

Skills, Migration, and Urban Amenities over the Life Cycle*

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February 2024

Abstract

We examine sorting behavior across metropolitan areas by skill over individuals' life cycles. We show that high-skill workers disproportionately sort into high-amenity areas, but do so relatively early in life. Workers of all skill levels tend to move towards lower-amenity areas during their thirties and forties. Consequently, individuals' time use and expenditures on activities we identify as leisure on local amenities are U-shaped over the life cycle. This contrasts with well-documented life-cycle consumption profiles, which are hump-shaped and peak during middle age. We present evidence that the move towards lower-amenity (and lower-cost) metropolitan areas is driven by changes in the number of household children over the life cycle—individuals, particularly the college-educated, tend to move towards lower-amenity areas following the introduction of their first household child. We develop an equilibrium model of location choice, labor supply, and amenity consumption and introduce life-cycle shocks to household composition that affect consumption choices and required home production time. Key to the model is a complementarity between leisure time and local amenities, which we estimate to be large and significant. Ignoring this complementarity misses the dampening effect child rearing has on urban agglomeration. Since the value of local amenities is capitalized into housing prices, individuals will tend to move to lower-cost locations to avoid paying for a good they are not consuming.

Keywords: urban amenities, sorting, migration, life-cycle dynamics

JEL Classifications: J30, J61, R23

*We are grateful to Gadi Barlevy, Rebecca Diamond, Xiaozhou Ding, Peter Heinrichs, Erik Hurst, Marti Mestieri, Clara Santamaria, and Dan Wilson, as well as various seminar and conference participants, for thoughtful discussions and comments, and Bill Kluender and Kelley Sarussi for excellent research assistance. This research was conducted with restricted access to Bureau of Labor Statistics data. The views expressed here are our own and do not necessarily reflect those of the Federal Reserve Bank of Chicago, the Federal Reserve System, or the Bureau of Labor Statistics.

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1 Introduction

In the standard model of spatial equilibrium, workers will accept negative compensating real-wage differentials to live in a city with urban amenities. Demand to live in these higher quality-of-life areas drive up their costs-of-living relative to the nominal wages that they offer (Rosen, 1979; Roback, 1982). Work by Black et al. (2009) on urban sorting finds that higher-educated individuals accept lower returns to education to live in high-amenity areas. Diamond (2016) finds that the higher-educated improve the amenities of areas that they move to, while Bilal and Rossi-Hansberg (2021) characterize the job opportunities and amenities provided by a location as a household asset choice. The literature, however, has not delved deeply into the timing of worker sorting, particularly based on skill. There is a well-established literature on the behavior of consumption and leisure over the life cycle (Browning, Deaton, and Irish, 1985; Attanasio and Weber, 1995; Aguiar and Hurst, 2005, 2013; among many others), yet we know little about the life-cycle behavior of the consumption of local amenities. There is reason to believe that local amenities are a key determinant in workers' sorting decisions.¹ Therefore, understanding the life-cycle behavior of amenity consumption is critical to understanding individuals' migration decisions over time.

In this paper, we explore how much sorting based on worker skill is driven by a desire to live in high-amenity cities and how this sorting evolves over the life cycle. If higher-skill individuals sort into urban areas with higher wages, this will exaggerate observed wage differences across cities. If they sort into places with better amenities, it will lead to an underestimate of the compensating wage differential attributed to these amenities, since high-skill individuals tend to earn higher wages. Furthermore, it is well known that migration rates decline with age and that consumption expenditures are hump-shaped over the life cycle. Changes in household composition (i.e., the presence of household children) is a key driver of the hump-shaped pattern. If urban amenities are normal (or luxury) goods that drive migration decisions, then sorting based on urban amenities may have a life cycle component. To our knowledge, with limited exceptions (Chen and Rosenthal, 2008), there is scant research on the life-cycle behavior of urban amenity

¹Recent research (Combes et al. 2010) has claimed that non-random worker sorting into metropolitan areas can account for a sizeable fraction of observed wage variation across cities. Yet, so far, relatively little—with a notable exception by Glaeser and Mare (2001)—examines how underlying skills are distributed across space, change over the life cycle, or influence our understanding of income mobility.

consumption.

We examine sorting behavior using the migration patterns observed in the restricted-access geocode data for the 1979 and 1997 cohorts of the National Longitudinal Surveys of Youth (NLSY). Measuring the value of local amenities through a quality-of-life index derived by Albouy (2012, 2016), we show that college-educated individuals disproportionately sort into higher-amenity metropolitan areas, but tend to do so relatively early in their lives. Other individuals also sort into higher-amenity areas early in their lives, but to a lesser degree. The quality-of-life value of one’s metropolitan area peaks by age 30 for the college educated (and somewhat earlier for those with less than a college degree) and then gradually falls over time. The decline reflects moves towards lower-amenity areas during individuals’ thirties through their early fifties, which is when our longest longitudinal sample ends. The moves also reflect moves across metropolitan areas—i.e., these are not moves from center cities to suburbs. We show that changes in the quality-of-life values of where one lives is driven primarily by the housing price component of the index rather than its wage component, and we show that the patterns hold for multiple measures of skill.

Using data from the American Time Use Survey (ATUS) and the Consumer Expenditure Survey (CEX), we show that these migration patterns are consistent with individuals’ time use and expenditures on activities we identify as leisure spent on local amenities. The college educated spend the most time and income on local amenities, in absolute terms and as a fraction of their total leisure (expenditure). Those with a high school degree or less spend most of their leisure on activities within the home. In addition, time spent on local amenities is U-shaped over the life cycle, especially for the college educated. This starkly contrasts with the well-documented hump-shape in consumption expenditures observed over the life cycle. More importantly, when we aggregate the time use data by geographic region, we find a strong positive relationship between time spent on local amenities and our quality of life index and a strong negative relationship between leisure time spent at home and our quality of life index, suggesting that those who migrate to higher quality-of-life areas in fact consume a greater degree of local amenities. Together, the evidence also highlights the importance of distinguishing between leisure time spent on amenities and other types of leisure.

We argue that the incidence of household children drives the observed migration and amenity

consumption patterns, and provide evidence that supports this notion. The literature on life-cycle consumption finds that the hump-shape in consumption expenditures is driven in large part by the presence of household children (Browning, 1992; Banks, Blundell, and Preston, 1994; among others). If local amenities require both income and time to enjoy, then the presence of household children will affect a household’s local amenity consumption, since children tend to require more home production time (Aguiar and Hurst, 2013). All else equal, high-amenity, high-rent cities, should be less attractive during child rearing simply because individuals will have less time to enjoy the local amenities that are priced into their rents. Since high-skilled individuals tend to also be high-income individuals, they tend to consume more local amenities when possible. We also show that their amenity consumption is more variable over the life cycle. Given this, we should also expect individuals to migrate back towards high-amenity areas after their child-rearing years. In fact, this is the behavior Chen and Rosenthal (2008) observe for retirees, and our evidence on local amenity consumption later in life from the ATUS is consistent with their findings.

We find that the incidence of household children drives migration decisions across metropolitan areas. First, we show that individuals who never report having children in the NLSY tend to move to metropolitan areas with a higher quality-of-life value than those that have at least one child. The gap between the groups is particularly large among the college-educated. Second, using an event study framework, we show that the incidence of the first child in a household leads to movements towards lower quality-of-life areas over the subsequent six years, again, with the largest effects among the college educated. The evidence is comparable to recent work by Brulhart et al. (2021), who show that the incidence of household children affect the household’s responsiveness to changes in local taxes, and Moreno-Maldonado and Santamaria (2022), who show that delayed childbearing causally increased average incomes in U.S. downtown areas.

We develop a life-cycle model of consumption, labor supply, and location choice that incorporates the key features of our findings. Individuals differ in their skills, which affects the wages that they earn. They gain utility from leisure, consumption goods (a tradable good and a local nontraded good), and the amenities of their location, and must allocate their time between work, leisure (either at home or enjoying the local amenities), and home production. Locations differ in the amenities offered and their local productivity, both of which affect local prices and

wages along the lines of Rosen (1979) and Roback (1982). Finally, shocks to preferences over the life cycle, which capture changes in household composition, affect the relative demand of the traded and nontraded goods and the required level of home production time. Key to the model is a complementarity between the value of local amenities (i.e., the local quality of life) and the fraction of leisure time allocated to them. As shocks to household composition increase the demand for home production, they reduce the time available to enjoy local amenities. Since the value of the local amenity is capitalized into the price of the nontraded good (i.e., through housing), individuals with high home production demands will move to lower-amenity locations in equilibrium to avoid paying for a good that they are not consuming. Shocks to household composition that increase the relative demand for the nontraded good have a similar effect on migration behavior through the price of the nontraded good.

We calibrate the model using synthetic panel data we construct from the demographic information, household composition, earnings, and migration data we observe in the NLSY, the time use patterns we observe in the ATUS, and the expenditure patterns we observe in the CEX. We aggregate the data into cells categorized by demographics and age. This provides us with all the moments necessary to identify the key parameters of the model, which we do by exploiting the cross-sectional and life-cycle variation in the empirical moments of our synthetic panel. Our approach is similar to that of Blundell, Pistaferri, and Saporta-Eksten (2018), who combine the ATUS and CEX with PSID data to examine the role of children in household labor supply and consumption insurance decisions. We estimate the key parameters of the model using a Generalized Method of Moments (GMM) approach on our synthetic panel. Our estimates suggest a large, positive complementarity between time spent enjoying local amenities and the quality-of-life value of an individual’s location. Specifically, we find that the elasticity of amenity time with respect to quality-of-life is about 1.2. The high elasticity underscores the dampening effect the presence of household children have on urban agglomeration since it highlights the importance of the time demands of child rearing when it comes to a household’s ability to enjoy the amenities of its location. We perform a counterfactual exercise where we shut down the complementarity—equivalent to embedding the standard Rosen-Roback model of amenities into a life-cycle labor supply model—and evaluate the response of location choice. The exercise suggests that individuals would sort into higher-amenity cities, and more so earlier in life, which is

when they go out to enjoy local amenities more in the data. One can interpret the results as the compensation individuals need to replace the complementarity, measured in local quality-of-life value. Quantitatively, it is about one-third of the quality-of-life value of the average area in our sample.

The next section describes the data that we use and our methodologies for measuring migration, quality of life, and amenity consumption. Section 3 presents our empirical evidence. Section 4 presents the model. We describe and present the estimation of our model and our counterfactual exercise in Section 5. Section 6 concludes.

2 Data and Measurement

Our study uses data from the 1979 and 1997 cohorts of the National Longitudinal Surveys of Youth (NLSY), including the restricted-access geocode data for each survey. The surveys each follow a cohort annually (later, bi-annually) starting in their teenage years, providing a longitudinal profile for their respondents. The data include a range of information on demographics, education, employment, household composition, and other aspects of an individual's life. They also include multiple measures of skill, including the respondent's score on the Armed Forces Qualifier Test (AFQT). The geocode data include the state and county of residence during each survey interview and during the respondent's adolescent years (age 14 for the NLSY79 and age 12 for the NLSY97). These data allow us to track the residences of each individual throughout the survey and therefore study their migration behavior over their life cycle. We use the data from both NLSY surveys through 2020 for the NLSY79 and 2019 for the NLSY97. In 2020, the NLSY79 cohort is between 55 and 64 years old and in 2019, the NLSY97 cohort is between 34 and 40 years old. Throughout our analysis, we exclude from our sample those in the NLSY79 military oversample and those on active military duty since their location choices are at least partially determined by their military service.

We supplement the NLSY with data from the American Time Use Survey (ATUS) and Consumer Expenditure Survey (CEX) to study time use and expenditures, respectively, on amenity consumption and other activities. The ATUS is an annual survey of individual time-use behavior. Individuals fill out a detailed time diary for all of their activities on a single day. The ATUS also

includes demographic and labor force information for its respondents that is comparable to the information collected in the NLSY. The CEX is an annual survey that collects detailed information on household expenditures from its survey respondents for each quarter of the year. The survey has additional information on household demographics, composition, and income that are comparable to those collected in the NLSY. We use the ATUS data for the 2003 through 2019 survey years and the CEX data for the 1996 through 2019 surveys years. For each survey, we focus on individuals 18 to 74 years old, and again exclude individuals on active military duty.

We use the NLSY geocode data to match individuals to one of 367 Metropolitan Statistical Areas (MSAs) or the non-metropolitan portion of their state, using the 1999 MSA definitions throughout our analysis.² We then match each individual to a quality-of-life index value estimated at the county level using the methodology from Albouy (2012, 2016) and generate a population-weighted average of these estimates for each MSA or non-metropolitan portion of each state. The quality-of-life estimates use data from 2000 on housing costs and wages, taking into account federal taxes as well.³ The estimates are a weighted difference of a housing price component and a wage component. The quality-of-life index is based on the premise that the places with the most desirable amenities have the highest costs-of-living, which are measured through housing, relative to (after-tax) incomes, which are measured through wages. When workers are mobile, the index will reflect the typical household’s willingness to pay for local amenities. Both the housing cost and wage components are estimated to control for individual housing and worker characteristics. Households with a higher willingness-to-pay for local amenities will sort towards more expensive areas while those with a lower willingness-to-pay for local amenities will view these areas as not worth the cost, and therefore sort into more affordable areas.

We use the ATUS and CEX data to estimate the time and income spent on leisure, work, and other activities, with a particular focus time and income spent on local amenities. In both surveys, we distinguish leisure activities by whether they are done at home or away from home, under the identifying assumption that the latter reflect the consumption of local amenities. We relate these estimates to the migration behavior and the quality-of-life estimates of an individual’s location

²Throughout the paper, we use “metropolitan area” to refer to both the Metropolitan Statistical Areas and the non-metropolitan portions of each state.

³In the online appendix, we replicate our main analysis using 1980 data on local housing costs, wages, etc., and obtain very similar results.

over the life cycle in our empirical analysis and in the quantitative evaluation of our model.

Each survey has advantages and disadvantages in measuring leisure done at home versus leisure done outside the home. In the ATUS, we can only identify leisure spent away from home, and cannot distinguish between leisure enjoyed in an individual's local area and leisure enjoyed further away on vacations. For some activities, we cannot identify whether or not they were done at home. These activities include eating and drinking time (though we can identify time spent grocery shopping, preparing food, and purchasing food away from home), socializing, and leisure time with children. We allocate time spent eating and drinking or socializing to leisure time away from home. We also include in this category time spent on local entertainment (e.g., museums, sporting events, social events), sports and recreation (e.g., exercise, sports leagues, camping) and travel for leisure. Leisure at home includes personal and relaxation time, home entertainment (e.g., watching television, listening to music), and leisure time with children.⁴ We also create an estimate of home production time, which includes time spent on household maintenance and management, food at home (e.g., food preparation and grocery shopping), shopping, personal care, child care, and other activities related to the care of pets, adults, vehicles, etc.

In the CEX data, we categorize leisure expenditures into those spent locally but for activities outside the home, those spent on leisure during trips, and those spent on leisure at home. In general, the CEX data afford a more reliable disaggregation of expenditures on leisure by place than the ATUS data afford for time use by place. At the same time, expenditures may not best reflect the consumption value of certain leisure activities. For example, we find that expenditures on home entertainment (e.g., buying a television) is a small fraction of total expenditures on leisure at home but accounts for nearly all time spent on leisure at home. Public transit is a local amenity that one can use for commuting as much as going out for fun. We define expenditures on local leisure in the CEX as those spent on local food and drink, local entertainment, sports and recreational equipment, and local public transit. We define expenditures for leisure on trips as the sum of spending on food and drink on trips, vacation housing, and other trip expenditures (e.g., vehicle rentals). As with the ATUS, we identify expenditures on home production and classify them as the sum of expenditures on home production services (e.g., repairs for vehicles

⁴In the online appendix, we report the changes in leisure time in the ATUS and leisure expenditures in the CEX by more detailed categories for those with at least a college degree and those with a high school degree or less.

and appliances, paid child care) and personal care. In our model calibration, we distinguish expenditures as local leisure expenditures, nontradable goods (local housing, measured as its rental equivalent value, utilities, and maintenance), or tradable goods (all other expenditures, including home production and leisure at home).⁵

3 Evidence

We present our evidence in three steps. First, we show that college-educated individuals sort into higher-amenity metropolitan areas, but tend to do so early in their adult lives. They then tend to gradually move to metropolitan areas with relatively lower amenity values as they get older. Next, we show that, consistent with the evidence on their location choices, college-educated individuals consume relatively more leisure from local amenities. Local amenity consumption measured by time and expenditure shares is highest for those with at least with a college degree and is U-shaped over their life cycle. Finally, we argue that the U-shape pattern reflects the influence of child rearing on household spending decisions and time allocation, and we present evidence in support of this argument.

3.1 Local Quality of Life over the Life Cycle

We begin with our analysis of migration patterns over the life cycle. Specifically, we use the longitudinal aspect of the NLSY cohort data to examine how the average value of our quality-of-life index evolves as the cohorts age. Since we fix the quality-of-life index value for each metropolitan area over our sample period, changes in quality of life over the life cycle occur solely through migration. Increases in average quality of life reflect moves towards higher-amenity areas, while decreases reflect moves towards lower-amenity areas. We measure the quality of life index using its 2000 values and relative to its value for an individual's residence during adolescence (age 14 for the NLSY79 and age 12 for the NLSY97). We do this to control for the potentially endogenous initial sorting of individuals into areas of differing amenity values based on their family background and parents' location choices.

Note also that our focus is on across-metropolitan area migration. There are also interesting

⁵Throughout our analysis we also deflate all income and expenditure estimates to their 2019 values using the Consumer Price Index.

