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A Comparison of Living Standards Across the States of America*

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Abstract

We use an expected utility framework to examine how living standards vary across the United States and how each state's living standards have evolved over time. Our welfare measure accounts for cross-state variations in mortality, consumption, education, inequality, and cost of living. We find that per capita income is a good indicator of living standards, with a correlation of 0.80 across states. Living standards in most states, however, appear closer to those in the richest states than their difference in per capita income would suggest. Whereas high-income states benefit from higher life expectancy, consumption, and college attainment, low-income states benefit from lower cost of living. All states experienced positive welfare growth, and hence rising living standards, between 1999 and 2015. The annual welfare growth rate, however, varied from 1.38 to 3.76 percent across states due to varying gains in life expectancy, consumption, and college attainment, with life expectancy accounting for 50.3 percent of the variation. Finally, the growth rate of per capita income is a poor proxy for how fast living standards are rising in a particular state since the correlation between welfare growth and per capita income growth is only 0.38, and deviations are often large.

JEL codes: D63; I31; O50; R13.

Keywords: Welfare comparison; Expected utility; Inequality; Living standards.

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1 Introduction

While a large literature has examined how welfare, or living standards, vary *across* countries, much 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. We examine how living standards vary across the United States and how each state's living standards have evolved over time. Our analysis is motivated by the considerable heterogeneity in per capita income levels across the U.S., ranging from $33,900 in Mississippi to $65,800 in Connecticut in 2015. Moreover, consumption per capita varies by a factor of 1.7 across states, and life expectancy at birth varies by almost 7 years.[1] There is also substantial heterogeneity in educational attainment, income inequality, and in the cost of living as measured by both consumption-good prices and housing prices, all of which are likely to have large implications for living standards.

We construct a welfare measure that can be used to examine how living standards vary across the U.S. The welfare measure extends the measure that Jones and Klenow (2016) use to study cross-country differences in living standards. In particular, we compare living standards across states by quantifying how much spending must adjust in all ages in the state with the highest per capita income, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared to any other state.[2] To illustrate our welfare analysis, suppose we wish to compare living standards in California and Connecticut. The unborn individual has to choose to live her entire life in either California or Connecticut without knowing anything about how her life is going to turn out. That is, she does not know how long she will live, whether she will be highly educated or not, or whether she will be rich or poor. She knows that consumption-good prices and housing prices vary between the two states. Over her life, she will draw from the cross-sectional distribution of spending and from the cross-sectional mortality distribution corresponding to each age, education, and state. By how much do we have to adjust spending in all ages in Connecticut—holding fixed Connecticut's survival probabilities, educational attainment, inequality, consumption-good prices, and housing prices—to make this individual indifferent between living her entire life in California and Connecticut? The answer to this question provides a consumption-equivalent measure of the difference in living standards between these two states.

Our welfare measure enables us to derive closed-form solutions for the welfare differences across states. It also allows us to additively decompose the welfare differences into six components: life expectancy, college attainment, average spending, inequality, consumption-good prices, and housing prices. Moreover, our analysis allows us to quantify each state's welfare growth rate, and therefore to examine how each state's living

[1] Data on income and consumption are from the Bureau of Economic Analysis. Life expectancy at birth is calculated using mortality statistics from the Centers for Disease Control and Prevention. Further details are given in Section 2.

[2] We compare living standards both across states and over time using a common, non-state-dependent, specification for preferences. In particular, we use the preferences of an average individual in the U.S.

standards have evolved over time, and to decompose this growth rate into changes in the six components.

We use a combination of micro and macro data to estimate the key inputs in the welfare measure. Survival probabilities are assumed to vary with the individual's age, education, and state of residence. We show that these probabilities can be derived by combining data from the Underlying Cause of Death database and the National Vital Statistics System reported by the Centers for Disease Control and Prevention. Similarly, the process for spending is also assumed to be age-, education-, and state-specific. We assume that spending in the U.S. is drawn from a log-normal distribution and estimate its parameters using data from the Consumer Expenditure Survey. We then adjust the parameters of this spending process to account for heterogeneity in spending per capita and variation in inequality across states relative to the national average. Finally, we show how the remaining inputs in the welfare measure such as educational attainment and the state-specific consumption-good prices and housing prices can be derived directly from the data.

Since income per capita is the most commonly used measure of living standards in the literature, we start by comparing each state's welfare level with its corresponding per capita income level in 2015. Similarly to the literature studying cross-country welfare differences, we find that per capita income is a good indicator of welfare, with a correlation of 0.80 between the two measures. This shows that richer states tend to have higher living standards than poorer states. Note, however, that the correlation between per capita income and welfare across the U.S. (0.80) is lower than the corresponding correlation between GDP per capita and welfare across countries (0.98) found by Jones and Klenow (2016).

While welfare and per capita income are positively correlated, deviations between the two measures are often large. We find that living standards in most states appear closer to those of the richest state, Connecticut, than their difference in per capita income would suggest. In particular, whereas a comparison of income per capita would lead one to conclude that average living standards in the U.S. are 29.1 percent lower than in Connecticut, our welfare measure shows that average living standards in the U.S. are only 21.9 percent lower than in Connecticut. As an example, consider the case of South Dakota. While income per capita is 29.7 percent lower in South Dakota than in Connecticut, living standards as measured using our welfare metric are only 2.9 percent lower in South Dakota than in Connecticut. Living standards in several states in the South, however, appear *lower* relative to Connecticut when we account for differences in life expectancy, college attainment, spending, inequality, and cost of living. As an example, Oklahoma has 35.8 percent lower income per capita than Connecticut, but 44.8 percent lower welfare.

To better understand these results, we next decompose the welfare differences into differences in: life expectancy, college attainment, average spending, inequality, consumption-good prices, and housing prices. To illustrate this welfare decomposition, consider the state with the lowest welfare level, Mississippi. We find that lower life expectancy at birth reduces welfare by 31.9 percentage points in Mississippi relative to

Connecticut. That is, average spending would have to decline by 31.9 percent in all ages in Connecticut—holding fixed Connecticut's mortality rates, educational attainment, inequality, and cost of living—to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut and Mississippi if the difference in life expectancy was the *only* difference between these states. Similarly, lower college attainment and lower average spending reduce welfare by, respectively, 16.3 and 35.4 percentage points in Mississippi relative to Connecticut. Conversely, lower inequality and lower cost of living increase welfare by, respectively, 1.7 and 28.3 percentage points in Mississippi compared to Connecticut.

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 spending in low-income states account for most of the lower welfare in these states compared to high-incomes states. Lower college attainment further reduces welfare in low-income states. Low-income states, however, generally benefit from lower consumption-good prices and lower housing prices. To illustrate, we find that lower consumption-good prices and lower housing prices increase welfare in states such as Alabama, Arkansas, Kentucky, Mississippi, and West Virginia by a total of 25.3–28.3 percentage points compared to Connecticut. Therefore, failure to account for the heterogeneity in both consumption-good prices and housing prices would lead one to overestimate the dispersion in welfare between high- and low-income states.

Our welfare measure allows us to examine why states with similar per capita income levels have different welfare levels. To illustrate, Delaware and South Dakota have comparable per capita income levels. Yet, living standards as measured using our welfare metric are 22.5 percent higher in South Dakota than in Delaware. This is due to higher life expectancy, lower inequality, and lower cost of living in South Dakota. In general, we find that heterogeneity in life expectancy at birth is the main reason welfare varies across states with comparable per capita income levels.

Next, we examine how each state's living standards have evolved over time by quantifying each state's welfare growth rate between 1999 and 2015. This is motivated by the fact that changes in life expectancy, college attainment, spending, inequality, consumption-good prices, and housing prices have varied considerably across states. We find that all states experienced positive welfare growth, and hence rising living standards, over this period, with a population-weighted average welfare growth rate of 2.49 percent per year across states. North Dakota had the highest growth in welfare between 1999 and 2015, with an average growth rate of 3.76 percent per year over this period. In contrast, New Mexico had the lowest growth in welfare, with an average growth rate of 1.38 percent per year between 1999 and 2015. To put this in perspective, it means that, given current trends, living standards are expected to double every 18.4 years in North Dakota, compared to every 50.2 years in New Mexico.

We find that welfare growth and per capita income growth are only weakly correlated, with a correlation of 0.38 across states. This is considerably lower than the correlation between welfare growth and per capita GDP growth across countries (0.97) found by Jones and Klenow (2016). Moreover, deviations between welfare growth rates and per capita income growth rates are often large. In particular, we find that welfare growth exceeds per capita income growth by 1.09 percentage points on average. To illustrate, whereas income per capita increased by 0.39 percent per year in Nevada between 1999 and 2015, its welfare increased by 2.99 percent per year. Similarly, whereas Oklahoma and South Dakota experienced comparable per capita income growth rates, their welfare growth rates varied by 1.38 percentage points. These findings show that per capita income growth is not necessarily a good indicator of how fast living standards are rising in a particular state.

Our welfare measure allows us to decompose each state's welfare growth rate into six components: changes in life expectancy, changes in college attainment, changes in average spending, changes in inequality, changes in consumption-good prices, and changes in housing prices. We use this decomposition to examine the determinants of the 2.38 percentage point dispersion in annual welfare growth rates across states. 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. This heterogeneity in life expectancy gains had large implications for welfare growth. A variance decomposition of the dispersion in welfare growth rates shows that variations in life expectancy gains account for 50.3 percent of the dispersion in welfare growth rates in the U.S. Changes in college attainment, as measured by the change in the percentage of 25–29 year-olds with a college degree between 1999 and 2015, have also varied significantly across states. We find that variations in college attainment gains account for 13.0 percent of the dispersion in welfare growth rates across states. Next, whereas most of the welfare growth in the U.S. can be attributed to spending growth, the increase in spending has not been uniform across states. As a result, we find that variations in spending growth account for 28.4 percent of the variation in welfare growth rates. Lastly, while inequality, relative consumption-good prices, and relative housing prices have changed over time, these changes have generally had limited implications for welfare growth, and thus only account for a small share of the variation in welfare growth rates across states.

We then use the model to examine if states with a lower welfare level at the beginning of the sample period have experienced a higher welfare growth. To do so, we study the relationship between each state's welfare ranking in 1999 and its annual welfare growth rate between 1999 and 2015. We find that a state's welfare growth rate is not systematically related to its welfare ranking in 1999, which suggests that states are not converging toward similar welfare levels. In particular, we find similar dispersions in welfare growth rates among high- and low-ranked states in the country.

The benchmark analysis compares living standards across states by quantifying how much spending 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 to any other state. This model allows us to derive closed-form solutions for the welfare differences across the states. We also consider an alternative environment where the individual can move between states. In particular, we assume that an individual in state s exogenously moves to state s' in the following period with probability $q(s, s')$, and use migration statistics from the American Community Survey to compute these transition probabilities. We then compare living standards across states by quantifying how much spending must adjust in all ages in Connecticut to make an unborn individual behind the veil of ignorance indifferent between *born* in Connecticut compared to being born in any other state. For simplicity, we refer to this model as the model with migration. We find that the welfare ranking in the model with migration is very similar to the ranking in the benchmark model, with a correlation of 0.96 between the two rankings. As expected, we find that most states have higher welfare levels relative to Connecticut in the model with migration, with a weighted average difference of 6.1 percentage points. We also study the sensitivity of the results to using alternative utility functions, to varying the values of the parameters of the model, to including durable consumption goods, to excluding expenditures on health care, to including leisure in the utility function, and to starting the model at age 2 rather than at age 0 to eliminate the effect of heterogeneous infant mortality rates. We find that our results are robust to these changes.

Literature review This paper is related to a large literature that develops welfare measures to compare living standards across countries, regions, and time (see Fleurbaey 2009 for a review of this literature). 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; Cordoba and Verdier (2008) account for lifetime consumption inequality; and Fleurbaey and Gaulier (2009) account for life expectancy, leisure, and inequality. We extend this literature by also accounting for educational attainment, consumption-good prices, and housing prices. More importantly, while these papers compare welfare across countries (or, in the case of Nordhaus and Tobin 1972, across time in the U.S.), we compare welfare both across the U.S. and over time.

The paper is most closely related to Jones and Klenow (2016), who develop a model to quantify the welfare differences across countries. Their welfare measure incorporates differences in consumption, leisure, mortality, and inequality across countries. We extend their model by incorporating differences in educational attainment, consumption-good prices, and housing prices, while simultaneously allowing for differences in spending, mortality, and inequality. We also consider an alternative model in the sensitivity section where we include leisure. Whereas Jones and Klenow (2016) use their model to compare welfare across countries, we use our model to compare welfare across the states of America. 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. Moreover, this is the first paper that applies an expected utility framework to quantify each state's evolution of living standards while taking into account changes in mortality risk, educational attainment, spending, inequality, and cost of living.

The paper also relates to the microeconomics literature that compares quality of life across cities and states. Gabriel, Mattey, and Wascher (2003) estimate the evolution in quality-of-life rankings for US states between 1981 and 1990. They focus on cross-state variations in pollution, taxation, crime rates, and public spending. 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 (both housing and non-housing), federal taxes, and non-labor income, and use this measure to estimate the quality of life across US cities and states in 2000.[3] Unlike Gabriel, Mattey, and Wascher (2003) and Albouy (2011), we focus on differences in mortality risk, educational attainment, 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 model to compare living standards across states for an unborn individual behind the veil of ignorance in the tradition of Lucas (1987).

The rest of the paper is organized as follows. The following section shows how income, consumption, life expectancy, educational attainment, inequality, and cost of living 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 explains how we estimate the mortality probabilities and the process for spending, and discusses 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.

2 Data

This section reports the differences in income and consumption per capita, life expectancy at birth, educational attainment, inequality, and cost of living as measured by both relative consumption-good prices and

[3] Note that our welfare measure is likely to underestimate living standards in states with high cost of living. This follows because quality of life (or, more generally, amenities) is positively correlated with cost of living measures such as housing prices (see for example Albouy 2016).

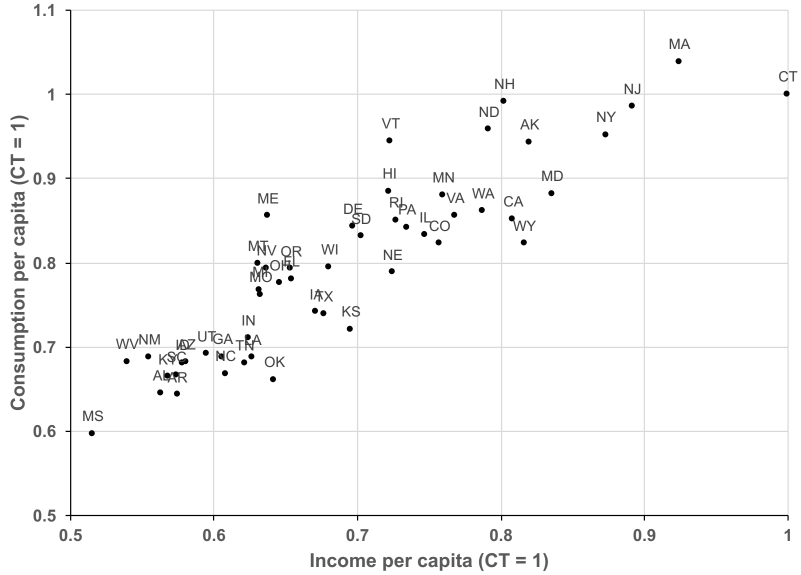

Figure 1: Relationship between income per capita and consumption per capita in 2015

Notes: The graph plots the relationship between personal income per capita and consumption per capita in 2015. Both series have been deflated by the national Personal Consumption Expenditures price index and normalized by the corresponding values in Connecticut (income and consumption per capita was \$65,800 and \$46,300 in Connecticut in 2015, respectively). Source: BEA.

relative housing prices across the U.S. in 2015.

2.1 Income and consumption

Figure 1 plots the relationship between personal income per capita and consumption per capita across the states in 2015.[4] Both series are obtained from the Bureau of Economic Analysis (BEA). We deflate both series by means of the national Personal Consumption Expenditures price index reported by the BEA. Both income and consumption have been normalized by the corresponding values in Connecticut (income and consumption per capita was \$65,800 and \$46,300 in Connecticut in 2015, respectively). As illustrated in the graph, income per capita is almost 50 percent higher in Connecticut than in the state with the lowest per capita income, Mississippi, and more than 30 percent higher than in the state with the median income per capita, Texas. Similarly, consumption per capita varies considerably across the states, ranging from \$27,600 in Mississippi (that is, 40 percent lower than in Connecticut), to \$48,100 in Massachusetts (that is, 4 percent higher than in Connecticut). As expected, richer states tend to have higher consumption than poorer states, with a correlation of 0.90 between income and consumption per capita across states.

