Skills, Migration, and Urban Amenities Over the Life Cycle

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

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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 related to local amenities are U-shaped over the life cycle. This contrasts with well-documented life-cycle consumption profiles, which have an opposite inverted-U shape. 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 after having their first child. We develop an equilibrium model of location choice, labor supply, and amenity consumption and introduce life-cycle changes in household composition that affect leisure preferences, consumption choices, and required home production time. Key to the model is a complementarity between leisure time spent going out and local amenities, which we estimate to be large and significant. Ignoring this complementarity and the distinction between types of leisure 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 amenities they are not consuming.

Keywords: urban amenities, sorting, migration, life-cycle dynamics
JEL Classifications: J30, J61, R23

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1 Introduction

In the standard model of spatial equilibrium, workers will accept lower real wages to work and live in areas with desirable urban amenities. Demand to live in areas with greater quality of life bids up their costs-of-living relative to the nominal wages they offer (Rosen, 1979; Roback, 1982). Work by Black et al. (2009) on urban sorting finds that college-educated individuals accept a lower return to their degree to live in high-amenity areas. Diamond (2016) finds that the college educated improve the amenities of the areas they move to. 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 when workers sort with respect to their life cycle. 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 local amenity consumption over the life cycle. 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 over the life cycle is driven by a desire to live in high-amenity cities and how this sorting varies by skill. When higher-skill individuals sort into urban areas with higher wages, this exaggerates observed wage differences across cities. If they sort into places with better amenities, not properly controlling for skill will lead to an underestimate of the compensating wage differential attributed to these amenities, since high-skill individuals tend to earn higher wages.

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) are 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, especially prior to middle age. To our knowledge, with limited

[1] Recent 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 research——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.

exceptions—i.e., Chen and Rosenthal (2008), who focus on location choices at retirement—there is scant research on the life-cycle behavior of urban amenity 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 the college educated disproportionately sort into higher-amenity metropolitan areas, but tend to do so relatively early in their lives. Those without a college degree also sort into higher-amenity areas early in their lives, but to a lesser degree. The quality-of-life one experiences peaks at age 30 for the college educated, and earlier for those with less education, before gradually declining over time. The decline reflects moves towards lower-amenity areas during individuals' thirties through their early fifties. These are 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 are driven primarily by the housing price component of the index rather than its wage component, and in our appendix, 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 contrasts with the well-documented hump-shape in consumption expenditures. More importantly, when we examine time-use data by geographic region, we find a strong positive relationship between our quality-of-life index and time spent on local amenities. We also find a strong negative relationship between quality of life and leisure time spent at home. These correlations support the idea that those who migrate to higher quality-of-life areas consume a greater degree of local amenities. The correlations also highlight the importance of distinguishing between leisure time spent enjoying local amenities and other types of leisure.

We provide evidence that household children explain much of the changes in migration and amenity consumption patterns seen during prime-age years. The literature on life-cycle consumption finds that the hump-shape in consumption expenditures is driven in large part by raising children (Browning, 1992; Banks, Blundell, and Preston, 1994; among others). If local amenities require both income and time to enjoy, then children will affect a household's amenity consumption, since children require more home-production time (Aguiar and Hurst, 2013). All else equal, high-amenity, high-rent cities, are less attractive during child rearing simply because parents have less time to enjoy the local amenities that are priced into their housing costs. Children also require more housing, which is more expensive in high-amenity cities. Since high-skilled individuals have higher income, they can better afford enjoying local amenities and more-expensive housing. We also show that their amenity consumption varies more 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 present two findings that highlight how children affect location choices across metropolitan areas. First, individuals who never report having children in the NLSY tend to move to areas with a higher quality of life than those that eventually have a child. This holds within education groups, and the gap is particularly large for the college educated. Second, using an event study framework, the arrival of a first child leads households to move to lower quality-of-life areas over the subsequent six years, with the largest effects, again, among the college educated. The evidence is comparable to Brulhart et al. (2021), who show that children increase households' demand for local public goods, while Moreno-Maldonado and Santamaria (2022) show that delayed childbearing helped spur revival in U.S. downtown areas. The evidence also suggests a countervailing effect against the relatively high implicit migration costs identified by Kennan and Walker (2011). While migration costs may reduce incentives to move, having children reduces the amenity-related returns to one's current location and puts greater weight on assessing the relative housing costs of different locations. If one's current location is high-amenity but costly, both will act as push factors towards moving somewhere else.

We deepen our analysis by developing a life-cycle model of consumption, leisure, and location choice. Individuals differ in their skills, affecting their earnings. They gain utility from leisure, consumption goods (a tradable good and a local nontraded good), and the amenities of their location. They 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, we allow household preferences for housing and leisure to shift over the life cycle. This captures changes in household composition that affect the relative demand of traded and nontraded goods and required home production time. Key to the model is a complementarity between local amenities and the leisure time allocated to enjoying them. Changes in household composition reduce the time available to enjoy local amenities. Since the value of local amenities is capitalized into the price of the nontraded good (i.e., through housing), individuals with less time (i.e., high home production demand) move to lower-amenity locations to avoid paying for amenities they do not enjoy. Changes in the relative demand for housing have a similar effect on migration behavior through local housing prices.

We calibrate the model using synthetic panel data from the skills, demographics, 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 defined by education, age, and other demographics. This provides us with the moments necessary to identify the parameters of the model, 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 Generalized Method of Moments (GMM) 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 metropolitan area. Specifically, we find that the elasticity of amenity time with respect to the local quality of life value is about 3. The large elasticity highlights how the time demands of child rearing dampen a household's propensity to enjoy urban amenities.

We highlight key implications of our model by evaluating a hypothetical move of individuals to a higher quality-of-life metropolitan area. The evaluation reveals two key insights. First, a Rosen-Roback framework with a simple labor-leisure time tradeoff cannot properly capture the responses of local amenity consumption without distinguishing between leisure time spent at home and leisure time spent going out. We find that total leisure time falls slightly when individuals move to a higher quality-of-life metro. This is in response to the higher prices and wages at the new location. The time they spend enjoying local amenities, however, increases by around 20 log points as individuals substitute their leisure time away from home. Second, ignoring the complementarity between amenity time and quality of life understates how much individuals would enjoy greater local amenities. Without the complementarity, we find a much smaller increase in local amenity time of about 4 log points.

