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A Comparison of Living Standards Across the United States of America*

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Abstract

We use an expected utility model to examine how living standards, or welfare, vary across the U.S. and how each state's welfare has evolved over time. Our welfare measure accounts for cross-state variations in mortality, consumption, education, leisure, and inequality. We find that average living standards differ considerably across states. This is robust to allowing for endogenous interstate migration and to including housing in the model, and holds even when computing welfare conditional on education, gender, and race. Although states experienced heterogeneous welfare growth rates between 1999 and 2015 (ranging from 1.68 to 3.73 percent per year), there is no evidence of convergence in welfare levels, including during the sub-periods preceding and following the Great Recession. Whereas the level of real per-capita income is a good indicator of the level of welfare across states (correlation=0.75), the growth rate of real per-capita income is a poor proxy for the growth rate in welfare (correlation=0.42). Our welfare decomposition analysis can help identify what policies are likely to be most effective at increasing average living standards in the United States.

JEL codes: I31; O51; R13.

Keywords: Welfare comparison; Living standards; Inequality.

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1 Introduction

While a large literature has examined how welfare, or living standards, varies across countries, less is known about how welfare varies within a given country. This paper seeks to fill this gap in the context of the United States. Our analysis is motivated by the considerable heterogeneity in real (i.e., cost-of-living-adjusted) per-capita income levels across the U.S., ranging from \$38,800 in New Mexico to \$60,700 in Connecticut in 2015. Moreover, real consumption per capita varies by a factor of 1.5 across states and life expectancy at birth differs by almost seven years. There is also substantial cross-state variation in educational attainment, leisure, and income inequality. Given that each of these variables is likely to impact living standards, this heterogeneity indicates that there might exist cross-state differences in average welfare. Understanding whether this is indeed the case and, if so, why living standards differ across states, can guide the design of policies aimed at increasing average welfare in the U.S.

We examine whether living standards differ across states by extending the welfare measure developed by Jones and Klenow (2016). To illustrate our welfare analysis, suppose we wish to compare living standards in California and Connecticut. We do so by means of consumption-equivalent variation. In particular, we quantify how much consumption must adjust in all ages in the richest state, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in these two states. The variables that we include in our welfare measure follow closely the recommendations by the Stiglitz, Sen, and Fitoussi (2009) Commission, whose report emphasized numerous factors that are likely to impact people's well-being.

Our main finding is that there exists considerable heterogeneity in average living standards across U.S. states in 2015. This remains the case even if we compute welfare conditional on the individual's educational attainment, gender, and race, which shows that the heterogeneity is not driven by state-specific compositional effects. In fact, we find that the dispersion in welfare levels across states in the benchmark model exceeds the corresponding dispersion in real per-capita income levels, the latter of which is the most-commonly used proxy for living standards in the literature. Despite the sometimes-large deviations between welfare and real per-capita income, however, the two measures remain highly correlated, with a population-weighted correlation of 0.75 across states.

This cross-state heterogeneity in welfare levels might simply reflect that some states are further along the transition path toward a common steady state. To examine if living standards are in the process of converging across the U.S., we apply our welfare measure to quantify each state's welfare growth rate between 1999 and 2015. The welfare growth analysis shows that living standards increased in all states over this period, but that states have experienced heterogeneous annual welfare growth rates, ranging from 1.68 to 3.73 percent with an average of 2.61 percent. We then apply these results to test for convergence in welfare by examining whether states with lower welfare levels in 1999 have exhibited faster growth in welfare than states with higher welfare levels in 1999. We find no evidence of convergence during the 21st century, including the sub-periods preceding and following the Great Recession. Interestingly, the welfare growth analysis also reveals that the rise in welfare and the growth rate in real per-capita income, the latter of which is the most-commonly used proxy for the rise in living standards, are only weakly correlated, with a correlation of 0.42 across states. A decomposition analysis shows that this is largely due to the low correlation between the states' real per-capita income growth and life expectancy gains.

The benchmark analysis assumes that the individual will live her entire life in the state that she is born in. While this assumption is inconsistent with data on internal migration in the U.S., it does not drive our cross-state welfare results. In particular, we find very similar results in a model where, in each period, individuals can choose what state to reside in. That model assumes that individuals who choose to reside in a state other than their birth state suffer a utility cost that we calibrate to match each state's retention rate, given by the percentage of each state's residents that were also born in that state. Consistent with estimates by Kennan and Walker (2011), we find that the utility costs required to rationalize observed retention rates are substantial, thus indicating that there are large pecuniary and non-pecuniary costs associated with moving. These costs, in turn, explain why interstate migration does not equalize average living standards in the various states.

Finally, contrary to what we find, suppose instead that average living standards did not differ across states. If that were the case, the difference in welfare levels that we find would merely provide an estimate of the utility value of all state-level characteristics that are missing in our welfare measure, the most important of which is likely to be the value of amenities. This interpretation would in turn imply that the quality of amenities is negatively correlated with per-capita income. Such a correlation, however, would be inconsistent with microeconomic evidence (see e.g. Albouy, 2016) that shows that the quality of amenities is positively correlated with housing prices, which tend to be higher in high-income states. In fact, our cross-state welfare results are robust to including housing in the model. That model specifically accounts for the heterogeneity in both consumption-good prices and housing prices across states, and is consistent with the heterogeneity in expenditure shares on housing in the various states. Accordingly, while our welfare measure does not account for all state-level features that might impact living standards, these features are unlikely to account for the welfare heterogeneity that we find unless they are both economically-large and negatively correlated with the states' cost of living.

Put together, our results imply that there is room for policy to improve average living standards in the U.S., with at least two potential paths for policymakers. First, policymakers can implement policies that facilitate more interstate migration from lower- to higher-welfare states, for example through relocation subsidies. Second, policymakers can implement targeted state-specific policies that are guided by our welfare decomposition analysis. As an example, given the considerable role of life expectancy in accounting for the cross-state differences in welfare, our findings suggest that states with below-average life expectancy would benefit significantly from policies promoting increased access to health care.

Literature review This paper is related to a large macroeconomics literature that develops welfare measures to compare living standards across countries, regions, and time (see Fleurbaey, 2009, for a review). In an early contribution, Nordhaus and Tobin (1972) developed a measure that accounts for consumption, leisure, non-market work, and urban amenities to examine if welfare had increased in the U.S. Becker, Philipson, and Soares (2005) measure welfare by accounting for income and life expectancy; Boarini, Johansson, and d'Ercole (2006) account for leisure, economies of scale in consumption, and inequality; Córdoba and Verdier (2008) account for lifetime consumption inequality; and Fleurbaey and Gaulier (2009) account for life expectancy, leisure, and inequality. Following recommendations by the Stiglitz, Sen, and Fitoussi (2009) Commission, we extend this literature by incorporating education in the welfare measure to account for the considerable cross-state heterogeneity in educational attainment (related to Recommendation 6). We further extend the literature in the sensitivity analysis by distinguishing between consumption-goods and housing in the welfare measure, thereby allowing us to better account for differences in consumption baskets across states that might impact living standards (related to Recommendation 1). More importantly, while these papers compare welfare across countries (or, in the case of Nordhaus and Tobin, 1972, over time in the U.S.), we compare welfare both across U.S. states and over time.

The paper is most closely related to Jones and Klenow (2016). Similarly to their welfare measure, our model accounts for differences in consumption, leisure, mortality, and inequality. In addition to including education and housing, we further extend their model in the sensitivity analysis by allowing for endogenous migration and to including gender and race. Whereas Jones and Klenow (2016) use their model to compare welfare across countries, we use our model to compare welfare across the U.S. To the best of our knowledge, this is the first paper that applies an expected utility framework to compare living standards across the U.S and to quantify each state's evolution of living standards while taking into account changes in mortality risk, educational attainment, leisure, consumption, and inequality. Our cross-state welfare analysis by gender, race, and educational attainment is also related to Brouillette, Jones, and Klenow (2021), who compare welfare for Black and White Americans, and to Curtis, Garín, and Lester (2021), who compare welfare by race, gender, and educational attainment in the U.S.

The paper also complements the microeconomics literature that compares quality of life across cities and states.[1] Gabriel, Mattey, and Wascher (2003) account for cross-state variations in pollution, taxation, crime rates, and public spending to estimate the evolution in quality-of-life rankings for U.S. states. Albouy (2011) extends the quality-of-life measure commonly used in the literature (see Rosen, 1979, and Roback, 1982) by accounting for cost of living, federal taxes, and amenities, and uses this measure to estimate the quality of life across U.S. cities and states. Unlike these papers, we focus on differences in mortality risk, educational attainment, leisure, and inequality. Moreover, the methodology applied in these papers differs from our approach. In particular, these papers use current residents' revealed preference for residing in a given location to estimate the quality of life in that location using hedonic models. In contrast, we use an expected utility life cycle model to compare living standards across states for an unborn individual behind the veil of ignorance in the tradition of Lucas (1987).

Finally, our paper is related to the literature that attempts to gauge the satisfaction and happiness of societies by drawing on data on people's subjective well-being.[2] Oswald and Wu (2011) use microdata from the Behavioral Risk Factor Surveillance System to examine how mental health and life satisfaction varies across U.S. states. Using the same dataset, Glaeser, Gottlieb, and Ziv (2016) find evidence of persistent differences in self-reported subjective well-being across U.S. metropolitan areas. Whereas this literature focuses on individuals' subjective well-being at a particular point in their lifetime, we focus on the expected lifetime utility of an unborn individual by applying a welfare measure that accounts for several of the factors identified by the Stiglitz, Sen, and Fitoussi (2009)

[1] More broadly, it relates to the microeconomics literature that studies spatial equilibrium in U.S. cities (see, e.g., Moretti, 2004, Shapiro, 2006, and Diamond, 2016, for papers studying the geographic sorting of individuals across cities and Glaeser and Gottlieb, 2009, for a review of the spatial equilibrium in U.S. cities and how it has evolved).

[2] Bond and Lang (2019) show that it is generally not possible to rank two groups on the basis of their mean happiness when using the type of survey questions that are often applied in this literature. They outline conditions under which it is possible to identify the rank ordering of group happiness and find that nine prominent results from the happiness literature fail to satisfy these conditions.

Commission that are likely to impact people's well-being.

The rest of the paper is organized as follows. Section 2 shows how income, consumption, life expectancy, leisure, educational attainment, and inequality vary across the U.S. Section 3 develops a model that can account for this heterogeneity and that can be used to compare welfare both across states and over time. Section 4 discusses the estimation of the mortality probabilities, the process for consumption and leisure, and the parameterization of the preferences in the model. Section 5 applies the model to compare welfare across the states in 2015 and to quantify each state's welfare growth rate between 1999 and 2015. Finally, Section 6 concludes and gives directions for future research. Further details about the data as well as additional mathematical derivations and sensitivity analyses are reported in the online appendix.

2 Data

This section presents the state-level data that motivate our welfare analysis.

2.1 Income and consumption

Figure 1 plots the relationship between real personal income per capita and real consumption per capita across the states in 2015, both of which are obtained from the Bureau of Economic Analysis (BEA).[3] Both series have been deflated by means of Regional Price Parities (RPPs) reported by the BEA to account for the considerable heterogeneity in cost of living across the states. The average price level ranges from 13.6 percent below the national average in Mississippi to 18.6 percent above the national average in Hawaii, with richer states generally exhibiting higher prices than poorer states (see Appendix Section A.4 for details). Both series in Figure 1 have also been normalized by the corresponding values in Connecticut (real income and real consumption per capita were $60,700 and $42,700 in Connecticut in 2015, respectively). As illustrated in the graph, real per-capita income is 36 percent higher in the richest state, Connecticut, than in the state with the lowest real per-capita income, New Mexico, and 24 percent higher than in the state with the median real per-capita income, Missouri. Similarly, real consumption per capita varies considerably across the states, ranging from $32,000 in Mississippi (that is, 25 percent lower than in Connecticut), to $48,600 in North Dakota

[3] We always report average values for five-year periods because of small sample sizes for certain low-population states in the various survey data that we use. This also enables us to control for the fact that business cycles are not necessarily synchronized across states. Throughout, we identify a time period by the mid-point of the period (e.g., 2015 refers to the average value between 2013 and 2017). We deflate income and consumption series by means of the national Personal Consumption Expenditures price index reported by the BEA, with a base year of 2012.

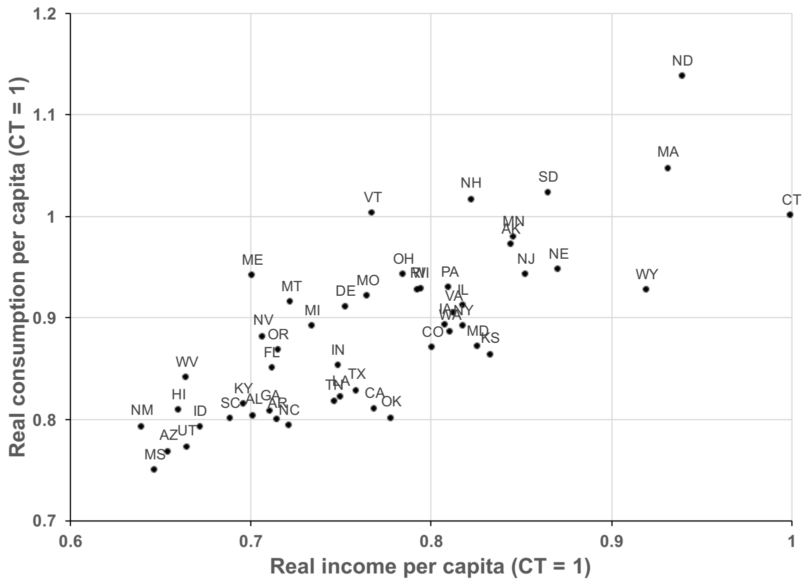

Figure 1: Relationship between real income per capita and real consumption per capita in 2015

Notes: The graph plots the relationship between personal income per capita and consumption per capita in 2015. Both series have been deflated to account for state-specific differences in cost of living by means of Regional Price Parities reported by the BEA, deflated by the national Personal Consumption Expenditures price index, and normalized by the corresponding values in Connecticut. Source: BEA.

(that is, 14 percent higher than in Connecticut). As expected, richer states tend to have higher real consumption than poorer states, with a correlation of 0.78 between real income and real consumption per capita across states.

2.2 Life expectancy

We next examine how life expectancy at birth varies across the U.S. To do so, we use age- and state-specific mortality probabilities as reported by the Centers for Disease Control and Prevention (CDC) (see Section 4.1 for details). The results are illustrated in Figure 2, which plots the relationship between real income per capita and life expectancy at birth. Life expectancy at birth varies by almost seven years across the U.S., from 74.6 years in Mississippi to 81.5 years in Hawaii. Life expectancy at birth tends to be higher in richer states than in poorer states. To illustrate, life expectancy at birth is about five years higher in Connecticut, Massachusetts, and New York than in Alabama, Mississippi, and West Virginia. As seen in the graph, life expectancy is also geographically concentrated, with several states in the South having particularly low life expectancy compared with

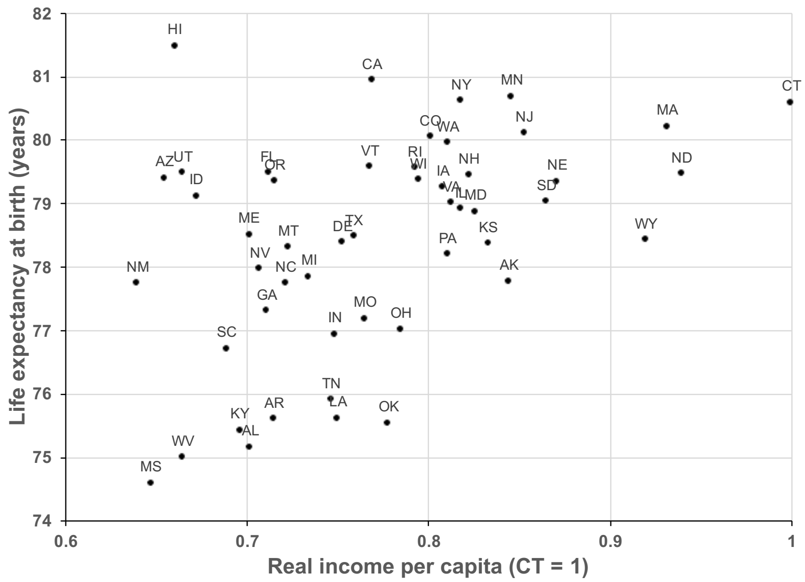

Figure 2: Relationship between real income per capita and life expectancy at birth in 2015

Notes: The graph plots the relationship between personal income per capita and life expectancy at birth in 2015. Income per capita has been deflated to account for state-specific differences in cost of living by means of Regional Price Parities reported by the BEA, deflated by the national Personal Consumption Expenditures price index, and normalized by the value in Connecticut. Sources: BEA and CDC.

the other regions.

2.3 Leisure

We use data from the Current Population Survey (CPS) to examine how leisure varies across states by computing each state's annual hours worked per capita. The results, which are illustrated in Figure 3, show that annual hours worked per capita in 2015 ranges from about 800 in Mississippi to more than 1,150 in North Dakota. As shown in the graph, richer states tend to have lower leisure (equivalently, higher annual hours worked) than poorer states, with particularly low leisure in several Midwestern states. Note that part of this heterogeneity in leisure is due to the states' different demographic characteristics such as the age composition of their residents. We address this in our welfare analysis by using each state's age- and education-specific average leisure.

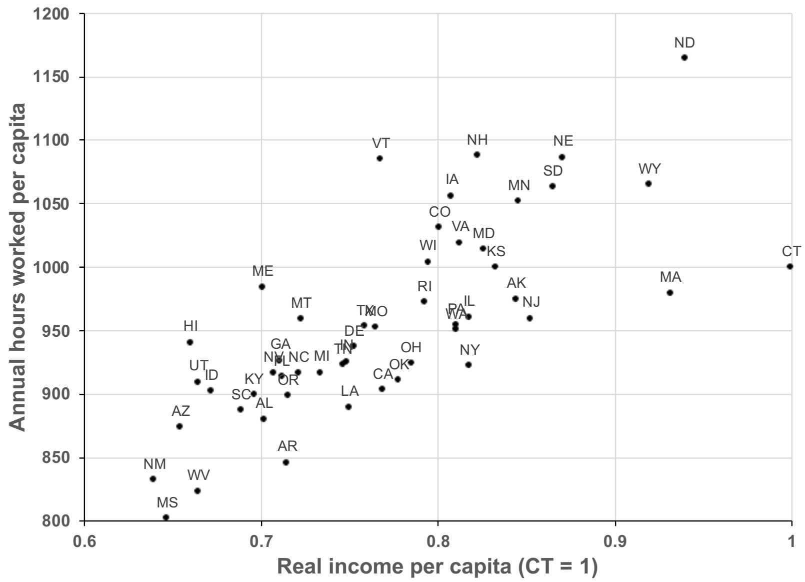

Figure 3: Relationship between real income per capita and annual hours worked per capita in 2015

Notes: The graph plots the relationship between personal income per capita and annual hours worked per capita in 2015. Income per capita has been deflated to account for state-specific differences in cost of living by means of Regional Price Parities reported by the BEA, deflated by the national Personal Consumption Expenditures price index, and normalized by the value in Connecticut. Sources: BEA and CPS.

2.4 College attainment

We use data from the CPS to examine how educational attainment varies across states. Figure 4 plots the relationship between real per-capita income and college attainment, where the latter is given by the percentage of 25–29 year-olds with at least a bachelor's degree or a minimum of four years of college. College attainment varies considerably across the U.S., ranging from 19.1 percent in New Mexico to 51.1 percent in Massachusetts. With some notable exceptions such as Wyoming, richer states tend to have higher college attainment rates than poorer states.

2.5 Inequality

Lastly, we examine how inequality varies across the U.S. Ideally, we would want data on consumption inequality at the state level, such as the state-specific standard deviation of consumption. Such data, however, is not available.[4] We therefore focus on income inequality, measured as the GINI coefficient

[4] The Consumer Expenditure Survey (CEX) and the Survey of Consumer Finances (SCF) collect data on consumption and socioeconomic characteristics for a representative sample of U.S. households. While the CEX and SCF report each household's state of residence, the surveys are not designed to be representative at the state level and can therefore not be used to infer state-specific consumption inequality. Further details are given in Section 4.2.

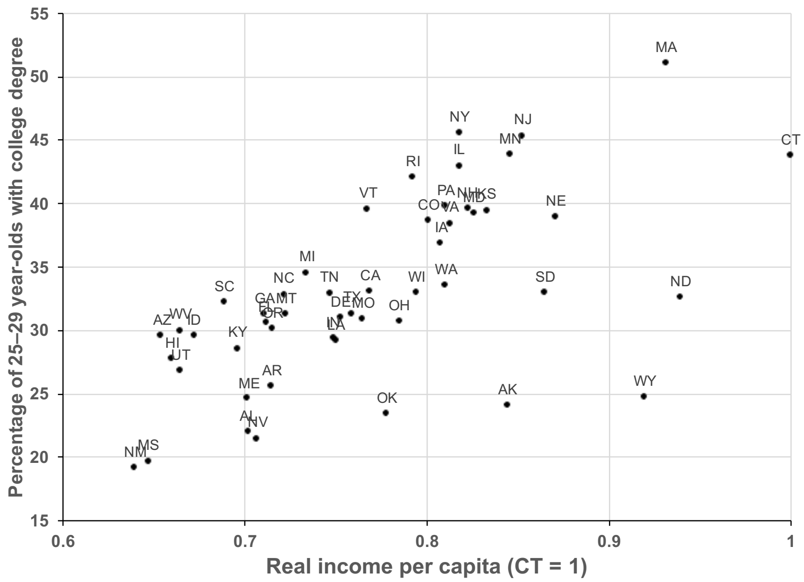

Figure 4: Relationship between real income per capita and college attainment in 2015

Notes: The graph plots the relationship between personal income per capita and college attainment in 2015, where the latter is given by the percentage of 25–29 year-olds with at least a bachelor's degree or a minimum of four years of college. Income per capita has been deflated to account for state-specific differences in cost of living by means of Regional Price Parities reported by the BEA, deflated by the national Personal Consumption Expenditures price index, and normalized by the value in Connecticut. Sources: BEA and CPS.

of household income as derived from the American Community Survey (ACS) conducted by the Census. Because consumption is highly correlated with income (see Section 2.1) and a state's GINI coefficient of income is informative about how income is distributed across households in that state, this measure is likely to also be informative about how consumption is distributed across households in that state. Figure 5 reports the relationship between real income per capita and income inequality. There is large heterogeneity in the GINI coefficient of household income in the U.S., ranging from less than 0.42 in Alaska to more than 0.51 in New York. While real consumption per capita, life expectancy, leisure, and college attainment are correlated with real income per capita, we do not find evidence that inequality varies systematically with income. This is evident from the graph, which shows that inequality varies considerably across states with similar real per-capita income levels. To illustrate, while Mississippi and Utah have comparable real per-capita income levels, their GINI coefficient of income varies by more than 0.05.

