%	0.71%	0.66%	0.60%	0.66%	0.33%	0.51%
Diabetes Prevalence in 2000	Area-SES measure alone	0.78%	0.66%	0.67%	0.24%	0.68%	0.63%	0.65%	0.56%
	Incremental Pseudo-R^2	0.11%	0.17%	0.16%	0.05%	0.09%	0.11%	0.04%	0.07%
Diabetes Incidence over 2000-2005	Area-SES measure alone	0.40%	0.48%	0.24%	0.26%	0.06%	0.33%	0.25%	0.23%
	Incremental Pseudo-R^2	0.09%	0.09%	0.08%	0.04%	0.05%	0.06%	0.05%	0.06%
Average across outcomes	**Area-SES measure alone**	**0.69%**	**0.73%**	**0.65%**	**0.49%**	**0.54%**	**0.65%**	**0.48%**	**0.52%**
Average across outcomes	**Incremental Pseudo-R^2**	**0.26%**	**0.32%**	**0.32%**	**0.25%**	**0.25%**	**0.28%**	**0.14%**	**0.21%**

Table App-21. Area under the ROC Curve

Table shows area under the ROC curve (AUC) at zip-code and tract level for the indicated outcomes and area-SES measures. Incremental AUC is increase in AUC when areas-SES measure is added to regression with the other covariates used for each measure, which generally include age, gender, race/ethnicity, sometimes comorbidities, and selected interactions (e.g., male*age). Covariates are same as in text Table 3. **Panel A.** Zip-code level. **Panel B.** Tract level.

Panel A. Zip-code level

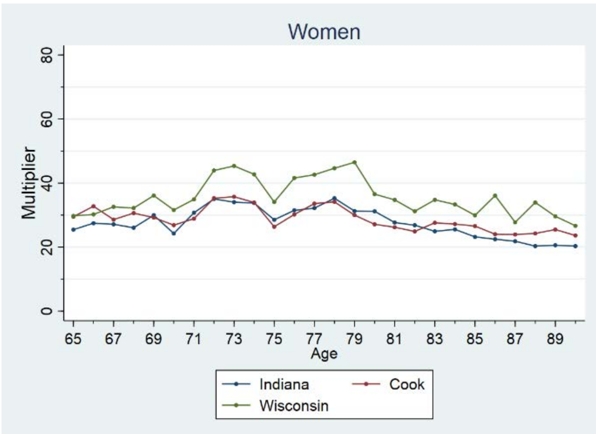
Outcome	Model	SDI	ADI_{std}	ADI_{mod}	ADI_{orig}	SVI	SVI_{mod}	TDI	Poverty
COVID-19 Mortality	SES alone	55.9%	56.3%	56.1%	55.5%	56.3%	56.5%	54.3%	54.6%
	Incremental AUC	0.04%	0.07%	0.06%	0.06%	0.05%	0.06%	0.01%	0.03%
All-cause elderly mortality	SES alone	55.1%	55.6%	55.7%	55.4%	54.9%	55.3%	53.3%	54.9%
	Incremental AUC	0.07%	0.08%	0.08%	0.08%	0.06%	0.07%	0.04%	0.06%
Diabetes Prevalence 2000	SES alone	54.8%	54.7%	54.6%	52.8%	54.6%	54.7%	53.9%	54.2%
	Incremental AUC	0.2%	0.3%	0.3%	0.1%	0.2%	0.3%	0.1%	0.1%
Diabetes Prevalence 2019	SES alone	55.9%	55.4%	55.3%	53.1%	55.9%	55.8%	54.4%	54.5%
	Incremental AUC	0.6%	0.6%	0.6%	0.5%	0.7%	0.7%	0.2%	0.6%
Diabetes Incidence 2000-2005	SES alone	53.3%	53.4%	52.9%	52.7%	51.8%	53.3%	53.1%	52.5%
	Incremental AUC	0.3%	0.3%	0.2%	0.2%	0.2%	0.3%	0.3%	0.1%
Drug Overdose Mortality	SES alone	59.4%	56.8%	56.6%	52.4%	59.0%	58.8%	59.3%	58.4%
	Incremental AUC	0.02%	0.01%	0.02%	0.02%	0.02%	0.02%	0.03%	0.02%
Average across outcomes	**SES alone**	**55.73%**	**55.37%**	**55.20%**	**53.65%**	**55.42%**	**55.73%**	**54.72%**	**54.85%**
Average across outcomes	**Incremental AUC**	**0.21%**	**0.23%**	**0.21%**	**0.16%**	**0.21%**	**0.24%**	**0.11%**	**0.15%**

Panel B. Tract level

Outcome	Model	SDI	ADI_{std}	ADI_{mod}	ADI_{orig}	SVI	SVI_{mod}	TDI	Poverty
All-cause elderly mortality	SES alone	56.3%	56.8%	56.8%	56.5%	56.2%	56.6%	54.8%	55.9%
	Incremental AUC	0.09%	0.10%	0.11%	0.10%	0.09%	0.10%	0.06%	0.08%
Diabetes Prevalence 2000	SES alone	55.6%	55.2%	55.3%	53.2%	55.4%	55.3%	54.9%	54.6%
	Incremental AUC	0.4%	0.4%	0.5%	0.4%	0.2%	0.4%	0.2%	0.2%
Diabetes Incidence 2000-2005	SES alone	53.5%	53.9%	52.6%	52.6%	51.7%	53.3%	52.9%	52.5%
	Incremental AUC	0.4%	0.5%	0.5%	0.4%	0.3%	0.3%	0.2%	0.3%
Average across outcomes	**SES alone**	**55.13%**	**55.30%**	**54.90%**	**54.10%**	**54.43%**	**55.07%**	**54.20%**	**54.33%**
Average across outcomes	**Incremental AUC**	**0.30%**	**0.33%**	**0.37%**	**0.30%**	**0.20%**	**0.27%**	**0.15%**	**0.19%**

Figure App-1. Multipliers to Convert 5% Medicare FFS Random Sample to Synthetic Population for Three Midwest Areas

Figure shows for women (left-hand graphs) and men (right-hand graphs) the multipliers we use to convert the 5% Medicare random sample to a population-representative synthetic population for each of the three Midwest areas, for ages 65-95. Multipliers are averaged across race/ethnicity, in proportion to number of Medicare FFS beneficiaries. We suppress estimates for ages above 90, which become erratic due to the small numbers of both decedents and persons in our 5% Medicare FFS sample.



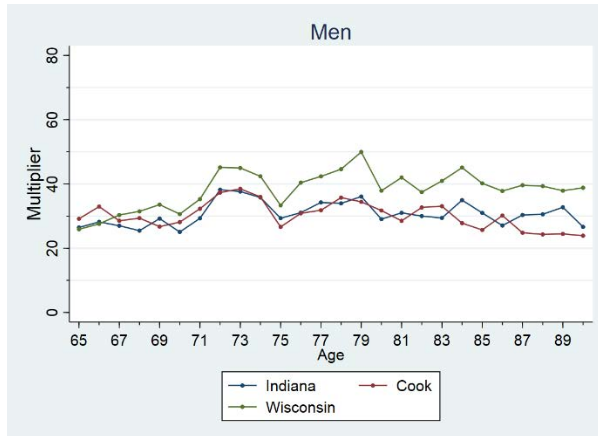
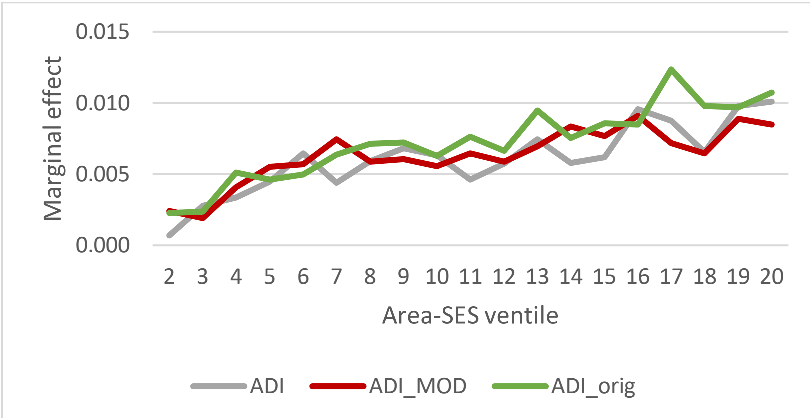


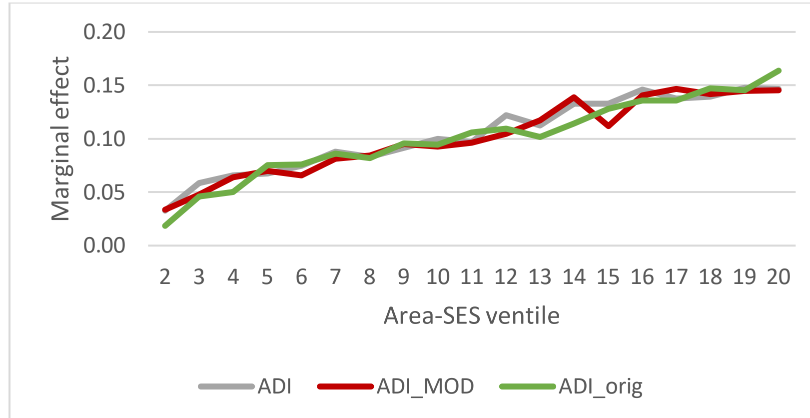
Figure App-2. Comparison of ADI_{orig}, ADI_{std} and ADI_{mod}

Figure compares marginal effects of ventiles of ADI_{std}, ADI_{mod} and ADI_{orig} for the indicated outcomes and geographic levels. **Panel A.** Zip-code level. **Panel B.** Same but at tract level, for outcomes for which tract level estimates are available. **Panel C.** Same but at tract level, for outcomes for which block-group level estimates are available. **Panel D.** Same but at county level. Outcomes, sample, and covariates are same as for regressions reported in text Table 3. **All panels.** ADI measure is ADI_{std}.

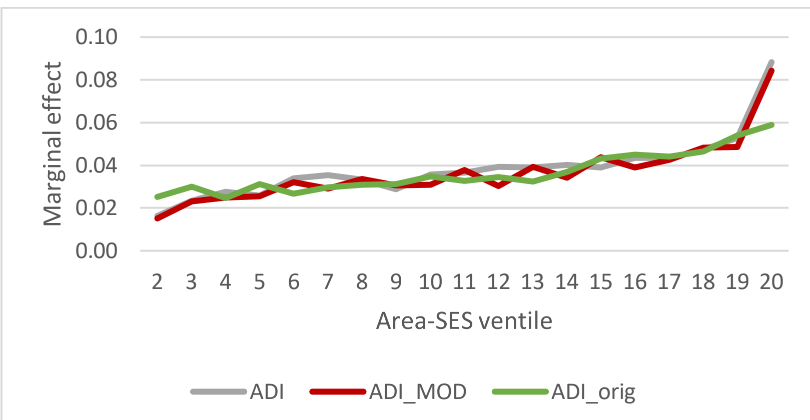
Zip-Code level: Panel A1. COVID-19 Mortality



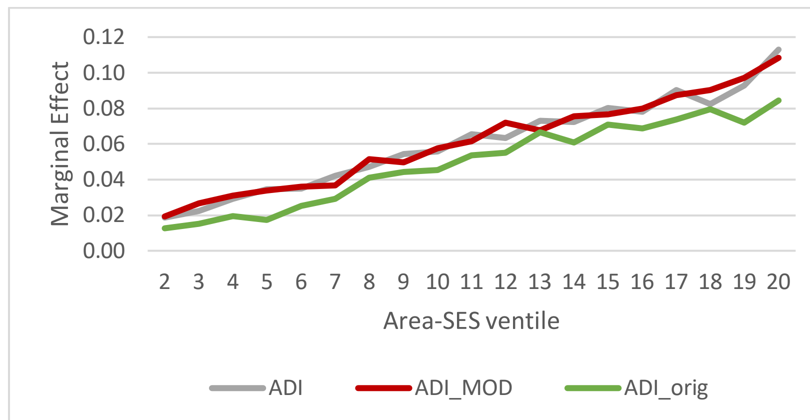
Panel A2. All-Cause Elderly Mortality



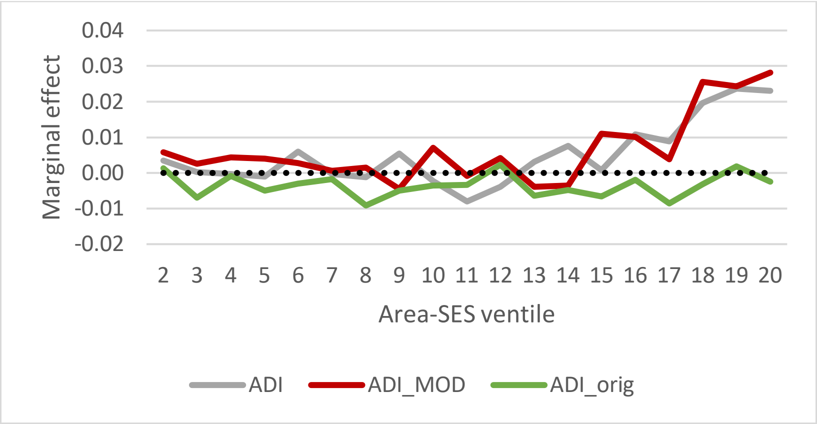
Zip-Code level: Panel A3. Diabetes Prevalence in 2000



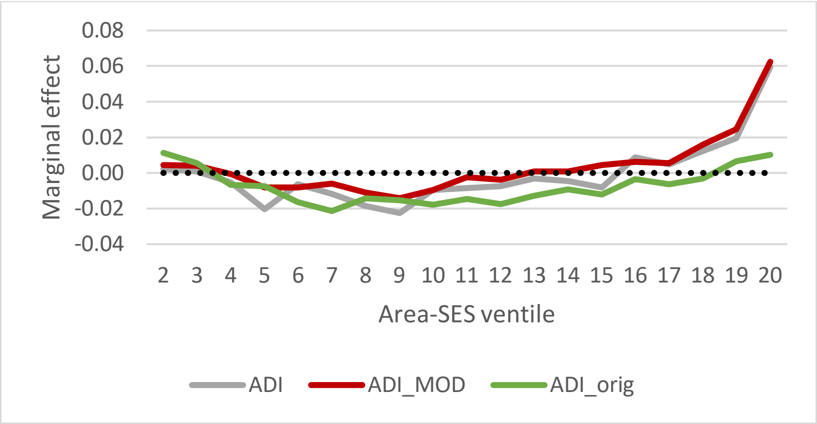
Panel A4. Diabetes Prevalence in 2019



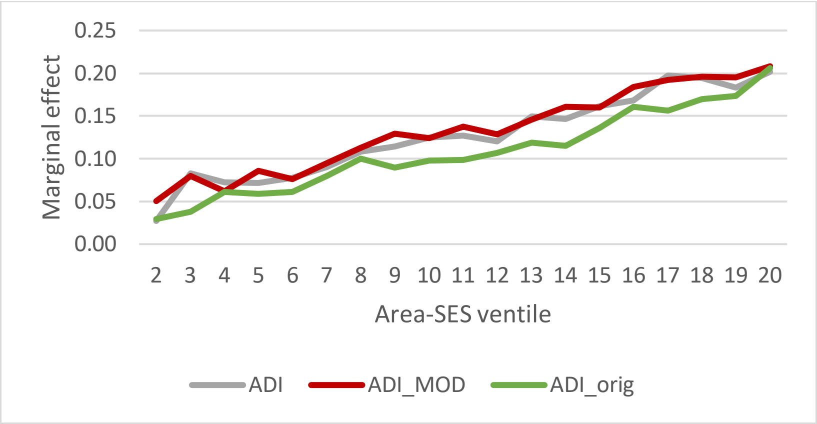
Zip-Code level: Panel A5. Drug Overdose Mortality