We conclude that our analysis uncovers an important age component for geographic sorting that, analogous to many studies of life-cycle labor supply, has a strong role for children. We also conclude that distinguishing between the types of leisure that households enjoy, and how they interact with local quality of life, is important for understanding the sorting patterns of individuals across space and their welfare implications.

Our study brings together several well-established strands of literature and complements recent research on local amenities and sorting behavior. First, to our knowledge, we are the first to use the Rosen-Roback framework within a rich life-cycle setting (though Kennan and Walker, 2011, study life-cycle migration decisions with a focus on regional wage differences). We do so using empirical methods that closely relate to those used by Blundell, Pistaferri, and Saporta-Eksten (2018) and earlier work by Attanasio and Weber (1995). We take seriously the distinction between household time use and expenditures—particularly as it pertains to local amenities—in a way comparable to Aguiar and Hurst (2005, 2013), and recent work in an urban setting by Su (2022). Our work complements others that examine sorting behavior on amenities within metropolitan areas, such as Fogli and Guerrieri (2019), Couture et al. (2023), and Amalgro and Domínguez-Iino (2024), including recent studies that also put a focus on children and household composition (Brulhart et al., 2021; Moreno-Maldonado and Santamaria, 2022; and Coeurdacier et al., 2024). Finally, while we do not evaluate its effects on inequality directly, our findings by education have relevance for recent studies that examine the role of urban sorting and amenities for inequality (Baum-Snow and Pavan, 2013; Diamond and Gaubert, 2022) over the life cycle, and studies that examine consumption inequality relative to income inequality going at least back to Krueger and Perri (2006) and Aguiar and Bils (2015).

The next section describes the data we use and our methodologies for measuring migration, quality of life, time use, and consumption. Section 3 presents our empirical evidence. Section 4 presents the model. We describe and present the estimation of our model and its evaluation 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 also 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 using the methodology from Albouy (2012, 2016). This index uses data from 2000 on housing costs and wages, taking into account federal taxes, taking a weighted difference between housing costs and wages.[3] The index is based on the premise that the places with the most desirable amenities are the least affordable, i.e., a ratio of costs-of-living relative to income, adjusted for housing and worker quality. When households are mobile, the index should reflect the typical willingness to pay for local amenities. 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 and leisure devoted to local amenities. We relate these estimates to the migration behavior and the quality-of-life estimates of an individual's location 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 leisure enjoyed locally from leisure enjoyed further away on vacation. 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

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

[3] Our quality-of-life index uses MSA-level estimates built from Public Use Microdata Areas (PUMAs) from the decennial censuses. In the online appendix, we replicate our main analysis using 1980 data on local housing costs, wages, etc., and obtain very similar results.

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 at home, and those spent on leisure during trips. In general, the CEX data allow a more reliable disaggregation by place than the ATUS data. 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 the 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 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]

[4]In 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.

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

3 Evidence

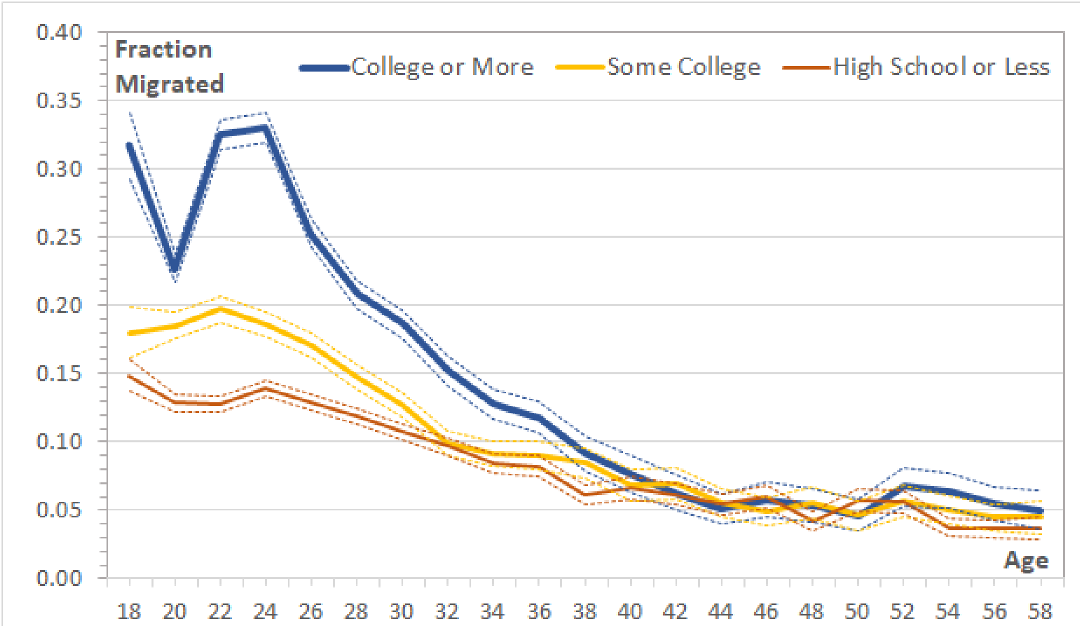
We present our evidence in three steps. First, we show that college-educated individuals sort into higher-amenity metropolitan areas, but tend to do so early in their adult lives. They then tend to gradually move to metropolitan areas with relatively lower amenity values as they get older. Next, we show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

3.1 Local Quality of Life over the Life Cycle

We begin with our analysis of location choices over the life cycle. Specifically, we use the longitudinal NLSY cohort data to examine how the average value of the quality-of-life index evolves as cohorts age. The quality-of-life index value for each metro area is fixed so that changes in the index only occur through migration. Increases in quality of life reflect moves towards higher-amenity areas, while decreases reflect moves away. We plot quality of life relative to each individual's residence in adolescence (age 14 for the NLSY79 and age 12 for the NLSY97). This controls for the initial sorting of individuals into areas based on their parents' location choices.

