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Growing old in rural America: Measuring late-life health and economic well-being ☆

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ABSTRACT

We estimate well-being among older rural Americans with an expected utility framework and simulations using longitudinal data spanning nearly 30 years from the Health and Retirement Study. At age sixty, we find mean rural consumption expenditures of $24,105, a retirement probability of 53%, and a remaining life expectancy of 20.3 years for the cohort born 1931–36. When adjusting life expectancy for living in poor health, we obtain an age sixty quality adjusted life expectancy (QALE) of only 15.4 years. Our welfare metric suggests well-being among rural residents who report loneliness is only about half that of the non-lonely rural residents—largely driven by substantial consumption and QALE gaps. We also document substantial regional variation in rural well-being. Moreover, we find that older rural Americans are generally falling further behind older urban Americans across birth cohorts. Most of this widening gap is driven by declining relative consumption and wealth as opposed to health.

Introduction

Growing old in rural America presents a unique set of opportunities and challenges. While ageing populations are a national trend, rural areas are experiencing this phenomenon at an accelerated pace (Cohen and Greaney, 2023; Smith and Trevelyan, 2019). Factors such as ageing-in-place, the out-migration of young adults, reduced international immigration, declining fertility rates, and the influx of retirees from metropolitan regions have contributed to population ageing in rural areas (Cohen and Greaney, 2023; Slack and Jensen, 2020; Johnson and Lichter, 2019; Glasgow and Brown, 2012; Carr and Kefalas, 2009). More than 20% of Americans aged 65 and older now live in rural areas, accounting for over 20% of the rural population—a proportion that is expected to increase as the baby boomer generation continues to age (Davis et al., 2022; Smith and Trevelyan, 2019). This demographic transition underscores the importance of understanding the dynamics of ageing, particularly the nuanced and evolving gaps between rural and urban residents.

For older Americans, the rural environment shapes their experiences through its distinct community dynamics, lifestyle patterns, and health implications. Some research indicates that older adults in rural areas experience closer family ties and community relationships, which can significantly improve their well-being (Henning-Smith et al., 2019; Carver et al., 2018). Rural environments also provide a slower pace of life and greater access to nature, which can reduce stress and promote a sense of peace (Cohen and Greaney, 2023; Levinger et al., 2022; Butler and Cohen, 2010). However, these social and material benefits can vary significantly across different rural communities. While some older adults maintain strong social connections, others face social isolation or loneliness (Pickering et al., 2023; Jensen et al., 2020; Kaye, 2017). In particular, older adults experiencing loneliness are at increased risk of negative health outcomes such as functional disability, depression, declined cognitive functioning, and death (Park et al., 2020; Donovan et al., 2017; Holt-Lunstad et al., 2015). In addition, a disproportionate number of chronically ill individuals in the U.S. are found in rural

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regions, a disparity arguably compounded by limited access to primary care and higher poverty rates (Aggarwal et al., 2021; Miller and Vasan, 2021; Leider et al., 2020; Spencer et al., 2018; Glasgow and Brown, 2012). These structural barriers may place rural older populations at a distinct health disadvantage compared to their urban counterparts.

While these social benefits and challenges for older rural residents are well-documented, existing research has often focused on singular health metrics such as activities of daily living (ADL) limitations, self-rated health, mortality, or mental health to assess late-life well-being. Yet, well-being is a multifaceted concept influenced by a variety of factors. In addition to health, outcomes such as leisure activities, consumption patterns, wealth, social interactions, and environmental factors have all been linked to well-being at older ages (Chun et al., 2024; Nikitin et al., 2024; Miller and Bairoliya, 2023; Chin, 2023; Chin and Miller, 2024; Levasseur et al., 2015; Seonglim et al., 2014; Miller et al., 2022). Moreover, within the older demographic, rural residents often lag behind in related economic indicators such as consumption expenditures, retirement, and overall wealth (Brown and Swanson, 2015; Seonglim et al., 2014; Costa, 1998). Consequently, questions persist regarding the adequacy of narrowly defined metrics in comprehensively understanding spatial variations in well-being across different stages of the life cycle.

In this paper, we estimate well-being among older rural Americans using an expected utility framework that incorporates differences in consumption, leisure, health, mortality, and wealth. We take a life-cycle approach to better quantify aggregate well-being by incorporating contemporaneous and dynamic spillovers across all modeled outcomes at the individual level. For example, if economic and health outcomes are strongly correlated, rural well-being measures based on cross-sectional health might underestimate aggregate well-being gaps and would only be presenting a part of the bigger story.

Our measure of rural well-being is constructed using the method proposed by Miller and Bairoliya (2023). Specifically, we use a panel vector autoregressive (VAR) model to forecast the joint late-life evolution of consumption, leisure, health, mortality, and wealth (valued as bequests at death). We use longitudinal data from the Health and Retirement Study (HRS) spanning nearly 30 years to estimate the system. We then use the model to simulate and analyze potential outcome paths for a representative sub-sample of HRS respondents across multiple birth cohorts. Using the simulated paths, we construct a welfare metric for each individual at age sixty measured in ex ante consumption equivalents. The metric can be conceptualized as an individual's expected well-being over remaining life at age sixty, measured relative to a set of reference outcome profiles. As the measure is forward looking based on expected remaining lifetime utility, it provides a parsimonious setup for studying both the contemporaneous as well as dynamic effects of expected leisure, health, mortality, consumption, and wealth in driving well-being differences.

Our main findings are summarized as follows:

1. At age sixty, we estimate that rural consumption expenditures average $24,105, with a retirement probability of 53% and a remaining life expectancy of 20.3 years for our oldest cohort (born 1931–36). When adjusting life expectancy to account for poor health, the quality-adjusted life expectancy (QALE) at age sixty drops to 15.4 years.
2. Our consumption-equivalent welfare metric indicates that average rural late-life well-being has improved for more recent birth cohorts, primarily due to increasing life expectancy. However, these gains in life expectancy, and consequently improvements in welfare, have recently stagnated.
3. Counterfactual experiments reveal that hypertension, heart disease, and arthritis are the most significant morbidities affecting average rural late-life well-being.
4. Average late-life well-being among rural residents who report loneliness is 45% of non-lonely rural residents in the oldest cohort with available data (born 1942–47). This substantial difference is mainly due to large disparities in consumption and QALE. The QALE gap between lonely and non-lonely rural residents is also widening over birth cohorts. However, the consumption gap is narrowing, resulting in some decline in the estimated overall well-being gap over time.
5. Average well-being for older rural residents is 69% of older urban residents in our oldest cohort, driven mostly by disparities in consumption and QALE. Moreover, older rural residents are falling further behind their urban counterparts across birth cohorts, with declining relative consumption and wealth playing a more significant role than health. However, the rate at which the rural–urban welfare gap is widening has started to slow down across younger cohorts.
6. Average welfare among older rural residents is lowest in the south central regions of the country, while it is highest on the west coast. The rural–urban divide is most pronounced in the south and east coast and generally diminishes moving west.

Unlike previous studies that often focus on singular health metrics or economic indicators (e.g., Eggebeen and Lichter, 1993; Kivett and Schwenk, 1994; Arcury et al., 2006; Sparks, 2011; Baernholdt et al., 2012; Inder et al., 2012; Singh and Siahpush, 2014; Dahlberg and McKee, 2018; Ferdows et al., 2020; Kosar et al., 2020; Moss et al., 2021; Glauber, 2022; Saha et al., 2022; Cohen et al., 2022), our approach captures the interplay between these factors, allowing for a broader examination of rural well-being dynamics across different life stages. Our longitudinal approach also allows us to more accurately track changes in well-being over birth cohorts and better understand the evolving dynamics of late-life well-being in rural areas.

Our paper builds on the framework developed in Miller and Bairoliya (2023), which provided a novel measure of welfare by incorporating consumption, leisure, health, and mortality into an expected utility framework. While the earlier work focused on the older U.S. population as a whole, it did not differentiate between urban and rural individuals. This omission left important questions about spatial disparities in well-being unexplored. In contrast, this paper explicitly examines rural–urban and regional differences, leveraging the same methodological foundation to uncover key drivers of well-being disparities across geographic regions. By incorporating rurality into the analysis, we highlight the unique opportunities and challenges faced by older rural Americans, including variation in consumption, health, and levels of loneliness. These insights expand the welfare framework's scope and offer a new perspective on the evolving disparities both across rural areas and between rural and urban populations in the U.S.

Our study also makes a significant contribution by identifying key determinants influencing well-being among older rural populations. Through counterfactual experiments, we highlight the substantial impact of hypertension, heart disease, and arthritis on late-life well-being in rural areas. Moreover, our analysis underscores the potential role of loneliness in exacerbating disparities in well-being, with lonely rural residents experiencing significantly lower levels of well-being compared to their non-lonely counterparts. This highlights a critical gap in current research: the understudied yet important role of loneliness in shaping well-being outcomes beyond isolated health metrics for older rural populations.

Finally, our results shed new light on the widening disparities between rural and urban residents in terms of late-life well-being. By analyzing data spanning nearly three decades from the HRS, we uncover significant gaps in consumption, QALE, and overall welfare between older rural and urban populations. These gaps are particularly acute in the south and eastern U.S. Moreover, our findings suggest that these disparities are not only persistent but also widening over time, with declining relative consumption emerging as a primary driver.

This insight underscores the need for targeted policy interventions to promote the many advantages and address the unique challenges faced by rural older populations and mitigate the growing rural–urban divide in well-being outcomes.

The rest of the paper is structured as follows: In Section "Data and methods", we describe our data and empirical methods. Section "Welfare measure" provides a detailed discussion of our rural well-being measure. In Section "Results", we present the results of our analyses. This includes a summary of age sixty initial conditions and mean rural welfare, counterfactual experiments to assess health risk factors, results by social connectedness status, rural–urban and regional comparisons, and sensitivity analyses. We end with concluding remarks in Section "Conclusion".

Data and methods

Data

We leveraged data from the Health and Retirement Study (HRS), an ongoing longitudinal survey focused on individuals aged fifty and older within the U.S., along with their respective spouses. Our data primarily comes from the publicly available RAND HRS Longitudinal File 2020. This dataset includes respondent information on various dimensions, including health, mortality, and economic outcomes, spanning the period from 1992 to 2020.