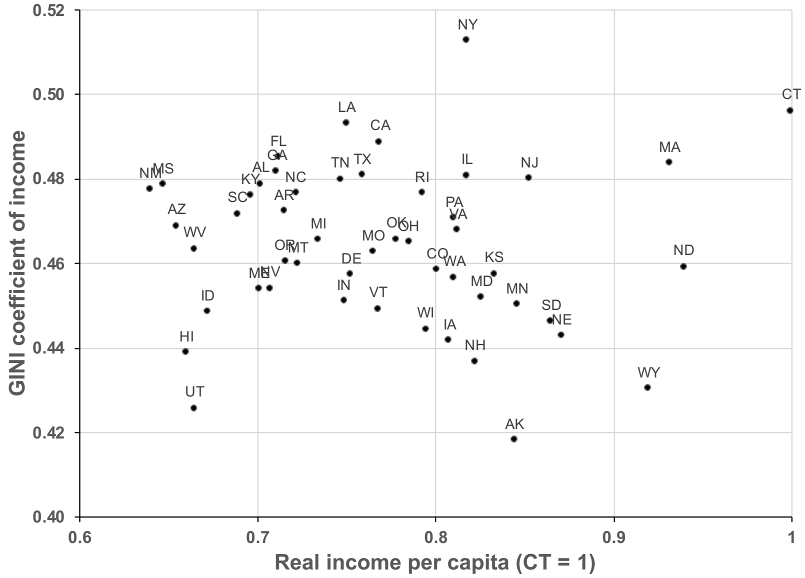

Figure 5: Relationship between real income per capita and income inequality in 2015

Notes: The graph plots the relationship between personal income per capita and the GINI coefficient of household income in 2015. Income per capita has been deflated to account for state-specific differences in cost of living by means of Regional Price Parities reported by the BEA, deflated by the national Personal Consumption Expenditures price index, and normalized by the value in Connecticut. Sources: ACS and BEA.

3 Model

This section presents the model that we will apply to quantify the welfare differences across the U.S. The choice of variables in our model is motivated by the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz, Sen, and Fitoussi, 2009), whose report stressed the many factors that affect living standards that are incorporated imperfectly, if at all, by the most-commonly used measure of living standards, GDP per capita. Following recommendations by the Commission, we assume that individuals derive utility from consumption (related to Recommendation 1); we adopt the perspective of individuals (related to Recommendation 2); we account for inequality in consumption (related to Recommendation 4); we account for leisure (related to Recommendation 5); and we account for mortality risk and educational attainment (related to Recommendation 6). The model is an extension of the model that Jones and Klenow (2016) use to study cross-country differences in welfare. To be able to compare welfare across states, we use a common state-independent specification for preferences given by the preferences of an average individual in the U.S.

3.1 General setup

Let an individual's idiosyncratic state be given by her age, a, educational level, e, and state of residence, s. As in Krueger and Perri (2003), the individual derives utility from both consumption, c, and leisure, ℓ. Assume that consumption grows at a common, state-independent, annual rate g.[5] Let β denote the discount factor and let $\Psi_{ae}^{s} = \prod_{k=0}^{a-1} \psi_{ke}^{s}$ denote the education- and state-specific probability of surviving from age 0 to age $a \geq 1$, with $\Psi_{0e}^{s} = 1$ for all e and s. We assume that the individual enters the model at age 0 and lives at most 100 years. The individual will live her entire life in the state she is born in.[6] We assume that the educational level, $e = \{e_1, \ldots, e_n\}$, is revealed at birth and stays constant over the individual's lifespan. Over her life, the individual will draw from the cross-sectional distribution of consumption, leisure, and mortality corresponding to each age, education, and state. Lifetime expected utility in state s is then given by

$$U^{s} = \mathbb{E}_{ae}^{s} \sum_{e=e_1}^{e_n} \pi_{e}^{s} \sum_{a=0}^{100} \beta^{a} \Psi_{ae}^{s} u\left(c_{ae}^{s} \exp\left(ga\right), \ell_{ae}^{s}\right), \tag{1}$$

where π_e^s is the state-specific probability of drawing educational level e and $\mathbb{E}_{ae}^{s}$ is the expectation operator conditional on age, education, and state.

Let $U^{s}\left(\lambda\right)$ denote lifetime expected utility in state s if we multiply consumption by a factor λ in all ages:

$$U^{s}\left(\lambda\right) = \mathbb{E}_{ae}^{s} \sum_{e=e_1}^{e_n} \pi_{e}^{s} \sum_{a=0}^{100} \beta^{a} \Psi_{ae}^{s} u\left(\lambda c_{ae}^{s} \exp\left(ga\right), \ell_{ae}^{s}\right). \tag{2}$$

Consider two states s and $\hat{s}$. We quantify the welfare difference between state s and $\hat{s}$ by computing how much consumption must adjust in all ages in state $\hat{s}$ to equalize lifetime expected utility in the two states. This corresponds to deriving the scaling factor, λ^s, that solves

$$U^{\hat{s}}\left(\lambda^{s}\right) = U^{s}\left(1\right). \tag{3}$$

3.2 Parameterization and welfare decomposition

Assume that preferences over consumption and leisure are given by

$$u\left(c_{ae}^{s} \exp\left(ga\right), \ell_{ae}^{s}\right) = b + \log\left(c_{ae}^{s} \exp\left(ga\right)\right) + v\left(\ell_{ae}^{s}\right), \tag{4}$$

[5]An alternative would be to forecast each state's future consumption growth for the next 100 years based on data for the period 1999–2015. Such forecasts, however, would suffer from very large standard errors.

[6]Section 5.4 considers an environment where, in each period, the individual can choose what state to reside in.

where b governs the value of life as in Hall and Jones (2007) and $v\left(\ell_{ae}^s\right)$ captures the utility from leisure.[7] Assume that consumption is drawn from an age-, education-, and state-specific lognormal distribution with mean of logarithmic values, μ_{ae}^s, and standard deviation of logarithmic values, σ_{ae}^s. Then $\mathbb{E}_{ae}^s\left[\log\left(c_{ae}^s\right)\right] = \log\left(\bar{c}_{ae}^s\right) - \frac{\left(\sigma_{ae}^s\right)^2}{2}$, where $\bar{c}_{ae}^s = \exp\left(\mu_{ae}^s + \frac{\left(\sigma_{ae}^s\right)^2}{2}\right)$ is the age-, education-, and state-specific arithmetic mean of consumption. Lifetime expected utility in state s is then given by

$$U^s = \sum_{e=e_1}^{e_n} \pi_e^s \sum_{a=0}^{100} \beta^a \Psi_{ae}^s \left[b + ga + \log\left(\bar{c}_{ae}^s\right) - \frac{\left(\sigma_{ae}^s\right)^2}{2} + v\left(\bar{\ell}_{ae}^s\right)\right], \tag{5}$$

where we have replaced leisure by type-specific average leisure, $\bar{\ell}_{ae}^s$. We continue to let $U^s(\lambda)$ denote the lifetime expected utility in state s if we multiply consumption by a factor λ in all ages:

$$U^s(\lambda) = \sum_{e=e_1}^{e_n} \pi_e^s \sum_{a=0}^{100} \beta^a \Psi_{ae}^s \left[b + ga + \log(\lambda) + \log\left(\bar{c}_{ae}^s\right) - \frac{\left(\sigma_{ae}^s\right)^2}{2} + v\left(\bar{\ell}_{ae}^s\right)\right]. \tag{6}$$

Recall that we quantify the welfare difference between state s and $\hat{s}$ by computing how much consumption must adjust in all ages in state $\hat{s}$ to equalize lifetime expected utility in the two states. Using the functional form for the utility function, we then get the following expression for $\log(\lambda^s)$ when we apply Equation (3):

$$\log\left(\lambda^s\right) = \frac{\sum_{e=e_1}^{e_n}\sum_{a=0}^{100}\beta^a\left[\pi_e^{\hat{s}}\left(u_{ae}^s\left[\Psi_{ae}^s - \Psi_{ae}^{\hat{s}}\right] + \Psi_{ae}^{\hat{s}}\left[u_{ae}^s - u_{ae}^{\hat{s}}\right]\right) + \Psi_{ae}^s u_{ae}^s\left[\pi_e^s - \pi_e^{\hat{s}}\right]\right]}{\sum_{e=e_1}^{e_n}\sum_{a=0}^{100}\pi_e^{\hat{s}}\beta^a\Psi_{ae}^{\hat{s}}}, \tag{7}$$

where u_{ae}^s, for every s, is given by

$$u_{ae}^s \equiv b + ga + \log\left(\bar{c}_{ae}^s\right) - \frac{\left(\sigma_{ae}^s\right)^2}{2} + v\left(\bar{\ell}_{ae}^s\right). \tag{8}$$

Assume that education can take two values, college or non-college educated, which implies that $\pi_1^s = 1 - \pi_2^s$ for all s. To ease notation, let $\chi_a^{\hat{s}} \equiv \frac{\beta^a}{\sum_{e=1}^{2}\sum_{a=0}^{100}\pi_e^{\hat{s}}\beta^a\Psi_{ae}^{\hat{s}}}$, $\phi_{ae}^{\hat{s}} \equiv \frac{\beta^a\pi_e^{\hat{s}}\Psi_{ae}^{\hat{s}}}{\sum_{e=1}^{2}\sum_{a=0}^{100}\pi_e^{\hat{s}}\beta^a\Psi_{ae}^{\hat{s}}}$, and $\Delta\phi_{ae}^{\hat{s}} \equiv \frac{\beta^a\pi_e^{\hat{s}}\left[\Psi_{ae}^s - \Psi_{ae}^{\hat{s}}\right]}{\sum_{e=1}^{2}\sum_{a=0}^{100}\pi_e^{\hat{s}}\beta^a\Psi_{ae}^{\hat{s}}}$. We then get the following additive decomposition for the welfare

[7] We let the preferences in the benchmark model be given by Equation (4) because these preferences enable us to additively decompose the welfare differences across states into differences in life expectancy, college attainment, consumption, leisure, and inequality. Appendix Section C.2 shows that the results are robust to alternative utility specifications.

difference between state s and $\hat{s}$:

$$\begin{array}{rcll} \log(\lambda^s) & = & \sum_{e=1}^{2}\sum_{a=0}^{100}\Delta\phi_{ae}^{\hat{s}}u_{ae}^{s} & \text{Life expectancy} \\ & & +\sum_{a=0}^{100}\chi_a^{\hat{s}}\left(\left[\pi_2^s-\pi_2^{\hat{s}}\right]\left[\Psi_{a2}^s u_{a2}^s-\Psi_{a1}^s u_{a1}^s\right]\right) & \text{College attainment} \\ & & +\sum_{e=1}^{2}\sum_{a=0}^{100}\phi_{ae}^{\hat{s}}\left(\log\left(\bar{c}_{ae}^s\right)-\log\left(\bar{c}_{ae}^{\hat{s}}\right)\right) & \text{Average consumption} \\ & & +\sum_{e=1}^{2}\sum_{a=0}^{100}\phi_{ae}^{\hat{s}}\left(v\left(\bar{\ell}_{ae}^s\right)-v\left(\bar{\ell}_{ae}^{\hat{s}}\right)\right) & \text{Average leisure} \\ & & +\sum_{e=1}^{2}\sum_{a=0}^{100}\frac{\phi_{ae}^{\hat{s}}}{2}\left(\left(\left(\sigma_{ae}^{\hat{s}}\right)^2-\left(\sigma_{ae}^s\right)^2\right)\right) & \text{Inequality of consumption.} \end{array} \tag{9}$$

That is, the welfare difference between state s and $\hat{s}$ can be decomposed into the differences in: life expectancy weighted by flow utility; college attainment weighted by how much a college degree affects utility (that is, weighted by how much a college degree affects mortality risk, consumption, and leisure); average consumption; average leisure; and inequality of consumption.

4 Calibration

This section discusses the calibration of the model.

4.1 Survival probabilities

Recall from Section 3 that survival probabilities are assumed to be age-, education-, and state-specific, ψ_{ae}^s.[8] We follow a three-step procedure to derive these probabilities (see Appendix Section A.3 for further details). First, we pool all death records for the period 2013–2017 from the Underlying Cause of Death (UCD) database reported by the CDC. The UCD database reports each person's age and state of legal residence at the time of death in the U.S., with age top-coded at 85. For 0–84 year-olds, we first compute age- and state-specific mortality probabilities from observed mortality rates. We then smooth the logarithm of the mortality probabilities by means of step-wise fifth-order polynomials in age. This helps ensure smooth mortality probabilities for smaller states such as Vermont and Wyoming. Beyond the age of 84, we approximate age- and state-specific mortality probabilities by means of Gompertz survival models as in Chetty et al. (2016). In a Gompertz model, the logarithm of the mortality rate is linear in age, $\log(m_a^s) = \delta_1^s + \delta_2^s a$, where m_a^s is the

[8] Note that differences in mortality risk across states are likely to be partially due to differences in health behavior (for example, rates of smoking and obesity), which in turn might be due to heterogeneity in preferences across states. We abstract from preference heterogeneity and assume that variations in mortality risk is due to state-specific factors. This assumption is supported by recent research by Finkelstein, Gentzkow, and Williams (2021) who compare mortality outcomes of individuals that migrate from the same location to different destinations. Their estimates imply that moving from a tenth percentile area in terms of impact on life expectancy to a ninetieth percentile area would increase life expectancy at age 65 by 1.1 years, or about half of the 90–10 cross-sectional difference (see Deryugina and Molitor, 2021, for a review of this literature).

mortality rate of individuals of age a in state s and where δ_1^s and δ_2^s are state-specific coefficients. This log-linear approximation fits the UCD mortality rates for 40+ year-olds almost perfectly. We then use the estimated mortality regressions to predict age- and state-specific mortality probabilities for 85–99 year-olds. Given our assumption that individuals live at most 100 years, we assume that survival probabilities at age 100 is equal to 0 for all states. Let the derived age- and state-specific survival probabilities be denoted by ψ_a^s.

Second, we pool all death records for the period 2013–2017 from the National Vital Statistics System (NVSS). The NVSS reports each person's age and educational attainment at the time of death in the U.S.[9] We split individuals into two educational categories: those with and those without a college degree, where a college degree is defined as having at least a bachelor's degree or a minimum of four years of college. We then use the NVSS data to obtain the number of deaths by age and education over this period. Next, we use data from the CPS for the period 2013–2017 to compute the number of individuals by age and education. Combining the NVSS and CPS data then allows us to compute age- and education-specific survival probabilities, ψ_{ae}. Due to small sample sizes for college-educated individuals that are younger than 25, we only compute age- and education-specific survival probabilities for 25+ year-olds and assume that survival probabilities are independent of education prior to age 25. The *college survival premium*, defined as the difference between the age-specific survival probability of college and non-college educated individuals, is reported in Table 1 (numbers in square brackets show age-specific one-year survival probabilities for individuals with a college degree). College-educated individuals have higher one-year survival probabilities than non-college educated individuals across all age groups, ranging from 0.12 percentage points for 25–29 year-olds to 3.54 percentage points for 85+ year-olds.[10] This translates into large differences in remaining life expectancy. As an example, at age 25, a college-educated individual can expect to live nearly seven years longer than a non-college educated individual.

Lastly, given an initial guess, we derive age-, education-, and state-specific survival probabilities by iterating on the guess to match the age- and state-specific survival probabilities from the UCD database, ψ_a^s, and the age-specific college survival premium from the NVSS, $\psi_{a2} - \psi_{a1}$. For each age

[9]Due to a restriction imposed by the states, the NVSS no longer reports the individual's state of legal residence. We are therefore unable to estimate age-, education-, and state-specific survival probabilities directly from the data. Note that, because we use data from both the UCD and the NVSS database, our welfare results might suffer from dual data source bias (Hendi, 2017). The magnitude of this potential bias, however, is likely to be limited because the two datasets report nearly identical age-specific mortality counts (see Appendix Section A.3 for details).

[10]Due to small sample sizes for some age groups, we group individuals into five-year age groups when we compute the college survival premium. The difference between the age-specific survival probability of college and non-college educated individuals is assumed to be the same within each five-year age group.

Table 1: College survival premium by age

Age	25	30	35	40	45	50	55	60	65	70	75	80	85
$\psi_{a2} - \psi_{a1}$	0.12 [99.98]	0.14 [99.97]	0.16 [99.96]	0.20 [99.95]	0.28 [99.92]	0.41 [99.87]	0.57 [99.77]	0.73 [99.59]	0.86 [99.32]	1.15 [98.95]	1.45 [98.14]	1.57 [96.38]	3.54 [94.71]

Notes: The numbers report the difference between the age-specific one-year survival probability of college-educated, ψ_{a2}, and non-college educated, ψ_{a1}, individuals. Numbers in square brackets report age-specific one-year survival probabilities for individuals with a college degree, ψ_{a2}. College-educated individuals refer to individuals with at least a bachelor's degree or a minimum of four years of college. Sources: CPS and NVSS.

and state, this corresponds to deriving the ψ_{ae}^s that solve the following system of equations:

$$\begin{aligned} \psi_a^s &= \sum_{e=1}^{2} \Lambda_{ae}^s \psi_{ae}^s \\ \psi_{a2} - \psi_{a1} &= \psi_{a2}^s - \psi_{a1}^s, \end{aligned} \tag{10}$$

where Λ_{ae}^s denotes the distribution of education given age and state from the CPS.[11] Note that this approach relies on the assumption that the age-specific mortality difference between college and non-college educated individuals is common across all states.

4.2 Consumption

We use data from the Consumer Expenditure Survey (CEX) for the period 1997–2017 to estimate the process for consumption (see Appendix Section A.2 for further details).[12] This survey is conducted on a quarterly basis and consists of a rotating panel of households that are selected to be representative of the U.S. population. The CEX reports detailed information on consumption expenditures for all interviewed households. The survey also reports detailed information on all household members such as age and education. In our benchmark analysis, we focus on consumption of non-durables and services.[13] This includes expenditures on food, alcohol, tobacco, apparel, health care, education, reading, utilities, personal care, insurance, and other miscellaneous expenditures. It also includes the non-durable or service component of housing expenses, transportation expenses, and entertainment expenses. We approximate services from housing for owner-occupied dwellings by means of the imputed rental value, defined as the income the homeowner could have received if the house had been rented to a tenant.

We first aggregate household-level consumption from a quarterly to an annual basis and then de-

[11] Attanasio, Kitao, and Violante (2010) and Conesa, Kehoe, Nygaard, and Raveendranathan (2020) follow an analogous approach to derive survival probabilities.
[12] We extend the dataset used by Heathcote and Perri (2018).
[13] Appendix Section C.2 considers alternative cases where we exclude expenditures on health care and include durable consumption expenditures.

flate the series by means of the national Personal Consumption Expenditures price index reported by the BEA. We then convert the data from household-level to individual-level by allocating consumption uniformly across all household members. Because the CEX underestimates total consumption, we correct for the underestimation by scaling total consumption in the CEX to match each year's per-capita consumption in the U.S. as reported by the BEA.[14]

Although the CEX reports the household's state of residence, the survey is not designed to be representative at the state level and can therefore not be used to estimate state-specific consumption processes. Instead of using the CEX-information on state of residence, we use the following approach to derive the parameters of the state-specific consumption processes. First, we assume that consumption in the U.S. is drawn from a lognormal distribution with age- and education-specific mean, μ_{ae}, and standard deviation, σ_{ae}, both of which are estimated from the CEX. We then adjust the parameters of this lognormal consumption process to account for each state's average consumption and inequality as discussed in Section 2. In particular, we jointly calibrate the state-specific parameters of the lognormal consumption process, μ^s_{ea} and σ^s_{ae}, to match both the ratio of each state's demographic-adjusted per-capita consumption of non-durables and services relative to the U.S. and the difference in consumption inequality as measured by the state's GINI coefficient of consumption relative to the corresponding GINI coefficient in the U.S.[15] By demographic-adjusted, we mean that we adjust for variations in the age- and education-composition across the states. Using properties of the lognormal distribution, this corresponds to solving for the two parameters, ν^s and κ^s, that solve the following system of equations:

$$\begin{aligned}
\frac{\sum_e \sum_a \Lambda^s_{ae} \exp\left(\mu_{ae}+\nu^s+\frac{(\sigma_{ae}\kappa^s)^2}{2}\right)}{\sum_e \sum_a \Lambda^{US}_{ae} \exp\left(\mu_{ae}+\frac{\sigma^2_{ae}}{2}\right)} &= \frac{C^s}{C^{US}} \\
\mathrm{GINI}^s\left(\mathbf{\Lambda}^s, \boldsymbol{\mu}, \boldsymbol{\sigma}; \nu^s, \kappa^s\right) - \mathrm{GINI}^{US}\left(\mathbf{\Lambda}^{US}, \boldsymbol{\mu}, \boldsymbol{\sigma}\right) &= d^s,
\end{aligned} \tag{11}$$

where Λ^s_{ae} and Λ^{US}_{ae} denote the distribution of education given age in state s and in the U.S., C^s and C^{US} denote per-capita consumption of non-durables and services in state s and in the U.S.,

[14] This is in line with recommendations by the High-Level Expert Group on the Measurement of Economic Performance and Social Progress (see Stiglitz, Fitoussi, and Durand, 2018), who emphasize the importance of reconciling aggregate estimates from microdata with corresponding aggregates from national accounts. Although we exclude expenditures on durables in the benchmark analysis, we include durable expenditures as part of consumption when we scale the CEX data to match the values reported by the BEA.

