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Community Wealth Protects Cognitive Health for Older Adults

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Abstract

Using a new database on the net worth and self-reported cognitive impairment for almost two million adults, this paper provides the first large-scale evidence linking community wealth to age-related cognitive decline. This assessment is timely as widening geographic wealth gaps in the USA fuel disparities in access to public goods and amenities, positioning community wealth as a critical determinant of cognitive health. Conditioning on personal wealth and other risk factors, we find that a standard deviation increase in community wealth is associated with a 6.7% relative risk reduction in cognitive impairment across the national population of older adults, rising to 13.7% for those residing in the poorest fifth of communities. Community wealth matters more than relative inequality, and its associated protective effects are larger for non-white, non-college educated, and low net worth householders. This is plausibly because these individuals rely more on the public goods and services underwritten by local affluence. The economic fragmentation of American communities thus poses a growing threat to the cognitive health of Americans, especially among those from socially vulnerable and marginalized backgrounds.

Significance Statement: This analysis reveals a powerful link between community wealth and rates of subjective cognitive impairment (SCI), an early risk factor for mild cognitive impairment and dementia. As community wealth inequality rises and the population ages, this work identifies a growing threat to healthy aging, underscoring the importance of community resources for America's most vulnerable and marginalized populations. These findings challenge the primacy of individual-focused models and demand renewed attention to place-based wealth disparities. Based on static simulations, equalizing wealth for the poorest three fifths of communities could, as an upper bound estimate, reduce the burden of cognitive impairment by over 86,000 cases (6.7%). Place-based wealth redistribution is thus a potent, yet overlooked, force for promoting public health and reducing disparities in cognitive aging.

***K*eywords** Spatial Wealth Inequality · Aging · Subjective Cognitive Impairment · Cognitive Health · ADRD

1 Introduction

This study provides the first large-scale investigation into the connection between two of the most profound societal shifts in the United States: a rapidly aging population and an unprecedented wealth polarization across its towns and cities [1, 2]. Our examination is timely given that cases of Alzheimer's Disease and Related Dementia (ADRD) are projected to increase from approximately 6 million in 2020 to nearly 14 million by 2060 [3], trends which could be exacerbated by rising wealth disparities within and between communities.

This article addresses two questions with respect to these patterns: What is the relationship between the cognitive health of older adults and their community's wealth—specifically, its average level and its inequality? And, how are these relationships moderated by an individual's own age, gender, race, and socioeconomic status? By wealth, we mean accumulated net worth, calculated as a household's total assets minus debts, whereas community wealth and inequality refers to the average level and distribution of net worth among local residents.

Our study contributes to larger efforts aimed at understanding the factors shaping risk of ADRD and other forms of age-related cognitive impairment. Longevity and lower disease risk have long been observed among individuals with higher levels of education and income [4, 5, 6, 7, 8]. More recently, however, there is a growing recognition that wealth holdings are a central feature of the socioeconomic gradient in health and cognition [9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]. Wealth matters for cognition as a buffer against extreme stress [20, 21], providing choice and stability in housing and nutrition [22, 23, 24], and sustaining older populations after retirement [25]. Wealth is thus closely connected to core social determinants of cognitive health, and, as shown here, perhaps even more so than one's flow of income.

The risk of cognitive impairment, however, is shaped not only by an individual's personal resources but also by the community in which they live [26, 27, 28, 29, 30]. In the United States, where local public finances rely heavily on property taxes, the distinction between community wealth and income is especially critical. A larger tax base allows affluent towns and cities to invest more in services and amenities known to support cognitive health [31, 32, 33, 34]. These include resources like healthcare infrastructure [35, 36, 37], libraries and parks to foster cognitive reserve and social engagement [38, 39, 40, 41], and sanitation to mitigate environmental hazards [42, 43, 44]. While the link from affluence to cognitive health is intuitive, it has lacked large-scale empirical validation, a gap this study addresses.

It is not necessarily true that community wealth will uniformly expand fiscal capacity for the public good. Notably, the distribution of wealth and income within a community may itself affect whether private resources are redistributed to fund public services [31, 45, 46]. High levels of inequality may lead to social frictions, narrow the tax base, and make it more challenging for municipalities to make collective investments and fund public goods [47, 48], particularly where wealthy households attempt to hoard resources and avoid taxation [49]. Sharp local wealth divides could also ultimately weaken social cohesion and lead to reduced interaction between social groups, a known risk factor for mortality and disease [50, 51, 52]. These observations point to plausible pathways through which community wealth inequality could negatively affect cognitive health-a hypothesis that has yet to be directly tested at scale.

While the nation's wealthiest communities are often also its most unequal, our data reveal that this relationship is not universal. For instance, New York (NY) and Salt Lake City (UT) are both wealthy metropolitan areas, but in New York the top tenth of households in terms of net worth hold 67% of local wealth, a figure that is only 60% in Salt Lake. If wealth inequality fuels frictions in local government, the enormous tax base of a place like New York may not produce commensurate public investment. The range of inequality is even starker among poorer places: the top tenth of households in Shreveport (LA) possess 72% of the city's total wealth, whereas their counterparts in Duluth (MN) hold only 59%. Separate investigation of both wealth and wealth inequality with respect to cognition is further merited given that the two characteristics are very weakly correlated ($r = 0.013$) in 2020.

The relationship between community wealth and cognition has so far proved difficult to study, mainly due to absence of large-scale spatially disaggregated data on both wealth and cognition. This study overcomes this limitation by constructing a new database on over 1.8 million householders aged 50 and older ($n = 1,835,306$). Within this database, we observe a wide range of householder characteristics, including personal wealth holdings, as well as wealth conditions in their community of residence. Communities are defined based on 722 commuting zones (CZs). CZs are widely used spatial units for approximating local labor markets [53, 34], making them theoretically appropriate for studying the link between local wealth and cognitive health.

Wealth is measured through GEOWEALTH-US, a new compendium that overcomes longstanding limitations in wealth research. GEOWEALTH-US links Federal Reserve survey data and Census microdata through machine learning to generate the first granular estimates of net worth and its distribution over time. We measure the level and distribution of wealth across both households and commuting zones from 2009 to 2021 [2]. The share of local wealth held by the top decile of households is our preferred indicator of wealth inequality, as it is more intuitive and better suited to handling negative values of net worth than alternative indicators (e.g., Gini, Theil).

These wealth metrics were integrated with American Community Survey (ACS) responses on measures of subjective cognitive impairment (SCI). While previous work has established the reliability and validity of these SCI measures as a risk factor for mild cognitive impairment and dementia [54], we provide further new validation here via recently published administrative data on dementia prevalence (SI Figures 1-4). SCI provides significant additional value as a general indicator of psychological distress, anxiety, and depression, even for respondents who do not ultimately progress to dementia [55]. The collection of annual SCI data for a large sample of the American population highlights the great potential of the ACS for broader ecological analysis and monitoring of population health.

With our newly constructed database, we employ a two-way fixed effects (TWFE) estimator, a quasi-experimental method that alleviates concerns that the link between community wealth and cognitive health is merely correlation. By exploiting changes within communities between 2009 and 2021, the TWFE framework allows us to control for unobserved, time-invariant local characteristics (e.g., local genetic risk, cost-of-living, cultural settlement patterns, environmental hazards) while explicitly conditioning on personal and community risk factors (e.g., household wealth, education, race, urbanization) that might otherwise confound the results. We also provide a large suite of robustness checks to address alternate pathways, such as the migration of healthier people to wealthy places over the study period.

2 Results

2.1 Patterns of community wealth and cognitive impairment

We begin by using a binned scatterplot to provide a first broad description of the relationship between community wealth and risk of cognitive impairment. Figure 1 plots the age-adjusted prevalence of cognitive impairment after age 50 for each percentile in the commuting zone wealth distribution. The relationship is strongly negative ($r = -0.477$), indicating a strong link between local average household wealth and risk of cognitive impairment. However, the departure of commuting zones with low net worth from the trendline highlights the exceptionally high prevalence of cognitive impairment among the poorest communities. In fact, the rate of cognitive impairment in the poorest tenth of communities is 80 percent higher than in the wealthiest decile. SI Figure 5 provides examples of where specific communities fall in the community wealth distribution.

The mapping of these variables provides further intuition as to the source of the underlying relationships. Figure 2A maps spatial prevalence of age-adjusted cognitive impairment among all householders over the age of 50. The first point of note is the wide range of cognitive impairment outcomes across the country. In some regions, less than one older adult in twenty reports experiencing cognitive impairment. In other regions, however, prevalence rises to one in ten older adults, and in some cases as high as almost one in five.

Cognitive impairment varies widely and exhibits strong spatial patterning: prevalence is very high in some regions of the country and much lower in others. Prevalence is highest in Appalachia, the Deep South, and in western states including New Mexico and areas of Oregon and Washington. The high prevalence of these regions stands in sharp contrast to the low levels prevailing across other relatively rural regions in the Midwest and Northern Plains, particularly in Minnesota, Wisconsin and the Dakotas. Furthermore, the most urbanized regions, including those on the northeastern seaboard, the San Francisco Bay Area, and in urban Florida exhibit low rates of cognitive impairment.

The spatial prevalence of cognitive impairment closely tracks patterns of community wealth (Figure 2B). The poorest areas with respect to wealth tend to be in the South, Appalachia, the Southern Plains states, and to a lesser degree, the industrialized Midwestern states; all of which have elevated rates of cognitive impairment. The combination of deindustrialization and stagnant economic growth can help account for the low wealth levels of these regions, conditions linked to sharp increases in mortality and morbidity over recent decades [56].

Disparities in the share of community wealth held by the top decile moderately resemble the patterns described above (Figure 2C). Again, Southern labor markets rank high in terms of inequality. In many cases, the top 10 percent of households in the South hold as much as 70 percent of total local wealth. Contrastingly, households in the Upper Midwest often live in places where the top decile hold less than 60 percent of local wealth. Spatial patterns of wealth inequality deviate from those above in being high in urban and coastal communities, places which perform relatively favorably in terms of cognitive health and wealth holdings.