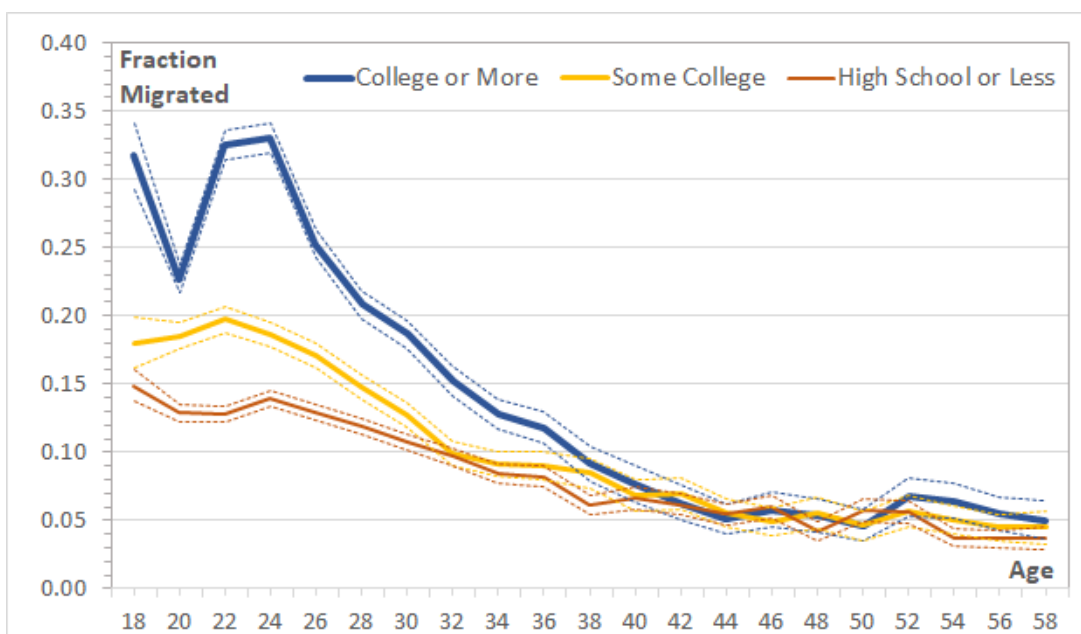
migration decisions within metropolitan areas over the life cycle that are likely complementary to our evidence and consistent with our model (see, for example, Coutre, Gaubert, Hansbury, and Hurst, forthcoming). The factors that drive within-metropolitan area migration decisions (e.g., school quality, crime, commuting costs), however, are arguably less related to leisure than the amenities that individuals throughout a metropolitan area may enjoy (e.g., museums, sports teams, beaches). Moreover, individuals who move within a metropolitan area remain in the same local labor market, so changes in their cost of living likely occur without a change in wages earned. Finally, housing prices in the suburbs of a city likely also reflect access to its amenities to some degree. For example, consider a young couple living in downtown San Francisco who are planning to start a family and move. They may consider moving further out to, say, Marin County, CA. This county, while more affordable than downtown San Francisco, still has a relatively high cost-of-living. Our couple may look instead to move to a more affordable MSA, choosing, say, Davis, CA. Presumably, though, the same factors that led them to leave downtown San Francisco will also lead them to choose a neighborhood within the Davis, CA, metropolitan area that maximizes their utility. In this sense, one can think of the across-MSA moves we focus on as envelope theorem outcomes that encapsulate optimal neighborhood choices with respect to schooling, crime, and other localized amenities. As a check on this logic, we replicate our analysis from this section controlling for MSA differences in average crime and school quality and obtain very similar results.⁶

Figure 1 shows how two-year migration rates across MSAs vary by age and education (measured as the highest degree attained). The figure reports the estimates for all individuals in both NLSY cohorts pooled together and grouped into two-year age intervals.⁷ Migration rates are highest for the college educated and lowest for those with a high school degree or less. The differences are greatest during their early twenties, when about 32 percent of the college educated

⁶Specifically, we replicate our analysis in this section using a quality of life index that conditions out the variation due to local school quality and crime, where we measure each as their population-weighted averages across counties. The results are nearly identical to those reported here, primarily because school quality and crime are essentially unrelated to our quality of life measure at the metropolitan area level (though there is obviously considerable variation within metropolitan areas) We report the results in the online appendix.

⁷Throughout our analysis, we pool individuals into two-year age intervals to increase the precision of our estimates. The pooling also ensures that we capture all individuals in the cohort within each interval during the years when the NLSY is only administered biannually. The biannual nature of the survey in later years is also the reason we focus on two-year migration rates.

Figure 1: Two-Year Migration Rates across Metropolitan Areas

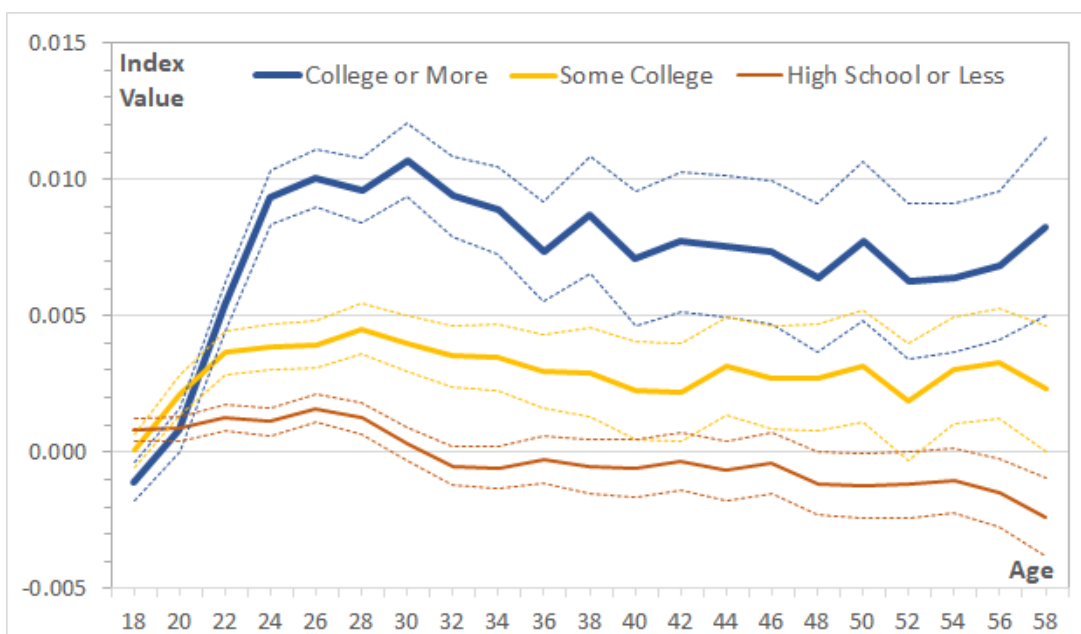


Notes: Estimates from authors' calculations using pooled data on individuals from the NLSY79 and NLSY97 surveys. The figure reports two-year migration rates of individuals across Metropolitan Statistical Areas (or to/from the nonmetropolitan portion of a state). Individuals are pooled by two-year age bins and their highest degree attained. Dashed lines represent 95 percent confidence intervals.

and 13 percent of those with a high school degree or less migrate over a two-year period. By age 42, however, two-year migration rates are about 5 percent regardless of educational attainment.

Figure 2 presents the first of our main results: the evolution of the quality of life index over the life cycle by educational attainment. Within each age interval, we calculate the mean (relative) quality-of-life value of one's current metropolitan area across all individuals (relative to their residence during adolescence). We repeat the calculation for the housing price and wage components and report those in Figure 3. In general, the quality of life of one's location rises during their twenties, peaking by age thirty. It then gradually declines during their thirties and forties. The quantitative differences in these patterns across education groups are substantial, however. On average, people who have at least a college degree move to higher quality-of-life areas. The quality of life of their location increases by over a log point relative to where they lived during adolescence by age thirty, and falls by over 40 percent by their fifties. To put this into perspective, the increase in quality of life of their residence is just over 20 percent of the across-MSA standard deviation of quality-of-life values. In contrast, those with a high school degree or less move to locations with quality-of-life values that are less than 0.2 log point better

Figure 2: Average MSA Quality of Life Estimates over the Life Cycle

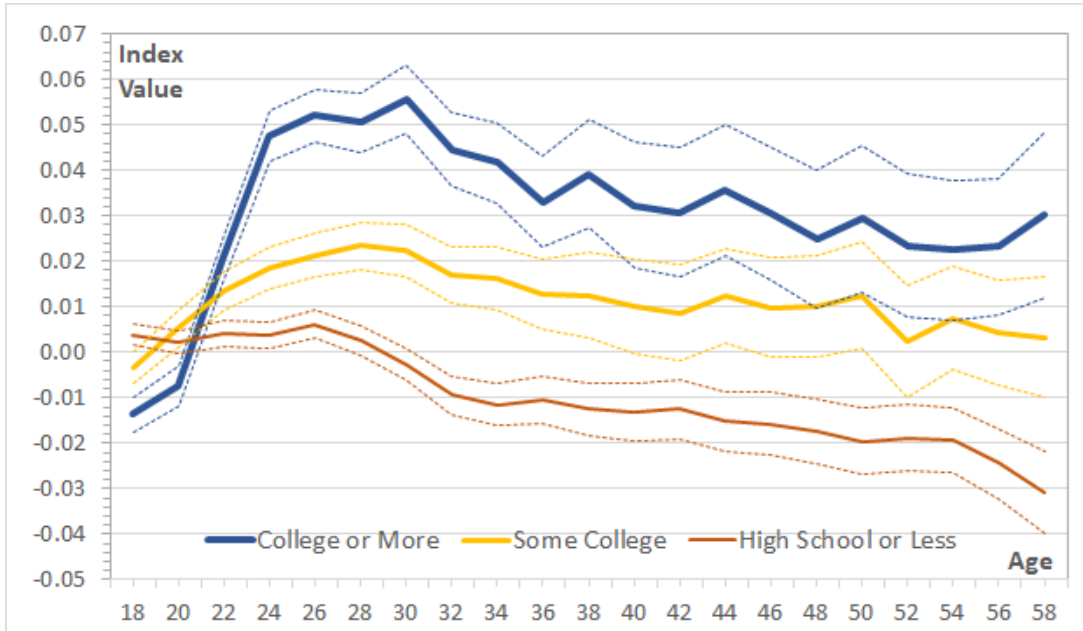


Notes: Estimates from authors' calculations using pooled data from the NLSY79 and NLSY97 samples matched to MSA quality-of-life estimates by current residence and highest education attained. Estimates are the sample-weighted mean quality of life index value (relative to the index value for residence at age 14 for the NLSY79 or age 12 for the NLSY97) for two-year age intervals. Dashed lines represent 95 percent confidence intervals.

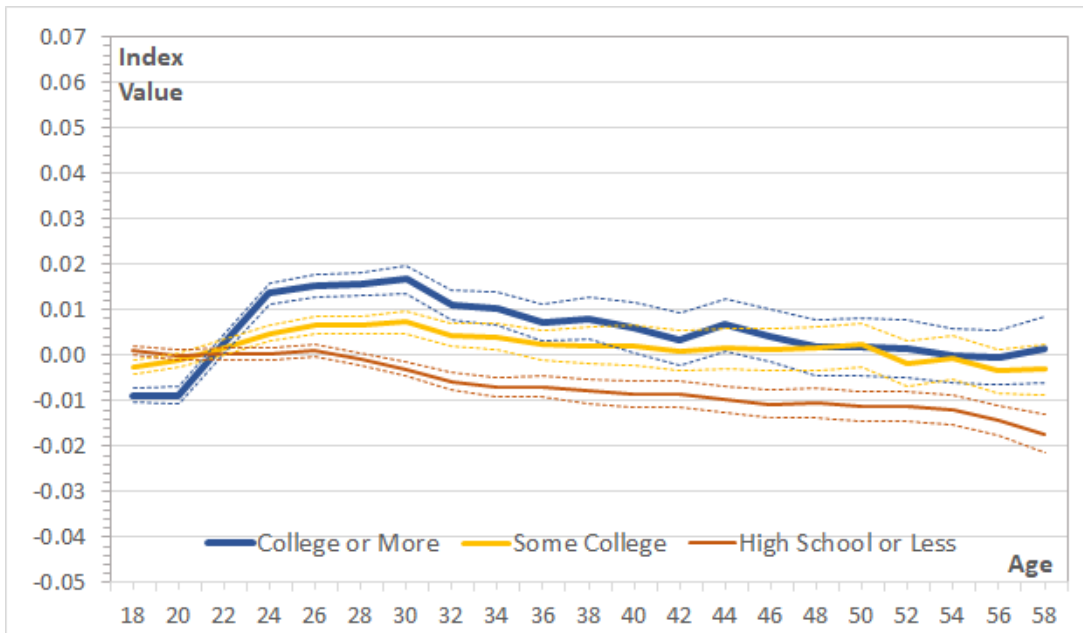
than their residence during adolescence, and this peak occurs around age 26. In addition, by their mid-thirties, the average quality of life of the metropolitan areas for those with a high school degree or less is comparable to, or somewhat worse than, the quality of life value of where they lived during adolescence. The net result in the differential migration behavior by education is an increasing gap in quality of life between the college-educated and those with a high school degree or less over the life cycle. At age 22, the difference between the two education groups is about 0.004, but the difference quickly rises to 0.010 by age 30 and remains between 0.007 and 0.010 through age 59. In the online appendix, we show that the fraction of individuals living away from the metropolitan area of their adolescence is continuously rising with age for all education groups, suggesting that return migration, studied recently by Johnson and Schulhofer-Wohl (2019), is not driving these results. In the online appendix, we also show that the patterns are remarkably similar using alternative measures of skill, including AFQT score and average income per household member (a measure of permanent income). They are also similar when restricting the sample to a balanced panel of NLSY respondents, separate samples for the NLSY79

Figure 3: MSA Quality of Life Estimates: Component Behavior over the Life Cycle

(a) **Panel A:** Housing Price Component



(b) **Panel B:** Local Wage Component



Notes: Estimates from authors' calculations using pooled data from the NLSY79 and NLSY97 samples matched to quality-of-life estimates by current residence and highest education attained. Estimates are the sample-weighted mean quality of life index housing price and local wage component values (relative to their index values for residence at age 14 for the NLSY79 or age 12 for the NLSY97) for two-year age intervals. Dashed lines represent 95 percent confidence intervals.

and NLSY97 cohorts, and when using quality-of-life estimates based on 1980 data. Remarkably, once we control for cohort differences in initial locations, we find similar patterns by age and

education in the American Community Survey micro data as well.⁸

Figure 3 shows that the majority of the gap between the college educated and high school educated is driven by differences in the housing cost component of the quality-of-life index over the life cycle. The patterns in both the housing cost and wage components are qualitatively similar to the patterns for the quality of life index from Figure 2, but quantitatively, the price component exhibits at least twice the variation over the life cycle than the wage component for each education group. Higher values of the wage and housing price components indicate that the areas where the college educated move to are more productive, but the relatively greater values of the housing price component imply that their net real wages fall even as their nominal wages rise. The interpretation is that they are trading off lower real wages for greater amenities. The fact that the housing price component exhibits greater variation suggests that life-cycle variation in amenity consumption is relatively more important for migration decisions. At age 22, the college-high school difference in their average housing costs is 0.017 but rises sharply to 0.058 by age 30. The difference remains elevated, between 0.042 and 0.054, through age 59. In contrast, the college-high school difference in their average wage component is essentially negligible at age 22. It peaks at 0.020 at age 30 and remains in a range between 0.011 and 0.017 through age 59.

Taken together, the evidence from Figures 1 through 3 highlight several patterns of individual sorting across metropolitan areas over the life cycle. First, individuals tend to move to areas with increasingly higher amenity values during their twenties. They move less frequently during their thirties and forties, but when they do move, they tend to move to areas with relatively lower amenity values. Second, changes in average quality of life are driven primarily by variation in the housing prices of one's metropolitan area over their life cycle. There is considerably less life-cycle variation in the wages of these areas. Third, the college educated exhibit larger movements toward higher-amenity areas early in their life cycle and while they also tend to move towards relatively lower quality-of-life areas afterwards, they generally remain in higher quality-of-life locations,

⁸While our qualitative patterns hold in all of these robustness exercises, a couple quantitative deviations stand out. First, when we split the sample by NLSY cohort and when we replicate our analysis using the American Community survey, we find strong cohort effects for those with less than a college degree—younger cohorts of these groups are essentially less likely to move to nicer places than their predecessors. Second, when we replicate our analysis using the 1980 quality-of-life estimates, we find less divergence by education group. Both results suggest that the wedge in local quality of life has been getting larger over time, driven partly by poorer migration prospects for the less educated.

in absolute terms, throughout their prime-age working years. Those with some college exhibit similar migration behavior over their lives, but the changes in the average quality of life of their residences are more muted. In contrast, those with a high school degree or less move to areas during their twenties that are only marginally better than their residences during adolescence. By their early thirties, they tend to live in locations that are comparable to their residence during adolescence, and tend to move towards areas with lower amenity values thereafter. Finally, the differential sorting patterns between the college educated and those with a high school degree or less lead to a large gap in the average quality of life enjoyed by the two education groups. The gap is greatest in their early thirties and remains large throughout their prime-age working years.

3.2 Quality of Life, Leisure, and Amenity Consumption

Our results thus far establish a positive relationship between an individual's education and the average amenity value of their metropolitan area. These results are robust across various measures of skill and quality of life, and across cohorts, but they do not necessarily speak to differences in amenity *consumption* by skill. Just because the high-skilled are more likely to sort into high quality-of-life cities, it does not necessarily mean that they take advantage of the local amenity opportunities. For example, movements in the average quality of life value over the life cycle may reflect the fact that high-skilled individuals can more easily afford expensive, high-wage areas, and move there for the higher earnings potential rather than the local amenities (Black et al. 2009).

Therefore, we use the ATUS and the CEX data to estimate the allocation of time and expenditures over the life cycle and by education. We identify the allocation of time and expenditures on leisure activities, differentiating between leisure spent at home and leisure spent on local amenities. To our knowledge, we are the first to empirically differentiate leisure activities along these dimensions. If those in high quality-of-life locations have a high consumption of local amenities, then based on our evidence thus far, we should see a greater allocation of time and expenditures on these activities by the college educated, especially early in their life cycle. In contrast, leisure activities done at home should be unrelated, or even negatively related, to the changes in local quality of life over time since these are activities that one can enjoy regardless of where they live. Indeed, someone who spends all of their leisure time watching television might as well do it

somewhere affordable.

We begin by examining time use and expenditure shares across detailed leisure and other categories for the high school and college educated. Table 1 reports the time use estimates in average minutes per day and Table 2 reports the expenditure estimates as a share of total expenditures. Both surveys pool individuals aged 18 to 74 across all survey years together within each education group. Table 1 shows that, on average, individuals spend nearly three hours per day on leisure away from home, though over three-quarters of it is on eating and drinking (48 percent) and socializing (30 percent), activities that may potentially occur at home. On average, individuals spend nearly 4.0 hours per day on leisure at home, with the bulk of this (88 percent) devoted to home entertainment. In comparison, individuals spend roughly four hours per day on home production, with time spread about evenly across the various home production categories, and spend roughly four hours per day working. There are notable differences in time allocation by education. Specifically, the college educated spend about 18 percent more time on leisure activities away from home. The largest differences are in time spent on local entertainment, sports and recreation, and eating and drinking. Note that the latter category cannot distinguish between eating or drinking out or at home, but it does exclude time spent on food preparation and grocery shopping (both part of home production time), which are arguably specific to eating and drinking at home. In contrast, the college educated spend 29 percent less time on leisure activities at home. The fact that those with a high school degree or less spend over 65 more minutes per day on home entertainment accounts for most of this difference. Notably, there is almost no difference between the two education groups in their time spent on home production, though the college educated do spend about 33 percent more time on child care.