[15] Appendix Section C.2 shows that the welfare results are robust to two alternative calibrations of the consumption process: one where we target a higher level of consumption inequality derived from the SCF as in Fisher, Johnson, Smeeding, and Thompson (2022) to account for the underestimation of consumption inequality in survey data such as the CEX due to both underreporting and nonresponse bias for households at the top of the income distribution; and one where we use an alternative measure of state-level income inequality derived from federal tax returns as in Frank (2014).

$\text{GINI}^s\left(\mathbf{\Lambda}^s, \boldsymbol{\mu}, \boldsymbol{\sigma}; \nu^s, \kappa^s\right)$ and $\text{GINI}^{US}\left(\mathbf{\Lambda}^{US}, \boldsymbol{\mu}, \boldsymbol{\sigma}\right)$ denote the GINI coefficient of consumption in state s and in the U.S. ($\boldsymbol{\mu}$, $\boldsymbol{\sigma}$, $\mathbf{\Lambda}^{US}$, and $\mathbf{\Lambda}^s$ are vectors of μ_{ae}, σ_{ae}, Λ_{ae}^{US}, and Λ_{ae}^s), and d^s is the difference in the GINI coefficient of consumption between state s and the U.S.[16] The state-specific mean and standard deviation of logarithmic values are then given by $\mu_{ae}^s = \mu_{ae} + \nu^s$ and $\sigma_{ae}^s = \sigma_{ae}\kappa^s$, respectively.

4.3 Leisure

Following Jones and Klenow (2016), we let the disutility of working, $1-\ell$, be given by

$$v(\ell) = -\frac{\theta\epsilon}{1+\epsilon}(1-\ell)^{\frac{1+\epsilon}{\epsilon}}, \tag{12}$$

where ϵ is the Frisch elasticity and θ is the weight on disutility from working in the utility function. We use the same values as Jones and Klenow (2016) and set $\epsilon = 1$ and $\theta = 14.2$. As noted in Section 2.3, we use each state's age- and education-specific average leisure as derived from the CPS, $\bar{\ell}_{ae}^s$.

4.4 Preferences

Because we compare living standards across states for an unborn individual behind the veil of ignorance, we use a common state-independent specification for preferences given by the preferences of an average individual in the U.S. A period in the model is one year. We let the discount factor, β, be equal to 0.99. The growth rate of consumption, g, is set to 2 percent per year. Lastly, we follow Jones and Klenow (2016) and calibrate the constant term in the utility function, b, such that an average 40-year-old—facing the average mortality risk, educational uncertainty, consumption uncertainty, and leisure in the U.S. in 2015—has a value of remaining life equal to \$6.5 million in 2012 prices (see Appendix Section B.1 for further details). Given a remaining life expectancy at age 40 of about 41 years, this target corresponds to an annual value of life of approximately \$160,000. This lies within the \$100,000–\$400,000 range typically used in the literature (see for example Hall, Jones, and Klenow, 2020, for references) and implies that a year of life is worth about five times annual consumption of non-durables and services (roughly equal to \$32,000). This leads to a value of 6.21 for b when consumption of non-durables and services per capita in the U.S. in 2015 is normalized to 1. To put the units of the constant term in perspective, an increase in b by 1.00 units would result

[16] As noted in Section 2.5, because data on consumption inequality at the state level is not available, we let the inequality target for the calibration, d^s, be given by the difference in the GINI coefficient of household income between state s and the U.S.

in an increase in the value of life at age 40 in the benchmark model by approximately $1.0 million, or alternatively, an increase in welfare equivalent to approximately 170 percent higher consumption in all ages for the average 40-year-old.

5 Results

Sections 5.1 and 5.2 apply the model from Section 3 to quantify the welfare differences across the U.S. in 2015 and to quantify each state's welfare growth rate between 1999 and 2015, respectively. Section 5.3 compares welfare across states conditional on educational attainment, gender, and race, and Section 5.4 studies the sensitivity of the benchmark welfare results to an environment that allows for interstate migration. Section 5.5 summarizes the results from other sensitivity analyses. Finally, Section 5.6 compares the results from our cross-state welfare analysis with the corresponding cross-country welfare results in Jones and Klenow (2016).

5.1 Welfare across states

To illustrate how we quantify the welfare differences across the U.S. in 2015, suppose we wish to compare living standards in Connecticut and Massachusetts. To do so, we quantify how much consumption would have to change in every age in Connecticut—holding fixed Connecticut's survival probabilities, educational attainment, leisure, and inequality—to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut and Massachusetts. The factor by which we have to adjust consumption provides a consumption-equivalent measure of the difference in welfare between these two states. We assume that the individual draws from the cross-sectional distribution of consumption, leisure, and mortality corresponding to each age, education, and state.[17] Because educational attainment has been increasing continuously in the U.S. since the 1960s, we assume that the individual draws her educational attainment from the current distribution of 25–29 year-olds.

5.1.1 Comparing welfare with real income per capita

Section 2 showed that there exists considerable heterogeneity in consumption, life expectancy, leisure, educational attainment, and inequality across the U.S., all of which are likely to have implications

[17]Note that it does not matter for the welfare results whether consumption inequality is permanent from birth or i.i.d. given age, education, and state. This follows because preferences are assumed to be additively separable and because we compare welfare across states for an unborn individual behind the veil of ignorance.

for living standards. While some of these variables are positively correlated across states (e.g., consumption and life expectancy), others are negatively correlated (e.g., consumption and leisure) or uncorrelated (e.g., consumption and inequality). It is thus ambiguous, both quantitatively and qualitatively, how living standards vary across the states. We therefore apply Equation (7) to compute each state's average living standards and then compare each state's welfare level with its corresponding real per-capita income level. The latter allows us to test the common practice, both among economists and policymakers, of using real per-capita income as a proxy for living standards. The results are depicted in Figure 6, which illustrates the relationship between each state's welfare level (vertical axis) and real per-capita income level (horizontal axis), both of which have been normalized by the corresponding value in Connecticut. We find that real per-capita income is positively correlated with welfare, with a population-weighted correlation of 0.75 across states. Hence, richer states tend to have higher living standards than poorer states according to our welfare measure. To illustrate, Connecticut has the highest real per-capita income level in the U.S. and the third highest welfare level; Iowa has both the 18th highest real per-capita income level and the 18th highest welfare level; and Mississippi has the second-lowest real per-capita income level and the lowest welfare level.

The high correlation between welfare and real per-capita income lends some support to the common practice of using real per-capita income as a proxy for the average living standards in the various states. That said, while the ranking of real per-capita income and the ranking of welfare across states are highly correlated, there are large variations in the ranking for some states. As an example, Hawaii has the fourth lowest real per-capita income level but the 13th highest welfare level in the U.S. Conversely, Oklahoma has the 23rd highest real per-capita income level but the third lowest welfare level. There are also economically-large differences between the level of real per-capita income and the corresponding welfare level for some states. As an example, while real income per capita is 15.4 percent lower in Minnesota than in Connecticut, living standards as measured using our welfare metric are 2.9 percent higher in Minnesota than in Connecticut.

We find that average living standards in the U.S. appear marginally closer to those of the richest state, Connecticut, than the corresponding difference in real per-capita income would suggest. In particular, whereas average real income per capita in the U.S. is 23.2 percent lower than in Connecticut, average welfare in the U.S. is 20.1 percent lower than in Connecticut. The dispersion in welfare across states, however, is larger than the corresponding dispersion in real per-capita income levels. While real per-capita income is 34.0 percent higher in Connecticut than in the poorest state, New

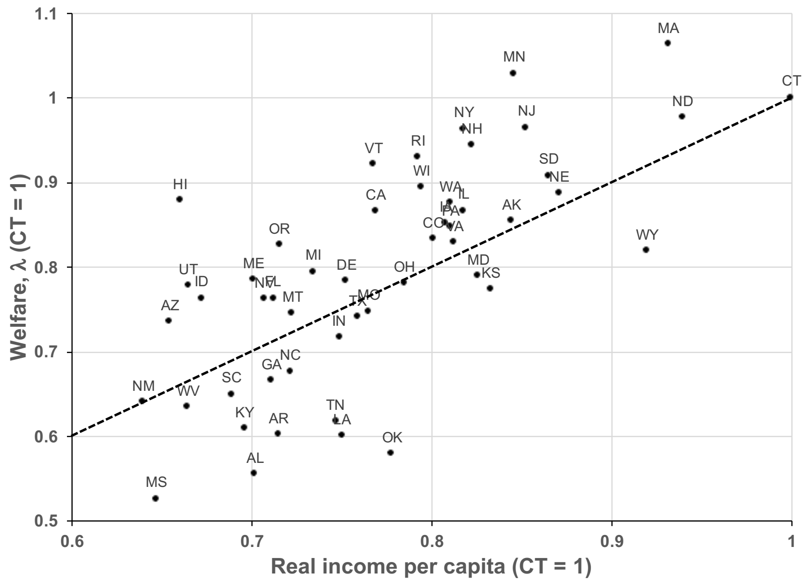

Figure 6: Relationship between real income per capita and welfare in 2015

Notes: The graph plots the relationship between real income per capita and welfare across the states in 2015, where the latter is derived as in Equation (7). We quantify the welfare differences across states by computing how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state. Both welfare and real per-capita income have been normalized by the corresponding value in Connecticut. The dotted line depicts the 45-degree line. The population-weighted correlation between real per-capita income and welfare is 0.75.

Mexico, welfare relative to Connecticut varies from a low of 52.6 percent in Mississippi to a high of 106.3 percent in Massachusetts. As illustrated in Figure 6, welfare is particularly low relative to real income per capita in several states in the South. As an example, Alabama has 29.8 percent lower real income per capita but 44.5 percent lower living standards relative to Connecticut according to our welfare metric.

Our finding that welfare varies considerably across states is in line with evidence from a recent microeconomic literature that uses data on movers to study the causal effect of place of residence. For example, Chetty, Hendren, and Katz (2016), Chyn (2018), Chetty and Hendren (2018), Finkelstein, Gentzkow, and Williams (2021), and Nakamura, Sigurdsson, and Steinsson (2021) find that where one lives matters for health, longevity, earnings (and therefore consumption), and educational attainment, all of which are included in our welfare measure.

The cross-state heterogeneity in living standards could indicate that people are misallocated in the U.S. and therefore that policies that incentivize people to move to higher-welfare states might be welfare enhancing. Given the geographic concentration of living standards displayed in Figure 6, the results suggest that migration from the South to the Northeast, and to a lesser extent from the South to the Midwest and the West, could raise average living standards in the U.S.[18] That said, the gains from moving would likely be smaller than what is implied by Figure 6. This follows because large migration waves across the U.S. would likely be associated with general equilibrium effects that can alter each state's welfare level such as changes in prices and wages across states as well as changes in the states' health care utilization which can lead to changes in state-level life expectancy. Instead of focusing on policies that incentivize people to migrate from lower- to higher-welfare states, policymakers can also raise average living standards in the U.S. by implementing targeted state-specific policies. To better understand what policies the various states should implement, we next apply Equation (9) to decompose each state's welfare level relative to Connecticut to examine why welfare differs across the states.

5.1.2 Decomposing welfare differences across states

The results from this exercise are reported in Table 2, which provides an additive decomposition of the determinants of the welfare differences. Columns 2 and 3 report each state's levels of welfare and real income per capita relative to Connecticut, respectively, with states ordered in descending order from the state with the highest to the lowest welfare level. Using Equation (9), we decompose $\log(\lambda^s)$ into five parts: life expectancy, college attainment, average consumption, average leisure, and inequality of consumption. The decomposition is given in columns 4–8 of Table 2. For each state, values in square brackets in columns 4–8 report, in the following order: life expectancy at birth, percentage of 25–29 year-olds with a college degree, demographic-adjusted per-capita consumption of non-durables and services (in thousands), demographic-adjusted per-capita annual hours worked, and demographic-adjusted standard deviation of the logarithm of consumption.[19]

Consider for example the state with the median welfare level, Maryland. Our decomposition shows that the 1.7 year lower life expectancy in Maryland compared to Connecticut reduces welfare in Maryland by 13 log points. That is, consumption would have to decline by approximately 13

[18] As will be discussed below in Sections 5.3–5.5, the finding that welfare varies across states is robust to several model changes, such as allowing for interstate migration, and is also robust to computing welfare conditional on the individual's educational attainment, gender, and race. Moreover, the cross-sectional heterogeneity in both welfare and real income per capita is not unique to 2015 but applies to every year between 1999 and 2015.

[19] In particular, for each state s, we report the value of $\sum_a \sum_e \Lambda_{ae}^{US} \exp\left(\mu_{ae}^s + \frac{(\sigma_{ae}^s)^2}{2}\right)$ for the demographic-adjusted per-capita consumption of non-durables and services, $\sum_a \sum_e \Lambda_{ae}^{US}\left(1 - \bar{\ell}_{ae}^s\right) \times 5840$ for the demographic-adjusted per-capita annual hours worked assuming $16 \times 365 = 5840$ annual hours available given 8 hours of sleep, and $\sum_a \sum_e \Lambda_{ae}^{US} \sigma_{ae}^s$ for the demographic-adjusted standard deviation of the logarithm of consumption. Here, Λ_{ae}^{US} is the distribution of education given age in the U.S.

Table 2: Comparing welfare across the U.S. in 2015

State	Welfare λ	Income	Decomposition					Inequality
			Life expec.	College	Consumption	Leisure		
MA	106.3	93.2	-0.044 [80.2]	0.047 [51.1]	0.029 [36.9]	0.011 [929]		0.018 [0.59]
MN	102.9	84.6	0.024 [80.7]	0.001 [43.8]	-0.012 [35.4]	-0.046 [1048]		0.062 [0.51]
CT	100.0	100.0	0.000 [80.6]	0.000 [43.8]	0.000 [35.8]	0.000 [960]		0.000 [0.62]
ND	97.7	94.0	-0.038 [79.5]	-0.083 [32.6]	0.140 [41.2]	-0.088 [1143]		0.047 [0.54]
NJ	96.4	85.3	-0.029 [80.1]	0.011 [45.3]	-0.056 [33.9]	0.016 [933]		0.022 [0.59]
NY	96.3	81.8	0.021 [80.6]	0.012 [45.6]	-0.068 [33.4]	0.027 [894]		-0.029 [0.67]
NH	94.4	82.3	-0.076 [79.4]	-0.028 [39.6]	0.005 [36.0]	-0.038 [1040]		0.079 [0.48]
RI	93.0	79.3	-0.050 [79.6]	-0.011 [42.0]	-0.043 [34.3]	0.006 [945]		0.025 [0.58]
VT	92.2	76.8	-0.065 [79.6]	-0.028 [39.5]	-0.013 [35.4]	-0.040 [1043]		0.065 [0.51]
SD	90.8	86.5	-0.061 [79.0]	-0.078 [33.0]	0.051 [37.7]	-0.070 [1110]		0.062 [0.51]
WI	89.4	79.5	-0.035 [79.4]	-0.075 [32.9]	-0.035 [34.6]	-0.030 [1016]		0.063 [0.51]
NE	88.7	87.1	-0.053 [79.3]	-0.033 [38.9]	-0.026 [34.9]	-0.077 [1115]		0.070 [0.50]
HI	87.9	66.0	0.095 [81.5]	-0.118 [27.8]	-0.186 [29.8]	0.004 [952]		0.077 [0.48]
WA	87.6	81.1	-0.027 [80.0]	-0.066 [33.5]	-0.103 [32.4]	0.009 [930]		0.054 [0.53]
IL	86.7	81.8	-0.096 [78.9]	-0.005 [42.9]	-0.061 [33.7]	0.000 [955]		0.019 [0.59]
CA	86.6	76.9	0.046 [80.9]	-0.072 [33.1]	-0.161 [30.5]	0.032 [887]		0.010 [0.61]
AK	85.4	84.5	-0.176 [77.8]	-0.128 [24.1]	0.057 [38.0]	-0.009 [987]		0.100 [0.43]
IA	85.2	80.8	-0.039 [79.3]	-0.047 [36.8]	-0.080 [33.1]	-0.061 [1076]		0.066 [0.51]
PA	84.7	81.0	-0.130 [78.2]	-0.026 [39.7]	-0.046 [34.2]	0.006 [951]		0.030 [0.57]
CO	83.3	80.1	-0.055 [80.1]	-0.035 [38.7]	-0.133 [31.4]	-0.016 [996]		0.056 [0.53]
VA	82.9	81.3	-0.099 [79.0]	-0.034 [38.4]	-0.078 [33.2]	-0.015 [982]		0.038 [0.56]
OR	82.7	71.6	-0.057 [79.4]	-0.092 [30.1]	-0.123 [31.7]	0.036 [886]		0.047 [0.54]
WY	81.9	92.0	-0.093 [78.4]	-0.134 [24.7]	-0.007 [35.6]	-0.046 [1068]		0.081 [0.47]
MI	79.4	73.4	-0.150 [77.8]	-0.057 [34.5]	-0.077 [33.2]	0.017 [920]		0.037 [0.56]
MD	79.0	82.6	-0.128 [78.9]	-0.029 [39.2]	-0.133 [31.4]	-0.009 [976]		0.063 [0.51]
ME	78.5	70.1	-0.109 [78.5]	-0.118 [24.6]	-0.064 [33.6]	-0.005 [965]		0.055 [0.53]
DE	78.3	75.3	-0.124 [78.4]	-0.082 [31.0]	-0.090 [32.8]	0.001 [948]		0.051 [0.53]
OH	78.1	78.5	-0.203 [77.0]	-0.078 [30.7]	-0.005 [35.6]	0.003 [947]		0.037 [0.56]
UT	77.7	66.5	-0.049 [79.5]	-0.110 [26.8]	-0.179 [30.0]	-0.004 [975]		0.090 [0.46]
KS	77.4	83.3	-0.130 [78.4]	-0.027 [39.4]	-0.120 [31.8]	-0.032 [1028]		0.053 [0.53]
ID	76.3	67.2	-0.052 [79.1]	-0.098 [29.6]	-0.188 [29.7]	0.005 [954]		0.061 [0.51]
FL	76.3	71.2	-0.042 [79.5]	-0.090 [30.6]	-0.168 [30.3]	0.017 [919]		0.012 [0.60]
NV	76.2	70.7	-0.128 [78.0]	-0.144 [21.4]	-0.066 [33.6]	0.013 [930]		0.053 [0.53]
MO	74.7	76.5	-0.204 [77.2]	-0.080 [30.9]	-0.041 [34.4]	-0.008 [977]		0.043 [0.55]
MT	74.5	72.3	-0.133 [78.3]	-0.082 [31.3]	-0.117 [31.9]	-0.013 [991]		0.051 [0.53]
TX	74.1	75.9	-0.109 [78.5]	-0.078 [31.3]	-0.124 [31.7]	-0.008 [970]		0.019 [0.59]
AZ	73.5	65.4	-0.046 [79.4]	-0.092 [29.5]	-0.227 [28.6]	0.021 [903]		0.037 [0.56]
IN	71.7	74.9	-0.202 [76.9]	-0.085 [29.4]	-0.096 [32.6]	-0.005 [961]		0.055 [0.53]
NC	67.6	72.2	-0.152 [77.7]	-0.067 [32.8]	-0.202 [29.3]	0.008 [932]		0.022 [0.59]
GA	66.5	71.1	-0.194 [77.3]	-0.076 [31.3]	-0.168 [30.3]	0.012 [922]		0.017 [0.59]
SC	64.9	68.9	-0.227 [76.7]	-0.068 [32.2]	-0.185 [29.8]	0.019 [903]		0.029 [0.57]
NM	64.0	64.0	-0.168 [77.7]	-0.150 [19.1]	-0.195 [29.5]	0.037 [873]		0.030 [0.57]
WV	63.4	66.5	-0.325 [75.0]	-0.069 [30.0]	-0.124 [31.7]	0.031 [865]		0.033 [0.57]
TN	61.7	74.7	-0.282 [75.9]	-0.060 [32.9]	-0.161 [30.5]	0.003 [942]		0.017 [0.59]
KY	60.9	69.6	-0.298 [75.4]	-0.081 [28.6]	-0.141 [31.1]	0.006 [924]		0.017 [0.59]
AR	60.1	71.5	-0.283 [75.6]	-0.104 [25.5]	-0.166 [30.4]	0.021 [895]		0.024 [0.58]
LA	60.0	75.0	-0.300 [75.6]	-0.080 [29.2]	-0.142 [31.1]	0.013 [915]		-0.002 [0.63]
OK	57.9	77.8	-0.302 [75.5]	-0.115 [23.4]	-0.170 [30.3]	0.002 [956]		0.038 [0.56]
AL	55.5	70.2	-0.329 [75.2]	-0.120 [22.0]	-0.175 [30.1]	0.017 [905]		0.019 [0.59]
MS	52.6	64.7	-0.356 [74.6]	-0.127 [19.6]	-0.210 [29.0]	0.034 [863]		0.017 [0.59]

Notes: Column 2 reports how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state in 2015. Column 3 reports each state's real income per capita relative to Connecticut. The welfare decomposition in columns 4–8 is based on Equation (9), which decomposes $\log(\lambda^s)$ into five parts: life expectancy, college attainment, average consumption, leisure, and inequality in consumption. Values in square brackets report state-specific life expectancy at birth, college attainment of 25–29 year-olds, real per-capita consumption of non-durables and services (in thousands), per-capita annual hours worked, and standard deviation of the logarithm of real consumption. The latter three are computed using a common distribution for age and education in all states given by the average distribution in the U.S., Λ_{ae}^{US}.

percent in all ages in Connecticut—holding fixed Connecticut's mortality rates, educational attainment, leisure, and inequality—to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut and Maryland if the difference in life expectancy was the only difference between these two states. The 4.6 percentage point lower college attainment, the $4,400 lower average real consumption, and the 16 hour lower annual leisure in Maryland further reduce welfare by 3, 13, and 1 log points, respectively. In contrast, lower inequality in Maryland increases welfare 6 log points. As a result, we find that consumption has to decrease by 21.0 percent in Connecticut to equalize welfare in Connecticut and Maryland.