Wealth and cognitive impairment therefore exhibit nuanced geographic patterns. The South is characterized by low levels of wealth, high levels of inequality, and high rates of cognitive impairment. Highly urbanized and coastal regions of the country display moderate levels of cognitive difficulty but high levels of average wealth and wealth inequality. The upper midwestern states have moderate wealth levels, low inequality, and low rates of cognitive impairment. The next section formally examines these relationships.

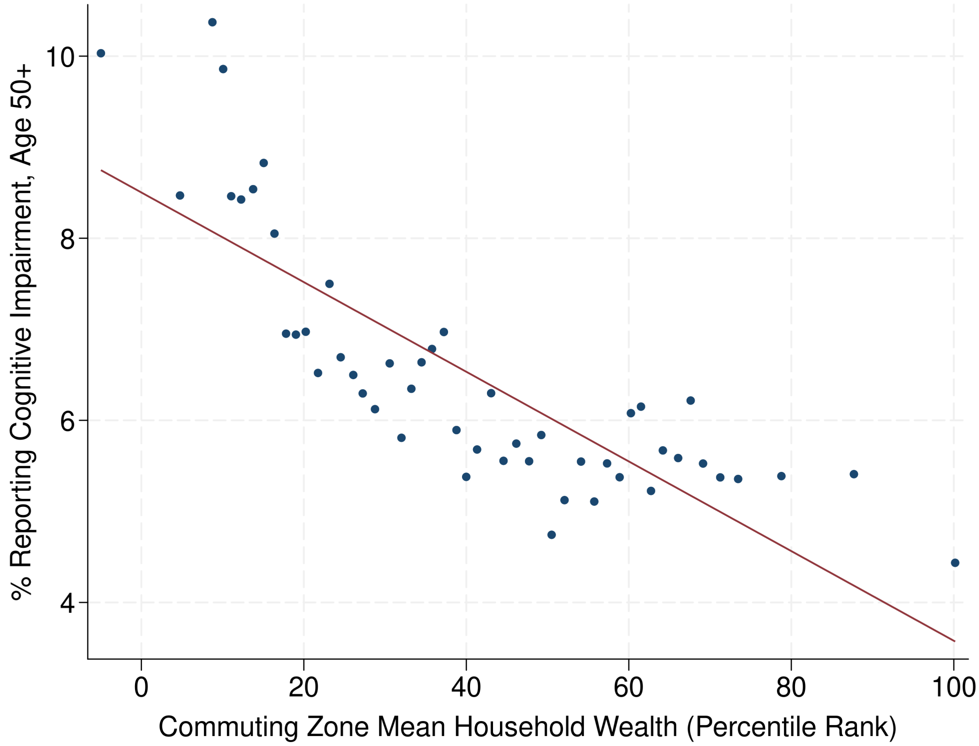

Figure 1: Mean household wealth and cognitive impairment among older adults across local labor markets, 2009-2021. Notes: A figure showing a binned scatterplot of the relationship between a commuting zone percentile rank in terms of average household wealth and the age-adjusted share of adults over the age of 50 reporting cognitive impairment in the American Community Survey for every commuting zone in the United States. Community wealth is clustered into 50 bins across the commuting zone wealth distribution. The data are pooled across the 2009-2011 and 2019-2021 ACS periods, and the data are detrended for period of observation and for age, using single year fixed effects. SI Figure 5 presents a comparable graph without percentile adjustments.

2.2 Regression analysis

Figure 3A presents the coefficients from our preferred TWFE framework, estimating the implied effect of community wealth and wealth inequality on householders' probability of reporting cognitive impairment after age 50. Estimates are conditional on a range of covariates including household wealth, education, race/ethnicity, and single-year fixed effects for year of birth, which adjust for non-linearities in age-related cognitive decline.

Our main specification highlights community wealth as a substantial risk factor for cognitive impairment. A one standard deviation increase in local wealth reduces the probability of an older householder reporting cognitive impairment by 0.46 percentage points, or 6.7 percent relative to the baseline prevalence of 0.0692. For reference, the coefficient for local wealth is approximately 14% of the size of the estimated effect size for household wealth (SI Table 5). Residence in a community with higher wealth levels is thus meaningfully associated with reduced risk of subjective cognitive impairment.

In this main specification, we do not find the hypothesized negative association between local wealth inequality and cognitive impairment. The coefficient for the share of wealth held by the top decile is considerably smaller than the comparable estimate for local wealth levels. Furthermore, in our main specification the 95% confidence interval includes zero, indicating a lack of statistical significance.

Changes in community wealth and inequality could plausibly matter more for poorer communities, which lack the resource base required to invest in basic services and amenities. Figure 3B thus tests whether the association between local wealth and cognitive impairment varies according to the initial wealth levels of places. We find that the association between local average wealth and cognition is substantially larger for the poorest commuting zones (Quintile 1-3). The coefficient associated with local wealth is six times larger for the bottom fifth of the communities (Q1) than the top fifth

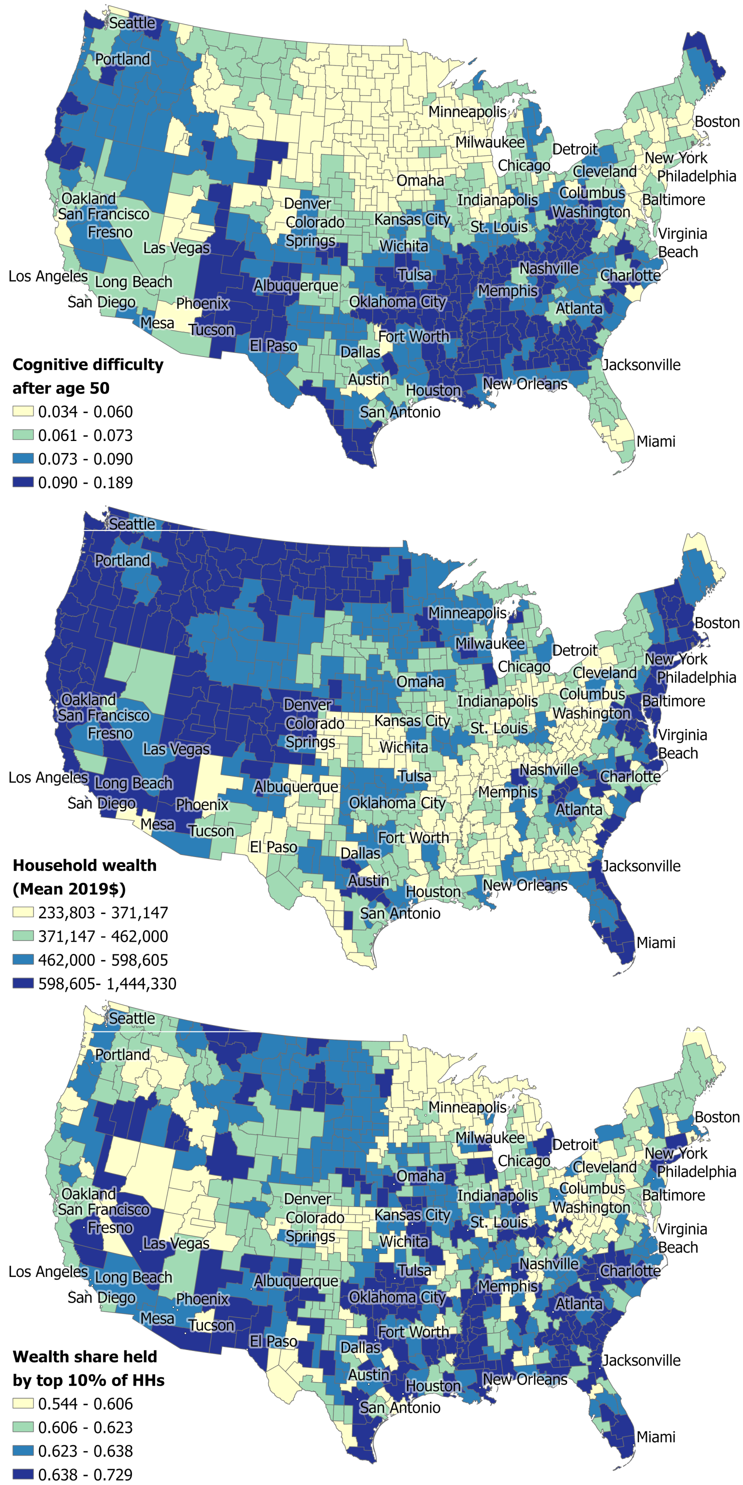

Figure 2: Maps of cognitive impairment and local wealth characteristics across the United States. Notes: Three maps of commuting zones showing age-adjusted share of the population experiencing cognitive difficulty (A), average wealth level across households of all ages (B), and the local share of total wealth held by the top 10% of the local wealth distribution (C). The map of cognitive difficulty is measured from the 2019-2021 estimates of the American Community Survey. The wealth variables were extracted from the GEOWEALTH-US data for the year of 2020. Place names reflect the largest incorporated or census designated place within a commuting zone. Maps are classified using quantile breaks.