Table 2 shows similar patterns using the CEX expenditure data. Spending on local leisure accounts for 5.7 percent of total expenditures, and just over 20 percent of leisure expenditures. Most of this spending is on local food and drink. Spending on leisure during trips accounts for 2.7 percent of total expenditures (10 percent of leisure expenditures), with vacation housing and other trip expenditures, primarily transportation-related, accounting for most of this spending. Spending on leisure at home accounts for 18.1 percent of total expenditures, and most of this (76 percent) is spent on food and drink at home. Table 1 showed that home entertainment accounts for the bulk of time spent on home leisure, but Table 2 shows that it only accounts for 2.5

Table 1: Average Time Spent on Leisure and Other Activities

Time use (minutes per day)	College or High School			College-HS Ratio
	All	More	or Less	
<i>Leisure away from home</i>	159.1	174.0	147.9	1.18
Eating & drinking	76.4	86.5	69.8	1.24
Socializing	47.0	44.2	48.4	0.91
Sports & recreation	18.9	23.5	15.8	1.49
Local entertainment	13.7	17.0	10.9	1.57
Travel for leisure	3.0	2.8	3.1	0.91
<i>Leisure at home</i>	235.3	193.0	270.9	0.71
Home entertainment	207.2	170.7	236.0	0.72
Personal & relaxation time	18.5	11.1	25.9	0.43
Leisure time with children	9.6	11.1	9.1	1.23
<i>Home production</i>	242.2	243.4	242.1	1.01
Household maintenance & management	72.2	70.5	72.2	0.95
Personal care	47.0	46.4	46.4	1.00
Food at home	44.6	44.1	44.6	0.92
Child care	26.5	31.4	23.7	1.33
Shopping (excl. gas & groceries)	22.2	23.2	21.0	1.10
Other home production time	29.7	27.8	30.2	0.92
<i>Work time</i>	236.7	282.3	204.3	1.38
<i>N</i>	190,434	65,107	71,537	

Notes: Estimates are mean minutes per day spent on each category from authors' calculations using the ATUS data pooled over all individuals aged 18-74 for 2003-2019. Estimates are the sample-weighted means of time spent on each activity for each listed group.

percent of total expenditures. Home production accounts for 2.1 percent of total expenditures. Housing accounts for about one-third of all expenditures. The remainder are accounted for by vehicles, healthcare, and education. Again, there are notable differences in expenditure patterns by education, with somewhat stronger differences than those found for time use. The college educated spend a 37 percent larger fraction of their total expenditures on local leisure than those with a high school degree or less. Differences in the expenditure shares on local food and drink and local entertainment account for most of the disparity. The college educated spend 2.6 times as much of their total expenditures on trips for leisure. Putting the two together, the college educated spend 10.8 percent of their total expenditures on leisure away from home while the high school educated spend only 6.4 percent of their total expenditures on leisure away from home.⁹ In contrast, the college educated spend a 36 percent smaller fraction of their expenditures on leisure activities at home. The largest contributor to this difference is the fraction spent on food

⁹Note that while expenditures on trips highlight the disparity in leisure expenditures by education, we only focus on the expenditure differences for local leisure in our model since these capture the differences in local amenity consumption that are the focus of our study.

Table 2: Average Shares of Expenditures on Leisure and Other Activities

Percent of Total Expenditures	College or High School			College-HS Ratio
	All	More	or Less	
<i>Local leisure</i>	5.7	6.6	4.8	1.37
Local food & drink	4.3	4.6	3.8	1.21
Local entertainment	0.8	1.3	0.5	2.93
Sports & recreational equip.	0.3	0.4	0.2	1.76
Local public transit	0.3	0.3	0.3	0.84
<i>Leisure on trips</i>	2.7	4.2	1.6	2.58
Vacation housing	0.9	1.5	0.5	2.73
Food & drink on trips	0.6	0.9	0.4	2.32
Other trip expenditures	1.2	1.9	0.7	2.60
<i>Leisure at home</i>	18.1	13.9	21.7	0.64
Food & drink at home	13.8	10.6	16.9	0.63
Entertainment at home	2.5	2.2	2.6	0.85
Other home leisure expenditures	1.9	1.2	2.4	0.49
<i>Home production</i>	2.1	2.6	1.8	1.48
Home production services	1.4	1.8	1.1	1.73
Personal care	0.7	0.8	0.7	1.09
<i>Housing, utilities, & maintenance</i>	33.5	32.5	34.6	0.94
<i>Vehicles</i>	13.4	12.2	13.8	0.89
<i>Healthcare & education</i>	8.0	8.1	7.6	1.06
<i>Total expenditures (annualized 2019 \$)</i>	\$56,054	\$77,539	\$41,799	
<i>N</i>	598,002	183,020	233,964	

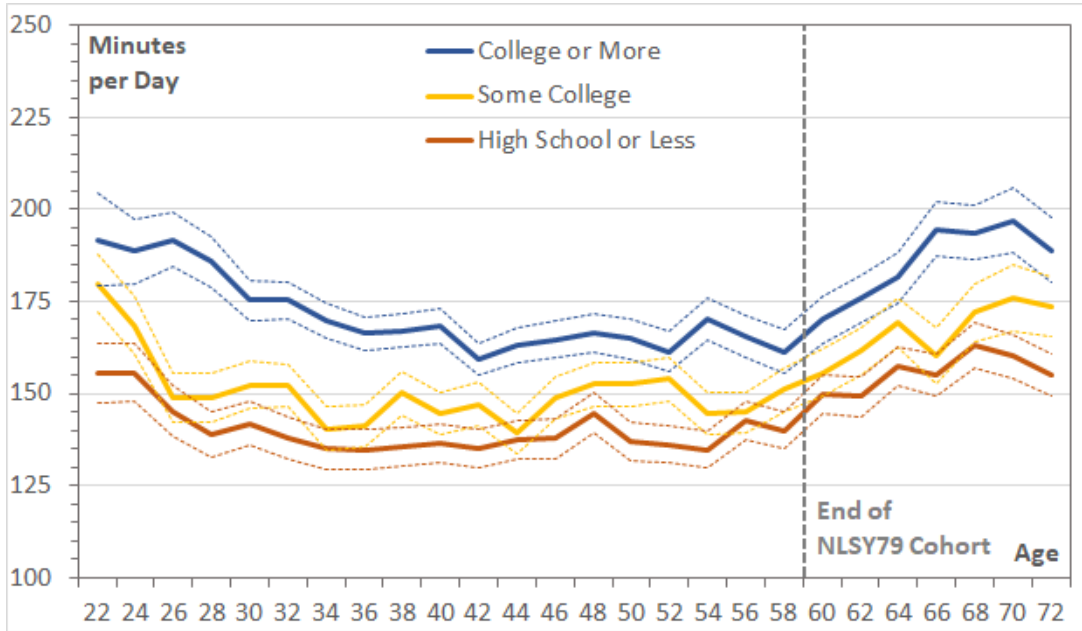
Notes: Estimates are fraction of total expenditures spent on each category from authors' calculations using the CEX data pooled over all individuals aged 18-74 for 1996-2019. Estimates are the sample-weighted mean percentages of total expenditures for each expenditure category for each listed group.

and drink at home. The college educated spend 10.6 percent of their total expenditures on food and drink at home while the high school educated spend 16.9 percent of their total expenditures on food and drink at home. Unlike time use, expenditure shares show a clear difference in the fraction spent on home production by education in favor of the college educated, who spend 1.5 times more of their total expenditures on home production. Thus, at least across all ages, the college educated tend to consume more amenities away from home and less leisure in the home.

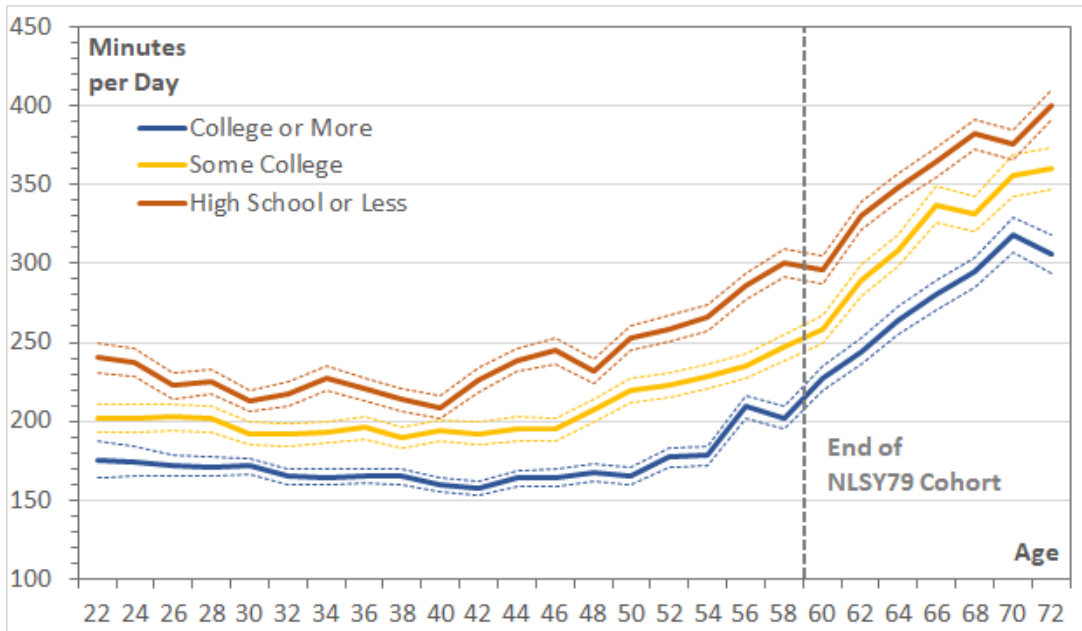
Figures 4 and 5 show these differences evolve over the life cycle. For the amenity consumption behavior to be consistent with the migration patterns we observed in the previous subsection, we would expect that time use and expenditure shares spent on local amenities would be highest for the college educated and higher primarily early in their life cycle. In addition, since we are able to examine individuals past their late fifties, we may find a rise in consumption behavior later in life, which would be consistent with Chen and Rosenthal (2008), who find that individuals tend

Figure 4: Time Spent on Leisure Activities over the Life Cycle

(a) Time Spent on Leisure Away from Home



(b) Time Spent on Leisure at Home



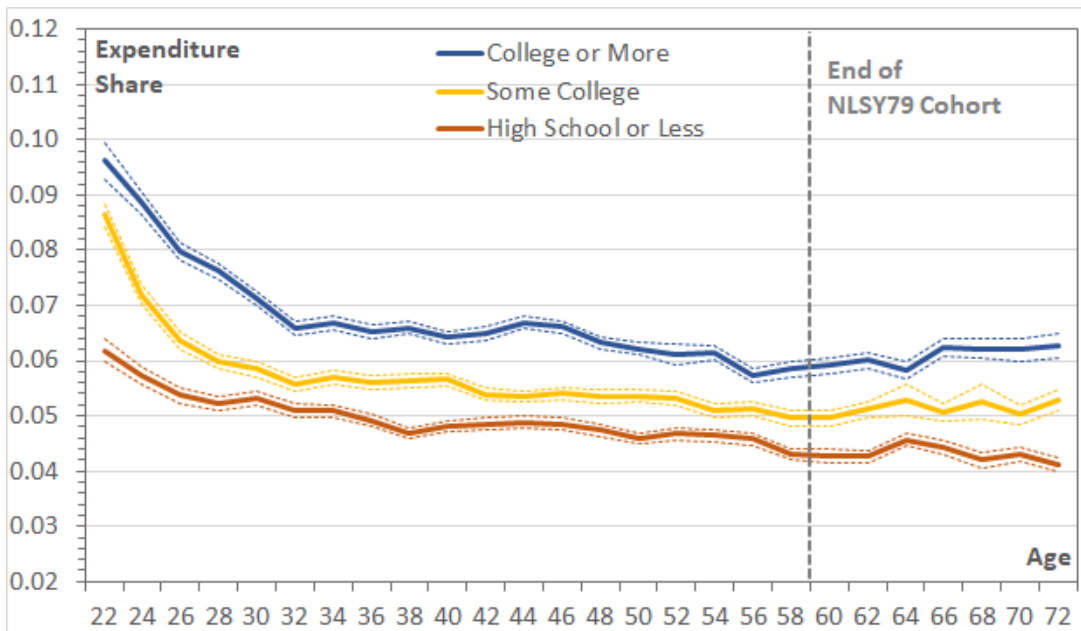
Notes: Estimates from authors' calculations using the ATUS data pooled over 2003-2019. Estimates represent the sample-weighted means of individuals' time spent on each activity for two-year age intervals by (current) education. Dashed lines represent 95 percent confidence intervals.

to move (back) to higher amenity areas upon retirement.

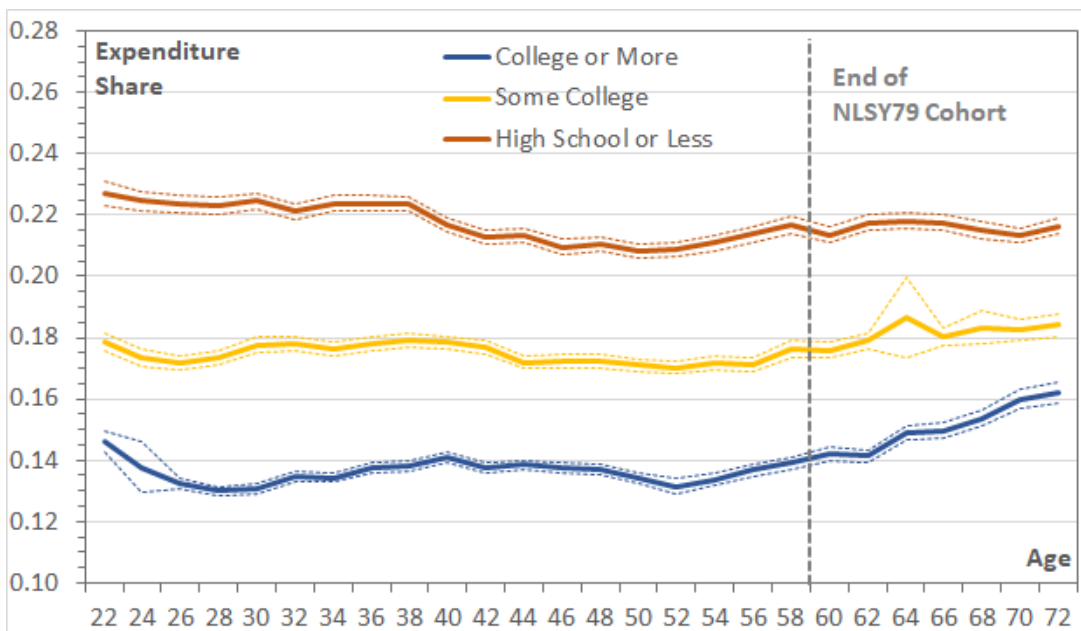
Figure 4 presents our estimates of time spent on leisure away from home (top panel) and leisure at home (bottom panel) by education group, with individuals pooled into two-year age

Figure 5: Expenditure Shares on Leisure Activities over the Life Cycle

(a) Expenditure Shares on Leisure Away from Home



(b) Expenditure Shares on Leisure at Home



Notes: Estimates from authors' calculations using the CEX data pooled over 1996-2019. Estimates represent the sample-weighted means of individuals' share of their total expenditures on each activity for two-year age intervals by (current) education. Dashed lines represent 95 percent confidence intervals.

intervals. Two patterns stand out for the behavior of time spent on leisure away from home. First, consistent with the estimates in Table 1, the college educated devote the most time to leisure activities outside their home at all ages. Second, there is a clear U-shaped pattern of time

spent on leisure away from home over the life cycle for all education groups, though the pattern is most pronounced for the college educated. Time spent on leisure away from home is lowest during one’s thirties through early fifties. Panel (b) of Figure 4 shows a notably different pattern. Consistent with the estimates from Table 1, those with a high school degree or less spend the most time on leisure activities at home throughout their life cycle. Second, time spent on these activities is essentially constant for all groups until about age 50, when the time dedicated to these activities gradually increases for all groups. The increased amount of leisure at home is likely a consequence of an overall increase in available time as individuals retire and substitute towards home-based activities later in the life cycle, as documented by Aguiar and Hurst (2007).

Figure 5 presents our estimates of the share of total expenditures spent on local leisure (top panel) and leisure at home (bottom panel) by education group, with individuals again pooled into two-year age intervals. Two similar patterns stand out for the behavior of these shares. First, consistent with the estimates in Table 2, the college educated devote the highest share of their expenditures to local leisure throughout their life cycle. Second, all individuals, but especially the college educated, devote a higher fraction of their expenditures to local leisure early in life. The share falls throughout their twenties and remains relatively constant thereafter. In contrast to the time allocated to leisure away from home (Figure 4), there is no rise in the expenditure share later in life, though we show in the online appendix that the share of expenditures spent on leisure during trips rises for the college educated after their mid-fifties.¹⁰ Panel (b) of Figure 5 shows that the life cycle patterns by education are essentially reversed for the expenditure shares spent on leisure activities at home. Those with a high school degree or less have the highest expenditure shares on leisure at home, while the college educated have the lowest expenditure shares on leisure on home. In addition, expenditures spent on leisure at home are essentially constant over the life cycle for each education group. The notable exception is a gradual rise in the expenditure share spent by the college educated starting in their late fifties.

In summary, both the time use data and the expenditures data show that the college educated devote more time and income to leisure outside of the home. Much of this is spent on eating and drinking and local entertainment. Furthermore, the gap in the consumption of local amenities

¹⁰We also report time use and expenditure shares by detailed leisure categories for the college educated and those with a high school degree or less over the life cycle in the online appendix.

between the college educated and those with a high school degree or less is greatest early in the life cycle, precisely when the NLSY data suggest that the college educated are most likely to move to higher-amenity areas. The differences are also large later in life, past the age range of our NLSY sample. In contrast, those with a high school degree or less tend to spend higher fractions of their time and expenditures on leisure at home, particularly on home entertainment and eating and drinking at home. Thus, it would be natural for them to seek out more affordable cities with relatively fewer local amenities.