Similarly, a comparison between Connecticut and the state with the lowest welfare level, Mississippi, shows that lower life expectancy, lower college attainment, and lower average real consumption reduce welfare by a total of 69 log points in Mississippi. Conversely, higher leisure and lower inequality increase welfare in Mississippi a total of 5 log points. Consequently, we find that consumption has to decrease by 47.4 percent in Connecticut to equalize lifetime expected utility in Connecticut and Mississippi. The welfare comparison between Connecticut and Mississippi is representative of the welfare comparison between high- and low-income states. In particular, lower life expectancy and lower average real consumption in low-income states account for most of the lower welfare in these states compared with high-income states, with lower college attainment further reducing welfare in low-income states. These states, however, generally benefit from higher leisure, which increases welfare in the poorest states up to 4 log points.

The results from the decomposition analysis can be used to guide the design of policies aimed at increasing living standards. Our results suggest that low-income states would benefit, on average, from policies promoting increases in life expectancy (such as through increased access to health care and increased quality of health care) and in college attainment (such as through subsidies for higher education or through loan forgiveness), in addition to policies promoting higher economic activity and therefore higher consumption (such as changes in tax laws). In contrast, high-income states would benefit from policies aimed at reducing cost of living (such as through income-based housing programs to address the higher housing prices in these states; see Appendix Section A.4). Further equalization of average living standards can also be facilitated federally through redistribution from higher- to lower-income states. As noted in the previous subsection, however, the extent to which such policies can raise average living standards in the various states depends on both the magnitude of general equilibrium effects as well as on the extent to which these policies would alter the states' welfare levels by inducing people to migrate.

5.2 Welfare across time

Section 5.1 quantified the cross-sectional welfare differences across the U.S. This section, instead, quantifies each state's annual welfare growth rate between 1999 and 2015.[20] To do so, we follow Jones and Klenow (2016) and let the growth rate of welfare be given by:

$$g_{\lambda}^{s} = -\frac{1}{T}\log\left(\lambda^{s}\right), \tag{13}$$

where $T = 2015 - 1999 = 16$ is the number of years. Here, λ^s is the factor by which we have to adjust real consumption in state s in 2015 to make an unborn individual behind the veil of ignorance indifferent between being born in state s in 2015 compared with being born in that same state in 1999.[21]

This analysis allows us to examine how welfare has evolved in the different states over time. It also allows us to examine whether living standards are in the process of converging in the U.S. Evidence of convergence in welfare levels would indicate that average living standards might simply be temporarily higher in the states that are further along the transition path toward a common steady state. If that were the case, policies inducing people to move to higher-welfare states would not be associated with higher long-run average living standards. Conversely, evidence of divergence or of persistent heterogeneity in welfare levels across states would suggest that there might exist frictions that prevent welfare from being equalized in the U.S.—as we find in Section 5.4 when we allow for interstate migration—in which case the previously-discussed policy implications from the no-migration environment would likely continue to apply.

5.2.1 Comparing growth in welfare with growth in real income per capita

Figure 7 plots the relationship between each state's annual welfare growth rate (vertical axis) and real per-capita income growth rate (horizontal axis) between 1999 and 2015. We find that living standards increased in all states over this time period, with a population-weighted average welfare growth rate of 2.61 percent per year. North Dakota exhibited the highest growth in welfare between 1999 and 2015, with an average growth rate of 3.73 percent per year. In contrast, New Mexico exhibited the lowest growth in welfare, with an average growth rate of 1.68 percent per year over this period. This dispersion in welfare growth rates has large implications for the evolution of living

[20] Due to small sample sizes for some states, we continue to pool data for five-year periods. Throughout, 1999 refers to data for the period 1997–2001 and 2015 refers to data for the period 2013–2017.

[21] Following Jones and Klenow (2016), we average the equivalent and compensating variations when we compute welfare growth rates.

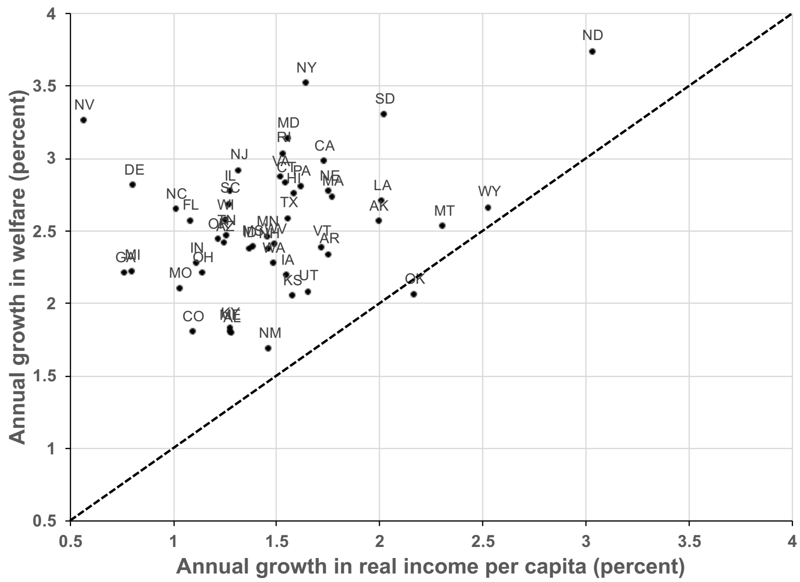

Figure 7: Relationship between growth in real income per capita and growth in welfare between 1999 and 2015

Notes: The graph plots the relationship between real per-capita income growth and welfare growth between 1999 and 2015, where the latter is derived as in Equation (13). We quantify each state's annual welfare growth rate by computing how much consumption would have to change in all ages in state s in 2015 to make an unborn individual behind the veil of ignorance indifferent between being born in state s in 2015 compared with being born in that same state in 1999. The dotted line depicts the 45-degree line. The population-weighted correlation between real per-capita income growth and welfare growth is 0.42.

standards. Given current trends, living standards are expected to double every 41.6 years in New Mexico compared to every 18.9 years in North Dakota.

As shown in Figure 7, welfare has risen more rapidly than real per-capita income in all states except for Oklahoma. The population-weighted average real per-capita income growth rate across states was 1.41 percent per year between 1999 and 2015, or roughly one percentage point lower than the states' average annual welfare growth rate. Moreover, we find that the growth rate of welfare and the growth rate of real per-capita income are only weakly correlated, with a population-weighted correlation of 0.42 across states. Deviations between the states' welfare growth rates and real per-capita income growth rates are also often economically large. As an example, while real income per capita increased 0.57 percent per year in Nevada between 1999 and 2015, its welfare increased 3.25 percent per year over this time period. Hence, whereas the growth rate in real income per capita would suggest that living standards barely rose in Nevada between 1999 and 2015, the growth rate in welfare shows that living standards increased considerably over this period. These findings call to question the common practice, both among economists and policymakers, of using real per-capita income growth rates to measure how fast living standards are rising in various states.

5.2.2 Decomposing each state's annual welfare growth rate

Table 3 provides further details about the welfare growth results discussed in the previous subsection. Column 2 reports the annual growth rate in welfare between 1999 and 2015, g_λ^s, ordered in descending order from the state with the highest to the lowest annual welfare growth rate, and column 3 reports each state's annual growth rate in real income per capita, g_Y^s. To understand why welfare has grown at heterogeneous rates as well as why the rise in living standards and the growth rate in real per-capita income are only weakly correlated, we decompose each state's annual welfare growth rate by applying the same methodology that we used in Section 5.1.2. In particular, we use an equation analogous to Equation (9) to decompose g_λ^s into changes in five parts: life expectancy, college attainment, average consumption, average leisure, and inequality of consumption. The decomposition is given in columns 4–8 of Table 3. For each state, values in square brackets in columns 4–8 report, for both 1999 and 2015, in the following order: life expectancy at birth, percentage of 25–29 year-olds with a college degree, demographic-adjusted per-capita consumption of non-durables and services (in thousands), demographic-adjusted per-capita annual hours worked, and demographic-adjusted standard deviation of the logarithm of consumption (see Section 5.1.2 for details).[22]

The decomposition analysis enables us to examine the determinants of the 2.05 percentage point dispersion in annual welfare growth rates across states (from 1.68 to 3.73 percent). While life expectancy at birth increased in all states between 1999 and 2015, the increase varied considerably across the U.S., ranging from 0.1 years in Oklahoma to 3.2 years in New York. The heterogeneity in longevity gains had large implications for welfare growth rates, increasing welfare 0.01 percent per year in Oklahoma compared to 1.45 percent per year in New York. Note that the experience of Oklahoma is representative of several states in the South. For instance, Alabama, Arkansas, Kentucky, and Mississippi all experienced limited gains in life expectancy over this period. We find that gains in life expectancy increased population-weighted average welfare 0.84 percent per year. A variance decomposition of the dispersion in welfare growth rates across states shows that heterogeneity in life expectancy gains has been the most important driver of the variance in welfare

[22] What matters for welfare growth are changes in ψ_{ae}^s, π_e^s, μ_{ae}^s, σ_{ae}^s, and $\bar{\ell}_{ae}^s$ (see Section 3 for details). An increase in an aggregate statistic such as the demographic-adjusted annual hours worked, which is what is reported in square brackets in Table 3, is therefore not necessarily associated with a reduction in the state's welfare growth rate.

Table 3: Comparing welfare across time: Annual growth rate in welfare between 1999 and 2015

			Decomposition				
State	g_λ^s	g_Y^s	**Life expec.**	**College attain.**	**Consumption**	**Leisure**	**Inequality**
ND	3.73	3.04	0.83 [77.4, 79.5]	0.15 [28.8, 32.6]	2.80 [24.8, 41.2]	-0.02 [1106, 1143]	-0.03 [0.53, 0.54]
NY	3.51	1.64	1.34 [77.4, 80.6]	0.44 [32.6, 45.6]	1.63 [24.3, 33.4]	0.14 [914, 894]	-0.03 [0.66, 0.67]
SD	3.30	2.03	0.79 [77.2, 79.0]	0.19 [28.1, 33.0]	2.16 [25.1, 37.7]	0.15 [1129, 1110]	0.01 [0.52, 0.51]
NV	3.25	0.57	1.16 [75.0, 78.0]	0.20 [15.6, 21.4]	1.57 [24.5, 33.6]	0.38 [1029, 930]	-0.06 [0.51, 0.53]
MD	3.13	1.56	0.99 [76.2, 78.9]	0.29 [30.4, 39.2]	1.52 [23.2, 31.4]	0.35 [1042, 976]	-0.02 [0.51, 0.51]
RI	3.03	1.54	0.76 [77.6, 79.6]	0.47 [28.1, 42.0]	1.62 [25.0, 34.3]	0.27 [995, 945]	-0.10 [0.56, 0.58]
CA	2.97	1.73	1.23 [77.7, 80.9]	0.22 [26.8, 33.1]	1.37 [23.1, 30.5]	0.23 [937, 887]	-0.08 [0.58, 0.61]
NJ	2.91	1.32	1.00 [77.6, 80.1]	0.37 [34.9, 45.3]	1.37 [25.7, 33.9]	0.23 [973, 933]	-0.06 [0.57, 0.59]
VA	2.87	1.52	0.97 [76.7, 79.0]	-0.03 [39.4, 38.4]	1.78 [23.5, 33.2]	0.14 [998, 982]	0.01 [0.56, 0.56]
CT	2.82	1.55	0.97 [78.1, 80.6]	0.41 [32.1, 43.8]	1.27 [27.5, 35.8]	0.19 [990, 960]	-0.03 [0.62, 0.62]
DE	2.81	0.81	0.99 [76.0, 78.4]	0.11 [27.7, 31.0]	1.42 [24.6, 32.8]	0.35 [1033, 948]	-0.06 [0.52, 0.53]
PA	2.80	1.62	0.81 [76.3, 78.2]	0.28 [31.5, 39.7]	1.52 [25.3, 34.2]	0.20 [977, 951]	-0.01 [0.57, 0.57]
IL	2.77	1.28	0.88 [76.8, 78.9]	0.33 [33.2, 42.9]	1.31 [25.8, 33.7]	0.29 [1015, 955]	-0.04 [0.58, 0.59]
NE	2.76	1.76	0.71 [77.5, 79.3]	0.33 [29.7, 38.9]	1.52 [25.8, 34.9]	0.19 [1140, 1115]	0.01 [0.50, 0.50]
HI	2.75	1.58	0.81 [79.2, 81.5]	0.11 [24.8, 27.8]	1.59 [21.8, 29.8]	0.20 [982, 952]	0.04 [0.50, 0.48]
MA	2.73	1.78	0.91 [77.8, 80.2]	0.27 [43.1, 51.1]	1.29 [28.3, 36.9]	0.30 [996, 929]	-0.04 [0.58, 0.59]
LA	2.70	2.01	0.73 [73.8, 75.6]	0.24 [21.1, 29.2]	1.59 [22.6, 31.1]	0.19 [946, 915]	-0.05 [0.61, 0.63]
SC	2.68	1.28	0.69 [74.9, 76.7]	0.40 [20.2, 32.2]	1.22 [23.0, 29.8]	0.36 [993, 903]	0.01 [0.58, 0.57]
WY	2.65	2.53	0.37 [77.4, 78.4]	0.20 [19.3, 24.7]	2.01 [24.3, 35.6]	-0.02 [1038, 1068]	0.09 [0.50, 0.47]
NC	2.64	1.02	0.99 [75.4, 77.7]	0.19 [27.2, 32.8]	1.10 [23.1, 29.3]	0.40 [1029, 932]	-0.03 [0.58, 0.59]
TX	2.58	1.56	0.89 [76.2, 78.5]	0.26 [23.6, 31.3]	1.19 [24.6, 31.7]	0.21 [1008, 970]	0.03 [0.60, 0.59]
WI	2.57	1.25	0.67 [77.8, 79.4]	0.22 [27.1, 32.9]	1.42 [25.9, 34.6]	0.31 [1091, 1016]	-0.05 [0.50, 0.51]
FL	2.56	1.09	0.94 [77.0, 79.5]	0.23 [24.2, 30.6]	1.09 [23.9, 30.3]	0.33 [1003, 919]	-0.03 [0.60, 0.60]
AK	2.56	2.00	0.43 [76.4, 77.8]	0.22 [18.0, 24.1]	1.73 [27.0, 38.0]	0.15 [1010, 987]	0.02 [0.44, 0.43]
MT	2.53	2.31	0.35 [77.1, 78.3]	0.28 [23.5, 31.3]	1.89 [22.2, 31.9]	0.05 [985, 991]	-0.04 [0.52, 0.53]
TN	2.46	1.26	0.84 [73.8, 75.9]	0.35 [21.4, 32.9]	0.97 [24.5, 30.5]	0.27 [994, 942]	0.03 [0.60, 0.59]
MN	2.45	1.46	0.88 [78.7, 80.7]	0.27 [36.4, 43.8]	1.14 [27.8, 35.4]	0.17 [1074, 1048]	-0.01 [0.51, 0.51]
OR	2.44	1.22	0.77 [77.3, 79.4]	0.19 [25.0, 30.1]	1.17 [24.7, 31.7]	0.36 [981, 886]	-0.05 [0.53, 0.54]
AZ	2.41	1.25	0.98 [76.8, 79.4]	0.31 [20.6, 29.5]	0.90 [23.3, 28.6]	0.27 [968, 903]	-0.05 [0.55, 0.56]
WV	2.41	1.49	0.08 [74.8, 75.0]	0.22 [21.8, 30.0]	1.90 [22.0, 31.7]	0.22 [892, 865]	-0.01 [0.57, 0.57]
MS	2.38	1.39	0.32 [73.8, 74.6]	-0.06 [21.7, 19.6]	1.67 [20.9, 29.0]	0.40 [965, 863]	0.07 [0.61, 0.59]
VT	2.38	1.72	0.60 [77.9, 79.6]	0.20 [34.1, 39.5]	1.58 [25.9, 35.4]	0.07 [1037, 1043]	-0.06 [0.49, 0.51]
ID	2.37	1.37	0.31 [78.2, 79.1]	0.28 [22.0, 29.6]	1.55 [21.8, 29.7]	0.32 [1037, 954]	-0.08 [0.49, 0.51]
NH	2.37	1.47	0.35 [78.2, 79.4]	0.47 [26.5, 39.6]	1.49 [26.7, 36.0]	0.11 [1036, 1040]	-0.06 [0.46, 0.48]
AR	2.33	1.76	0.16 [75.1, 75.6]	0.26 [17.5, 25.5]	1.58 [22.1, 30.4]	0.34 [982, 895]	-0.01 [0.58, 0.58]
WA	2.27	1.49	0.75 [77.9, 80.0]	0.19 [28.0, 33.5]	1.15 [25.3, 32.4]	0.18 [970, 930]	0.00 [0.53, 0.53]
IN	2.27	1.12	0.35 [75.9, 76.9]	0.33 [19.2, 29.4]	1.25 [25.1, 32.6]	0.38 [1050, 961]	-0.04 [0.52, 0.53]
MI	2.22	0.80	0.60 [76.4, 77.8]	0.27 [26.4, 34.5]	1.07 [26.3, 33.2]	0.33 [993, 920]	-0.06 [0.55, 0.56]
OH	2.21	1.15	0.34 [76.2, 77.0]	0.14 [26.2, 30.7]	1.49 [26.4, 35.6]	0.27 [1000, 947]	-0.04 [0.55, 0.56]
GA	2.20	0.77	0.97 [74.8, 77.3]	0.00 [31.2, 31.3]	0.92 [24.6, 30.3]	0.34 [1010, 922]	-0.04 [0.59, 0.59]
IA	2.19	1.55	0.43 [78.4, 79.3]	0.17 [32.4, 36.8]	1.41 [24.9, 33.1]	0.20 [1116, 1076]	-0.03 [0.50, 0.51]
MO	2.09	1.03	0.82 [75.3, 77.2]	-0.10 [34.0, 30.9]	1.05 [27.4, 34.4]	0.34 [1043, 977]	0.00 [0.55, 0.55]
UT	2.07	1.66	0.56 [77.9, 79.5]	0.04 [25.8, 26.8]	1.34 [22.8, 30.0]	0.18 [1006, 975]	-0.04 [0.44, 0.46]
OK	2.05	2.17	0.01 [75.4, 75.5]	0.02 [22.6, 23.4]	1.76 [21.4, 30.3]	0.20 [983, 956]	0.06 [0.57, 0.56]
KS	2.05	1.58	0.28 [77.7, 78.4]	0.17 [34.4, 39.4]	1.32 [24.3, 31.8]	0.29 [1082, 1028]	-0.01 [0.53, 0.53]
KY	1.82	1.28	0.08 [75.2, 75.4]	0.18 [22.6, 28.6]	1.35 [23.6, 31.1]	0.24 [971, 924]	-0.02 [0.59, 0.59]
ME	1.80	1.28	0.27 [77.4, 78.5]	0.02 [23.9, 24.6]	1.29 [25.7, 33.6]	0.25 [998, 965]	-0.03 [0.52, 0.53]
CO	1.80	1.10	0.88 [77.7, 80.1]	-0.07 [40.6, 38.7]	0.71 [26.4, 31.4]	0.23 [1046, 996]	0.05 [0.54, 0.53]
AL	1.79	1.28	0.27 [74.4, 75.2]	-0.04 [23.3, 22.0]	1.20 [23.3, 30.1]	0.34 [984, 905]	0.03 [0.60, 0.59]
NM	1.68	1.47	0.13 [77.0, 77.7]	-0.07 [21.3, 19.1]	1.42 [22.1, 29.5]	0.24 [927, 873]	-0.04 [0.56, 0.57]

Notes: Column 2 reports each state's annual welfare growth rate between 1999 and 2015 as defined by Equation (13). Column 3 reports each state's annual real per-capita income growth rate over this time period. Columns 4–8 decompose each state's annual welfare growth rate, g_λ^s, into changes in: life expectancy, college attainment, average consumption, leisure, and inequality in consumption. Values in square brackets report, for each state, for both 1999 and 2015: life expectancy at birth, college attainment of 25–29 year-olds, real per-capita consumption of non-durables and services (in thousands), per-capita annual hours worked, and standard deviation of the logarithm of real consumption. The latter three are computed using a common distribution for age and education in all states given by the average distribution in the U.S., Λ_{ae}^{US}, in 1999 and 2015. The sum of columns 4–8 yields each state's annual welfare growth rate as reported in column 2. Numbers might not add up due to rounding error.

growth rates across the U.S. over this time period, accounting for 61.0 percent of the dispersion in welfare growth rates.[23]

Table 3 shows that the change in college attainment rates varied from a 3.1 percentage point reduction in Missouri to a 14.0 percentage point increase in Rhode Island. Higher college attainment rates increased population-weighted average welfare 0.22 percent per year in the U.S. and accounts for 10.3 percent of the dispersion in welfare growth rates across states. Increased college attainment was a particularly important driver of welfare growth for several states in the Northeast, increasing welfare at least 0.41 percent per year in Connecticut, New Hampshire, New York, and Rhode Island. Most of the increase in the population-weighted average welfare can be attributed to real consumption growth, which increased welfare 1.32 percent per year on average. The welfare increase due to higher real consumption, however, has not been uniform across states, ranging from 0.71 percent per year in Colorado to 2.80 percent per year in North Dakota, and accounts for 37.8 percent of the variance in welfare growth rates. Living standards have also benefitted from an increase in average leisure, which increased population-weighted average welfare 0.26 percent per year. In contrast to consumption growth, the leisure growth has been more uniform across states and only accounts for 3.5 percent of the variance in welfare growth rates. Finally, while within-state inequality has changed over time, these changes only account for 0.9 percent of the variance in welfare growth rates.