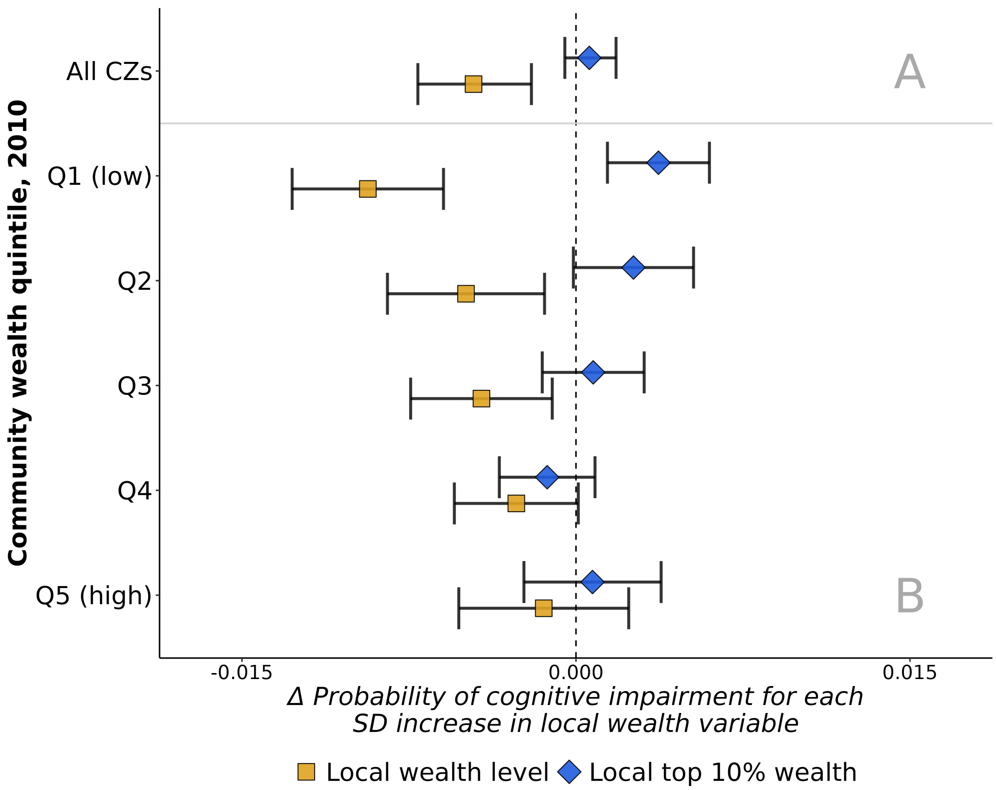

Figure 3: Estimates of the relationship between local wealth characteristics and cognitive impairment among older adults. Notes: Estimates from two TWFE regression models of the relationship between householder cognitive impairment and the wealth characteristics of commuting zones. Estimates derived from the first model (A) are based on all commuting zones in the data ("All CZs"). Estimates derived from the second model (B) are also based on all commuting zones but where the variables of interest - wealth level and the share of wealth held by the top decile of households – are interacted with the 2010 baseline wealth quintile for commuting zone. Quintile 1 refers to the poorest fifth commuting zones and Quintile 5 refers to the wealthiest fifth of commuting zones. The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods. The regression models include standard controls for the total number of households in a commuting zone, education level, race, sex, race and Hispanic ethnicity, veteran status, and year of birth, with additional fixed effects for commuting zone and period. The variables of interest are transformed into standard units, with a mean of zero and a standard deviation of one. Standard errors are clustered at the level of commuting zones.

(Q5), and roughly twice as large as what we reported in our main specification (Figure 3A). The role of increasing local wealth in reducing cognitive impairment thus appears to matter most for communities with limited resources to begin with.

Contrary to our main specification, this decomposition analysis provides stronger evidence for the link between local wealth inequality and cognitive impairment. For the poorest fifth of commuting zones at baseline (Q1), there is a positive association between cognitive impairment and the share of wealth held by the top decile of wealth holders within the commuting zone, suggesting that inequality is predictive of higher cognitive impairment risk in the poorest fifth of community zones. The coefficients on inequality for the remaining quintiles (Q2-Q5) are not statistically significant. Wealth inequality thus tends to be associated with cognitive impairment but only when it is bundled with wealth poverty.

Based on the model presented in Figure 3B, we conducted static simulations to provide a sense of how reductions in community wealth disparities may affect prevalence of cognitive impairment. First, we identified all householders residing outside of the wealthiest tier of communities, which we define as the bottom three fifths of the national community wealth distribution. These households were then computationally assigned the wealth level of the community at the 60th percentile, holding all other covariates constant, including household wealth levels. Under this scenario, the aggregate rate of cognitive impairment in 2019-2021 among householders over the age of 50 would fall by 6.7% (baseline prevalence = 0.0572), a reduction of 86,536 from the total baseline prevalent cases of 1,315,765. Given that we cannot fully account for biased sorting across locations on the risk of cognitive decline (see Validation and Robustness), this estimate is best viewed as an upper bound.

Householder	Sample %	Household Wealth	Commuting Zone Wealth	Cognitive Difficulty
All householders over age 50	1.000	$573,741	$516,785	0.066
Household net worth >= $100,000	0.695	$775,882	$529,528	0.047
Household wealth < $100,000	0.305	$39,706	$483,081	0.118
Aged 50-69	0.662	$523,824	$516,447	0.058
Aged 70 plus	0.338	$665,047	$517,404	0.081
Female	0.476	$498,491	$515,234	0.072
Male	0.524	$649,656	$518,350	0.061
Non-college	0.766	$428,684	$503,321	0.077
College	0.234	$1,002,827	$556,612	0.032
White	0.906	$615,750	$520,078	0.063
Black	0.070	$239,341	$449,428	0.091
Hispanic	0.054	$351,179	$510,624	0.070

Table 1: Descriptive statistics by group in 2020.

Notes: A table presenting group-based descriptive statistics for different sociodemographic populations. Cognitive difficulty refers to the proportion of each group experiencing cognitive difficulty. Household wealth refers to mean household wealth. Commuting zone wealth refers to the average wealth of the commuting zone of residence.

2.3 Group decomposition

Do rising economic tides within a community lift all households equally? It may be the case that changes in local wealth matter more for some community members than others. For example, marginalized households or those experiencing wealth poverty may be relatively more reliant on the public provision of goods and services that flow from concentrated wealth. Conversely, a high degree of inequality within a wealthy community could fuel health disparities between wealthier and poorer households through a variety of mechanisms. This section thus evaluates whether householder characteristics moderate the link between community wealth and cognitive impairment.

Figure 4 presents predictive margins of the association between community wealth and cognitive impairment by household wealth, education level, age, sex, and race/ethnicity. We find no significant association between community wealth and cognitive impairment for householders with higher levels of net worth or those with a college degree. The association is also weaker for White householders than it is for Blacks or Hispanics. Taken together, these findings imply that the relationship between community wealth and cognition is strongest for non-white, non-college educated, and low net worth householders, and weaker for households already advantaged based on their financial, educational, and racial positionality.

These patterns of differential sensitivity to community wealth conditions notably intersect with patterns of residential segregation. While racialized and economically vulnerable householders tend to be more sensitive to place-based disadvantage, they also disproportionately live in poorer places (Table 1). Wealthier households thus experience a compounding advantage through their greater ability to pay for health benefits (e.g., private healthcare, access to gyms, education) and also their disproportionate residence in wealthy communities, which convey benefits for cognitive health. Conversely, the economic segregation of less advantaged householders thus leads to a form of 'double jeopardy' for the health of poor and marginalized households.

There is a notable deviation from the main results across age categories. The association between community wealth and cognitive impairment is most strongly evident among householders aged from 50 to 69. This finding suggests that with respect to cognitive health, community wealth may matter most in mitigating the early onset of cognitive impairment toward the end of middle adulthood. This finding is particularly noteworthy given broader concerns regarding the crisis of health and mortality in midlife in the United States [57].

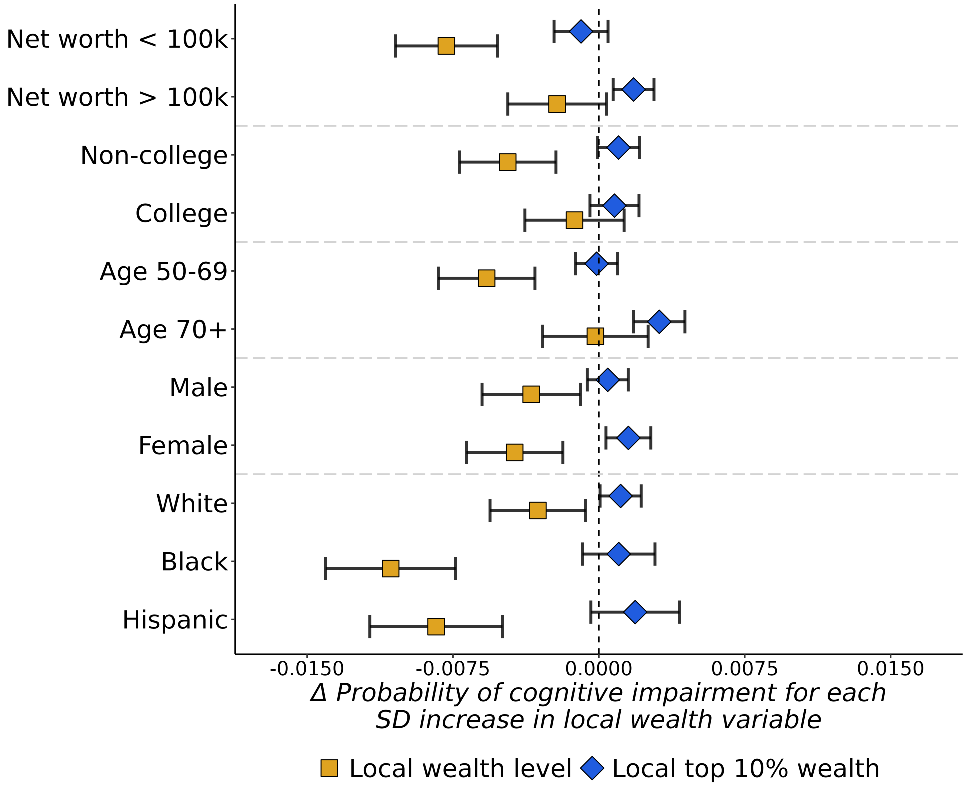

Figure 4: Estimates of the relationship between local wealth characteristics and cognitive impairment among older adults, interacted with householder characteristics. Notes: Estimates from a single linear probability regression model of the relationship between householder cognitive impairment and the wealth characteristics of commuting zones with interactions for various subgroups. The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods. Regression models include standard controls for the total number of households in a commuting zone, education level, race, sex, race and Hispanic ethnicity, veteran status, and year of birth. The local wealth variables are interacted with the householder characteristics net worth (dummy for greater than or less than 100k in net worth), sex, education, and race/ethnicity. All estimates are passed on the 2010-2020 pooled model, which is estimated with additional fixed effects for commuting zone and period. The wealth variables of interest are transformed into standard units, with a mean of zero and a standard deviation of one. Standard errors are clustered at the level of commuting zones.

3 Discussion

This work provides the first large-scale, quasi-experimental evidence linking accumulated community wealth to cognitive impairment across the United States. By leveraging a two-way fixed effects design on a novel dataset of 1.8 million older adults, we assess the potentially protective effects of community affluence. Our findings are critical given the confluence of rising community wealth inequality [2] and the increasing prevalence of Alzheimer's Disease and Related Dementia [3]. A causal connection between community affluence and cognition would be of great concern, as it would imply that current wealth dynamics may compound existing challenges to the health and longevity of an aging American population.