To reinforce the empirical link between amenity consumption and the quality of life index, we aggregate individuals in the ATUS based on the most disaggregated geographic detail that the data allow. Specifically, we group individuals based on whether they live in the metropolitan or nonmetropolitan portion of their state. This provides 100 distinct regions.¹¹ We then generate population-weighted means of the quality of life index (and its components) for each of these regions, aggregating from the county level. The drawback of this approach is that we count both small MSAs and large MSAs within a state as a single entity (though population weighting deals with this somewhat). The advantage, however, is that we are able to provide unique evidence on the relationship between time use behavior and the quality of life index directly.

Figure 6 presents scatter plots of average time use behavior plotted against the quality of life index value for these 100 state-metro area regions. We estimate average time use behavior as the mean time spent across all individuals (age 18 to 74) residing in the state-metro area region pooled across all survey years. We estimate the relationship for the mean time spent on leisure away from home, leisure at home, home production, and (market) work. In each panel of the figure, we plot the fitted line and coefficient estimates from the population-weighted regression of the time use estimate (expressed as a fraction of daily time) on the quality-of-life index. The main results are in Panels (a) and (b) of the figure. Panel (a) shows that there is a positive, significant relationship between time spent on leisure away from home and the quality-of-life index value of an individual's region. A 100 basis point increase in average quality of life is associated with

¹¹The District of Columbia and New Jersey do not have nonmetropolitan portions. We only perform the analysis using the ATUS data because of censoring issues with the geographic data in the CEX. The CEX does not report the state of residence for most individuals in the nonmetropolitan portion of their state. Given that we have to aggregate both small and large MSAs into a single metropolitan region within each state, this severely limits the geographic variation available to us in the CEX data.

Figure 6: Relationships between Local Quality of Life and Time Use



Notes: Estimates from authors' calculations using the ATUS sample matched to quality-of-life estimates by the metropolitan or nonmetropolitan portions of each respondent's state of residence, with respondents pooled across the 2003-2019 survey years. Each observation represents the mean time use (as a percent of total daily time) and the mean quality-of-life index value for 100 metropolitan or non-metropolitan area components of each state. OLS regression coefficients (using 2000 population as weights) and the associated trendline are reported for each activity.

a 7.5 percentage point increase (with a standard error of 1.2 percentage points) in the fraction of daily time devoted to leisure away from home. The top left panel shows that this increase in average quality of life is also associated with a 13.6 percentage point decrease (with a standard error of 2.5 percentage points) in the fraction of daily time spent on leisure at home.

Panel (c) shows the relationship between home production time and the quality-of-life index as a validity check. We find essentially no relationship between the two, with a 100 basis point increase in the quality-of-life index associated with a statistically insignificant 1.3 percentage point decrease (standard error of 1.8 percentage points) in home production time. Finally, Panel (d)

shows that higher average quality of life is associated with increased work time. A 100 basis point increase in the index is weakly associated with a statistically insignificant 5.3 percentage point increase (standard error of 4.4 percentage points) in time spent working. This is not surprising since we observed that the wage component of the quality of life index increases in a similar way by education and age to the overall index (Figure 3), though to a lesser degree. Thus, despite the crudeness of our geographic measures, we find evidence of a significantly positive relationship between local amenity consumption and the quality-of-life index, as well as a significantly negative relationship between leisure time spent at home and the quality-of-life index.

3.3 The Role of Children in the Household

Overall, our evidence shows that the consumption of local amenities is greater for higher-skilled individuals and for individuals early (and potentially much later) in their life cycle. The peak in the quality-of-life index early in the life cycle is in contrast with the peak in conventional measures of consumption found in life-cycle studies (e.g., Attanasio and Weber, 1995, among others), which typically occurs in one's mid-forties. We conjecture that the difference in the life cycle behavior of the quality-of-life index, and the associated behavior of migration and amenity consumption, is due to a higher demand for local amenities by individuals, particularly high-skill individuals, outside of their child-rearing years.¹² Specifically, we argue that the rapid increase in average quality of life among the college educated (and to a lesser extent, among those with some college) reflects a bunching of local amenity consumption in response to the anticipation of having children later in the life cycle. If amenity consumption requires both time and income, then the presence of household children will tend to reduce amenity consumption. Since amenities are valued through housing prices, it would imply that households with children would pay for a good that they are inefficiently under-consuming if they remain in unaffordable, high quality-of-life areas. Consequently, we observe individuals gradually moving towards more affordable, lower quality-of-life areas during their child-rearing years.

We conclude our empirical analysis with evidence in support of this hypothesis. First, we split the NLSY79 cohort by whether or not we observe individuals ever having children present in their

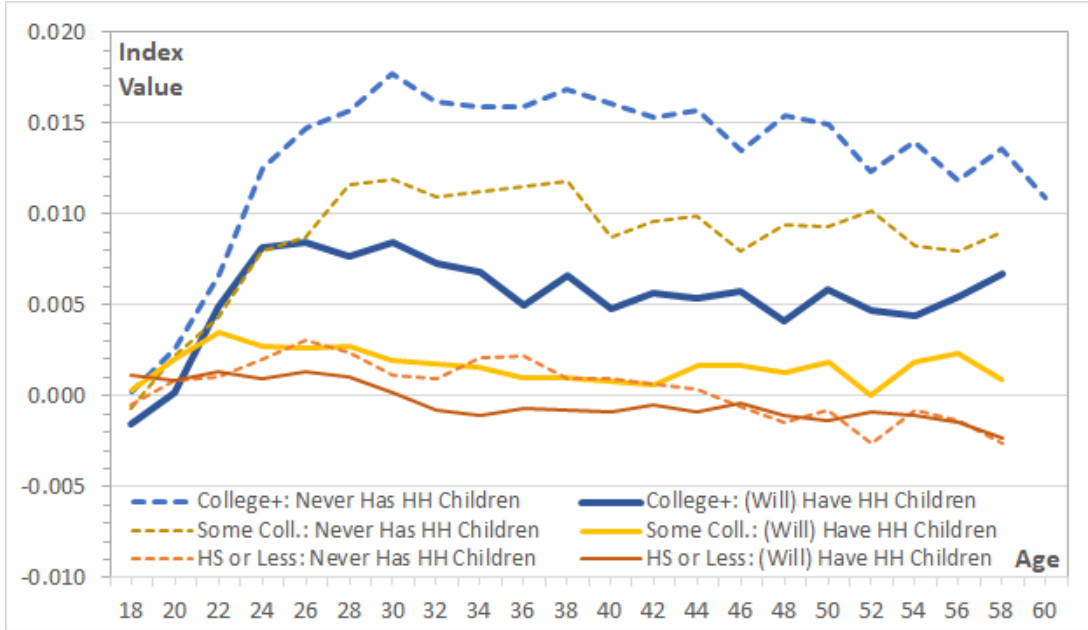
¹²In the online appendix, we show that the fraction of households with children present peaks between age 32 and age 42, with the peak occurring later for more-educated individuals.

household after age 18 and again estimate average quality of life for individuals over their life cycle.¹³ We use this distinction to account for the potential selection issues that would arise over the life cycle if we split the sample by whether or not individuals currently have any children in the household. We also split each subsample by the highest degree attained so that the results are comparable to the estimates in Figure 2. Figure 7 shows that individuals who never have children tend to move towards higher-amenity areas regardless of their education. The difference based on incidence of household children is essentially negligible for those with a high school degree or less, and they tend to move towards lower-quality of life locations independent of ever having household children. The difference for the college educated is substantial, however. By age 24, those who never have household children move to metropolitan areas with a quality-of-life value 0.4 log point higher than those who eventually do have household children. The gap rises to about 1.1 log points by age 40 and between 0.7 and 1.1 log points through their early 50s. Moreover, those with a college degree whom never have children tend to remain in high-amenity areas, while those with children, regardless of their education, tend to gradually move to lower-amenity areas starting in their late twenties. To put this difference into perspective, the gap in quality-of-life values of between the college educated and those with a high school degree or less in Figure 2 (i.e., regardless of having household children) peaks at 1.0 log point. We take this as strongly suggestive evidence that household children drive migration decisions across metropolitan areas. The evidence is consistent with the migration patterns of gay men documented by Black, Gates, Sanders, and Taylor (2002). Black et al. make a similar argument to our own, under the premise that gay men are less likely to have children, which frees up income to devote towards higher housing costs and greater amenity consumption.

Next, we use an event study analysis to examine how the incidence of household children explicitly affects the quality of life value of where one chooses to live. Specifically, we use our pooled NLSY sample to regress the quality of life of their current metropolitan area on a set of time dummies that identify the years prior to, during, and after the incidence of their first child in the household, controlling for various demographic and other characteristics. Our model

¹³We exclude the NLSY97 respondents since they are not old enough to have finished having children by the end of our sample period.

Figure 7: Average MSA Quality of Life Estimates by Incidence of Household Children



Notes: Estimates from authors' calculations using the NLSY79 sample matched to quality-of-life estimates by current residence, highest education attained, and whether or not the individual ever had children in their household throughout the NLSY survey. Estimates represent the sample-weighted mean quality of life index values (relative to the index value for residence at age 14) for two-year age intervals.

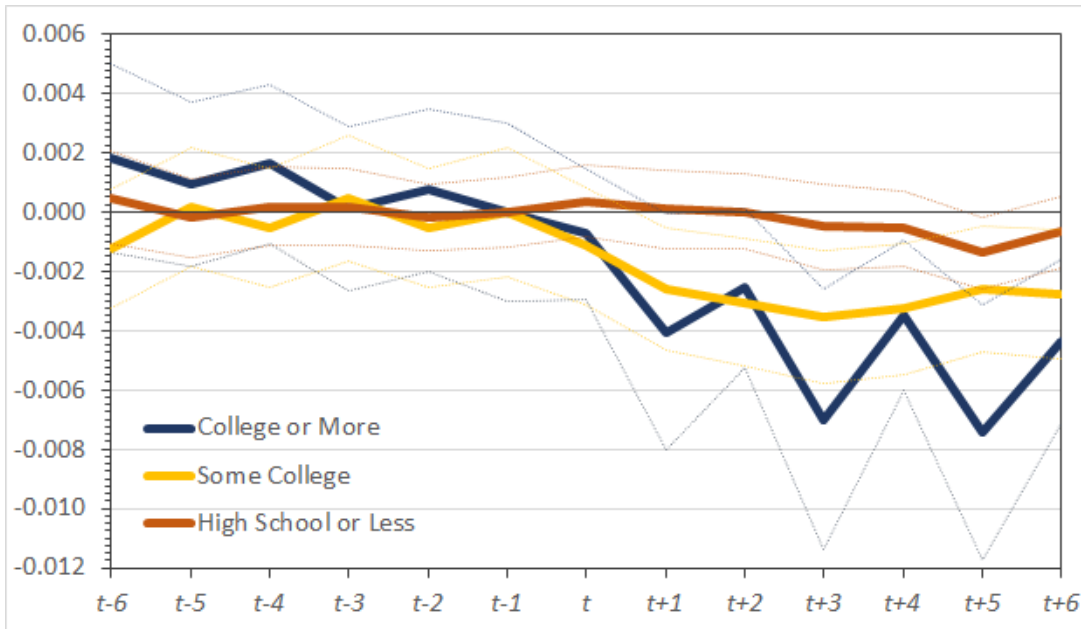
specification is

$$Q_{j(i)st} = \sum_{k=-n}^n \alpha_{s,t+k} + X_{it}\beta + \gamma_s + \delta_{st} + \eta_\tau + \epsilon_{ist},$$

where $Q_{j(i)st}$ is the quality of life value of metropolitan area j that individual i with educational attainment s lives in at age t , and $\alpha_{s,t+k}$ represents a set of education-specific dummy variables for the k years prior to, during, and after the incidence of the individual's first child in the household. The vector of demographic controls is X_{it} and includes indicators for gender, marriage, gender \times marriage, and four race categories; γ_s represents a set of dummies for each educational attainment category; δ_{st} represents a set of dummies for educational attainment \times two-year age categories; and η_τ represents a set of dummies for τ calendar years (interacted with an indicator for NLSY cohort). The regressions are sample-weighted and standard errors are clustered by metropolitan area. We estimate the model for $n = 6$ years of lead and lag variables around the event.

Our results are in Figure 8. We report the $\alpha_{s,t+k}$ coefficients separately by educational attainment and normalize each set of coefficients by setting the education category's $t-1$ estimate to zero. The figure shows strong evidence that the first child to enter one's household causes

Figure 8: Estimated Changes in MSA Quality of Life in Response to First Household Child



Notes: Figure reports the event study coefficients from regressing the quality of life index value of an individual's current residence (relative to its value at age 14, for the NLSY79 cohort, or age 12, for the NLSY97 cohort) on the 6 years prior through the 6 years after the incidence of the first child observed in the household using the pooled sample of NLSY79 and NLSY97 respondents aged 18 and over. The sample-weighted regression includes additional controls for gender, gender \times marriage, race, highest education attained, education \times age, and NLSY cohort \times calendar year. Dashed lines represent 95 percent confidence intervals based on standard errors clustered by Metropolitan Statistical Area.

them to migrate to lower quality-of-life metropolitan areas over time, particularly for the college educated. In the six years prior to the first child, the quality of life of one's metropolitan area is roughly constant for all education groups. Following the entrance of the first child into the household, it falls for those with at least some college, though the decline is only statistically significant for the college educated. Those with a high school degree or less migrate to locations with a quality of life index value that is roughly 0.1 log point lower five years after the incidence of the first child, but the decline is not statistically significant. Those with a college degree migrate to locations with a quality-of-life index value that is 0.1 log point lower on impact and about 0.7 log point lower after three years (relative to its value prior to the first child). Thus, the incidence of household children appears to drive migration towards more affordable, lower quality-of-life metropolitan areas, and its effects are largest for the college educated. We take this as more direct evidence that household children drive migration decisions across metropolitan areas.

4 A Model of Life-Cycle Amenity Consumption

We develop a general equilibrium model of wages, amenities, and housing prices where households choose their consumption, leisure, labor supply, and local amenities (through their location choice) taking the housing prices and wages they face at each location as given. Workers differ in skill and face shocks to their utility over their life cycle via taste parameters. These shocks represent changes in household composition over time and affect the household's demands for traded and locally nontradable goods, as well as their value of leisure. Changes in household composition also affect the cost of local amenities (i.e., going out is more expensive for larger households) and the required amount of home production time. Wages are determined in equilibrium through hiring and production in the two goods sectors while housing prices are determined in equilibrium through a competitive nontradable goods sector. In equilibrium, utility is equalized across locations of differing amenity levels for individuals of a given type and a given household composition. Mobility across locations is costless. Households maximize lifetime utility subject to their lifetime budget constraint and their series of (normalized) within-period time constraints, and do so with perfect foresight.

4.1 Households

At each period t and within each location j , household i receives utility from consuming a traded good, x_{it} , a locally nontraded good, y_{it} , the value of local amenities, Q_{jt} , and leisure time. We distinguish leisure time into the time a household spends enjoying local amenities, a_{it} , and all other forms of leisure, l_{it} (which we refer to as leisure at home). The latter reflects leisure that is costless and generates the same utility regardless of where one lives. One can interpret expenditures on the nontraded good as expenditures on local housing and related costs, and expenditures on the traded good as expenditures on all other goods and services that are not related to one's location. The household receives disutility from its nonleisure activities—i.e., time spent on market work, n_{it} , and the time required for home production, $\tau(z_{it})$, where the latter depends on the household composition shock, z_{it} . Expenditures on the nontraded good are subject to local prices, p_{jt} , while the price of the tradeable good is numeraire. Time spent enjoying local amenities is costly as well, with $p^a(z_{it})$ representing the expenditure cost of a unit

of a_{it} . The local wage households earn (per unit of labor time), $w_{j(k)t}$, depends on the household's location and type, k . Finally, households have nonwage income and (net) savings each period equal to $s_{it} + \tilde{I}_{it} \equiv I_{it}$. Since our data are for a single household respondent, the nonwage income represents any spousal or additional unearned income in our estimation.

Households maximize their lifetime utility given their type, k , the household composition shock z_{it} , and the quality of amenities at their location, Q_{jt} . We interpret z_{it} as capturing the effects of household formation—and the presence of household children in particular—on required home production time, goods demand, and leisure demand over the life cycle. Therefore, it determines $\tau(z_{it})$, $p^a(z_{it})$, and the preference shocks to goods and leisure demand. Formally, the household's utility maximization problem is:

$$V(s_{it}, \cdot; k, z_{it}) = \max_{\{x_{it}, y_{it}, a_{it}, l_{it}, n_{it}\}} \exp\{\phi^x(z_{it}, \epsilon_{it}^x)\} \ln x_{it} + \exp\{\phi^y(z_{it}, \epsilon_{it}^y)\} \ln y_{it} + \mu Q_{jt} h(a_{it}) \\ - \frac{\exp\{\gamma_0(z_{it}, \epsilon_{it}^n)\}}{1+\gamma_1} n_{it}^{1+\gamma_1} \tau(z_{it})^{\gamma_2} + \beta V(s_{i,t+1}, \cdot; k, z_{i,t+1}),$$

subject to
$$s_{i,t+1} = (1+r) [I_{it} + w_{j(k)t} n_{it} - x_{it} - p_{jt} y_{it} - p^a(z_{it}) a_{it}],$$

and
$$n_{it} + \tau(z_{it}) + a_{it} + l_{it} = 1 \text{ for all } t.$$

The household's discount rate is β and the real interest rate is r . The function $h(a_{it})$ defines the utility derived from the time spent consuming amenities regardless of location. So long as $h'(a_{it}) > 0$, the value of local amenities and the time spent enjoying them will be complements. In our counterfactual exercises we relax the assumption of complementarity so that utility from local amenities is that of the standard Rosen-Roback framework (i.e., from Q_{jt} alone, regardless of time devoted to local amenities). Work time, defined as the combined time spent on market work and home production, generates disutility. Our functional form is a common characterization of the consumption-leisure tradeoff that assumes separable utility and implies an elasticity of labor supply equal to $1/\gamma_1$.