These results show that variations in life expectancy gains, consumption growth, and college attainment gains account for almost all of the variation in welfare growth rates across states, with high-growth states generally experiencing higher gains in all these three variables compared to low-growth states. Moreover, the results show that the low correlation and the large deviations between real per-capita income growth and welfare growth across states are to a large extent due to the low correlation between real per-capita income growth and life expectancy gains.[24]

5.2.3 Testing for convergence in welfare levels

Average living standards, from the point of view of an unborn individual, should eventually converge in the various states as long as there are no interstate migration frictions. If this assumption holds,

[23] Let $g_\lambda^s = \sum_{i=1}^5 g_i^s$, where g_λ^s is the growth rate of welfare in state s, g_1^s is the growth rate of welfare due to increased life expectancy in state s, g_2^s is the growth rate of welfare due to increased college attainment in state s, etc. We decompose the variance of the welfare growth across states, $Var\left(g_\lambda^s\right)$, into the sum of the weighted variances plus covariance terms, where each state s is weighted by its population size relative to the total U.S. population in 2015. The numbers reported in the text ignore the covariance terms, and can therefore sum to more than 100 percent, and are given by $\frac{Var\left(g_i^s\right)}{Var\left(g_\lambda^s\right)}$ for each $i \in \{1, \ldots, 5\}$.

[24] The population-weighted correlation between the growth rate of welfare due to increased life expectancy and the growth rate of real per-capita income is equal to 0.12.

the heterogeneity in welfare that we found in Section 5.1 might simply reflect that some states are further along the transition path toward a common steady state. Motivated by this, we test whether states are converging toward similar welfare levels by examining whether states with lower welfare levels in 1999 have exhibited faster growth in welfare than states with higher welfare levels in 1999.[25] The results are illustrated in Figure 8, where states have been ordered in descending order from the state with the highest to the lowest welfare ranking in 1999. We find no evidence of convergence in average welfare over this time period, with a population-weighted correlation between the states' 1999 welfare ranking and their welfare growth rate between 1999 and 2015 equal to -0.08. This finding indicates that the heterogeneity in living standards across states that we found is not transitory. It also questions the common conjecture of no migration costs or free mobility as it indicates that there might exist frictions that prevent welfare from equalizing across the U.S. (see Section 5.4 for how missing variables in our welfare measure such as amenities might affect this conclusion).

Because the 1999–2015 time period that we study includes the Great Recession of 2008–2009, we assess the sensitivity of this finding by testing for convergence in welfare during the two sub-periods preceding and following the Great Recession (1999–2007 and 2007–2015). The results are reported in Table 4. Columns 2–4 show average welfare rankings by year and region and columns 5–7 show average annual welfare growth rates by time period and region. As shown in the first line of the table, the Great Recession had considerable implications for the rise in living standards in the U.S., reducing the growth rate in welfare from 3.59 percent per year between 1999 and 2007 to 1.65 percent per year between 2007 and 2015. We find that average welfare was moderately diverging across the states prior to the Great Recession, with a correlation between the states' 1999 welfare ranking and their welfare growth rate between 1999 and 2007 of -0.30. This period of moderate divergence was followed by a period whereby welfare was neither converging nor diverging in the U.S., with no correlation between the states' 2007 welfare ranking and their welfare growth rate between 2007 and 2015. Hence, our finding that average living standards have not been converging across the states during the 21st century is not sensitive to whether one focuses on the period preceding or following the Great Recession.

Lastly, we examine whether our finding is driven by any specific (sub)-regions. As shown in the second part of Table 4, average living standards in the Midwest and the West converged be-

[25] This is related to a large literature that studies whether countries are converging toward similar GDP per capita levels (see for example Baumol, 1986, and Barro, 1991). Relatedly, Barro and Sala-i-Martin (1992) test for convergence in income per capita across U.S. states.

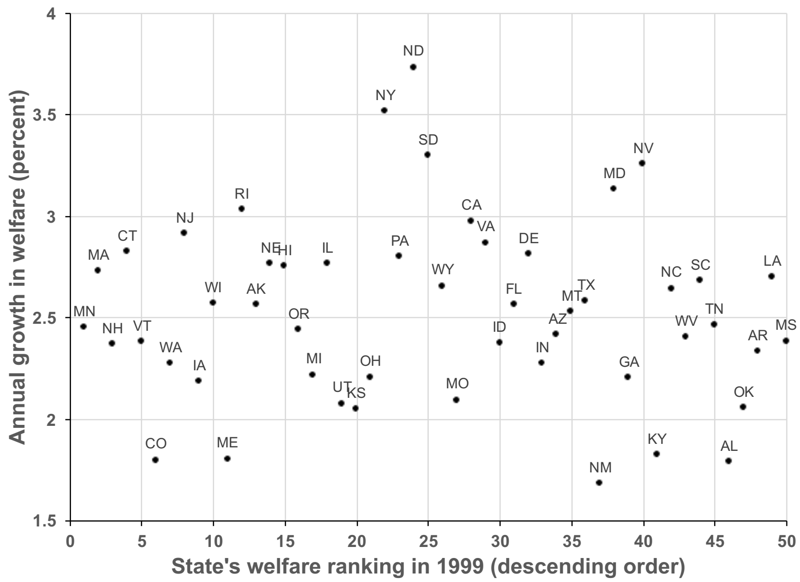

Figure 8: Relationship between ranking of welfare in 1999 and annual growth rate of welfare between 1999 and 2015

Notes: The graph plots the relationship between each state's welfare ranking in 1999 and annual welfare growth rate between 1999 and 2015. States have been ordered in descending order from the state with the highest to the lowest welfare ranking in 1999.

tween 1999 and 2015 due to below- and above-average growth in welfare in the former and latter region, respectively. The convergence between these regions can mostly be attributed to the post-2007 period, during which Midwestern states such as Michigan experienced large job losses because of the 2008–2010 automotive industry crisis. The above-average welfare growth in the West was solely due to the Pacific states, especially during the 2007–2015 period, which more than offset the considerably-lower rise in living standards in the Mountain states. While several Southern states have experienced above-average growth in welfare since 1999—which contributed to a slight welfare convergence between the South and non-Southern states—this growth has not been uniform within the region, with East South Central states experiencing the lowest average rise in living standards in the U.S. because of their limited gains in life expectancy. Finally, while there has been some convergence in welfare within non-Northeastern states, there has been divergence between Northeastern and non-Northeastern states since 1999, with the former region experiencing the fastest rise in living standards in the country. This high growth is due to very rapid welfare growth in the Northeast prior to 2007, when the region's annual growth rate exceeded the other regions by 0.8–1.0 percentage

Table 4: Comparing welfare across time by region and time-period

	Average welfare ranking (year)			Average annual wealth growth (percent)		
Region	**1999**	**2007**	**2015**	**1999–2007**	**2007–2015**	**1999–2015**
United States				3.59	1.65	2.62
Midwest	18	21	22	3.46	1.33	2.40
East North Central	20	23	23	3.40	1.43	2.41
West North Central	15	17	19	3.59	1.12	2.35
Northeast	15	9	9	4.33	1.73	3.03
Middle Atlantic	19	12	10	4.36	1.97	3.17
New England	4	3	5	4.23	1.06	2.64
South	39	38	37	3.34	1.69	2.51
East South Central	45	45	46	3.36	0.88	2.12
South Atlantic	36	35	33	3.54	1.72	2.63
West South Central	40	41	39	2.98	2.07	2.52
West	24	23	21	3.51	1.82	2.66
Mountain	26	29	31	3.18	1.34	2.25
Pacific	24	20	16	3.64	2.02	2.83

Notes: Columns 2–4 report population-weighted average welfare rankings by region—ordered in descending order where 1 refers to the highest-welfare region—with weights given by each region's population size relative to the total U.S. population in that year. Columns 5–7 report population-weighted average annual welfare growth rates by region and time-period, with weights given by each region's population size relative to the total U.S. population in the first year of the time-period. Regions are as classified by the 2010 Census: Midwest is comprised of East North Central (IL, IN, MI, OH, and WI) and West North Central (IA, KS, MN, MO, ND, NE, and SD); Northeast is comprised of Middle Atlantic (NJ, NY, and PA) and New England (CT, MA, ME, NH, RI, and VT); South is comprised of East South Central (AL, KY, MS, and TN), South Atlantic (DE, FL, GA, MD, NC, SC, VA, and WV), and West South Central (AR, LA, OK, and TX); and West is comprised of Mountain (AZ, CO, ID, MT, NM, NV, UT, and WY) and Pacific (AK, CA, HI, OR, and WA).

points. The moderate pre-2007 cross-state divergence in living standards discussed earlier was hence to a large extent driven by the heterogeneous experience of Northeastern and non-Northeastern states.

5.3 Welfare across states given educational attainment, gender, and race

The following subsections compare welfare across states in 2015 conditional on the individual's educational attainment, gender, and race. The results are reported in columns 3–9 in Table 5 (we report the benchmark results in column 2 for reference).

5.3.1 Welfare conditional on educational attainment

The benchmark cross-state welfare analysis in Section 5.1 assumes that educational attainment depends on the individual's state of birth and that the probability of being college-educated is

Table 5: Comparing welfare across the U.S. in 2015 conditional on educational attainment, gender, race, and Hispanic origin

		College attain.		**Race and ethnicity**			**Gender**	
State	**Bench.**	**Non-col.**	**Col.**	**White NH**	**Hispanic**	**Black NH**	**Female**	**Male**
MA	106.3	103.1	99.5	102.8	102.8	106.0	103.9	107.1
MN	102.9	102.7	102.9	95.2	97.6	104.5	103.6	100.0
CT	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
ND	97.7	103.2	109.9	92.0	89.1	104.6	105.1	94.0
NJ	96.4	95.6	95.2	101.1	95.9	95.0	97.7	92.2
NY	96.3	95.7	94.5	98.1	98.9	99.1	95.5	94.3
NH	94.4	97.4	96.6	85.2	107.2	90.2	95.9	93.7
RI	93.0	95.7	92.0	90.0	91.6	90.8	89.4	94.6
VT	92.2	95.2	94.3	82.5	108.6	101.6	93.0	92.8
SD	90.8	96.2	100.7	86.2	89.3	97.5	94.0	89.5
WI	89.4	95.7	97.1	84.2	92.6	91.4	90.1	89.2
NE	88.7	91.5	91.8	83.0	83.1	89.4	87.9	86.9
HI	87.9	96.3	102.3	91.1	104.6	95.9	92.9	87.4
WA	87.6	94.8	92.1	85.5	86.4	94.2	88.9	88.6
IL	86.7	88.6	85.3	87.2	85.8	94.0	84.8	86.2
CA	86.6	93.0	93.1	92.9	89.2	96.4	87.7	85.2
AK	85.4	98.3	95.8	88.1	100.2	97.6	90.0	86.7
IA	85.2	89.0	89.6	78.2	79.9	83.6	86.9	82.4
PA	84.7	88.1	85.6	81.0	88.6	86.0	82.7	84.6
CO	83.3	86.0	86.5	82.6	82.9	86.6	86.8	82.8
VA	82.9	87.2	84.0	86.6	82.5	91.9	83.5	82.9
OR	82.7	90.5	90.9	81.0	80.5	89.2	85.3	83.8
WY	81.9	92.5	95.2	75.7	82.0	84.8	86.9	78.2
MI	79.4	86.0	81.9	77.4	82.0	84.0	79.2	79.6
MD	79.0	82.5	79.8	87.7	89.7	91.6	77.3	81.8
ME	78.5	90.7	85.6	72.7	86.7	88.7	82.2	79.8
DE	78.3	86.0	83.8	84.1	81.7	86.1	79.9	79.4
OH	78.1	87.2	81.3	74.7	84.4	85.8	76.8	79.1
UT	77.7	87.6	85.8	73.3	75.3	78.6	80.1	76.4
KS	77.4	80.7	78.1	73.9	75.1	80.2	76.1	77.2
ID	76.3	83.4	85.0	71.1	71.1	79.8	76.1	75.4
FL	76.3	82.9	84.2	77.4	89.1	84.1	76.5	75.8
NV	76.2	89.1	86.7	78.9	82.4	91.2	76.0	78.6
MO	74.7	82.6	79.1	72.2	74.0	79.3	73.4	76.1
MT	74.5	81.2	80.5	68.0	75.7	78.1	74.5	73.7
TX	74.1	81.5	78.6	79.1	79.1	84.9	74.5	71.9
AZ	73.5	81.4	79.8	78.8	75.7	81.6	73.7	73.5
IN	71.7	80.6	75.1	67.2	70.7	74.6	71.1	69.2
NC	67.6	73.9	70.3	71.1	70.0	76.8	66.1	67.1
GA	66.5	73.5	69.7	74.1	71.7	77.1	65.0	66.4
SC	64.9	71.7	66.9	67.2	70.6	74.2	63.2	64.7
NM	64.0	76.1	72.4	69.5	74.1	73.1	63.7	65.6
WV	63.4	72.9	62.5	57.4	53.6	64.6	60.9	65.6
TN	61.7	68.7	61.9	60.9	61.0	67.1	58.9	62.8
KY	60.9	69.7	61.8	57.4	56.7	65.2	59.0	63.6
AR	60.1	69.3	63.8	59.3	60.8	69.5	58.7	62.2
LA	60.0	68.2	61.3	64.9	68.3	70.1	58.8	60.5
OK	57.9	67.6	61.8	58.6	62.3	67.0	56.0	58.2
AL	55.5	65.5	59.2	58.2	55.6	66.0	55.3	56.4
MS	52.6	63.0	55.9	56.3	62.9	65.1	51.1	53.6

Notes: Column 2 repeats the cross-state welfare results from the benchmark model (see Table 2), i.e., it reports how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state in 2015. The remaining columns report the corresponding welfare results conditional on educational attainment (columns 3–4), race and Hispanic ethnicity (columns 5–7), and gender (columns 8–9).

given by the percentage of 25–29 year-olds with a college degree in that state. It is well-known, however, that high-skilled/college educated individuals often migrate to areas where the return to their skills/college-degree is higher (see for example Borjas, Bronars, and Trejo, 1992; Dahl, 2002; and Diamond, 2016). The benchmark analysis is therefore likely to overestimate living standards in states with high college attainment rates. We therefore consider an alternative case where we compare welfare across states conditional on educational attainment. That is, we compute how much consumption must adjust in all ages in Connecticut to make an unborn individual behind the veil of ignorance—but for whom college attainment (that is, college or non-college) has been revealed—indifferent between living her entire life in Connecticut compared with any other state. The welfare results conditional on being non-college- and college-educated are reported in columns 3 and 4 of Table 5, respectively. As expected, conditioning on education increases welfare in states with low educational attainment relative to states with high educational attainment such as Massachusetts, thereby reducing the disparity in welfare across states relative to the benchmark model. In particular, we find that average welfare conditional on being non-college- (college-) educated in the U.S. is 14.5 (16.8) percent lower than in Connecticut, compared to 20.1 percent in the benchmark model. That said, the welfare analyses conditional on educational attainment lead to qualitatively-similar results as the benchmark welfare analysis, with a population-weighted correlation of at least 0.95 between the benchmark welfare results and the results conditional on educational attainment.

5.3.2 Welfare conditional on race

Data from the CEX show that consumption not only varies with age and education, but also with gender and race. Similarly, data from the CDC and the CPS show that mortality risk and leisure also vary with gender and race. Motivated by this, this subsection computes welfare across states conditional on race (corresponding results conditional on gender are reported in the next subsection and results conditional on both gender and race are reported in Appendix Section C.2). This analysis is related to recent work by Brouillette, Jones, and Klenow (2021), who construct a consumption-equivalent welfare measure to compute welfare for Black and White Americans since 1940, and by Curtis, Garín, and Lester (2021), who construct a similar measure to compute welfare by race, gender, and educational attainment. For the purpose of our analysis, individuals are split into three groups: non-Hispanic White, Asian, and Pacific Islanders; non-Hispanic African American, Native American, and Alaska Native; and Hispanic (for brevity, we refer to the three groups as "White Americans," "African Americans," and "Hispanic Americans"). We apply the same methodology as discussed in Section 4 to derive state-specific educational attainment by gender and race as well as to derive age-, education-, gender-, race-, and state-specific survival probabilities, leisure, and consumption (see Appendix Section A for details).

The results are reported in columns 5–7 of Table 5. Conditioning on race reduces the disparity in welfare across states relative to the benchmark model because the benchmark cross-state welfare results partially suffer from a compositional effect. In particular, the geographic concentration of welfare depicted in Figure 6 shows that low-welfare states are more likely to be in the South, where African Americans—who, on average, suffer from lower life expectancy, consumption, and educational attainment—account for a larger share of the total population. In contrast, higher-welfare states are more likely to be in the Midwest and the Northeast, where White Americans—who, on average, benefit from higher life expectancy, consumption, and educational attainment—account for above-average shares of their populations. Similarly, welfare results for states with above-average shares of Hispanic Americans are partially driven by the average characteristics of this demographic group. Therefore, while average welfare is 20.1 percent lower in the U.S. than in Connecticut in the benchmark model, we find that controlling for race fixed effects, which eliminates the demographic compositional effect, reduces this average welfare difference to 18.9, 17.3, and 13.5 percent for White Americans, Hispanic Americans, and African Americans, respectively. This analysis, however, yields qualitatively-similar results as the benchmark welfare analysis, with a correlation of at least 0.92 between the benchmark welfare results and the results conditional on race.

5.3.3 Welfare conditional on gender

The welfare results conditional on being female and male are reported in columns 8 and 9 of Table 5, respectively. While there are differences in the distribution of gender by state, the differences are quantitatively small. Given that we assume equal sharing of consumption across all household members, it is therefore unsurprising that the welfare analyses conditional on gender lead to very similar results as the benchmark welfare analysis, with a correlation of 0.99 between the benchmark welfare results and the results conditional on either gender.[26]

[26]The assumption of equal sharing of consumption within households leads to the well-known "gender paradox" discussed in the poverty literature: men are statistically recorded as poorer than women under the poverty approach but more women than men are poor from a low-paid perspective. This is unlikely to alter the findings from the cross-state welfare results by gender unless the distribution of consumption within households vary systematically across states.

5.4 Allowing for interstate migration

The benchmark cross-state welfare analysis assumes that the individual will live her entire life in the state that she is born in. A large share of Americans, however, currently reside in a state other than their birth state (see e.g. Molloy, Smith, and Wozniak, 2011, for an analysis of internal migration in the U.S. between 1900 and 2010). This subsection therefore considers an alternative environment where individuals, in each period, can choose what state to reside in. Let s_b denote the individual's state of birth and let s denote the individual's current state of residency. Individuals that choose to reside in a state other than their birth state suffer a utility cost, $m(s; s_b) > 0$, $\forall s \neq s_b$. The problem solved by an individual of age a, educational attainment e, gender x, race r, current state of residency s, and state of birth s_b is then given by:

$$V(a, e, x, r, s; s_b) \quad \max_{s'} \quad u^s_{aexr} - m(s; s_b) + \beta \psi^s_{aexr} V(a+1, e, x, r, s'; s_b), \tag{14}$$

where $u^s_{aexr} \equiv b + ga + \log(\bar{c}^s_{aexr}) - \frac{(\sigma^s_{aexr})^2}{2} + v\left(\bar{\ell}^s_{aexr}\right)$ is the age-, education-, gender-, race-, and state-specific flow utility.[27] We calibrate the utility cost of residing in a state other than one's birth state, $m(s; s_b)$, to match each state's retention rate, given by the percentage of residents in a particular state that were also born in that state, which varies from 45.4 percent in Wyoming to 82.0 percent in Texas (derived from U.S. Census population data reported by the Minnesota Population Center). Appendix Figure A1 shows that the model almost perfectly matches the observed retention rates in the various states.

We find that the results are both qualitatively and quantitatively robust to allowing for migration. As illustrated in Figure 9, which plots each state's welfare level relative to Connecticut in the benchmark model (horizontal axis) and the model with endogenous migration (vertical axis), all states are located closely along the 45-degree line. This shows that the assumption in the benchmark model that the individual will live her entire life in the state that she is born in does not drive the welfare results reported in Section 5.1.

To understand the magnitude of the utility cost required to rationalize the states' retention rates, recall that we normalize units such that consumption of non-durables and services per capita in the U.S. is equal to 1 and that we calibrate the model such that an average 40-year-old has

[27] Data limitations prevent us from conditioning variables in the welfare measure such as consumption and mortality risk on state of birth. Following the discussion in Section 5.3, we condition on gender and race in this subsection. The results reported here are robust to excluding these features from the model. For consistency with the benchmark model, we assume that the individual draws her education, gender, and race at birth from the corresponding state-specific distribution using data from the CPS.