Our focus is on across-metro area migration. Migration decisions within metro areas over the life cycle are complementary to our evidence and consistent with our model (see, for example, Couture, Gaubert, Handbury, and Hurst, 2024). The amenities individuals consider during within-metro migration decisions (e.g., school quality, crime, commuting costs) arguably differ from those considered for across-metro area migration. As Davis and Dingel (2020) highlight, individuals consider where they would live within their new metro area when considering an across-metro move. For example, consider a young couple living in downtown San Francisco who are planning to move and start a family. 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 that prices in the amenities available throughout the metro area. Our couple may instead look to a more affordable metro area, such as Davis, CA. Presumably,

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.

the same factors that led them to leave downtown San Francisco will also lead them to choose a neighborhood within Davis, CA, that reflects their new family-friendly location preferences. As a check on this logic and how much it may affect our results, we replicate our analysis from this section controlling for metro area differences in average crime and school quality. We obtain very similar results.[6]

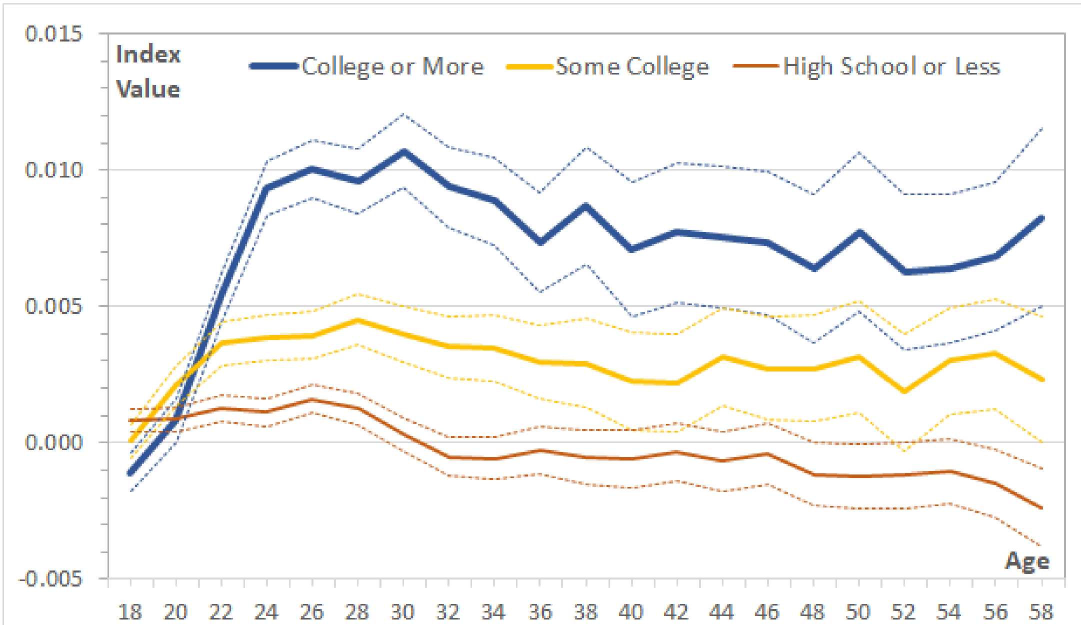
Figure 1 shows how two-year migration rates across metros vary by age and education (measured as the highest degree attained). The figure reports the estimates for all individuals in both NLSY cohorts pooled together and grouped into two-year age intervals.[7] Migration rates are highest for the college-educated 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

[6]Specifically, 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.

[7]Throughout 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.

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: Average Metro Quality of Life Estimates over the Life Cycle

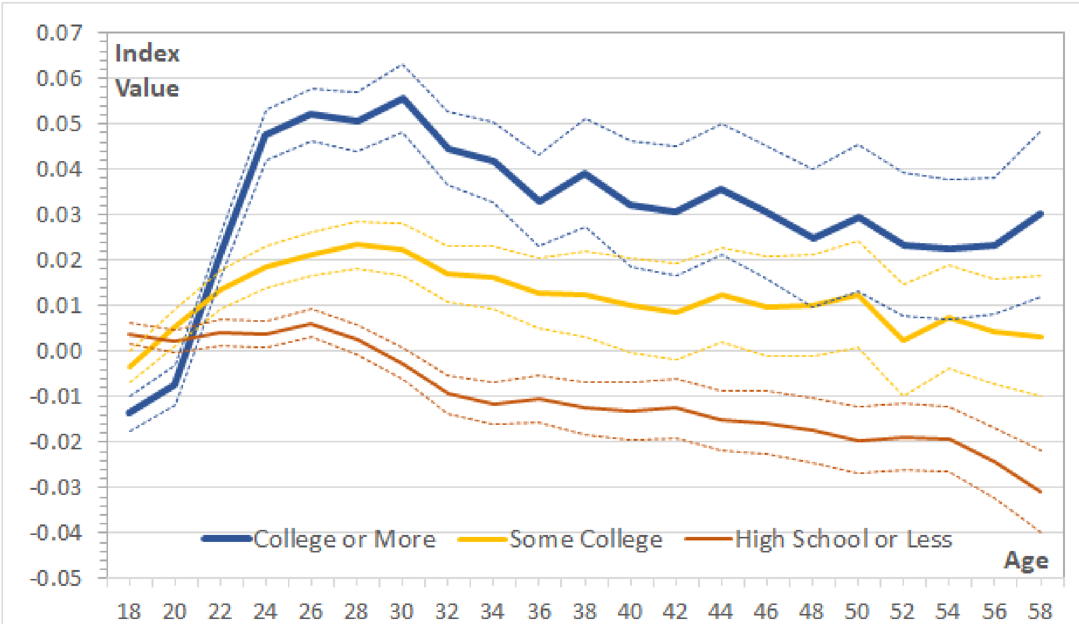


Notes: Estimates from authors' calculations using pooled data from the NLSY79 and NLSY97 samples matched to metro area quality-of-life estimates by current residence and highest education attained. Estimates are the sample-weighted mean quality of life index value (relative to the index value for residence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