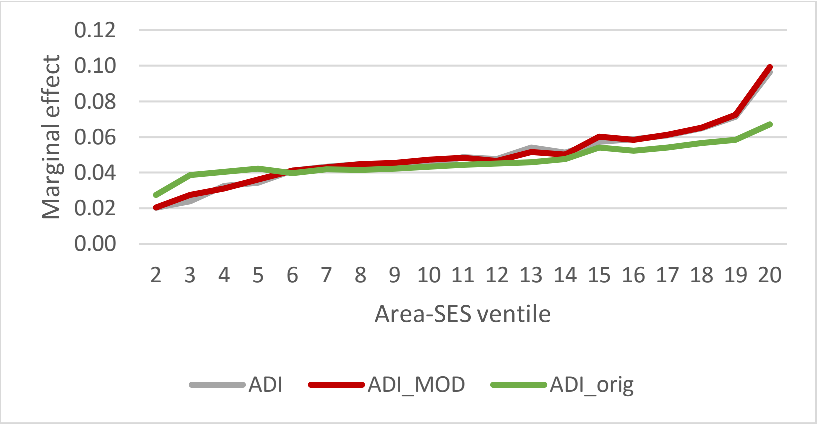
Panel A6. Diabetes incidence over 2000-2005



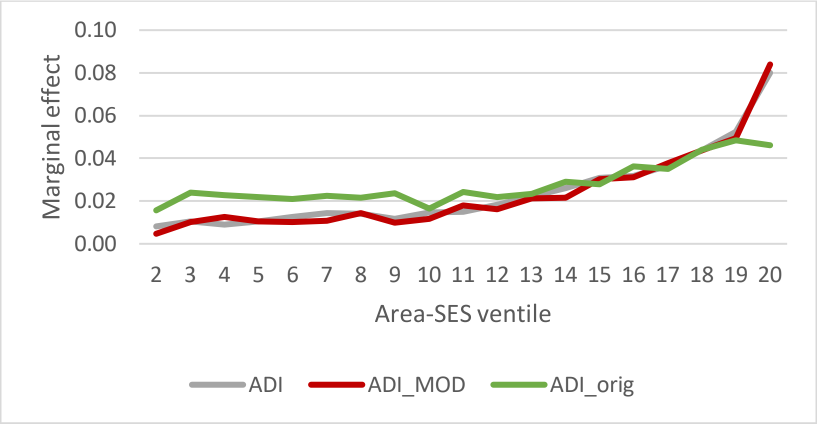
Tract level: Panel B1. All-Cause Elderly Mortality



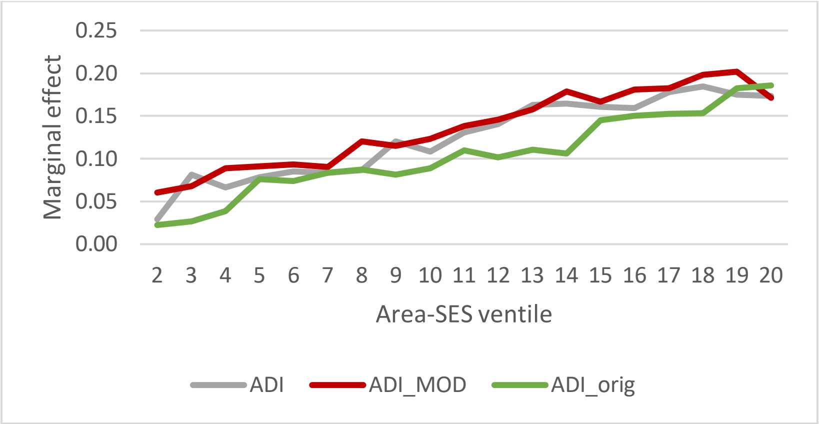
Panel B2. Diabetes Prevalence in 2000



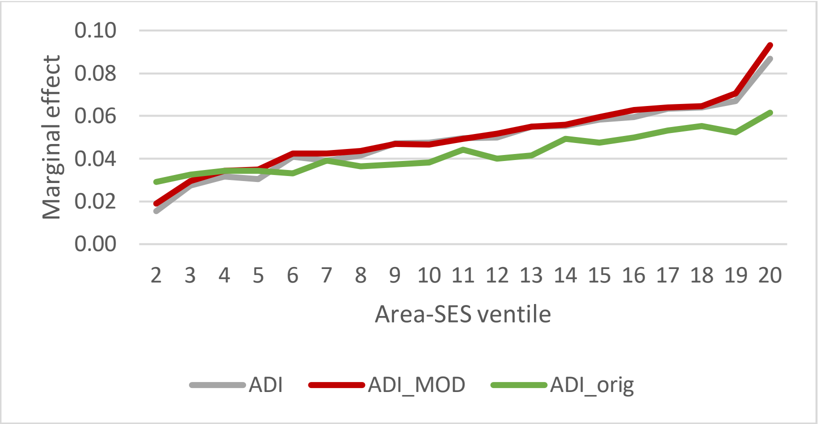
Tract level: Panel B3. Diabetes incidence 2000-2005



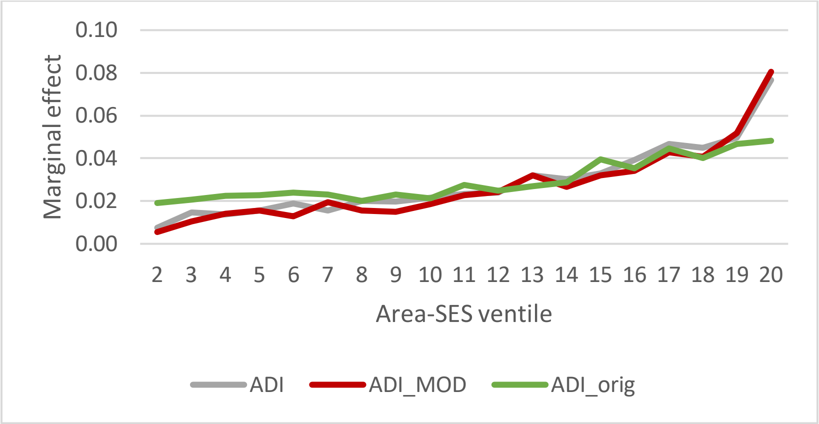
Block group level: Panel C1. All-Cause Elderly Mortality



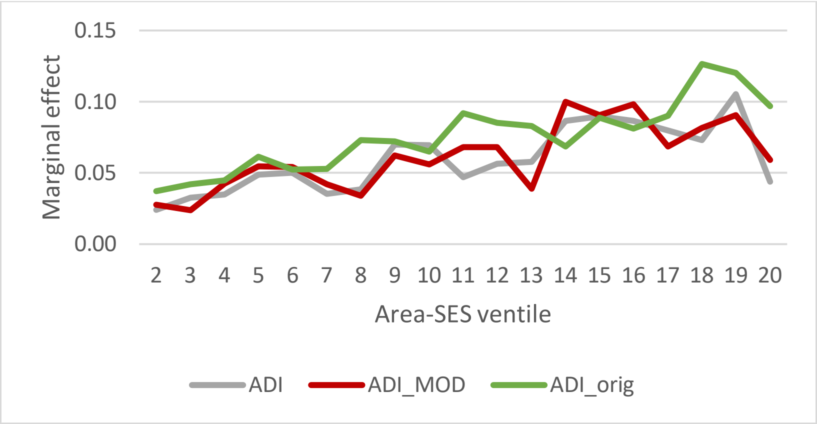
Panel C2. Diabetes Prevalence in 2000



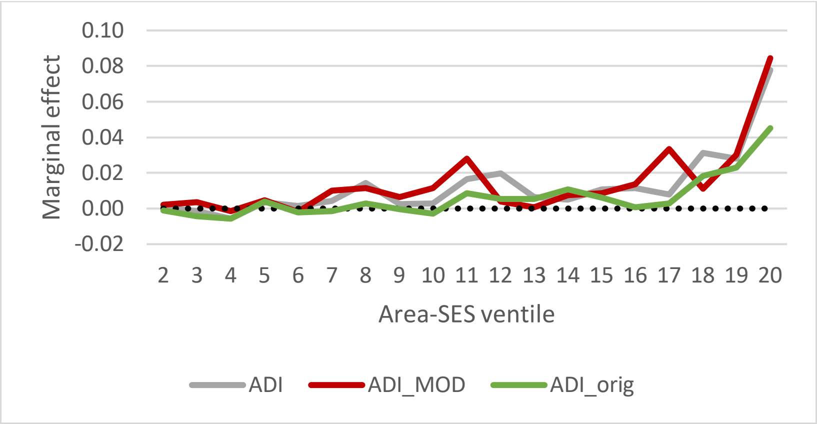
Block group level: Panel C3. Diabetes incidence over 2000-2005



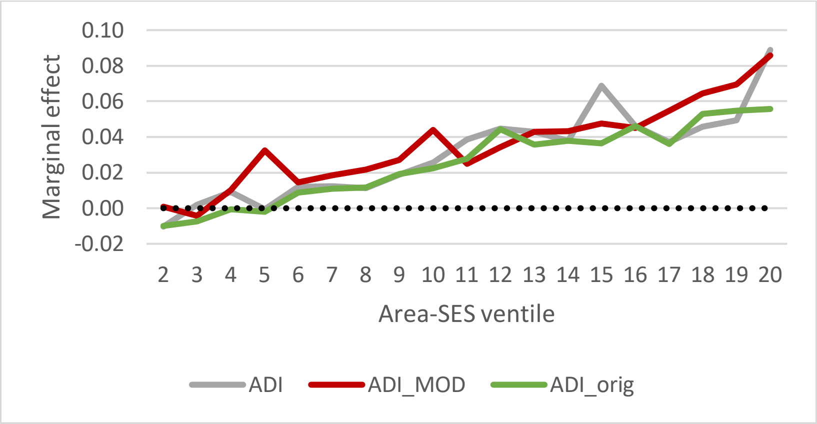
County level: Panel D1. All-Cause Elderly Mortality



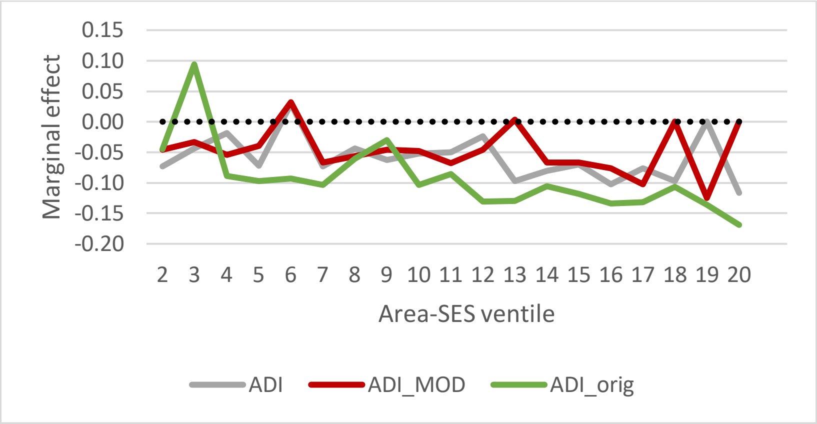
Panel D2. Diabetes Prevalence in 2000



County level: Panel D3. Diabetes Prevalence in 2019



Panel D4. Drug Overdose Mortality



County level: Panel D5. Diabetes incidence over 2000-2005

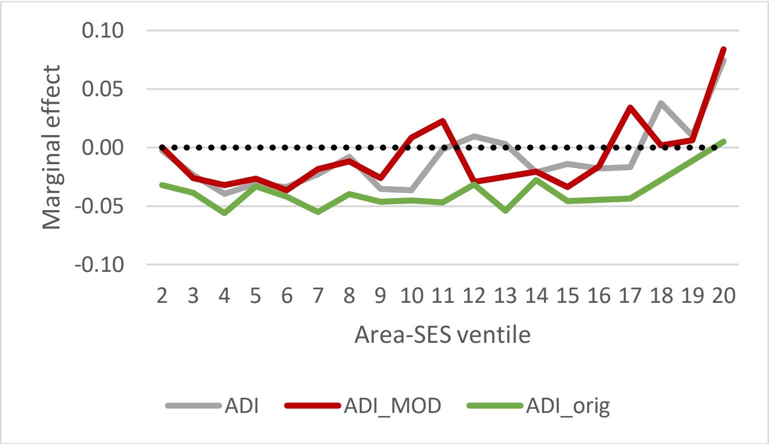
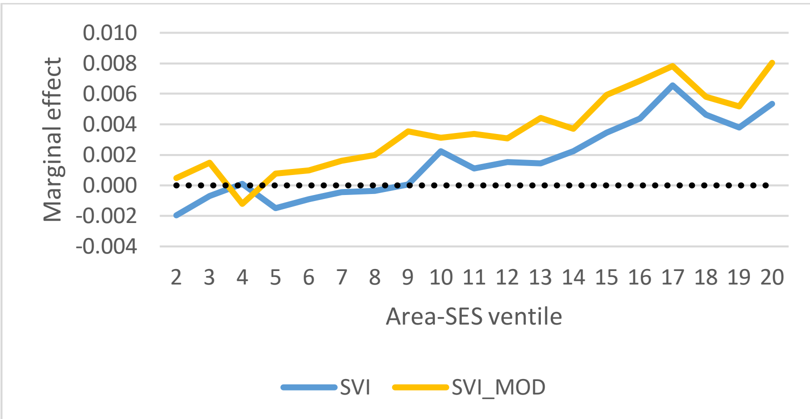


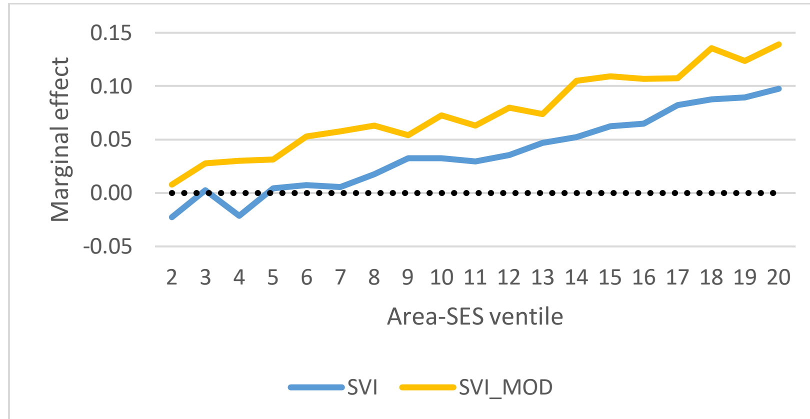
Figure App-3. Comparison of SVI and SVI$_{mod}$

Figure compares marginal effects of ventiles of SVI and modified SVI for the indicated outcomes and geographic levels. **Panel A.** Zip-code level. **Panel B.** Same but at tract level, for outcomes for which tract level estimates are available. **Panel C.** Same but at tract level, for outcomes for which block-group level estimates are available. **Panel D.** Same but at county level. Outcomes, sample, and covariates are same as for regressions reported in text Table 3.