We first provide new findings that community wealth levels predict lower rates of cognitive impairment after age 50, even after conditioning on household wealth, education, income, race/ethnicity, and community characteristics. This means that traditional risk factors for cognitive impairment are compounded by residence in places with low wealth levels. Our calculations indicate that the attenuation of community wealth disparities could reduce the burden of cognitive impairment by over eighty-six thousand cases or 6.7% among householders over the age of 50.

While future work is needed to definitively explain how community wealth affects cognitive impairment, we do provide preliminary evidence of the mediating forces. We argue that, by virtue of their large tax bases, wealthier towns and cities can invest more in local services and amenities, enhancing physical activity, social interaction, and mental stimulation for residents. Community wealth may therefore act as a public good, which may contribute positively to the cognitive aging trajectories of older adults.

This proposed mechanism—wealthier communities investing more in health-promoting amenities—is supported by correlational evidence in SI Table 11. Incorporating comprehensive public finance data from Feler and Senses [58], we show that wealthier communities tend to collect more in tax revenues from properties and sales, and they spend more on parks, education, welfare, housing, safety, and sanitation. They also tend to have more businesses, which provide valuable essential and recreational services for residents. Our hypothesis that community wealth reduces cognitive impairment through the local provision of public and private services is consistent with descriptive facts and studies of other health outcomes [59]. However, future work is needed to move beyond this correlational evidence and reliably establish the causal chain.

Perhaps our most critical findings show that the benefits associated with community affluence are not distributed equally. The fact that the association between local wealth and cognitive impairment is more than twice as high among the bottom quintile of communities than at the median, implies that rising community wealth confers outsized benefits for health in the poorest communities. This is intuitive when one considers that these places may be particularly exposed to shortfalls in the basic infrastructure, services, and amenities that can be funded by community wealth. Practically, this means that the health returns to economic stimulus may be largest in places without a strong base of existing wealth.

The protective effects associated with community wealth are also stronger for Black and Hispanic householders, and those lacking a college degree or with low net worth. Plausibly, these patterns reflect the greater reliance of economically vulnerable and racialized households on the public provision of social infrastructure and services. The local resources funded by community wealth may therefore act as a vital buffer for those lacking private resources. Our findings of differential effects of local wealth by householder demographic characteristics imply that local wealth may matter more among those with higher cognitive impairment risk by virtue of belonging to low socioeconomic status [60] or racial minority populations [61].

Conversely, more advantaged householders are better positioned to 'buy' good health. Wealth can expand one's range of lifestyle choices, reduce stress, and provide exclusive access to critical services including healthcare. Wealthier households may therefore be less reliant on local government expenditures and less sensitive to community wealth conditions. Given the greater sensitivity and lower exposure of vulnerable and racialized households to community wealth, the ongoing economic polarization of American communities may further fuel cognitive divides by race and socioeconomic status.

More optimistically, our findings suggest that wealth inequality is not invariably detrimental to cognition as its material effects appear to depend on the overall level of community affluence. For wealthier communities, the frictions, underinvestment, and psychosocial costs, accompanying inequality may be offset by the sheer presence of wealth-funded amenities. The capacity for wealthier communities to invest locally may offer advantages that are unattainable for poorer communities with less inequality. It may not merely be the presence of wealth that protects cognitive health, but also the *absence* of wealth that allows the corrosive effects of inequality to manifest.

Our nuanced findings on wealth inequality and cognitive health is in line with earlier work by economists, showing that unequal municipalities actually tend to collect more in tax and spend more on public services [31]. Whether or not inequality proves to be pernicious may depend, in part, on the resource base of the community in question. Nonetheless, given our findings, there may be a case for a softer emphasis on inequality within communities, and an expanded focus on place-based redistribution to reduce wealth disparities between communities [62, 63].

At a high level, our findings imply that the neurobiological, environmental, and social mechanisms shaping cognitive function are deeply embedded within and mediated by localized wealth contexts, validating the core claims of ecological theories of cognition [39]. Previous individualized research on the association between socioeconomic characteristics and cognition may be mischaracterizing this relationship because they do not include place-based measures of wealth. Our work thus challenges the primacy of individual-focused models, calling for renewed attention to community wealth disparities.

Finally, a critical point of novelty is our focus on the accumulated wealth of communities, beyond their flows of income, and the cognitive health trajectories of residents; an analysis which was unattainable prior to the advent of the GEOWEALTH-US. This data compendium has made it possible, for the first time, to investigate the community consequences of wealth polarization across range of societal outcomes [64]. While our work is just one demonstration of its utility in the domain of health, there are many others.

4 Validation and Robustness

To ensure the integrity of our cognition measure, we validate our findings relative to those of earlier studies, based on high quality survey data. The relationship between household wealth and subjective cognitive impairment documented in our data strongly align with prior research relying on the Health and Retirement Survey (HRS) relating to subjective memory problems (SI Table 1-2). This provides assurance that our basic findings are not driven by any peculiarities related specifically to the ACS.

Furthermore, the large observation count of our data allows for a stronger comparison of the importance of household and community wealth relative to other social determinants of health. We undertake this comparison through a Shapley decomposition [65], a method that partitions the model's explanatory power among different sets of variables. From this decomposition, we determine that low levels of household and local wealth are substantial risk factors for cognitive impairment, beyond more widely studied socioeconomic determinants (e.g., education, income, race/ethnicity, location) (SI Table 3). In fact, age is the only variable that contributes more to model fit than household wealth when predicting cognitive impairment. This decomposition also demonstrates that local wealth levels further improve model fit, albeit contributing substantially less than household characteristics. For reference, commuting zone of residence is comparable to education level in accounting for the total variation in cognitive impairment.

We also assess the robustness of our estimates to a series of critical assumptions and analytic decisions. First and most importantly, the core identifying assumption behind our analysis is that the composition of respondents within a commuting zone is not changing in ways which are related to community wealth and cognitive impairment, beyond what is captured by our household-level controls. Perhaps the primary concern is the bias in our estimates due to householders with lower cognitive impairment risk moving to places where wealth levels were increasing. To address this concern, we generate our estimates again while restricting the sample to householders who have lived at their current address for multiple decades prior to the study period and also to those who lived in their state of birth across both time periods (SI Table 7 and 9). Conceptually, this means that we estimate the relationship between community wealth and cognitive impairment for long-term residents of their current address, and among those who are of the same age, sex, race/ethnicity, education, and household wealth level. Even with these restrictions, our main results persist, mitigating concerns that selective migration patterns are the source of our findings.

Second, addressing the concern that community wealth may be correlated with other local characteristics of relevance to cognition, we show that our results are robust to a wide range of community zone characteristics including average household income levels, racial composition, homeownership rates, and population size (SI Table 4). Third, we show that the relationship is not the result of any data distortions or patterns introduced by the COVID-19 pandemic (SI Table 4). Fourth, a further concern may be that our findings are primarily driven by unusually low levels of wealth and high levels of cognitive impairment in the South: our results hold when the models are estimated separately for households living in and outside of the Southern states (SI Table 4). Fifth, the results strengthen when we take a more conservative definition of cognitive impairment and include households with additional independent living, self-care, or hearing difficulties (SI Table 4). Sixth, the role of local wealth in predicting cognitive outcomes hold across all 10-year age bands between age 50 and 100, indicating that these patterns are not driven by selective patterns of mortality toward the end of life (SI Table 5). Seventh, our statistical findings hold even when adjusting standard errors more stringently for spatial and temporal dependence between locations (SI Table 6). Eighth, we show consistent estimates when using alternate measures of inequality to the top 10% wealth share, such as the share of wealth held by the bottom half of the wealth distribution or the Gini coefficient (SI Table 10).

We undertake further validation of the SCI data to ensure that our findings are consistent when using official dementia statistics. Recent work has established the strong validity and agreement of SCI measures relative to the gold-standard Aging, Demographics, and Memory Study-based criteria [54]. We also draw on Medicare statistics on state- and county-level prevalence rates in 2020 [66]. We show strong correlations between our measure of subjective cognitive impairment with dementia prevalence at the scale of states and counties for individuals aged 65 and over (SI Figures 1-2). Moreover, the relationship between average household wealth and cognition in older age, also holds when examining dementia prevalence in the Medicare data (SI Figures 3-4). These comparisons confirm that our documented relationships between community wealth and cognitive impairment are reliably linked to true dementia risk.

Finally, while our use of the two-way fixed effects design and our suite of robustness analyses mitigate many of the concerns regarding the potential causal connection between community wealth and cognition, we cannot conclusively rule out confounders. While we have adjusted our estimates for time-varying economic and demographic conditions (SI Table 4), our analysis is based on observational data meaning that it is still possible that there are unobserved local shocks that could simultaneously affect community wealth and SCI. Therefore, our findings should be interpreted as highly suggestive evidence of a causal relationship, warranting further experimental investigation into the specific mechanisms linking community wealth to cognition.

5 Materials and methods

This work is based on a novel database integrating self-reported indicators of cognitive difficulty with measures of local and household wealth characteristics. Local and household wealth estimates are derived from the newly developed and validated GEOWEALTH-US compendium [2], which uses ensemble machine learning to estimate household wealth in public-use Census population survey data.

5.1 Subjective cognitive impairment data

Our analysis of subjective cognitive impairment is based on responses to the cognitive difficulty item of the Census Bureau's Disability Questionnaire. This item is subjective and does not constitute a clinical diagnosis of cognitive condition. It is available as a variable from NHGIS [67] and in IPUMS [68] microdata ("DIFFREM"). It is a binary report to the following question: "Because of a physical, mental, or emotional problem, does this person have difficulty remembering, concentrating, or making decisions?"

Recent work supports the use of this measure for dementia surveillance [54]. By comparison to a validated probable dementia algorithm in the National Aging Health and Trends Study (NHAT), the authors find high levels of agreement (90%), specificity (92.5%), sensitivity (63.4%), and comparability to the gold-standard Aging, Demographics, and Memory Study-based criteria. The ACS item therefore has high credibility for dementia monitoring and analysis among older adults. Furthermore, subjective measures of cognition and cognitive difficulties have been related to a higher risk of incident dementia [69], particularly so with advanced age [70].