[4] We always report average values for 5-year periods since business cycles are not necessarily synchronized across states. We identify the time period by the mid-point of the period. Throughout, 2015 therefore refers to the average value between 2013 and 2017.

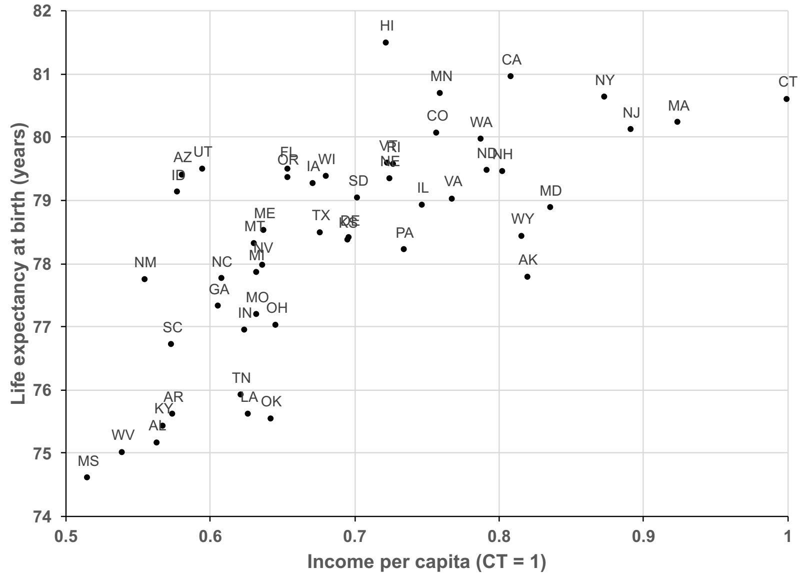

Figure 2: Relationship between income per capita and life expectancy at birth in 2015

Notes: The graph plots the relationship between personal income per capita and life expectancy at birth in 2015. Income per capita has been deflated by the national Personal Consumption Expenditures price index and normalized by income per capita in Connecticut, which was $65,800 in 2015. Sources: BEA and CDC.

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 for the period 2013–2017 as reported by the Centers for Disease Control and Prevention (CDC). Further details are given in Section 4.1. The results are illustrated in Figure 2, which plots the relationship between income per capita and life expectancy at birth. Life expectancy at birth varies by almost 7 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. As an example, life expectancy at birth is about 5 years higher in Connecticut, Massachusetts, and New Jersey than in Alabama, Mississippi, and West Virginia. As illustrated in the graph, life expectancy is also geographically concentrated, with several states in the South having particularly low life expectancy compared to the other regions.

2.3 College attainment

We use data from the Current Population Survey (CPS) to examine how educational attainment varies across states. Figure 3 plots the relationship between per capita income and college attainment across the states 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 4 years of college. As illustrated in the graph, college attainment varies considerably across

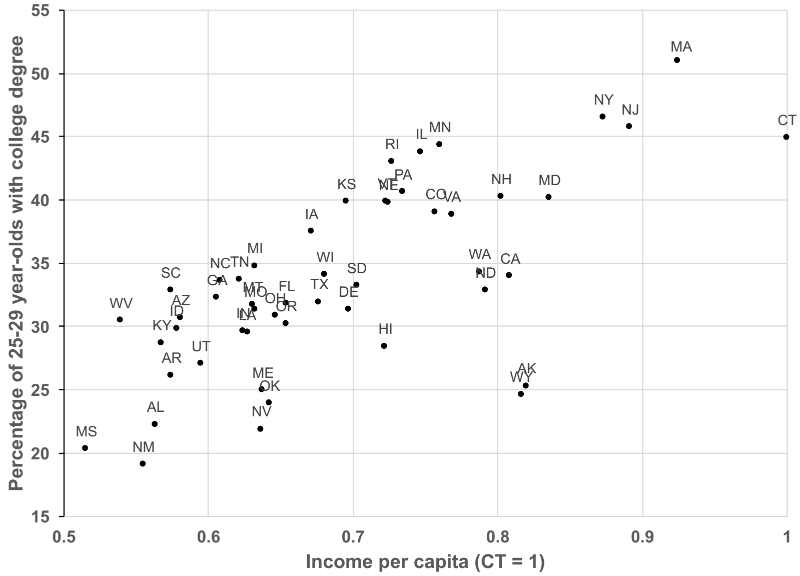

Figure 3: Relationship between income per capita and college attainment in 2015

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 4 years of college. Income per capita has been deflated by the national Personal Consumption Expenditures price index and normalized by income per capita in Connecticut, which was $65,800 in 2015. Sources: BEA and CPS.

the U.S., ranging from 19.1 percent in New Mexico to 50.9 percent in Massachusetts. With some notable exceptions such as Alaska and Wyoming, richer states tend to have higher college attainment rates than poorer states.

In the benchmark analysis we will assume that educational attainment depends on the state of birth and that the probability of being college-educated is 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 returns to their skills/college-degree is higher, thereby increasing the concentration of college-graduates in states such as Massachusetts (see for example Borjas, Bronars, and Trejo 1992 and Diamond 2016). We therefore consider an alternative environment in the Appendix where we simultaneously allow for migration and assume that educational attainment depends on the state of residence at age 25.

2.4 Inequality

We next examine how inequality varies across the U.S. Since data on consumption inequality at the state level is not available, we focus on income inequality, measured as the GINI coefficient of household income as reported by the Census. Figure 4 reports the relationship between income per capita and income inequality in 2015. There is large heterogeneity in the GINI coefficient of household income in the U.S., ranging from

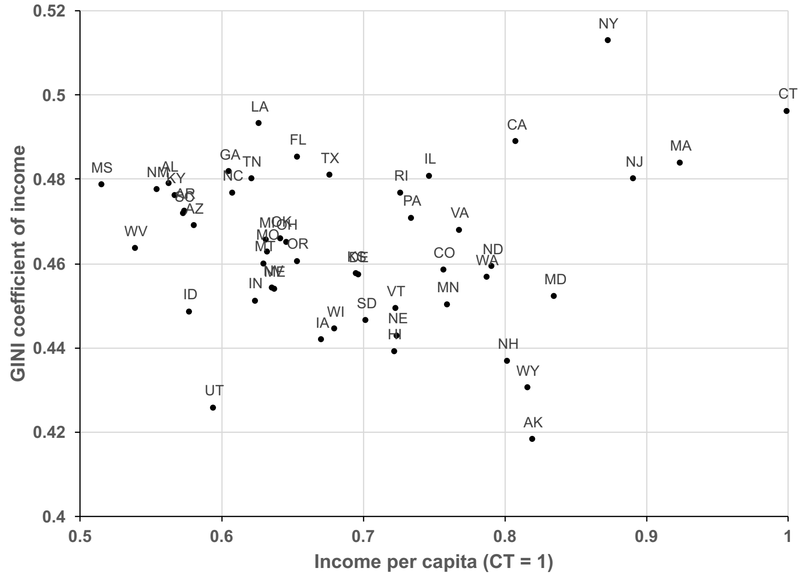

Figure 4: Relationship between income per capita and income inequality in 2015

Notes: The graph plots the relationship between per capita income and the GINI coefficient of household income in 2015. Income per capita has been deflated by the national Personal Consumption Expenditures price index and normalized by income per capita in Connecticut, which was $65,800 in 2015. Sources: BEA and Census.

less than 0.42 in Alaska to almost 0.52 in New York. While consumption per capita, life expectancy, and college attainment are positively correlated with 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 per capita income levels. To illustrate, whereas Louisiana and Utah have comparable per capita income levels, their GINI coefficient of income inequality still varies by almost 0.07. Similarly, while income per capita is almost the same in Alaska and California, their GINI coefficient of income inequality still varies by more than 0.07.

2.5 Relative prices

Lastly, we examine how cost of living varies across states. To do so, we use data on Regional Price Parities (RPPs) reported by the BEA. 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 4 consumption categories: all items, goods, rents, and other. We use the RPP for rent to approximate the price of housing. Using state-specific expenditure shares on rents, we then aggregate the RPPs for the other two components, goods and other, into one RPP. For simplicity, we refer to the latter as the price on consumption goods. The top panel of Figure 5 plots the relationship between per capita income and the price of consumption goods across the states in 2015, where we have normalized the latter by the average price level in the U.S. (that is, by RPP all items in the U.S.). Consumption good prices vary across the U.S., ranging from 8.8 percent below the national average in Mississippi to 9.7 percent above the national average in New York. As illustrated in the graph, consumption-good prices are positively correlated with per capita income, with richer states generally having higher consumption-good prices than poorer states.

The lower panel of Figure 5 plots the corresponding relationship between per capita income and housing prices across the states in 2015, where the latter has again been normalized by the average price level in the U.S. Housing prices vary more than consumption 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 are thus likely to overestimate the overall price level in these states. Moreover, higher housing prices are often associated with higher quality of amenities (see for example Albouy 2016), which our welfare measure does not account for. The welfare analysis in Section 5.1 is thus likely to underestimate welfare in states with high housing prices.

So far, we have shown that there exists considerable heterogeneity in average spending, life expectancy at birth, college attainment, inequality, consumption-good prices, and housing prices across the states, all of which are likely to have large implications for welfare. The next section develops a model that can be used to quantify the welfare differences across the U.S. Moreover, the model will allow us to examine how each of the components discussed in this section affects a state's welfare level.

3 Model

This section presents the model that we will apply to quantify the welfare differences across the U.S. It extends the model that Jones and Klenow (2016) use to study cross-country differences in welfare. We compare welfare across states using a common specification for preferences even though individuals in different states might have different preferences. In particular, we use the preferences of an average individual in the U.S.

3.1 General setup

Let the individual's idiosyncratic state be given by her age, a, educational level, e, and state of residence, s. The individual derives utility from consumption goods, c, and housing, h. Let p_c^s and p_h^s denote the price of

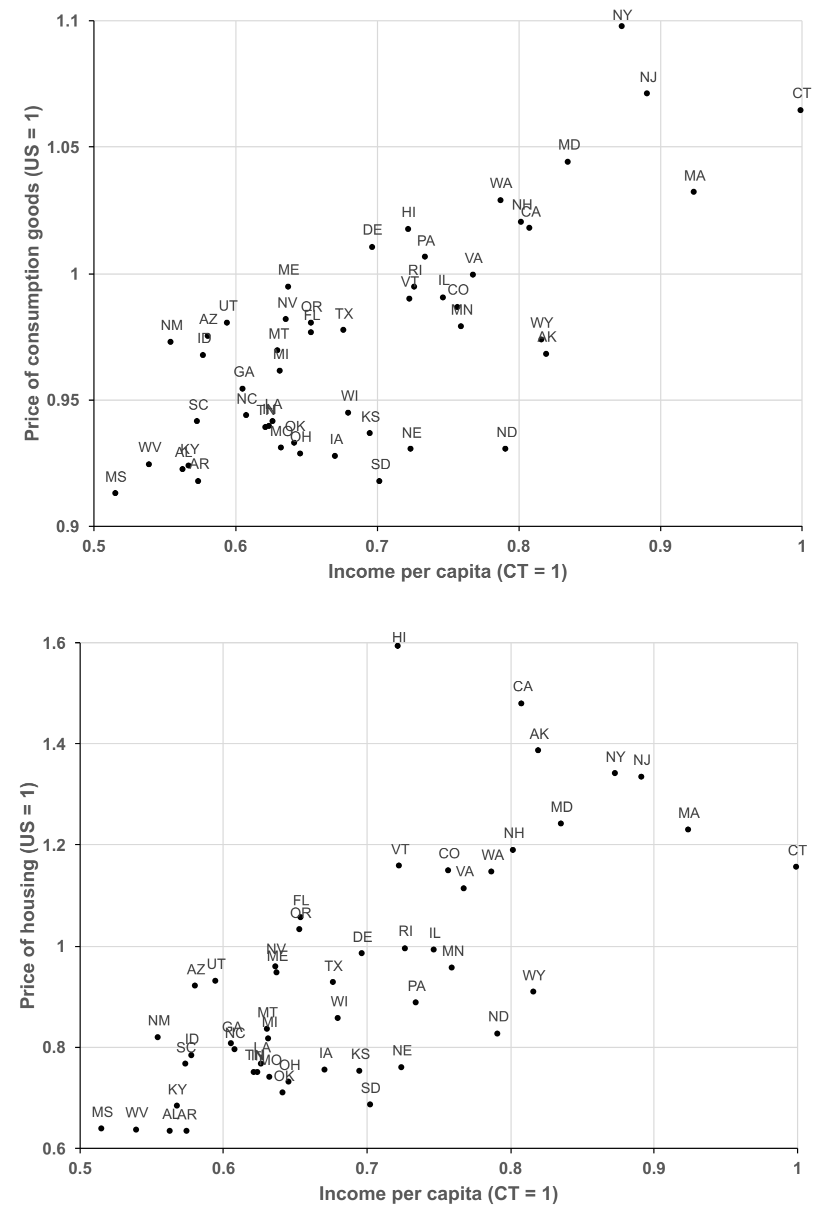

Figure 5: Relationship between income per capita and the price of consumption goods (top panel) and housing (bottom panel) in 2015

Notes: The top panel plots the relationship between per capita income and consumption-good prices in 2015. The lower panel plots the corresponding relationship between per capita income and housing prices in 2015. Both consumption-good prices and housing prices have been normalized by the average price level in the U.S. Income per capita has been deflated by the national Personal Consumption Expenditures price index and normalized by income per capita in Connecticut, which was $65,800 in 2015. Source: BEA

consumption goods and the price of housing in state s relative to the national average price level, p, which we normalize to one. Let $E^s_{ae} = p^s_c c^s_{ae} + p^s_h h^s_{ae}$ denote total expenditures given the individual's age, education, and state of residence. Assume that total expenditures grows at a common, non-state dependent, annual rate

g.[5] Next, let β denote the discount factor and let $\Psi^s_{ae} = \prod_{k=0}^{a-1} \psi^s_{ke}$ denote the education- and state-specific probability of surviving from age 0 to age $a \geq 1$, with $\Psi^s_{0e} = 1$ for all e and s. We assume that the individual enters the model at age 0 and lives at most 100 years. As mentioned earlier, the individual will live her entire life in the state she is born in. We assume that the educational level is revealed at birth and stays constant over the individual's lifespan. We test the sensitivity of the results to these assumptions in the robustness section of the paper. Over her life, the individual will draw from the cross-sectional distribution of expenditures and from the cross-sectional mortality distribution corresponding to each age, education, and state. Lifetime expected utility in state s is then given by

$$U^s = \mathbb{E}^s_{ea} \sum_e \pi^s_e \sum_{a=0}^{100} \beta^a \Psi^s_{ae} u\left(c\left(E^s_{ae} e^{ga}\right), h\left(E^s_{ae} e^{ga}\right)\right), \tag{1}$$

where π^s_e is the state-specific probability of drawing educational level e.[6]

Let $U^s(\lambda)$ denote lifetime expected utility in state s if we multiply total expenditures by a factor λ in all ages:

$$U^s(\lambda) = \mathbb{E}^s_{ea} \sum_e \pi^s_e \sum_{a=0}^{100} \beta^a \Psi^s_{ae} u\left(c\left(\lambda E^s_{ae} e^{ga}\right), h\left(\lambda E^s_{ae} e^{ga}\right)\right). \tag{2}$$

Consider two states s and $\hat{s}$. We quantify the welfare difference between state s and $\hat{s}$ by computing how much spending 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

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

3.2 Parameterization and welfare decomposition

Assume that preferences over consumption and housing are given by

$$u\left(c\left(E^s_{ae} e^{ga}\right), h\left(E^s_{ae} e^{ga}\right)\right) = b + \alpha \log\left(c\left(E^s_{ae} e^{ga}\right)\right) + (1-\alpha) \log\left(h\left(E^s_{ae} e^{ga}\right)\right), \tag{4}$$

where b governs the value of life as in Hall and Jones (2007) and α is the weight on consumption goods in the utility function.[7] Given the preferences in Equation (4), lifetime expected utility in state s can be written

[5] An alternative would be to forecast each state's future expenditure growth for the next 100 years based on data for the period 1999–2015. While such an approach is feasible, these forecasts would suffer from very large standard errors.

[6] Section 5.3.2 considers an alternative environment where we also include leisure in the utility function.