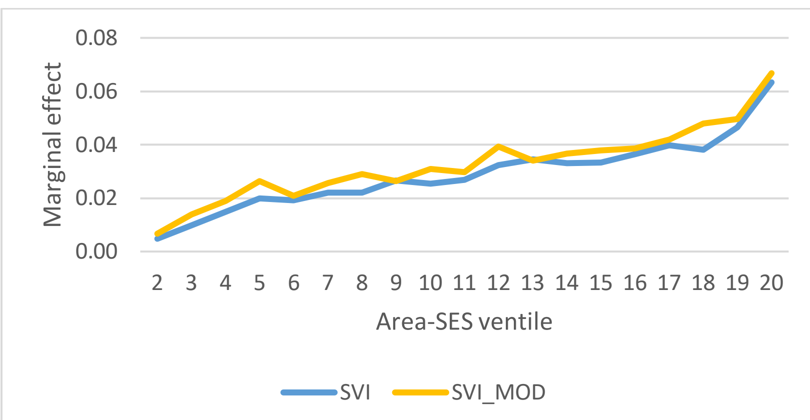
Zip-Code level: Panel A1. COVID-19 Mortality



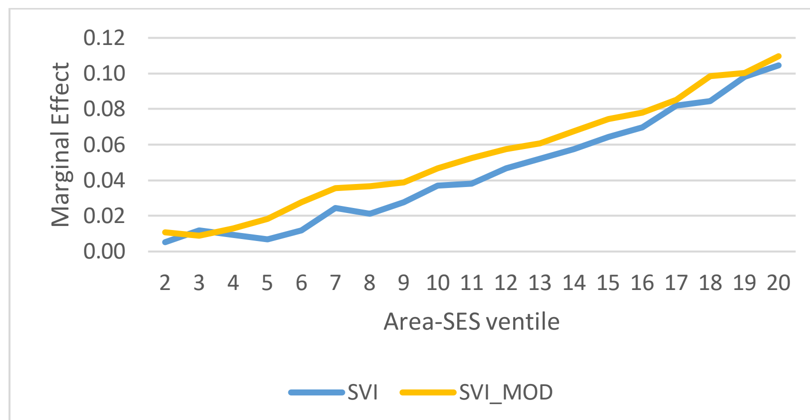
Panel A2. All-Cause Elderly Mortality



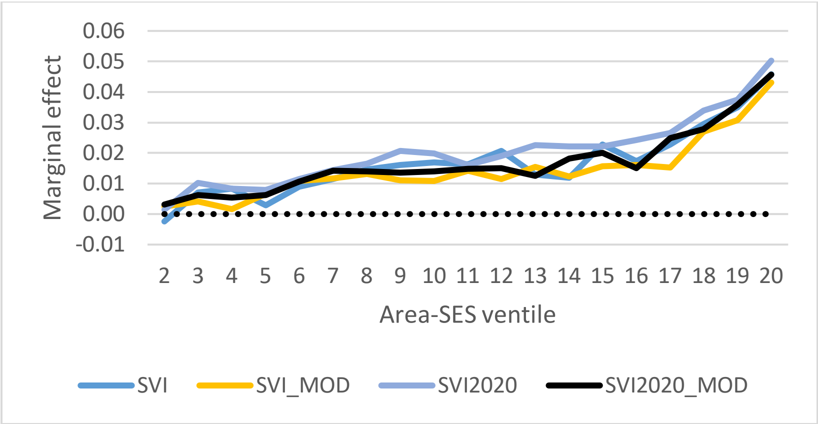
Zip-Code level: Panel A3. Diabetes Prevalence in 2000



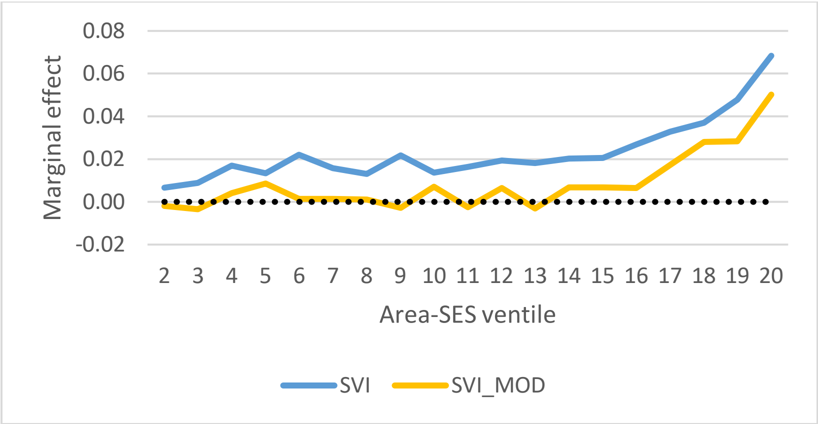
Panel A4. Diabetes Prevalence in 2019



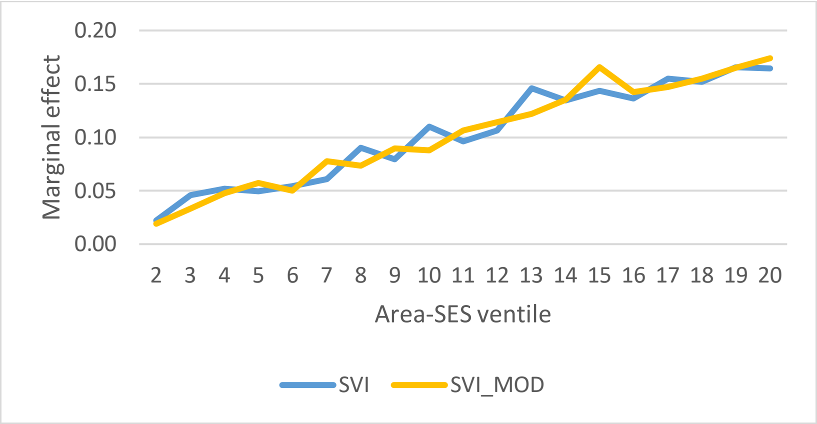
Zip-Code level: Panel A5. Drug Overdose Mortality



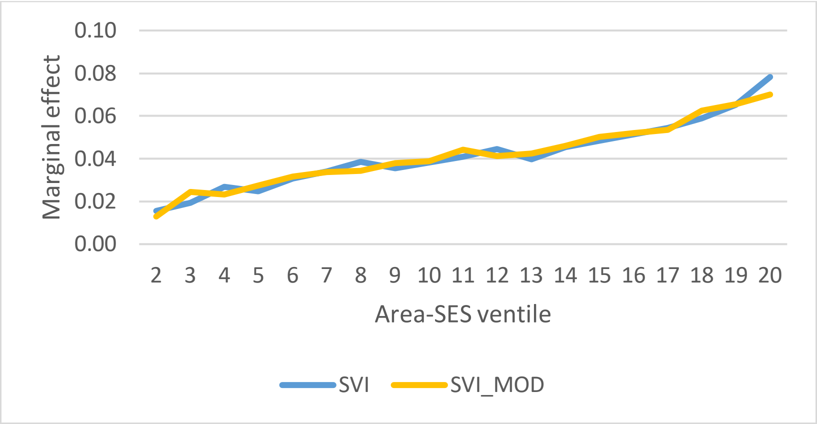
Panel A6. Diabetes incidence over 2000-2005



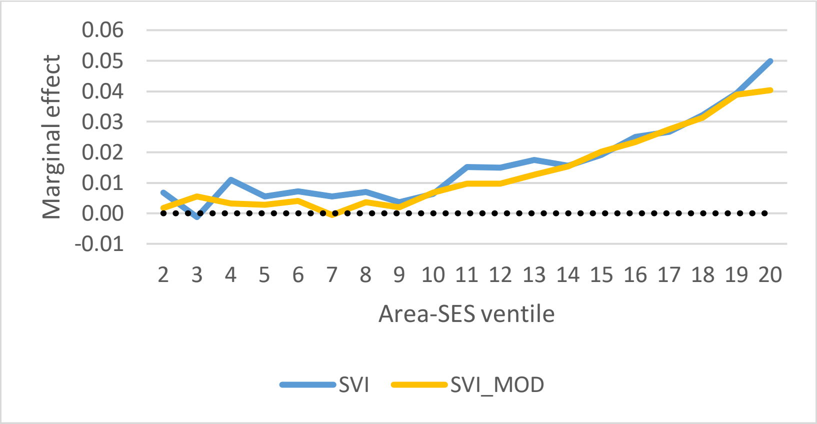
Tract level: Panel B1. All-Cause Elderly Mortality



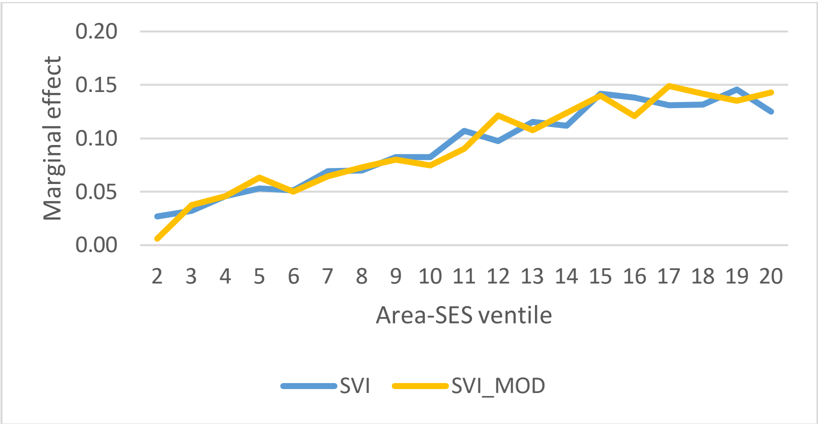
Panel B2. Diabetes Prevalence in 2000



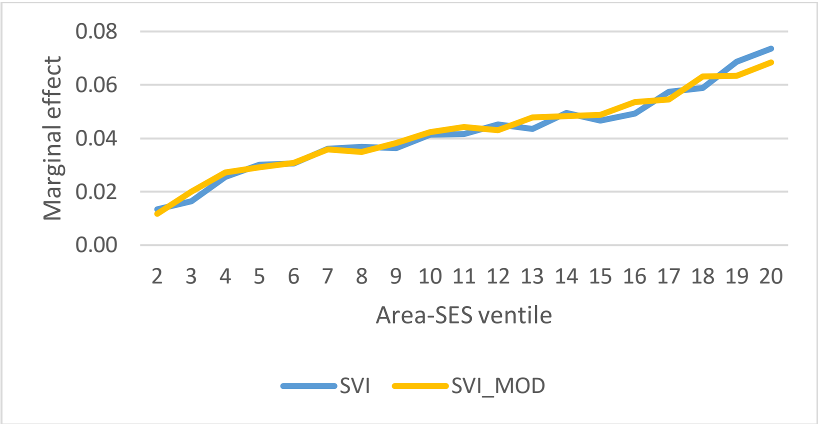
Tract level: Panel B3. Diabetes incidence over 2000-2005



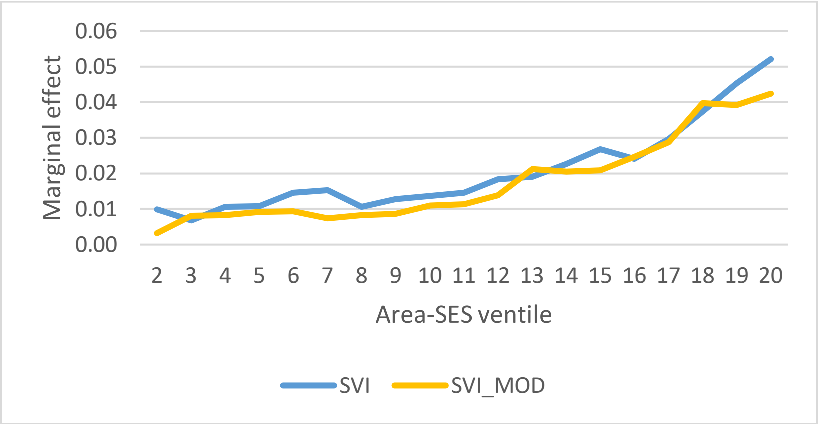
Block group level: Panel C1. All-Cause Elderly Mortality



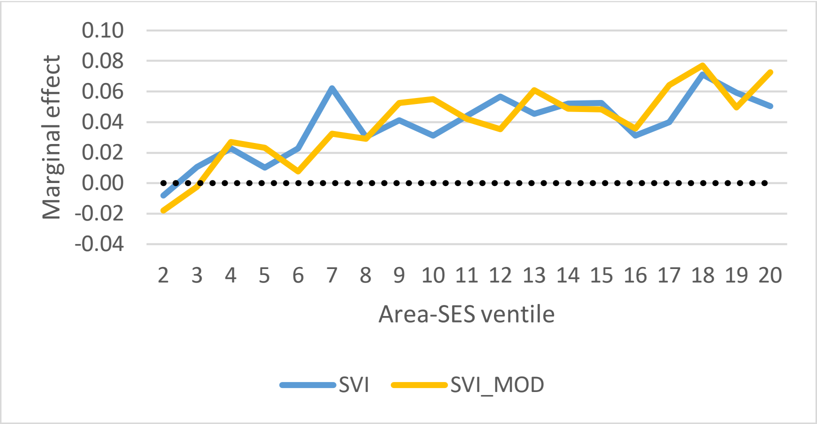
Panel C2. Diabetes Prevalence in 2000



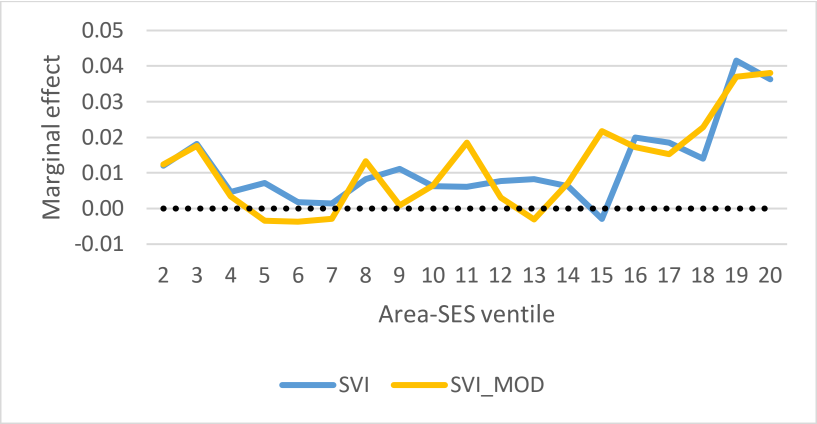
Block group level: Panel C3. Diabetes Incidence over 2000-2005



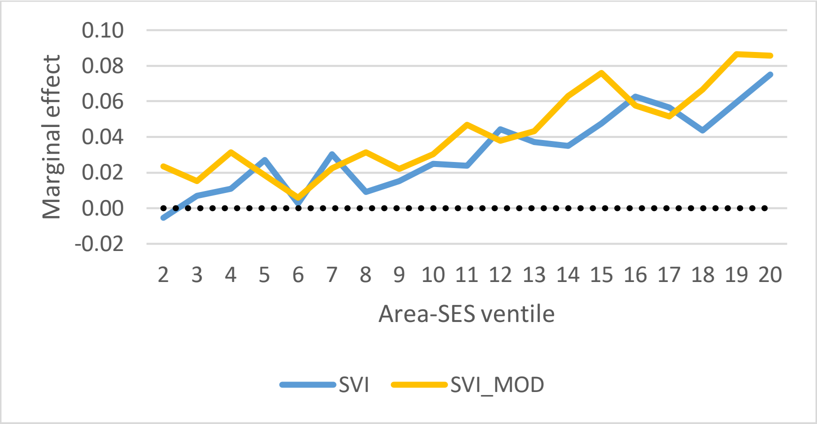
County level: Panel D1. All-Cause Elderly Mortality



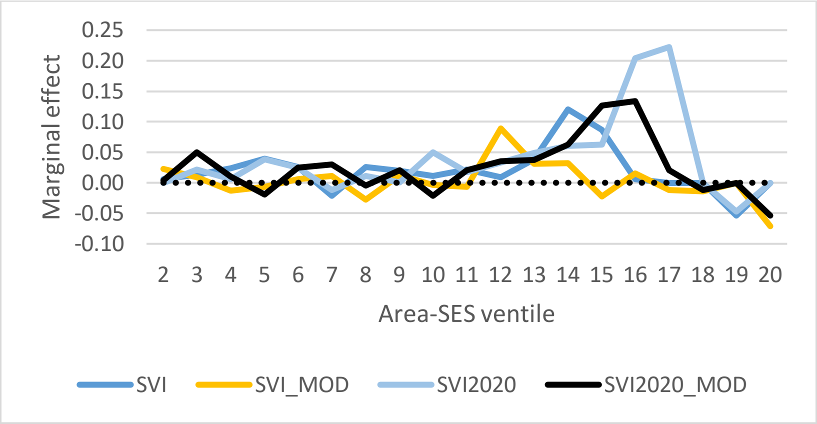
Panel D2. Diabetes Prevalence in 2000



County level: Panel D3. Diabetes Prevalence in 2019



Panel D4. Drug Overdose Mortality



County level: Panel D5. Diabetes Incidence over 2000-2005

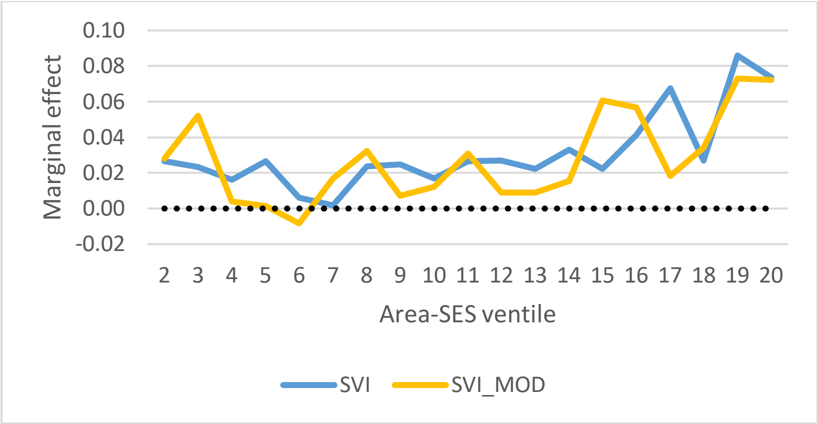
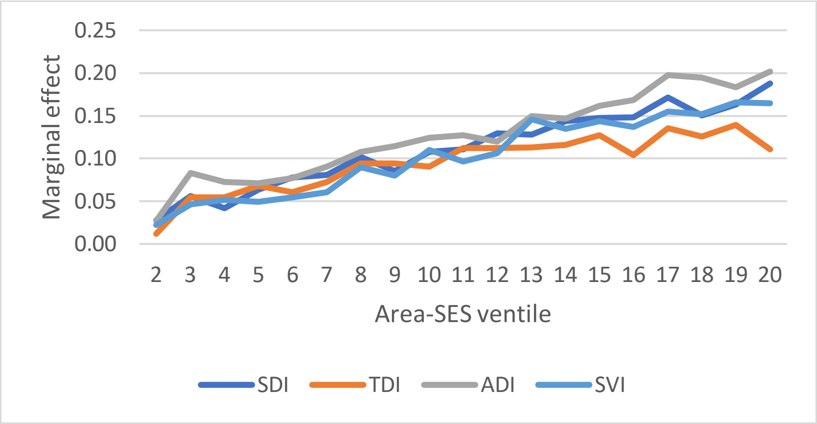