We acknowledge that SCI is a self-reported indicator of cognitive difficulty and not a clinical diagnosis of dementia. SCI may capture a range of conditions, including psychological distress, depression, and anxiety, that are also important public health concerns. This point is particularly relevant as the mechanism linking community wealth to cognitive impairment is likely fueled, in part, by broader improvements in mental health associated with prosperous economic conditions. Nonetheless, the variable's credibility as an early risk factor for incident dementia [69, 70], its use of this measure in previous, high-quality studies [71, 72, 73, 74, 75], its reliability and validity as established by the Census Bureau and elsewhere [54, 76] (SI Figures 1-4), make it a uniquely valuable source of information for assessing population-level cognitive burden across the United States at a scale unattainable with clinical data.

5.2 Household and local wealth data

Our wealth estimates are based on the strongly validated GEOWEALTH-US data infrastructure [2]. GEOWEALTH-US is the first data compendium on US spatial wealth inequality from 1960-2023. These data are derived from a machine-learning approach that generates highly predictive models of household wealth based on the Federal Reserve's gold-standard Survey of Consumer Finances (SCF) and then applies these models to impute wealth among households in successive iterations of the Decennial Census and ACS. Prior to the development of GEOWEALTH-US, there were no alternative data sources measuring the dynamics of household wealth within and between locales over this period.

Suss et al. (2024) provide a large number of validation exercises to establish the credibility and reliability of the GEOWEALTH database. Using a 10% holdout sample of the SCF, a strong correlation between actual and predicted positive wealth is evident ($r = 0.94$). The Panel Study of Income Dynamics was also used to demonstrate low spatial bias in the GEOWEALTH-US estimates. Spatial estimates of wealth inequality are comparable to those generated by the Survey of Income and Program Participation, and, estimates strongly align with leading measures of national wealth concentration [77].

5.3 Estimation strategy

Our regression analysis is based on a series of linear probability models with a binary dependent variable and fixed effects for location and time across pooled cross sections of data. We use these models to address confounding influences in the relationship between cognitive difficulty and local wealth characteristics. Our model takes the following form:

$$Y_{ict} = \alpha + \beta_1 W_{ct} + \beta_2 I_{ct} + \gamma X_{ict} + \delta_c + \lambda_t + \epsilon_{ict} \tag{1}$$

where we estimate the probability of cognitive difficulty for individual i in a Commuting Zone c at time t, δ_c represents commuting zone fixed effects that absorb all time-invariant local characteristics, and λ_t represents time fixed effects that account for secular trends.

The variables of interest are the mean household wealth in the individual's location of residence (W_{ct}) and the share of total local wealth held by households in the top decile of the local wealth distribution (I_{ct}). All variables are standardized to have a mean of zero and a standard deviation of one. The model also includes a vector of individual control variables, X_{ict}, which captures characteristics such as household wealth, age, race/ethnicity, and education. The traditional idiosyncratic error term ϵ_{ict} is supplemented by locational fixed effects δ_c, which capture place-specific but time-invariant unobserved heterogeneity, and time fixed effects λ_t that absorb potential bias from broader time-varying factors, such as business cycles.

We estimate separate models across subsets of the data to examine how these relationships vary by wealth, poverty status, race/ethnicity, sex, and education level. To ensure robust inference, we cluster standard errors at the Commuting Zone level to account for within-CZ spatial and temporal correlation. As noted, our estimates are robust to stricter adjustments for spatial and temporal dependence (SI Table 5 and 6).

Given growing recognition that average effects produced by the TWFE framework may be misleading if the relationships of interest exhibit heterogeneity [78], we test for heterogenous associations across a set of key categories. We extend the modeling framework described in equation 1 to estimate heterogenous associations based on the wealth quintile of commuting zones in the 2010 base period. We follow a similar strategy to estimate group-based differences (race, ethnicity, sex, education, wealth level) by interacting householder characteristics with local wealth characteristics. These estimates are then used to generate the marginal effects shown in Figures 3 and 4.

Equation 1 was also used for our calculation of the counterfactual levels of cognitive impairment under scenarios of reduced community wealth disparities. We first determined the relationship between local wealth levels and cognitive impairment using our preferred model. We then restrict the sample to the 2019-2021 observations in our data. Using this subset of households, we then calculated baseline the prevalence rates and total cases (factual calculation: $0.0572 \times 22,992,964 = 1,315,765$). Then, for householders living in the local labor markets in the bottom three quintiles of the community wealth distribution, we inflated their average wealth level to that of the community at the 60th percentile (mean net worth = $584,234). These modifications were then used to generate revised counterfactual predictions (counterfactual calculation: $0.0534 \times 22,992,964 = 1,229,229$). The difference between the factual and the counterfactual scenarios was used to assess the potential impact of wealth equalization on cognition.

Our choice of a linear probability model over the unconditional or conditional logit model is justified on multiple grounds. In the context of a fixed-effect logistic regression, the incidental parameter problem leads the unconditional logit model to generate inconsistent and biased estimates [79] when the number of fixed effect groups is large, as is the case here. While the conditional logit addresses this problem [80], it is computationally infeasible for a data structure of our size and with high dimensional fixed effects. The linear probability models addresses each of these problems while also being easier to interpret than the marginal effects that would be required in the logit framework.

5.4 Spatial units

Our preferred spatial units - 1990-vintage commuting zones - were defined by using clusters of counties based on county-to-county commuting patterns [81]. Commuting zones are the preferred unit as they represent functional labor market areas, which have consistent spatial boundaries over time and cover the entire United States. The 1990 boundaries are preferred to more recent vintages as these are used widely in the literature as approximations of regional labor markets and provide consistent spatial units over time [82]. They are therefore theoretically meaningful for the study of wealth. As the commuting zone geography is not provided as a variable in the IPUMS' public use microdata, all households were assigned to commuting zones based on their public use microdata area of residence (PUMA) using the weighted proportional allocation method described in Dorn [53]. For all statistics and regression analyses, households are weighted according to this proportional allocation factor. We also show that our core results hold when we use PUMAs instead of commuting zones (SI Table 8). PUMAs are more widely used and finer spatial units ($n = 1,066$) than are commuting zones ($n = 722$). Nonetheless, our findings are not particularly sensitive to decisions regarding spatial units.

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Data and materials availability: All data will be available for purposes of replication and reproducibility.

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A Supplementary Materials

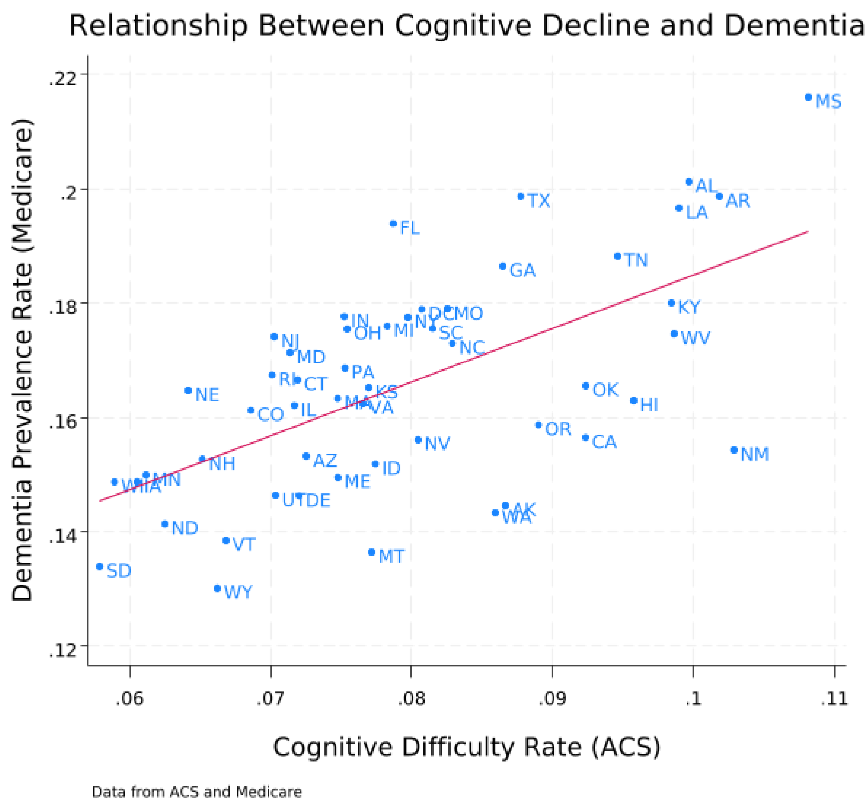

Figure S1: Comparison of cognitive difficulty and dementia prevalence, state comparison. Notes: A scatterplot of the rate of cognitive difficulty from the American Community Survey and dementia prevalence as recorded in Medicare for each state. To match the population reporting of the Medicare data, the two data sources are restricted to all individuals over the age of 65. The state-level cognitive difficulty rates were retrieved from the National Historical Geographic Information System (NHGIS) and the dementia prevalence data were accessed through the Dementia DataHub at NORC at the University of Chicago [66]. Pearson correlation coefficient is 0.62.