We can simplify the household's problem by substituting its time constraint into its lifetime budget constraint—and similarly into the disutility of work—to derive its “full income” budget constraint in the spirit of Becker (1965),

$$s_{i,t+1} = (1+r) [I_{it} + w_{j(k)t}(1 - \tau(z_{it})) - x_{it} - p_{jt} y_{it} - (p^a(z_{it}) + w_{j(k)t}) a_{it} - w_{j(k)t} l_{it}] \quad (1)$$

The full-income budget constraint in equation (1) highlights several features of the model.

First, as in a standard consumption-leisure model, the opportunity cost of leisure time spent at home (measured as its price in expenditure units) is the wage. Second, the opportunity cost of leisure time spent on local amenities is higher since it includes both the wage and the expenditure cost of actually going out, $p^a(z_{it})$. Finally, shocks to home production demand over the life cycle affect the household's available full income.

With this simplification, we reduce the problem to a single constraint and an endogenous choice of four variables (the two consumption expenditures and the two measures of leisure time). The first order conditions for this problem are

$$\frac{\exp\{\phi^x(z_{it}, \epsilon_{it}^x)\}}{x_{it}} = \lambda_{it} [\beta(1+r)], \quad (2a)$$

$$\frac{\exp\{\phi^y(z_{it}, \epsilon_{it}^y)\}}{y_{it}} = \lambda_{it} [\beta(1+r)] p_{jt}, \quad (2b)$$

$$\mu Q_{jt} h'(a_{it}) + \exp\{\gamma_0(z_{it}, \epsilon_{it}^n)\} n_{it}^{\gamma_1} \tau(z_{it})^{\gamma_2} = \lambda_{it} [\beta(1+r)] (p^a(z_{it}) + w_{j(k)t}), \quad (2c)$$

$$\exp\{\gamma_0(z_{it}, \epsilon_{it}^n)\} n_{it}^{\gamma_1} \tau(z_{it})^{\gamma_2} = \lambda_{it} [\beta(1+r)] w_{j(k)t}, \quad (2d)$$

where λ_{it} is the Lagrange multiplier on the lifetime budget constraint. Furthermore, combining equations (2c) and (2d) implies that

$$\mu Q_{jt} h'(a_{it}) = \lambda_{it} [\beta(1+r)] p^a(z_{it}). \quad (2e)$$

We can also express the household's intertemporal choices as a series of Euler equations that equate consumption and time use choices in period t to those in period $t+1$ via the Lagrange multiplier on the lifetime budget constraint. We highlight the Euler equations for time use since they will be useful in our model calibration. Appealing to equations (2b), (2d), and (2e), we can show that the relevant Euler equations are

$$\left(\frac{p_{j,t+1} y_{i,t+1}}{p_{jt} y_{it}} \right) = [\beta(1+r)] \left(\frac{\lambda_{it}}{\lambda_{i,t+1}} \right) \left(\frac{\exp\{\phi^y(z_{i,t+1}, \epsilon_{i,t+1}^y)\}}{\exp\{\phi^y(z_{it}, \epsilon_{it}^y)\}} \right), \quad (3a)$$

$$\left(\frac{n_{i,t+1}}{n_{it}} \right)^{\gamma_1} = [\beta(1+r)]^{-1} \left(\frac{\lambda_{i,t+1}}{\lambda_{it}} \right) \left(\frac{w_{j(k),t+1}}{w_{j(k)t}} \right) \frac{\exp\{\gamma_0(z_{it}, \epsilon_{it}^n)\}}{\exp\{\gamma_0(z_{i,t+1}, \epsilon_{i,t+1}^n)\}}, \quad (3b)$$

$$\frac{h'(a_{i,t+1})}{h'(a_{it})} = [\beta(1+r)]^{-1} \left(\frac{\lambda_{i,t+1}}{\lambda_{it}} \right) \left(\frac{p^a(z_{i,t+1})}{p^a(z_{it})} \right) \frac{Q_{jt}}{Q_{j,t+1}}. \quad (3c)$$

Equation (3a) relates changes in nontradable expenditures to their preference shocks and changes in the marginal utility of income over the life cycle. Equation (3b) is equivalent to a

standard labor supply equation that equates the growth in work hours to the growth in wages over time and preference shocks to leisure. Equation (3c) implies that changes in the marginal utility of time spent enjoying local amenities are increasing in their marginal cost and decreasing in the value of the local amenity. Keep in mind that, in the model, wages and the value of local amenities only change over time through the household’s migration to a new location.

4.2 Equilibrium

In equilibrium, the supply of the tradable and nontradable goods equals their demand, labor supply equals labor demand for each skill level, and utility is equalized across locations. Workers are paid $w_{j(k)t}$ per unit of market work to produce the tradable good at its numeraire price the nontradable good at the local price p_{jt} . Wages are set competitively so that they equal the marginal productivity of labor in the tradable sector. The nontradable sector additionally uses land in its production and determines the local price level by setting it to the marginal cost of production. Finally, since migration is costless, households’ indirect utility must be equal across locations and for a given skill and household composition shock. Letting the value of this indirect utility be value $\kappa(s, z)$, we have that

$$V(s_{it}, \cdot; k, z) = \kappa(k, z). \tag{4}$$

5 Model Estimation and Quantitative Analysis

5.1 Identification

We can identify all of the model’s endogenous variables with synthetic panel data constructed from the NLSY, ATUS, and CEX. We can also use the data to identify the key outcomes of our underlying household shock process, z_{it} , over the life cycle. Specifically, we can derive the time spent on home production, $\tau(z_{it})$, from the ATUS, and infer the cost of enjoying local amenities, $p^a(z_{it})$, from expenditures on local amenities in the CEX and time spent on local amenities in the ATUS. We assume that the shocks to goods and leisure preferences depend on an individual’s

marital status and the presence of household children, so that

$$\begin{aligned}\phi^x(z_{it}, \epsilon_{it}^x) &= \phi_t^x + \phi_{mt}^x z_{it}^m + \phi_{ct}^x z_{it}^c + \epsilon_{it}^x \\ \phi^y(z_{it}, \epsilon_{it}^y) &= \phi_t^y + \phi_{mt}^y z_{it}^m + \phi_{ct}^y z_{it}^c + \epsilon_{it}^y \\ \gamma_0(z_{it}, \epsilon_{it}^n) &= \gamma_t^0 + \gamma_{mt}^0 z_{it}^m + \gamma_{ct}^0 z_{it}^c + \epsilon_{it}^n,\end{aligned}$$

where z_{it}^m is an indicator for whether the individual is married and z_{it}^c is an indicator for whether the individual has any household children. We identify time spent on leisure at home, l_{it} , and local amenity consumption, a_{it} , from the ATUS. We identify expenditures on tradable goods, x_{it} , nontradable goods, $p_{jt}y_{it}$, and local amenities, $p^a(z_{it})a_{it}$, from the CEX. We use the NLSY to identify earnings per unit of work time, n_{it} (so that earnings, hours, and the hourly wage are internally consistent). We also use the NLSY geocode data to identify location over the life cycle, which gives us our estimates of the local value of amenities, Q_{jt} (estimated as the local quality-of-life index) and the corresponding local price index, p_{jt} .

We assume that $h(a_{it}) = \left(\frac{\eta}{\eta-1}\right) a_{it}^{\frac{\eta-1}{\eta}}$, so that $h'(a_{it}) = a_{it}^{-1/\eta}$. Substituting this into equations (2e) and (3b) and taking logs of each shows that this implies an elasticity of time spent enjoying local amenities with respect to the value of those amenities of η .

5.2 Moment Construction

We generate estimates of the necessary moments from our data for three education groups (high school or less, some college, college or more), gender, marital status, and household children status (i.e., whether there are any children currently in the household) over 19 two-year age bins that cover ages 22 to 59. This gives us up to 456 cells in our synthetic panel, of which we have 445 with enough observations to disclose our geocode-dependent estimates.

In using our synthetic panel, we must address the fact that the estimates come from different surveys, all with their own sampling, time frame, and measurement differences. Therefore, we first generate predicted estimates of expenditures and time use for individuals in our pooled NLSY sample. The predicted measures are out-of-sample estimates of each expenditure or time use category.¹⁴ For expenditures, we first estimate the predicted relationship between each major

¹⁴We take a similar approach to Blundell, Pistaferri, and Saporta-Eksten (2018) in constructing our synthetic panel, who match estimates from the ATUS and CEX to PSID data. We diverge from their methodology in that we build our estimates up from the microdata using variables common to all three data sets and use estimates of time use and expenditures that are out-of-sample predictions for NLSY respondents.

expenditure category generated from the CEX (in 2019 dollars) on a set of observable demographic and labor market characteristics: gender, marital status, indicators for zero, one, or two or more household children, three education categories, four race categories, five birth cohort categories, an indicator for any additional adults in the household, full-time employment status, full-time school enrollment status, and spouse’s full-time employment status. We include a rich set of interactions for all of these variables.¹⁵ For time use, we use the same approach, regressing major time use categories generated from the ATUS (measured in minutes) on the same set of observable demographic and labor market characteristics.¹⁶ In both cases, we take the coefficients from each regression and interact them with the same variables in the NLSY data to generate the predicted expenditure and time use estimates for each individual-year observation. We then generate time use and expenditure estimates for each of our synthetic panel cells across its k demographic groups and t age categories as the sample-weighted means of their predicted values. We also generate predicted estimates of income, hours, wages, and the quality-of-life estimates (along with its components) for each cell using our pooled sample of NLSY data. We use the same approach and empirical specifications, but the estimates are within-sample since they use the data of the NLSY respondents. Consequently, our quality-of-life estimates are comparable to those reported in Figures 2 and 3, except that we remove the residual component of the estimates that are not predicted by demographic and household characteristics.

We then rescale our measures so that they are internally consistent within our model’s framework. We express all time use estimates as their fraction of total “relevant” time in a given day, where we define relevant time as the sum of work time, home production time, and leisure time

¹⁵Specifically, we interact gender with marital status, household children, education, and age. We interact birth cohorts (which identify individuals as born before, during, between, or after our two NLSY cohort periods) with gender, marital status, household children, and education. We interact household adults with gender, marital status, and age. We interact race with gender, marital status, household children, and education. We interact own and spouse’s full-time employment status each with gender, household children, and education. Finally, we interact school enrollment status with gender and education.

¹⁶For the CEX, the expenditure categories we use in the predicted regressions (i.e., the dependent variables) are: food, drink, and tobacco at home; entertainment and other leisure at home; clothing and vehicles; health and education; leisure on trips; housing and housing maintenance; local leisure activities; and home production services. The categories correspond to those reported in Table 3. For the ATUS, the time use categories we use in the predicted regressions are: leisure time at home, eating and drinking time, socializing, other leisure time away from home, household maintenance and management time, food shopping and preparation; other shopping; personal care time; child care time; other home production time; work time, education time, religious and volunteer time; and sleep. In both cases, we estimate the sample-weighted regressions using pooled individuals across all years of the sample and for all individuals age 18 to 65.

(both at home and away from home). We add the amount of sleep time in excess of the sleep time reported by those at the 25th percentile of the sleep distribution to leisure time at home under the assumption that it represents the leisure portion of sleep. We also use the total aggregate hours worked in the previous year reported in the NLSY (and measured as their average minutes per day) as our estimates of work time, n_{kt} . This is a more direct measure of work time for individuals in our sample than the predicted ATUS work time (which comes from a daily time diary) and it is also internally consistent with the NLSY wage and income estimates we use to calibrate the model. We estimate the share of time spent on leisure at home, l_{kt} , local amenity consumption, a_{kt} , and home production, $\tau(z_{kt})$, using the categories for leisure at home, leisure away from home, and home production in Table 1, respectively. We measure expenditures on nontradable goods, $p_{jt}y_{kt}$, as expenditures on housing, utilities, and housing maintenance. Our tradable goods expenditure estimates include expenditures on every other category reported in Table 2 except local leisure (which is equal to $p^a(z_{kt})a_{kt}$ in our calibration). We assume that I_{kt} is equal to all (disposable) household income plus net savings in excess of the NLSY respondent's earnings. The additional income includes the earnings of any spouse or partner and total household nonwage income. We also rescale the wage, $w_{j(k)t}$, so that it is consistent with our estimate for the share of time devoted to work, n_{kt} . Finally, we identify $p^a(z_{kt})$ as the ratio of local leisure expenditures to time spent on local amenities.

Table 3 reports the mean predicted moment estimates we identify directly from the data. Consistent with the evidence in Table 2, we estimate that about 42 percent of total expenditures are on nontradables. Just over half of income (net of savings) comes from the respondent's own earnings (the product of the daily wage and work time), with the remainder coming from spousal earnings or other sources. A quarter of relevant daily time is spent on home production, while 27 percent of it is spent working. The remaining time is spent on leisure, and of this time, 32 percent is spent on leisure at home and 16 percent is spent on enjoying local amenities.

Figure 9 reports the time series behavior of selected calibrated values identified from the data and aggregated by education and age bin. The top row reports expenditures per day on tradable and nontradable goods. Both expenditures are hump-shaped over the life cycle for all education groups, and the levels of both expenditures are also strongly increasing with educational attainment. Expenditures on tradable goods exhibit a greater fanning out by educational

Table 3: Sample Means for Moments Used in Estimation

Variable	Sample		Data Source
	Mean	Description	
x_{kt}	80.08	Tradeable goods expenditures (per day)	Predicted CEX expenditures on food, drink, tobacco, clothing, vehicles, health, education, home production services, leisure at home, and leisure on trips
$p_{jt}y_{kt}$	58.13	Nontradable goods expenditures (per day)	Predicted CEX expenditures on rental equivalent of housing, utilities, and housing maintenance
$p^a(z_{kt})a_{kt}$	8.58	Local amenity expenditures (per day)	Predicted CEX expenditures on local leisure
$w_{j(k)t}$	417.98	Real daily wage	NLSY real annual earnings per hour worked in prior year
I_{kt}	82.36	Additional real income and net savings (per day)	Net difference between total predicted CEX expenditures and wage earnings, $w_{j,st}n_{st}$
$\tau(z_{kt})$	0.245	Share of time spent on home production	Predicted ATUS time spent on home production (share of available time)
a_{kt}	0.163	Share of time spent on local leisure	Predicted ATUS time spent on leisure away from home (share of available time)
l_{kt}	0.319	Share of time spent on leisure at home	Predicted ATUS time spent on leisure at home (share of available time)
n_{kt}	0.273	Share of time spent working	NLSY hours worked last year (normalized to daily share based on ATUS available time)
$\ln Q_{j(k)t}$	-0.0080	(log) Quality of life value of current residence	Quality of life index
$\ln p_{j(k)t}$	-0.0396	(log) Local price index of current residence	Price component of quality of life index

Notes: Notes: Table reports the correspondence between the moments used to estimate the model's parameters and the data used to generate these moments. See text for descriptions of the creation of predicted estimates of CEX expenditures, predicted estimates of ATUS time use, and all normalizations. The means are the sample-weighted averages across the NLSY observations used to estimate the 445 gender \times marital status \times household children \times education \times age categories used in the model calibration, and represent the normalized (daily) values.

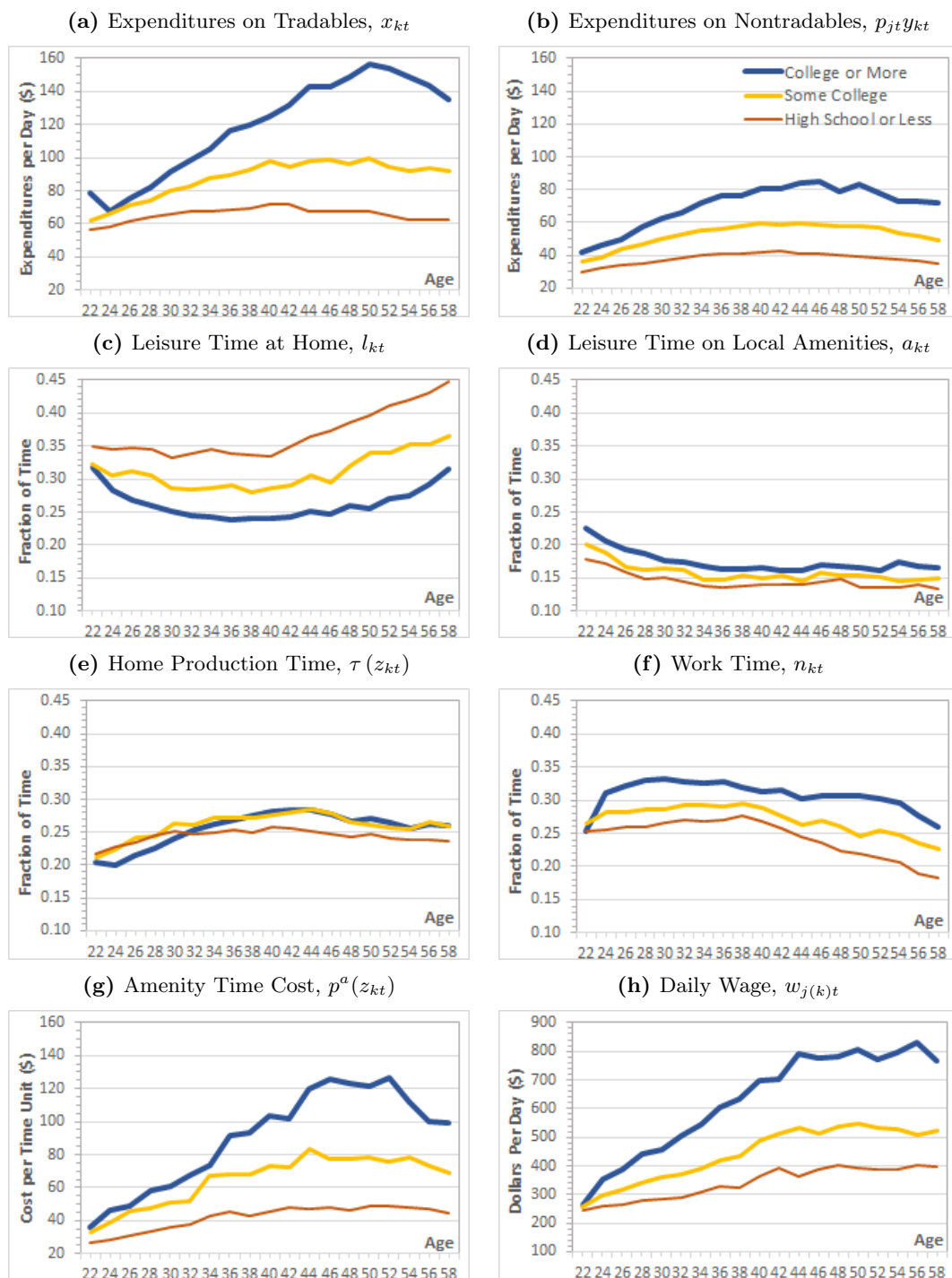
attainment that occurs later in the life cycle (during one's mid-forties) compared to expenditures on nontradable goods. The left panel of the second row reports the fraction of available time spent on leisure at home while the right panel of the second row reports the fraction of available time spent enjoying local amenities. Those with a high school degree or less spend the most time on leisure at home while the college educated spent the least amount of time on leisure at home. The difference between the two education groups grows over the life cycle. The college educated spend the highest share of their available time enjoying local amenities. Their difference with the other two education groups is greatest early in life, with some evidence on convergence between the three education groups by middle age. The left panel of the third row reports the fraction of time devoted to home production by education group. All three groups exhibit a similar hump-

shaped life cycle pattern, though the peak time devoted to home production (between 26 and 29 percent of total available time) occurs later for more educated individuals. The right panel of the third row reports work time by education group. Work time is higher for the more educated and somewhat hump-shaped over the life cycle, declining for all three education groups starting in their forties. The left panel of the bottom row reports the amenity time cost implied by predicted expenditures and time spent on local amenities. Amenity costs generally rise over the life cycle, with a higher over cost and greater rise for the college educated. Much of the life-cycle variation is due to changes in household composition—e.g., a married individual will probably report about twice the expenditure but the same time spent going out to dinner as a single individual since the former is likely to dine with their spouse. Finally, the right panel of the bottom row reports the daily wage by education group. This is the wage individuals would earn if they devoted all relevant time to work. The wage rises over the life cycle for all education groups, but more so for the more educated. Note that our estimates of the value of the local amenity, $Q_{j(k)t}$, and the local price index, $p_{j(k)t}$, are nearly identical to what report in Figures 2 and 3A, respectively.