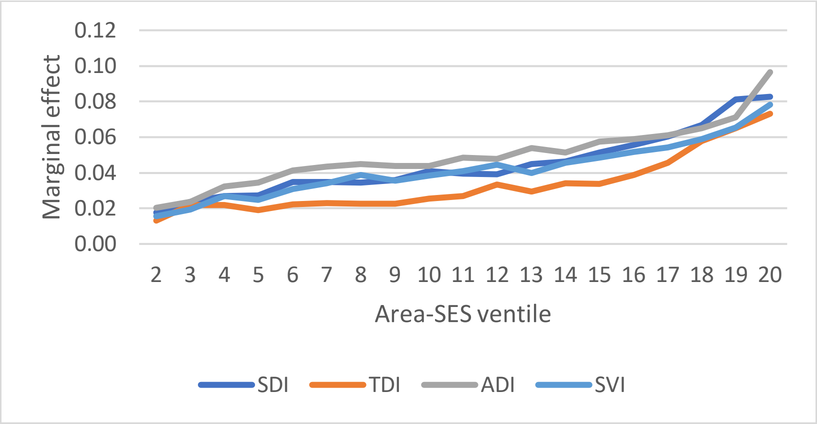
Figure App-4. Area-SES Marginal Effects for Ventiles at Tract Level

Figure shows marginal effects of ventiles of SDI, ADI, SVI, and TDI for indicated outcomes at tract level. Highest SES ventile is omitted. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes Incidence over 2000-2005. Covariates are same as in text Table 3. **All panels.** ADI is ADI_{std}.

Panel. A. All-Cause Elderly Mortality over 2000-2019



Panel B. Diabetes Prevalence in 2000



Panel C. Diabetes Incidence over 2000-2005

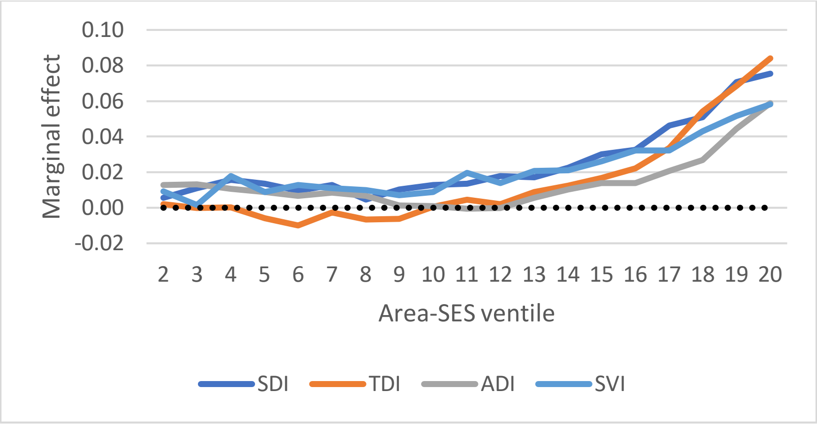
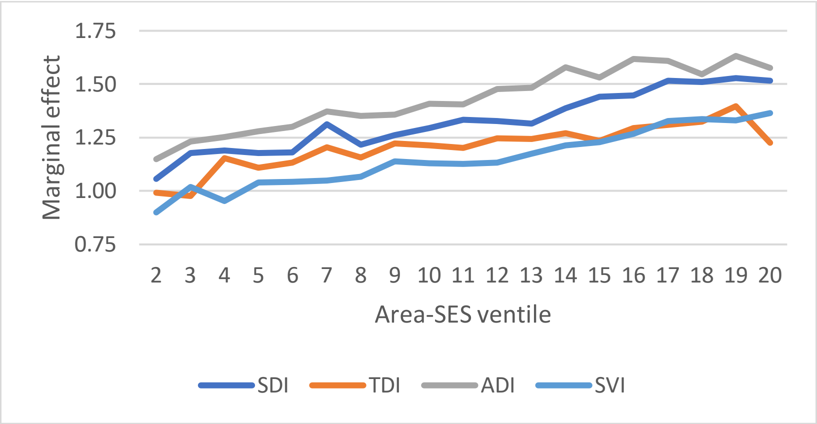


Figure App-5. Area-SES Marginal Effects for Ventiles for Cox Model: Zip-Code and Tract Level

Figure shows marginal effects of ventiles of SDI, ADI_{std}, SVI, and TDI for all-cause elderly mortality using Cox model, at zip-code and tract level. Highest SES Ventile is omitted. Sample uses Medicare-FFS beneficiaries aged 66 as of January 1, 2000. **Panel A.** Zip-code level. **Panel B.** Tract level. Covariates are same as in text Table 3, Panel B. **All panels.** ADI measure is ADI_{std}.

Panel A. Zip-Code level: All-cause Elderly Mortality over 2000-2019



Panel B. Tract level: All-cause Elderly Mortality over 2000-2019

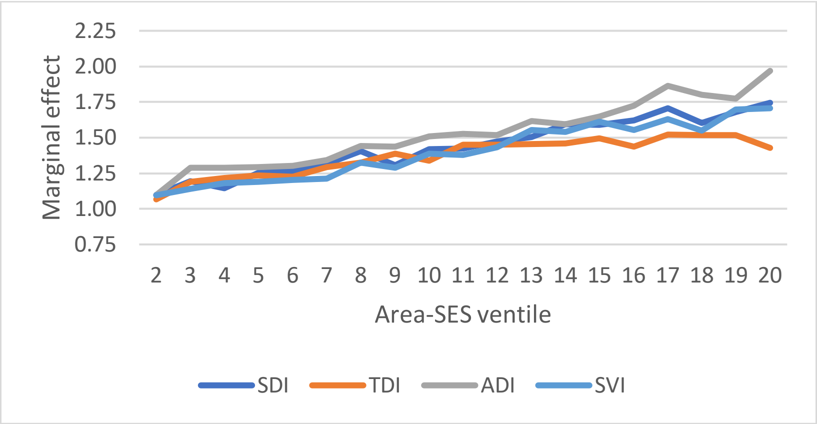
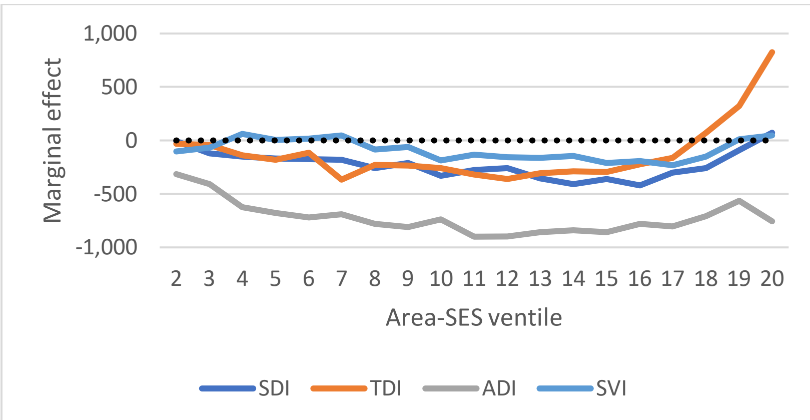


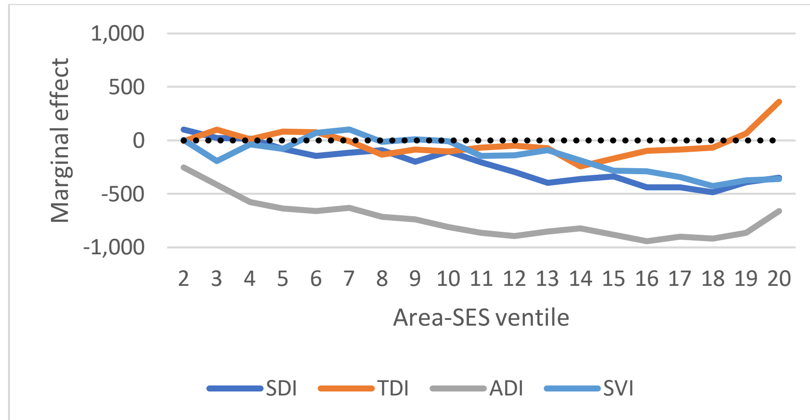
Figure App-6. Medicare Spending in 2000 and 2019

Graph shows marginal effects for Medicare spending in 2000 and 2019, for ventiles, for SDI, ADI_{std}, SVI, and TDI, for indicated geographic levels. Highest SES 5-percentile is omitted. **Panel A.** Medicare spending in 2000 at zip-code level. **Panel B.** Medicare spending in 2019 at zip-code level. **Panel C.** Medicare Spending in 2000 at county level. **Panel D.** Medicare Spending in 2019 at county level. Covariates are same as in Table App-13. Amounts in 2000$. **All panels.** ADI measure is ADI_{std}.

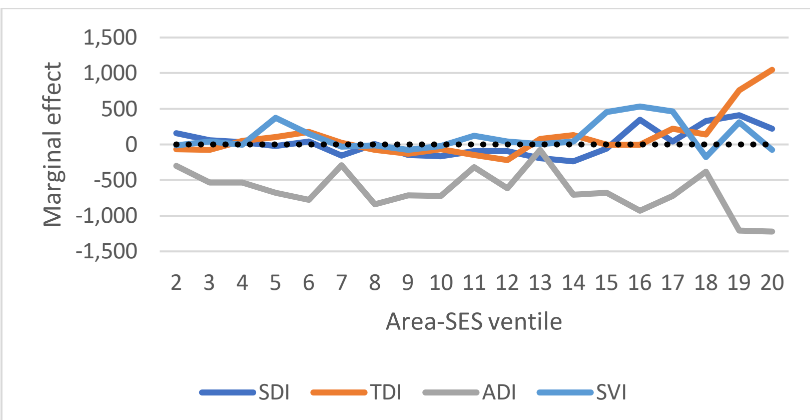
Panel A. Zip-code level: Medicare Spending in 2000



Panel B. Zip-code level: Medicare Spending in 2019



Panel C. County level: Medicare Spending in 2000



Panel D. County level: Medicare Spending in 2019

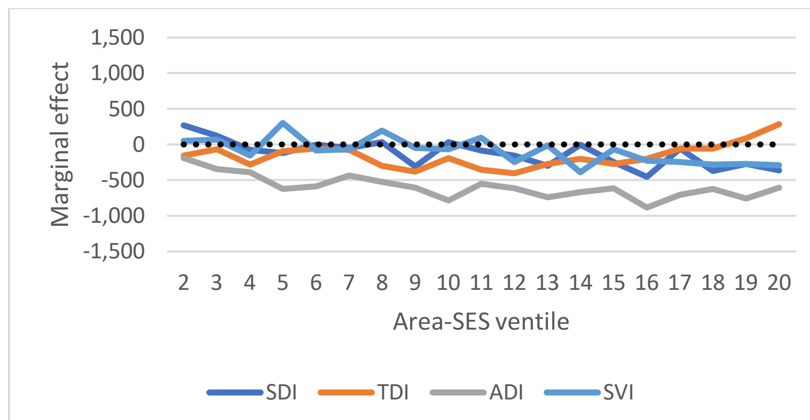
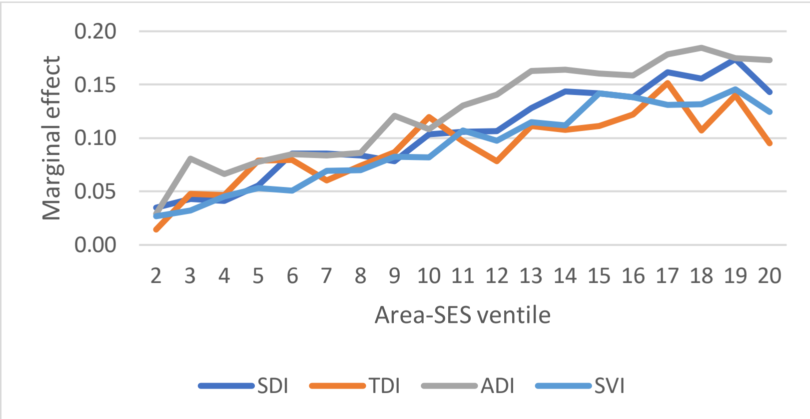


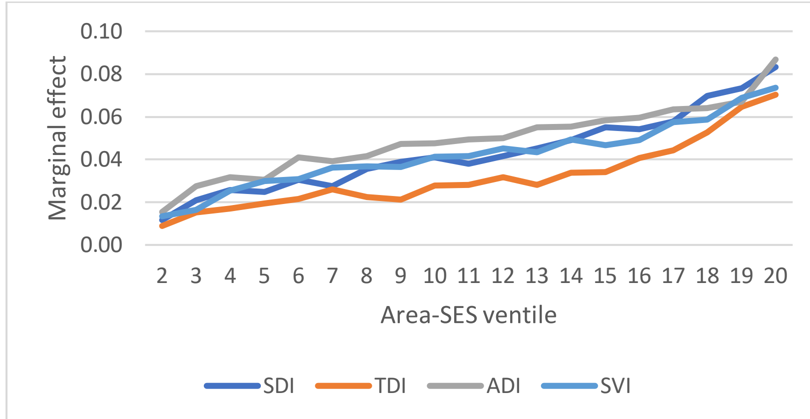
Figure App-7 Area-SES Marginal Effects for Ventiles at Block Group Level

Figure shows marginal effects of ventiles of SDI, ADI_{std}, SVI, and TDI for indicated outcomes at block-group for outcomes with data available at block-group level. Highest SES 5-percentile is omitted. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes incidence over 2000-2005. Covariates are same as in text Table 3. **All panels.** ADI measure is ADI_{std}.