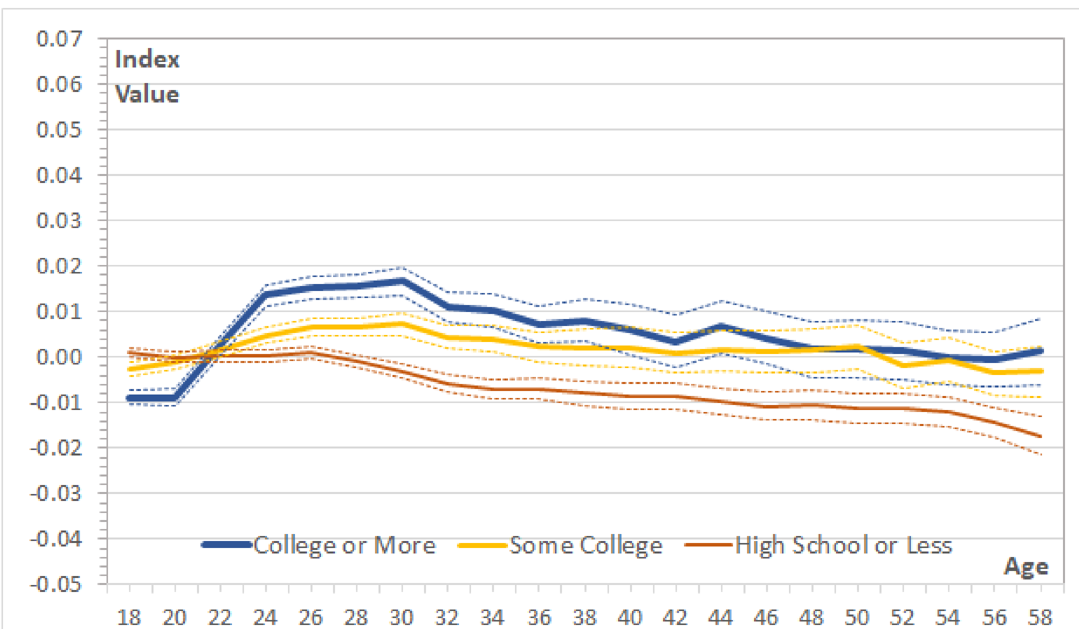
Figure 2 presents the first of our main results: how local quality of life evolves over the life cycle, by educational attainment. Each age interval captures the mean quality-of-life value metro area across all individuals by each age-education cell relative to their residence during adolescence. We repeat the calculation for the housing price and wage components and report those in Figure 3. In general, quality of life rises over one's twenties, peaks around age thirty, and gradually declines over their thirties and forties. The quantitative differences in these patterns across education groups are substantial. By age thirty, those with a college degree see the quality of life of their location rise by over a log point relative to where they lived during adolescence. To put this into perspective, the increase in quality of life is over 20 percent of the across-metro standard deviation of quality-of-life values. In contrast, those with high school or less move to locations with quality-of-life values only 0.2 log points better than at adolescence, peaking at age 26. By their mid-thirties, their average quality of life is somewhat worse than at adolescence.

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

(a) Housing-Cost Component



(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.

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 by Johnson and Schulhofer-Wohl (2019), does not explain these reductions in quality of life. In the online appendix, we also show that the patterns are 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 and NLSY97 cohorts, and when using quality-of-life estimates based on 1980 data. Remarkably, we find similar patterns by age and education in the American Community Survey micro data, once we control for cohort differences in initial locations.[8]

Figure 3 shows that most of the gap between the college 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-cost components indicate that the areas where the college educated move to are more productive, but the relatively greater values of the housing-cost component imply that their net real incomes fall even as their nominal incomes rise. The interpretation is that they are trading off lower real incomes 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

[8] While our qualitative patterns hold in all of these robustness exercises, two quantitative deviations stand out. First, when we split the sample by NLSY cohort and 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, which vary less, 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 outcomes for the less educated.

in their average housing costs is 1.7 log points but rises sharply to 5.8 log points by age 30. The difference remains elevated, between 4.2 and 5.4 log points, through age 59. In contrast, the college-high school difference in their average wage component is essentially negligible at age 22. It peaks at 2.0 log points at age 30 and remains in a range between 1.1 and 1.7 log points 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 lower amenity values. Second, changes in quality of life are reflected primarily in variation in the housing costs of one's metropolitan area over their life cycle. There is less life-cycle variation in local wages, which allows us to abstract from factors related to productivity differences across cities somewhat more confidently. Third, the college educated move toward higher-amenity areas early in life. While they move towards areas with lower amenities later, they generally remain in higher-amenity locations throughout their prime-age years. Those with some college exhibit similar migration behavior over their lifetimes, but the changes in their quality of life 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 during their adolescence; by their early thirties, their locations become progressively worse. Putting these patterns together, the college educated retain a relatively large and stable quality-of-life advantage over those with a high school degree or less during their thirties and afterwards.

3.2 Quality of Life, Leisure, and Amenity Consumption

Our results thus far establish a positive relationship between an individual's education and the metropolitan quality of life they move to after age twenty. These results are robust across various measures of skill and quality of life, and across cohorts, but they do not speak to differences in amenity *consumption*. While the highly-skilled sort into higher quality-of-life cities, they may not take the time to enjoy local amenity opportunities. For example, changes in quality of life 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).

For more direct evidence on amenity consumption, we use the ATUS and the CEX data to estimate the allocation of time and expenditures by age and education. In particular, we differentiate between leisure spent at home and leisure spent on local amenities. To our knowledge, we are the first to empirically differentiate the two. If those in high quality-of-life locations consume more local amenities, our evidence thus far suggests we should see more time and expenditures on amenity-related activities by the college educated, especially early in life. In contrast, leisure activities at home should be unrelated, or even negatively related, to life-cycle changes in quality of life, as these are activities that one can enjoy regardless of location. Someone who spends all of their leisure time watching television may as well do it somewhere affordable.