5.3 Model Estimation

We identify the remaining parameters of the model by estimating the first order conditions for amenity consumption in (2e) and labor supply in (2d), in each case substituting in the first-order condition for nontradable good consumption from (2b) for the Lagrange multiplier (i.e., the marginal utility of income). This gives us a pair of marginal rate of substitution conditions to estimate, both with respect to nontradeable goods demands. We also estimate the related Euler equations from (3a) and (3b). We estimate these equations using GMM on our synthetic panel. We estimate the system in logs (or log changes, in the case of the Euler equations), using the means of the log of each moment to deal with the aggregation biases in synthetic data highlighted by Attanasio and Weber (1993). To deal with heterogeneity (both across and within synthetic cells), we include an interaction of fixed effects for gender \times education \times marital status and gender \times education \times the presence of household children, which we denote with θ_k^x (these fixed effects are differenced out of the Euler equations), along with the share of each cell that is Black, Hispanic, or other Nonwhite, $s_{r,kt}$. We do this so that our estimated model parameters are identified through the life-cycle variation within demographic groups.

Figure 9: Life Cycle Behavior of Model Moments by Education



Notes: Estimates from authors' calculations using pooled data from the NLSY79 and NLSY97 samples, predicted estimates of expenditures from the CEX, and predicted estimates of time use from the ATUS. The top panels report the estimated expenditures on tradable and local nontradable goods, expressed in normalized dollar amounts. The second row of panels report the share of available time spent on leisure at home and leisure on local amenities. The third row of panels report the share of available time spent on home production and work. The bottom panels report the cost of amenity time (implied from expenditures and time spent on local amenities) and the daily wage (expressed as the earnings received from devoting all time to work).

Our four estimating equations are,

$$\begin{aligned} \ln n_{kt} &= \frac{1}{\gamma_1} [\phi^y(z_{kt}) - \gamma_0(z_{kt}) + \ln w_{j(k)t} - \ln p_{j(k)t} y_{kt}] - \frac{\gamma_2}{\gamma_1} \ln \tau(z_{kt}) \\ &\quad + \theta_k^n + \sum_r \theta_r^n s_{r,kt} + u_{kt}^n \end{aligned} \quad (5a)$$

$$\begin{aligned} \ln a_{kt} &= \eta [-\phi^y(z_{kt}) + \ln \mu + \ln Q_{j(k)t} + \ln p_{j(k)t} y_{kt} - \ln p^a(z_{kt})] \\ &\quad + \theta_k^a + \sum_r \theta_r^a s_{r,kt} + u_{kt}^a \end{aligned} \quad (5b)$$

$$d \ln n_{kt} = \frac{1}{\gamma_1} [\phi_t^y - \gamma_t^0 + d \ln w_{j(k)t} - d \ln p_{j(k)t} y_{kt}] - \frac{\gamma_2}{\gamma_1} d \ln \tau(z_{kt}) + \sum_r \theta_r^n ds_{r,kt} + du_{kt}^n \quad (5c)$$

$$d \ln a_{kt} = \eta [-\phi_t^y + d \ln Q_{j(k)t} + d \ln p_{j(k)t} y_{kt} - d \ln p^a(z_{kt})] + \sum_r \theta_r^a ds_{r,kt} + du_{kt}^a \quad (5d)$$

where the dX terms represent the change in the variable X , the $d \ln X$ terms represent the change in the log of the variable X between age categories t and $t + 1$, and u_{kt} and du_{kt} are error terms.

In our model, nontradable expenditures are endogenous. Furthermore, wages and amenity costs, while exogenous, are potentially subject to measurement error that is correlated with the error terms, since both are calculated using the left-hand side variables in their denominators. Consequently, we need to instrument our model. Our instruments are the log of other household income (plus net savings), the share of the panel cell that has a full-time employed spouse, the share of the panel cell that has an additional adult (besides any spouse), and two-age bin lags of log nontradable expenditures, log wages (in 5b), and log amenity costs (in 5b). The labor supply equations additionally uses the log of the quality-of-life price component as an instrument. The Euler equations use the (log) difference of these instruments (excluding the lag variables).

The main results of our estimates are in the first column of Table 4. Our estimate of $\hat{\gamma}_1$ is 5.49, though it is estimated with considerable noise. It implies a labor supply elasticity of about 0.18, which is on the low end of most micro labor supply estimates (see Chetty et al., 2011), but consistent with our estimate being the Marshallian elasticity. Our estimate is also somewhat lower than estimates that account for extensive-margin employment adjustments and home production (e.g., Rupert, Rogerson, and Wright, 2000). We estimate that $\hat{\gamma}_2$ is 0.30. Together with $\hat{\gamma}_1$ this implies an elasticity of work time with respect to home production time of $-\hat{\gamma}_2/\hat{\gamma}_1 = 0.05$, or essentially zero. Importantly, we estimate a complementarity between time spent on local amenities and the local quality of life to be 0.83, suggesting a strong response of individuals' local amenity consumption to the quality of those amenities. Specifically, we estimate that a

Table 4: Estimated Model Parameters

Parameter	All Individuals	All Men	All Women	Single, No Children	Married, w/ Children
$\hat{\gamma}_1$, inverse of labor supply elasticity	5.489 (4.603)	5.619 (5.310)	1.149 (0.238)	1.688 (0.503)	2.345 (0.834)
$\hat{\gamma}_2$, disutility share of home production time	0.300 (0.359)	-0.174 (0.334)	0.140 (0.174)	0.018 (0.170)	0.267 (0.154)
$\hat{\mu}$, utility from local quality of life	0.110 (0.040)	0.202 (0.052)	0.009 (0.012)	0.091 (0.036)	0.196 (0.073)
$\hat{\eta}$, elasticity of amenity time w.r.t. $Q_{j(k)t}$	0.833 (0.122)	1.055 (0.153)	0.450 (0.116)	0.716 (0.109)	1.153 (0.154)

Notes: Table reports the parameter estimates from the GMM estimation of our model on a set of expenditure, time use, income, and local quality of life moments from a synthetic panel of 445 demographic \times age cells. Standard errors are in parentheses. See text for details.

doubling of the quality-of-life value of local amenities will increase the time individuals spend enjoying them by 83%.

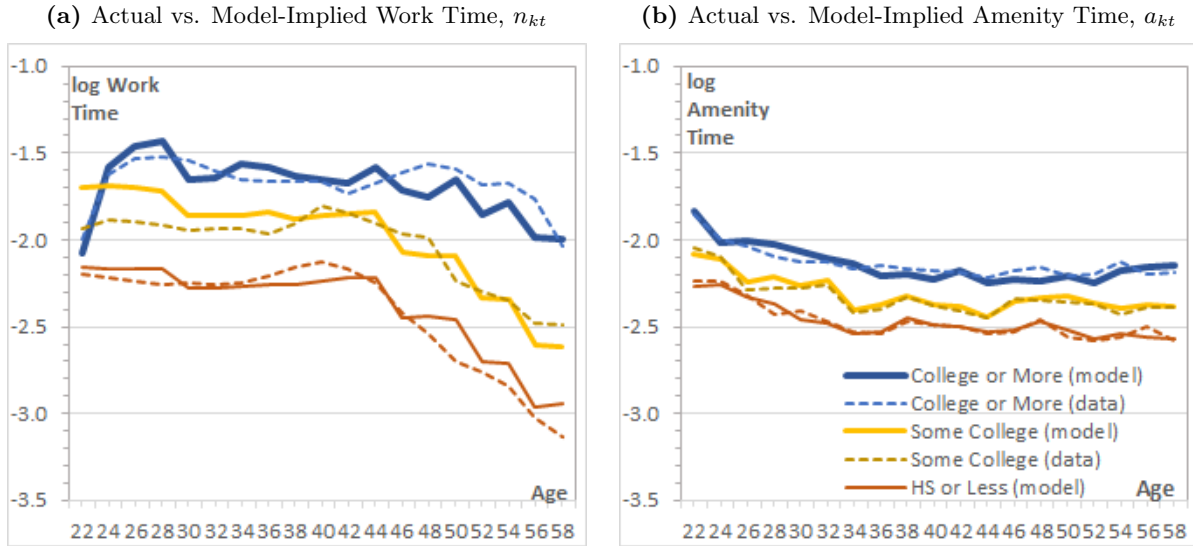
The remaining columns of Table 4 report the results of reestimating our model for various subsets of our synthetic panel. All subgroups have a large and statistically significant complementarity between amenity time and quality of life. Men have a somewhat higher elasticity than women, and married individuals with household children have almost double the elasticity of single individuals without children. The latter result is consistent with our empirical evidence on migration patterns following the incidence of household children.

Figure 10 presents two evaluations of the model’s fit of the data for our baseline estimation across all individuals. The left panel compares the model’s predicted log work time to the empirical log work time fed into the model, while the right panel compares the model’s predicted log amenity time to the empirical log amenity time fed into the model. Both panels aggregate the estimates into education \times age cells. Overall, the model does an excellent job matching the data. For work time, the model captures the both the levels by education and the variations over the life cycle very well. The fit of amenity time by education over the life cycle is also very tight.

5.4 Counterfactual Analyses

We conclude with a counterfactual exercise where we shut down the complementarity between amenity consumption and local quality of life. We reestimate our model, where we respecify the utility gained from local amenities as $\tilde{\mu}Q_{jt}$, where $\tilde{\mu}$ is a normalization that keeps equilibrium

Figure 10: Evaluations of Model Fit



Notes: Dashed lines are the times spent on market work (left panel) and amenities (right panel) estimated from pooled data from the NLSY79 and NLSY97 samples and predicted estimates of ATUS time use. Solid lines are the estimates of each variable implied from our model’s parameter estimates. See text for more details.

utility for each demographic-age cell equal at $\kappa(k, z_t)$ in the baseline and counterfactual cases. In this case, households only gain utility from the quality of life of their location, and not from how much time they spend enjoying the amenities reflected in that quality-of-life value. This specification is equivalent to the standard in Rosen-Roback model used in most studies of urban amenities, extended to account for endogenous labor supply.

An immediate implication of this specification is that time spent on local amenities is a corner solution ($a_{kt} = 0$). Enjoying local amenities still faces a cost of $p^a(z_{kt})$, but the time devoted to them no longer appears in the utility function. As such, households will receive the same utility from their location regardless of whether they go out to enjoy it. The home production demands of households will be less relevant to their location choices as well, since their constraint on going out to enjoy local amenities no longer binds (these demands will still have some effect on location choice through local wages and labor supply). This implication underscores the fact that, given our empirical evidence and quantitative model estimates, the standard Rosen-Roback model will miss the dampening effects child rearing has on urban agglomeration. In the standard model, reflected in our counterfactual here, individuals enjoy the same utility from their location regardless of how they spend their time.

We perform our counterfactual by first estimating equilibrium utility, $\kappa(k, z_t)$ for each demographic-

age cell in our synthetic panel, using our model parameter estimates and the equilibrium values of expenditures and time-use implied from the first-order conditions. We then solve for the (counterfactual) optimal location choice using $\tilde{\mu}Q_{jt}$ for the utility value of one's location, holding utility constant at $\kappa_t(k, z_t)$.

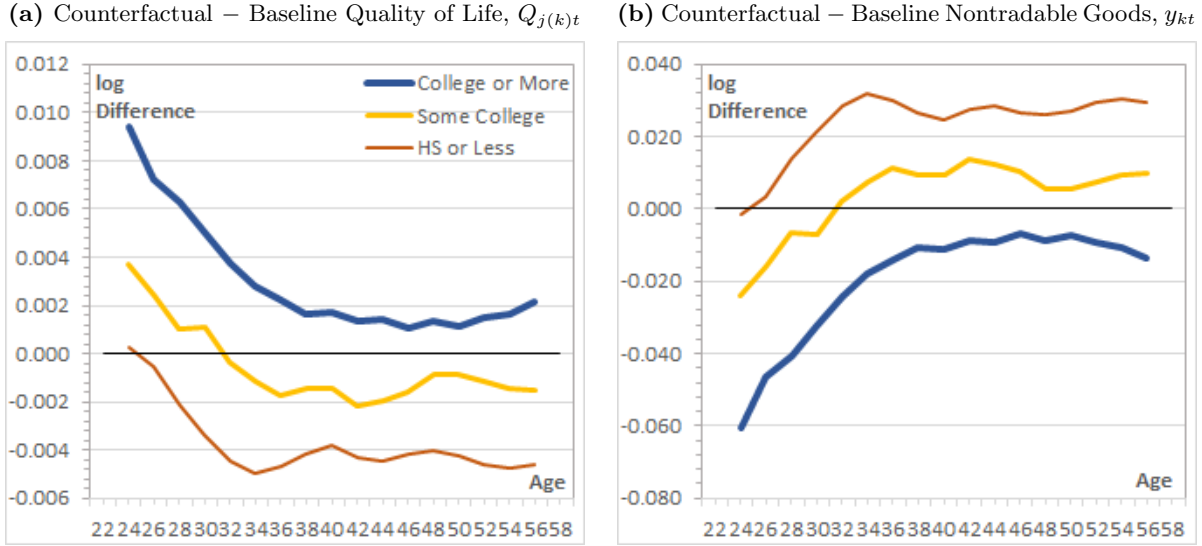
In doing so, we face several empirical challenges in estimating our counterfactual. The first is the normalization of $\tilde{\mu}$. We set $\tilde{\mu} = \hat{\mu} \left(\frac{\hat{\eta}}{\hat{\eta}-1} \right) \prod_{k,t} \omega_{kt} a_{kt}^{\frac{\hat{\eta}-1}{\hat{\eta}}}$, where “hats” denote estimated model parameters and $\prod_{k,t} \omega_{kt} a_{kt}^{\frac{\hat{\eta}-1}{\hat{\eta}}}$ is the geometric mean utility gained from time spent enjoying local amenities across all demographic-age cells in the baseline model. This ensures that utility in both cases do not diverge because of the exclusion of the $h(a)$ function, on average. The second challenge is how to identify the prices and wages associated with any counterfactual location choice. We deal with this by estimating an empirical, log-linear relationship between our local price index and the quality of life index and between the daily wage and the quality of life index. We then use the coefficients to generate values for the price of the nontraded good and daily wage as a function of $\ln Q_{j(k)t}$. Specifically, we estimate

$$\begin{aligned} \ln p_{j(k)t} &= \pi_0^p + \pi_1^p \ln Q_{j(k)t} + u_{kt}^p \\ \ln w_{j(k)t} &= \pi_{gmc}^w + \pi_{gst}^w + \pi_1^w \ln Q_{j(k)t} + u_{kt}^w, \end{aligned}$$

where π_{gmc}^w is a set of interacted gender \times marital status \times household children fixed effects and π_{gst}^w is a set of gender \times education \times age fixed effects. For a given (log) quality-of-life value, $\ln Q$, we can generate the predicted values from these regression coefficients to determine the associated local price and wage. Finally, we must take a stand on how to solve for the counterfactual demand for nontraded goods. We do so using the compensated, “lambda-constant” demands for these goods. Given the first-order condition in equation (2b), this will imply that the counterfactual demand for the nontraded good will be $y_{kt}^{cf} = p_{j(k)t} y_{kt} / p(Q_{j(k)t}^{cf})$, where $p(Q_{j(k)t}^{cf})$ is the local price associated with the quality-of-life value of the counterfactual location choice. Our approach leaves us with a single equation (the indirect utility function) and a single unknown, $\ln Q$, to solve for.

We solve for the counterfactual location's quality-of-life value given this setup and plot its difference from the empirically-observed quality-of-life value for each cell of our synthetic panel, along with the difference between the compensated and baseline estimates of the nontradable

Figure 11: Counterfactual vs. Baseline Equilibrium Demands, Ignoring the Complementarity between Amenity Consumption and Quality of Life



Notes: Figure reports the difference between the counterfactual and empirically-observed (log) quality-of-life value of one’s location (Panel A) and the difference between the counterfactual and model-implied nontradable goods demand (Panel B) for each demographic \times age category cell of our synthetic panel. The difference is between the sample-weighted means of each estimate, aggregated into education groups (high school or less, some college, college or more) by age category.

goods’ demand. We plot the (weighted) mean of this difference for education \times age categories in Figure 11. Given the nature of our counterfactual exercise, one can interpret the difference in quality-of-life as the compensation households require (measured in the quality-of-life value of their location) to account for the loss of utility from the complementarity. One can interpret the difference between compensated and baseline nontradables demand as how much housing they are willing to forego to live in a more expensive location (or how much they are willing to substitute towards in the absence of the complementarity). Since individuals no longer spend income on going out to enjoy local amenities in our counterfactual, they can use that income to move to a higher-amenity (and thus more expensive) location. Since young people, regardless of education, tend to enjoy more local amenities, they require more compensation in the form of a higher quality-of-life location, and therefore move to such places in the counterfactual. There is a divergence by education after those years, however. In the data, the college educated spend more time enjoying local amenities throughout their lives. Therefore, they need to live in higher quality-of-life locations to be compensated throughout their life cycles (though less so during their child-rearing years). As a consequence, Panel B of Figure 11 shows that they choose to consume

fewer nontradable goods (i.e., they consume less housing) to do so. Those with a high school degree or less take the opposite route. Since they spent relatively little time going out, they are less harmed by shutting down the complementarity. Furthermore, their (local) real wages are such that they are better off moving to a lower quality-of-life location, where they can afford to consume more housing with little change to their nominal wage earned.