This HRS survey was initiated in 1992 and has consistently gathered data at biennial intervals. Over time, new birth cohorts have been periodically integrated into the study. Presently, the study includes seven birth cohorts, each characterized by its unique set of birth years: the original HRS cohort (born 1931–1941), the AHEAD cohort (born prior to 1924), the Children of Depression cohort (born between 1924–1930), the War Babies cohort (born 1942–1947), the early Baby Boomers cohort (born 1948–1953), the mid-Baby Boomers cohort (born 1954–1959), and the late-Baby Boomers cohort (born 1960–1965). We further divide the HRS cohort into the early HRS cohort (born 1931–1936) and the late HRS cohort (born 1937–1941) to maintain roughly equivalent birth cohort intervals across our primary sample.

Rural and urban designation

We classify individuals in the HRS based on the 2013 Beale Rural–Urban Continuum Codes. Urban individuals are defined as those residing in metro counties with a population greater than 250,000 (Beale codes 1–2).[1] Rural individuals are defined as residing in non-metro counties or in metro counties with fewer than 250,000 people (Beale codes 3–9). While there is no universal agreement, it is perhaps more common to exclude all metro counties from a definition of rural residency. However, public HRS data groups Beale codes 3–9 together to protect respondent anonymity. Moreover, only about 7% of the HRS sample reside in metro counties with fewer than 250,000 people, so the large majority of rural residents reside in non-metro counties.

Health outcomes

In addition to rural and urban variables, we use data on comorbidities. These include eight binary indicators for individuals who have ever been diagnosed by a doctor with the following health problems: (1) high blood pressure or hypertension; (2) diabetes or high blood sugar; (3) cancer or malignant tumor of any kind except skin cancer; (4) chronic lung disease, excluding asthma, such as chronic bronchitis or emphysema; (5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; (6) stroke or transient ischemic attack (TIA); (7) emotional, nervous, or psychiatric problems; and (8) arthritis or rheumatism. Additionally, we include an indicator for individuals who have ever reported difficulty with any activity of daily living (ADL), such as bathing, getting dressed, or walking across a room. ADL difficulties are a common health metric in older populations.

As a final health measure, we use self-rated health status reported on a five-point scale ranging from poor (one) to excellent (five). Self-rated health has been demonstrated to be predictive of mortality in the HRS and other datasets, even after controlling for other health conditions, health behaviors, and socioeconomic characteristics (Idler and Benyamini, 1997; Stenholm et al., 2014). This may reflect the fact that individuals possess private information about their health beyond diagnosed diseases.

Economic outcomes

We used consumption data from the Consumption and Activities Mail Survey (CAMS), which was given to a random sub-sample of participants in off-years of the core survey of the HRS. Specifically, we used the RAND 2019 CAMS data file, which contains a computed estimate of total household consumption spanning the years 2001 to 2019. This estimate is derived from reported household spending across various categories, including durables, nondurables, transportation, and housing.

We followed the procedure of Miller and Bairoliya (2023) to create our measure of individual consumption. First, we subtracted out-of-pocket health expenditures from total household consumption and then divided this value by the total number of individuals within the household. We then merged each off-cycle CAMS wave with the HRS core data from the preceding year, providing consumption estimates for approximately 20% of HRS respondents from 2000 to 2018. We then leveraged closely related available data such as wealth and income to impute missing consumption data for remaining respondents (see online appendix for further detail on imputation procedure).

It is important to note that we do not make any geographic cost-of-living adjustments for our analysis, including when comparing across rural and urban areas. The conventional wisdom that rural areas are systematically cheaper to live in compared to urban areas has been widely questioned in recent research. Zimmerman et al. (2023) provide compelling evidence that there is no consistent trend of lower prices or a reduced cost of living in rural counties compared to urban ones. Using an item-by-item price comparison across geographic areas, their findings indicate that price differences often depend on the specific good or service, and some rural areas even experience higher prices for certain categories, such as groceries or transportation costs. Moreover, conventional cost-of-living indices like the Consumer Price Index (CPI) do not incorporate rural data, as they rely on urban-centric metrics, making them unsuitable for accurately capturing rural pricing patterns. Consequently, applying these indices to adjust for rural–urban price differences risks extrapolating from urban norms that may not hold in rural contexts.

Further complicating the issue, rural areas often face unique costs, such as higher transportation expenses due to greater travel distances and limited competition in local markets, which can increase the prices of essential goods and services. These factors highlight that rural cost structures are diverse and not easily comparable to urban areas through standardized indices. Given these limitations, and the absence of robust, nationally representative cost-of-living data specific to rural areas, we do not adjust for cost-of-living differences in our analysis. Adjustments based on urban-based metrics could misrepresent the true economic experiences of rural residents and potentially obscure the observed welfare disparities.

In addition to consumption, we also incorporate expected bequest into our analysis, using asset wealth at the time of death as a proxy. Estimates for asset holdings come from the RAND HRS data file and include financial assets, housing, and other durable wealth (e.g., vehicles, jewelry, etc.).

[1] In our forecasting model, we split the urban group into two based on their Beale code to increase precision, but for welfare analysis we present results for all urban residents together (i.e, Beale codes one and two).

Lastly, we examine labor supply as a final economic outcome. As we focus on individuals approaching the end of their working lives, we limit labor-related considerations to retirement. Moreover, retirement is treated as an absorbing state, with retired individuals defined as those reporting less than 500 annual hours of paid work in the most recent survey wave or any previous survey wave.

Loneliness

Loneliness is commonly defined as the perception that one's social needs are not being met by the quantity or quality of their social relationships (Hawkley and Cacioppo, 2010). While related, loneliness is distinct from objective social isolation. The HRS provides a 3- and 11-item loneliness score based on the Revised UCLA Loneliness Scale (Russell, 1996). We use the 11-item score to divide individuals into three loneliness groups—low loneliness (score < 1.5), medium loneliness ($1.5 \le$ score < 2), and high loneliness (score ≥ 2). The scale was collected as part of a leave-behind survey starting in 2008. To preserve sample size, we assign each individual their mean score over all available survey waves.

Forecasting model

Our analysis of the well-being of rural individuals is based on estimating expected lifetime utility. This method necessitates an estimate of all possible life paths for each individual for the outcomes of interest. It is important to note that in longitudinal datasets, we can only observe the actual path taken by an individual, not every conceivable path. Moreover, many HRS respondents are still living and some are lost to sample attrition. To overcome these limitations, we use a dynamic forecasting model that approximates the joint evolutionary process of consumption, health, mortality, and wealth over time using the modeling approach of Miller and Bairoliya (2023). Through this approach, we can make predictions about how these factors change and interact as individuals progress through their lives.

The core features of the forecasting model are depicted in Fig. 1, with full details provided in the online appendix. Morbidities are modeled as absorbing states, as the HRS records whether respondents have ever been diagnosed with each disease. At the beginning of each model time period, an individual's morbidity status is updated based on a vector of random shocks, which may be correlated across morbidities. Subsequently, based on these updated morbidity conditions and an additional random shock, individuals adjust their self-rated health. Both morbidities and self-rated health then influence labor supply, impacting individuals' decisions regarding retirement, and consequently affecting consumption, wealth, and the likelihood of surviving to the next time period.

It is important to note that upstream outcomes can influence downstream outcomes both directly and indirectly. For instance, heart disease may affect an individual's self-rated health status, subsequently reducing their current consumption. However, heart disease may also independently impact consumption, irrespective of changes in self-rated health. Additionally, the model allows for health and labor supply to have general lagged effects. For example, retirement in the current period may directly influence self-rated health in the next period.

In a dynamic context, the forecasting model can be conceptualized as a panel vector autoregression (VAR) of order ρ. Alongside the relationships depicted in Fig. 1, the evolution of all outcomes are allowed to depend on a set of exogenous characteristics. These include age, education, gender, race, urbanicity, census division, census occupation code, birth cohort, a post-2008 indicator to account for the Great Recession, and a linear trend for the calendar year. To estimate parameters in the forecasting model, we utilize data from all respondents over the age of fifty in the HRS. This yields an estimation sample comprising 40,973 unique individuals and a total of 269,299 individual-year observations.

Following the estimation of the forecasting model, we use it to repeatedly simulate outcomes from age sixty onward for individuals in the HRS. These simulations are limited to cohorts with observed data at age sixty to serve as initial conditions. This approach provides us with representative results across five birth cohorts: early HRS (EHRS), late HRS (LHRS), War Babies (WB), early Baby Boomers (EBB), and mid-Baby Boomers (MBB). Further information about the forecasting VAR model, including its identifying assumptions, details on model estimation procedures and results, as well as simulations, can be found in the online appendix.

Welfare measure

The basic strategy for estimating rural well-being is to embed simulations from the forecasting model into a preference function in order to calculate a consumption-equivalent variation measure of welfare. We begin by defining expected remaining lifetime utility for individual i at age j as:

$$U_{ij} = E\left[\sum_{a=j}^{J} \psi_{ia}\beta^{a-j}\phi(h_{ia})[\bar{u} + log(c_{ia}) + v(l_{ia})] + (1-\psi_{ia})\beta^{a-j}\zeta(b_{ia})\right].$$

In this equation, c is consumption (measured in thousands of 2010 dollars), l leisure, h health, b bequests, and ψ is a survival indicator. We assume log utility over consumption and additive separability with leisure, which allows for a straightforward decomposition of the results. We also present additional analyses where we relax these assumptions.

The health measure h is a vector that includes self-rated health and indicators for each available morbidity. The function $\phi(.)$ maps this vector into a utility score between zero and one. Specifically, $\phi(h) = 1$ indicates the utility for a person in the best possible health state, while $\phi(h) = 0$ represents the utility for a deceased individual. This approach relates directly to the widely used notion of quality-adjusted life years (QALYs). For example, a year of life in the best health state represents a single QALY. However, all else equal, two years of life with $\phi(h) = 0.5$ is equivalent in utility to one year in the best health state, or a single QALY.