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 within each education group. Table 1 shows that individuals spend as much as three hours per day on leisure away from home. A caveat is that 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 about four hours per day on leisure at home, with the bulk of this (88 percent) devoted to home entertainment, an activity clearly done within the home. 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.

Time allocation varies considerably by education. Specifically, the college educated spend about 18 percent more time on leisure away from home. The largest differences are in local entertainment, sports and recreation, and eating and drinking. Eating and drinking does not distinguish between going out or staying at home, but it does exclude time spent on food preparation and grocery shopping—both part of home production time—which are specific to eating and drinking at home. In contrast, the college educated spend 29 percent less time on leisure at home, which is mostly accounted for by less time spent on home entertainment. Notably, both education groups spend nearly the same time on home production, though the college educated do spend a third more time on child care, and slightly less on food preparation.

Table 2 shows similar patterns using the CEX expenditure data. The CEX allows us to

Table 1: Average Time Spent on Leisure and Other Activities

Time use (minutes per day)	All	College or More	High School or Less	College-HS Ratio
Leisure (potentially) away from home	*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
Leisure at home	*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
Home production	*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
Work time	*236.7*	*282.3*	*204.3*	*1.38*
N	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.

differentiate leisure at home from leisure away from home locally as opposed to trips. Spending on local leisure accounts for 5.7 percent of total expenditures, and just over 20 percent of all expenditures associated with leisure. Most of this spending is on food and drink. In contrast to our time-use evidence, local food and drink expenditures clearly reflect consumption outside the home but within the metro area. 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 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 is accounted for by vehicles, healthcare, and education.

Again, the expenditure patterns vary by education, with stronger differences than for time

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

Percent of Total Expenditures	All	College or More	High School or Less	College-HS Ratio
Local leisure	*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
Leisure on trips	*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
Leisure at home	*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
Home production	*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
Housing, utilities, & maintenance	*33.5*	*32.5*	*34.6*	*0.94*
Vehicles	*13.4*	*12.2*	*13.8*	*0.89*
Healthcare & education	*8.0*	*8.1*	*7.6*	*1.06*
Total expenditures (annualized 2019 $)	$56,054	$77,539	$41,799	
N	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.

use. The college educated spend 37 percent more of their total expenditures (1.8 percentage points) on local leisure than those with a high school degree or less. Expenditures on local food and drink and local entertainment account for most of the disparity. Incidentally, the college educated spend 2.6 times as much of their total expenditures (2.6 percentage points) on trips for leisure.[9] In contrast, the college educated spend 36 percent less (7.8 percentage points) on leisure activities at home. This difference is driven by food and drink at home, comprising 10.6 percent of expenditures for the college educated and 16.9 percent the high school educated. In home production, the college-educated spend 0.8 percentage points more, although these include services such as housekeeping and lawn care. Regardless, the college educated spend relatively more on amenities away from home and less at home.

To examine changes over the life cycle, figures 4 and 5 present time-use and expenditure shares

[9]While expenditures on trips exhibit a disparity in leisure expenditures by education, we maintain our focus on expenditures on amenities within the metro area.

by age and education. To match amenity-related location patterns from the previous subsection, time-use and expenditure shares spent on local amenities should be highest in early adulthood, especially for the college educated. Since we observe adults past their fifties, we may find a rise in consumption behavior later in life, consistent with Chen and Rosenthal (2008), who find that individuals tend to move (back) to higher-amenity areas when they retire.

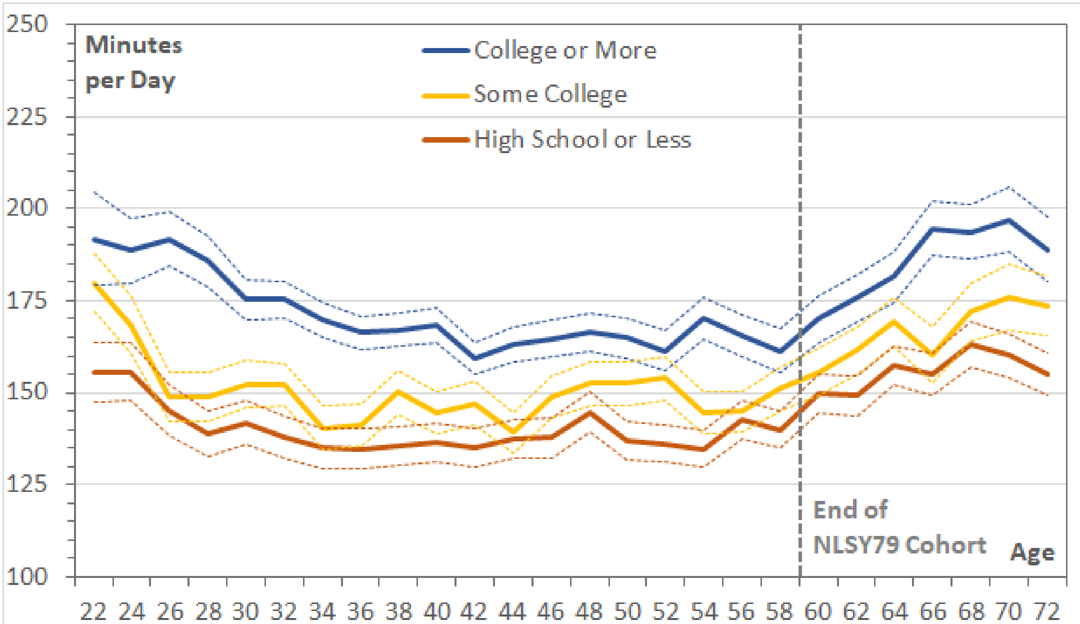
Figure 4 presents time spent on leisure away from home (top panel) and leisure at home (bottom panel) by education group, with individuals pooled into two-year age intervals. Two patterns stand out. First, at every age the college educated devote the most time to leisure outside the home, showing that the patterns in Table 1 apply throughout the life cycle. Second, over the life cycle, each education group has a U-shaped pattern of time on leisure away from home, though it 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 for leisure at home. Those without any college spend more time on leisure at home at every age, reinforcing the differences seen in Table 1. Second, time spent on home leisure changes little until about age 40, when it rises for those without college; at age 45 for those with some college; and at age 50 for those with a college degree. Rising leisure time at home is likely due to increases 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 shows the share of total expenditures spent on local leisure (top panel) and leisure at home (bottom panel) by education and age. Two similar patterns stand out. 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, and the college educated in particular, 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 leisure time 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 expenditure share for 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 expenditure shares for leisure activities at home.