6 Conclusions

In this paper, we study the migration behavior of individuals by skill over their life cycle, focusing on the quality of life of the metropolitan areas that they choose. In a model of spatial equilibrium, places with greater amenities will be the least affordable, offering the highest costs-of-living paired with relatively low real wages. We find that individuals tend to move to higher-amenity metropolitan areas early in their life cycle, with the college educated making moves towards the highest-amenity locations. As a result, the quality of life individuals enjoy peaks around age 30, much earlier than measures of consumption of goods and services. Thereafter, individuals of all skill groups tend to gradually move towards lower-amenity, and consequently, more affordable, metropolitan areas. The pattern holds for multiple measures of skill and permanent income, and across both cohorts of the NLSY.

Using data on time use and consumption expenditures, we show that these patterns are consistent with greater consumption of local amenities by the more educated and greater consumption of leisure at home by the less educated. Moreover, individuals of all education levels tend to consume local amenities when young and in retirement, though the resulting U-shaped pattern of local amenity consumption is more pronounced for the college educated. Using geographically coarse measures, we show that there is a direct, positive relationship between time spent on local amenities and the quality of life of where one lives.

We argue that these patterns are consistent with migration and sorting decisions that respond to changes in the number of household children over the life cycle because of the added demands for housing and time that come from child rearing. This reduces a household's demand for local amenities and causes households to value and move to more affordable, lower quality-of-life areas. We argue that the key mechanism behind this behavior is a complementarity between local

quality of life and time spent on local amenity consumption. Since amenity values are priced into housing costs, individuals who are mobile will seek more affordable areas to avoid paying for the amenities they no longer have time to consume. Rising mobility costs with age may slow this process. We find evidence in support of this hypothesis. Individuals whom never have children live in higher quality-of-life areas throughout their adult lives, and the gap based on the incidence of household children is highest for the college educated. Furthermore, an event study analysis suggests that individuals move towards lower quality-of-life (and more affordable) metropolitan areas following the entrance of the first child into the household. The decline in quality of life is greatest for the college educated.

We develop a general equilibrium model of wages, amenities, and housing prices where households choose their consumption, labor supply, and local amenities (through their location choice) to reconcile the theory with our findings. The key innovations in our model are a complementarity between local amenity consumption and the quality-of-life value of a household's location, and shocks to housing demand and home production time that reflect the effects of household children over the life cycle. We estimate elasticity associated with the complementarity to be large, positive, and statistically significant. The model, and its quantitative estimates underscore the dampening effect child rearing has on urban agglomeration. Individuals, particularly the college educated, prefer to sort into high-amenity locations. When doing so, they have a high propensity to go out and enjoy the amenities of those locations. Since children increase housing demand (whose price includes the value of these local amenities) and decrease available time to enjoy amenities, households with children tend to move to lower quality-of-life locations during their child-rearing years. We highlight how the standard Rosen-Roback model fails to capture this dampening effect through a counterfactual exercise. We conclude that examining migration and local amenities through a life-cycle lens uncovers an important age component for geographic sorting that, analogous to many studies of life-cycle labor supply, has a strong role for the presence of children.

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ONLINE APPENDIX

for “Skills, Migration, and Urban Amenities over the Life Cycle”

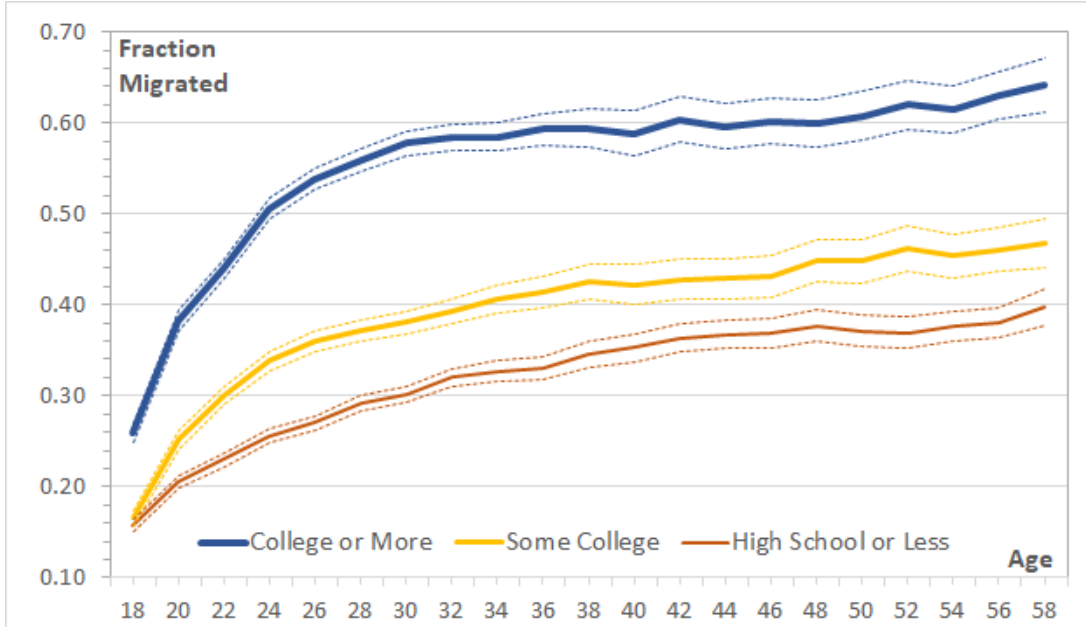
by David Albouy and R. Jason Faberman

A Robustness and Additional Empirical Results

A.1 Additional Results from the NLSY, ATUS, and CEX

Figure A1 reports the fraction of individuals living away from the metropolitan area of their youth (age 14 for the NLSY79 cohort and age 12 for the NLSY97 cohort). The fraction living away from the residence of their youth rises as they age and is highest for the college educated. By age 50, about 60 percent of the college educated live somewhere other than the metropolitan area of their youth, while 36 percent of those with a high school degree or less live somewhere other than the metropolitan area of their youth. The main takeaway is that return migration, studied recently by Johnson and Schulhofer-Wohl (2019), is not a major factor for the subsequent results in this section.

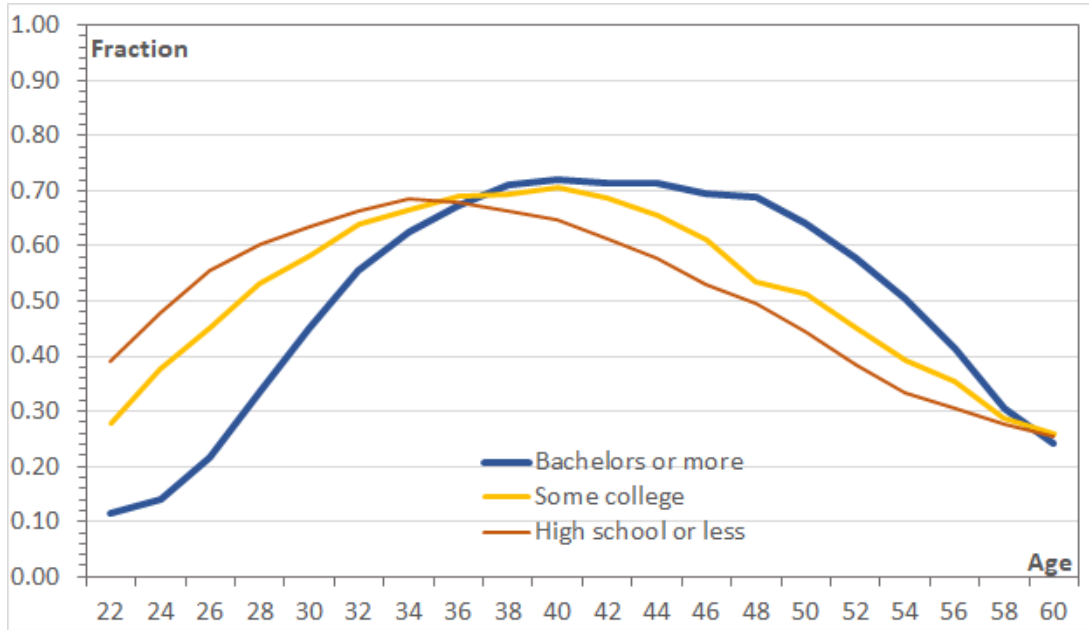
Figure A1: Permanent Migration Rates (Relative to MSA at Adolescence) by Education and Age



Notes: Figure reports fraction of individuals from the pooled sample of NLSY79 and NLSY97 respondents who reside in a different MSA than the one they lived in at age 14 (NLSY79) or age 12 (NLSY97) by highest degree attained and two-year age bins. Dashed lines represent 95 percent confidence intervals.

Figure A2 shows that the fraction of households with children present peaks between age 32 and age 42, with the peak occurring later for more-educated individuals. Our evidence thus far suggests that these are the years when the consumption of local amenities is at its lowest.

Figure A2: Mean Number of Household Children by Education and Age



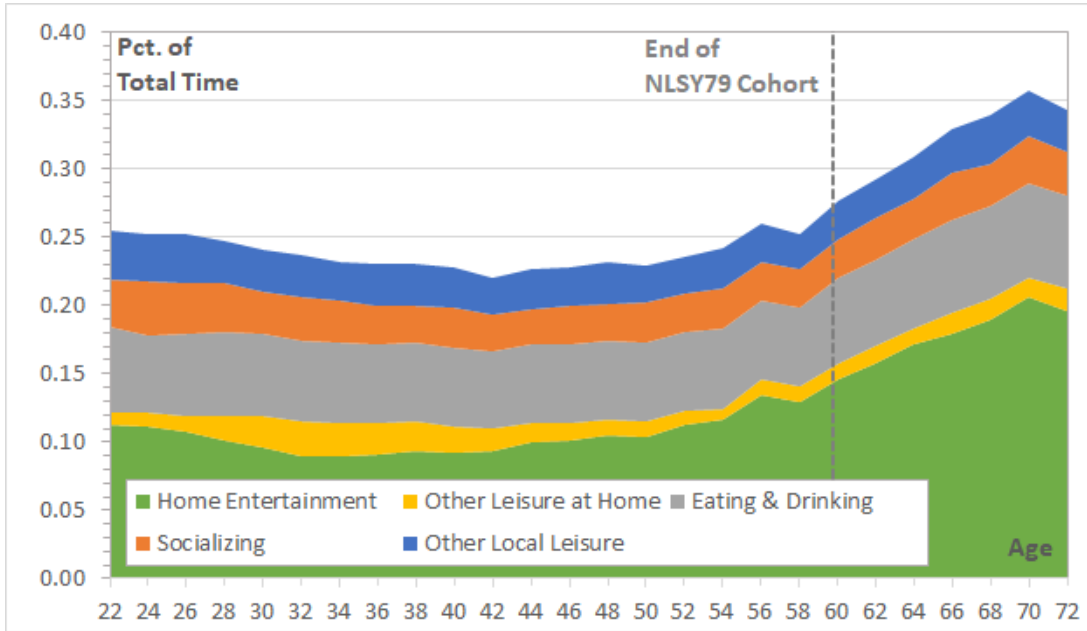
Notes: Figure reports mean number of children in the household by highest degree attained and two-year age bins. Sample is all individuals pooled from the NLSY79 and NLSY97 cohorts.

Figures A3 and A4 examine the life cycle behavior of all leisure activities by their major components. In each figure, the top panel reports the patterns for the college educated and the bottom panel reports the patterns for those with a high school degree or less. Figure A3 reports the share of daily time allocated to leisure broken out by time spent on home entertainment, other leisure within the home, eating and drinking, socializing, and other leisure away from home. The categories line up with those reported in Table 1 in the main text. Overall, the differences in time spent on each leisure category by education group remain roughly constant over the life cycle. The college educated spend much more time socializing during their college years, and have an increase in time devoted to other leisure at home (which includes leisure time with children) during their thirties and early forties. For both the college educated and those with a high school degree or less, total leisure time is U-shaped over the life cycle, and rises consistently starting in their mid-forties. As we document in the main text, however, there are stark differences in the allocation of this leisure time between activities at home and activities outside the home.

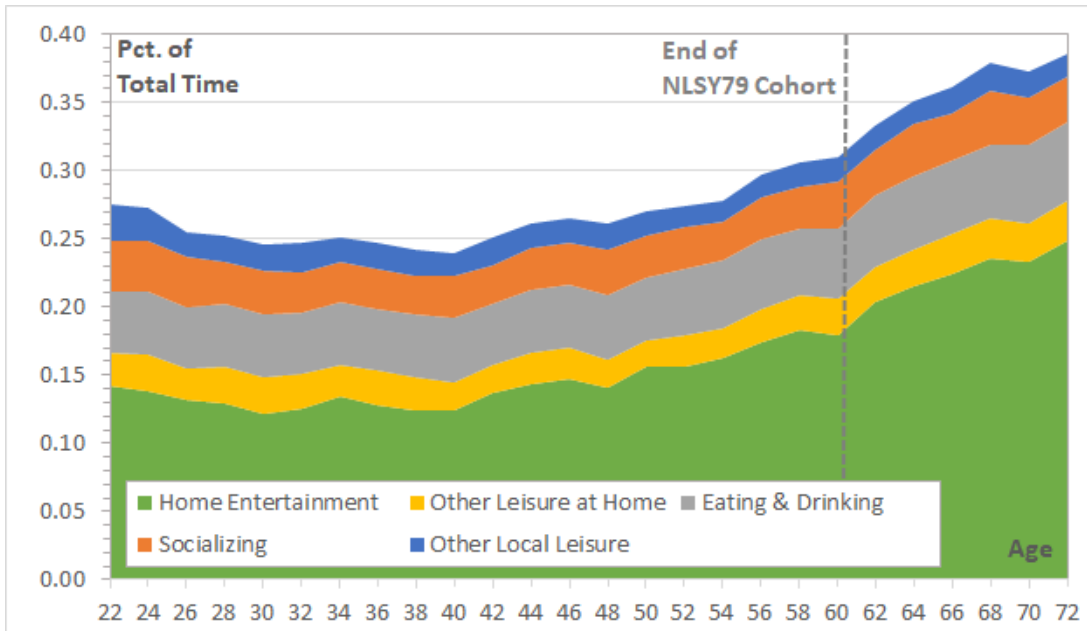
Figure A4 reports the share of expenditures dedicated to leisure activities by expenditures on food and drink at home, other leisure at home, food and drink consumed locally, other local leisure, and leisure on trips. The categories line up with those reported in Table 2 of the main text. Unlike time use, there are more stark differences in leisure expenditures by education over the life cycle. First, total leisure expenditures for those with a high school degree or less exhibit

Figure A3: Time Spent on Leisure Activities by Category

(a) Highest Degree: College or More



(b) Highest Degree: High School or less



Notes: Estimates from authors' calculations using the ATUS data pooled over 2003-2019. Estimates represent the sample-weighted shares of individuals' time spent on each activity for two-year age intervals. The stacked shares sum to total time spent on all leisure activities (at home and away).

a slight U-shaped pattern over the life cycle, while total leisure expenditures for the college educated is roughly flat early in their life cycle then gradually increasing over time starting in their forties, with larger increases after their mid-fifties. The big difference is driven in large part

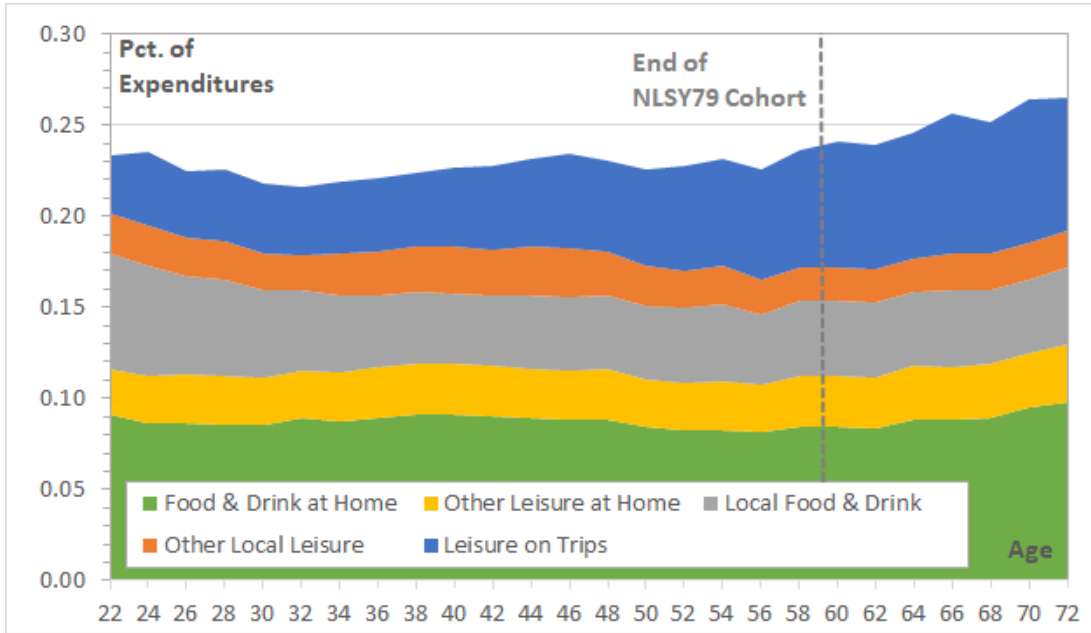
by a gradual increase in the share of expenditures spent on leisure during trips by the college educated. The expenditures shares spent on eating out (local food and drink) are largest for both the college educated and those with a high school degree or less during their twenties, but the college educated have a higher expenditure share on eating out than those with a high school degree or less throughout. Finally, the fraction of expenditures that those with high school degree or less spend on food and drink at home fall somewhat during their twenties, then remains roughly constant afterwards.