Using a consumption-equivalent variation measure, the welfare for individual i at age j satisfies the following condition:

$$U_{ij} = E\left[\sum_{a=j}^{J} \psi_{ma}\beta^{a-j}\phi(h_{ma})[\bar{u} + log(\lambda_{ij}) + v(l_{ma})] + (1-\psi_{ma})\beta^{a-j}\zeta(b_{ma})\right].$$

In this equation, ψ_m, h_m, l_m, and b_m are fixed reference profiles for survival, health, leisure, and bequests. The welfare measure λ_{ij} is defined as the fixed annual consumption that, when combined with the reference health, leisure, survival, and bequest profiles, yields the same expected lifetime utility as the individual's outcome profiles. For example, if $\lambda_{ij} = 30$, it means that the individual would be indifferent between continuing with their own stochastic outcome profiles or receiving an annual consumption of \$30,000, along with the reference profiles for health, leisure, bequests, and survival.

Solving the welfare condition for $log\left(\lambda_{ij}\right)$ yields the following additive decomposition for each outcome:

$$log\left(\lambda_{ij}\right) = \tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left[E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]E_{\psi}\left[log\left(c_{ia}\right)\right] + \Phi\right] \quad (1)$$

$$+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]\left(E_{\psi}\left[v\left(l_{ia}\right)\right] - E_{\psi}\left[v\left(l_{ma}\right)\right]\right) \quad (2)$$

$$+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left(E\left[\psi_{ia}\right] - E\left[\psi_{ma}\right]\right)E_{\psi}\left[\phi\left(h_{ma}\right)\right]E_{\psi}\left[u_{ia}\right] \quad (3)$$

$$+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}\left(E_{\psi}\left[\phi\left(h_{ia}\right)\right] - E_{\psi}\left[\phi\left(h_{ma}\right)\right]\right)E\left[\psi_{ia}\right]E_{\psi}\left[u_{ia}\right] \quad (4)$$

$$+\tilde{\psi}\sum_{a=j}^{J}\beta^{a-j}E\left[(1-\psi_{ia})\zeta(b_{ia}) - (1-\psi_{ma})\zeta(b_{ma})\right]. \quad (5)$$

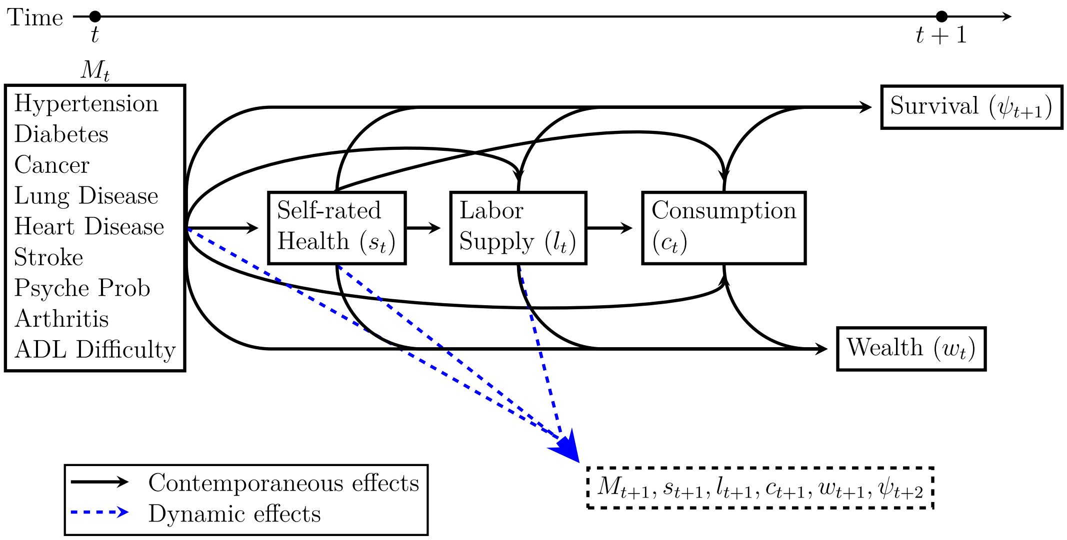


Fig. 1. Simulation model with one period lag.

Here, Φ is defined as follows:

$$\Phi = \left(E\left[\psi_{ia}\phi\left(h_{ia}\right)u_{ia}\right] - E\left[\psi_{ia}\phi\left(h_{ia}\right)\right]E_{\psi}\left[u_{ia}\right]\right) \\ - \left(E\left[\psi_{ma}\phi\left(h_{ma}\right)v\left(l_{ma}\right)\right] - E\left[\psi_{ma}\phi\left(h_{ma}\right)\right]E_{\psi}\left[v\left(l_{ma}\right)\right]\right).$$

Additionally, $\tilde{\psi}$ represents the reciprocal of the reference discounted quality-adjusted life expectancy, and E_{ψ} denotes expected values conditional on survival.

In Eq. (1), the first term represents the expected lifetime utility derived from consumption, weighted by the reference quality-adjusted life expectancy. The Φ term acts as an adjustment for uncertainty throughout the life cycle. Together, these terms yield an individual's consumption-equivalent welfare before accounting for adjustments related to expected leisure, survival, health, or bequests.

Adding Eq. (2) provides a welfare adjustment for leisure. It captures the difference between the individual's expected leisure utility and the reference leisure utility. Eq. (3) further adjusts welfare for the difference in life expectancy. This difference is weighted by the expected flow utility of the individual, reflecting the utility value of each additional year of life. Similarly, (4) adjusts for expected health differences between the individual and the reference over the remaining lifespan. Lastly, the term in Eq. (5) adjusts welfare for differences in expected bequests.

Calibration

In order to conduct an analysis using the welfare measure, it is necessary to calibrate preference parameters. This includes choosing functional forms for $\phi(.)$, $v(.)$, and $\zeta(.)$ as well as values for the discount factor β and the flow utility intercept $\bar{u}$. The benchmark preference parameters chosen for calibration are detailed in this section and are summarized in Table 1.

We begin by assuming that health utility is a linear function of our health state vector: $\phi(h_t) = \gamma h_t$, where γ is a vector of health utility weights. These weights are determined based on the Health Utilities Index Mark 3 (HUI3) instrument. This instrument was collected from approximately 1200 respondents in the HRS in the year 2000. The HUI3 was developed to produce cardinal utility scores on the standard utility scale, ranging from zero (representing death) to one (indicating the best health state). It has been extensively utilized in the literature on health utilities (e.g., Furlong et al., 1998; Feeny et al., 2002; Horsman et al., 2003).

Consistent with the conceptual development of the instrument, we assume $HUI3_i = \gamma h_i$. The utility weights γ can then be estimated by simply regressing the available HUI3 utility scores on self-rated health and all morbidity indicators. Implicitly, this approach assumes HUI3 respondents were comparing across hypothetical health states while holding consumption and leisure constant. This is consistent with the HUI3 interview script, which reads: *"when imagining yourself in these health states please remember that where you live, your income, your friends, and family would be the same as now"*. Nonetheless, we also check robustness of results when relaxing the assumption that respondents were holding consumption and leisure fixed.

The benchmark health utility weights are presented in Table 1, with additional details available in the online appendix. These weights indicate that self-rated health is a strong predictor of health utility. For instance, improving from poor health (the base category) to excellent health results in a 42-percentage point (pp) increase in health utility. Conditions like hypertension, diabetes, and cancer exhibit minimal independent effects on health utility once adjusted for their correlation with self-rated health and other comorbidities. Conversely, other conditions such as stroke and arthritis have more pronounced independent negative impacts.

Leisure preferences are given by $v(l) = -\frac{\theta_\epsilon}{1+\epsilon}(1-l)^{\frac{1+\epsilon}{\epsilon}}$, where $l = 1$ for retired individuals and ϵ is the constant Frisch elasticity of labor supply. In line with Jones and Klenow (2016), we use a benchmark value of $\epsilon = 1$. We follow Miller and Bairoliya (2023) and set the disutility weight ϕ such that the marginal cost of leisure equals the marginal benefit for the median individual in our sample, providing us with a benchmark value of $\theta = 9.1$. For individuals that are not retired, we set $l = 0.66$, based on an assumed annual time endowment of 5840 h (16 h a day × 365 days in a year) and 2000 h of work.[2]

Preferences over bequests are taken from De Nardi (2004): $\zeta(b) = \Phi_1\left(1+\frac{b}{\Phi_2}\right)^{1-\sigma}$. In this specification, Φ_1 reflects the strength of the bequest motive and Φ_2 measures the extent to which bequests are a luxury good. We follow De Nardi (2004) and set $\Phi_1 = -9.5$, $\Phi_2 = 11.6$, and $\sigma = 1.5$ for our benchmark calibration.

Based on our benchmark preferences, a retired individual will have positive utility in the current period of life if the sum of the flow utility intercept $\bar{u}$ and the log of consumption is positive. We set the benchmark $\bar{u} = log(2)$, indicating that \$2000 of consumption is

[2] Extending the model to incorporate the intensive margin of labor supply is feasible. However, given that retirement is likely the primary labor supply change within this age group, and considering that leisure through retirement has a relatively minor impact on our welfare estimates, it is unlikely that the intensive margin would fundamentally alter our results.

Table 1
Calibrated benchmark parameter values.

Functional Form	Parameter Description	Value	Source/Target
$\phi(h_t) = \gamma h_t$	Self-rated health		
	Fair	$\gamma_1 = 0.226$	HUI3
	Good	$\gamma_2 = 0.312$	HUI3
	Very good	$\gamma_3 = 0.402$	HUI3
	Excellent	$\gamma_4 = 0.420$	HUI3
	Hypertension	$\gamma_5 = 0.005$	HUI3
	Diabetes	$\gamma_6 = -0.002$	HUI3
	Cancer	$\gamma_7 = 0.010$	HUI3
	Lung disease	$\gamma_8 = -0.026$	HUI3
	Heart disease	$\gamma_9 = -0.030$	HUI3
	Stroke	$\gamma_{10} = -0.076$	HUI3
	Psych problem	$\gamma_{11} = -0.070$	HUI3
	Arthritis	$\gamma_{12} = -0.062$	HUI3
	Diff with ADL	$\gamma_{13} = -0.162$	HUI3
	Constant	$\gamma_{14} = 0.517$	HUI3
$v(l) = -\frac{\theta_t}{1+\epsilon}(1-l)^{\frac{1+\epsilon}{\epsilon}}$	Frisch elasticity of labor supply	$\epsilon = 1$	Jones and Klenow (2016)
	Disutility weight	$\theta = 9.1$	Miller and Bairoliya (2023)
$\zeta(b) = \Phi_1\left(1 + \frac{b}{\Phi_2}\right)^{1-\sigma}$	Strength of the bequest motive	$\Phi_1 = -9.5$	De Nardi (2004)
	Extent to which bequests are a luxury good	$\Phi_2 = 11.6$	De Nardi (2004)
	Risk aversion	$\sigma = 1.5$	De Nardi (2004)
	Discounting factor	$\beta = 0.98$	1% annual discounting
	Flow utility intercept	$\bar{u} = log(2)$	10% annual consumption

necessary for a retiree to maintain positive flow utility. This amounts to approximately 10% of the mean annual consumption in our sample, a parameterization of the flow intercept that has been considered reasonable (Murphy and Topel, 2006). This calibration also results in an estimated median value of remaining life for sixty-year-olds at about $60,000 per QALY in our sample, a figure well within the range reported in the literature (Ryen and Svensson, 2015; Kaplan and Bush, 1982).