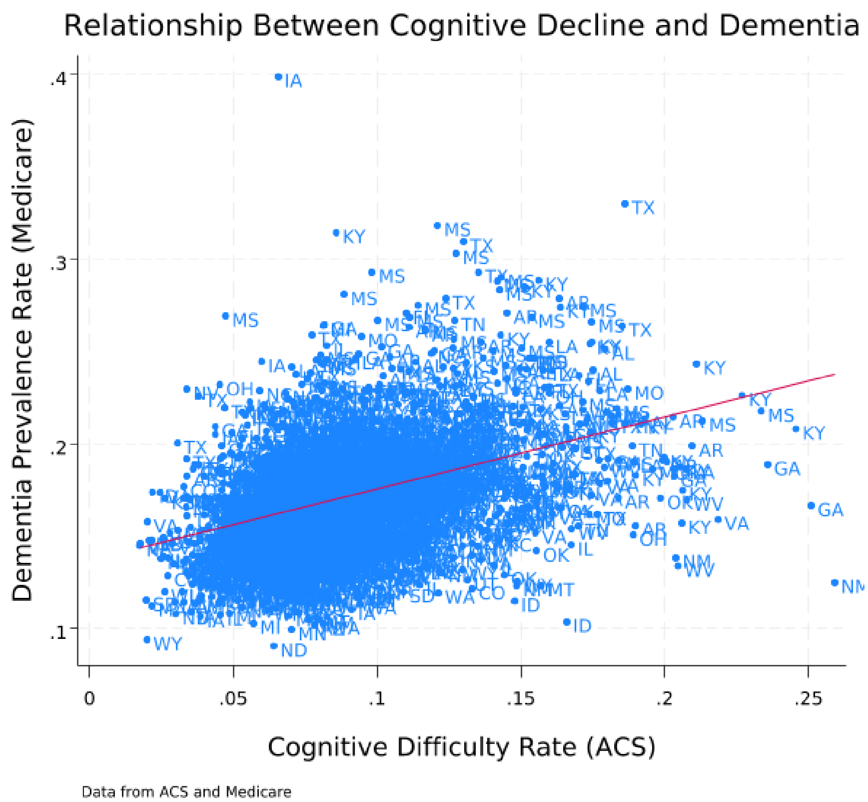

Figure S2: Comparison of cognitive difficulty and dementia prevalence, county comparison. Notes: A scatterplot of the rate of cognitive difficulty from the American Community Survey and dementia prevalence as recorded in Medicare for each county. To match the population reporting of the Medicare data, the two data sources are restricted to all individuals over the age of 65. The county-level cognitive difficulty rates were retrieved from the National Historical Geographic Information System (NHGIS) and the dementia prevalence data were accessed through the Dementia DataHub at NORC at the University of Chicago [66]. Pearson correlation coefficient is 0.41.

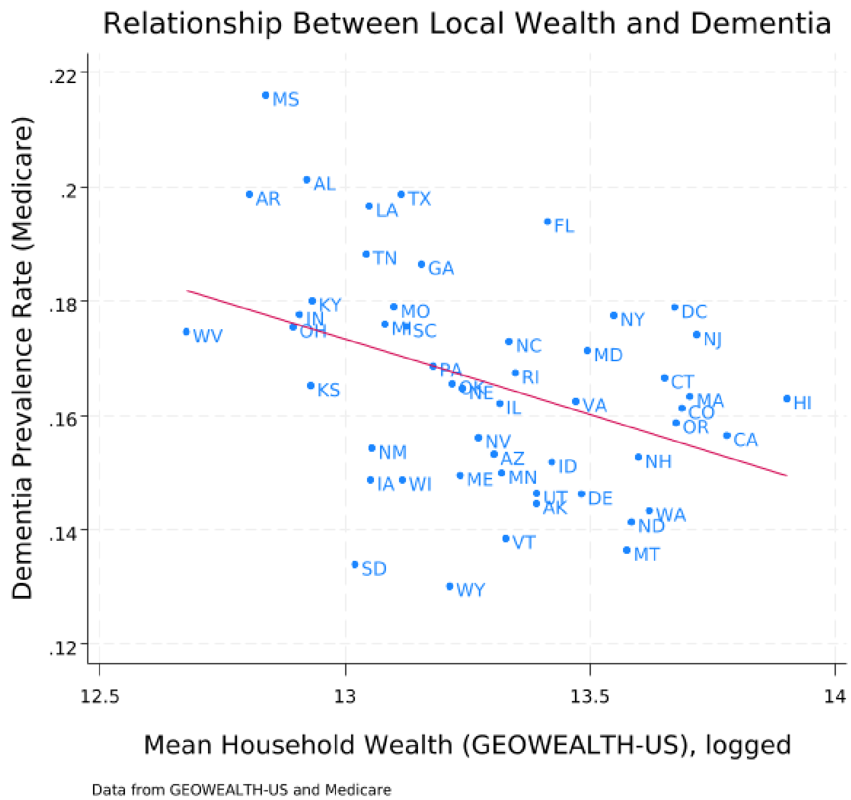

Figure S3: Relationship between average household wealth and dementia prevalence, state comparison. Notes: A scatterplot of average household wealth from GEOWEALTH-US and dementia prevalence as recorded in Medicare for each state. The Medicare data are restricted to all individuals over the age of 65. The GEOWEALTH-US data are based on all households in the state. The state-level cognitive difficulty rates were retrieved from the National Historical Geographic Information System (NHGIS) and the dementia prevalence data were accessed through the Dementia DataHub at NORC at the University of Chicago [66]. Pearson correlation coefficient is -0.39.

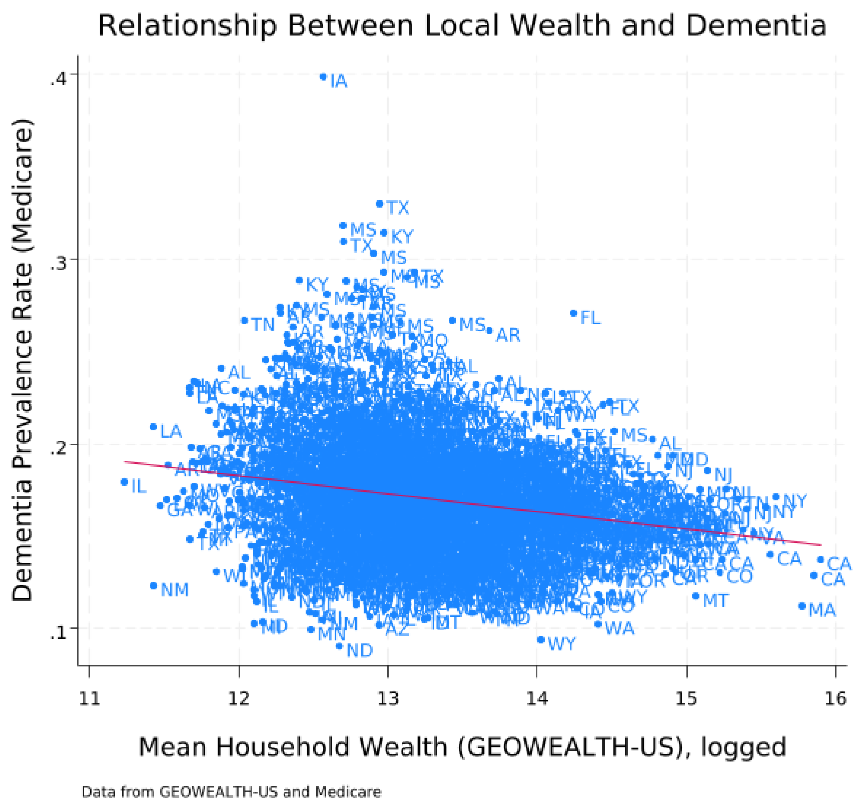

Figure S4: Relationship between average household wealth and dementia prevalence, county comparison. Notes: A scatterplot of average household wealth from GEOWEALTH-US and dementia prevalence as recorded in Medicare for each county. The Medicare data are restricted to all individuals over the age of 65. The GEOWEALTH-US data are based on all households in the county. The county-level cognitive difficulty rates were retrieved from the National Historical Geographic Information System (NHGIS) and the dementia prevalence data were accessed through the Dementia DataHub at NORC at the University of Chicago [66]. Pearson correlation coefficient is -0.22.

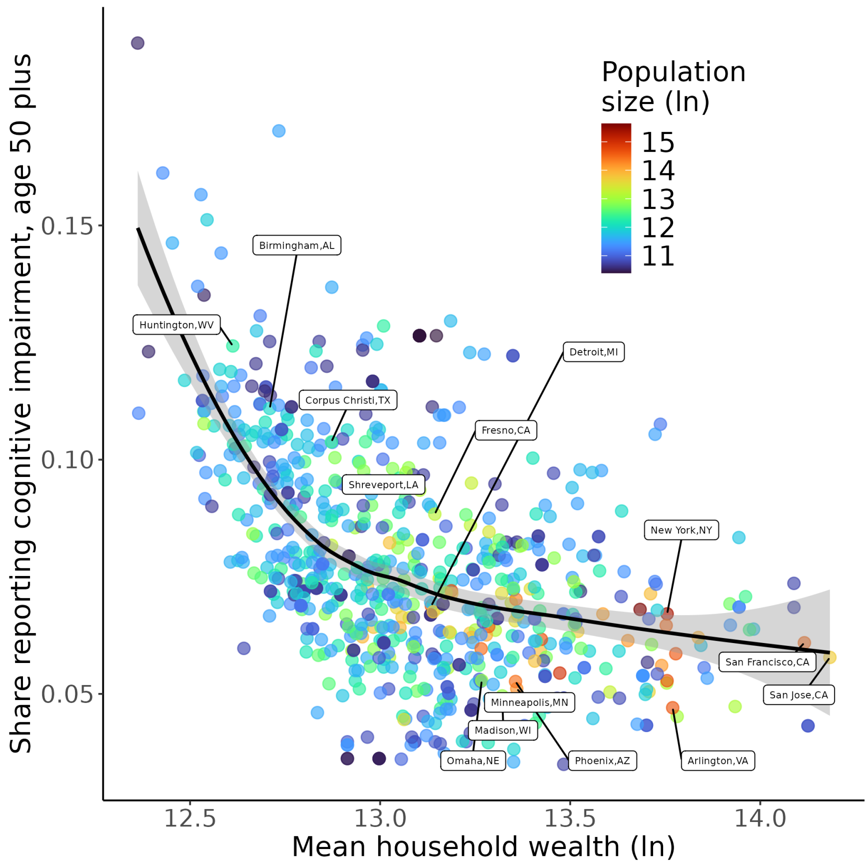

Figure S5: Mean household wealth and cognitive impairment among older adults across local labor markets, 2019-2021. Notes: A figure showing the relationship between the natural log of average household wealth and the age-adjusted share of adults over the age of 50 reporting cognitive impairment in the American Community Survey for every commuting zone in the United States. Points are colored according to the logged total number of households in each commuting zone. The place labels reflect the largest incorporated or census designated place within a commuting zone.