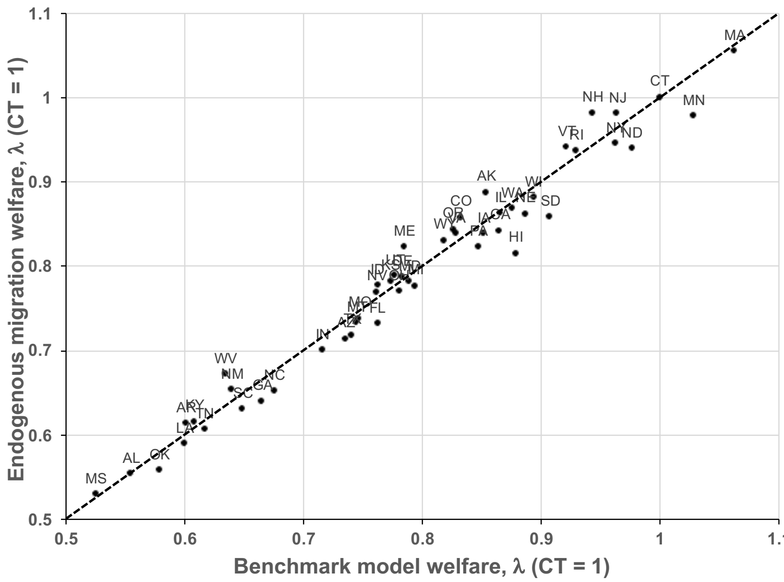

Figure 9: Benchmark model vs. model with endogenous migration

Notes: The graph plots each state's welfare level relative to Connecticut in the benchmark model (horizontal axis) and the model with endogenous migration (vertical axis). The dotted line depicts the 45-degree line.

a value of remaining life equal to \$6.5 million. We derive a population-weighted average utility cost of 0.45, which with our utility function implies that residing in a state other than one's birth state reduces consumption-equivalent welfare by 36.3 percent when the welfare payoff to moving is ignored. The utility cost, however, is heterogeneous across states, ranging from 0.09 in Alaska to 0.80 in Kentucky, with a median of 0.36. It is also strongly negatively correlated with the states' welfare levels (population-weighted correlation $= -0.86$), showing that higher utility costs are required to rationalize the retention rate in lower-welfare states. In terms of the dollar-equivalent of the utility cost, we find that permanently residing in a state other than one's birth state would lower the value of remaining life of an average 40-year-old by approximately \$462,000 when the welfare payoff to moving is ignored, or roughly \$11,000 per year given a remaining life expectancy of about 41 years. While this value is high, it is generally consistent with estimates in the literature. For example, Kennan and Walker (2011) estimate a moving cost for the average mover of \$326,000 (converted to 2012 dollars) when the payoff to moving is ignored.

Our calibrated utility cost captures both pecuniary and non-pecuniary moving costs. Pecuniary moving costs are more likely to be binding for low-income and credit-constrained individuals, and are also more likely to be binding for non-college-educated individuals whose jobs are less likely to cover relocation expenses. Given the positive correlation between real per-capita income and welfare depicted in Figure 6, these costs are thus more likely to be binding in low-welfare states. This suggests that targeted policies that facilitate more interstate migration (such as by offering relocation subsidies) might improve average living standards in the country. That said, the high retention rate in low-welfare states indicates that non-pecuniary moving costs also represent a large share of the calibrated utility cost. The so-called home-state bias or premium, for example, has been found to be a significant aspect in people's migration decisions in the labor literature (e.g., Diamond, 2016), capturing factors such as the impact of social and professional networks (e.g., the preference for residing close to one's family). These non-pecuniary costs are therefore likely to increase the subsidies required to induce people to move by an amount far exceeding the direct pecuniary moving costs (e.g., the value of the home premium estimated by Kennan and Walker, 2011, is equivalent to a wage increase of $24,000 when converted to 2012 dollars).

So far, we have argued that average living standards differ across states, with no evidence of convergence since 1999, and that interstate migration does not equalize welfare due to moving costs. An alternative assumption is that average living standards do not differ across the U.S., a common conjecture if one assumes perfect labor mobility across states as in for example Caliendo, Parro, Rossi-Hansberg, and Sarte (2018). If so, the difference in welfare levels across states reported in Section 5.1 merely provides an estimate of the utility value of all state-level characteristics that are missing in our welfare measure. For example, a large microeconomics literature has shown that amenities such as the quality of restaurants, air quality, climate, sunshine, and coastal proximity—none of which are directly accounted for in our welfare measure—can have large implications for quality of life.[28] Such amenities, however, are unlikely to account for the heterogeneity in welfare that we find because it would imply that the states' quality of amenities should be negatively correlated with their real per-capita income and should be particularly high in lower-income states with high retention rates such as Kentucky. This is inconsistent with microeconomic evidence that shows that the quality of amenities is positively correlated with housing prices (Albouy, 2016), which tend to be higher in high-income states (see Appendix Section A.4). To examine this more formally, we exploit the positive correlation between amenities and housing prices to test the robustness of our results to an alternative utility function that includes housing, h:

[28]Note that some amenities are indirectly accounted for in our welfare analysis. For example, air quality affects mortality risk and is therefore accounted for by the state-specific survival probabilities.

$$u(c, h, \ell) = b + \min\{f_c c, f_h h\} + v(\ell), \tag{15}$$

where $f_c > 0$ and $f_h > 0$ are parameters. This model specifically accounts for the heterogeneity in both consumption-good prices and housing prices across states.[29] As shown in column 5 of Appendix Table A2, the two models give very similar results, with a population-weighted correlation of 0.97 between the benchmark welfare results and the results from the model that includes housing. Therefore, while our welfare measure undoubtedly leaves out many state-level features that might matter for living standards, these features are unlikely to account for the welfare differences that we find unless they are both economically-large and negatively correlated with the states' cost of living.

5.5 Sensitivity

We run a number of robustness exercises to test the sensitivity of the cross-state welfare results. The results are reported in Appendix Tables A2 and A3 (see Appendix Section C.2 for details). As shown in those tables, the results are qualitatively and to a large extent quantitatively robust to: including gender and race in the welfare measure; allowing for exogenous and probabilistic interstate migration; targeting a higher level of consumption inequality derived from the SCF; using an alternative measure of state-level income inequality derived from federal tax returns; allowing the constant term in the utility function to vary with age or consumption; excluding education from the welfare measure; comparing welfare using compensating rather than equivalent variation; using alternative utility functions; varying the targets for the calibrated parameters in the model; excluding expenditures on health care; including durable consumption goods; starting the model at age 2 rather than at age 0 to eliminate the effect of heterogeneous infant mortality rates; and ending the model at age 84 due to top-coding of age in the survey data used in the paper.

5.6 Comparison with Jones and Klenow (2016)

We end by comparing the main results from our cross-state welfare analysis with the corresponding results from the cross-country welfare analysis in Jones and Klenow (2016). One of the main take-aways from their analysis is that GDP per capita is an excellent indicator of welfare across a broad

[29] See Appendix Section B.2 for mathematical details. The Leontief preferences over consumption and housing can account for the considerable heterogeneity in expenditure shares on housing in the U.S., which range from 15 percent in West Virginia to 29 percent in Hawaii. This model extension is also in line with Recommendation 1 by the Stiglitz, Sen, and Fitoussi (2009) Commission because it enables us to better account for differences in consumption baskets across states that might matter for living standards.

range of countries, with a correlation of 0.98 between the two measures. While the two measures are also positively correlated across states in the U.S., Section 5.1 found that the correlation is weaker (0.75) and that there are economically-large differences between the two measures for some states.[30] This indicates that real per-capita income is less correlated with the various inputs in the welfare measure across states than it is across countries, with the most economically-significant factor being life expectancy. As shown in Figure 2, life expectancy at birth is nearly uncorrelated with real per-capita income for the poorest thirty states. This low correlation is partially due to region-specific compositional effects (see Section 5.3 for a discussion on the impact of gender and race on the welfare results). Hence, using real per-capita income as a proxy for living standards in the various states would fail to capture that states with similar real per-capita income levels can differ considerably in their levels of life expectancy at birth, a key driver of the welfare differences across states. This is less of a concern in the cross-country welfare analysis because of the stronger relationship between GDP per capita and life expectancy across countries.

A second key take-away from Jones and Klenow (2016) is that the growth rate in per-capita GDP is also an excellent indicator of the growth rate in welfare across countries, with a correlation of 0.97 between the two measures. This is substantially higher than the corresponding correlation across states (0.42). As discussed in Section 5.2, this weak relationship between welfare growth and real per-capita income growth across states is to a large extent driven by the low correlation between real per-capita income growth and life expectancy gains. Therefore, while GDP per capita is an excellent indicator for both the level and rise in living standards across countries, our analysis suggests that caution needs to be exercised when doing the same in the cross-state context because of the weak relationship between real per-capita income and both the level and rise in life expectancy.

6 Conclusion

This paper developed a welfare measure to examine how living standards, or welfare, vary across the U.S. in 2015 and how each state's living standards evolved between 1999 and 2015. Our welfare measure accounts for cross-state variations in mortality risk, college attainment, consumption, leisure, and inequality. We compared living standards across states by quantifying how much consumption

[30] Recall that we extend the welfare measure in Jones and Klenow (2016) to including educational attainment. Moreover, we also use the states' real per-capita personal income rather than GDP per capita as in Jones and Klenow (2016). The weaker correlation between real per-capita income and welfare, however, is robust to both excluding education from the welfare measure (correlation = 0.70) and to using real GDP per capita rather than real personal income per capita (correlation = 0.64).

must adjust in all ages in the state with the highest real per-capita income, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state. Our main finding is that there exists considerable cross-state heterogeneity in average living standards. This result is robust to computing welfare conditional on the individual's educational attainment, gender, and race, and is also robust to including housing in the welfare measure and to allowing for endogenous interstate migration. We then examined if living standards are in the process of converging across the U.S. by testing whether states with lower welfare levels in 1999 have exhibited faster growth in welfare than states with higher welfare levels in 1999. While states have experienced heterogeneous welfare growth rates—ranging from 1.68 to 3.73 percent per year—we found no evidence of convergence during the 21st century, thus indicating that the heterogeneity in living standards across states is unlikely to be a transitory result.

Our welfare measure does not directly account for cross-state variation in amenities. Accounting for amenities in the welfare measure is challenging because some amenities, such as the number of restaurants per capita, directly affect the quality of consumption, whereas others, such as air quality, directly affect mortality risk. Amenities such as better air quality are hence already indirectly accounted for in our welfare analysis in the form of higher state-specific survival probabilities. Moreover, while data on most amenities at the city or urban level are easily obtainable, amenity data for non-urban areas are scarcer. State-level measures of amenities built from city-level amenity data might therefore be more representative of the urban areas within each state rather than the state as a whole. That said, we think a promising direction for future research would be to extend our welfare measure to also include amenities, which requires disentangling the direct effect of amenities for welfare from the corresponding indirect effects that are already accounted for in our welfare analysis. Finally, while our results imply that there is room for policy to improve average living standards in the U.S., our results cannot be used to quantify the welfare implications of various policy reforms. This follows because large policy reforms would likely be associated with general equilibrium effects and might also induce people to migrate. Our results, however, can be used both to guide the development of structural models and to identify what policies are likely to be most effective at raising average living standards in the various states.

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Online Appendix

A Data

This section provides further details about the data.

A.1 Current Population Survey

This section provides information about the Current Population Survey (CPS) data used in the paper. The CPS data are publicly available and can be downloaded from "https://cps.ipums.org/cps/index.shtml."

Educational attainment

We use the following variables to compute educational attainment by age and state:

1. "year": survey year. We use data for the period 1997–2017. We always pool five-year data samples and identify the year of the sample by the mid-point of the sample (e.g., year=1999 means that data for the period 1997–2001 are used, year=2000 means that data for the period 1998–2002 are used, etc.).
2. "age": person's age.
3. "asecwt": person-level survey weight.
4. "statecensus": identifies the household's state of residence using Census state codes.
5. "educ": respondent's educational attainment.
   (a) We drop individuals with educ=1 (NIU or blank) and educ=999 (Missing/Unknown).
   (b) We define "college-educated" as having a minimum of a bachelor's degree or at least four years of college.
6. We compute the share of college-educated individuals for each state, five-year age-group (25+), and year. Observations are weighted by means of asecwt.
   (a) Due to top-coding of age at 85 in several of the datasets used in the paper, we always pool all 85+ year-olds.

In addition to the variables listed above, we also use the following variables to compute educational attainment by age, gender, race, and state:

1. "sex": person's gender.

2. "race" and "hispan": person's race and Hispanic ethnicity. For the purpose of this analysis, individuals are split into three race and Hispanic ethnicity groups:

   (a) Non-Hispanic White, Asian, or Pacific Islander.

   (b) Hispanic (all races).

   (c) Non-Hispanic Black, American Indian, Alaska Native, or other (including multiple races).

3. We use ten-year age-groups (25+) to compute gender- and race-specific educational attainment by state due to small sample sizes for some states. Observations are weighted by means of asecwt.

Leisure

In addition to the variables listed above, we use the following variables to compute leisure by age, gender, race, and state:

1. "wkswork1": weeks worked last year.

2. "uhrsworkly": usual hours worked per week (last yr).

   (a) We compute leisure as follows (annual hours available given eight hours of sleep, 16*365=5840): leisure=(5840-wkswork1*uhrsworkly)/5840.

3. We compute average leisure for each state, college attainment, five-year age-group (15+), and year. Observations are weighted by means of asecwt.

   (a) We assume leisure=1 for all individuals aged 0–14.

   (b) We pool all 85+ year-olds.

4. We use ten-year age-groups (15+) to compute gender- and race-specific leisure by state due to small sample sizes for some states. Observations are weighted by means of asecwt.

A.2 Consumer Expenditure Survey

This section provides information about the Consumer Expenditure Survey (CEX) data used in the paper. The CEX data are publicly available and can be downloaded from "https://www.bls.gov/cex/pumd_data.htm."

MEMI files

The MEMI interview files provide demographic information about the various household members. We use these files to derive the following information:

1. "age": person's age.
2. "educa": highest level of school the member has completed or the highest degree the member has received.
   (a) We define "college-educated" as having a minimum of a bachelor's degree or at least four years of college.
3. "sex": person's gender.
4. "horigin": person's Hispanic ethnicity.
5. Race as reported by the the respondent ("rc_white," "rc_asian," "rc_pacil," "rc_black," "rc_natam," "rc_other," and "rc_dk"). For the purpose of this analysis, individuals are split into three race and Hispanic ethnicity groups:
   (a) Non-Hispanic White, Asian, or Pacific Islander.
   (b) Hispanic (all races).
   (c) Non-Hispanic Black, American Indian, Alaska Native, or other (including multiple races).

FMLI files

We use the household-level expenditure data reported in the FMLI files. We obtain expenditures for the three months prior to the interview by summing current-quarter and past-quarter variables for each expenditure category. As noted in Section 4.2, the benchmark model focuses on consumption of non-durables and services. This includes expenditures on food, alcohol, tobacco, apparel, health care, education, reading, utilities, personal care, insurance, and other miscellaneous expenditures. It also includes the non-durable or service component of housing expenses, transportation expenses, and entertainment expenses. Quarterly services from housing for owner-occupied dwellings are approximated by means of the imputed rental value using three times the value of "renteqvx," whereby homeowners are asked the following question: "If someone were to rent your home today, how much do you think it would rent for monthly, unfurnished and without utilities?" We convert the data from household-level to individual-level by allocating consumption uniformly across all household members. We compute the age- and education-specific mean and standard deviation of the logarithm of consumption using five-year age-groups, with all 85+ year-olds pooled together due to top-coding of age. Similarly, we compute the age-, education-, gender-, and race-specific mean and standard deviation of the logarithm of consumption using ten-year age-groups. Observations are weighted by means of finlwt21.

A.3 Mortality data

Underlying Cause of Death

We use data from the Underlying Cause of Death (UCD) database reported by the CDC to derive age- and state-specific survival probabilities.[31] The UCD data are available from 1999 and can be publicly accessed from "https://wonder.cdc.gov/ucd-icd10.html." We group the results by state and single-age to derive the number of deaths and the size of the population by age and state. The UCD database does not report the number of deaths or the size of the population by single-age if there are fewer than ten deaths in a single-age/state bin. We address this by grouping the results by state and five-year age groups, and then use the five-year age group mortality and population data to interpolate the number of deaths and the population by single-age if those are missing. Because we always pool data for five-year periods (e.g., data for 2015 refers to pooled data for the period 2013–2017), we only have to interpolate the single-age mortality and population data by means of five-year age group mortality and population data for a few low-population states.

We also use the UCD database to derive age-, gender-, and race-specific survival probabilities for the U.S. We do this by grouping the results by single-age, gender, Hispanic origin, and race to derive the number of deaths and the size of the population for a given demographic group. For the purpose of this analysis, individuals are split into three race and Hispanic ethnicity groups: Non-Hispanic White, Asian, or Pacific Islander; Hispanic (all races); and Non-Hispanic Black or African American, American Indian, or Alaska Native.

[31] What matters for the welfare analysis are age- and education-specific survival probabilities, ψ^s_{ae}, rather than life expectancy at birth, which is what we report in square brackets in Tables 2 and 3. Life expectancy at birth in a given year is a hypothetical measure that reports the number of years a newborn is expected to live if mortality rates prevailing at the time of birth pertain throughout the individual's lifespan. In contrast, age- and education-specific death rates represent the observed number of deaths at one point in time for people of a particular age and educational attainment. Period-life tables are used to convert age- and education-specific death rates in a particular year into age- and education-specific survival probabilities, which in turn can be used to compute year-specific life expectancy at birth (as well as remaining life expectancy conditional on age and educational attainment).

National Vital Statistics System

We use Multiple Cause-of-Death Data from the National Vital Statistics System (NVSS). This publicly available data can be downloaded from the NBER: "https://www.nber.org/research/data/mortality-data-vital-statistics-nchs-multiple-cause-death-data." We use this data to compute the number of deaths by age and state of occurrence for 1999 and 2000 (based on pooled data for the period 1997–2001 and 1998–2002, respectively). We combine this data with population data by age and state to derive age- and state-specific death rates for 1999 and 2000. As noted in Section 4.1, we also use the NVSS to compute the college survival premium for each year between 1999 and 2015, defined as the difference between the age-specific survival probability of college and non-college educated individuals.

Because we use data from both the UCD database and the NVSS, our welfare results might suffer from dual data source bias. For example, Hendi (2017) finds that the dual data source bias tends to overstate mortality among the less-educated and the degree of error varies with time, age, race, and gender. While we acknowledge that this bias might affect the benchmark cross-state welfare results, we believe this bias is less problematic in our context for two reasons. First, we only use the NVSS data in the cross-state welfare analysis to derive the college survival premium. As shown in column 10 of Appendix Table A2, however, the results are robust to excluding education from the model, in which case we solely rely on data from the UCD database. Second, a comparison of the mortality data from the UCD and the NVSS database for the period 2013–2017 show that the two datasets report nearly identical age-specific death counts for 0–84 year-olds—with a maximum difference of 1.3 percent, or a difference of 29 deaths—which indicates that the magnitude of the potential dual data source bias is likely to be limited.

Deriving survival probabilities by gender and race

We derive age-, education-, gender-, race-, and state-specific survival probabilities, ψ^{s}_{aexr}, by means of a two-step procedure. First, we use the NVSS data to compute the gender-specific college survival premium as given by the difference between the age- and gender-specific survival probability of college and non-college educated individuals, $\psi^{\text{NVSS}}_{ax2} - \psi^{\text{NVSS}}_{ax1}$. Given an initial guess, we then derive age-, education-, gender-, and race-specific survival probabilities for the U.S. by iterating on the guess to match the age-, gender-, and race-specific survival probabilities from the UCD database reported by the CDC, ψ^{CDC}_{axr}, and the age-, gender-, and education-specific survival premium from the NVSS, $\psi^{\text{NVSS}}_{ax2} - \psi^{\text{NVSS}}_{ax1}$. For each age, gender, and race, this corresponds to deriving the ψ^{US}_{axre} that solve the following system of equations:

$$\begin{aligned}\psi_{axr}^{\text{CDC}} &= \textstyle\sum_{e=1}^{2} \Lambda_{axre}^{\text{US}} \psi_{axre}^{\text{US}} \\ \psi_{ax2}^{\text{NVSS}} - \psi_{ax1}^{\text{NVSS}} &= \psi_{axr2}^{\text{US}} - \psi_{axr1}^{\text{US}},\end{aligned}$$

where $\Lambda_{axre}^{\text{US}}$ denotes the distribution of education given age, gender, and race in the U.S. from the CPS. Note that this approach relies on the assumption that the age- and gender-specific mortality difference between college and non-college educated individuals is common across all races.

Second, we derive age-, education-, gender-, race-, and state-specific survival probabilities, ψ_{axre}^{s}, by first computing the age-specific scaling factor, q_a^s, required to match the age- and state-specific survival probabilities from the CDC, ψ_a^s:

$$q_a^s = \frac{\psi_a^s}{\sum_{x=1}^{2}\sum_{r=1}^{3}\sum_{e=1}^{2} \Lambda_{axre}^{s} \psi_{axre}^{\text{US}}},$$

where $\Lambda_{axre}^{\text{s}}$ denotes the distribution of education given age, gender, race, and state from the CPS. Age-, education-, gender-, race-, and state-specific survival probabilities are then given by $\psi_{axre}^{s} = q_a^s \psi_{axre}^{\text{US}}$.

A.4 Cost of living

We use data on Regional Price Parities (RPPs) reported by the BEA to examine how cost of living varies across states. These price parities measure how expensive specific consumption categories are in a state relative to the national average. The BEA reports state-specific RPPs for four consumption categories: "all items," "goods," "rents," and "other." The benchmark analysis uses RPPs on "all items," which ranges from 13.6 percent below the national average in Mississippi to 18.6 percent above the national average in Hawaii, with richer states generally exhibiting higher prices than poorer states. Note that the BEA only reports state-specific RPPs for the period 2008–2017. We therefore approximate each state's average price level in 1999 by the corresponding average price level for the period 2008–2010.[32]

Section 5.4 considers an alternative model where we distinguish between consumption-goods and housing. That model enables us to account for the considerable heterogeneity in housing expenditure shares in the U.S. (see Appendix Section B.2 for details). We use the RPP for rent to approximate the price of housing in this model. Using state-specific expenditure shares on rents from the BEA,

[32] Analogously, due to data limitations, we use the average GINI coefficient of household income for the period 2006–2008 to approximate for inequality in 1999.

we then aggregate the RPPs for the other two components, goods and other, into one RPP, which we for simplicity refer to as consumption goods. Consumption-good prices are on average higher in richer states and vary from 8.8 percent below the national average in Mississippi to 9.7 percent above the national average in New York. Housing prices vary more than consumption-good prices across the U.S., ranging from 36.8 percent below the national average in Arkansas to 59.1 percent above the national average in Hawaii. Housing prices tend to be higher in richer states than in poorer states and are particularly high in some of the Pacific and Northeastern states.