Finally, we choose a discount factor $\beta = 0.98$. Given that model periods correspond to two years in alignment with the HRS data, this equates to an annual discount rate of one percent (with additional implicit discounting due to mortality risk).

Reference outcomes

In addition to calibrating preference parameters, we must also select reference profiles for our welfare calculations. These reference profiles include survival (ψ_{ma}), health (h_{ma}), leisure (l_{ma}), and bequests (b_{ma}). These reference profiles will be applied to every individual within each cohort. This allows for direct comparison of welfare across cohorts, as the reference is held fixed.

Our benchmark reference profiles are summarized in Table 2. Reference age sixty survival is set to 24 years, implying a total reference lifespan of 84 years. This is approximately the average estimated life expectancy in our sample. We use a constant reference health level of $\phi(h_{ma}) = 0.8$. This choice conforms to the standard approach for calculating health-adjusted welfare equivalents. It is grounded in the idea of using "normal" or "good" health as the reference, a concept well-supported in previous literature (e.g., Fleurbaey, 2005, 2009; Fleurbaey and Gaulier, 2009; Fleurbaey et al., 2013; Schokkaert et al., 2013; Samson et al., 2018). The underlying logic is that when two individuals are in good health, we can compare them based only on consumption differences. In a similar spirit, we set reference leisure $l_{ma} = 1$ (i.e., retired) from age sixty onward. Finally, for bequest b_{ma}, we choose a reference value of $500,000.

Table 2
Reference profiles for welfare measure.

Reference Profile	Value
Survival: ψ_{ma}	*24 years*
Health: $\phi(h_{ma})$	0.8
Leisure: l_{ma}	*Retired at* 60
Bequest: b_{ma}	$500,000

Results

This section presents our empirical results in segments. We begin by summarizing the initial conditions (at age sixty) of respondents in both rural and urban areas within our simulation sample. Subsequently, we present the mean rural outcomes and welfare estimates across all available cohorts in the HRS. We further explore the implications of removing late-life morbidities at age sixty on these results. Our analysis expands to examine the gaps in rural outcomes and welfare by loneliness status. Moreover, we compare outcomes and welfare between rural and urban settings. Lastly, we explore regional variations in outcomes and welfare across the U.S.

Descriptive statistics

Table 3 presents a summary of initial conditions at age sixty in the simulation sample, categorized by respondents in rural and urban areas. Cross-sectional consumption at age sixty averaged $22,770 for rural respondents, in contrast to $29,000 for urban respondents, representing a 1.3-fold difference. In most regards, health outcomes also demonstrated a significant geographical gradient, with cancer being the clear exception. For instance, 9.5% of rural respondents reported lung disease, but only 6.7% of urban respondents. In line with these patterns, 7.5% of rural respondents reported poor health, as opposed to just 5.4% of urban respondents. Perhaps related, 55% of rural residents were already retired at age sixty, compared to only 50% of urban residents. Furthermore, about 21% of rural respondents had less than a high school education and 88% were white, while only 17% and 82% of urban respondents fell into these respective categories. Regarding cohort distribution in our simulation sample, younger cohorts were somewhat more urban than older cohorts. Loneliness also exhibited significant disparities, with 17.7% of rural respondents reported as having high loneliness compared to 14.7% of urban respondents, suggesting a potential influence of geographical location on social connectedness.

Simulation fit

Fig. 2 compares mean simulated consumption and health utility levels to those observed in the HRS data, broken down by age and

Table 3
Simulation sample age sixty descriptive statistics.
Source: HRS.

	Rural	Urban
Individuals (N)	4002	11,707
Individuals (%)	26.45	73.55
Hypertension (%)	49.01	45.21
Diabetes (%)	17.33	17.49
Cancer (%)	9.17	9.24
Lung disease (%)	9.51	6.66
Heart disease (%)	17.49	14.58
Stroke (%)	4.88	4.05
Psyche problem (%)	20.49	17.01
Arthritis (%)	53.90	47.03
Difficulty with ADLs (%)	23.74	19.22
Self-rated health (%)		
Poor	7.50	5.38
Fair	18.41	16.18
Good	32.51	29.83
Very good	30.94	34.08
Excellent	10.63	14.52
Retired (%)	55.13	50.54
Annual consumption ($1000s, mean)	22.77	29.00
Male (%)	47.05	47.39
Education (%)		
<HS	21.23	16.71
HS	32.92	24.64
Some college	24.81	26.75
College	21.04	31.90
Race (%)		
White	88.74	81.71
Black	6.54	11.53
Other	4.72	6.76
Cohort (%)		
EHRS	10.73	10.46
LHRS	14.13	13.04
WB	24.52	20.66
EBB	23.58	24.69
MBB	27.04	31.15
Loneliness (%)		
Low	47.68	53.67
Medium	34.64	31.62
High	17.69	14.71

Notes: Estimates using base year respondent analysis weights except for N. Consumption is reported in real 2010 dollars.

urbanicity. Recall that for the forecasting model, we distinguished between urban and suburban areas to increase precision. Here, we focus exclusively on the EHRS cohort, as it is the oldest cohort and has the longest available panel of data. Results for other cohorts and outcomes are similar and are provided in the online appendix.

The simulations align closely with the aggregated data, indicating that the forecasting model provides a reasonable approximation of the underlying data-generating processes. By design, the data and simulations coincide at age sixty. Importantly, this strong alignment persists up to 26 years later, as the EHRS cohort reaches age 86.

Rural welfare

Table 4 provides an overview of the mean rural outcomes and welfare for sixty-year-olds by their respective cohorts. Panel A presents the mean consumption, retirement, life expectancy, quality-adjusted life expectancy (QALE), and expected financial bequests at age sixty. Panel B shows the cumulative contribution of each of these outcomes to our aggregate welfare measure (i.e., the cumulative addition of terms (1)–(5) in our previously detailed additive decomposition of welfare).

The estimates from Panel A highlight several noticeable trends across cohorts. Looking at the first row of Panel A, we see that average annual consumption for the EHRS cohort at age sixty is $24,105, while for the Mid Baby Boomers, it is $21,061. This indicates a declining trend in consumption expenditure across cohorts. While there is variation in the probability of early retirement, with 58% of War Babies retired at age sixty compared to 53% in the EHRS cohort, there is not a clear trend discernible across cohorts. Contrary to consumption expenditure and retirement likelihood, life expectancy and QALE show a consistent increase across the first four cohorts. The EHRS cohort has a life expectancy of 20.3 years compared to 23.8 years in the EBB cohort. However, when adjusting life expectancy to account for the utility cost of living in less than perfect health, QALE at age sixty drops significantly to just 15.4 years for the EHRS cohort and 17.5 years in the EBB cohort. This suggests that while sixty-year-olds in the EHRS cohort can expect to live for more than two decades, their expected health utility is equivalent to only 15.4 years in perfect health. While health generally shows an improving trend across the first four cohorts, there are small declines in life expectancy and QALE between the youngest two cohorts, suggesting a recent stagnation in rural late-life health gains. Finally, the last row of Panel A shows that average financial bequests (i.e., expected wealth at the time of death) increased substantially across all cohorts. The EHRS cohort is estimated to leave behind an average of $328,499, whereas the Mid Baby Boomers are projected to leave behind $421,239.

Table 4
Mean rural outcomes and welfare by cohort.

	EHRS	LHRS	WB	EBB	MBB
Panel A: Outcomes					
Consumption	24.105	23.886	23.685	23.099	21.061
Retired	0.529	0.567	0.577	0.532	0.541
Life expectancy	20.334	21.263	22.123	23.803	23.572
QALE	15.448	15.978	16.250	17.537	17.159
Bequests	328.499	354.211	360.703	400.028	421.239
Panel B: Welfare					
Consumption	19.102	19.057	18.679	19.029	17.680
Leisure	17.627	17.620	17.266	17.464	16.090
Life expectancy	16.790	18.320	19.694	22.442	20.703
Health	14.460	15.846	16.624	18.786	17.451
Bequests	12.696	14.177	15.245	17.326	16.128

Notes: Estimates use base year respondent analysis weights. Consumption and welfare reported in $1000s. Life expectancy and QALE reported in years. Retired is an indicator. Panel B presents cumulatively adjusted welfare estimates.

The first row of Panel B presents our consumption-equivalent welfare metric without adjustments for leisure, life expectancy, health, or bequests. It simply reflects average expected annual consumption after age sixty.[3] The general trend of modesty falling consumption over cohorts observed in age sixty cross-sectional consumption is still present. Adjusting estimates to reflect lost leisure due to working past age sixty results in fairly uniform declines in welfare for all cohorts. For example, adjusting welfare for later retirement lowers average welfare by $1475 ($\$19,102 - \$17,627$) in the EHRS cohort. This implies that rural respondents in this cohort would be willing to give up an average of $1475 in expected annual consumption to retire at age sixty.

Continuing with the EHRS example, adjusting for life expectancy leads to an additional $837 decrease in the average welfare for this cohort. This implies that individuals would sacrifice an average of $837 in expected annual consumption to obtain the reference life expectancy. Similarly, accounting for the costs associated with living in poor health lowers the average EHRS welfare by $2330, suggesting a substantial average utility cost of morbidities. The last row in Panel B shows the adjustments for expected financial bequests, yielding our fully-adjusted welfare measure. Adjusting for bequests reduces the average EHRS welfare by an additional $1764. When examining welfare across cohorts, it becomes evident that life expectancy, health, and to a lesser extent, bequests, are the primary drivers of increasing welfare over time. However, we again note that the gains in life expectancy and health, and consequently, the improvements in welfare, have recently stagnated.