[7] Note that the assumption of Cobb-Douglas preferences and non-state dependent weights on housing in the utility function is inconsistent with data from the BEA, which show that expenditure shares on housing vary from 0.15 in West Virginia to 0.29 in Hawaii in 2015. We let the preferences in the benchmark model be given by Equation (4) since these preferences enables us to additively decompose the welfare differences across states into differences in life expectancy, college attainment, average expenditures, inequality, consumption-good prices, and housing prices. We test the sensitivity of the results to alternative utility specifications in Section 5.3.6.

as

$$U^s = \mathbb{E}^s_{ea} \sum_e \pi^s_e \sum_{a=0}^{100} \beta^a \Psi^s_{ae} \left[b + ga + \alpha \log\left(\frac{\alpha}{p^s_c}\right) + (1-\alpha)\log\left(\frac{1-\alpha}{p^s_h}\right) + \log\left(E^s_{ae}\right)\right]. \tag{5}$$

Assume that total expenditures are drawn from an age-, education, and state-specific lognormal distribution with mean of logarithmic values, μ^s_{ae}, and standard deviation of logarithmic values, σ^s_{ae}. Then $\mathbb{E}^s_{ae}\left[\log\left(E^s_{ae}\right)\right] = \log\left(\bar{E}^s_{ae}\right) - \frac{(\sigma^s_{ae})^2}{2}$, where $\bar{E}^s_{ae} = \exp\left(\mu^s_{ae} + \frac{(\sigma^s_{ae})^2}{2}\right)$ is the age-, education-, and state-specific arithmetic mean of spending. Lifetime expected utility in state s is then given by

$$U^s = \sum_e \pi^s_e \sum_{a=0}^{100} \beta^a \Psi^s_{ae} \left[b + ga + \alpha \log\left(\frac{\alpha}{p^s_c}\right) + (1-\alpha)\log\left(\frac{1-\alpha}{p^s_h}\right) + \log\left(\bar{E}^s_{ae}\right) - \frac{\left(\sigma^s_{ae}\right)^2}{2}\right]. \tag{6}$$

We continue to let $U^s(\lambda)$ denote lifetime expected utility in state s if we multiply total expenditures by a factor λ in all ages. Given the utility function and the assumption that total expenditures are drawn from a lognormal distribution, we get the following expression for $U^s(\lambda)$:

$$U^s(\lambda) = \sum_e \pi^s_e \sum_{a=0}^{100} \beta^a \Psi^s_{ae} \left[b + ga + \alpha \log\left(\frac{\alpha}{p^s_c}\right) + (1-\alpha)\log\left(\frac{1-\alpha}{p^s_h}\right) + \log(\lambda) + \log\left(\bar{E}^s_{ae}\right) - \frac{\left(\sigma^s_{ae}\right)^2}{2}\right], \tag{7}$$

where we have used that $u\left(c\left(\lambda E^s_{ae} e^{ga}\right), h\left(\lambda E^s_{ae} e^{ga}\right)\right) = b + ga + \alpha \log\left(\frac{\alpha}{p^s_c}\right) + (1-\alpha)\log\left(\frac{1-\alpha}{p^s_h}\right) + \log\left(\lambda E^s_{ae}\right)$ and that $\mathbb{E}^s_{ae}\left[\log\left(\lambda E^s_{ae}\right)\right] = \log(\lambda) + \log\left(\bar{E}^s_{ae}\right) - \frac{(\sigma^s_{ae})^2}{2}$.[8]

Recall that we quantify the welfare difference between state s and $\hat{s}$ by computing how much spending 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 $\log(\lambda^s)$:

$$\log(\lambda^s) = \frac{\sum_e \sum_{a=0}^{100} \beta^a \left[\pi^s_e\left(u^s_{ae}\left[\Psi^s_{ae} - \Psi^s_{ae}\right] + \Psi^s_{ae}\left[u^s_{ae} - u^{\hat{s}}_{ae}\right]\right) + \Psi^s_{ae} u^s_{ae}\left[\pi^s_e - \pi^{\hat{s}}_e\right]\right]}{\sum_e \sum_{a=0}^{100} \pi^s_e \beta^a \Psi^{\hat{s}}_{ae}}, \tag{8}$$

where u^s_{ae} is given by

$$u^s_{ae} \equiv b + ga + \alpha \log\left(\frac{\alpha}{p^s_c}\right) + (1-\alpha)\log\left(\frac{1-\alpha}{p^s_h}\right) + \log\left(\bar{E}^s_{ae}\right) - \frac{\left(\sigma^s_{ae}\right)^2}{2}. \tag{9}$$

To ease notation, let $\phi^{\hat{s}}_{ae} \equiv \frac{\pi^{\hat{s}}_e \beta^a \Psi^{\hat{s}}_{ae}}{\sum_e \sum_{a=0}^{100} \pi^{\hat{s}}_e \beta^a \Psi^{\hat{s}}_{ae}}$, $\Delta\phi^{\hat{s}}_{ae} \equiv \frac{\pi^{\hat{s}}_e \beta^a \left(\Psi^s_{ae} - \Psi^{\hat{s}}_{ae}\right)}{\sum_e \sum_{a=0}^{100} \pi^{\hat{s}}_e \beta^a \Psi^{\hat{s}}_{ae}}$, and $\Delta\pi^s_{ae} \equiv \frac{\beta^a \Psi^s_{ae}\left(\pi^s_e - \pi^{\hat{s}}_e\right)}{\sum_e \sum_{a=0}^{100} \pi^{\hat{s}}_e \beta^a \Psi^{\hat{s}}_{ae}}$. We can then rewrite the expression for $\log(\lambda^s)$ as

$$\log(\lambda^s) = \sum_e \sum_{a=0}^{100} \left(u^s_{ae}\left[\Delta\phi^{\hat{s}}_{ae} + \Delta\pi^s_{ae}\right] + \phi^{\hat{s}}_{ae}\left[u^s_{ae} - u^{\hat{s}}_{ae}\right]\right). \tag{10}$$

[8] Note that it does not matter for the welfare results in Section 5.1 whether spending 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.

Let $\overline{\Delta\phi_a^{\hat{s}} u_a^s} \equiv \sum_e \Delta\phi_{ae}^{\hat{s}} u_{ae}^s$ and $\chi_{ae}^{\hat{s}} \equiv \frac{\beta^a}{\sum_e \sum_{a=0}^{100} \pi_e^{\hat{s}} \beta^a \Psi_{ae}^{\hat{s}}}$. Moreover, assume that education can take on two values, college or non-college educated. We then get the following additive decomposition of the welfare difference between state s and $\hat{s}$:

$$
\begin{aligned}
\log(\lambda_s) \quad = \quad & \textstyle\sum_{a=0}^{100} \overline{\Delta\phi_a^{\hat{s}} u_a^s} && \text{Life expectancy} \\
& + \textstyle\sum_{a=0}^{100} \chi_{ae}^{\hat{s}} \left(\left[\pi_2^s - \pi_2^{\hat{s}}\right] \left[\Psi_{a2}^s u_{a2}^s - \Psi_{a1}^s u_{a1}^s\right] \right) && \text{College attainment} \\
& + \textstyle\sum_e \sum_{a=0}^{100} \phi_{ae}^{\hat{s}} \left(\log\left(\bar{E}_{ae}^s\right) - \log\left(\bar{E}_{ae}^{\hat{s}}\right) \right) && \text{Average expenditures} \\
& + \textstyle\sum_e \sum_{a=0}^{100} \frac{\phi_{ae}^{\hat{s}}}{2} \left(\left(\left(\sigma_{ae}^{\hat{s}}\right)^2 - \left(\sigma_{ae}^s\right)^2 \right) \right) && \text{Inequality of expenditures} \\
& + \textstyle\sum_e \sum_{a=0}^{100} \phi_{ae}^{\hat{s}} \alpha \left(\log\left(p_c^{\hat{s}}\right) - \log\left(p_c^s\right) \right) && \text{Consumption-good prices} \\
& + \textstyle\sum_e \sum_{a=0}^{100} \phi_{ae}^{\hat{s}} (1-\alpha) \left(\log\left(p_h^{\hat{s}}\right) - \log\left(p_h^s\right) \right) && \text{Housing prices.}
\end{aligned}
\tag{11}
$$

That is, the welfare difference between state s and $\hat{s}$ can be decomposed into six terms: the difference in life expectancy weighted by flow utility; the difference in college attainment weighted by how much a college degree affects utility (that is, weighted by how much a college degree decreases mortality risk and increases spending); the difference in average expenditures; the difference in inequality of expenditures; the difference in consumption-good prices scaled by the weight on consumption goods in the utility function; and the difference in housing prices scaled by the weight on housing in the utility function.

4 Calibration

This section is organized as follows. We start by explaining how we derive age-, education-, and state-specific survival probabilities. Next, we discuss how we estimate the process for spending, and how we adjust this process to account for the heterogeneity in average spending and the variation in inequality across the states. Lastly, we discuss the parameterization of the life-cycle parameters 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.[9] We follow a three-step procedure to derive these probabilities. First, we pool all death records for the period 2013–2017 from the Underlying Cause of Death database reported by the Centers for Disease Control and Prevention (CDC). The CDC reports each person's age and state of legal residence at the time

[9] 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 (2019), who compare mortality outcomes of patients that migrate from the same location but to different destinations. They find that current location has a large causal impact on mortality. In particular, their estimates imply that moving from a 10th percentile area in terms of impact on life expectancy to a 90th percentile area would increase life expectancy at age 65 by 1.1 years, or about half of the 90-10 cross-sectional difference.

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 directly 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. In a Gompertz model, the logarithm of the mortality rate is linear in age, $\log(m_{as}) = \alpha_s + \beta_s a$, where m_{as} is the mortality rate of individuals of age a in state s, and where α_s and β_s are state-specific coefficients. This log-linear approximation fits the CDC 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 United States.[10] 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 4 years of college. We then use the NVSS data to obtain the number of deaths by age and education over this time period. Next, we use data from the Current Population Survey (CPS) for the period 2013–2017 to compute the number of individuals by age and education. Since the CPS top-codes age at 85, we assume that the distribution of age and education of 85+ year-olds is the same as that for 80–84 year-olds. 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. 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. 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 3.56 percentage points for 85+ year-olds.[11] This translates into large differences in remaining life expectancy. As an example, at age 25, a college-educated individual can expect to live more than 7 years longer than a non-college educated individual.

Lastly, given an initial guess, $\hat{\psi}_{ae}^s$, we derive age-, education-, and state-specific survival probabilities by adjusting $\hat{\psi}_{ae}^s$ to match the age- and state-specific survival probabilities from the CDC, ψ_a^s, and the age- and

[10] 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.

[11] Due to small sample sizes for some age groups, we group individuals into 5-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 thus assumed to be the same within each 5-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	0.14	0.16	0.20	0.28	0.41	0.57	0.73	0.85	1.15	1.45	1.56	3.56

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. Each age refers to a 5-year age group: 25–29, 30–34, ... College-educated individuals refer to individuals with at least a bachelor's degree or a minimum of 4 years of college. Source: CPS and NVSS.

education-specific survival probabilities from the NVSS, ψ_{ae}. For each age, a, this corresponds to deriving the scaling terms, q^s_{ae}, that solve the following system of equations:

$$\begin{aligned} \psi^s_a &= \textstyle\sum_{e=1}^{2} \Lambda^s_{ae} q^s_{ae} \hat{\psi}^s_{ae} \\ \psi_{a2} - \psi_{a1} &= q^s_{a2}\hat{\psi}^s_{a2} - q^s_{a1}\hat{\psi}^s_{a1}, \end{aligned} \tag{12}$$

where Λ^s_{ae} denotes the distribution of age and education by state from the CPS. Age-, education-, and state-specific survival probabilities are then given by $\psi^s_{ae} = q^s_{ae}\hat{\psi}^s_{ae}$.[12] 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 Spending and inequality

We use data from the Consumer Expenditure Survey (CEX) for the period 1997–2017 to estimate the process for spending. 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, including age, education, and hours worked.[13]

We aggregate the data from a quarterly to an annual basis and deflate the series by means of the national Personal Consumption Expenditures price index reported by the BEA. In our benchmark analysis, we focus on consumption of non-durables and services as defined by the BEA. This includes expenditures on food, alcohol, tobacco, clothing, health care, education, reading, utilities, personal care, insurance, and other miscellaneous expenditures.[14] 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

[12] Attanasio, Kitao, and Violante (2010) and Conesa, Kehoe, Nygaard, and Raveendranathan (2020) use an analogous approach to derive survival probabilities.
[13] We extend the dataset used by Heathcote and Perri (2018).
[14] Section 5.3.3 studies the sensitivity of the results when we exclude expenditures on health care and Section 5.3.4 considers an alternative environment where we also include durable consumption goods.

received if the house had been rented to a tenant.

It is well known that the CEX underestimates total expenditures in the U.S. For each year, we correct for this by scaling total expenditures in the CEX to match per capita expenditures in the U.S. as reported by the BEA.[15] Since spending is reported at the household level, we allocate spending uniformly across all household members. Although the CEX reports the household's state of residence, the survey is not designed to be representative at the state-level. Rather than using the information on state of residence, we use the following approach to derive the state-specific spending processes. First, we assume that spending in the U.S. is drawn from a lognormal distribution with age- and education-specific mean, μ_{ea}, and standard deviation, σ_{ea}, both of which are estimated from the CEX. We then adjust the parameters of this lognormal spending process to account for the cross-state variations in spending per capita and inequality discussed in Section 2. In particular, we jointly calibrate the state-specific parameters of the lognormal spending process, μ^s_{ea} and σ^s_{ae}, to match both the demographic-adjusted per capita consumption of non-durables and services relative to the U.S. and the difference in inequality as measured by the GINI coefficient relative to the U.S. 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:

$$\begin{aligned} \frac{\sum_e \sum_a \Lambda^s_{ae} \exp\left(\mu_{ae}+\nu^s+\frac{(\sigma_{ae}\kappa^s)^2}{2}\right)}{\sum_e \sum_a \Lambda^{US}_{ae} \exp\left(\mu_{ae}+\frac{\sigma^2_{ae}}{2}\right)} &= \frac{C^s}{C^{US}} \\ \text{GINI}^s &= \text{GINI}^{US} + d^s, \end{aligned} \tag{13}$$

where Λ^s_{ae} and Λ^{US}_{ae} denote the distribution of age and education in state s and 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., GINI^{US} is the GINI coefficient of consumption in the U.S., and d^s is the difference in the GINI coefficient of consumption between the U.S. and state s.[16] The state-specific mean and standard deviation of logarithmic values are then given by $\mu^s_{ae} = \mu_{ae} + \nu^s$ and $\sigma^s_{ae} = \sigma_{ae}\kappa^s$, respectively.

4.3 Preferences

As noted earlier, we compare welfare across states using a common specification for preferences even though individuals in different states might have different preferences. In particular, we use the preferences of an average individual in the U.S. Since a period in the model is one year, we let discount factor, β, be equal

[15] Although we exclude expenditures on durables in the benchmark analysis, we include durable expenditures as part of spending when we scale the CEX data to match the values reported by the BEA.

[16] Since data on consumption inequality at the state level is not available, we let d^s be given by the difference in the GINI coefficient of household income between the U.S. and state s. We use data from the CEX for the period 2013–2017 to compute the GINI coefficient of spending in the U.S., GINI^{US}.

to 0.99. The growth rate of expenditures, g, is set to 2 percent per year. We use data on Regional Price Parities reported by the BEA to estimate the weight on housing, $1-\alpha$, in the utility function. In particular, we let the weight on housing be given by the weighted average expenditure share on housing rents across the states in 2015, where weights are given by the size of each state's population relative to the U.S. in 2015. This leads to a weight of 0.22 on housing and a corresponding weight of 0.78 on consumption goods in the utility function. 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, spending uncertainty, inequality, consumption-good prices, and housing prices in the U.S. in 2015—has a value of remaining life equal to $7 million in 2012 prices. This leads to a value of 7.21 for b when spending on non-durables and services per capita in the U.S. in 2015 is normalized to 1. We study the sensitivity of the results to alternative parameterizations of the model in Section 5.3.6.

5 Results

This section applies the model presented in Section 3 to quantify the welfare differences across the U.S. in 2015. We also use the model to quantify each state's welfare growth rate between 1999 and 2015. The final subsection studies the sensitivity of the results to various assumptions.