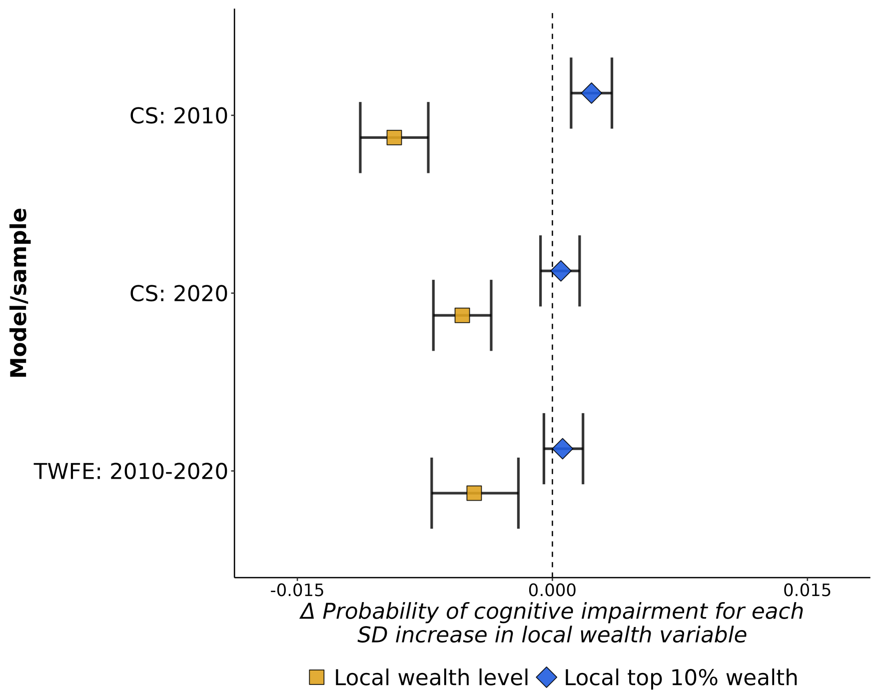

Figure S6: Estimates of the relationship between local wealth characteristics and cognitive impairment among older adults. Notes: Estimates from three separate linear probability regression models of the relationship between householder cognitive impairment and the wealth characteristics of commuting zones. The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods. The regression models include standard controls for the total number of households in a commuting zone, education level, race, sex, race and Hispanic ethnicity, veteran status, and year of birth. Separate cross-sectional models are estimated for the 2009-2011 ("CS: 2010") and 2019-2021 ("CS: 2020") periods. The preferred estimates are derived from the pooled model ("TWFE: 2010-2020"), which is estimated with additional fixed effects for commuting zone and period. The wealth variables are transformed into standard units, with a mean of zero and a standard deviation of one. Standard errors are clustered at the level of commuting zones.

	Health and Retirement Survey Cognitive difficulty		American Community Survey Cognitive difficulty	
Wealth quintiles	(1)	(2)	(3)	(4)
Q1 vs Q5	3.27***	2.00***	7.33***	5.39***
	(0.25)	(0.17)	(0.27)	(0.21)
Q2 vs Q5	2.44***	1.61***	3.33***	2.62***
	(0.19)	(0.14)	(0.13)	(0.11)
Q3 vs Q5	2.05***	1.53***	2.23***	1.87***
	(0.17)	(0.13)	(0.09)	(0.08)
Q4 vs Q5	1.21*	1.05	1.53***	1.37***
	(0.11)	(0.09)	(0.07)	(0.06)
N	9,795	9,795	542,870	542,870
Controls	No	Yes	No	Yes

Table S1: Comparison of estimates between HRS and ACS, ages 50-69.

Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Notes: A table showing results from four logistic regression models (odds ratios), where cognitive difficulty is regressed on the wealth quintile for individuals aged 50-69. The estimates in Columns 1-2 are based on data from the Health and Retirement Survey (HRS) from 2014. We use 2014 as it is approximately at the midpoint of our study period. The dependent variable for the HRS analysis is a dummy variable indicating self-rated memory, where individuals reporting fair or poor memory are coded as 1 and persons reporting good, very good or excellent memory are recoded as 0. The estimates in Columns 3-4 are based on data from the American Community Survey (ACS). The dependent variable for the ACS analysis is the measure of cognitive difficulty. Controls include age, race/ethnicity, and years of education.

	Health and Retirement Survey Cognitive difficulty		American Community Survey Cognitive difficulty	
Wealth quintiles	(1)	(2)	(3)	(4)
Q1 vs Q5	2.35***	1.40***	3.569***	2.566***
	(0.20)	(0.13)	(0.111)	(0.088)
Q2 vs Q5	1.88***	1.24*	2.218***	1.727***
	(0.15)	(0.11)	(0.073)	(0.060)
Q3 vs Q5	1.68***	1.28**	1.659***	1.354***
	(0.12)	(0.10)	(0.056)	(0.047)
Q4 vs Q5	1.42***	1.21*	1.280***	1.148***
	(0.11)	(0.09)	(0.045)	(0.041)
N	7,360	7,360	307,722	307,722
Controls	No	Yes	No	Yes

Table S2: Comparison of estimates between HRS and ACS, ages 70 plus.

Standard errors in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$
Notes: A table showing results from four logistic regression models (odds ratios), where cognitive difficulty is regressed on the wealth quintile for individuals aged 70 and older. The estimates in Columns 1-2 are based on data from the Health and Retirement Survey (HRS) from 2014. We use 2014 as it is approximately at the midpoint of our study period. The dependent variable for the HRS analysis is a dummy variable indicating self-rated memory, where individuals reporting fair or poor memory are coded as 1 and persons reporting good, very good or excellent memory are recoded as 0. The estimates in Columns 3-4 are based on data from the American Community Survey (ACS). The dependent variable for the ACS analysis is the measure of cognitive difficulty. Controls include age, race/ethnicity, and years of education.

Variable	Scale	Model 1		Model 2		Model 3		Model 4	
		Shapley Value	Share (%)	Shapley Value	Share (%)	Shapley Value	Share (%)	Shapley Value	Share (%)
Wealth	HH	0.00965	20.59	0.00928	19.78	0.00942	20.10	0.00952	21.09
Total family income	HH	0.00729	15.55	0.00695	14.83	0.00699	14.92	0.00712	15.77
Age	HH	0.01238	26.41	0.01242	26.48	0.01249	26.64	0.01245	27.58
Race/Ethnicity	HH	0.00134	2.86	0.00126	2.68	0.00121	2.58	0.00124	2.75
Sex	HH	0.00033	0.71	0.00034	0.72	0.00032	0.69	0.00033	0.72
Education	HH	0.00484	10.33	0.00446	9.50	0.00458	9.77	0.00473	10.47
Homeownership	HH	0.00547	11.67	0.00560	11.95	0.00557	11.87	0.00553	12.25
Year	HH	0.00012	0.26	0.00017	0.36	0.00012	0.25	0.00012	0.26
Wealth	CZ	-	-	0.00077	1.65	-	-	-	-
Other characteristics	CZ	-	-	0.00118	2.51	-	-	-	-
Fixed effect	CZ	-	-	-	-	0.00383	8.17	-	-
Fixed effect	State	-	-	-	-	-	-	0.04514	5.10

Table S3: Variable importance estimates from models regressing cognitive difficulty on covariates.

Notes: A table presenting a Shapley decomposition of variable importance for four separate regression models for householders aged 50 and over. The scales of observation are households (HH), commuting zones (CZ), and states. The dependent variable for all models is cognitive difficulty. The independent variables are household wealth (inverse hyperbolic sine transformation), total family income (inverse hyperbolic sine transformation), age (age and age squared), education (four categories), race and ethnicity indicators (nine categories), homeownership dummy, year of observation dummy, CZ wealth characteristics (mean household wealth, top 10% wealth share), other CZ characteristics (total households, homeownership rate, average household income per capita, Black population share, Hispanic population share), commuting zone fixed effects (722 categories). Models estimated with OLS for computational efficiency and assessed using R squared values. All estimates were generated using the Shapley2 package in Stata.

	Cognitive difficulty						
	Additional CZ Controls (1)	2020-2021 dropped (2)	South excluded (3)	South only (4)	Independent living disability (5)	Activity and daily living (6)	Hearing disability (7)
Household wealth	-0.0340***	-0.0323***	-0.0362***	-0.0311	-0.0196***	-0.0101***	-0.0077***
	[-0.0350,-0.0331]	[-0.0334,-0.0313]	[-0.0375,-0.0350]	[-0.0311,-0.0311]	[-0.0203,-0.0189]	[-0.0105,-0.0096]	[-0.0081,-0.0074]
CZ Wealth level	-0.0053***	-0.0064***	-0.0033**	-0.0038	-0.0016*	-0.0017***	-0.0016**
	[-0.0079,-0.0027]	[-0.0097,-0.0032]	[-0.0063,-0.0004]	[-0.0038,-0.0038]	[-0.0034,0.0002]	[-0.0030,-0.0005]	[-0.0031,-0.0002]
CZ Top 10% share	0.0013**	0.0010	-0.0001	0.0015	-0.0000	0.0003	0.0002
	[0.0001,0.0025]	[-0.0005,0.0026]	[-0.0014,0.0012]	[0.0015,0.0015]	[-0.0008,0.0008]	[-0.0003,0.0008]	[-0.0004,0.0007]
CZ Total households	-0.0045						
	[-0.0267,0.0177]						
CZ Homeownership %	0.0036						
	[-0.0009,0.0080]						
CZ Household inc p.c.	0.0051**						
	[0.0010,0.0092]						
CZ Black share	0.0034						
	[-0.0037,0.0104]						
CZ Hispanic share	0.0013						
	[-0.0064,0.0089]						
N	6,430,408	4,310,845	4,005,897	2,424,511	6,430,408	6,430,408	6,430,408

Table S4: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality with alternate specifications.

95% confidence intervals in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from various robustness analyses. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Both models include fixed effects for commuting zone and year. Additional household controls include education, race, sex, veteran status, and year of birth. Standard errors are clustered at the level of commuting zones. Models specified as follows: Column 1 includes additional commuting zone level predictors; Column 2 drops the 2020 and 2021 data because of the COVID-19 pandemic; Column 3 drops all households living in the South; Column 4 restricts the analysis only to households living in the South; Column 5 codes households as having a cognitive disability only if an independent living disability is also present (“DIFFMOB”); Column 6 codes households as having a cognitive disability only if activity and daily living disability is also present (“DIFFCARE”); Column 7 codes households as having a cognitive disability only if hearing disability is also present (“DIFFHEAR”). The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods.