[3] Term (1) simplifies to expected annual consumption plus $\tilde{\psi}\Phi$ when reference health and life expectancy are known constants.

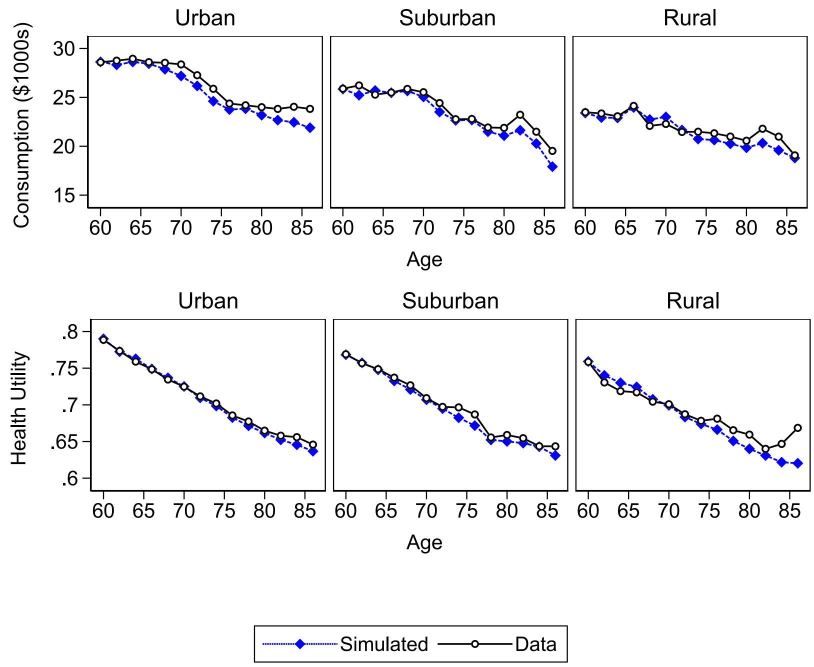


Fig. 2. Mean of life-cycle consumption and health utility profiles by location.

Role of morbidities

This section seeks to investigate how health risk factors influence the outcomes and well-being of rural residents in our sample. Morbidities, or illnesses, play a crucial role in overall well-being, both directly and indirectly. Previous research consistently shows significantly higher rates of cardiovascular mortality and diabetes in rural areas compared to urban areas (Aggarwal et al., 2021). These studies also identify well-known risk factors like hypertension and diabetes as contributors to various subsequent health complications such as stroke, ischemic heart disease, renal dysfunction, kidney failure, and other medical issues (Lewington et al., 2003; Rapsomaniki et al., 2014; Huang et al., 2014; Kokubo and Iwashima, 2015; Raghavan et al., 2019).

Given the high incidence of diabetes as a known risk factor, we utilize it as an illustrative example to better understand how morbidities influence the dynamics of other outcomes in the system. Specifically, we re-simulate our estimates for the EHRS cohort, exogenously removing the incidence of diabetes after age sixty. Fig. 3 illustrates the average percentage change in various expected outcomes resulting from this experiment. The elimination of diabetes after age sixty leads to a reduction in the average probability of hypertension, stroke, psychiatric problems, arthritis, ADLs, and poor health among rural EHRS cohort members. For instance, by age eighty, individuals experience an average decrease in the probability of stroke by about 1.8%. Similarly, the probability of ADLs by age eighty decreases by approximately 1.4%, and there is a notable decrease of around 17% in the probability of poor health. Despite observing slight increases in annual consumption following the elimination of diabetes after age sixty, these gains are relatively minor, rising by only 0.7%.

Similar to the previous experiment with diabetes, Table 5 shows the mean change in selected outcomes resulting from the elimination of each late-life morbidity within the EHRS sample after the age of sixty. Specifically, we examine the impact on age sixty QALE, expected lifetime consumption (ELC), expected bequests, and fully-adjusted welfare.

Hypertension and heart disease are prevalent in rural areas and are significant contributors to mortality. Therefore, eliminating these health risk factors at age sixty leads to greater increases in QALE and ELC compared to most other morbidities. Moreover, the increased life expectancy also leads to a more substantial reduction in bequests, as

Table 5
Mean change in outcomes from eliminating late-life morbidities at age sixty.

	QALE	ELC	Bequest	Welfare
Hypertension	1.177	24.697	−7.864	1.753
Diabetes	0.652	14.330	−2.987	0.846
Cancer	0.706	17.771	−10.168	1.147
Lung disease	0.887	20.402	−4.359	1.035
Heart disease	1.334	26.360	−6.235	2.054
Stroke	0.508	11.610	0.207	0.818
Psyche problem	0.635	9.259	1.127	0.846
Arthritis	1.510	0.380	7.718	2.651

Notes: Estimates use base year respondent analysis weights. Expected lifetime consumption (ELC), bequests, and welfare reported in $1000s. QALE reported in years.

rural residents may end up using more of their wealth during their extended lifespan.

While cancer is crucial for mortality, its prevalence in the population is much lower than most other morbidities. Consequently, the average gains in QALE and ELC are smaller when cancer is eliminated. Conversely, arthritis presents the most significant QALE and welfare gains due to its high prevalence and substantial direct utility cost. Although arthritis does not significantly impact mortality, it greatly affects quality of life. Hence, there is not much improvement in ELC, but eliminating arthritis at age sixty leads to considerable average welfare gains, especially given that approximately half of the rural population already experiences it by this age, with more likely to develop it over time.

In summary, our counterfactual experiments suggest that hypertension, heart disease, and arthritis are the morbidities with the most substantial impact on the average well-being of rural individuals in late life.

Loneliness

Previous studies consistently find that feelings of belonging and social connection are related to life satisfaction in older adults (Hawton et al., 2011; Mellor et al., 2008; Nicholson, 2012; Victor et al., 2000; Xia and Li, 2018). Therefore, this section aims to offer further insights on welfare gaps among rural residents based on social connectedness. As

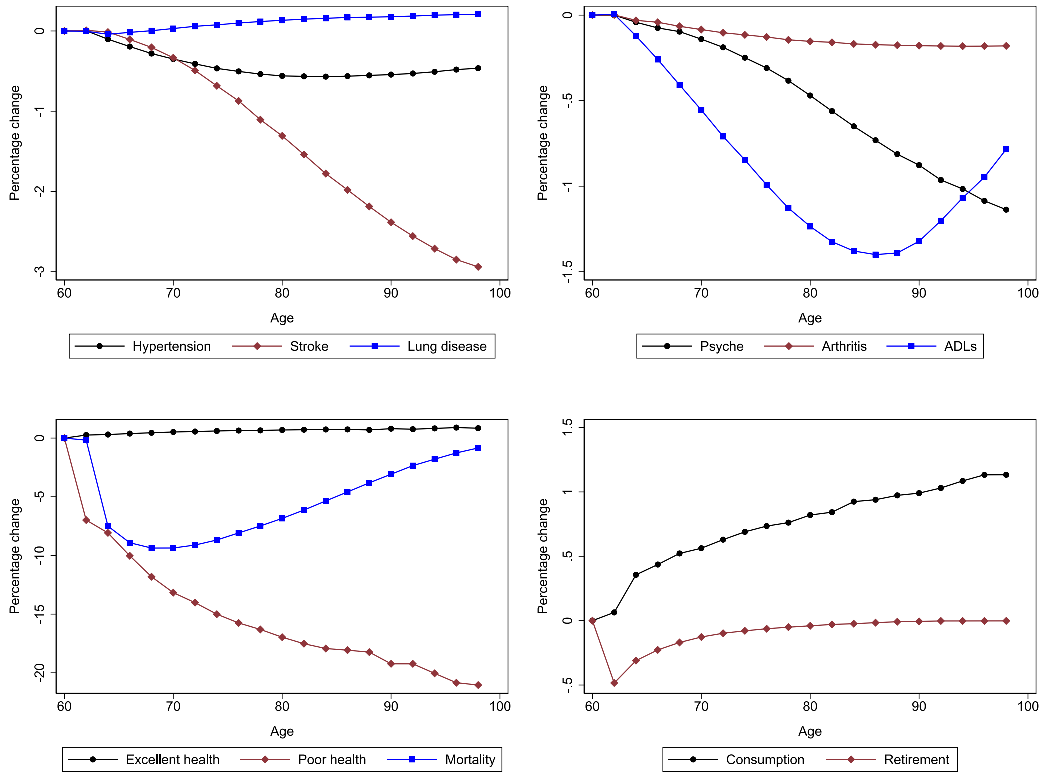


Fig. 3. Impulse response to elimination of diabetes after age 60.

Table 6
Outcomes and welfare in rural War Babies cohort by loneliness score.

	Low	Medium	High	Medium/Low	High/Low
Panel A: Outcomes					
Consumption	26.929	22.970	18.987	0.853	0.705
Retired	0.531	0.623	0.594	1.173	1.118
Life expectancy	23.895	21.644	20.204	0.906	0.846
QALE	18.274	15.704	13.897	0.859	0.760
Bequests	460.762	324.629	222.149	0.705	0.482
Panel B: Welfare					
Consumption	21.124	18.174	15.711	0.860	0.744
Leisure	19.368	16.875	14.849	0.871	0.767
Life expectancy	24.388	18.308	14.213	0.751	0.583
Health	21.339	15.282	10.771	0.716	0.505
Bequests	20.055	13.820	9.203	0.689	0.459

Notes: Estimates use base year respondent analysis weights. Consumption and welfare reported in $1000s. Life expectancy and QALE reported in years. Retired is an indicator. Panel B presents cumulatively adjusted welfare estimates.

loneliness data was not collected until 2008 in the HRS, we are missing scores for many respondents in our oldest two cohorts. Therefore, we limit this analysis to the younger three cohorts, where loneliness scores are available for about 90% of respondents. Table 6 begins with providing mean outcomes and cumulative welfare by loneliness status for War Babies, which is the oldest of the younger three cohorts. Additionally, outcome and welfare ratios across low/medium/high loneliness groups are provided in the final two columns for ease of exposition.