Note that the BEA mainly uses data from cities to compute rent-specific RPPs. As a result, rent-specific RPPs are likely to largely reflect the prices in specific cities within a given state, such as San Francisco in California and New York City in New York, and might therefore overestimate the overall housing prices in these states. Moreover, because homeownership rates vary by state and housing prices vary more across places than rents (Molloy, Nathanson, and Paciorek, 2022), our measure might only provide a noisy estimate of the average housing price in the various states. That said, given that we find a population-weighted correlation of 0.97 between the benchmark welfare results and the results from the model that includes housing, substantial housing price mismeasurements would be required to change the results discussed in Section 5.4.

B Mathematical derivations

B.1 Derivation of b in the benchmark model

As explained in Section 4.4, we calibrate the constant term in the utility function, b, as in Jones and Klenow (2016) such that an average 40-year-old has a value of remaining life equal to \$6.5 million in 2012 prices. We convert the dollar-amount of the statistical value of life to utility units by multiplying by the marginal utility of consumption, evaluated using average consumption of a 40-year-old in the U.S, $\bar{c}\,(40) \equiv \sum_{e=1}^{2} \pi_e^{US} \exp\left(\mu_{40e} + \frac{\sigma_{40e}^2}{2}\right)$ (we use the college attainment distribution for 25–29 year-olds for consistency with the welfare analysis). The constant term can then be derived from the following equation:

$$\begin{aligned} \frac{\$6{,}500{,}000}{\bar{c}(40)} &= \sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US} \left[b + g\,(a-40) + \mu_{ae} + v\left(\bar{\ell}_{ae}^{US}\right)\right] \\ b &= \frac{\frac{\$6{,}500{,}000}{\bar{c}(40)} - \sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US} \left[g(a-40) + \mu_{ae} + v\left(\bar{\ell}_{ae}^{US}\right)\right]}{\sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US}}, \end{aligned}$$

where S_{ae}^{US} is the education-specific probability of surviving from age 40 to age $a \geq 41$, with $S_{40e}^{US} = 1$ for all e, and where we have replaced leisure by type-specific average leisure, $\bar{\ell}_{ae}^{s}$, and used that $\mathbb{E}_{ae}\left[\log\left(c_{ae}\right)\right] = \mu_{ae}$. As noted in Section 4.4, this leads to a value of 6.21 for b when consumption of non-durables and services per capita in the U.S. in 2015 is normalized to 1.

B.2 Model with consumption, leisure, and housing

Suppose the individual derives utility from consumption goods, c, housing, h, and leisure, ℓ. Let p_c^s and p_h^s denote the price of consumption goods and the price of housing in state s relative to the national average price level, p, which we normalize to one. Let $E_{ae}^s = p_c^s c_{ae}^s + p_h^s h_{ae}^s$ denote total expenditures given the individual's age, education, and state of residence.

Data from the BEA show that expenditure shares on housing vary considerably across the U.S., from a low of 0.15 in West Virginia to a high of 0.29 in Hawaii in 2015. As will be shown below, these statistics are well-approximated by Leontief preferences over consumption and housing. We therefore let flow utility from consumption goods, housing, and leisure be given by:

$$u\left(c_{ae}^s, h_{ae}^s, \ell_{ae}^s\right) = b + \min\left\{f_c c_{ae}^s, f_h h_{ae}^s\right\} + v\left(\ell_{ae}^s\right),$$

where $f_c > 0$ and $f_h > 0$ are parameters and where $v\left(\ell_{ae}^s\right)$ is as given in Equation (12). Given these preferences, it follows that $f_c c_{ae}^s = f_h h_{ae}^s$ in equilibrium, which together with the budget constraint gives the following expression for c_{ae}^s and h_{ae}^s:

$$\begin{aligned} c_{ae}^s &= \tfrac{E_{ae}^s f_h}{p_c^s f_h + p_h^s f_c} \\ h_{ae}^s &= \tfrac{E_{ae}^s f_c}{p_c^s f_h + p_h^s f_c}. \end{aligned}$$

Assume that total expenditures, E_{ae}^s, grow at a common, non-state dependent, annual rate g. Flow utility can then be rewritten as follows after substituting for c_{ae}^s or h_{ae}^s:

$$u\left(E_{ae}^s \exp\left(ga\right), \ell_{ae}^s\right) = b + \frac{f_c f_h}{p_c^s f_h + p_h^s f_c} E_{ae}^s \exp\left(ga\right) + v\left(\ell_{ae}^s\right).$$

We continue to assume that total expenditures are drawn from an age-, education-, and state-specific lognormal distribution with mean of logarithmic values, μ_{ae}^s, and standard deviation of logarithmic values, σ_{ae}^s. The arithmetic mean is therefore given by $\exp\left(\mu_{ae}^s + \frac{\left(\sigma_{ae}^s\right)^2}{2}\right)$. Expected utility can then be rewritten as follows:

$$\mathbb{E}_{ae}^{s}\left[u\left(E_{ae}^{s}\exp\left(ga\right),\ell_{ae}^{s}\right)\right]=b+\frac{f_c f_h}{p_c^s f_h+p_h^s f_c}\exp\left(\mu_{ae}^{s}+\frac{\left(\sigma_{ae}^{s}\right)^2}{2}\right)\exp\left(ga\right)+v\left(\bar{\ell}_{ae}^{s}\right),$$

where we have replaced leisure by type-specific average leisure, $\bar{\ell}_{ae}^{s}$.

We calibrate the parameters of the three-good model with consumption, housing, and leisure to match the average expenditure share on housing in the U.S. and the average remaining value of life at age 40. The expenditure share on housing given age, education, and state of residence is given by

$$\frac{p_h^s h_{ae}^s}{E_{ae}^s}=\frac{p_h^s\frac{E_{ae}^s f_c}{p_c^s f_h+p_h^s f_c}}{E_{ae}^s}=\frac{p_h^s f_c}{p_c^s f_h+p_h^s f_c}.$$

We set f_c to match the 21.6 percent average expenditure share on housing in the U.S., ω_h^{US}, in 2015 as reported by the BEA, $f_c=\frac{\omega_h^{US}p_c^{US}f_h}{\left(1-\omega_h^{US}\right)p_h^{US}}$. The derived value for f_c depends on the value for f_h. We therefore jointly calibrate b and f_h to match a value of remaining life equal to \$6.5 million in 2012 prices as well as the level of b in the benchmark model, 6.21. This ensures that the level of flow utility is comparable in the benchmark model and the robustness model with two goods. The equation used to derive the constant term can be derived by following the same steps as discussed in Section B.1:

$$\begin{aligned}\$6,500,000\frac{f_c f_h}{p_c^{US}f_h+p_h^{US}f_c} &= \sum_{e=1}^{2}\pi_e^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}\left[b+\frac{f_c f_h}{p_c^{US}f_h+p_h^{US}f_c}\exp\left(\mu_{ae}+\frac{\sigma_{ae}^2}{2}\right)\exp\left(g\left(a-40\right)\right)+v\left(\bar{\ell}_{ae}^{US}\right)\right]\\ b &= \frac{\$6{,}500{,}000\frac{f_c f_h}{p_c^{US}f_h+p_h^{US}f_c}-\sum_{e=1}^{2}\pi_e^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}\left[\frac{f_c f_h}{p_c^{s}f_h+p_h^{s}f_c}\exp\left(\mu_{ae}+\frac{\sigma_{ae}^2}{2}\right)\exp(g(a-40))+v\left(\bar{\ell}_{ae}^{US}\right)\right]}{\sum_{e=1}^{2}\pi_e^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}},\end{aligned}$$

where $\frac{f_c f_h}{p_c^{US}f_h+p_h^{US}f_c}$ is the marginal utility of total expenditures, $\frac{\partial u\left(E_{ae}^{US},\ell_{ae}^{US}\right)}{\partial E_{ae}^{US}}$, evaluated at age 40. The derived parameters lead to a population-weighted correlation between the state-specific expenditure share on housing in the model and the data of 0.91, which shows that the Leontief preferences over consumption and housing provides a very good fit of the data. The preferences match the full distribution of state-specific expenditure shares on housing, including the median (20.4 percent in the data vs. 20.5 percent in the model), bottom 1 percent (15.2 percent in the data vs. 15.7 percent in the model), and top 1 percent (27.1 percent in the data vs. 28.3 percent in the model).

B.3 Model with CRRA preferences

Separable between consumption and leisure Let flow utility from consumption and leisure be given by:

$$u\left(c_{ae}^{s}, \ell_{ae}^{s}\right) = b + \frac{\left(c_{ae}^{s}\right)^{1-\gamma} - 1}{1-\gamma} + v\left(\ell_{ae}^{s}\right),$$

where $v\left(\ell_{ae}^{s}\right)$ is as given in Equation (12). This utility function nests the benchmark utility function as the limit case when $\gamma = 1$. Assume that consumption grows at a common, non-state dependent, annual rate g. Flow utility can then be rewritten as

$$u\left(c_{ae}^{s} \exp\left(ga\right), \ell_{ae}^{s}\right) = b + \frac{\left(c_{ae}^{s}\right)^{1-\gamma}\left(\exp\left(ga\right)\right)^{1-\gamma} - 1}{1-\gamma} + v\left(\ell_{ae}^{s}\right).$$

We continue to assume that $c_{ae}^{s} \sim LN\left(\mu_{ae}^{s}, \sigma_{ae}^{s}\right)$. Then $\mathbb{E}_{ae}^{s}\left[\left(c_{ae}^{s}\right)^{1-\gamma}\right] = \exp\left(\left(1-\gamma\right)\mu_{ae}^{s} + \frac{(1-\gamma)^2\left(\sigma_{ae}^{s}\right)^2}{2}\right)$. Expected utility is then given by:

$$\mathbb{E}_{ae}^{s}\left[u\left(c_{ae}^{s} \exp\left(ga\right), \ell_{ae}^{s}\right)\right] = b + \frac{\exp\left(\left(1-\gamma\right)\mu_{ae}^{s} + \frac{(1-\gamma)^2\left(\sigma_{ae}^{s}\right)^2}{2}\right)\left(\exp\left(ga\right)\right)^{1-\gamma} - 1}{1-\gamma} + v\left(\bar{\ell}_{ae}^{s}\right),$$

where we have replaced leisure by type-specific average leisure, $\bar{\ell}_{ae}^{s}$.

We continue to calibrate the constant term in the utility function, b, such that an average 40-year-old has a value of remaining life equal to \$6.5 million in 2012 prices. The equation used to derive the constant term can be derived by following the same steps as discussed in Section B.1:

$$\begin{aligned}
\$6,500,000\bar{c}\left(40\right)^{-\gamma} &= \sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US}\left[b + \frac{\exp\left((1-\gamma)\mu_{ae} + \frac{(1-\gamma)^2\sigma_{ae}^2}{2}\right)\left(\exp(g(a-40))\right)^{1-\gamma} - 1}{1-\gamma} + v\left(\bar{\ell}_{ae}^{US}\right)\right] \\
b &= \frac{\$6,500,000\bar{c}(40)^{-\gamma} - \sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US}\left[\frac{\exp\left((1-\gamma)\mu_{ae} + \frac{(1-\gamma)^2\sigma_{ae}^2}{2}\right)\left(\exp(g(a-40))\right)^{1-\gamma} - 1}{1-\gamma} + v\left(\bar{\ell}_{ae}^{US}\right)\right]}{\sum_{e=1}^{2} \pi_e^{US} \sum_{a=40}^{100} \beta^{a-40} S_{ae}^{US}},
\end{aligned}$$

where $\bar{c}\left(40\right)^{-\gamma}$ is the marginal utility of consumption, evaluated using average consumption of a 40-year-old in the U.S., $\bar{c}\left(40\right) \equiv \sum_{e=1}^{2} \pi_e^{US} \exp\left(\mu_{40e} + \frac{\sigma_{40e}^2}{2}\right)$.

Non-separable between consumption and leisure Let flow utility from consumption and leisure be given by:

$$u\left(c_{ae}^{s},\ell_{ae}^{s}\right)=b+\frac{\left(c_{ae}^{s}\right)^{1-\gamma}}{1-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\ell_{ae}^{s}\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{1}{1-\gamma},$$

where ϵ is the Frisch elasticity and θ is the weight on disutility from working in the utility function. Assume that consumption grows at a common, non-state dependent, annual rate g. Flow utility can then be rewritten as

$$u\left(c_{ae}^{s}\exp\left(ga\right),\ell_{ae}^{s}\right)=b+\frac{\left(c_{ae}^{s}\right)^{1-\gamma}\left(\exp\left(ga\right)\right)^{1-\gamma}}{1-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\ell_{ae}^{s}\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{1}{1-\gamma}.$$

We continue to assume that $c_{ae}^{s}\sim LN\left(\mu_{ae}^{s},\sigma_{ae}^{s}\right)$. Then $\mathbb{E}_{ae}^{s}\left[\left(c_{ae}^{s}\right)^{1-\gamma}\right]=\exp\left(\left(1-\gamma\right)\mu_{ae}^{s}+\frac{(1-\gamma)^{2}\left(\sigma_{ae}^{s}\right)^{2}}{2}\right)$. Expected utility is then given by:

$$\mathbb{E}_{ae}^{s}\left[u\left(c_{ae}^{s}\exp\left(ga\right),\ell_{ae}^{s}\right)\right]=b+\frac{\exp\left(\left(1-\gamma\right)\mu_{ae}^{s}+\frac{(1-\gamma)^{2}\left(\sigma_{ae}^{s}\right)^{2}}{2}\right)\left(\exp\left(ga\right)\right)^{1-\gamma}}{1-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\bar{\ell}_{ae}^{s}\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{1}{1-\gamma},$$

where we have replaced leisure by type-specific average leisure, $\bar{\ell}_{ae}^{s}$.

We continue to calibrate the constant term in the utility function, b, such that an average 40-year-old has a value of remaining life equal to \$6.5 million in 2012 prices. The equation used to derive the constant term can be derived by following the same steps as discussed in Section B.1. Let $MU\equiv\bar{c}\left(40\right)^{-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\bar{\ell}\left(40\right)\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}$ denote the marginal utility of consumption, evaluated using average consumption, $\bar{c}\left(40\right)\equiv\sum_{e=1}^{2}\pi_{e}^{US}\exp\left(\mu_{40e}+\frac{\sigma_{40e}^{2}}{2}\right)$, and average leisure, $\bar{\ell}\left(40\right)\equiv\sum_{e=1}^{2}\pi_{e}^{US}\ell_{40e}^{US}$, of a 40-year-old in the U.S. The constant term in the utility function, b, can then be derived from the following equation:

$$\begin{aligned}\$6,500,000MU &= \textstyle\sum_{e=1}^{2}\pi_{e}^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}\left[b+\frac{\exp\left((1-\gamma)\mu_{ae}+\frac{(1-\gamma)^{2}\sigma_{ae}^{2}}{2}\right)\left(\exp(g(a-40))\right)^{1-\gamma}}{1-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\bar{\ell}_{ae}^{US}\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{1}{1-\gamma}\right]\\ b &= \frac{\$6{,}500{,}000MU-\sum_{e=1}^{2}\pi_{e}^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}\left[\frac{\exp\left((1-\gamma)\mu_{ae}+\frac{(1-\gamma)^{2}\sigma_{ae}^{2}}{2}\right)\left(\exp(g(a-40))\right)^{1-\gamma}}{1-\gamma}\left(1+(\gamma-1)\frac{\theta\epsilon}{1+\epsilon}\left(1-\bar{\ell}_{ae}^{US}\right)^{\frac{1+\epsilon}{\epsilon}}\right)^{\gamma}-\frac{1}{1-\gamma}\right]}{\sum_{e=1}^{2}\pi_{e}^{US}\sum_{a=40}^{100}\beta^{a-40}S_{ae}^{US}}.\end{aligned}$$

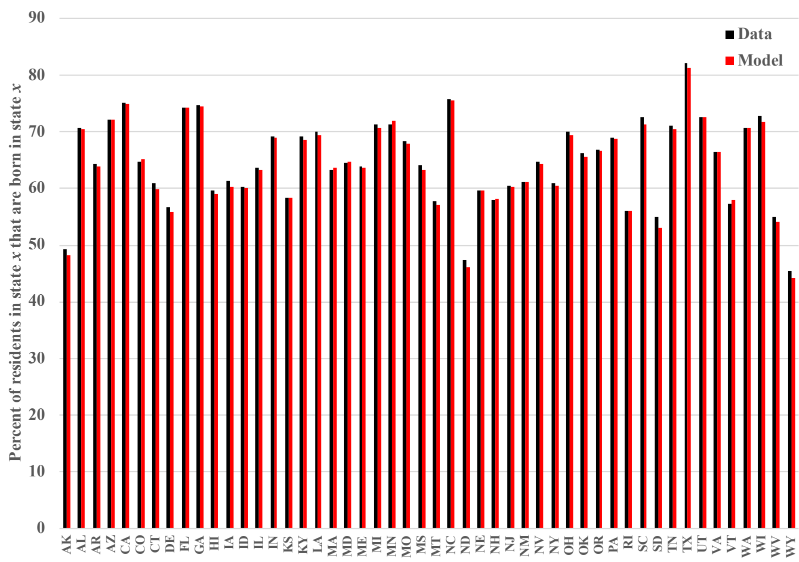

Figure A1: Percentage of each state's residents that were also born in that state: Data vs. model with endogenous migration

Notes: The graph plots the percentage of residents in a given state that were also born in that state in the data and in the model with endogenous migration analyzed in Section 5.4. Source: Census.

C Additional results

C.1 Calibration of the utility cost in the model that allows for migration

This section explains how we calibrate the utility cost of residing in a state other than one's birth state, $m(s; s_b)$, in the model with migration discussed in Section 5.4. We use U.S. Census population data reported by the Minnesota Population Center. The dataset reports each state's population count by state or country of birth. To illustrate, it reports how many individuals currently residing in California were born in California as well as, for example, Texas or Vermont. This dataset enables us to compute each state's retention rate, given by the percentage of residents in a particular state that were also born in that state. We calibrate the utility cost of residing in a state other than one's birth state to match each state's retention rate, where $m(s; s_b) > 0 \; \forall s \neq s_b$ and $m(s_b; s_b) = 0$. A comparison of each state's retention rate in the model and the data is illustrated in Figure A1, which shows that the model almost perfectly matches the retention rate in all states.

C.2 Robustness exercises

C.2.1 Compute welfare conditional on gender and race

Table A1 reports the results from the 2015 cross-state welfare analysis conditional on both gender and race. Columns 3–5 report the race-specific results for females and columns 6–8 report the corresponding results for males (we report the benchmark results in column 2 for reference). See Sections 5.3.2 and 5.3.3 for details. Similarly to the results reported in Table 5, we find that the model yields qualitatively-similar results as the benchmark welfare analysis, with a correlation of at least 0.90 between the benchmark welfare results and the results conditional on either race/gender-combination.

C.2.2 Other robustness exercises

Tables A2 and A3 report results from various sensitivity tests. A comparison of those results with the benchmark cross-state welfare results discussed in Section 5.1, which we for reference report in column 2 in both tables, show that the results are qualitatively and to a large extent quantitatively robust to these exercises, with a population-weighted correlation of at least 0.96 between the benchmark welfare results and the results from the various models.

Include gender and race in the welfare measure Sections 5.3.2 and 5.3.3 report welfare results conditional on the individual's race and gender. In contrast, column 3 of Table A2 reports the results from the model where we include gender and race in the welfare measure and assume that the individual draws her education, gender, and race at birth from the corresponding state-specific distribution using data from the CPS.

Allow for exogenous and probabilistic interstate migration It is well-known that migration tends to be between neighboring states or between states in the same region. As an example, Florida, Georgia, and Tennessee are the top three out-bound migration destinations for residents in Alabama. This can be accounted for in Equation (14) by letting the utility cost, $m(s; s_b)$, increase with the geographic distance between states s and s_b.[33] To further test the sensitivity of our results to migration, we consider an alternative environment where individuals exogenously and

[33]The model in Section 5.4 assumes that the individual's disutility of residing in a state other than her birth state is independent of the state she decides to reside in. This model might overestimate the welfare gains from migration because, conditional on migrating, the individual will choose to migrate to the state that results in the highest welfare, independent of how far that state is from her birth state.