5.1 Welfare across states

This section quantifies the welfare differences across the U.S. in 2015. To illustrate our welfare analysis, suppose we wish to compare living standards in Connecticut and Minnesota. We do this by quantifying how much average spending would have to change in every age in Connecticut—holding fixed Connecticut's survival probabilities, educational attainment, inequality, consumption-good prices, and housing prices—to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut and Minnesota. The factor by which we have to adjust spending provides a consumption-equivalent measure of the difference in living standards between these two states.[17] We assume that the unborn individual draws from the cross-sectional distributions of spending and from the cross-sectional mortality distribution corresponding to each age, education, and state (see Sections 2 and 4 for details). Since educational attainment has increased 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.

[17] The Appendix reports the results when we compare the welfare differences across states by means of *compensating variation* rather than *equivalent variation*.

5.1.1 Relationship between income per capita and welfare

Income per capita is the most commonly used measure of living standards in the literature. We therefore start by comparing each state's welfare level as given by Equation (10) with its corresponding per capita income level. This relationship is illustrated in Figure 6. Both income per capita and welfare have been normalized by the corresponding value in Connecticut. Consistent with the literature studying cross-country welfare differences, we find that per capita income is positively correlated with welfare, with a correlation of 0.80 across states. Note, however, that the correlation between per capita income and welfare across the states of America (0.80) is lower than the corresponding correlation between GDP per capita and welfare across countries (0.98) found by Jones and Klenow (2016). The positive correlation shows that richer states tend to have higher welfare levels than poorer states. As an example, consider the case of Arkansas, whose income per capita is 42.5 percent lower than that of Connecticut. We find that spending has to decrease by 42.8 percent in all ages in Connecticut to equalize lifetime expected utility in Connecticut and Arkansas. Similarly, Alaska has 18.0 percent lower income per capita and 17.4 percent lower welfare than Connecticut.

Figure 6 shows that inequality in welfare, as measured by the dispersion in welfare levels across states, exceeds the corresponding dispersion in per capita income levels. In particular, whereas income per capita is 48.4 percent higher in the state with the highest income, Connecticut, than in the state with the lowest income, Mississippi, welfare is 55.3 percent higher in the state with the highest welfare level, Minnesota, than in the state with the lowest welfare level, Mississippi.

While per capita income is a good indicator of a state's welfare level, there are economically important deviations between the two measures. Our results show that living standards in most states appear closer to those of the richest state, Connecticut, than their difference in per capita income would suggest. In particular, whereas a comparison of income per capita would lead one to conclude that average living standards in the U.S. are 29.1 percent lower than in Connecticut, our welfare measure shows that average living standards in the U.S. are only 21.9 percent lower than in Connecticut. As an example, consider the case of South Dakota. While income per capita is 29.7 percent lower in South Dakota than in Connecticut, living standards as measured using our welfare metric are only 2.9 percent lower in South Dakota than in Connecticut. Living standards in several states in the South, however, appear *lower* relative to Connecticut when we account for differences in life expectancy, college attainment, spending, inequality, consumption-good prices, and housing prices. As an example, Oklahoma has 35.8 percent lower income per capita than Connecticut, but 44.8 percent lower welfare.

The relationship between welfare and per capita income is further illustrated in Figure 7, which plots the ratio of welfare to income per capita across the states. As illustrated in the graph, we find that states

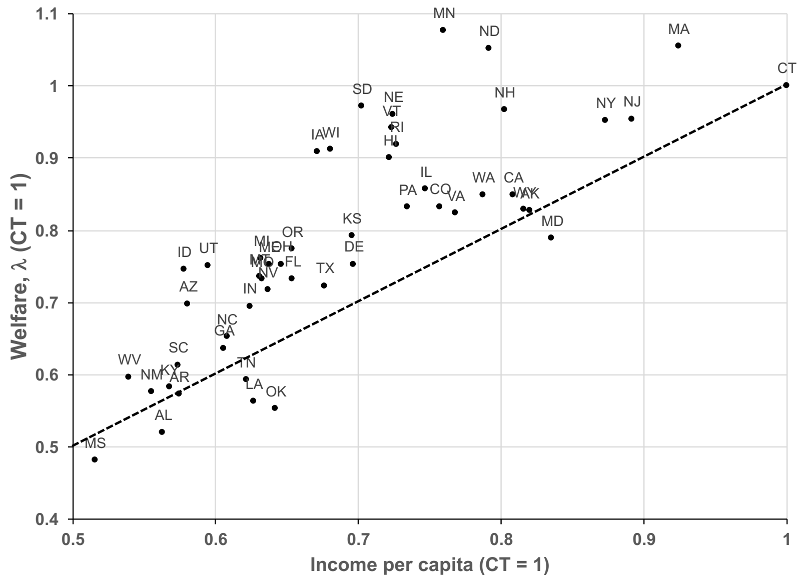

Figure 6: Relationship between income per capita and welfare in 2015

Notes: The graph plots the relationship between income per capita and welfare across the states in 2015, where the latter is given by Equation (10). We quantify the welfare differences across states by computing how much spending would have to change in all ages in the state with the highest personal income per capita, Connecticut, to make an unborn agent behind the veil of ignorance indifferent between living her entire life in Connecticut and any other state. Both welfare and per capita income have been normalized by the corresponding value in Connecticut. The dotted line depicts the 45-degree line. The correlation between per capita income and welfare is 0.80.

such as Iowa, Minnesota, and South Dakota have 35.3–41.6 percent higher welfare than income. In contrast, states such as Alabama, Louisiana, and Oklahoma have 7.8–14.1 percent lower welfare than income. Figure 7 shows that there is no relationship between the level of income per capita and the ratio of welfare to income per capita. In particular, richer (poorer) states do not generally have higher (lower) welfare than income. In fact, with the exception of Alabama, Arkansas, Louisiana, Maryland, Mississippi, Oklahoma, and Tennessee, we find that all states have higher welfare than per capita income, with the average state having 10.1 percent higher welfare than income. In contrast, Jones and Klenow (2016) find that richer (poorer) countries tend to have higher (lower) welfare than per capita income.

5.1.2 Decomposing welfare differences across states

To better understand the determinants of the welfare differences across states, we next apply Equation (11) to decompose each state's welfare level. The results are reported in Table 2, which provides an additive decomposition of the determinants of the welfare differences across the U.S. Columns 2 and 3 report each state's welfare and income per capita relative to Connecticut. Using Equation (11), we decompose $\log(\lambda)$ into six parts: life expectancy, college attainment, average spending, inequality, price of consumption goods,

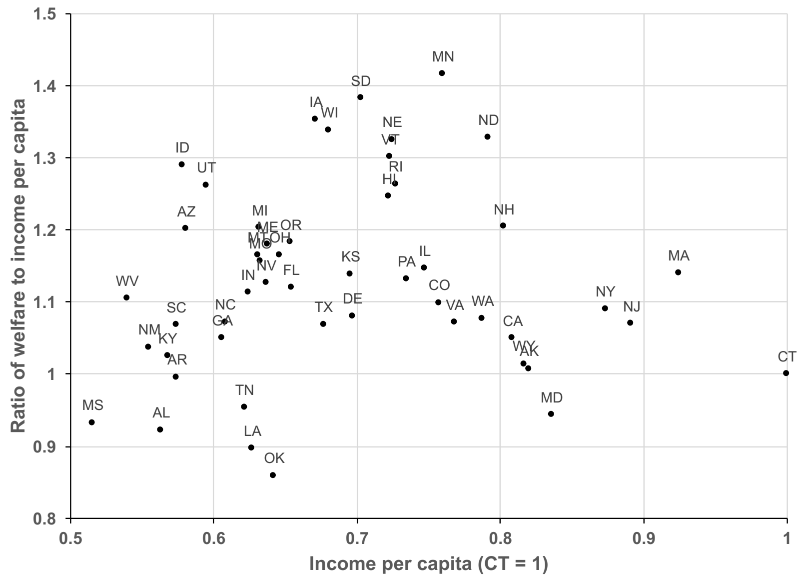

Figure 7: Ratio of welfare to income per capita in 2015

Notes: The graph plots the ratio of welfare to income per capita, where the former is given by Equation (8). Per capita income has been normalized by the corresponding value in Connecticut.

and price of housing. The decomposition is given in columns 4–9 of Table 2. Values in square brackets in the column titled "Life expectancy" report life expectancy at birth in the state. Values in square brackets in the column titled "College attainment" report the percentage of 25–29 year-olds with a college degree in the state. Values in square brackets in the column titled "Spending" report demographic-adjusted per capita consumption of non-durables and services in the state (see Section 4.2 for details). Values in square brackets in the column titled "Inequality" report the variance of spending in the state.[18] Values in square brackets in the column titled "Consumption prices" report the price of consumption goods in the state relative to the average price level in the U.S. Lastly, values in square brackets in the column titled "House prices" report the price of housing in the state relative to the average price level in the U.S. (see Section 2.5 for details).

Consider for example the state with the median welfare level, Oregon. Our decomposition shows that the 1.2 year lower life expectancy in Oregon compared to Connecticut reduces welfare in Oregon by 6 log points. That is, average spending would have to decline by approximately 6 percent in all ages in Connecticut—holding fixed Connecticut's mortality rates, educational attainment, inequality, and cost of living—to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut and

[18] In particular, for each state s, we report the value of $\sum_a \sum_e \Lambda_{ae}^{US} \frac{(\sigma_{ae}\kappa^s)^2}{2}$, where Λ_{ae}^{US} is the distribution of age and education in the U.S. in 2015, σ_{ae} is the age- and education-specific standard deviation of the logarithm of spending in the CEX, and κ^s is the factor by which we adjust the standard deviation to match the GINI coefficient of spending by state (see Section 4.2 for further details).

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

			Decomposition					
State	**Welfare λ**	**Income**	**Life expec.**	**College**	**Spending**	**Inequality**	**Cons. prices**	**House prices**
MN	107.6	76.0	0.028 [80.7]	-0.005 [44.3]	-0.118 [35.5]	0.062 [0.13]	0.066 [0.98]	0.041 [0.95]
MA	105.4	92.4	-0.049 [80.2]	0.051 [50.9]	0.021 [40.7]	0.019 [0.17]	0.024 [1.03]	-0.013 [1.23]
ND	105.1	79.2	-0.038 [79.5]	-0.105 [32.8]	-0.031 [38.7]	0.047 [0.15]	0.106 [0.93]	0.073 [0.83]
CT	100.0	100.0	0.000 [80.6]	0.000 [44.9]	0.000 [39.9]	0.000 [0.19]	0.000 [1.06]	0.000 [1.15]
SD	97.1	70.3	-0.064 [79.0]	-0.101 [33.2]	-0.156 [34.2]	0.062 [0.13]	0.116 [0.92]	0.113 [0.68]
NH	96.6	80.2	-0.082 [79.4]	-0.039 [40.2]	-0.020 [39.1]	0.079 [0.11]	0.033 [1.02]	-0.006 [1.19]
NE	96.0	72.5	-0.054 [79.3]	-0.044 [39.7]	-0.210 [32.4]	0.070 [0.12]	0.106 [0.93]	0.091 [0.76]
NJ	95.3	89.2	-0.031 [80.1]	0.007 [45.7]	-0.010 [39.5]	0.022 [0.17]	-0.005 [1.07]	-0.031 [1.33]
NY	95.2	87.3	0.024 [80.6]	0.014 [46.5]	-0.002 [39.7]	-0.030 [0.22]	-0.024 [1.10]	-0.032 [1.34]
VT	94.1	72.3	-0.070 [79.6]	-0.042 [39.9]	-0.072 [37.2]	0.065 [0.13]	0.057 [0.99]	0.000 [1.16]
RI	91.8	72.7	-0.052 [79.6]	-0.016 [43.0]	-0.128 [35.1]	0.025 [0.17]	0.053 [0.99]	0.032 [0.99]
WI	91.1	68.1	-0.034 [79.4]	-0.092 [34.1]	-0.189 [33.0]	0.063 [0.13]	0.094 [0.94]	0.065 [0.86]
IA	90.8	67.1	-0.036 [79.3]	-0.063 [37.4]	-0.263 [30.7]	0.066 [0.13]	0.108 [0.93]	0.092 [0.75]
HI	90.0	72.2	0.104 [81.5]	-0.152 [28.4]	-0.101 [36.1]	0.077 [0.12]	0.035 [1.02]	-0.069 [1.59]
IL	85.6	74.7	-0.103 [78.9]	-0.009 [43.8]	-0.151 [34.3]	0.019 [0.17]	0.056 [0.99]	0.033 [0.99]
CA	84.8	80.9	0.050 [80.9]	-0.095 [34.0]	-0.111 [35.7]	0.010 [0.18]	0.035 [1.02]	-0.054 [1.48]
WA	84.8	78.8	-0.027 [80.0]	-0.089 [34.3]	-0.132 [35.0]	0.055 [0.14]	0.027 [1.03]	0.002 [1.15]
CO	83.2	75.7	-0.061 [80.1]	-0.049 [39.0]	-0.190 [33.0]	0.056 [0.14]	0.060 [0.99]	0.001 [1.15]
PA	83.1	73.5	-0.138 [78.2]	-0.035 [40.6]	-0.143 [34.6]	0.030 [0.16]	0.044 [1.01]	0.057 [0.89]
WY	82.8	81.6	-0.098 [78.4]	-0.169 [24.6]	-0.125 [35.2]	0.081 [0.11]	0.070 [0.97]	0.052 [0.91]
AK	82.6	82.0	-0.191 [77.8]	-0.159 [25.3]	0.023 [40.9]	0.100 [0.09]	0.074 [0.97]	-0.039 [1.38]
VA	82.3	76.8	-0.107 [79.0]	-0.049 [38.8]	-0.135 [34.9]	0.038 [0.15]	0.050 [1.00]	0.008 [1.11]
KS	79.2	69.6	-0.139 [78.4]	-0.041 [39.8]	-0.300 [29.6]	0.053 [0.14]	0.100 [0.94]	0.093 [0.75]
MD	78.8	83.6	-0.141 [78.9]	-0.039 [40.2]	-0.122 [35.3]	0.063 [0.13]	0.015 [1.04]	-0.015 [1.24]
OR	77.3	65.4	-0.060 [79.4]	-0.122 [30.2]	-0.212 [32.3]	0.047 [0.15]	0.065 [0.98]	0.025 [1.03]
MI	76.0	63.2	-0.160 [77.8]	-0.081 [34.8]	-0.225 [31.8]	0.037 [0.16]	0.080 [0.96]	0.076 [0.81]
DE	75.2	69.7	-0.133 [78.4]	-0.111 [31.3]	-0.167 [33.8]	0.051 [0.14]	0.041 [1.01]	0.035 [0.98]
OH	75.2	64.6	-0.217 [77.0]	-0.111 [30.8]	-0.199 [32.7]	0.037 [0.16]	0.107 [0.93]	0.099 [0.73]
ME	75.2	63.8	-0.115 [78.5]	-0.162 [24.9]	-0.158 [34.1]	0.055 [0.14]	0.053 [0.99]	0.043 [0.95]
UT	75.1	59.5	-0.052 [79.5]	-0.147 [27.0]	-0.289 [29.9]	0.090 [0.10]	0.064 [0.98]	0.047 [0.93]
ID	74.5	57.8	-0.052 [79.1]	-0.125 [29.8]	-0.338 [28.5]	0.061 [0.13]	0.075 [0.97]	0.085 [0.78]
MT	73.5	63.1	-0.144 [78.3]	-0.107 [31.7]	-0.252 [31.0]	0.051 [0.14]	0.073 [0.97]	0.070 [0.83]
FL	73.2	65.4	-0.045 [79.5]	-0.112 [31.8]	-0.254 [30.9]	0.012 [0.18]	0.068 [0.98]	0.019 [1.06]
MO	73.2	63.3	-0.219 [77.2]	-0.107 [31.3]	-0.230 [31.7]	0.043 [0.15]	0.105 [0.93]	0.096 [0.74]
TX	72.3	67.7	-0.116 [78.5]	-0.105 [31.9]	-0.238 [31.4]	0.019 [0.17]	0.067 [0.98]	0.048 [0.93]
NV	71.7	63.7	-0.133 [78.0]	-0.187 [21.9]	-0.169 [33.7]	0.052 [0.14]	0.063 [0.98]	0.040 [0.96]
AZ	69.7	58.1	-0.049 [79.4]	-0.120 [30.7]	-0.346 [28.2]	0.037 [0.16]	0.069 [0.97]	0.049 [0.92]
IN	69.4	62.4	-0.215 [76.9]	-0.120 [29.6]	-0.276 [30.3]	0.055 [0.14]	0.098 [0.94]	0.094 [0.75]
NC	65.2	60.8	-0.162 [77.7]	-0.090 [33.6]	-0.374 [27.4]	0.022 [0.17]	0.094 [0.94]	0.081 [0.79]
GA	63.6	60.6	-0.208 [77.3]	-0.098 [32.3]	-0.327 [28.8]	0.017 [0.18]	0.086 [0.95]	0.078 [0.81]
SC	61.3	57.4	-0.244 [76.7]	-0.092 [32.9]	-0.368 [27.6]	0.029 [0.16]	0.096 [0.94]	0.089 [0.76]
WV	59.6	54.0	-0.351 [75.0]	-0.108 [30.4]	-0.331 [28.6]	0.033 [0.16]	0.111 [0.92]	0.129 [0.64]
TN	59.2	62.2	-0.304 [75.9]	-0.083 [33.7]	-0.344 [28.3]	0.017 [0.18]	0.098 [0.94]	0.093 [0.75]
KY	58.2	56.8	-0.320 [75.4]	-0.121 [28.7]	-0.343 [28.3]	0.017 [0.18]	0.111 [0.92]	0.114 [0.68]
NM	57.6	55.5	-0.183 [77.7]	-0.207 [19.1]	-0.338 [28.5]	0.030 [0.16]	0.071 [0.97]	0.075 [0.82]
AR	57.2	57.5	-0.304 [75.6]	-0.141 [26.1]	-0.384 [27.2]	0.024 [0.17]	0.116 [0.92]	0.130 [0.63]
LA	56.2	62.7	-0.324 [75.6]	-0.115 [29.5]	-0.320 [28.9]	-0.002 [0.20]	0.096 [0.94]	0.089 [0.76]
OK	55.2	64.2	-0.326 [75.5]	-0.156 [23.9]	-0.361 [27.8]	0.038 [0.16]	0.104 [0.93]	0.106 [0.71]
AL	51.9	56.3	-0.356 [75.2]	-0.166 [22.2]	-0.394 [26.9]	0.018 [0.17]	0.112 [0.92]	0.130 [0.63]
MS	48.1	51.6	-0.384 [74.6]	-0.178 [20.3]	-0.437 [25.8]	0.017 [0.18]	0.121 [0.91]	0.129 [0.64]