The first row of Panel A shows that among rural War Babies, individuals reporting high levels of loneliness have a mean annual consumption at age sixty that is approximately 71% (high-low ratio of 0.71) of those reporting no loneliness. Additionally, individuals experiencing loneliness are around 6 pp more likely to be retired at age sixty. Our simulations estimate that non-lonely rural residents have an average life expectancy of 23.9 years at age sixty. Conversely, respondents with a high level of loneliness have an estimated life expectancy of only 20.2 years—a stark difference of 3.7 years. Moreover, they are expected to spend those years in poorer overall health. This is evident in the comparison of QALE, which is 18.3 years for the non-lonely individuals and only 13.9 years for their counterparts. Finally, the expected financial bequests of those with a high level of loneliness is approximately half that of non-lonely rural residents.

Moving to Panel B in Table 6, the first row shows that the average expected annual consumption after age sixty among rural residents experiencing a high level of loneliness is about 74% of that of the non-lonely, consistent with the 71% gap observed in cross-sectional consumption at age sixty. Adjusting for lost leisure due to later retirement lowers average welfare by $862 for those experiencing a high level of loneliness. In contrast, the willingness to pay for earlier retirement for those with a low loneliness score is $1756. Adjusting the estimate for leisure differences associated with retirement timing increases the welfare ratio by about 2 pp. So while adjusting for earlier retirement lowers the overall welfare gap, the reduction is quantitatively small.

On the other hand, there is a substantial 18 pp reduction in the high-low welfare ratio when adjusting for life expectancy. Further adjustments for the welfare cost of living in poor health decrease the welfare ratio by an additional 8 pp. Lastly, the final row of Panel B provides adjustments for expected financial bequests, lowering the high-low welfare ratio by an additional 5 pp. These changes yield our fully-adjusted welfare ratio of 0.46, suggesting well-being among lonely rural residents is only 46% that of non-lonely rural residents. In terms of levels, our fully-adjusted welfare measure implies that rural residents experiencing a high level of loneliness would be willing to give up to $6508 ($\$15,711 - \$9203$) or about 41% of expected annual consumption to obtain reference profiles for health, leisure, bequests, and survival. In comparison, the analogous estimate for the non-lonely individuals is only $1069, or 5% of annual consumption.

Our examination of welfare disparities related to loneliness has so far focused on the rural War Babies cohort. Notably, the overall reported level of loneliness among rural residents has somewhat increased across cohorts. Specifically, the proportion of respondents

Table 7
Rural high-low loneliness ratios by cohort.

	WB	EBB	MBB
Welfare (λ)	0.459	0.503	0.595
Life expectancy	0.846	0.829	0.834
QALE	0.760	0.740	0.722
ELC	0.658	0.706	0.743

Notes: Estimates using base year respondent analysis weights.

Table 8
Outcomes and welfare in EHRS cohort by rural/urban.

	Rural	Urban	Ratio
Panel A: Outcomes			
Consumption	24.105	29.627	0.814
Retired	0.529	0.505	1.049
Life expectancy	20.334	21.724	0.936
QALE	15.448	16.887	0.915
Bequests	328.499	402.426	0.816
Panel B: Welfare			
Consumption	19.102	23.192	0.824
Leisure	17.627	21.353	0.825
Life expectancy	16.790	22.668	0.741
Health	14.460	20.052	0.721
Bequests	12.696	18.353	0.692

Notes: Estimates use base year respondent analysis weights. Consumption and welfare reported in $1000s. Life expectancy and QALE reported in years. Retired is an indicator. Panel B presents cumulatively adjusted welfare estimates.

Table 9
Rural–urban ratios by cohort.

	EHRS	LHRS	WB	EBB	MBB
Welfare (λ)	0.692	0.643	0.614	0.613	0.608
Life expectancy	0.936	0.953	0.935	0.952	0.944
QALE	0.919	0.934	0.909	0.928	0.914
ELC	0.785	0.744	0.735	0.764	0.748
Bequests	0.816	0.767	0.710	0.697	0.640

Notes: Estimates using base year respondent analysis weights.

reporting high levels of loneliness increased from 14.1% among War Babies to 16.5% among Early Baby Boomers, and further to 17.4% among Mid Baby Boomers. Table 7 presents high-low welfare ratios for each available birth cohort, enabling an exploration of the evolving dynamics of welfare disparities over time.

The first row of Table 7 reveals that the high-low welfare ratio has increased over the three cohorts, indicating a narrowing of welfare gaps. Particularly, welfare for individuals experiencing a high level of loneliness increased from 46% of that of the non-lonely among War Babies to approximately 60% among Mid Baby Boomers. However, as demonstrated in the subsequent two rows, this improvement did not arise from relative gains in health or life expectancy, as the gaps actually slightly increased across cohorts. In contrast, the final row indicates that the reduction in the welfare gap mainly stems from improvements in relative consumption for individuals experiencing a high level of loneliness. Of course, given the small increase in the share of lonely individuals, part of this improvement may reflect selection biases.

The rural–urban divide

Previous research has extensively documented significant disparities across various social and economic domains between rural and urban populations. Urban residents generally experience better economic and health outcomes compared to their rural counterparts, including differences in consumption patterns, leisure activities, health outcomes, and mortality rates (Glasgow and Brown, 2012; Jones et al., 2009; Spencer et al., 2018; Schwenk, 1994; Costa, 1998). We do not adjust for any cost of living differences across urbanicity, as Zimmerman et al. (2023) show that there is no consistent trend of lower prices nor reduced cost of living across rural counties, and the cost of living does not systematically differ between rural and urban areas. Table 8 provides our main results for urban residents in the oldest cohort. The first column also restates results for rural residents for easy comparison, while the final column provides the rural–urban ratio.

It is evident that an urban premium exists across most outcomes. For example, the average life expectancy of rural residents at age sixty is less than 94% that of their urban counterparts. Relative consumption is about 81%. The exception is retirement, where rural residents are 5% more likely to be retired at age sixty. To gain a deeper understanding of how gaps in outcomes persist over time across rural and urban residents, Fig. 4 plots the average life-cycle profiles for consumption, retirement, health utility, and life expectancy. Consistent with Table 8, differences in consumption, health, and life expectancy between rural and urban residents are evident by age sixty and tend to persist throughout the life span.

Panel B of Table 8 shows that the associated rural–urban gaps in consumption-equivalent welfare are substantial. For example, adjusting welfare for average differences in life expectancy and health decreases the estimated rural–urban welfare ratio by 8 pp and 2 pp, respectively. Adjusting for bequests lowers the ratio an additional 3 pp. Our fully-adjusted measure suggests that average well-being for older rural residents is only 69% of that for older urban residents in the EHRS cohort, primarily driven by disparities in consumption and QALE.

Our use of microsimulations from a life-cycle dynamics model also allows us to construct a measure at the individual level within a larger representative sample. This allows us to examine the entire distribution of welfare, rather than solely focusing on averages. Fig. 5 plots the distribution of log welfare and selected outcomes. The leftward shift in distribution across all outcomes clearly reflects the poorer overall outcomes in rural areas. Notably, there is a pronounced left tail bump in life expectancy and QALE for rural residents, but not for urban ones. This suggests that a larger portion of rural individuals, compared to their urban counterparts, enter late life in very poor health.

Finally, Table 9 displays rural–urban ratios for average welfare and selected outcomes across birth cohorts. The rural–urban welfare gap has widened over time, especially across the first three cohorts, with some stabilization thereafter. Specifically, rural welfare decreased from 69% of urban welfare in the EHRS cohort to only 60% among Mid Baby Boomers. Disparities in life expectancy and QALE have remained relatively consistent, with the increasing gap observed in the first three cohorts primarily attributable to rising gaps in consumption and wealth.

Regional variation

While much of the literature has focused on the rural–urban divide, it is equally important to recognize the geographically diverse nature of the U.S. and understand the regional variations in late-life well-being across the country. Indeed, the distributions plotted in Fig. 5 underscore the substantial variation in welfare and outcomes *within* rural America. Fig. 6 illustrates these regional disparities by presenting age sixty consumption, QALE, welfare, and rural–urban ratios. To maintain an adequate sample size, we aggregate data across all cohorts and present results by nine census divisions.

Panel (a) of Fig. 6 shows that age sixty consumption was generally lower in the southern regions and higher in New England and along the Pacific Coast. Average age sixty consumption ranged from $29,069 in the Pacific division (California, Oregon, and Washington) to $18,754 in the West South Central division (Texas, Oklahoma, Arkansas, and Louisiana), a difference of about 55%. Notably, we do not adjust for cost-of-living differences across census divisions, which could influence the welfare implications of these consumption disparities. Data from the U.S. Bureau of Economic Analysis (BEA) (2023) indicates significant

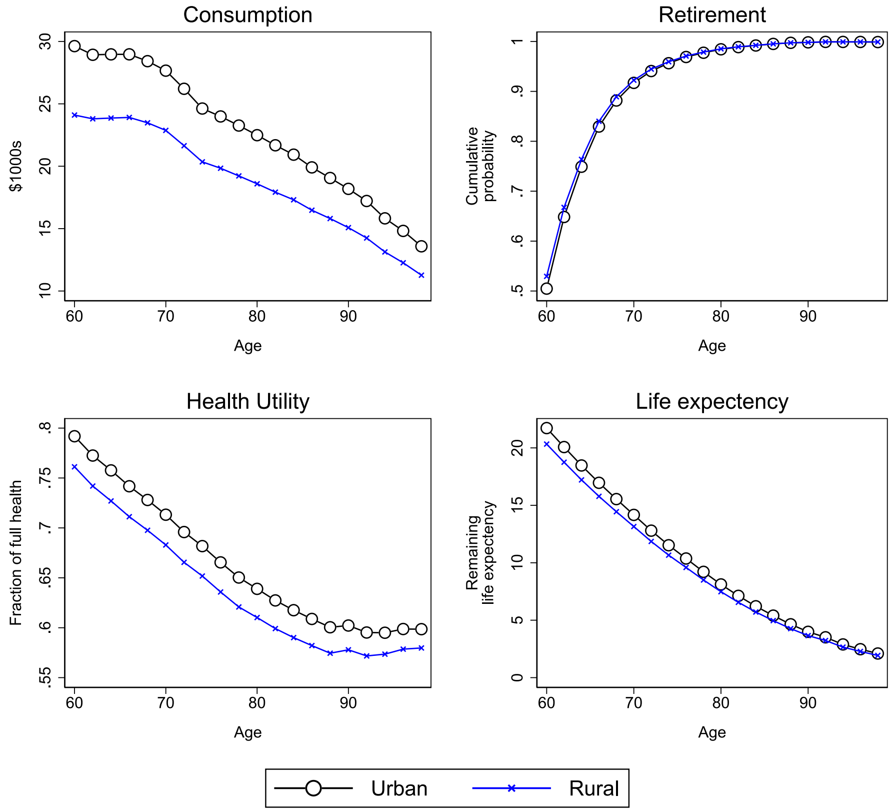


Fig. 4. Average life cycle profiles by rural/urban.