Table A1: Sensitivity: Comparing welfare across the U.S. in 2015 conditional on gender, race, and Hispanic origin

		Female			**Male**		
State	**Bench.**	**White NH**	**Hispanic**	**Black NH**	**White NH**	**Hispanic**	**Black NH**
MA	106.3	100.8	98.2	100.5	103.5	106.0	108.1
MN	102.9	97.1	94.8	108.5	93.5	103.0	102.3
CT	100.0	100.0	100.0	100.0	100.0	100.0	100.0
ND	97.7	98.3	103.6	109.5	87.9	84.0	98.1
NJ	96.4	102.4	99.9	95.6	97.9	90.3	92.1
NY	96.3	98.5	98.8	96.0	96.4	98.5	102.0
NH	94.4	85.9	98.1	95.0	84.3	110.7	82.8
RI	93.0	86.6	85.2	86.5	92.0	97.5	92.8
VT	92.2	82.5	103.8	100.3	83.1	102.8	96.4
SD	90.8	88.2	95.9	99.8	84.6	89.3	91.4
WI	89.4	85.2	92.0	90.0	83.8	94.6	93.2
NE	88.7	83.6	84.1	83.0	82.4	81.8	98.3
HI	87.9	93.7	104.9	103.7	88.9	102.8	90.0
WA	87.6	85.0	89.3	94.7	85.8	84.8	93.0
IL	86.7	86.0	86.5	92.0	87.8	85.6	95.7
CA	86.6	92.7	90.3	97.0	93.1	88.9	95.8
AK	85.4	91.7	103.7	97.3	85.9	95.0	100.2
IA	85.2	80.0	80.5	83.2	76.2	80.2	84.8
PA	84.7	80.8	83.9	81.7	80.6	93.5	90.8
CO	83.3	83.9	82.8	91.2	81.3	83.7	81.7
VA	82.9	86.8	81.9	90.8	84.6	83.5	91.8
OR	82.7	81.0	80.3	87.7	80.6	82.6	84.1
WY	81.9	79.8	81.8	86.5	71.6	86.5	83.7
MI	79.4	77.6	86.1	82.0	76.9	82.0	86.3
MD	79.0	85.8	89.0	90.5	89.0	90.4	91.9
ME	78.5	73.5	91.2	86.9	71.6	87.9	88.5
DE	78.3	85.5	81.8	86.2	82.8	82.3	84.7
OH	78.1	73.4	88.4	82.8	75.3	82.6	88.7
UT	77.7	73.3	76.6	76.8	70.9	73.1	78.1
KS	77.4	73.7	73.4	80.0	74.0	77.8	79.8
ID	76.3	70.5	73.6	76.7	71.1	69.0	84.1
FL	76.3	77.2	89.5	84.6	77.2	89.5	83.3
NV	76.2	76.5	82.1	91.6	81.4	83.0	88.9
MO	74.7	71.1	73.2	77.4	72.8	73.9	81.8
MT	74.5	68.2	79.6	79.5	68.2	67.8	76.6
TX	74.1	79.4	80.1	84.3	78.0	78.2	84.9
AZ	73.5	77.5	75.6	81.7	80.0	76.1	81.7
IN	71.7	67.7	69.5	72.6	65.0	70.7	76.2
NC	67.6	69.8	72.8	76.0	71.1	67.4	76.5
GA	66.5	73.5	72.8	75.9	72.8	70.1	76.9
SC	64.9	66.3	72.9	73.7	67.0	68.6	73.3
NM	64.0	67.9	72.9	70.0	70.7	75.8	76.1
WV	63.4	55.2	51.3	61.6	59.7	56.6	67.6
TN	61.7	58.3	63.1	66.0	62.7	58.8	67.6
KY	60.9	55.0	59.9	62.2	59.8	57.6	68.5
AR	60.1	57.6	62.4	66.8	60.5	58.3	72.2
LA	60.0	64.2	73.3	68.1	63.9	63.3	71.9
OK	57.9	57.0	62.1	66.0	59.2	61.2	67.5
AL	55.5	58.3	58.4	63.8	56.8	53.2	68.4
MS	52.6	57.0	63.3	62.0	54.3	61.4	68.4

Notes: Column 2 repeats the cross-state welfare results from the benchmark model (see Table 2), i.e., it reports how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state in 2015. The remaining columns report the corresponding welfare results conditional on race and Hispanic ethnicity (columns 3–5 for females and columns 6–8 for males).

Table A2: Sensitivity: Comparing welfare across the U.S. in 2015

State	**Bench.**	**Incl. gender & race**	**Exog. migr.**	**3 goods: Cons., housing, & leisure**	**Higher ineq. (SCF)**	**Diff. ineq. (IRS)**	$b(age)$	$b(cons.)$	**w/o educ.**	**Comp. var.**
MA	106.3	103.8	105.7	105.6	107.0	110.2	106.6	106.5	104.6	94.0
MN	102.9	99.8	98.4	99.2	105.0	109.2	102.8	103.1	99.9	97.2
CT	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
ND	97.7	95.9	91.6	104.5	99.3	104.4	97.9	97.0	98.4	102.4
NJ	96.4	96.7	100.6	95.0	97.2	99.9	96.6	96.8	95.1	103.7
NY	96.3	95.0	96.8	96.6	95.6	94.6	96.0	96.3	93.0	103.8
NH	94.4	96.0	102.2	93.9	96.8	99.3	95.2	94.6	96.1	106.0
RI	93.0	90.5	95.5	92.6	93.8	102.3	93.5	93.2	91.5	107.6
VT	92.2	92.6	99.1	91.9	94.0	98.8	93.0	92.2	93.8	108.6
SD	90.8	89.0	88.4	96.0	92.7	93.5	90.9	90.6	89.9	110.3
WI	89.4	89.1	90.7	88.3	91.4	95.3	90.0	89.7	88.5	112.0
NE	88.7	85.4	89.4	91.4	90.7	93.7	89.3	88.5	86.7	112.9
HI	87.9	86.4	79.7	82.4	90.1	94.2	87.0	88.9	93.0	113.7
WA	87.6	86.4	88.8	83.4	89.1	91.9	88.4	88.2	91.1	114.3
IL	86.7	85.1	89.5	89.2	87.2	91.3	87.2	86.6	84.6	115.6
CA	86.6	87.4	89.2	83.8	86.9	86.5	86.6	87.1	89.6	115.5
AK	85.4	85.7	82.1	85.3	88.1	90.3	86.6	86.1	92.1	117.7
IA	85.2	83.5	89.3	86.4	87.2	92.5	85.8	85.2	82.1	117.6
PA	84.7	83.0	89.4	87.8	85.6	91.0	85.4	84.9	81.9	118.4
CO	83.3	84.1	90.6	82.4	84.7	86.7	83.8	83.6	87.8	120.3
VA	82.9	82.9	87.6	84.8	83.9	89.6	83.8	83.0	84.6	121.0
OR	82.7	83.0	88.7	79.1	83.9	89.1	83.6	83.3	86.4	121.3
WY	81.9	82.3	85.7	83.1	84.1	77.0	82.8	82.1	84.0	122.7
MI	79.4	78.0	83.5	81.7	80.5	84.2	80.4	79.8	79.0	126.6
MD	79.0	78.5	83.2	80.5	80.4	84.0	79.6	79.3	82.1	127.2
ME	78.5	81.2	89.2	78.3	79.9	86.6	79.8	79.0	83.6	128.1
DE	78.3	78.2	82.9	79.2	79.6	85.6	79.0	78.7	80.7	128.5
OH	78.1	76.9	82.5	83.4	79.1	86.3	79.3	78.3	78.4	129.1
UT	77.7	78.1	86.4	72.9	80.0	79.0	78.7	78.5	82.7	129.2
KS	77.4	76.0	84.8	80.8	78.6	81.8	78.2	77.4	76.6	129.9
ID	76.3	76.3	85.8	73.8	77.8	78.4	77.1	76.8	77.1	131.6
FL	76.3	76.1	79.8	76.8	76.6	73.3	76.3	76.6	78.3	131.6
NV	76.2	77.0	82.3	75.8	77.5	72.0	77.4	76.7	80.3	132.3
MO	74.7	74.0	81.6	80.1	75.7	79.6	75.9	74.9	76.3	135.2
MT	74.5	73.3	83.6	76.9	75.6	78.4	75.4	74.8	77.0	135.2
TX	74.1	74.0	81.1	76.7	74.6	75.8	75.1	74.2	75.6	135.8
AZ	73.5	73.3	80.6	71.5	74.4	77.4	73.8	74.1	75.8	136.6
IN	71.7	69.7	79.0	74.9	73.0	77.3	72.9	72.0	72.0	141.2
NC	67.6	66.2	75.8	70.3	68.1	73.7	68.5	67.9	67.6	149.5
GA	66.5	64.7	73.0	70.4	66.9	70.2	67.7	66.8	68.2	152.3
SC	64.9	63.3	74.4	68.4	65.5	70.7	66.0	65.3	65.1	156.6
NM	64.0	64.7	74.1	64.5	64.4	70.2	64.8	64.6	70.5	159.0
WV	63.4	63.0	78.6	70.0	64.2	71.5	64.7	63.9	62.6	161.5
TN	61.7	60.1	74.3	68.1	62.1	66.8	63.0	61.9	61.7	165.5
KY	60.9	61.3	76.1	67.9	61.3	67.6	62.2	61.2	60.9	168.3
AR	60.1	59.9	71.5	65.7	60.6	64.0	61.4	60.6	60.6	170.5
LA	60.0	58.6	68.1	67.3	60.0	64.7	61.2	60.2	60.7	170.9
OK	57.9	55.6	68.2	62.9	58.5	61.5	59.3	58.3	60.2	177.9
AL	55.5	55.4	67.1	61.2	55.8	61.4	56.8	56.0	58.3	186.4
MS	52.6	51.8	62.2	57.2	52.8	58.0	53.9	53.2	54.8	198.1

Notes: Column 2 repeats the cross-state welfare results from the benchmark model (see Table 2), i.e., it reports how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state in 2015. The remaining columns report the corresponding welfare results from various sensitivity analyses. See the text for details.

Table A3: Sensitivity: Comparing welfare across the U.S. in 2015 (cont.)

State	**Bench.**	$\gamma = 2$ **(sep.)**	$\gamma = 2$ **(non-sep.)**	**SVL ($5.5m)**	**SVL ($7.5m)**	$\beta = 0.96$	**Excl. health**	**Incl. durables**	**Ages: 2+**	**Ages: 0–84**
MA	106.3	107.3	107.5	106.5	106.2	106.5	105.2	107.2	105.9	107.4
MN	102.9	109.1	109.1	102.5	103.2	102.4	101.6	105.2	103.0	102.8
CT	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
ND	97.7	100.9	90.8	98.9	96.5	103.9	94.1	104.4	97.8	98.0
NJ	96.4	98.6	97.6	96.7	96.2	97.3	98.6	97.4	96.2	97.1
NY	96.3	93.0	96.2	95.9	96.7	93.8	95.8	93.8	96.4	94.9
NH	94.4	101.4	93.6	95.5	93.3	100.9	94.3	96.3	93.7	97.3
RI	93.0	95.7	91.9	93.7	92.3	95.7	89.1	92.5	93.3	94.7
VT	92.2	98.2	91.2	93.1	91.2	98.4	88.6	93.9	91.4	95.5
SD	90.8	96.1	85.9	92.2	89.4	95.6	86.3	95.8	91.3	91.2
WI	89.4	96.3	88.4	90.4	88.4	94.0	85.3	91.9	89.8	91.7
NE	88.7	94.8	87.9	89.5	87.9	94.5	85.0	92.4	88.7	90.7
HI	87.9	97.3	95.4	87.9	88.0	86.5	92.2	88.9	88.3	83.8
WA	87.6	94.3	88.8	88.4	86.8	92.2	88.8	90.2	87.1	90.4
IL	86.7	88.8	83.0	87.8	85.6	90.3	85.4	88.5	87.2	89.0
CA	86.6	88.7	88.8	86.6	86.5	87.0	89.0	87.1	86.3	86.3
AK	85.4	94.5	78.4	88.3	82.7	97.0	78.6	88.2	85.5	90.9
IA	85.2	91.8	84.8	85.9	84.4	90.4	80.8	88.5	84.9	87.1
PA	84.7	88.2	79.9	86.4	83.2	90.0	80.7	86.9	85.1	87.6
CO	83.3	89.1	82.9	84.1	82.5	86.9	86.9	85.2	83.0	85.5
VA	82.9	87.3	79.9	84.2	81.6	88.8	84.6	84.8	83.1	86.3
OR	82.7	89.0	81.9	83.9	81.5	88.6	81.4	85.4	82.5	86.3
WY	81.9	90.5	78.1	83.8	80.0	91.6	79.6	84.9	81.4	85.3
MI	79.4	84.4	75.0	81.4	77.5	86.4	76.5	82.3	80.0	83.2
MD	79.0	85.3	77.1	80.5	77.5	84.2	78.1	81.1	79.5	81.3
ME	78.5	86.0	75.8	80.5	76.7	87.8	74.1	81.9	78.8	83.5
DE	78.3	84.7	74.5	80.2	76.5	84.5	71.1	82.5	79.1	81.2
OH	78.1	83.3	71.0	80.7	75.6	88.1	73.3	81.3	78.7	83.0
UT	77.7	87.9	80.2	79.0	76.5	84.3	78.9	82.1	77.6	81.7
KS	77.4	83.1	74.9	78.9	75.9	83.8	73.9	80.8	77.6	80.1
ID	76.3	83.8	76.9	77.4	75.2	81.8	74.2	80.4	76.2	79.5
FL	76.3	79.5	73.8	77.4	75.2	78.7	74.5	79.8	76.8	76.1
NV	76.2	84.0	72.2	78.4	74.1	86.5	78.1	79.9	76.0	80.7
MO	74.7	80.7	68.7	77.2	72.3	84.9	71.2	78.1	74.9	79.3
MT	74.5	81.0	71.0	76.3	72.7	81.7	71.3	80.8	74.4	78.0
TX	74.1	78.5	70.6	75.7	72.6	81.4	73.6	77.6	74.2	77.6
AZ	73.5	78.8	73.4	74.7	72.5	76.6	73.6	76.5	73.7	74.4
IN	71.7	79.0	67.6	74.1	69.3	81.6	65.9	75.2	72.2	76.3
NC	67.6	72.6	65.0	69.4	65.9	74.1	64.0	71.5	68.2	70.9
GA	66.5	71.7	62.9	68.7	64.5	74.9	65.5	70.2	67.1	70.8
SC	64.9	71.0	61.5	67.3	62.7	73.5	61.3	68.5	65.2	69.3
NM	64.0	71.0	62.0	66.4	61.7	72.6	61.1	67.6	63.8	67.2
WV	63.4	70.4	59.0	66.6	60.4	74.9	53.8	67.4	63.7	68.4
TN	61.7	67.8	58.0	64.4	59.2	72.3	58.1	65.8	62.0	66.7
KY	60.9	67.5	56.7	63.8	58.2	72.5	55.1	64.7	61.0	65.9
AR	60.1	67.3	56.5	63.0	57.4	70.6	55.1	64.8	60.7	64.9
LA	60.0	65.6	55.5	62.9	57.3	70.1	55.1	64.5	60.6	64.7
OK	57.9	66.5	55.2	60.8	55.1	70.0	52.7	62.7	58.2	63.0
AL	55.5	63.5	52.6	58.6	52.6	67.0	51.0	59.9	56.1	60.7
MS	52.6	61.1	50.8	55.7	49.6	64.4	45.8	56.6	53.3	57.7

Notes: Column 2 repeats the cross-state welfare results from the benchmark model (see Table 2), i.e., it reports how much consumption would have to change in all ages in the state with the highest real personal income per capita, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state in 2015. The remaining columns report the corresponding welfare results from various sensitivity analyses. See the text for details.

probabilistically move between states, and use annual migration data from the American Community Survey (ACS) for the period 2013–2017 to compute these state-to-state migration probabilities. The results are reported in column 4 of Table A2.

Include housing in the welfare measure Column 5 of Table A2 reports the results from the model where we also include housing in the utility function. See Section A.4 for data and Section B.2 for mathematical details.

Different measures of within-state inequality Survey data such as the CEX might underestimate consumption inequality due to both underreporting and nonresponse bias for households at the top of the income distribution. Column 6 of Table A2 reports the results from the model where we target a higher level of consumption inequality derived from the Survey of Consumer Finances as in Fisher, Johnson, Smeeding, and Thompson (2022).

We infer state-level inequality from data on income inequality, measured as the GINI coefficient of household income as derived from the ACS, and use the states' GINI coefficients to calibrate the benchmark model. Column 7 of Table A2 reports the results from the model where we instead infer state-level inequality from federal tax returns as in Frank (2014).

Different parameterizations of the constant term Córdoba and Ripoll (2017) discuss some counterfactual implications of the expected utility model. In particular, life could be undervalued by the poorer and the older. We address this by means of two robustness exercises. First, we replace the constant term in the utility function by $\tilde{b} = b\,(1 - \exp(b_1 + b_2 a))$, where a denotes the individual's age. This formulation nests the benchmark model as the limit-case when $b_1 = \lim_{\epsilon \to 0} \log(\epsilon)$ and $b_2 = 0$. Letting $b_2 \neq 0$ enables us to incorporate differences in quality-adjusted life-years over the life cycle. For example, aging can affect an individual's cognitive abilities and physical activity, which in turn might affect the individual's quality (and valuation) of life. This is related to Recommendation 6 of the Stiglitz, Sen, and Fitoussi (2009) Commission. We find that the results are robust to numerous parameterizations of b_1 and b_2 when we recalibrate b to match the same target as in the benchmark model. Column 8 of Table A2 reports the results from the model where b_1 and b_2 are chosen to match average frailty over the life cycle (see e.g. Nygaard, 2019).

Second, we replace the constant term in the utility function by $\tilde{b} = b + b_1\,(\bar{c}\,(40) - \bar{c}^s_{ae})$, where $\bar{c}\,(40)$ is average consumption of a 40-year-old in the U.S. This formulation nests the benchmark model as the case when $b_1 = 0$. An environment with $b_1 \neq 0$ means that the individual's marginal valuation of consumption is tied to how much higher or lower her consumption is relative to the average person. We find that the results are robust to numerous parameterizations of b_1 when we recalibrate b to match the same target as in the benchmark model. Column 9 of Table A2 reports the results from the model with $b_1 = 0.1$.

Model without education The benchmark model allows for differences in educational attainment. This is motivated by the considerable heterogeneity in educational attainment across states shown in Figure 4 and is related to Recommendation 6 of the Stiglitz, Sen, and Fitoussi (2009) Commission. In contrast, column 10 of Table A2 reports the results from the recalibrated model without education, in which case welfare depends on the states' age-specific survival probabilities (ψ_a^s), age-specific consumption process (μ_a^s and σ_a^s), and age-specific leisure (ℓ_a^s).

Compare welfare by means of compensating variation Section 5.1 compares welfare across states by quantifying how much consumption must adjust in all ages in Connecticut to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared with any other state. This provides an *equivalent variation* (EV) measure of the difference in living standards between states. Alternatively, we can compare welfare across states by quantifying how much consumption must adjust in all ages in state s to make an unborn individual behind the veil of ignorance indifferent between living her entire life in state s compared with Connecticut. This provides a *compensating variation* (CV) measure of the difference in living standards between states. The key distinction between these two measures is in how they penalize differences in life expectancy. In particular, differences in life expectancy between state s and Connecticut are valued using flow utility in state s under EV. In contrast, differences in life expectancy between state s and Connecticut are valued using flow utility in Connecticut under CV. The results when we compare welfare using CV rather than EV are reported in column 11 of Table A2. Because this is a compensating variation, a value exceeding 100 in state s means that the unborn individual behind the veil of ignorance would require a positive compensation to be indifferent between living her entire life in state s compared with Connecticut, and hence implies that welfare is lower in state s than in Connecticut. The welfare results computed using equivalent and compensating variation are therefore negatively correlated, with a population-weighted correlation of -0.98.

Different risk aversion Columns 3 and 4 of Table A3 report the welfare results from the model with CRRA preferences discussed in Section B.3 when the risk aversion parameter, γ, is equal to

2.00. Column 2 (3) considers the case where consumption and leisure are separable (non-separable) in the utility function.

Different targets for the value of life We calibrate the benchmark model such that an average 40-year-old in the U.S. has a value of remaining life equal to $6.5 million in 2012 prices (see Section 4.4 for details). Columns 5 and 6 of Table A3 report the welfare results from the recalibrated models when we target a lower ($5.5 million) and higher ($7.5 million) value of remaining life, respectively. A lower (higher) target for the value of remaining life leads to a lower (higher) calibrated value for the constant term, b, which in turn reduces (increases) the direct utility that individuals derive from each year of life and hence reduces (increases) the welfare loss due to lower life expectancy.

Lower discount factor Column 7 of Table A3 reports the results when we let the discount factor, β, be equal to 0.96 rather than 0.99 as in the benchmark model. A lower value for β reduces the welfare loss due to lower life expectancy.

Exclude health care expenditures from consumption Consumption in the benchmark model is given by consumption of non-durables and services as defined by the BEA, which includes expenditures on health care. While individuals might indirectly benefit from purchase of health care in the form of lower mortality risk, it is not clear that they also derive direct utility from the purchase of these goods and services. Data from the CMS show that health care expenditures per capita varies from $6,000 in Utah to $11,200 in Alaska in 2015. There is also considerable heterogeneity in the ratio of health care expenditures to total expenditures, from a low of 17.9 percent in Colorado to a high of 30.7 percent in West Virginia. Column 8 of Table A3 reports the results from the recalibrated model when we exclude expenditures on health care from consumption.

Include durable consumption goods The benchmark model focuses on consumption of non-durables and services. We exclude purchase of durable goods because the CEX only reports the household's (lumpy) durable expenditures rather than the household's stock of durable goods. Data from the BEA show that durable consumption per capita varies from a low of $3,000 in Mississippi to a high of $6,300 in North Dakota in 2015. Similarly, the ratio of durable consumption to total consumption ranges from 7.4 percent in New York to 14.4 percent in Montana. Column 9 of Table A3 reports the results from the recalibrated model when we include expenditures on durables as part of consumption.

Infant mortality Figure 2 shows that there are large variations in life expectancy at birth across states, ranging from 74.6 years in Mississippi to 81.5 years in Hawaii. Part of this variation in life expectancy at birth is due to heterogeneous infant mortality rates. Data from the CDC show that infant mortality rates vary from a low of 4.0 deaths per 1,000 births in Massachusetts to a high of 9.0 deaths per 1,000 births in Mississippi. Column 10 of Table A3 reports the results from the model where individuals enter the model at age 2 rather than at age 0 to mitigate the effect of heterogeneous infant mortality rates.

Top-coding of age Age is top-coded at 85 in the various survey data that we use in our analysis. We examine how extrapolation for 85+ year-olds affects the cross-state welfare results by considering an alternative environment where individual enters the model at age 0 and live to at most age 84. The results are reported in column 11 of Table A3.