Figure A5 shows that our evidence on migration patterns by an area's quality-of-life value holds regardless of how we measure an individual's skill, how we measure the quality-of-life index, or what NLSY cohort we use. The top left panel replicates the estimates from Figure 2 for individuals grouped by quartiles of their AFQT score. The results are nearly identical to those in Figure 2 of the main text. The top right panel replicates the results for individuals grouped by their average lifetime household earnings per household member, our preferred measure of permanent income, with individuals grouped by their quartile of the permanent income distribution. Again, the results are similar to those in Figure 2. If anything, the gap between the top and bottom income quartiles is even stronger than the differences by educational attainment. The middle left panel replicates the estimates from Figure 2 using a balanced panel of NLSY respondents that report data for all survey years of their adult life. Again, the results are nearly identical to those in Figure 2. The middle right panel replicates the estimates for Figure 2 using all observations grouped by educational attainment, but after conditioning out average MSA school quality and crime variation from the quality-of-life estimates.² Controlling for variations in school quality and crime implies a fairly constant quality-of-life for those with less than a college degree over the life cycle, but has little effect on the quality-of-life patterns for those with a college degree over the life cycle. The bottom right panel splits the NLSY sample into those from the NLSY79 cohort and those from the NLSY97 cohort. The latter cohort is only aged 34 to 40 in 2019, so we can only compare the cohort respondents during their overlapping ages. The notable differences between the two cohorts occur for those with less than a college degree, who show less movement towards higher-amenity value MSAs relative to the NLSY79 cohort in their 20s and 30s. Finally, the bottom right panel compares the estimates of quality of life based on local data from both 1980 and 2000. We restrict the sample to the NLSY79 since it is the only one of the two cohorts

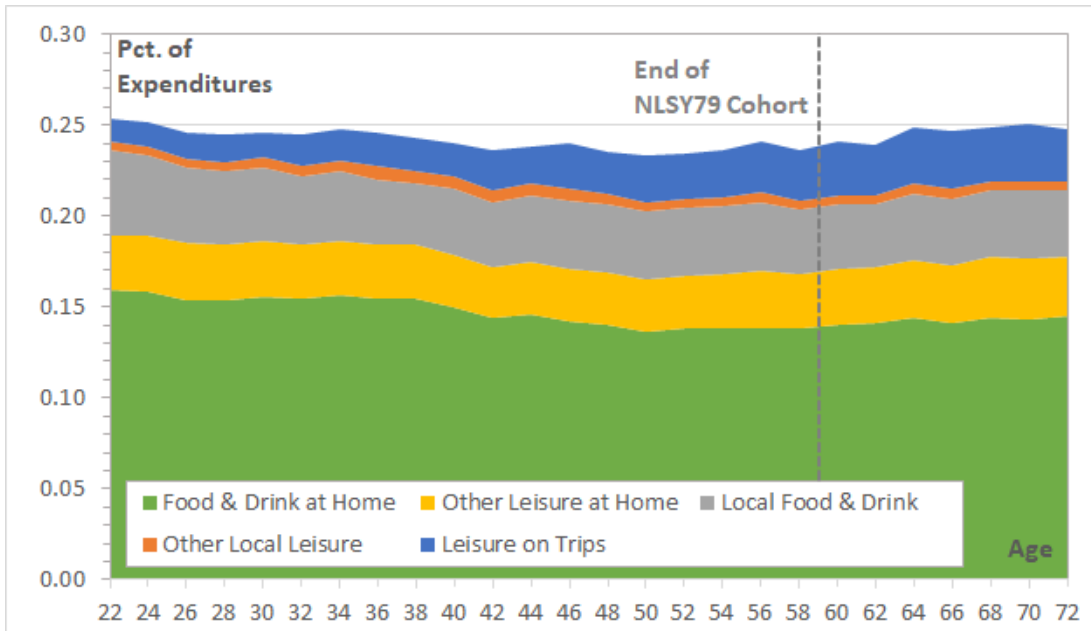
²We measure school quality using average reading and math scores from the Stanford Educational Data Archive (SEDA) at the county level, aggregated to our MSA definitions (available at: <https://exhibits.stanford.edu/data/catalog/db586ns4974>). We use data on mean violent and property crimes per capita for MSAs over the 1998-2010 period from the U.S. Housing and Urban Development's State of the Cities Data Systems (SOCDS) FBI Crime Data (available at: https://socds.huduser.gov/FBI/FBI_Home.htm?).

Figure A4: Expenditure Shares on Leisure Activities by Category

(a) Highest Degree: College or More



(b) Highest Degree: High School or less



Notes: Estimates from authors' calculations using the CEX data pooled over 1996-2019. Estimates represent the sample-weighted means of individuals' share of their total expenditures on each activity for two-year age intervals. The stacked shares sum to the total share of expenditures spent on all leisure activities (at home, locally, and on trips).

for which both years are relevant for their migration decisions. In short, both measures produce qualitatively similar results by educational attainment. Interestingly, the college educated appear

to move to locations whose quality-of-life values increased between 1980 and 2000, while those with a high school degree or less move to locations whose quality-of-life values decreased between 1980 and 2000 (keep in mind that the locations individuals move to are constant in this exercise; only the quality of life measure changes). The diverging changes in quality of life over time is consistent with the evidence on endogenous changes in local amenities put forth by Diamond (2016).

A.2 Additional Results from the NLSY, ATUS, and CEX

We also replicate our results using pooled microdata from the American Community Survey (ACS). We use the 1 percent Public-Use Micro Sample (PUMS) data for 2005 to 2021. The ACS asks a rich set of questions on demographics, income, and location to the households in its sample, including their location in the current and prior year. The ACS is an imperfect comparison to our NLSY results in that the data are not longitudinal, only follows the location of individuals over a short horizon, and only has information on their household characteristics at the time of the survey interview. Nevertheless, the data can provide at least a qualitative check to see if we observe similar patterns for quality of life estimates over the life cycle in other data sources.

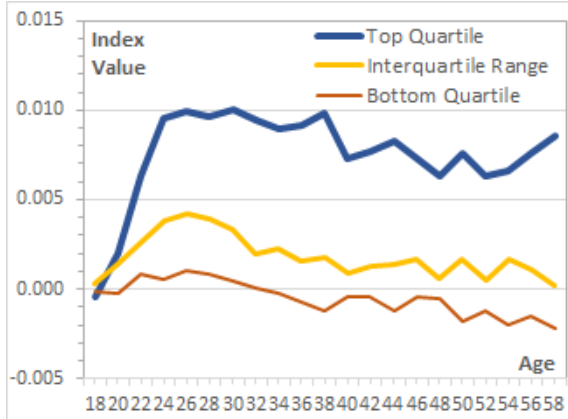
We identify the quality of life estimates for each individual using the Public-Use Microdata Area (PUMA) code of their residence matched to the 1999 MSA definitions we use in our main analysis. As before, we aggregate up the quality of life estimates we derive using the methodology from Albouy (2012, 2016) to the MSA level, including the nonmetropolitan portions of each state. We report quality-of-life estimates using geographic data from 2000, but also replicate our analysis (in unreported results) using 2010 data and obtain very similar patterns. To deal with potential changes in composition across the surveys, we aggregate individuals into seven-year birth cohorts and estimate the quality of life of their location by education (high school or less, some college, bachelors or more), two-year age bin, and birth cohort. We also rescale each cohort's estimates so that its first year of data is equal to the quality-of-life estimate for the same age bin of the subsequent cohort. This allows us to examine the evolution of the quality of life estimates both within and between cohorts, since it adjusts for cohort-specific differences over the life cycle.

Our results are in Figure A6. The top panel shows the life cycle behavior for those with at least a college degree, the middle panel shows the behavior for those with some college, and the bottom panel shows the behavior for those with a high school degree or less. In short, the figures show very similar patterns to what we find in the NLSY in Figure 2 of the main text and in our robustness exercises in Figure A5. Specifically, each education group exhibits a hump-

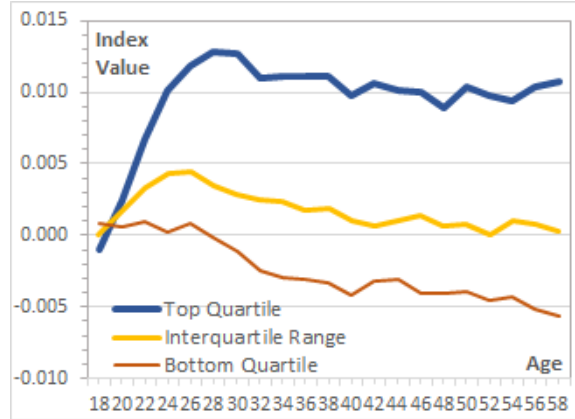
shape pattern for the quality of life of their location over the life cycle, with the hump peaking in their thirties. The estimates are highest throughout the life cycle for the college educated. Furthermore, the ACS allows us to examine quality of life estimates later in life. Consistent with Chen and Rosenthal (2008), the college educated appear to move towards higher quality-of-life locations in their sixties and seventies, while those with less than a college degree appear to at least stop moving towards lower quality of life locations at these ages.

Figure A5: Local Quality of Life over the Life Cycle: Robustness

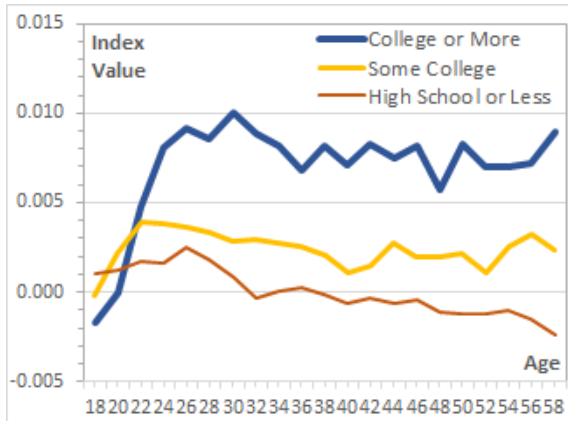
(a) By AFQT Score



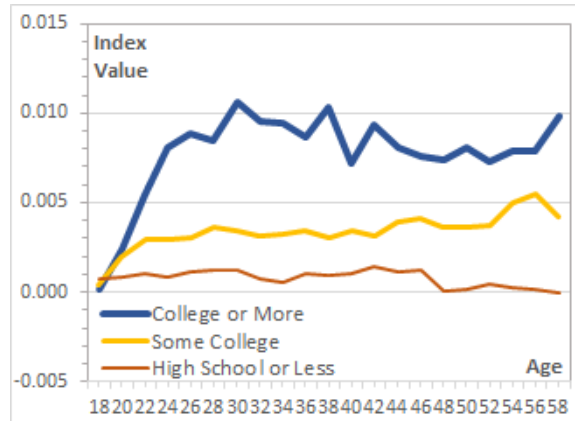
(b) By Avg. Income per HH Member



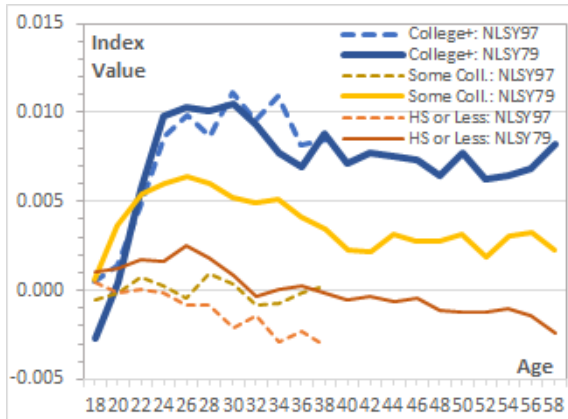
(c) Balanced NLSY Panels



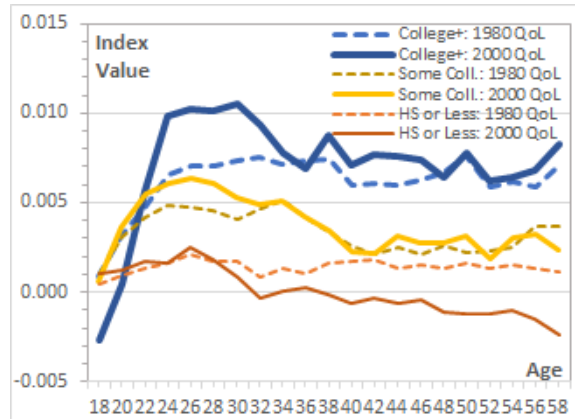
(d) Controlling for School Quality, Crime



(e) NLSY97 vs. NLSY79 Cohorts



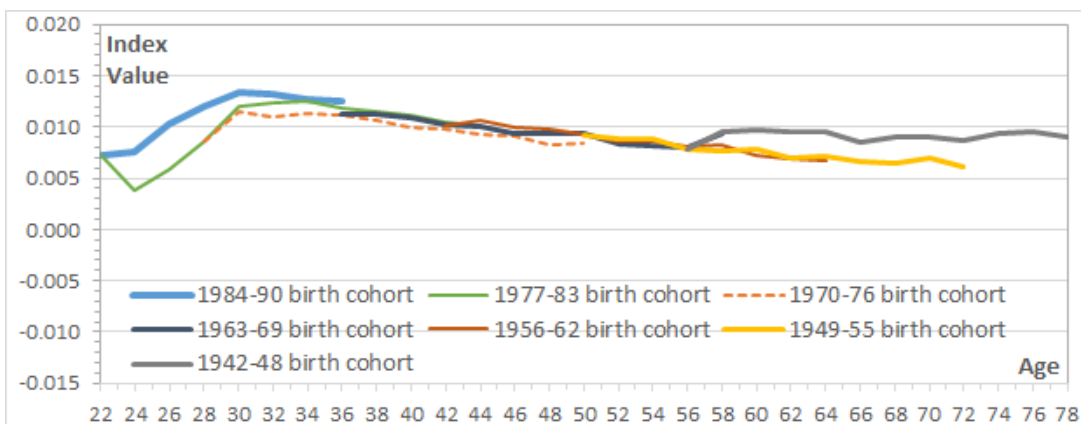
(f) 1980 vs. 2000 Quality-of-Life Indices



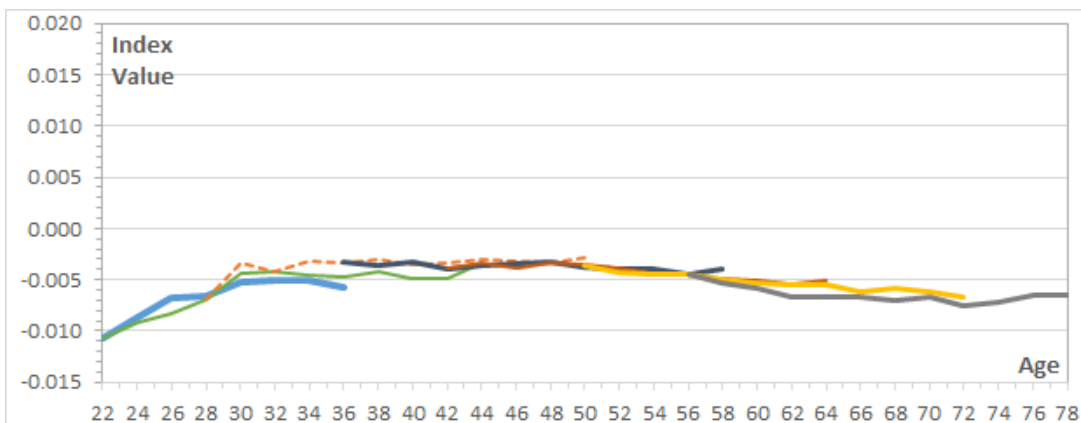
Notes: Estimates from authors' calculations using pooled data from the NLSY79 and NLSY97 samples matched to MSA quality-of-life estimates by current residence and highest education attained (unless otherwise noted). Estimates are the sample-weighted mean quality of life index value (relative to the index value for residence at age 14 for the NLSY79 or age 12 for the NLSY97) for two-year age intervals. Panels (a) and (b) group individuals by AFQT score and average household income per person, respectively, rather than education. Panel (c) restricts the sample to individuals with nonmissing observations after age 18. Panel (d) reports quality-of-life estimates residualized after controlling for local crime rates and school quality. Panel (e) splits the sample into the NLSY79 and NLSY97 cohorts. Panel (f) restricts the sample to the NLSY79 cohort and reports estimates using quality-of-life estimates using 1980 or 2000 MSA data.

Figure A6: Quality of Life over the Life Cycle: American Community Survey Data

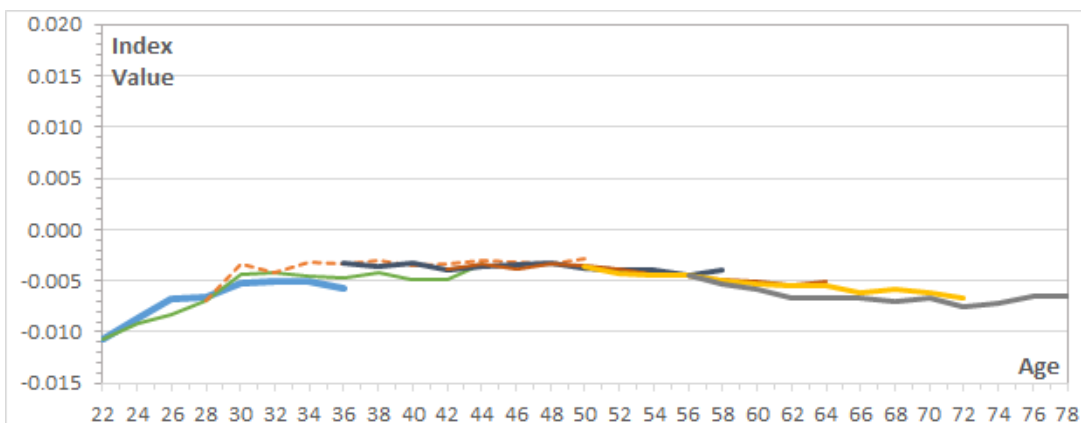
(a) Education: College or More



(b) Education: Some College



(c) Education: High School or less



Notes: Estimates from authors' calculations using the ACS 1 percent PUMS data pooled over 2005-21. Estimates represent the sample-weighted mean quality of life for all individuals by education for two-year age bins within seven-year birth cohorts. Quality of life is measured using 2000 data for individuals' residence at the time of their ACS interview. Birth cohort estimates are rescaled so that their first year of data is equal to the quality-of-life estimate for the same age bin of the subsequent cohort.