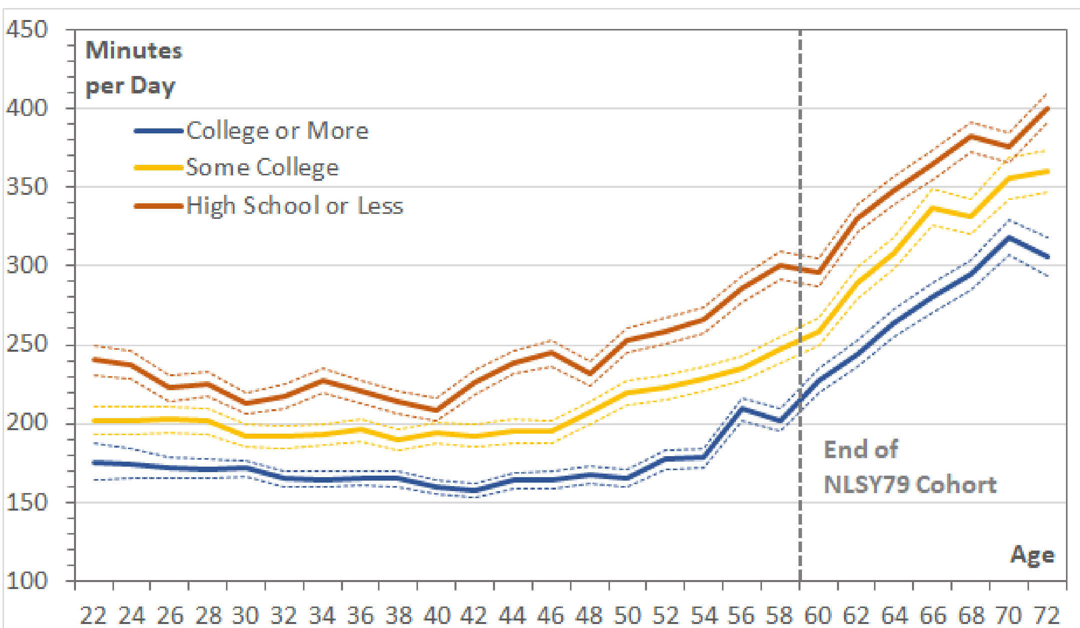
[10] We also report time use and expenditure shares by detailed leisure categories for the college educated and those with a high school degree or less by age in the online appendix.

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

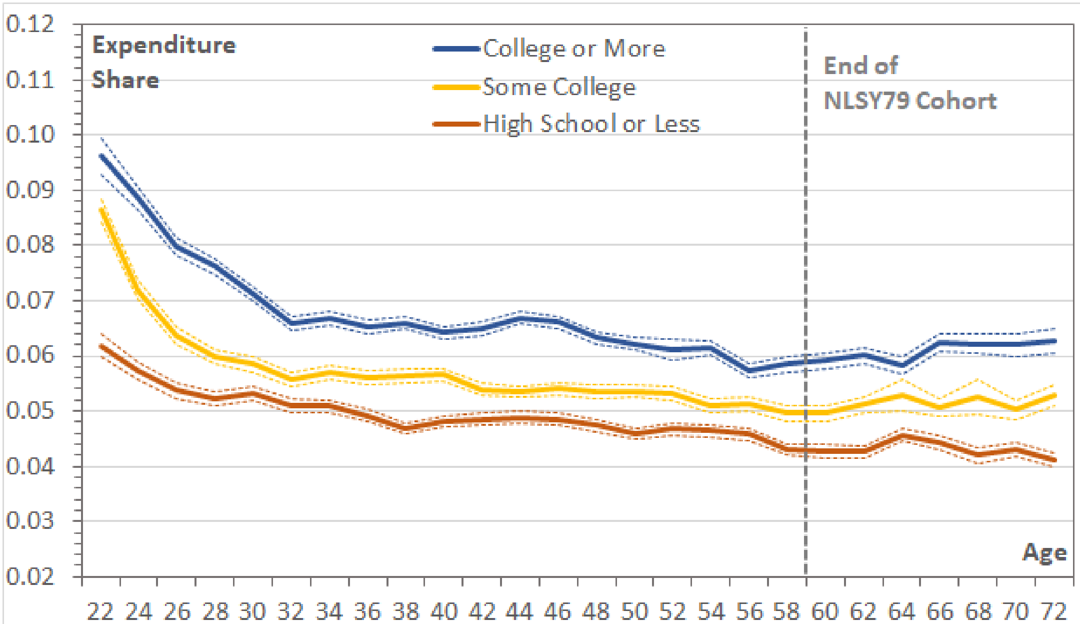


Notes: Estimates from authors' calculations using the ATUS data pooled over 2003-2019. Estimates represent the sample-weighted means of individuals' time spent on each activity for two-year age intervals by (current) education. Dashed lines represent 95 percent confidence intervals.