Notes: Column 2 reports how much spending would have to change in all ages in the state with the highest personal income per capita, Connecticut, to make an unborn agent behind the veil of ignorance indifferent between living her entire life in Connecticut and any other state in 2015. Column 3 reports each state's income per capita relative to Connecticut. The welfare decomposition in columns 4–9 is based on Equation (11), which decomposes $\log(\lambda)$ into six parts: life expectancy, college attainment, average spending, inequality, consumption-good prices, and housing prices. Values in square brackets report state-specific life expectancy at birth, college attainment of 25–29 year-olds, demographic-adjusted per capita consumption of non-durables and services, variance of spending, price of consumption goods relative to the average price level in the U.S., and price of housing relative to the average price level in the U.S.

Oregon if the difference in life expectancy was the *only* difference between these states. The 14.7 percentage point lower college attainment and the $7,600 lower average spending in Oregon further reduce welfare by 12 and 21 log points, respectively. In contrast, lower inequality in Oregon increases welfare 5 log points. Moreover, lower consumption-good prices and lower housing prices increase welfare by 7 and 3 log points, respectively. As a result, we find that consumption has to decrease by 22.7 percent in Connecticut to equalize welfare in Connecticut and Oregon. 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 spending reduce welfare by a total of 100 log points in Mississippi. Lower inequality, lower consumption-good prices, and lower housing prices, on the other hand, increase welfare in Mississippi by a total of 27 log points. Consequently, we find that consumption has to decrease by 51.9 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 spending in low-income states account for most of the lower welfare in these states compared to high-incomes states. Lower college attainment further reduces welfare in low-income states. Low-income states, however, generally benefit from lower consumption-good prices and lower housing prices. Table 2 shows that lower consumption-good prices increase welfare in states such as Alabama, Arkansas, Kentucky, Mississippi, and West Virginia by 11–12 log points compared to Connecticut. Lower housing prices further increase welfare in these states by 11–13 log points. The latter is consistent with the literature that shows that high housing prices have large implications for quality of life (see for example Albouy 2016). Therefore, failure to account for the heterogeneity in both consumption-good prices and housing prices would thus lead one to overestimate the dispersion in welfare between high- and low-income states.

Note that high housing prices is a key cause of out-migration, which can be interpreted as a revealed preference against states with high housing price. This is consistent with our finding that high housing prices have large negative welfare implications. Data from the CPS for the period 2013–2017 show that 44.5 percent of individuals that changed their state of residence moved due to “housing reasons,” 19.0 percent of whom cited “cheaper housing” as their main cause of moving. Interstate migration statistics for this time period show that states with high housing prices generally experienced net out-migration over this time period. To illustrate, Massachusetts, New Jersey, and New York, where higher housing prices reduce welfare by 1–3 log points relative to Connecticut, experienced net out-migration equivalent to 0.37–0.87 percent of their population over this time period. Similarly, the three states with the highest housing prices—Alaska, California and Hawaii, where higher housing prices reduce welfare by 4–7 log points relative to Connecticut—experienced net out-migration equivalent to 0.31–4.15 percent of their population. In contrast, states with lower housing prices such as Arizona, Maine, and Texas, where lower housing prices increase welfare by 4–5 log points compared with Connecticut, experienced net in-migration equivalent to 0.31–1.04 percent of their population.

5.1.3 Why do states with similar per capita income levels have different living standards?

Table 2 enables us to examine why states with similar per capita income levels have different living standards, and why living standards in several states are considerably higher than their per capita income would suggest. Consider for example the state with the highest welfare level, Minnesota. Although income per capita is approximately the same in Colorado, Illinois, Minnesota, Pennsylvania, and Virginia, we find that living standards as measured using our welfare criterion are 25.7–30.7 percent higher in Minnesota than in the other states. This is mainly due to higher life expectancy in Minnesota, which increases welfare by 3 log points in Minnesota compared with Connecticut, but decreases welfare by 6–14 log points in the other states. Higher college attainment, higher average spending, lower inequality, lower consumption-good prices, and (with the exception of Pennsylvania) lower housing prices in Minnesota lead to a further dispersion in welfare levels between these states.

We find that lower cost of living is the main reason welfare is higher in Minnesota than in the four richest states in the country: Connecticut, Massachusetts, New Jersey, and New York. Our decomposition shows that lower prices in Minnesota contribute to a 10–16 log point dispersion in welfare levels between Minnesota and these states. As a result, we find that living standards are at least 2.1 percent higher in Minnesota than in Connecticut, Massachusetts, New Jersey, and New York, even though income per capita is at least 12.9 percent higher in these states than in Minnesota.

As illustrated in Figure 7, Delaware, Iowa, Kansas, South Dakota, Texas, and Wisconsin have comparable per capita income levels. Yet, living standards as measured using our welfare metric are at least 14.6 percent higher in Iowa, South Dakota, and Wisconsin than in Delaware, Kansas, and Texas. This is predominately due to higher life expectancy in Iowa, South Dakota, and Wisconsin. Higher inequality in Delaware, Kansas, and Texas lead to a further dispersion in welfare levels between these states. Analogously, whereas Arizona, Georgia, Idaho, North Carolina, and Utah have comparable per capita income levels, we find that living standards are at least 6.9 percent higher in Arizona, Idaho, and Utah than in Georgia and North Carolina. This is mainly because life expectancy at birth is at least 1.4 years higher in Arizona, Idaho, and Utah.

Lower life expectancy is also the main reason welfare is lower in Louisiana, Oklahoma, and Tennessee than in Arizona, Idaho, and Utah. While life expectancy at birth is less than 76 years in Louisiana, Oklahoma, and Tennessee, it is more than 79 years in Arizona, Idaho, and Utah. Therefore, whereas lower life expectancy reduces welfare by at least 30 log points in Louisiana, Oklahoma, and Tennessee compared to Connecticut, it only reduces welfare by 5 log points in Arizona, Idaho, and Utah. As a result, we find that living standards are at least 17.7 percent higher in Arizona, Idaho, and Utah than in Louisiana, Oklahoma, and Tennessee, even though income per capita is at least 4.5 percent higher in the latter states. Lastly, we find that the low life expectancy in Maryland compared to states with similar per capita income levels is the main reason living standards are 5.8 percent lower in Maryland than its income per capita would predict. Lower average spending and relatively high price levels lead to a further dispersion in welfare levels between Maryland and states with comparable per capita income levels.

5.1.4 Comparing welfare across regions

We end this section with a comparison of welfare across regions. We find that living standards are highest in the Midwest and the Northeast. While states in the Midwest generally have lower average spending than states in the Northeast, this is generally offset by lower price levels in the Midwest. This can be seen from Table 2, which shows that lower average spending reduces welfare in states such as Iowa, Minnesota, Nebraska, North Dakota, South Dakota, and Wisconsin by 3–26 log points relative to Connecticut, whereas lower prices increase welfare by a total of 11–23 log points in these states. Moreover, whereas states in the Midwest benefit from lower inequality, states in the Northeast generally benefit from higher college attainment. Like the Midwestern states, states in the South generally benefit from lower inequality, lower consumption-good prices, and lower housing prices. These states, however, have lower welfare due to lower life expectancy, lower college attainment, and lower average spending. Lastly, states in the West are more heterogeneous, with the Mountain States benefiting from lower cost of living but performing relatively worse in terms of life expectancy, whereas the opposite is the case for the Pacific States.

5.2 Welfare across time

Section 5.1 quantified the welfare differences across the U.S. This section, instead, quantifies each state's welfare growth rate between 1999 and 2015.[19] To do so, we follow Jones and Klenow (2016) and let the growth rate of welfare be given by:

$$g_\lambda^s = -\frac{1}{T}\log\left(\lambda^s\right), \tag{14}$$

where $T = 2015 - 1999 = 16$ is the number of years.[20]

[19] Due to small sample sizes for some states, we continue to pool data for 5-year periods. Throughout, 1999 refers to data for the period 1997–2001 and 2015 refers to data for the period 2013–2017.

[20] The BEA only reports state-specific relative price series for the period 2008–2017. We therefore approximate consumption-good prices and housing prices in 1997–2001 by the corresponding average prices for the period 2008–2010. Similarly, due to data limitations, we use the average GINI coefficient of household income for the period 2006–2008 to approximate for inequality in 1997–2001.

5.2.1 Relationship between per capita income growth and welfare growth

The welfare growth results are reported in Table 3. Column 2 reports the annual growth rate in welfare, g_λ, ordered in descending order from the state with the highest to the lowest growth rate.[21] North Dakota had the highest growth in welfare between 1999 and 2015, with an average growth rate of 3.76 percent per year over this period. In contrast, New Mexico had the lowest growth in welfare, with an average growth rate of 1.38 percent per year between 1999 and 2015. This dispersion in welfare growth rates has large implications for the evolution of living standards. Given current trends, living standards are expected to double every 50.2 years in New Mexico. Living standards in North Dakota, on the other hand, are expected to double every 18.4 years, or 31.8 years more rapidly than in New Mexico.

Column 3 of Table 3 reports each state's annual growth rate in income per capita, g_Y, between 1999 and 2015. Income per capita increased in all states over this period, ranging from 0.39 percent per year in Nevada to 3.21 percent per year in North Dakota.[22] The 2.82 percentage point dispersion in annual income growth rates across states thus exceeded the corresponding 2.38 percentage point dispersion in annual welfare growth rates. We find that the growth rate of welfare and growth rate of per capita income are only weakly correlated, with a a correlation of 0.38 across states. This is considerably lower than the corresponding correlation between welfare growth and per capita GDP growth across countries (0.97) found by Jones and Klenow (2016). Moreover, deviations are often large, with welfare growth exceeding per capita income growth by 1.09 percentage points on average (weights are given by the size of each state's population relative to the U.S. in 1999). To illustrate, while income per capita increased by 0.39 percent per year in Nevada between 1999 and 2015, its welfare increased by 2.99 percent per year over this time period. Hence, whereas the growth rate in income would suggest that living standards barely increased in Nevada between 1999 and 2015, the growth rate in welfare shows that living standards increased considerably over this period.

The growth rate of income per capita in Oklahoma, on the other hand, exceeded its corresponding growth rate of welfare by 0.34 percentage points. Living standards in Oklahoma thus increased by less than what its per capita income growth would have suggested. Similarly, whereas a number of states experienced comparable per capita income growth over this time period, their welfare growth often differed substantially. For instance, while Oklahoma and South Dakota experienced similar per capita income growth over this time period, welfare increased by an additional 1.38 percentage points per year in South Dakota. These findings show that per capita income growth is not necessarily a good indicator of how fast living standards

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

[22] Growth in income per capita between 1999 and 2015 was lower than the historical average in the U.S. due to the Great Recession. Consequently, growth in consumption was also lower over this time period compared to its historical average. The Appendix reports the growth in welfare for the period leading up to the Great Recession.