Panel. A. All-Cause Elderly Mortality over 2000-2019



Panel B. Diabetes Prevalence in 2000



Panel C. Diabetes incidence over 2000-2005

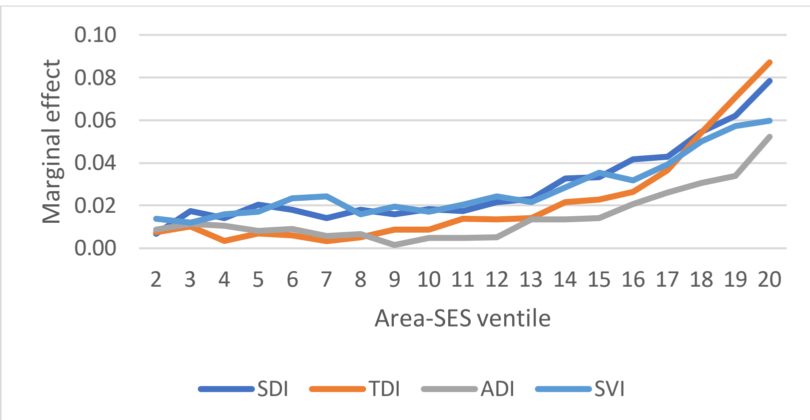
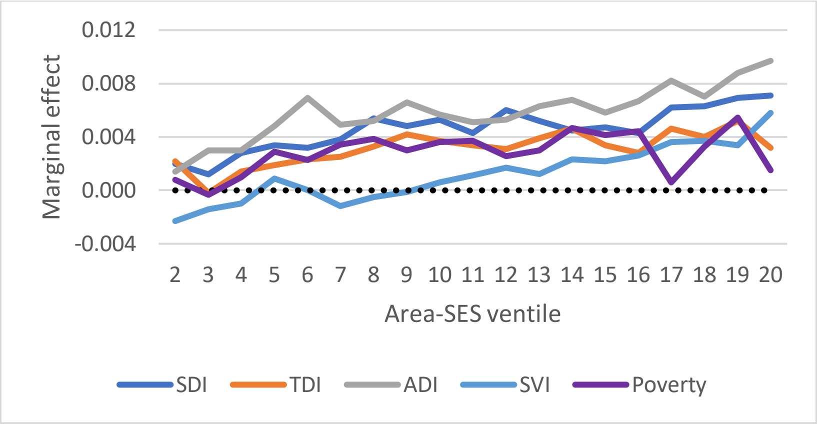


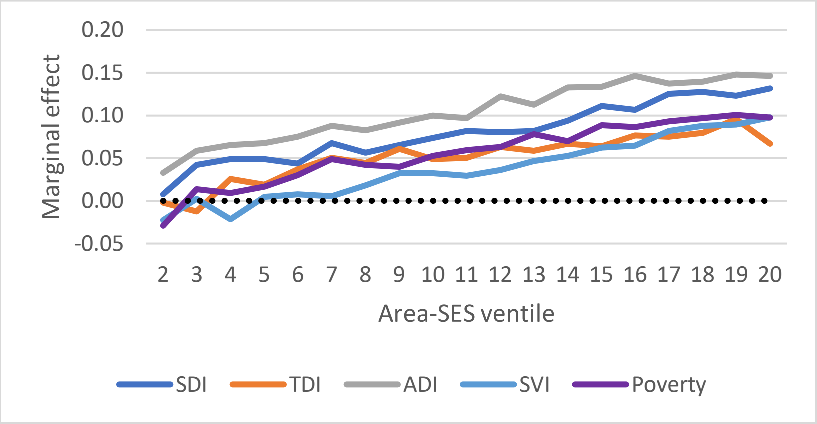
Figure App-8. Zip-Code Level: Comparing Poverty Alone to Area-SES Ventiles Alone

Figure shows marginal effects of ventiles of SDI, ADI_{std}, SVI, TDI, and Poverty for indicated outcomes at zip-code level. Highest SES ventile is omitted. Other covariates are same as in text Table 3. **A ll panels.** ADI measure is ADI_{std}.

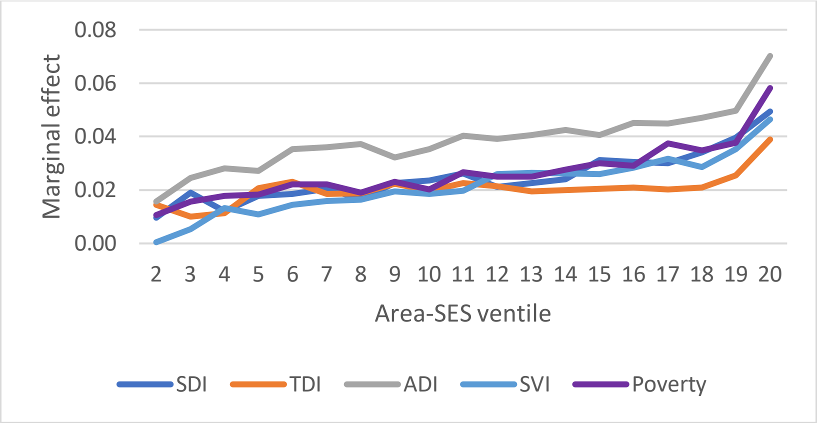
Panel. A. COVID-19 Mortality



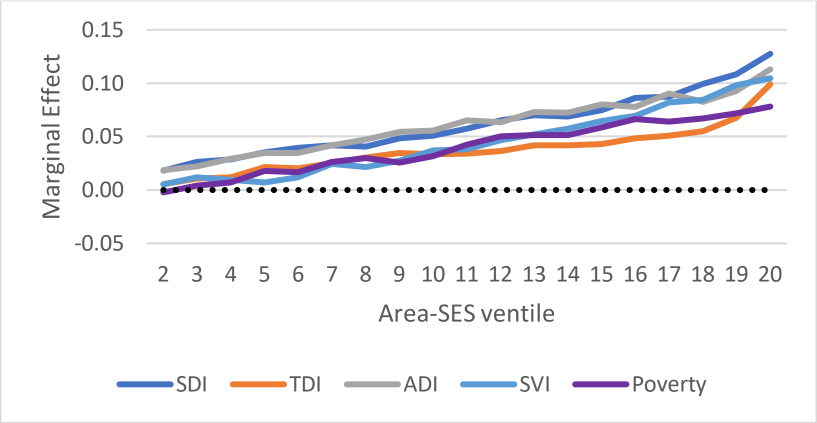
Panel. B. All-Cause Elderly Mortality over 2000-2019



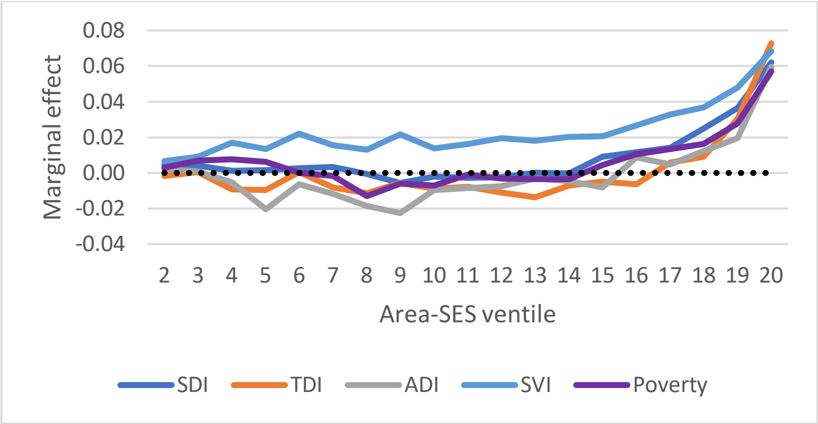
Panel C. Diabetes Prevalence in 2000



Panel D. Diabetes Prevalence in 2019



Panel E: Diabetes Incidence over 2000-2005



Panel F. Drug Overdose Mortality in 2017-2021

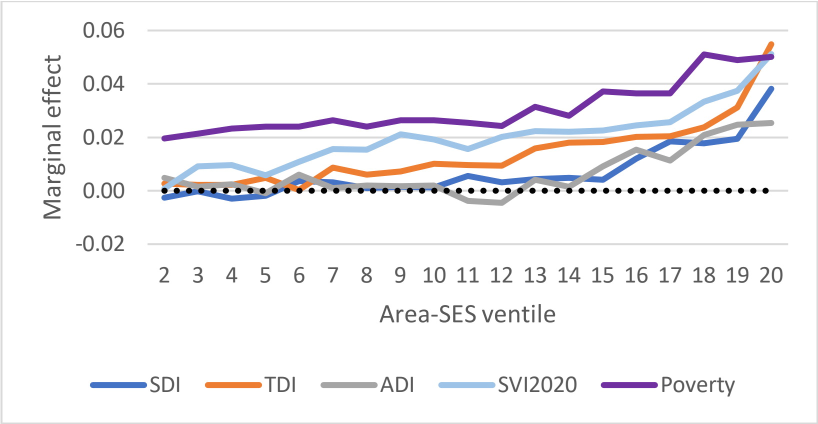
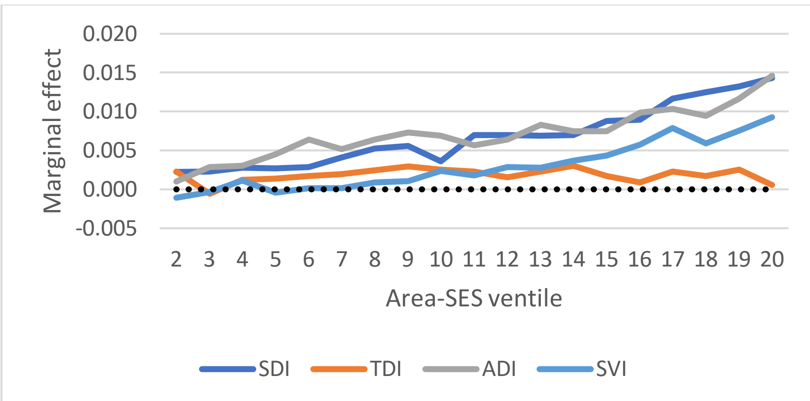


Figure App-9. Marginal Effects for Ventiles at Zip-code Level, Controlling for Poverty and Vice-Versa

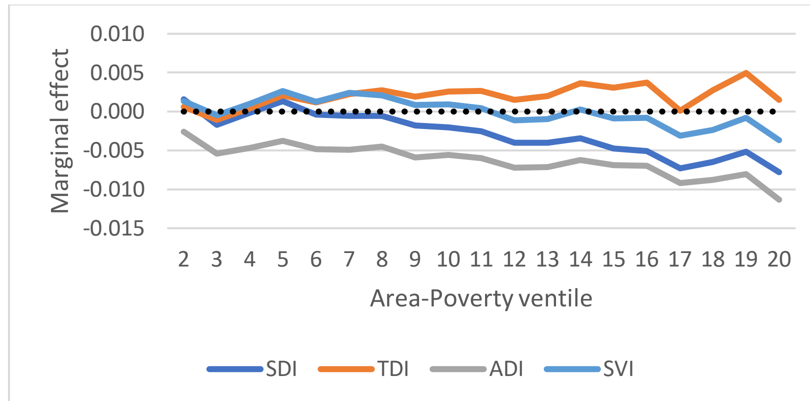
Left-hand graphs: marginal effects of ventiles of SDI, ADI_{std}, SVI, and TDI for indicated outcomes at zip-code level, controlling for ventiles of Poverty. Highest SES ventile is omitted. **Right-hand graphs:** marginal effects of Poverty ventiles, controlling for ventiles of the indicated area-SES measures. Highest income (lowest Poverty) ventile is omitted. **Panel A.** COVID-19 Mortality. **Panel B.** All-Cause Elderly Mortality over 2000-2019. **Panel C.** Diabetes Prevalence in 2000. **Panel D.** Diabetes Prevalence in 2019. **Panel E.** Diabetes Incidence over 2000-2005. **Panel F.** Drug Overdose Mortality in Illinois and Indiana, 2017-2021. Other covariates are same as in text Table 3. **All panels.** ADI measure is ADI_{std}.