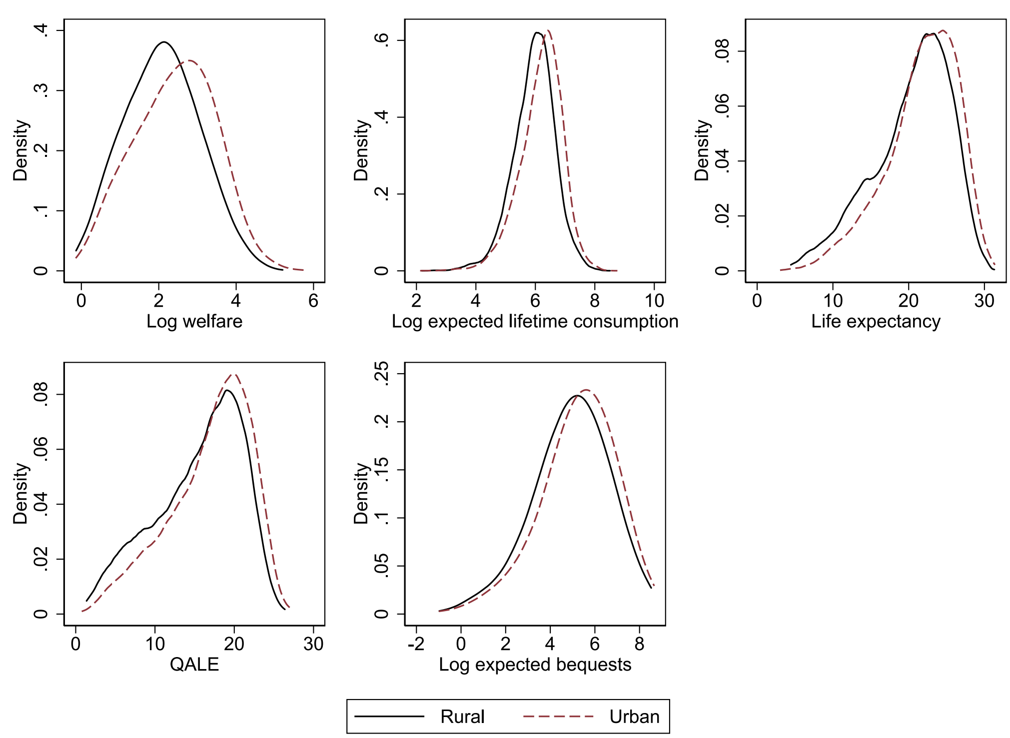
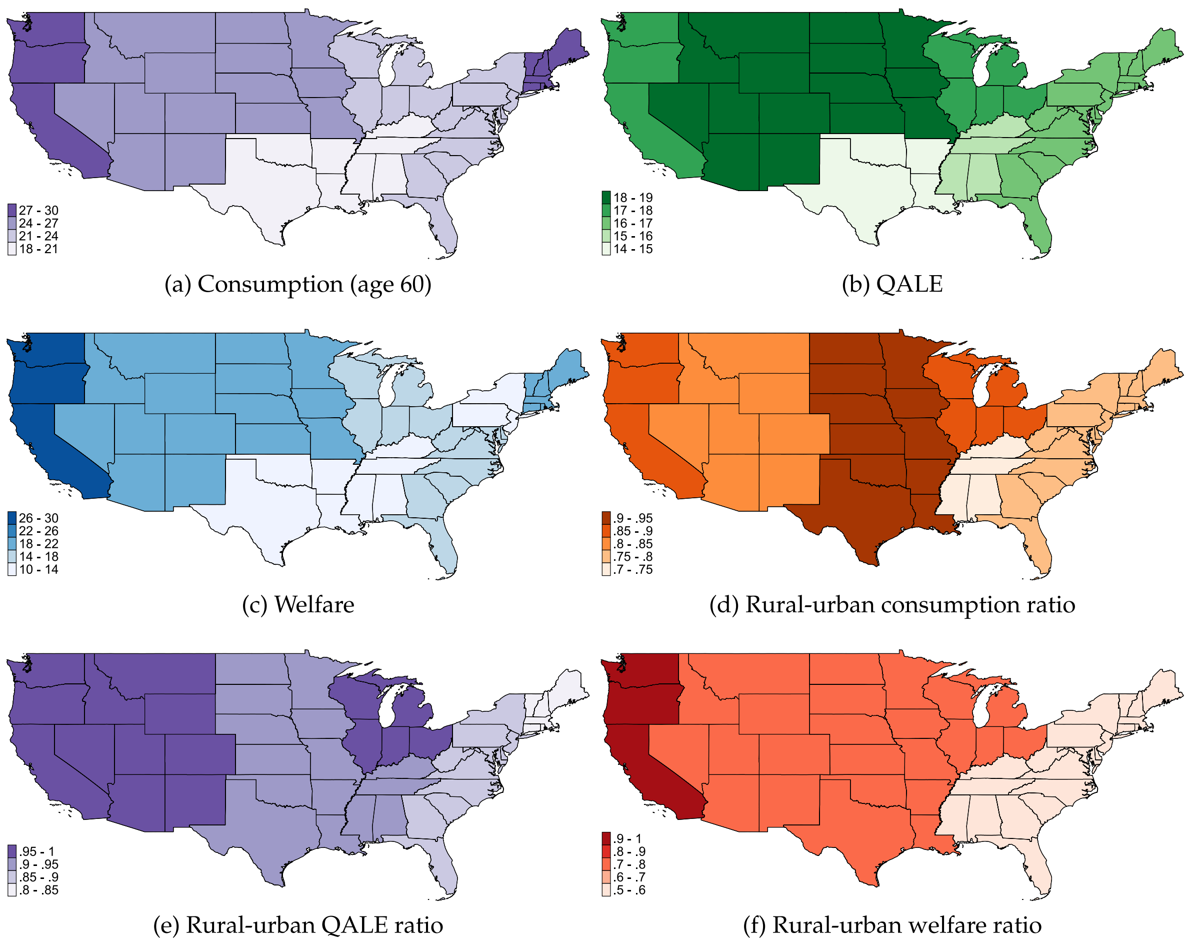


Fig. 5. Distribution of welfare and outcomes.

cost-of-living variation, with the West Coast and Northeast being the most expensive regions and the South and parts of the Central West being the least expensive. Even the largest cost-of-living gap between states, roughly 30% between California and Arkansas, suggests that consumption gaps would remain substantial after adjustments. However, since these cost-of-living estimates are primarily derived from urban areas, their applicability to rural settings is uncertain. As a result, we do not adjust for cost-of-living differences, but we acknowledge that



(a) Consumption (age 60) (b) QALE

(c) Welfare (d) Rural-urban consumption ratio

(e) Rural-urban QALE ratio (f) Rural-urban welfare ratio

Fig. 6. Mean rural outcomes and welfare by census division.

the observed consumption disparities may be somewhat overstated due to these regional variations.

Similar to consumption, the West South Central division exhibited the lowest age sixty QALE, at just 14.8 years, while the highest QALE – 18.4 years – was observed in the Mountain West, a difference of 3.6 years. More broadly, the poorer health outcomes in the South, illustrated in panel (b), align with prior findings and have been labeled the "southern rural health penalty" (James et al., 2018; Miller and Vasan, 2021). Explanations for this phenomenon include the geospatial clustering of individual risk factors and broader macrosocial determinants of health, such as socioeconomic status, structural racism, neighborhood conditions, and limited access to quality healthcare (Miller and Vasan, 2021).

Given these patterns, it is unsurprising that average welfare was also lowest in the rural South as shown in panel (c). The West South Central division recorded the lowest consumption-equivalent welfare, at \$10,445, while the Pacific division exhibited the highest welfare, at \$28,039—nearly three times higher.

The final three panels of Fig. 6 display the rural–urban ratios for mean outcomes by census division. Panels (d) and (e) highlight that the largest rural–urban gaps in consumption and health occur in the South and, somewhat unexpectedly, the Northeast. By contrast, these gaps are smaller in the Midwest and the western regions of the country. For example, the Pacific division has one of the smallest rural–urban gaps in both consumption (ratio of 0.86) and QALE (ratio of 0.95). In comparison, the analogous ratios are 0.73 and 0.91 in the East South Central division (Alabama, Kentucky, Mississippi, and Tennessee) and 0.77 and 0.88 in the Mid Atlantic division (New Jersey, New York, and Pennsylvania).

Combining these components into our single welfare metric, it is again unsurprising that the Pacific division shows the smallest rural–urban welfare gap, with a ratio of 0.91. In contrast, the largest gaps were observed in the East South Central division (ratio of 0.58) and the Mid Atlantic division (ratio of 0.51). The notably low Mid Atlantic ratio may reflect the presence of New York City, which may skew urban outcomes upward. More broadly, these results suggest that the rural–urban divide is most pronounced along the East Coast and diminishes moving westward, driven by smaller consumption and health disparities.

Sensitivity

We tested the robustness of our main findings by estimating results under various alternative modeling assumptions compared to our benchmark. These alternatives include adjustments to reference life expectancy, reference bequests, health utility weights, use of imputed data, and different preference parameter values. A summary of our results for the EHRS cohort is presented in Table 10. Average rural consumption-equivalent welfare showed some sensitivity to these variations, ranging from \$8500 to \$14,000 across modeling assumptions. However, more importantly, relative comparisons remained consistent. For example, the rural–urban ratio for the EHRS cohort consistently ranged between 0.68 and 0.74 across specifications.