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

			Decomposition					
State	g_λ	g_Y	**Life expec.**	**College attain.**	**Spending**	**Inequality**	**Cons. prices**	**House prices**
ND	3.76	3.21	0.89 [77.4, 79.5]	0.18 [29.0, 32.8]	2.95[22.8, 38.7]	-0.03 [0.14, 0.15]	-0.04 [0.92, 0.93]	-0.18 [0.72, 0.83]
NY	3.66	1.67	1.45 [77.4, 80.6]	0.62 [33.0, 46.5]	1.65[28.9, 39.7]	-0.03 [0.22, 0.22]	-0.02 [1.09, 1.10]	-0.01 [1.33, 1.34]
SD	3.22	2.14	0.84 [77.2, 79.0]	0.23 [28.3, 33.2]	2.26[22.5, 34.2]	0.02 [0.13, 0.13]	-0.06 [0.91, 0.92]	-0.06 [0.65, 0.68]
NV	2.99	0.39	1.25 [75.0, 78.0]	0.27 [15.8, 21.9]	1.38[25.4, 33.7]	-0.06 [0.13, 0.14]	-0.06 [0.97, 0.98]	0.22 [1.13, 0.96]
RI	2.99	1.51	0.82 [77.6, 79.6]	0.67 [28.3, 43.0]	1.58[25.7, 35.1]	-0.10 [0.15, 0.17]	-0.06 [0.98, 0.99]	0.08 [1.05, 0.99]
MD	2.95	1.49	1.07 [76.2, 78.9]	0.39 [31.4, 40.2]	1.45[26.5, 35.3]	-0.02 [0.13, 0.13]	0.06 [1.06, 1.04]	0.01 [1.25, 1.24]
CT	2.87	1.45	1.04 [78.1, 80.6]	0.60 [31.9, 44.9]	1.16[31.3, 39.9]	-0.03 [0.19, 0.19]	0.04 [1.07, 1.06]	0.06 [1.20, 1.15]
CA	2.87	1.78	1.33 [77.7, 80.9]	0.32 [27.0, 34.0]	1.40[26.9, 35.7]	-0.08 [0.17, 0.18]	-0.14 [0.99, 1.02]	0.05 [1.53, 1.48]
NJ	2.81	1.31	1.08 [77.6, 80.1]	0.46 [35.7, 45.7]	1.36[30.0, 39.5]	-0.06 [0.16, 0.17]	-0.09 [1.05, 1.07]	0.06 [1.40, 1.33]
VA	2.78	1.48	1.05 [76.7, 79.0]	-0.04 [39.8, 38.8]	1.73[25.0, 34.9]	0.01 [0.16, 0.15]	0.02 [1.00, 1.00]	0.02 [1.13, 1.11]
PA	2.77	1.62	0.87 [76.3, 78.2]	0.40 [31.6, 40.6]	1.51[25.7, 34.6]	-0.01 [0.16, 0.16]	0.01 [1.01, 1.01]	0.00 [0.88, 0.89]
NE	2.75	1.78	0.77 [77.5, 79.3]	0.45 [29.8, 39.7]	1.54[23.9, 32.4]	0.01 [0.13, 0.12]	-0.02 [0.93, 0.93]	0.00 [0.76, 0.76]
WY	2.69	2.54	0.38 [77.4, 78.4]	0.24 [19.2, 24.6]	2.01[24.1, 35.2]	0.09 [0.13, 0.11]	0.03 [0.98, 0.97]	-0.06 [0.87, 0.91]
IL	2.67	1.17	0.95 [76.8, 78.9]	0.45 [33.7, 43.8]	1.20[26.8, 34.3]	-0.04 [0.17, 0.17]	0.08 [1.01, 0.99]	0.02 [1.01, 0.99]
LA	2.65	1.98	0.78 [73.8, 75.6]	0.34 [21.4, 29.5]	1.55[21.3, 28.9]	-0.05 [0.19, 0.20]	0.04 [0.95, 0.94]	-0.01 [0.76, 0.76]
DE	2.55	0.67	1.07 [76.0, 78.4]	0.13 [28.5, 31.3]	1.27[26.0, 33.8]	-0.06 [0.13, 0.14]	0.12 [1.04, 1.01]	0.02 [1.00, 0.98]
HI	2.55	1.64	0.87 [79.2, 81.5]	0.17 [24.9, 28.4]	1.60[26.4, 36.1]	0.05 [0.12, 0.12]	-0.17 [0.98, 1.02]	0.04 [1.64, 1.59]
MA	2.55	1.74	0.96 [77.8, 80.2]	0.34 [43.4, 50.9]	1.25[31.6, 40.7]	-0.03 [0.17, 0.17]	0.02 [1.03, 1.03]	0.02 [1.24, 1.23]
MT	2.53	2.32	0.36 [77.1, 78.3]	0.36 [23.6, 31.7]	1.87[21.7, 31.0]	-0.04 [0.14, 0.14]	0.03 [0.98, 0.97]	-0.06 [0.80, 0.83]
TX	2.52	1.58	0.96 [76.2, 78.5]	0.36 [23.8, 31.9]	1.19[24.5, 31.4]	0.04 [0.18, 0.17]	0.04 [0.98, 0.98]	-0.06 [0.88, 0.93]
AK	2.51	1.93	0.45 [76.4, 77.8]	0.32 [18.1, 25.3]	1.63[29.7, 40.9]	0.03 [0.10, 0.09]	0.11 [0.99, 0.97]	-0.03 [1.35, 1.38]
SC	2.49	1.23	0.75 [74.9, 76.7]	0.54 [20.3, 32.9]	1.15[21.7, 27.6]	0.01 [0.17, 0.16]	0.05 [0.95, 0.94]	0.00 [0.76, 0.76]
MN	2.43	1.46	0.95 [78.7, 80.7]	0.37 [36.5, 44.3]	1.13[28.0, 35.5]	-0.01 [0.13, 0.13]	0.01 [0.98, 0.98]	-0.01 [0.95, 0.95]
WI	2.40	1.25	0.73 [77.8, 79.4]	0.30 [27.5, 34.1]	1.41[24.9, 33.0]	-0.05 [0.12, 0.13]	-0.03 [0.94, 0.94]	0.04 [0.88, 0.86]
TN	2.39	1.25	0.90 [73.8, 75.9]	0.51 [21.7, 33.7]	0.95[22.9, 28.3]	0.03 [0.18, 0.18]	0.03 [0.94, 0.94]	-0.02 [0.74, 0.75]
VT	2.38	1.84	0.63 [77.9, 79.6]	0.24 [34.5, 39.9]	1.69[26.8, 37.2]	-0.05 [0.12, 0.13]	-0.07 [0.98, 0.99]	-0.05 [1.11, 1.16]
NC	2.38	0.99	1.08 [75.4, 77.7]	0.26 [27.7, 33.6]	1.05[21.9, 27.4]	-0.03 [0.17, 0.17]	0.03 [0.95, 0.94]	-0.01 [0.79, 0.79]
FL	2.38	1.06	1.01 [77.0, 79.5]	0.33 [24.5, 31.8]	1.05[24.7, 30.9]	-0.03 [0.18, 0.18]	-0.05 [0.97, 0.98]	0.06 [1.10, 1.06]
NH	2.37	1.41	0.35 [78.2, 79.4]	0.60 [27.0, 40.2]	1.43[29.4, 39.1]	-0.05 [0.11, 0.11]	-0.01 [1.02, 1.02]	0.06 [1.24, 1.19]
AZ	2.34	1.02	1.05 [76.8, 79.4]	0.45 [20.7, 30.7]	0.65[24.0, 28.2]	-0.04 [0.15, 0.16]	0.12 [1.00, 0.97]	0.11 [0.99, 0.92]
WV	2.29	1.52	0.07 [74.8, 75.0]	0.36 [22.0, 30.4]	1.91[19.9, 28.6]	-0.01 [0.16, 0.16]	0.00 [0.92, 0.92]	-0.05 [0.61, 0.64]
WA	2.22	1.61	0.80 [77.9, 80.0]	0.28 [28.2, 34.3]	1.26[27.0, 35.0]	0.00 [0.14, 0.14]	-0.08 [1.01, 1.03]	-0.04 [1.12, 1.15]
OR	2.15	1.25	0.82 [77.3, 79.4]	0.22 [25.3, 30.2]	1.19[25.2, 32.3]	-0.05 [0.14, 0.15]	0.03 [0.98, 0.98]	-0.06 [0.99, 1.03]
ID	2.15	1.29	0.33 [78.2, 79.1]	0.35 [22.1, 29.8]	1.45[21.3, 28.5]	-0.08 [0.12, 0.13]	0.05 [0.98, 0.97]	0.05 [0.81, 0.78]
AR	2.07	1.76	0.17 [75.1, 75.6]	0.35 [17.9, 26.1]	1.57[19.9, 27.2]	-0.01 [0.17, 0.17]	0.00 [0.92, 0.92]	-0.02 [0.62, 0.63]
IA	2.07	1.63	0.47 [78.4, 79.3]	0.23 [32.5, 37.4]	1.49[22.8, 30.7]	-0.03 [0.12, 0.13]	-0.05 [0.92, 0.93]	-0.04 [0.73, 0.75]
IN	2.02	1.05	0.36 [75.9, 76.9]	0.45 [19.3, 29.6]	1.17[23.7, 30.3]	-0.04 [0.13, 0.14]	0.03 [0.95, 0.94]	0.04 [0.77, 0.75]
MI	2.01	0.68	0.64 [76.4, 77.8]	0.36 [26.7, 34.8]	0.94[25.9, 31.8]	-0.05 [0.15, 0.16]	0.07 [0.97, 0.96]	0.05 [0.85, 0.81]
OH	2.00	1.11	0.35 [76.2, 77.0]	0.20 [26.3, 30.8]	1.45[24.5, 32.7]	-0.04 [0.15, 0.16]	0.01 [0.93, 0.93]	0.04 [0.75, 0.73]
MS	1.99	1.39	0.35 [73.8, 74.6]	-0.07 [21.9, 20.3]	1.66[18.6, 25.8]	0.07 [0.19, 0.18]	0.01 [0.91, 0.91]	-0.02 [0.63, 0.64]
GA	1.94	0.73	1.05 [74.8, 77.3]	0.01 [31.9, 32.3]	0.87[23.6, 28.8]	-0.04 [0.17, 0.18]	0.01 [0.96, 0.95]	0.03 [0.82, 0.81]
UT	1.93	1.64	0.59 [77.9, 79.5]	0.04 [26.1, 27.0]	1.32[22.8, 29.9]	-0.04 [0.10, 0.10]	-0.01 [0.98, 0.98]	0.02 [0.95, 0.93]
OK	1.84	2.18	0.00 [75.4, 75.5]	0.05 [22.7, 23.9]	1.76[19.8, 27.8]	0.06 [0.17, 0.16]	0.02 [0.94, 0.93]	-0.05 [0.68, 0.71]
KS	1.83	1.64	0.31 [77.7, 78.4]	0.22 [35.0, 39.8]	1.37[22.4, 29.6]	-0.01 [0.14, 0.14]	-0.06 [0.93, 0.94]	0.00 [0.75, 0.75]
MO	1.80	1.15	0.89 [75.3, 77.2]	-0.13 [34.3, 31.3]	1.15[24.9, 31.7]	0.00 [0.15, 0.15]	-0.12 [0.91, 0.93]	0.01 [0.75, 0.74]
CO	1.63	1.20	0.94 [77.7, 80.1]	-0.08 [40.8, 39.0]	0.80[27.5, 33.0]	0.06 [0.15, 0.14]	0.03 [0.99, 0.99]	-0.11 [1.06, 1.15]
KY	1.63	1.26	0.08 [75.2, 75.4]	0.25 [22.8, 28.7]	1.31[21.6, 28.3]	-0.02 [0.17, 0.18]	0.03 [0.93, 0.92]	-0.02 [0.67, 0.68]
ME	1.56	1.34	0.27 [77.4, 78.5]	0.04 [24.0, 24.9]	1.33[25.9, 34.1]	-0.03 [0.13, 0.14]	-0.05 [0.98, 0.99]	-0.01 [0.94, 0.95]
AL	1.43	1.24	0.29 [74.4, 75.2]	-0.08 [24.1, 22.2]	1.14[21.1, 26.9]	0.03 [0.18, 0.17]	0.04 [0.93, 0.92]	0.01 [0.64, 0.63]
NM	1.38	1.44	0.11 [77.0, 77.7]	-0.10 [21.3, 19.1]	1.37[21.5, 28.5]	-0.03 [0.16, 0.16]	0.03 [0.98, 0.97]	0.00 [0.82, 0.82]

Notes: Column 2 reports each state's annual welfare growth rate between 1999 and 2015 as defined by Equation (12). Column 3 reports each state's annual per capita income growth rate over this time period. Columns 4–9 decompose each state's welfare growth rate, g_λ, into six parts: changes in life expectancy, changes in college attainment, changes in average spending, changes in inequality, changes in consumption-good prices, and changes in housing prices. Values in square brackets report state-specific life expectancy at birth in 1999 and 2015, college attainment of 25–29 year-olds in 1999 and 2015, demographic-adjusted per capita consumption of non-durables and services in 1999 and 2015, variance of spending in 1999 and 2015, price of consumption goods relative to the average price level in the U.S. in 1999 and 2015, and price of housing relative to the average price level in the U.S. in 1999 and 2015. Numbers might not add up due to rounding error.

are rising in a particular state.

5.2.2 Decomposing each state's welfare growth rate

We next study the determinants of each state's welfare growth between 1999 and 2015. In particular, we decompose the growth rate of welfare into six parts: changes in life expectancy, changes in college attainment, changes in average spending, changes in inequality, changes in consumption-good prices, and changes in housing prices. The decomposition of the growth rate is given in columns 4–9 of Table 3. Values in brackets in the columns titled "Life expectancy", "College attainment," "Spending," "Inequality," "Consumption prices," and "House prices" report life expectancy at birth in 1999 and 2015, the percentage of 25–29 year-olds with a college degree in 1999 and 2015, demographic-adjusted per capita consumption of non-durables and services in 1999 and 2015, variance of spending in 1999 and 2015, the price of consumption goods in the state relative to the average price level in the U.S. in 1999 and 2015, and the price of housing in the state relative to the average price level in the U.S. in 1999 and 2015.

To illustrate this decomposition, consider the state with the median growth rate in welfare, Vermont. Welfare increased by 2.38 percent per year in Vermont between 1999 and 2015. Our decomposition shows that the 1.7 year increase in life expectancy increased welfare by 0.63 percent per year over this time period, and that the 5.4 percentage point increase in college attainment increased welfare by 0.24 percent per year. We find that the increase in average spending was the main driver of the increase in welfare in Vermont. In particular, we find that the $10,400 surge in per capita consumption of non-durables and services increased welfare by 1.69 percent per year over this time period. In contrast, the increase in inequality reduced the growth rate of welfare by 0.05 percent per year. Similarly, the increase in relative consumption-good prices and the increase in relative housing prices reduced welfare by 0.07 and 0.05 percent per year, respectively.

Table 3 enables us to examine the determinants of the 2.38 percentage point dispersion in annual welfare growth rates across states. 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. This dispersion in life expectancy gains had large implications for welfare growth. In particular, whereas the increase in life expectancy increased welfare by 1.45 percent per year in New York over this time period, it increased welfare by less than 0.01 percent per year in Oklahoma. Note that the experience of Oklahoma is representative of several states in the South. That is, states such as Alabama, Arkansas, Kentucky, and Mississippi all experienced limited gains in life expectancy over this period. As a result, we find that improvements in life expectancy only increased welfare by 0.08–0.35 percent per year in these states. A comparison across all states shows that gains in life expectancy increased weighted average welfare by 0.90 percent per year, with a standard deviation of 0.36 across states. 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 dispersion in welfare growth rates across the U.S. over this time period.[23] In particular, we find that variations in life expectancy gains account for 50.26 percent of the dispersion in welfare growth rates.

Table 3 shows that the change in college attainment rates, as measured by the change in the percentage of 25–29 year-olds with a college degree between 1999 and 2015, varied significantly across states, from a 3.0 percentage point reduction in Missouri to a 14.7 percentage point increase in Rhode Island. These differences in college attainment rates contributed to a 0.80 percentage point dispersion in welfare growth rates between these states. We find that increased college attainment was a particularly important driver of welfare growth for several states in the Northeast. As shown in Table 3, higher college attainment increased welfare by at least 0.60 percent per year in Connecticut, New Hampshire, New York, and Rhode Island. Declining college attainment rates in Alabama, Colorado, Mississippi, Missouri, New Mexico, and Virginia, on the other hand, reduced welfare by 0.04–0.13 percent per year. A comparison across all states shows that higher college attainment rates increased weighted average welfare by 0.31 percent per year in the U.S., with a standard deviation of 0.18 across states. In terms of the variance decomposition, we find that variations in college attainment gains account for 13.03 percent of the dispersion in welfare growth rates across states.

Weighted average welfare increased by 2.49 percent per year in the U.S. between 1999 and 2015. Most of this can be attributed to higher spending, which increased average welfare by 1.30 percent per year. The increase in spending, however, has not been uniform across states. As a result, the contribution of spending growth to welfare growth has varied across states, ranging from 0.65 percent per year in Arizona to 2.95 percent per year in North Dakota. Our variance decomposition shows that variations in spending growth account for 28.41 percent of the variation in welfare growth rates between 1999 and 2015, and has hence been the second most important driver of the dispersion in welfare growth rates in the U.S.

While within-state inequality has changed over time, we find that these changes have only had limited implications for welfare growth. Our results show that changes to inequality reduced average welfare by 0.03 percent per year in the U.S., with a standard deviation of 0.04. Rhode Island experienced the largest increase in inequality, which in turn reduced its welfare by 0.10 percent per year between 1999 and 2015. In contrast, Wyoming experienced the largest reduction in inequality over this time period, which in turn increased its welfare by 0.09 percent per year. As a result, we find that changes in inequality contributed to a 0.19 percentage point dispersion in welfare growth across states, and that variations in inequality trends

[23] Let $g_\lambda^s = \sum_{i=1}^{6} g_i^s$, 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 then decompose the variance of the welfare growth across states, $Var\left(g_\lambda^s\right)$, into the sum of the variances plus covariance terms. Each state is weighted by its population size relative to the U.S. population in 1999.

account for 0.56 percent of the dispersion in welfare growth rates over this time period.

Within-state changes in consumption-good prices had somewhat larger implications for welfare growth. We find that changes to consumption-good prices reduced average welfare by 0.01 percent per year in the U.S., with a standard deviation of 0.07. As shown in Table 3, the reduction in consumption-good prices increased welfare in Alaska, Arizona, and Delaware by 0.11–0.12 percent per year. In contrast, increasing consumption-good prices in California, Hawaii, and Missouri reduced welfare by 0.12–0.17 percent per year. Varying trends in consumption-good prices thus contributed to a 0.29 percentage point dispersion in welfare growth rates across the U.S. Our variance decomposition shows that dispersions in the change in relative consumption-good prices account for 1.85 percent of the dispersion in welfare growth rates.

Lastly, changes to housing prices increased average welfare by 0.01 percent per year in the U.S., with a standard deviation of 0.05. Arizona, Nevada, and Rhode Island experienced the largest reduction in housing prices, which in turn increased their welfare by 0.08–0.22 percent per year. The increase in housing prices in Colorado and North Dakota, on the other hand, reduced welfare by 0.11–0.18 percent per year in these states. Varying trends in relative housing prices thus contributed to a 0.40 percentage point dispersion in welfare growth rates across states. We find that varying trends in relative housing prices account for 0.84 percent of the variation in welfare growth rates over this time period.

5.2.3 Examining whether states are converging toward similar welfare levels

To what extent are states converging toward similar welfare levels? In particular, does welfare grow faster (slower) in states with lower (higher) welfare levels? To address this question, we end this subsection by studying the relationship between each state's welfare ranking in 1999 and its annual growth rate in welfare between 1999 and 2015. This is 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 that a state's welfare growth rate is not systematically related to its welfare ranking in 1999, which suggests that states are not converging toward similar welfare levels. In particular, we find similar dispersions in welfare growth rates among high- and low-ranked states in the country.