Panel. A. COVID-19 Mortality

Area-SES Measures Controlling for Poverty

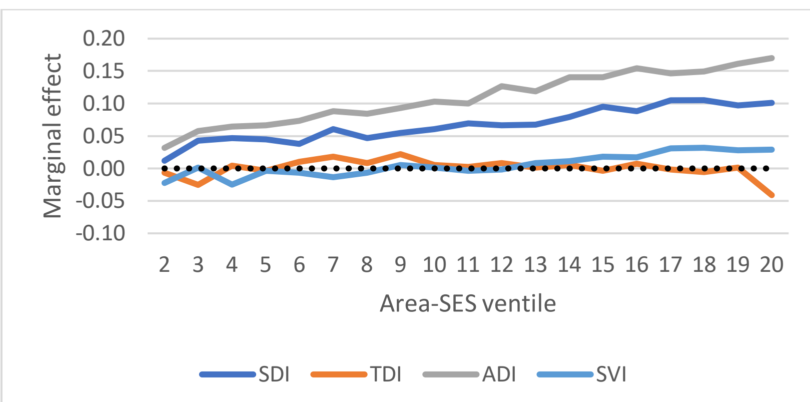


Poverty, Controlling for Indicated Area-SES Measure

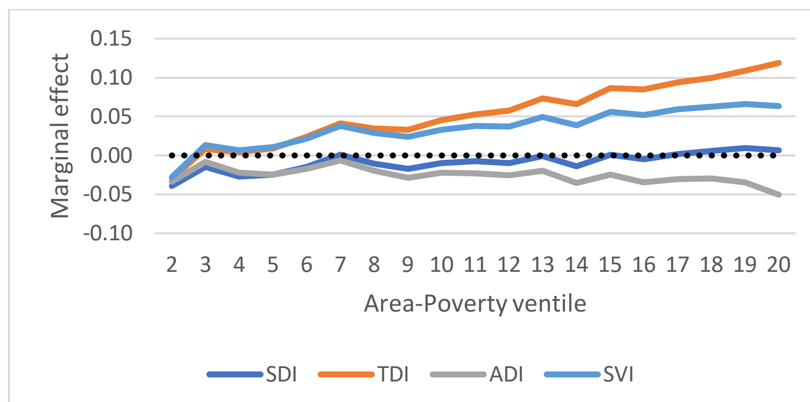


Panel B. All-Cause Elderly Mortality over 2000-2019

Area-SES Measures Controlling for Poverty

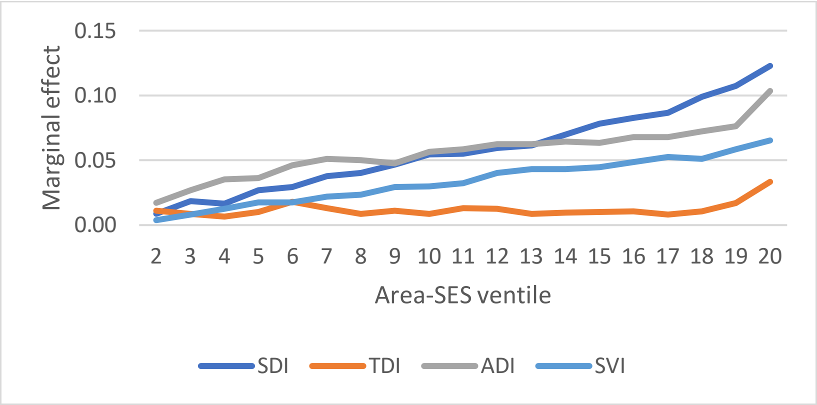


Poverty, Controlling for Indicated Area-SES Measure

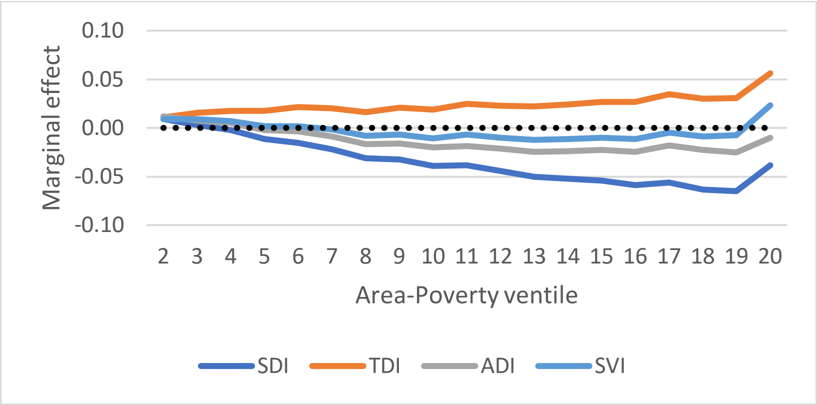


Panel C. Diabetes Prevalence in 2000

Area-SES Measures Controlling for Poverty

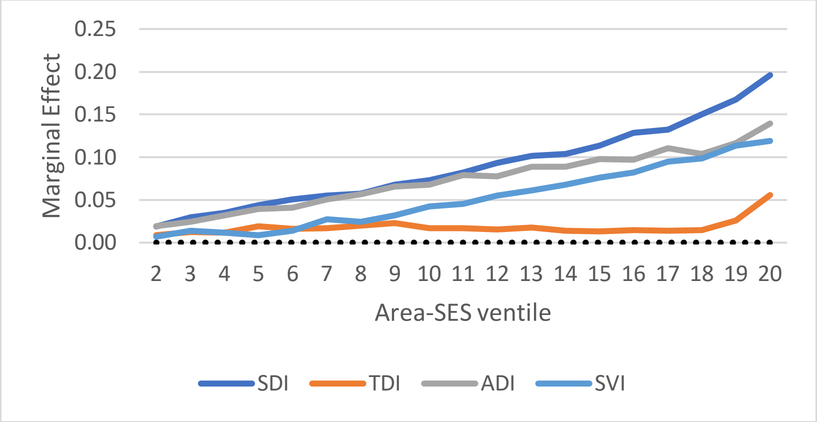


Poverty, Controlling for Each of the Area-SES Measures

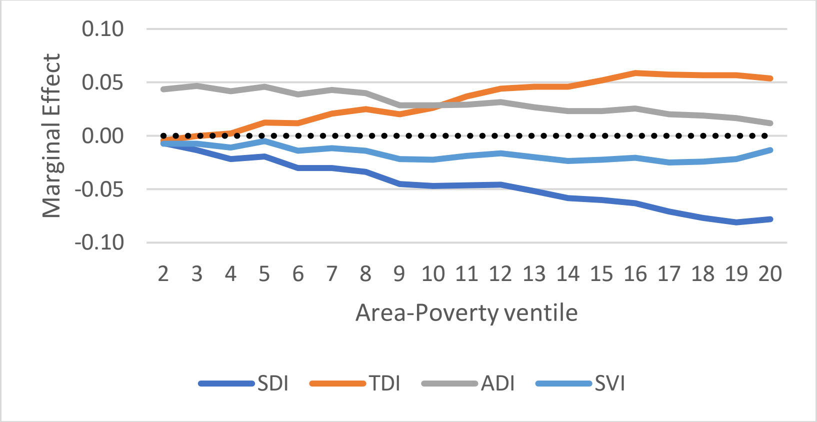


Panel D. Diabetes Prevalence in 2019

Area-SES Measures Controlling for Poverty

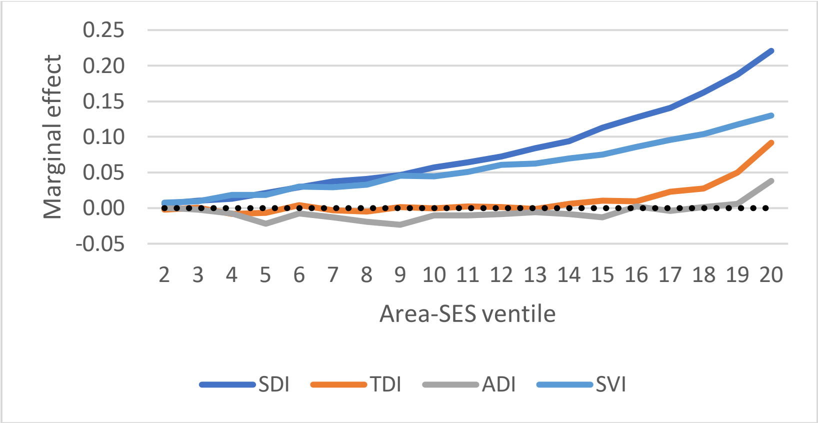


Poverty, Controlling for Each of the Area-SES Measures

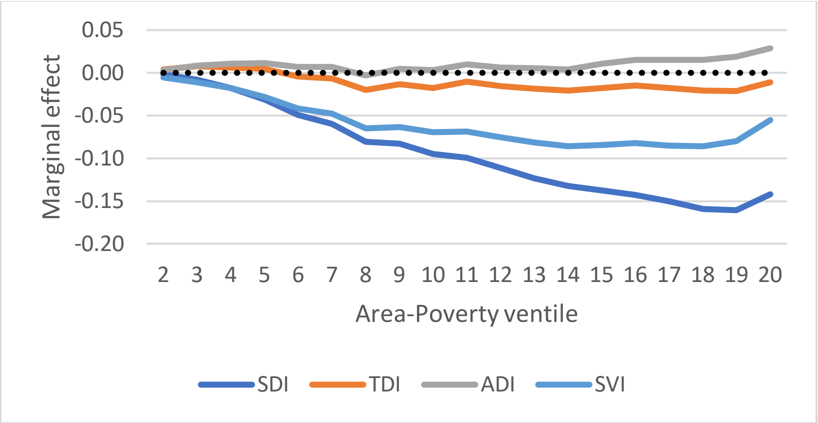


Panel E. Diabetes incidence over 2000-2005

Area-SES Measures Controlling for Poverty

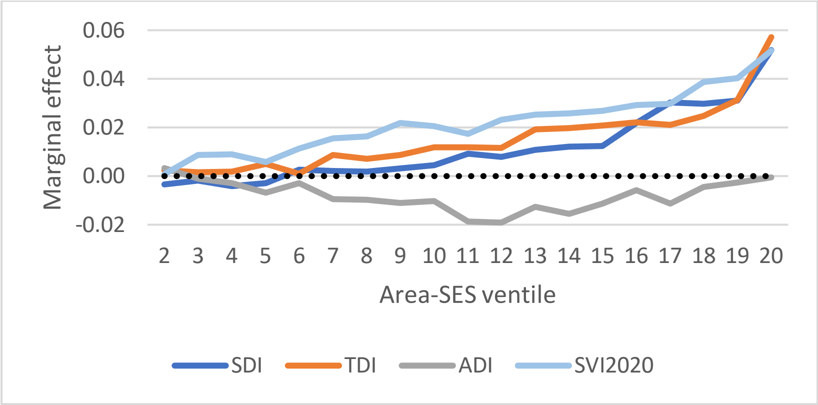


Poverty, Controlling for Each of the Area-SES Measure



Panel F. Drug Overdose Mortality over 2017-2021

Area-SES Measures Controlling for Poverty



Poverty, Controlling for Each of the Area-SES Measure

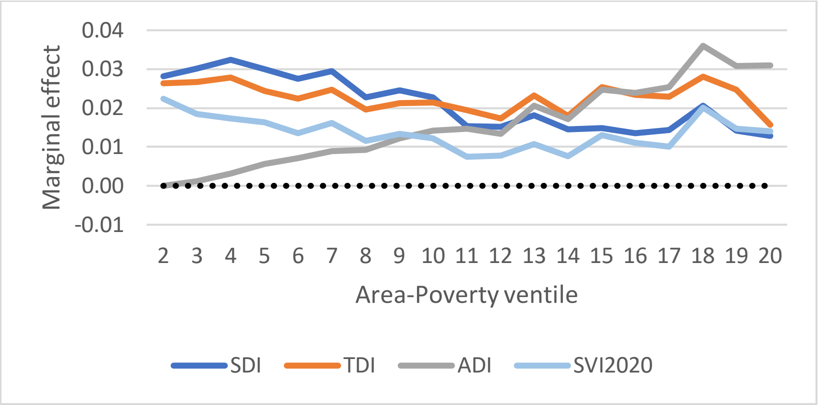
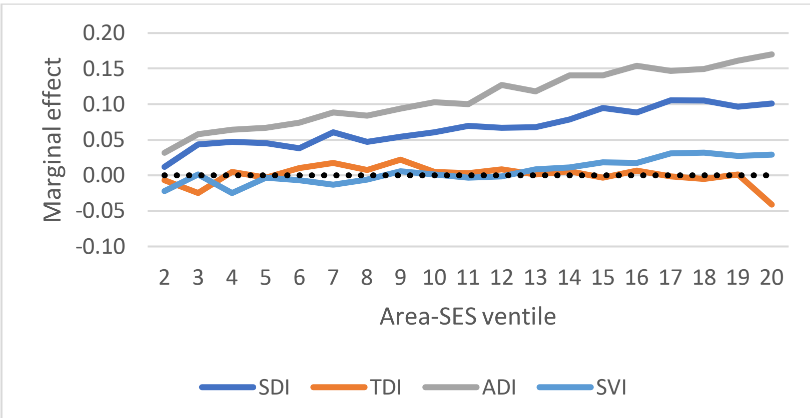


Figure App-10. Marginal Effects for Ventiles at Tract Level, Controlling for Poverty and Vice-Versa

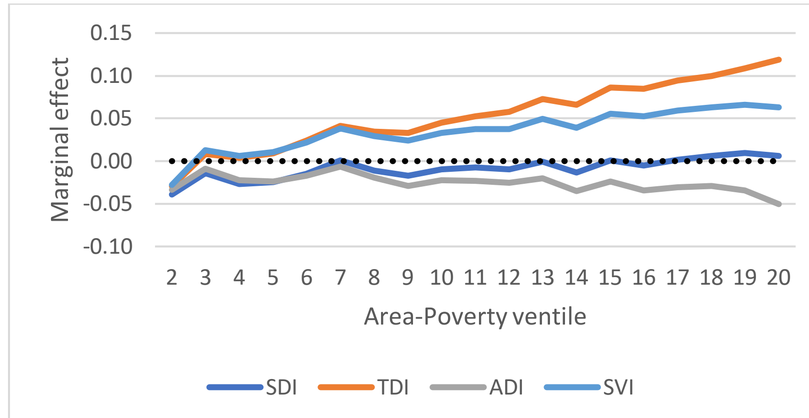
Graphs are similar to text Figure App-10, but for the outcomes that are available at tract level. **Left-hand graphs:** marginal effects of ventiles of SDI, ADI_{std}, SVI, and TDI for indicated outcomes at tract level, controlling for ventiles of Poverty. **Right-hand graphs**: marginal effects of Poverty ventiles, controlling for ventiles of SDI, ADI_{std}, SVI, and TDI. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes incidence over 2000-2019. Other covariates are same as in text Table 3. **All panels.** ADI measure is ADI_{std}.

Panel A. All-Cause Elderly Mortality over 2000-2019

Area-SES Measures, Controlling for Poverty

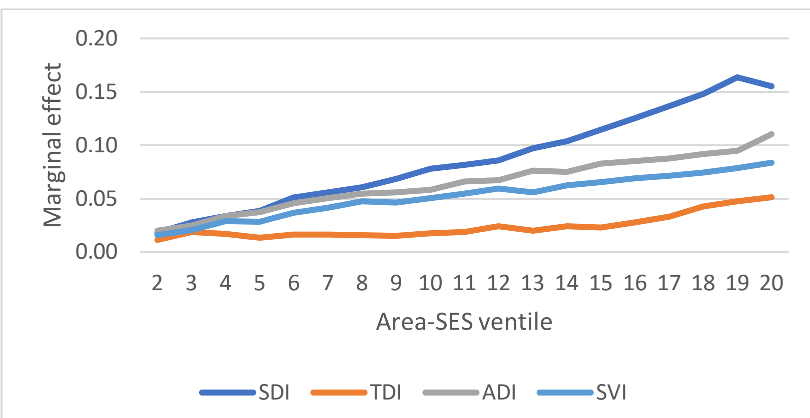


Poverty, Controlling for Each of the Area-SES Measures

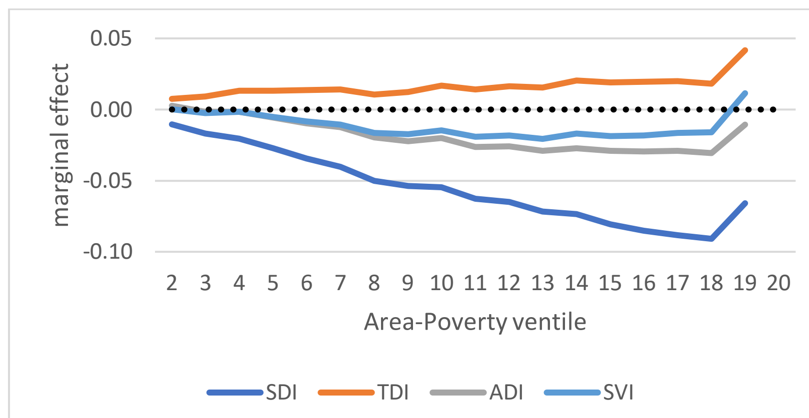


Panel B. Diabetes Prevalence in 2000

Area-SES Measures, Controlling for Poverty

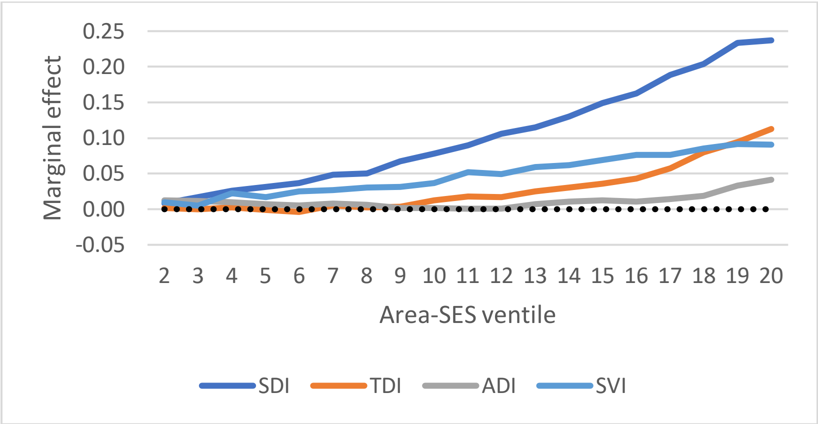


Poverty, Controlling for Each Area-SES Measure



Panel C. Diabetes Incidence over 2000-2005

Area-SES Measures, Controlling for Poverty



Poverty, Controlling for Each of the Area-SES Measures

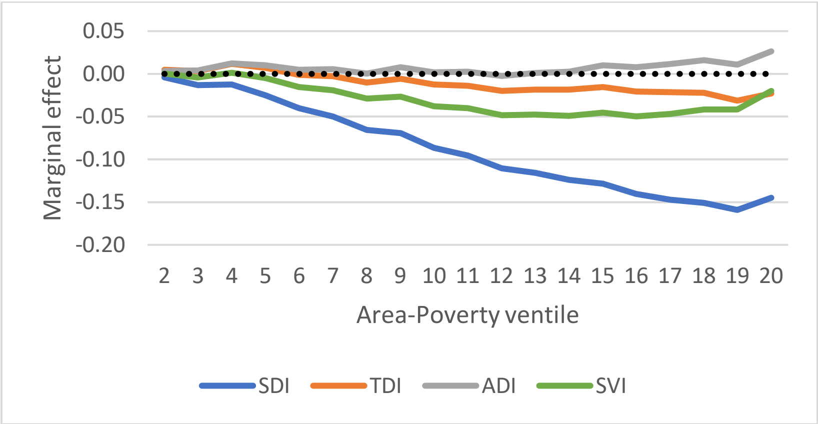
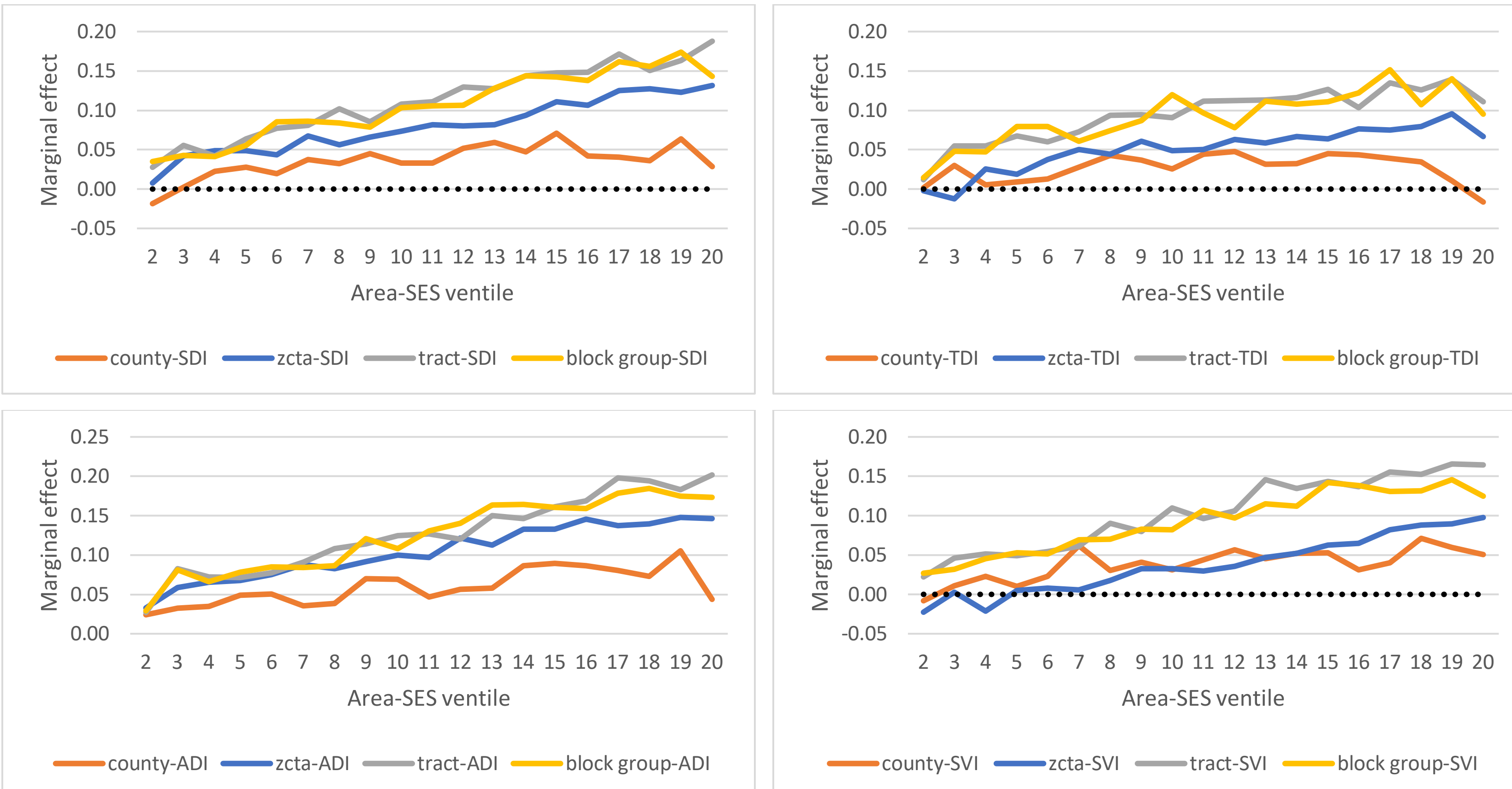