	Cognitive difficulty					
	Age: 50 plus (1)	Age: 50-59 (2)	Age: 60-69 (3)	Age: 70-79 (4)	Age: 80-89 (5)	Age: 90-99 (6)
Household wealth	-0.0340***	-0.0324***	-0.0346***	-0.0365***	-0.0424***	-0.0338***
	[-0.0350,-0.0330]	[-0.0337,-0.0312]	[-0.0360,-0.0331]	[-0.0381,-0.0349]	[-0.0457,-0.0391]	[-0.0419,-0.0257]
CZ Wealth level	-0.0046***	-0.0028	-0.0047***	-0.0053**	-0.0061	-0.0244**
	[-0.0071,-0.0020]	[-0.0061,0.0006]	[-0.0082,-0.0013]	[-0.0101,-0.0006]	[-0.0141,0.0018]	[-0.0449,-0.0038]
CZ Top 10% wealth share	0.0006	-0.0000	0.0004	0.0012	0.0004	-0.0002
	[-0.0005,0.0018]	[-0.0015,0.0015]	[-0.0010,0.0018]	[-0.0008,0.0032]	[-0.0032,0.0041]	[-0.0091,0.0088]
N	6,430,408	2,097,101	2,076,784	2,118,447	696,859	138,076

Table S5: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality, split by age.

95% confidence intervals in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from five regression analyses, where the sample is split into 10-year age bands. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Models include fixed effects for commuting zone and year. Additional household controls include education, race, sex, veteran status, and year of birth. Standard errors are clustered at the level of commuting zones. The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods.

	Cognitive difficulty			
	Age: 50-69		Age: 70 plus	
	(1)	(2)	(3)	(4)
CZ Wealth level	-0.0059***	-0.0056***	-0.0090***	-0.0087***
	[-0.0083,-0.0036]	[-0.0081,-0.0032]	[-0.0140,-0.0039]	[-0.0142,-0.0032]
CZ Top 10%	0.0009	0.0009	0.0017	0.0025**
wealth share	[-0.0003,0.0021]	[-0.0003,0.0022]	[-0.0009,0.0043]	[0.0001,0.0050]
N	1,444	1,444	1,444	1,444
Correct R2	0.94	0.95	0.91	0.92
Control variables	CZ fixed effects	CZ fixed effects	CZ fixed effects	CZ fixed effects
	Period fixed effects	Period fixed effects	Period fixed effects	Period fixed effects
		Other CZ		Other CZ

Table S6: Regression of cognitive difficulty on wealth at the commuting zone scale, standard errors adjust for spatial dependence and HAC.

95% confidence intervals in parentheses. * p < 0.10; ** p < 0.05; *** p < 0.01
Notes: A table presenting results from four commuting-zone regression analyses, where the sample is split into two age bands. Estimates are based on aggregations of pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). The commuting zone aggregation is performed to allow for efficient adjustment of the standard errors due to spatial dependence. The dependent variable is the average level of cognitive difficulty in the respective age band. Variables are transformed into standard units with a mean of zero and a standard deviation of one. All models include fixed effects for period and commuting zone. The "Other CZ" control variables refer to the commuting zone averages of total households, homeownership, total family income, Black population share, Hispanic population share, year of birth, education level, and male share. Standard errors are adjusted for spatial and temporal dependence. The corrections to the standard errors were made using the acreg package in Stata [83]. When correcting the standard errors for spatial dependence, it was assumed that there is no spatial interaction between commuting zones that are more than 200 kilometers apart, based on polygon centroids. Standard errors are Heteroskedasticity and Autocorrelation Consistent (HAC).

	Cognitive difficulty	
	Age: 50-69 (1)	Age: 70 plus (2)
Household wealth	-0.0372*** [-0.0385,-0.0360]	-0.0456*** [-0.0477,-0.0435]
CZ Wealth level	-0.0039*** [-0.0068,-0.0010]	-0.0086*** [-0.0146,-0.0026]
CZ Top 10% wealth share	0.0003 [-0.0011,0.0017]	-0.0011 [-0.0036,0.0014]
N	2,338,831	1,295,064

Table S7: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality, restricted to householders who live in their state of birth.

95% confidence intervals in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from two regression analyses, where the sample is restricted to householders who live in their state of birth. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Models include fixed effects for commuting zone and year. Additional household controls include education, race, sex, veteran status, year of birth, and state of birth. Standard errors are clustered at the level of commuting zones.

	Cognitive difficulty	
	Age: 50-69 (1)	Age: 70 plus (2)
Household wealth	-0.0284*** [-0.0295,-0.0273]	-0.0378*** [-0.0393,-0.0364]
PUMA Wealth level	-0.0084*** [-0.0096,-0.0073]	-0.0064*** [-0.0081,-0.0047]
PUMA Top 10% wealth share	0.0008 [-0.0002,0.0018]	-0.0007 [-0.0021,0.0006]
N	2,794,506	1,454,802

Table S8: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality, location defined by public use microdata areas.

95% confidence intervals in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from two regression analyses, where householders' location and local wealth characteristics are defined based on public use microdata areas (PUMAs) rather than commuting zones. PUMAs are geographic areas used by the Census Bureau to provide demographic and statistical data. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Models include fixed effects for PUMA and year. Additional household controls include education, race, sex, veteran status, year of birth, and state of birth. Standard errors are clustered at the level of PUMAs.

	Cognitive difficulty	
	Age: 50-69 (1)	Age: 70 plus (2)
Household wealth	-0.0278***	-0.0327***
	[-0.0298,-0.0258]	[-0.0356,-0.0298]
Commuting zone wealth level	-0.0040**	-0.0076***
	[-0.0079,-0.0001]	[-0.0132,-0.0020]
Commuting zone top 10% wealth share	-0.0002	0.0019
	[-0.0019,0.0014]	[-0.0005,0.0043]
N	1,497,215	1,249,927

Table S9: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality, sample restricted to householders who have resided at current residence for 20 or more years.

95% confidence intervals in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from two regression analyses, where the sample has been restricted to householders have lived in their current place of residence for 20 or more years. The sample restriction is made using the "movedin" variable from IPUMS, which records the number of years ago that each householder moved into their current dwelling unit. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Models include fixed effects for commuting zone and year. Additional household controls include education, race, sex, veteran status, year of birth, and state of birth. Standard errors are clustered at the level of commuting zones.

	(1)	(2)	(3)
Household wealth	-0.0340***	-0.0340***	-0.0340***
	[-0.0350,-0.0331]	[-0.0350,-0.0331]	[-0.0350,-0.0330]
CZ Wealth level	-0.0048***	-0.0043***	-0.0048***
	[-0.0073,-0.0023]	[-0.0067,-0.0019]	[-0.0072,-0.0025]
CZ Top 10% wealth share	0.0007		
	[-0.0004,0.0018]		
CZ Gini coefficient		0.0003	
		[-0.0009,0.0016]	
CZ Bottom 50% wealth share			-0.0013**
			[-0.0026,-0.0001]
NT	6,430,408	6,430,408	6,430,408
r2	0.0474	0.0474	0.0474

Table S10: Linear probability regression estimates of cognitive difficulty on measures of local wealth inequality, including alternate measure of inequality.

95% confidence intervals in parentheses. ** $p < 0.05$; *** $p < 0.01$
Notes: A table presenting results from three linear probability models with alternate measures of local wealth inequality. The dependent variable is an indicator of subjective cognitive impairment or cognitive difficulty. Estimates are based on pooled cross-sections of ACS data across two periods (2009-2011 and 2019-2021). Variables are transformed into standard units with a mean of zero and a standard deviation of one. Both models include fixed effects for commuting zone and year. Additional household controls include education, race, sex, veteran status, and year of birth. Standard errors are clustered at the level of commuting zones. CZ Gini coefficient refers to the gini coefficient for net worth for the commuting zone and the CZ Bottom 50% wealth share refers to the share of commuting wealth that is held by the poorest half of households. The units of observation are based on 1,835,306 householders over the age of 50, who are proportionally allocated across 722 commuting zones (6,430,408 person-CZ observations), drawn from two population cross-sections over two time periods.

Expenditures and revenues, 2007	2010 Mean HH Wealth	2010 Top 10% Wealth share	2000 Mean HH Wealth	2000 Top 10% Wealth share
Total business establishments	0.571	0.376	0.537	0.409
Student teacher ratio	0.283	0.294	0.348	0.158
Revenue: Total p.c.	0.546	0.283	0.546	0.286
Revenue: Property p.c.	0.629	0.162	0.639	0.132
Revenue: Sales p.c.	0.318	0.354	0.279	0.429
Expenditure: Total p.c.	0.520	0.259	0.528	0.254
Expenditure: Education p.c.	0.382	0.018	0.338	0.086
Expenditure: Health p.c.	0.009	0.095	0.044	0.115
Expenditure: Welfare & housing (p.c.)	0.543	0.167	0.497	0.154
Expenditure: Parks and natural resources (p.c.)	0.358	0.269	0.416	0.161
Expenditure: Safety (p.c.)	0.606	0.456	0.631	0.424
Expenditure: Sanitation (p.c.)	0.492	0.209	0.506	0.143
Expenditure: Transportation (p.c.)	0.148	-0.118	0.125	-0.231
Expenditure: Debt interest (p.c.)	0.226	0.186	0.258	0.206

Table S11: Correlation between community wealth characteristics and local public revenues and expenditures.

Notes: A table presenting Pearson correlation coefficients between the wealth characteristics of commuting zones and local revenues, expenditures, and business activity. The data on mean household wealth and the top 10% wealth share of the commuting zone come from the GEOWEALTH-US estimates for 2010. The data on total business establishments, student teacher ratios, public revenues and public expenditures are all drawn from Feler and Senses [58], who originally compiled these data from the US Census Bureau's historical data on State and Local Government Finances, National Center for Education Statistics, and County Business Patterns. The Feler and Senses data are based on 2007 data collection, the latest year in their study. As 2007 falls between the 2000 and 2010 estimates provided in GEOWEALTH-US, we show correlations for both years. Correlations are weighted by the total number of households in commuting zones.