Among all sensitivity results presented in Table 10, changes in reference life expectancy had the most significant impact on welfare. Specifically, the second row of the table provides results when increasing the reference age sixty life expectancy from 24 to 30 years. This adjustment imposes a higher welfare cost for individuals with higher flow utility, as indicated by Eq. (3). Consequently, we observed larger

Table 10
Sensitivity results: Mean welfare for the EHRS cohort.

	Rural	Urban	Ratio
Benchmark	12.696	18.353	0.692
Reference life expectancy	8.581	11.605	0.739
Reference bequests	12.227	17.674	0.692
$\bar{u} = -log(1.5)$	12.614	18.529	0.681
$\beta = 0.90$	12.572	17.299	0.727
$\epsilon = 0.5$	13.663	19.758	0.692
$\epsilon = 2$	11.367	16.425	0.692
$\theta = 17$	11.719	16.937	0.692
$\Phi_1 = -5$	13.442	19.069	0.705
$\Phi_2 = 6$	12.835	18.475	0.695
$\sigma = 2$	12.829	18.424	0.696
Health utility weights	12.902	18.653	0.692
No imputed forecasting data	12.235	17.556	0.697
No imputed data (pooled)	13.769	22.411	0.614

Notes: Estimates use base year respondent analysis weights. Welfare reported in $1000s. "Reference life expectancy" involves increasing life expectancy from 24 to 30 years. "Reference bequests" involves increasing bequests from $500,000 to one million dollars. "Health utility weights" involves allowing consumption and leisure to adjust across health states when calibrating these weights (see online appendix for full details). "No imputed forecasting data" excludes imputed data from the forecasting model. "No imputed data" further excludes imputed initial conditions and is pooled across birth cohorts. The remaining experiments involve adjusting parameter values as indicated.

mean declines in welfare for urban residents, resulting in a corresponding increase in the rural–urban welfare ratio of 4.7 pp relative to the benchmark. In the next row of Table 10, we present the results from increasing the reference bequest level from $500,000 to one million dollars. This adjustment had a much smaller effect on mean welfare compared to changes in reference life expectancy. The welfare ratio also remained unchanged compared to the benchmark.

The next portion of Table 10 provides sensitivity results concerning our chosen calibrated preference parameter values. First, we set flow intercept $\bar{u} = -\log(1.5)$, indicating that retirees require $1500 of consumption to maintain positive flow utility, compared to our benchmark value of $2000. This adjustment had a relatively minor effect on estimated welfare, reducing the reported rural–urban ratio by approximately 1.1 pp relative to the benchmark. Next, we lowered the time discount rate to $\beta = 0.9$. With this adjustment, the anticipated disparities in future consumption and health held less significance for welfare. Consequently, the rural–urban welfare ratio increased by around 3.5 pp. Changes in the Frisch elasticity of labor supply ϵ, disutility weight on labor supply θ, and bequest parameters (Φ_1, Φ_2, and σ) had minimal impacts on results. Finally, in our benchmark estimates, we calibrated health utility weights under the assumption that consumption and leisure were held constant by HUI3 respondents when comparing across health states. Table 10 indicates that our results are largely unaffected by relaxing this assumption.[4]

The final two rows of Table 10 assess how sensitive our main results are to the inclusion of imputed data. Both checks exclude all imputed values during the estimation of the forecasting model, instead relying exclusively on observed data.[5] While this approach reduces reliance on imputation, it also risks introducing imprecision or bias if missing data is systematically linked to individual characteristics.

In the first sensitivity test, labeled "no imputed forecasting data" in Table 10, the forecasting model is re-estimated using only raw data, but imputed values are still used for the initial age sixty conditions in the EHRS cohort simulations. The results show a modest decline in mean welfare across groups, yet the rural–urban welfare ratio remains nearly unchanged. This suggests that the imputation process has little influence on the dynamics captured by the forecasting model.

[4] See the online appendix for full discussion on this assumption and how it can be relaxed.

[5] To maintain sufficient sample sizes, we limit the forecasting model to one lag of consumption rather than the benchmark two lags.

Table 11
Sensitivity to higher curvature: Median welfare for EHRS cohort.

γ	VOL	Rural	Urban	Ratio
1.0	59.06	8.000	11.995	0.667
1.5	101.01	4.618	7.331	0.630
2.0	167.83	2.621	3.790	0.692
3.0	508.93	1.445	1.785	0.809

Notes: Estimates use base year respondent analysis weights. Welfare reported in $1000s.

In the second test, shown in the final row, we exclude all imputed data, including the initial age sixty conditions. This prevents simulations for the EHRS cohort, as no consumption data was collected for this group at age sixty. For other cohorts, the sample size shrinks by roughly 80%, mainly due to missing consumption data. To address this, we report results pooled across all cohorts to maintain a sufficient sample size. Although these results cannot be directly compared to the EHRS-specific findings at the top of Table 10, rural welfare levels are only slightly lower than benchmark levels for younger cohorts shown in Table 4. Moreover, the rural–urban welfare ratio remains consistent with the range observed across cohorts in Table 9. This supports the conclusion that our main results are robust and not unduly influenced by imputed data.

As a final sensitivity check, we examined results under the following non-separable function for flow utility over consumption and leisure:

$$\phi(h)\left[\frac{c^{1-\gamma}}{1-\gamma}\left(1-(1-\gamma)\frac{\theta\epsilon}{1+\epsilon}(1-l)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{\bar{u}^{1-\gamma}}{1-\gamma}\right]. \tag{6}$$

These preferences maintain a constant Frisch elasticity, and when $\gamma = 1$ and $\bar{u} = 2$, they coincide with our benchmark case of separable log utility for consumption. As detailed by Miller and Bairoliya (2023), producing welfare results for higher curvature over consumption ($\gamma > 1$) poses two challenges. First, high curvature over consumption precludes the calculation of consumption-equivalent welfare for the very healthiest individuals, as essentially no amount of consumption could be combined with reference health profiles to produce their expected lifetime utility. Therefore, we report median instead of mean welfare estimates. Second, the implied value of life increases sharply as γ increases (Murphy and Topel, 2006). This implies that results under higher curvatures should be interpreted with caution.

Table 11 presents median results in the EHRS cohort under alternate curvature values. In our benchmark case ($\gamma = 1$), the median value of life is $59,060 per QALY and the median rural–urban welfare ratio is 0.67, similar to the 0.69 found for the ratio of means. When $\gamma = 2$, the value of life increases to $167,830, which is high but in the plausible range of empirical estimates (Ryen and Svensson, 2015). This curvature pushes median welfare down substantially, to just $2621 for rural residents. However, the rural–urban ratio only changes slightly to 0.69. Further, raising $\gamma = 3$ increases the median value of life to $508,930 per QALY, which is substantially larger than most empirical estimates. This change pushes up the rural–urban ratio more substantially, reaching 0.81. These findings, though potentially impacted by overstated values of life, shed light on the sensitivity of key results to variations in the curvature of consumption utility. Despite potential overstatements in the value of life, welfare remains significantly lower for rural residents compared to their urban counterparts.

Conclusion

This study estimates well-being among older rural Americans using an expected utility framework that incorporates differences in consumption, leisure, health, mortality, and wealth. We take a life-cycle approach to better quantify aggregate well-being by incorporating contemporaneous and dynamic spillovers across all modeled outcomes at the individual level. We estimate that average rural well-being has improved for more recent HRS birth cohorts, primarily due to increasing life expectancy. However, we also find that the well-being of lonely rural residents is much lower than that of non-lonely rural residents, largely driven by significant gaps in consumption and QALE. Similarly, the well-being of older rural residents is declining compared to their urban counterparts across birth cohorts, with falling relative consumption playing a more significant role than health. Our counterfactual experiments highlight hypertension, heart disease, and arthritis as the most significant morbidities associated with average rural late-life well-being. Furthermore, we discover regional variations in average well-being among older rural residents across the U.S., with the lowest well-being observed in the south central regions, and the highest on the west coast.

While our study offers valuable insights into late-life well-being among rural Americans, it has its limitations. For instance, the forecasting model assumes that past trends for simulated outcomes will continue into the future. Additionally, our analysis does not consider the impacts of the COVID-19 pandemic since we rely on data collected before the outbreak. Incorporating post-pandemic data could provide insights into the resilience of rural communities and the effectiveness of emergency response measures.

Another limitation is our reliance on consumption as a central component of our welfare measure, which assumes that higher consumption reflects improved well-being. While this approach is common in economics, it does not fully account for broader considerations, such as the environmental impact of increased consumption. Expanding future analyses to incorporate sustainability metrics or alternative measures of well-being could offer a more holistic perspective.

While we include a wide range of health and economic outcomes in our analysis, there are other unaccounted factors that also influence late-life well-being. For example, integrating additional measures of social networks and spousal health could further reveal the significance of interpersonal relationships in late-life well-being. Similarly, considering environmental factors might highlight the importance of access to green spaces or exposure to pollution in rural areas. Or examining the quality of end-of-life healthcare could uncover disparities in palliative care and support services, ultimately improving the final stages of life for rural residents.

Despite these limitations, our findings hold significant policy implications for addressing disparities in late-life well-being, particularly in rural areas. First, the identification of hypertension, heart disease, and arthritis as major morbidities predicting rural welfare emphasizes the importance of targeted healthcare interventions to manage and prevent these conditions. Additionally, the observed disparities between lonely and non-lonely rural residents underscore the need for community-based initiatives to promote social integration and support networks for older adults. The widening rural–urban disparities also call for policy interventions focused on improving access to healthcare, social services, and economic opportunities in rural regions. Furthermore, the regional variations highlight the necessity for tailored policies that account for the unique socio-economic and healthcare benefits and challenges faced by older rural residents in different parts of the country. Overall, these findings stress the importance of comprehensive and inclusive policy approaches to promote equitable late-life well-being outcomes in diverse rural communities.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRediT authorship contribution statement

Yuulin An: Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Sayorn Chin:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Ray Miller:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no conflicts of interest.

Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeoa.2025.100565.

Data availability

Health and Retirement Study, (RAND HRS Longitudinal File 2020 (V1)) public use dataset. Produced and distributed by the University of Michigan with funding from the National Institute on Aging (grant numbers NIA U01AG009740 and NIA R01AG073289). Ann Arbor, MI, (2023). RAND HRS Longitudinal File 2020 (V1) and RAND HRS CAMS Data File 2019 (V1). Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA (2023).

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