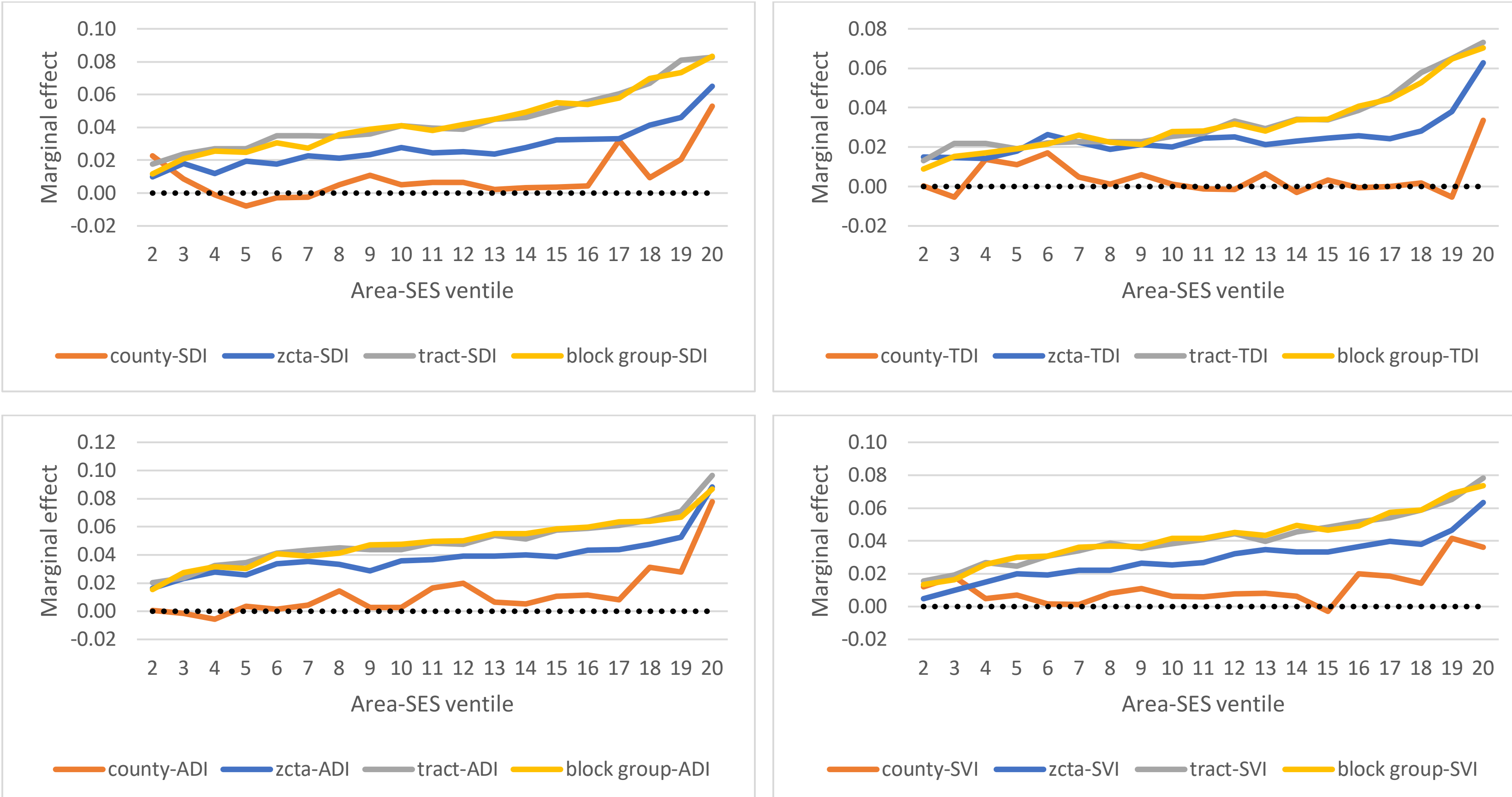
Figure App-11. Area-SES Marginal Effects for Ventiles at Different Geographic Levels

Each graph shows, for SDI, ADI_{std}, SVI, and TDI**,** marginal effects of ventiles for indicated outcomes at county, zip-code, tract and block-group level. Highest SES Ventile is omitted. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. **Panel C.** Diabetes incidence over 2000-2005. Covariates are same as in text Table 3. **All panels.** ADI measure is ADI_{std}.

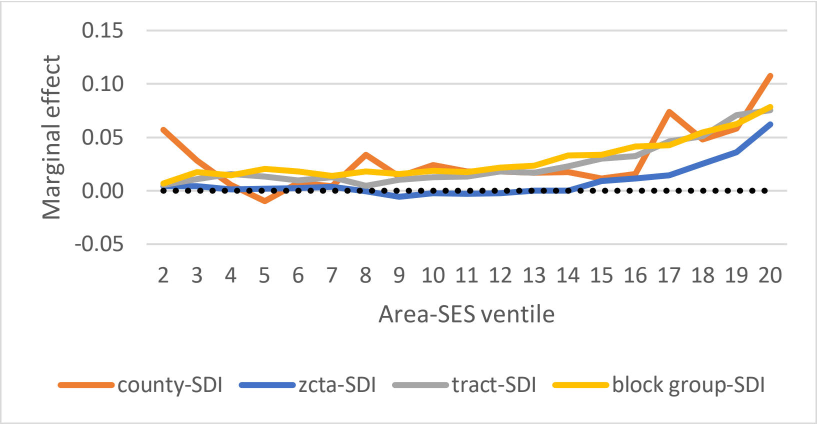
Panel A. All-Cause Elderly Mortality over 2000-2019

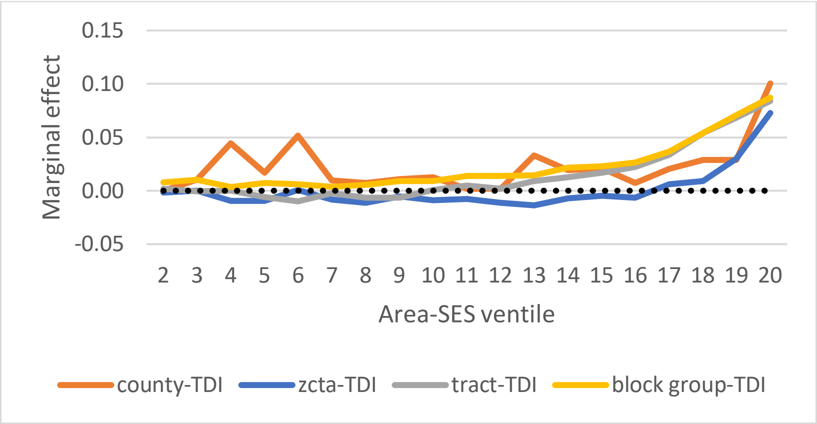


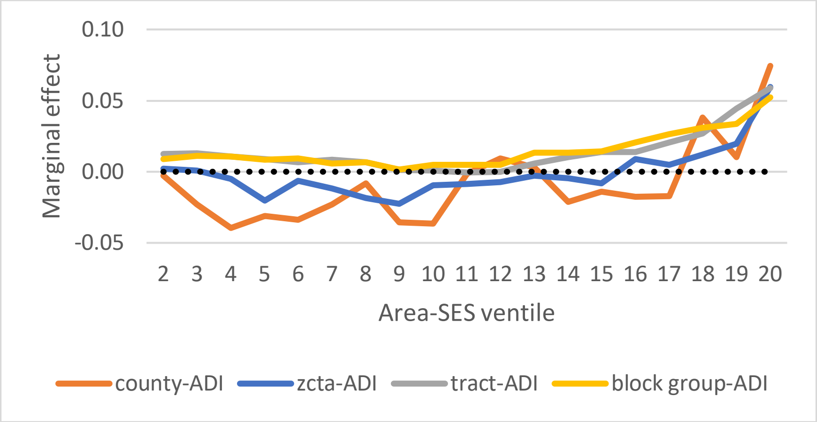
Panel B. Diabetes Prevalence in 2000



Panel C. Diabetes Incidence over 2000-2005







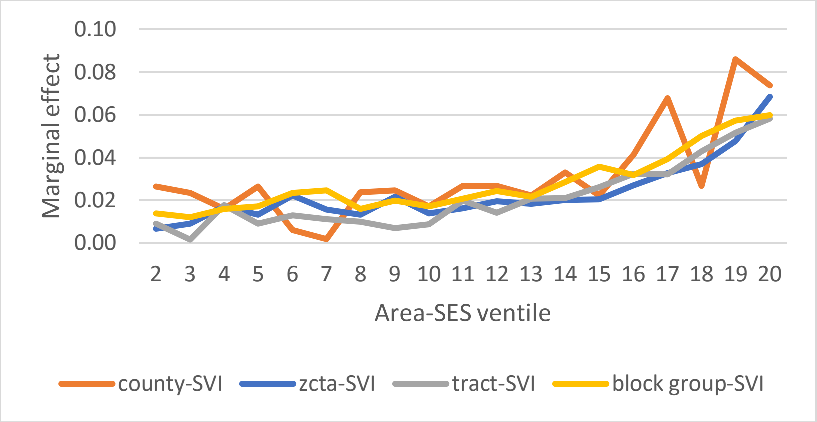
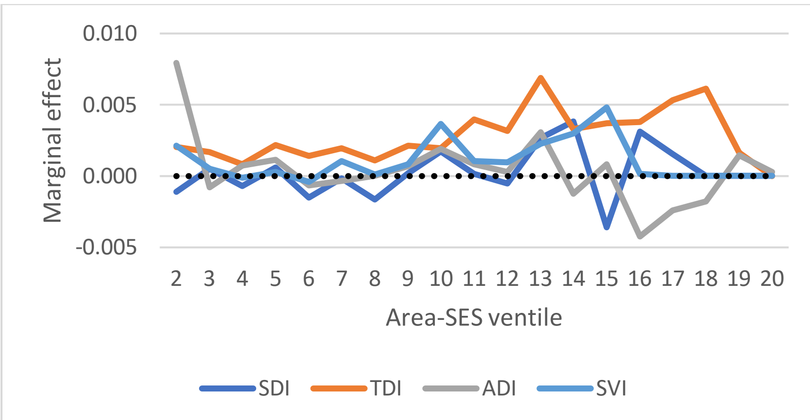


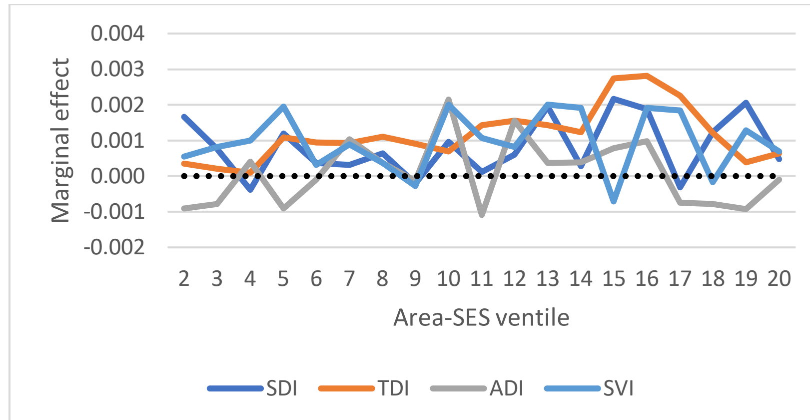
Figure App-12. Marginal Effects for Ventiles at County Level

Figure shows marginal effects of ventiles of SDI, ADI_{std}, SVI, and TDI for indicated outcomes at county level. Highest SES ventile is omitted. Panels, samples, and covariates are same as Table App-14. **Panel A.** COVID-19 Mortality in Indiana and Wisconsin in 2020. **Panel B.** COVID-19 Mortality in USA in 2020. **Panel C.** All-Cause Elderly Mortality over 2000-2019. **Panel D.** Diabetes Prevalence in 2000. **Panel E.** Diabetes Prevalence in 2019. **Panel F.** Diabetes Incidence over 2000-2005. **Panel G.** Drug Overdose Mortality over 2017-2021. Covariates are same as in text Table 3. **All figures.** ADI is $ADI_{std.}$

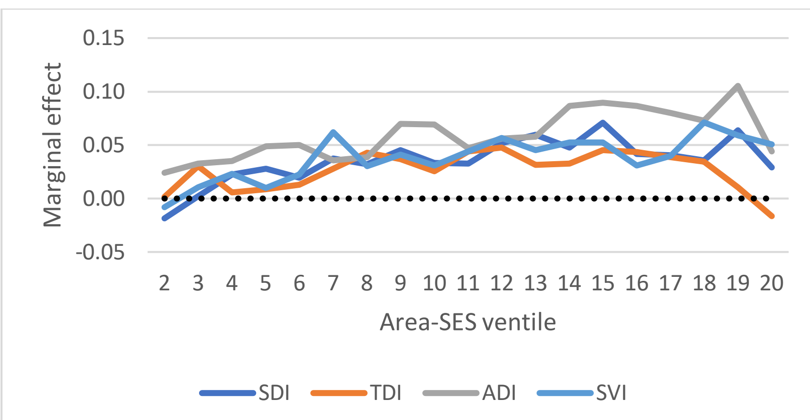
Panel. A. COVID-19 Mortality in Indiana and Wisconsin in 2020



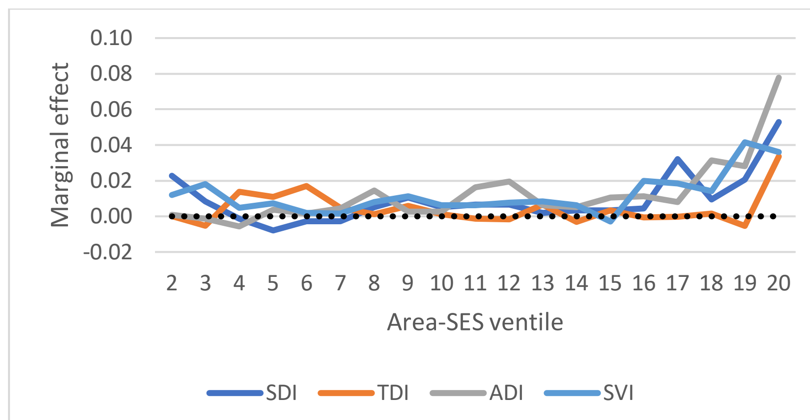
Panel. B. COVID-19 Mortality in USA in 2020