5.3 Sensitivity

This section tests the sensitivity of the welfare results in Section 5.1 to various assumptions. In particular, we test the sensitivity of the results to allowing for cross-state migration, to including leisure in the utility function, to excluding expenditures on health care, to including durable consumption goods, to starting the model at age 2 rather than at age 0 to eliminate the effect of heterogeneous infant mortality rates, to

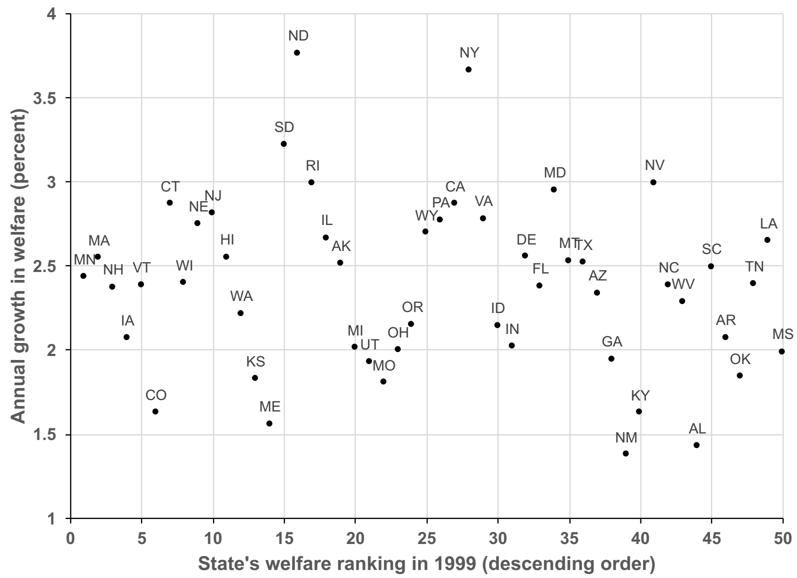

Figure 8: Relationship between ranking of welfare in 1999 and growth rate of welfare between 1999 and 2015

Notes: The graph plots the relationship between each state's welfare ranking in 1999 and 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.

alternative utility specifications, and to varying the values of the parameters of the model. Further sensitivity analyses are reported in the Appendix. The results are reported in Table 4. In each case, we recalibrate the parameters of the model to match the same targets as described in Section 4.

5.3.1 Migration

The benchmark analysis compares living standards across states by quantifying how much spending 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 to any other state. This subsection considers an alternative environment where the individual can move between states.[24] In particular, we assume that an agent in state s exogenously moves to state s' in the following period with probability $q(s, s')$. We use data from the American Community Survey for the period 2013–2017 to compute these transition probabilities. We then compare living standards across states by quantifying how much spending must adjust in all ages in Connecticut to make an unborn individual behind the veil of ignorance indifferent between *born* in Connecticut compared to being born in any other state. For simplicity, we refer to this

[24]For consistency with the benchmark model, we continue to assume that the agent's educational attainment is revealed at birth, and hence only depends on the state of birth. We consider an alternative environment in the Appendix where we simultaneously allow for migration and assume that educational attainment depends on the state of residence at age 25. This is motivated by Borjas, Bronars, and Trejo (1992) and Diamond (2016) who examine the implications of the geographic sorting of skills. In particular, high-skilled/college-educated individuals tend to migrate to areas where the returns to their skills/college-degree is higher.

Table 4: Sensitivity: Comparing welfare across the U.S. in 2015

State	**Bench.**	**Migration**	**Leisure**	**No med.**	**Incl. dur.**	**Age 2+**	**SVL=$6m**	**SVL=$8m**	β**=0.96**	γ**=2.00**
MN	107.6	103.8	109.1	106.7	110.1	107.9	107.3	108.0	106.4	115.7
MA	105.4	107.0	105.0	103.9	106.3	104.8	105.6	105.2	106.4	106.3
ND	105.1	93.7	109.6	99.3	112.4	105.6	106.5	103.7	110.8	109.1
CT	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0
SD	97.1	91.8	102.1	90.2	102.6	97.9	98.7	95.5	101.8	102.4
NH	96.6	97.8	98.0	94.7	98.7	95.9	97.8	95.4	103.2	103.6
NE	96.0	95.0	99.3	90.7	100.1	96.4	97.0	95.1	100.8	102.7
NJ	95.3	99.0	94.9	97.0	96.3	95.0	95.6	95.0	96.8	97.3
NY	95.2	97.8	94.1	95.2	92.6	95.2	94.8	95.5	93.4	92.0
VT	94.1	96.6	95.6	89.0	96.0	93.3	95.1	93.0	100.6	100.2
RI	91.8	96.1	93.2	87.0	91.3	92.2	92.5	91.1	95.3	94.2
WI	91.1	91.3	94.4	85.5	93.7	91.6	92.1	90.0	96.2	97.8
IA	90.8	92.1	94.1	85.0	94.4	90.7	91.6	90.0	95.9	97.7
HI	90.0	81.8	91.3	94.4	91.1	90.4	90.0	90.0	89.8	99.7
IL	85.6	91.5	87.2	82.8	87.4	86.3	86.8	84.5	89.9	87.4
CA	84.8	87.0	85.4	87.0	85.4	84.4	84.9	84.7	87.1	87.2
WA	84.8	87.4	86.2	84.7	87.4	84.2	85.6	84.0	91.1	91.0
CO	83.2	87.8	84.8	85.4	85.3	82.9	84.2	82.3	87.9	88.8
PA	83.1	90.1	85.3	76.9	85.3	83.5	84.8	81.5	89.5	85.9
WY	82.8	81.6	86.7	77.6	86.0	82.3	84.9	80.7	93.6	90.8
AK	82.6	81.5	86.1	72.2	85.4	82.6	85.6	79.7	95.7	90.2
VA	82.3	87.3	83.9	82.0	84.3	82.6	83.7	80.9	89.1	86.4
KS	79.2	86.4	82.2	73.5	82.8	79.5	80.8	77.6	86.3	84.3
MD	78.8	86.8	80.0	75.6	81.1	79.4	80.4	77.2	84.9	84.5
OR	77.3	83.5	79.7	74.3	80.0	76.9	78.6	76.0	85.5	83.3
MI	76.0	82.9	79.2	70.6	78.9	76.5	78.0	74.1	84.7	80.5
DE	75.2	82.0	77.9	65.9	79.5	76.1	77.2	73.4	83.1	81.1
OH	75.2	81.5	79.5	67.1	78.5	75.9	77.9	72.7	87.2	79.7
ME	75.2	81.4	78.4	68.3	78.6	75.4	77.2	73.3	86.2	82.1
UT	75.1	79.9	78.0	74.2	79.4	74.9	76.4	73.7	83.1	84.7
ID	74.5	81.5	77.6	70.9	78.7	74.4	75.8	73.4	81.4	81.7
MT	73.5	82.7	76.7	67.7	79.8	73.4	75.4	71.6	82.1	79.5
FL	73.2	78.4	75.6	70.0	76.7	73.7	74.3	72.1	77.0	76.4
MO	73.2	81.1	77.2	66.3	76.7	73.3	75.8	70.6	85.1	78.4
TX	72.3	79.4	74.8	69.5	75.8	72.3	73.9	70.7	80.9	76.4
NV	71.7	78.2	75.1	70.2	75.3	71.4	73.9	69.5	84.3	78.9
AZ	69.7	78.6	72.3	68.2	72.6	69.9	70.9	68.6	74.5	75.0
IN	69.4	78.1	73.3	60.7	73.0	70.0	71.9	67.0	80.9	76.1
NC	65.2	77.4	68.1	59.3	69.1	65.8	67.0	63.4	72.9	70.0
GA	63.6	75.5	66.6	59.7	67.2	64.2	65.8	61.5	73.2	68.7
SC	61.3	76.3	64.5	54.8	64.8	61.5	63.6	59.0	71.5	67.3
WV	59.6	74.5	63.8	46.9	63.5	59.8	62.8	56.6	73.2	66.3
TN	59.2	74.4	62.5	52.3	63.3	59.5	61.9	56.7	71.1	65.0
KY	58.2	72.3	62.1	49.1	61.9	58.2	61.1	55.4	71.8	64.6
NM	57.6	68.4	61.3	51.9	61.0	57.2	59.9	55.3	68.2	65.1
AR	57.2	69.8	61.3	48.9	61.8	57.7	60.0	54.5	69.9	64.3
LA	56.2	68.7	59.7	48.0	60.5	56.8	59.0	53.5	67.9	62.0
OK	55.2	69.8	59.1	46.6	59.9	55.4	58.1	52.4	69.1	63.5
AL	51.9	65.2	56.1	44.0	56.2	52.5	55.0	49.1	65.4	60.0
MS	48.1	61.9	52.2	38.3	52.0	48.6	51.1	45.2	61.5	57.0

Notes: Column 2 reports the welfare results from the benchmark model. In particular, it reports how much spending would have to change in all ages in the state with the highest personal income per capita, Connecticut, to make an unborn agent behind the veil of ignorance indifferent between living her entire life in Connecticut and any other state. Columns 3–11 report the corresponding results from: the model that allows for migration between states, the model that includes leisure in the utility function, the model that excludes expenditures on health care from spending, the model that includes durable expenditures, the model where agents enter at age 2 rather than at age 0, the model where we target a value of remaining life at age 40 equal to $6 million, the model where we target a value of remaining life at age 40 equal to $8 million, the model where we set β equal to 0.96, and the model where we set γ equal to 2.00.

model as the model with migration.

For consistency with the model, we abstract from foreign migration when we compute the transition probabilities, $q(s, s')$. That is, we exclude all foreign in-migration and focus only on migration flows between states. Note that migration patterns are likely to vary with socioeconomic characteristics such as age, education, and income. While CPS data can be used to estimate state-to-state migration probabilities as a function of various socioeconomic characteristics, these estimates suffer from very large confidence intervals since only a small share of respondents in the CPS changed their state of residence over the last two years. We therefore assume that migration probabilities in the model, $q(s, s')$, are independent of the agent's socioeconomic characteristics.

Migration patterns show that the vast majority of individuals remain in the same state over a two-year period. To illustrate, only 1.3 percent of residents in the state with the highest retention rate, California, changed their state of residence over a two-year period. In contrast, 5.1 percent of residents in the state with the lowest retention rate, North Dakota, changed their state of residence over a two-year period. Hence, across the U.S., 94.9–98.7 percent of individuals are expected to remain in their current state in the following year. Moreover, migration tend to be between neighboring states or between states in the same region. As an example, Florida, Georgia, and Tennessee are the top 3 out-bound migration destinations for resident in Alabama. Similarly, Illinois, Wisconsin, and North Dakota are the top 3 out-bound migration destinations for residents in Minnesota. The fact that migration tend to be between neighboring states or between states in the same region matters because of the geographic concentration of welfare levels documented in Section 5.1. That is, a large share of migration is between states with comparable welfare levels.

Given the observed migration patterns, it is not surprising that the welfare results from the model without migration are qualitatively similar to the welfare results from the model with migration, with a correlation of 0.96 between the welfare rankings in the two models. Quantitatively, however, we find that most states have higher welfare levels relative to Connecticut in the model that allows for migration, with a weighted average difference of 6.1 percentage points (weights are given by the size of each state's population relative to the U.S. in 2015). As a result, welfare inequality, as measured by the dispersion of welfare levels across states, is lower in the model with migration. The increase in welfare relative to Connecticut is particularly high for the states with the lowest welfare levels. As an example, whereas the benchmark model suggests that the 5 states with the lowest welfare level—Alabama, Arkansas, Louisiana, Mississippi, and Oklahoma—have 42.8–51.9 percent lower welfare than Connecticut, the model with migration suggests that these states have 30.2–38.1 percent lower welfare than Connecticut.

5.3.2 Leisure

Recall from Section 3 that the benchmark model abstracts from leisure. We test the sensitivity of our results to this assumption by replacing the utility function in Equation (4) by

$$u\left(c\left(E_{ae}^{s}e^{ga}\right), h\left(E_{ae}^{s}e^{ga}\right), \ell\right) = b + \alpha \log\left(c\left(E_{ae}^{s}e^{ga}\right)\right) + (1-\alpha)\log\left(h\left(E_{ae}^{s}e^{ga}\right)\right) + v\left(\ell\right), \tag{15}$$

where $v(\ell)$ captures the utility from leisure, ℓ. Following Jones and Klenow (2016), we let $v(\ell)$ be given by $v(\ell) = -\frac{\theta\epsilon}{1+\epsilon}(1-\ell)^{\frac{1+\epsilon}{\epsilon}}$, where ϵ is the Frisch elasticity and θ is the weight on leisure in the utility function. We use the same values as Jones and Klenow (2016) and set $\epsilon = 1$ and $\theta = 14.2$.

We use data from the CEX for the period 2013–2017 to estimate the process for leisure. For consistency with the data, we let leisure vary with age and education. The latter enables us to account for the fact that college-educated individuals have lower leisure on average than non-college educated individuals, most of which is due to their higher labor force participation rates. Moreover, to account for the negative relationship between spending and leisure, we also let leisure vary with spending. To estimate the process for leisure, we first discretize the CEX respondents' leisure into 10 categories.[25] We then estimate the leisure process by running an ordered logistic regression of leisure category on the logarithm of spending, age, age squared, education, a dummy variable for 65+ year-olds, and interaction terms. The probability of drawing a particular leisure category as a function of the individual's age, education, and spending is then given by the standard ordered logistic formula (further details are given in the Appendix).[26]

We find that the benchmark model and the model with leisure lead to both qualitatively and quantitatively very similar results, which shows that the welfare results in Section 5.1 are not sensitive to the assumption that leisure does not affect utility. While average living standards in the U.S. are 21.9 percent lower than in Connecticut in the benchmark model, they are 19.7 percent lower than in Connecticut in the model with leisure. The increase in welfare is higher in states with low spending. As an example, whereas welfare is 40.4 percent lower in West Virginia than in Connecticut in the benchmark model, it is 36.2 percent lower in the model with leisure. These results show that leisure matters for welfare, but do not drive the results.

[25] In particular, we let $\ell_1 = [\underline{\ell}, 0.2), \ell_2 = [0.2, 0.3), \ldots, \ell_9 = [0.9, 1), \ell_{10} = 1$, where $\underline{\ell}$ is the lowest value of leisure observed in the CEX and a value of 1 corresponds to working zero hours. For each point on the leisure grid, we let the value of leisure be given by the weighted average value of leisure for individuals in the CEX in that leisure category. Letting leisure be drawn from a discrete rather than a continuous process enables us to account for the fact that a large share of individuals do not participate in the labor force and that most individuals that participate in the labor force work 20, 40, or 60 hours per week.

[26] We apply the Rouwenhorst method to discretize the process for spending in the model by means of an AR(1) process since leisure depends on the value of spending. For consistency with the benchmark model, we let the persistence of the discretized spending process be equal to 0. The probability of drawing each spending value is given by the stationary distribution of the process. We use 101 grid points for spending in the model.

5.3.3 Health care spending

Spending in the benchmark model is given by consumption of non-durables and services as defined by the BEA. As noted in Section 4.2, this 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. We therefore consider an alternative environment where we exclude expenditures on health care from spending. Data from the Centers for Medicare & Medicaid Services show that health care spending per capita varies substantially across states, ranging from $6,000 in Utah to $11,200 in Alaska in 2015. There is also considerable heterogeneity in the ratio of health care spending-to-total spending, from a low of 17.9 percent in Colorado to a high of 30.7 percent in West Virginia.

The results from the model without health care spending are reported in column 5 of Table 4. We find that California, Colorado, Hawaii, New Jersey, and New York have higher welfare relative to Connecticut in the model without health care spending than in the benchmark model. The largest difference is for Hawaii, whose welfare is 10.0 percent lower than in Connecticut in the benchmark model, but 5.6 percent lower in the model where we exclude expenditures on health care from spending. All the other states have lower welfare relative to Connecticut in the model without health care spending than in the benchmark model, with welfare being 3.1 percentage points lower on average relative to Connecticut in the former model. The difference is particularly large in states such as Alaska, Mississippi, and West Virginia, where health care spending account for more than 25 percent of total spending. Our results show that welfare in these states is at least 9.7 percentage points lower relative to Connecticut in the model without health care spending than in the benchmark model. Therefore, although the two models lead to very similar welfare rankings across the states—with a correlation of 0.98 between the two—these results indicate that the benchmark model might overestimate welfare in states with high health care spending-to-total spending.