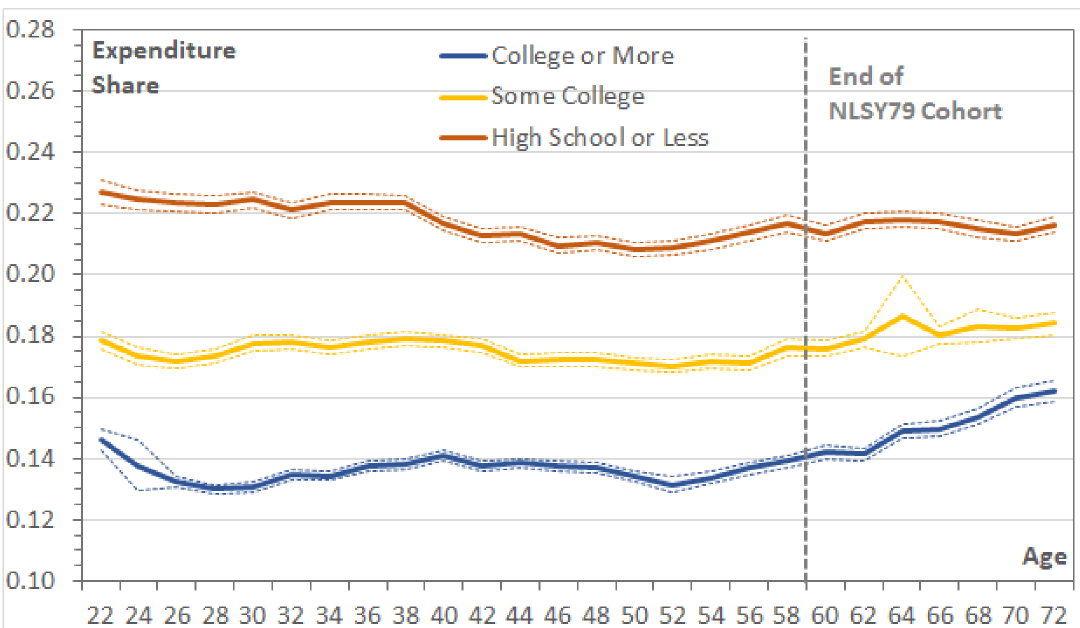
Those with a high school degree or less have the highest expenditure shares on leisure at home, while the college educated have the lowest expenditure shares on leisure at home. In addition, these expenditure shares are essentially constant over the life cycle for each education group.

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.

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 and expenditure data show that the college educated devote more time and income to leisure outside of the home. Much of this appears to be spent on dining out and local entertainment. Furthermore, there exists a gap in the consumption of local amenities between the college educated and those with a high school degree or less that 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. Those with a high school degree or less tend to spend higher fractions of their time and income on leisure at home, particularly on home entertainment and dining at home. In principle, it would be natural for them to seek out more affordable cities with relatively fewer local amenities.

To investigate the empirical link between time spent on leisure outside the home and the quality of local amenities, we examine ATUS data on the most disaggregated geographic detail available. Specifically, we observe whether individuals live in the metropolitan or nonmetropolitan portion of their state, providing 100 distinct regions.[11] We then compare (population-weighted) means of the quality-of-life index with time use in these regions. A drawback of this approach is that all metros, large and small, are aggregated together. An advantage is that we observe novel evidence relating time use and the quality-of-life index directly.

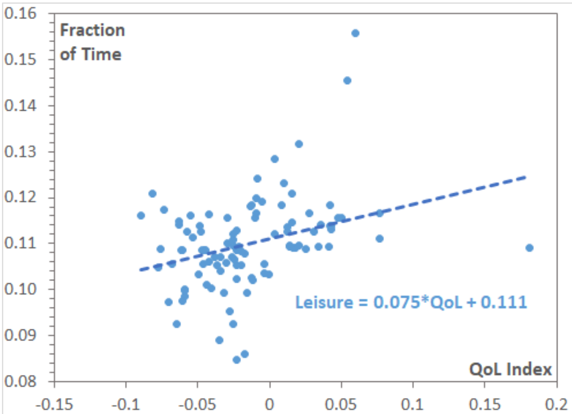
Figure 6 presents this evidence using scatter plots for four different measures of time use, averaged across all individuals, ages 18 to 74, residing in the 100 state-metro area regions, pooled across all survey years. The four plots are for leisure away from home, leisure at home, home production, and market work. Each panel plots the fitted line and presents coefficient estimates from the population-weighted regression of time use—expressed as a fraction of daily time—on the quality-of-life index. Panel (a) shows a positive, significant relationship between time spent on leisure away from home and local amenity quality: A 100 basis point increase in quality of life is associated with a 7.5 percentage point increase in the fraction of time devoted to leisure away from home (with a standard error of 1.2 percentage points). Panel (b) shows that a 100 basis point increase in quality of life is also associated with a 13.6 percentage point decrease in the fraction of time spent on leisure at home (with a standard error of 2.5 percentage points) .

Panel (c) shows the relationship between home production time and the quality-of-life index

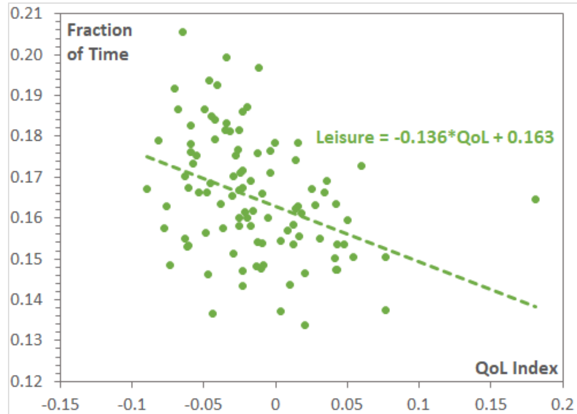
[11] The District of Columbia and New Jersey do not have nonmetro portions. We only perform the analysis using the ATUS because of censoring issues with the geographic data in the CEX, which does not report the state of residence for most individuals living in the nonmetro part of their state and has no greater geographic detail.