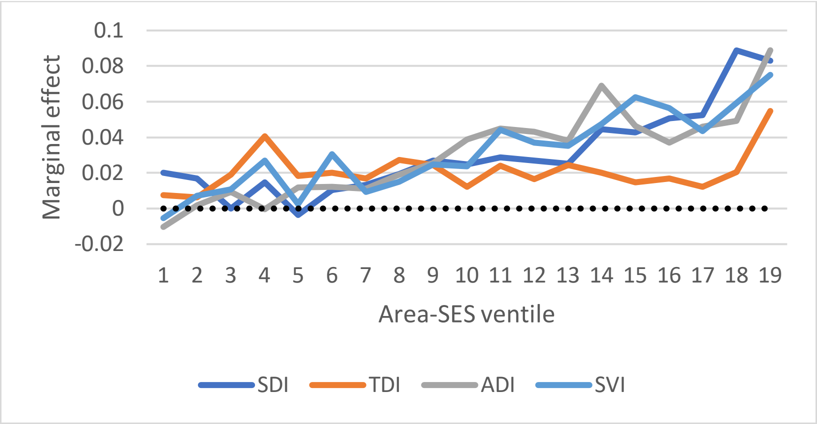
Panel C. All-Cause Elderly Mortality over 2000-2019



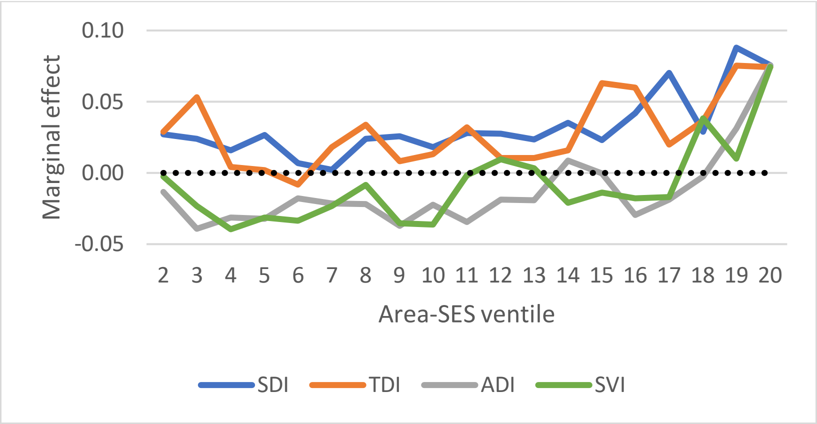
Panel D. Diabetes Prevalence in 2000



Panel E. Diabetes Prevalence in 2019



Panel F. Diabetes Incidence over 2000-2005



Panel G. Drug Overdose mortality over 2017-2021

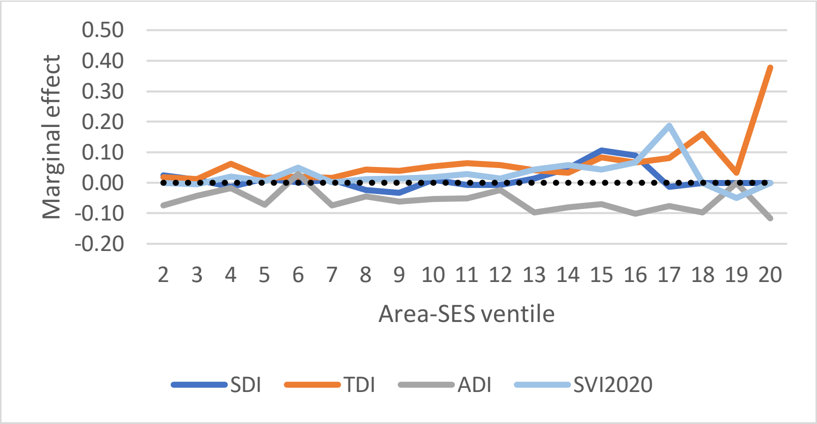
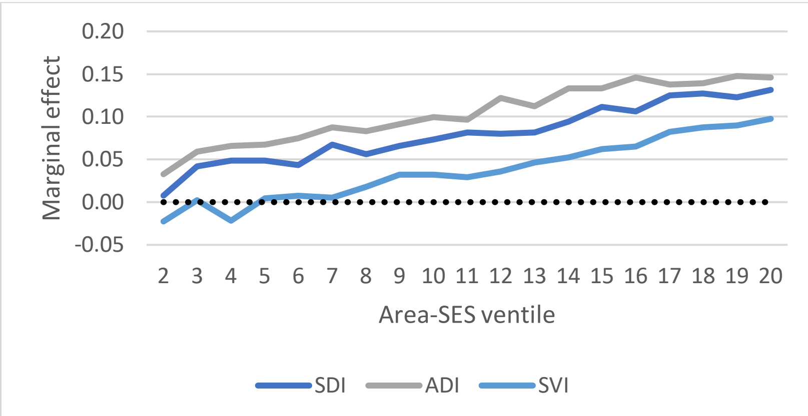
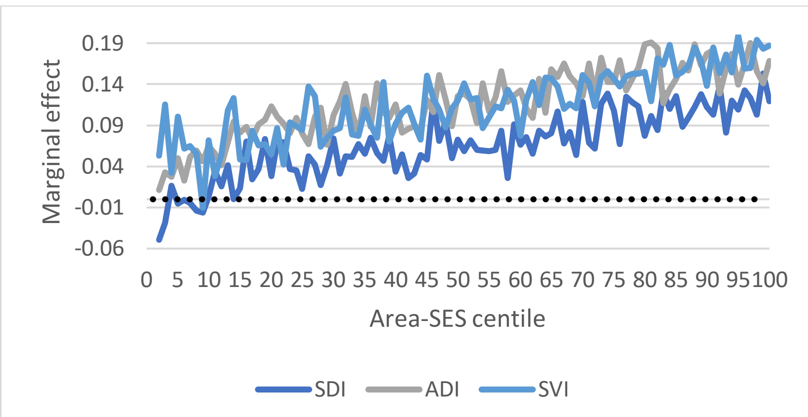


Figure App-13. Comparing Centile to Ventile Estimates at Zip-Code Level

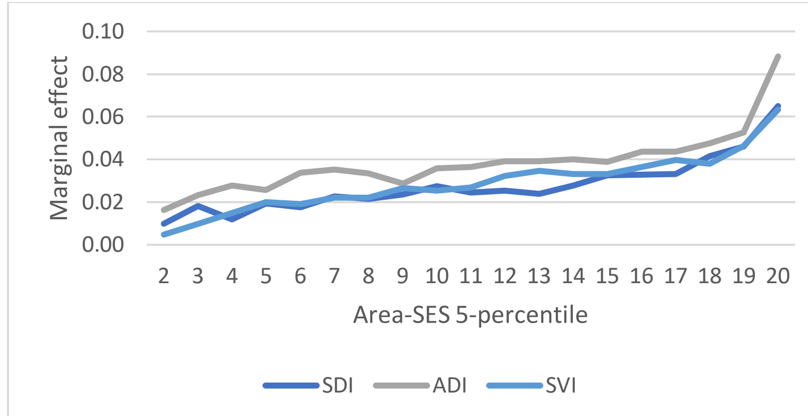
Graphs show, for SDI, ADI_{std}, and SVI at zip-code level**,** marginal effects of ventiles for all-cause elderly mortality over 2000-2019 and diabetes prevalence in 2000, for SDI, modified-ADI and modified-SVI measures. Top graphs show ventiles (same as text Figure 1). Bottom graphs show corresponding centile estimates. **Panel A.** All-cause elderly mortality over 2000-2019. **Panel B.** Diabetes prevalence in 2000. Covariates are same as in text Table 3. **All panels.** ADI measure is ADI_{std}.

Panel A. All-Cause Elderly Mortality over 2000-2019





Panel B. Diabetes Prevalence in 2000



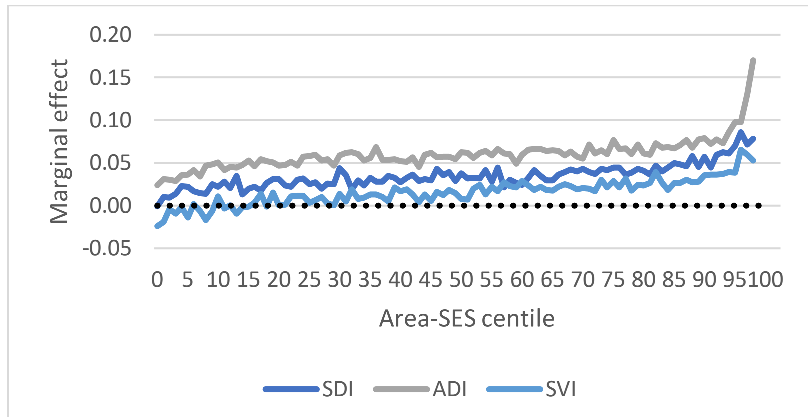
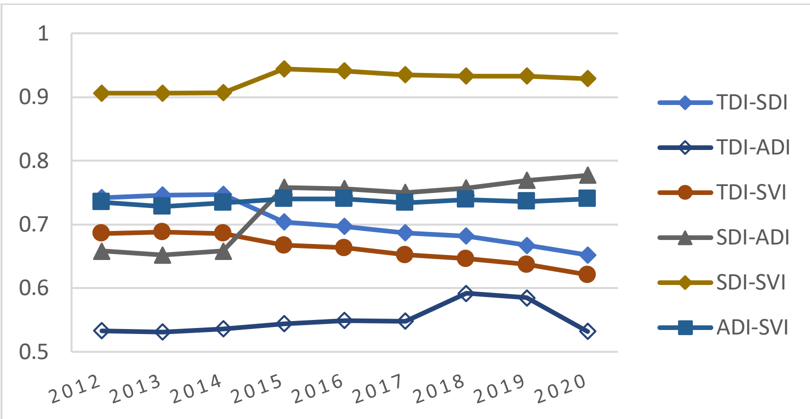


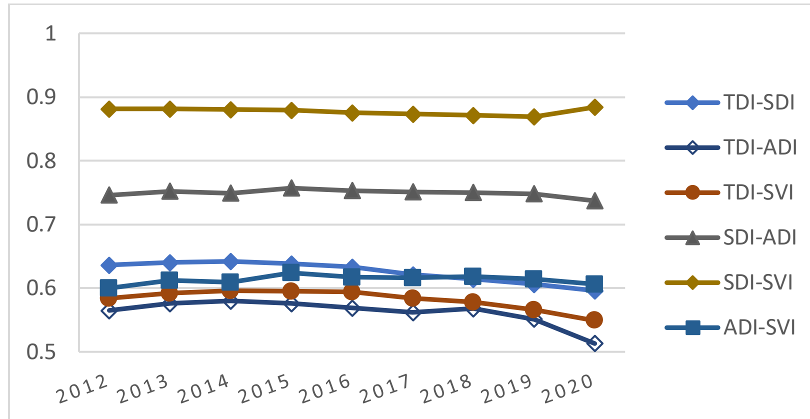
Figure App-14. Correlations between Area-SES Measures over 2012-2020

Figures show pairwise correlations at indicated geographic levels, between SDI, ADI_{std}, SVI, and TDI, annually over 2012-2020 (starting 2013 at block-group level). **Panel A.** Correlations at county level. **Panel B.** Correlations at ZCTA level. **Panel C.** Correlations at tract level. **Panel D**. Correlations at block-group level. **All panels.** ADI measure is ADI_{std}.

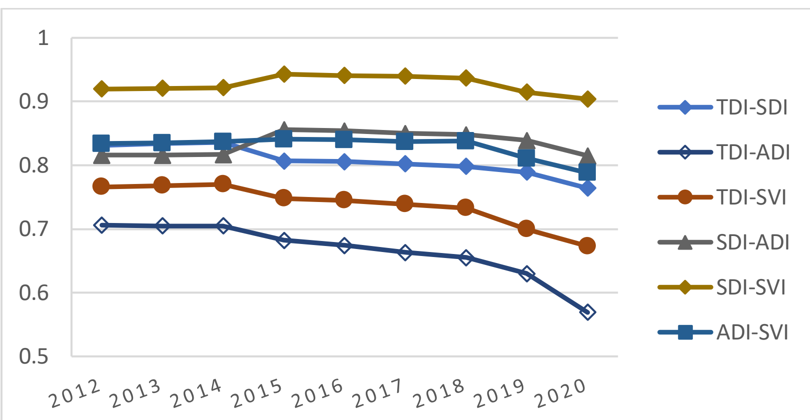
Panel A. County Level



Panel B. ZCTA level



Panel C. Tract Level



Panel D. Block group level

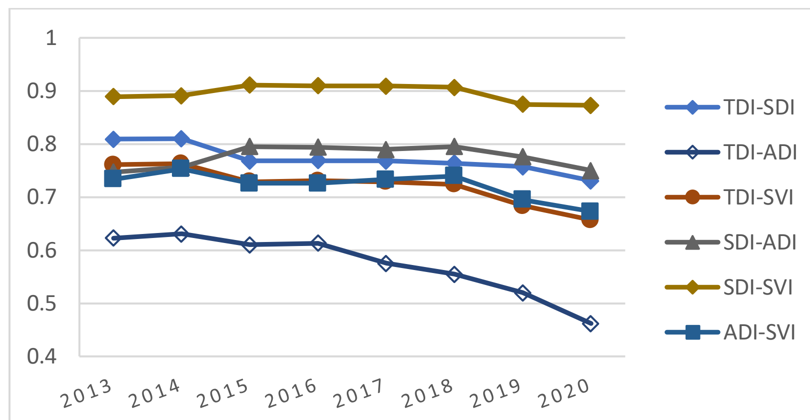
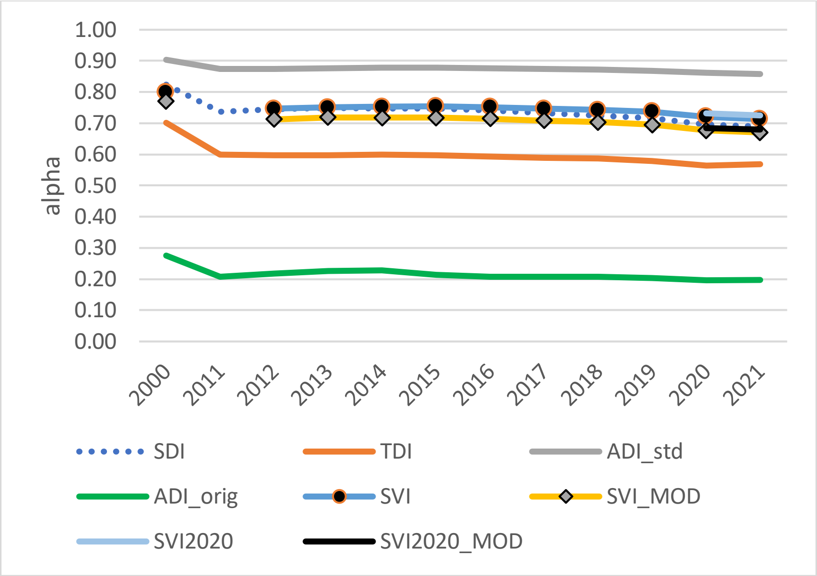


Figure App-15. Cronbach's Alpha for Area-SES Measures for 2000 and 2010-2021

Figures show Cronbach's Alpha at indicated geographic levels, for SDI, ADI_{orig}, ADI_{std}, SVI, SVI_{mod}, SVI_{2020}, SVI_{2020_mod}, and TDI, for 2000 and annually for 2010-2021 (starting 2011 at ZCTA level). **Panel A.** ZCTA level. **Panel B.** Tract level.

Panel A. Cronbach's Alpha at ZCTA level



Panel B. Cronbach's Alpha at Tract level