5.3.4 Durable consumption goods

The benchmark model focused on consumption of non-durables and services. We excluded purchase of durable goods since the CEX only reports the household's durable expenditures rather than the household's stock of durable goods. This section, instead, considers an alternative environment where we also include expenditures on durables. In particular, we approximate the utility that individuals derive from the service flow from their stock of durables by their current expenditures on durable goods. Data from the BEA show that durable spending per capita varies across states, from a low of $3,000 in Mississippi to a high of $6,300 in North Dakota in 2015. Similarly, the ratio of durable spending-to-total spending ranges from 7.4 percent in New York to 14.4 percent in Montana.

We find that the welfare results reported in Section 5.1 are not sensitive to the assumption that we exclude durables from spending. While average living standards in the U.S. are 21.9 percent lower than in Connecticut in the benchmark model, they are 19.4 percent lower than in Connecticut in the model with durables. Moreover, the two models lead to qualitatively similar results, with a correlation of 0.99 between the welfare rankings in the two models. We find that North Dakota experiences the largest increase in welfare when we include durables. In particular, whereas the benchmark model suggests that North Dakota has 5.1 percent higher welfare than Connecticut, the model with durables suggests that North Dakota has 12.4 percent higher welfare. In contrast, New York experiences the largest reduction in welfare when we include expenditures on durables as part of spending. A comparison of columns 2 and 6 of Table 4 shows that welfare is 4.8 percent lower in New York than in Connecticut in the benchmark model, but 7.4 percent lower in the model with durables. Therefore, these results show that expenditures on durables have implications for welfare, but do not drive the results in Section 5.1.

5.3.5 Infant mortality

Recall from Figure 2 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 1000 births in Massachusetts to a high of 9.0 deaths per 1000 births in Mississippi. To examine how this heterogeneity in infant mortality rates affect welfare, we next consider an alternative environment where agents enter the model at age 2 rather than at age 0.

The results are reported in column 7 of Table 4. We find that the two models lead to nearly identical results, with a correlation higher than 0.99 between the welfare rankings in the two models. While average living standards in the U.S. are 21.9 percent lower than in Connecticut in the benchmark model, they are 21.7 percent lower than in Connecticut in the model where agents enter at age 2. Accordingly, although there exists considerable heterogeneity in infant mortality rates across the U.S., we find that this variation does not drive the results.

5.3.6 Alternative preferences and parameterizations

Lastly, we study the sensitivity of the results to alternative utility specifications and parameterizations. Column 8 reports the results when we calibrate the constant term in the utility function, b, such that an average 40-year-old—facing the average mortality risk, educational uncertainty, spending uncertainty, inequality, consumption-good prices, and housing prices in the U.S. in 2015—has a value of remaining life equal to \$6 million in 2012 prices (compared to \$7 million in the benchmark model). Similarly, column 9 reports the results when we target a value of remaining life of \$8 million. This leads to a value of 6.19 and 8.23 for b, respectively, when spending on non-durables and services per capita in the U.S. in 2015 is normalized to 1. A lower value for b reduces the direct utility that individuals derive from each year of life, and hence reduces the welfare loss due to lower life expectancy. Accordingly, living standards in states with low life expectancy at birth such as Alabama, Mississippi, and West Virginia are higher relative to Connecticut in the model with a lower b (40.4–51.9 percent lower than in Connecticut in the benchmark model compared to 37.2–45.0 percent lower than in Connecticut in the model with a lower value for b). In contrast, a higher value for b increases the direct utility that individuals derive from each year of life, thereby further increasing welfare in states with higher life expectancy. To illustrate, whereas welfare is 4.8 percent lower in New York than in Connecticut in the benchmark model, it is 4.5 percent lower than in Connecticut in the model with a higher value for b. These results show that the value for b matters for welfare, but do not drive the welfare ranking.

Column 10 reports the results when we let discount factor, β, be equal to 0.96 rather than 0.99. We find that the two models lead to qualitatively similar results, with a correlation of 0.98 between the welfare rankings in the two models. Quantitatively, however, we find that average living standards relative to Connecticut are higher in the model with a lower β. In particular, while average living standards in the U.S. are 21.9 percent lower than in Connecticut in the model with β equal to 0.99, they are 15.6 percent lower than in Connecticut in the model with β equal to 0.96.

Lastly, we consider the case when the utility function is given by

$$u\left(c,h\right) = b + \frac{\left(c^{\alpha}h^{1-\alpha}\right)^{1-\gamma} - 1}{1-\gamma}. \tag{16}$$

This utility function nests the benchmark utility function in Equation (4) as the limit case when $\gamma = 1$. The utility function in Equation (16) allows us to study the sensitivity of the results to alternative values for risk aversion. Column 11 reports the results when γ is equal to 2. With the exception of New York, we find that a higher value for γ increases welfare in all states relative to Connecticut. The largest increase is in Hawaii, whose welfare is 10.0 percent lower than in Connecticut in the benchmark model, but 0.3 percent lower than in Connecticut in the model when γ is equal to 2. Accordingly, while average living standards in the U.S. are 21.9 percent lower than those in Connecticut in the model with γ equal to 1, they are 17.8 percent lower than those in Connecticut in the model with γ equal to 2. Qualitatively, however, we find that the two models lead to similar results, with a correlation of 0.99 between the welfare rankings in the two models. These results show that the results are robust to allowing for a higher risk aversion, but that the benchmark model might overestimate the difference in welfare between Connecticut and other states.

6 Conclusion

We have developed a welfare measure to examine how living standards, or welfare, vary across the United States in 2015 and how each state's living standards have evolved between 1999 and 2015. Our welfare measure accounts for cross-state variations in mortality risk, college attainment, average spending, inequality, consumption-good prices, and housing prices. We compared living standards across states by quantifying how much spending must adjust in all ages in the state with the highest per capita income, Connecticut, to make an unborn individual behind the veil of ignorance indifferent between living her entire life in Connecticut compared to any other state. We have shown that a state's welfare level is positively correlated with its per capita income level, with a correlation of 0.80 across states, but that deviations are often large. We have shown that living standards in most states appear closer to those in the richest state, Connecticut, than their difference in per capita income would suggest. In particular, whereas a comparison of income per capita would lead one to conclude that average living standards in the U.S. are 29.1 percent lower than in Connecticut, our welfare measure shows that average living standards in the U.S. are only 21.9 percent lower than in Connecticut. We have shown that lower life expectancy and lower average spending in low-income states account for most of the difference in welfare between these states and high-income states. Lower college attainment further reduces welfare in low-income states. Conversely, lower consumption-good prices and lower housing prices increase welfare in low-income states. Therefore, failure to account for differences in both consumption-good prices and housing prices would lead one to overestimate the dispersion in welfare between high- and low-income states.

We then examined how each state's living standards have evolved over time by quantifying each state's welfare growth rate between 1999 and 2015. We have shown that all states experienced positive welfare growth over this period, with a population-weighted average growth rate of 2.49 percent per year across states. The annual welfare growth rate, however, varied by 2.38 percentage points across states, from 1.38 percent in New Mexico to 3.76 percent in North Dakota, due to varying gains in life expectancy, spending, and college attainment, with life expectancy accounting for 50.3 percent of the variation. We have shown that welfare growth and per capita income growth are only weakly correlated, with a correlation of 0.38 across states. Moreover, deviations between welfare growth rates and per capita income growth rates are often large, with welfare growth exceeding per capita income growth by 1.09 percentage points on average. Consequently, we have argued that the growth rate of per capita income is a poor proxy for how fast living standards are rising in a particular state.

Our welfare measure does not account for variations in amenities. A vast microeconomics literature has shown that amenities can have large implications for quality of life. We think a worthwhile extension of our analysis would be to extend our welfare measure to account for cross-state variations in amenities. Endogenizing college attainment and allowing for preference heterogeneity are also promising directions for future research.

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Appendix

The Appendix is structured as follows. We start by going through the derivations of the benchmark model. Next, we go through the derivations of the model with the alternative utility function discussed in Section 5.3.6. Then we present regression results from the ordered logistic regression of leisure category on age, college attainment, and spending. Lastly, we report the results from additional welfare analyses.

Derivations (benchmark model)

Let flow utility from consumption goods, c, and housing, h, be given by:

$$u\left(c,h\right)=b+\alpha\log\left(c\right)+\left(1-\alpha\right)\log\left(h\right).$$

Let $C=p^{c}c+p^{h}h$ denote total spending. Substitute for $c=\left(C-p^{h}h\right)\frac{1}{p^{c}}$ and solve for h. This gives the following solution for c and h:

$$\begin{aligned}
\frac{\alpha}{\left(C-p^{h}h\right)\frac{1}{p^{c}}}\left(\frac{-p^{h}}{p^{c}}\right) &= -\frac{1-\alpha}{h}\\
\frac{p^{h}\alpha}{C-p^{h}h} &= \frac{1-\alpha}{h}\\
\left(1-\alpha\right)\left(C-p^{h}h\right) &= \alpha p^{h}h\\
h &= \frac{(1-\alpha)C}{p^{h}}\\
\\
c &= \left(C-p^{h}\frac{(1-\alpha)C}{p^{h}}\right)\frac{1}{p^{c}}\\
c &= \frac{\alpha C}{p^{c}}.
\end{aligned}$$

Assume C grows at rate g. Flow utility at age a can then be rewritten as

$$\begin{aligned}
u\left(c\left(C\right),h\left(C\right)|a\right) &= b+\alpha\log\left(\frac{\alpha C\exp(ga)}{p^{c}}\right)+\left(1-\alpha\right)\log\left(\frac{(1-\alpha)C\exp(ga)}{p^{h}}\right)\\
u\left(C|a\right) &= b+ga+\alpha\log\left(\frac{\alpha}{p^{c}}\right)+\left(1-\alpha\right)\log\left(\frac{1-\alpha}{p^{h}}\right)+\log\left(C\right).
\end{aligned}$$

Assume $C_{aes}\sim LN\left(\mu_{aes},\sigma_{aes}\right)$. Then $\mathbb{E}\left[\log\left(C_{aes}\right)\right]=\mu_{aes}=\log\left(\exp\left(\mu_{aes}+\frac{\sigma_{aes}^{2}}{2}\right)\right)-\frac{\sigma_{aes}^{2}}{2}\equiv\log\left(\bar{C}_{aes}\right)-\frac{\sigma_{aes}^{2}}{2}$, where $\bar{C}_{aes}$ is the age-, education-, and state-specific arithmetic mean of spending. Expected utility is then given by:

$$\begin{aligned}
\mathbb{E}_{aes}\left[u\left(C\right)\right] &= b+ga+\alpha\log\left(\frac{\alpha}{p_{s}^{c}}\right)+\left(1-\alpha\right)\log\left(\frac{1-\alpha}{p_{s}^{h}}\right)+\mathbb{E}_{aes}\left[\log\left(C_{aes}\right)\right]\\
&= b+ga+\alpha\log\left(\frac{\alpha}{p_{s}^{c}}\right)+\left(1-\alpha\right)\log\left(\frac{1-\alpha}{p_{s}^{h}}\right)+\log\left(\bar{C}_{aes}\right)-\frac{\sigma_{aes}^{2}}{2}.
\end{aligned}$$

Derivations (CRRA preferences)

Let flow utility from consumption goods, c, and housing, h, be given by:

$$u(c,h) = b + \frac{\left(c^{\alpha}h^{1-\alpha}\right)^{1-\gamma} - 1}{1-\gamma}.$$

This utility function nests the benchmark utility function as the limit case when $\gamma = 1$. Substitute for $c = \left(C - p^h h\right)\frac{1}{p^c}$ and solve for h. This gives the following solution for c and h:

$$\begin{aligned}
\alpha\left(\left(C - p^h h\right)\tfrac{1}{p^c}\right)^{\alpha(1-\gamma)-1}\left(\tfrac{-p^h}{p^c}\right)h^{(1-\alpha)(1-\gamma)} &= -(1-\alpha)\left(\left(C - p^h h\right)\tfrac{1}{p^c}\right)^{\alpha(1-\gamma)} h^{(1-\alpha)(1-\gamma)-1} \\
\tfrac{h}{C-p^h h} &= \tfrac{1-\alpha}{\alpha}\tfrac{1}{p^h} \\
h &= \tfrac{(1-\alpha)C}{p^h} \\
\\
c &= \left(C - p^h\tfrac{(1-\alpha)C}{p^h}\right)\tfrac{1}{p^c} \\
c &= \tfrac{\alpha C}{p^c}.
\end{aligned}$$

Assume C grows at rate g. Flow utility at age a can then be rewritten as

$$\begin{aligned}
u\left(c(C), h(C)\,|a\right) &= b + \frac{\left(\left(\frac{\alpha C\exp(ga)}{p^c}\right)^{\alpha}\left(\frac{(1-\alpha)C\exp(ga)}{p^h}\right)^{1-\alpha}\right)^{1-\gamma} - 1}{1-\gamma} \\
u\left(C|a\right) &= b + \frac{\left(\left(\frac{\alpha}{p^c}\right)^{\alpha}\left(\frac{1-\alpha}{p^h}\right)^{1-\alpha}\right)^{1-\gamma}\left(C\exp(ga)\right)^{1-\gamma} - 1}{1-\gamma}.
\end{aligned}$$

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

$$\begin{aligned}
\mathbb{E}_{aes}\left[u(C)\right] &= b + \frac{\left(\left(\frac{\alpha}{p_s^c}\right)^{\alpha}\left(\frac{1-\alpha}{p_s^h}\right)^{1-\alpha}\right)^{1-\gamma}\left(\exp(ga)\right)^{1-\gamma}\mathbb{E}\left[C_{aes}^{1-\gamma}\right]}{1-\gamma} - \frac{1}{1-\gamma} \\
&= b + \frac{\left(\left(\frac{\alpha}{p_s^c}\right)^{\alpha}\left(\frac{1-\alpha}{p_s^h}\right)^{1-\alpha}\right)^{1-\gamma}\left(\exp(ga)\right)^{1-\gamma}\exp\left((1-\gamma)\mu_{aes} + \frac{(1-\gamma)^2\sigma_{aes}^2}{2}\right)}{1-\gamma} - \frac{1}{1-\gamma}.
\end{aligned}$$

Leisure

Appendix Table A1 reports the regression results from the ordered logistic regression of leisure category on the logarithm of spending, age, age squared, college attainment, a dummy variable for 65+ year-olds, and interaction terms. We use 10 leisure categories, where the different categories are given by: $\ell_1 = [\underline{\ell}, 0.2)$, $\ell_2 = [0.2, 0.3), \ldots, \ell_9 = [0.9, 1)$, $\ell_{10} = 1$, where $\underline{\ell}$ is the lowest value of leisure observed in the CEX and a value of 1 corresponds to working zero hours. For each point on the leisure grid, we let the value of leisure be given by the weighted average value of leisure for individuals in the CEX in that leisure category. The probability

Table A1: Leisure as a function of age, education, and spending: Ordered logistic regression results

Dependent variable: Leisure category	
Logarithm of spending	-0.367
	(0.030)
Age	-0.303
	(0.003)
Education	-0.426
	(0.053)
Interaction between age and logarithm of spending	-0.006
	(0.001)
Interaction between age and education	0.003
	(0.001)
Age squared	0.004
	(4E-05)
Dummy: Age≥65	0.242
	(0.040)
Cut 1	-12.902
	(0.141)
Cut 2	-11.104
	(0.079)
Cut 3	-9.999
	(0.066)
Cut 4	-8.690
	(0.061)
Cut 5	-7.376
	(0.059)
Cut 6	-5.550
	(0.057)
Cut 7	-5.137
	(0.056)
Cut 8	-4.785
	(0.056)
Cut 9	-4.371
	(0.055)
Pseudo R^2	0.1168
Number of observations	94376

Notes: The table reports results from an ordered logistic regression of leisure category on the logarithm of spending, age, age squared, education, a dummy variable for 65+ year-olds, an interaction term between age and the logarithm of spending, and an interaction term between age and education. Education is split into two categories: college and non-college, where college refers to individuals with a minimum of a bachelor's degree or at least 4 years of college. See the text for further details. Data source: CEX.

of drawing a particular leisure category, $\ell_i \in \{\ell_1, \ldots, \ell_{10}\}$, as a function of the individual's age, college attainment, and spending, $\mathbb{P}(\ell_i|\mathbf{x})$, is then given by the standard ordered logistic formula:

$$\mathbb{P}(\ell_i|\mathbf{x}) = \frac{1}{1+\exp(-\kappa_i + \mathbf{x}\boldsymbol{\beta})} - \frac{1}{1+\exp(-\kappa_{i-1} + \mathbf{x}\boldsymbol{\beta})},$$

where $\mathbf{x}$ is the vector of variables, $\boldsymbol{\beta}$ is a vector of parameters, and the κ's denote cutoffs.