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

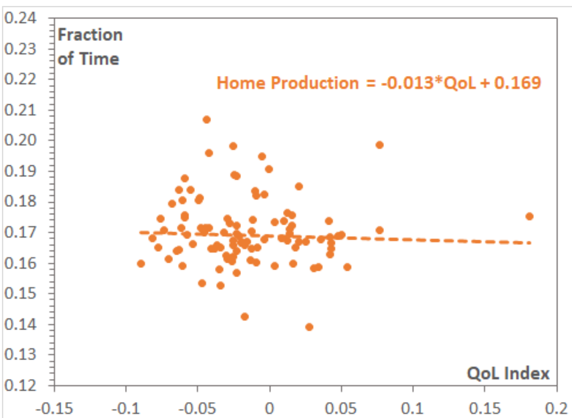
(a) Leisure Time Away from Home



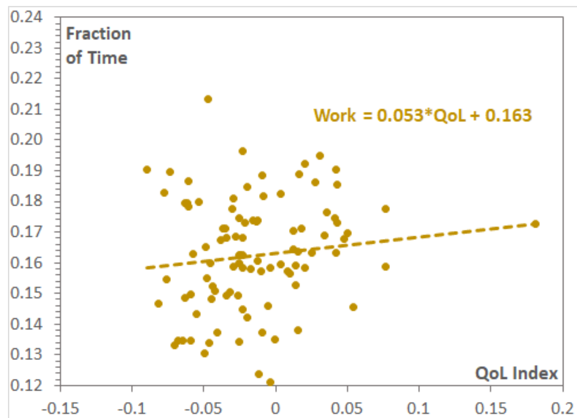
(b) Leisure Time at Home



(c) Home Production Time



(d) Work Time



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.

as a validity check. We find essentially no relationship between the two. Finally, Panel (d) shows that higher quality of life is associated with increased work time. A 100 basis point increase in the index is associated with a statistically insignificant 5.3 percentage point increase in time spent working (standard error of 4.4 percentage points). This is not surprising since the wage component of the quality-of-life index increases in a similar way by education and age to the overall index (Figure 3), albeit to a lesser degree. Thus, despite the crudeness of the geographic measures, we find evidence of a significantly positive relationship between local amenity quality, and time spent consuming them, as well as less time spent at home.[12]

[12] In the online appendix, we compare the slope coefficients in Figure 6 to a replication of the exercise where we

3.3 The Role of Children in the Household

Overall, our evidence shows that local amenities are consumed more by the young and the more educated. The peak in local amenity quality early in life contrasts with the later peak in conventional consumption measures seen in other life-cycle studies (e.g., Attanasio and Weber, 1995, among others). We conjecture that the life-cycle patterns of local amenity quality, and the associated migratory and amenity consumption behavior, are due to higher demand for local amenities by individuals outside of their child-rearing years, especially by the college educated.[13] 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 less affordable, high quality-of-life areas. Consequently, we should observe individuals gradually moving towards more affordable, lower quality-of-life areas during their child-rearing years.

We conclude our empirical analysis with evidence supporting this hypothesis. First, we split the NLSY79 cohort by whether or not individuals ever have children (observed after age 18) and estimate the average quality of life of where they live.[14] This distinction avoids the selection issues that arise from splitting the sample according to who currently has children. We report the estimates by education and age, 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. For those with a high-school degree or less, the difference between those who ever have children is rather small, and disappears around age 45. For the college educated, the difference is substantial: by age 24, those who never have children move

use CBSA definitions, which we only have in the ATUS from 2016 forward. The results show that the coefficient estimates are very similar to those reported in Figure 6. We eplicate the exercise for local leisure restricted only to time spent on local entertainment, sports, and recreation, and home leisure restricted only to time spent on home entertainment and personal and relaxation time. We find similar results to those in Figure 6 in both cases.

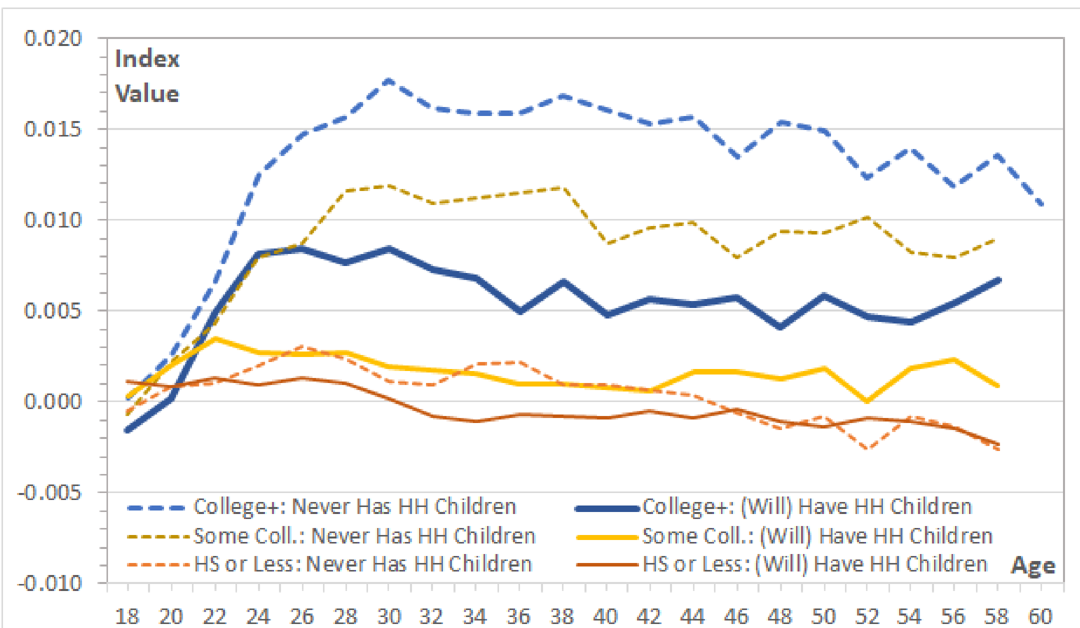
[13] In the online appendix, we show that the fraction of households with children present peaks between age 32 and age 42, with the peak occurring later for more-educated individuals.

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

to metro areas with a quality-of-life value 0.4 log points higher than their counterparts who do have 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 fifties. Thus, the childless remain in high-amenity areas, while those with children, regardless of education, 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 children) peaks at 1.0 log point. This evidence suggests that children affect their parents' migration choices across metropolitan areas. This behavior resembles the migration patterns of gay men documented by Black et al. (2002), who are typically childless, reducing their demand for housing, and allowing them to afford areas with greater amenities.

Figure 7: Average Metro Area 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.

Next, we use an event study analysis to examine how children affect location choices. Specifically, we use the pooled NLSY sample to regress the quality-of-life value of an individual's current metro area on a set of time dummies that identify the years prior to, during, and after the arrival of the first child observed in the household. The model conditions on various demographic and other characteristics in the following specification:

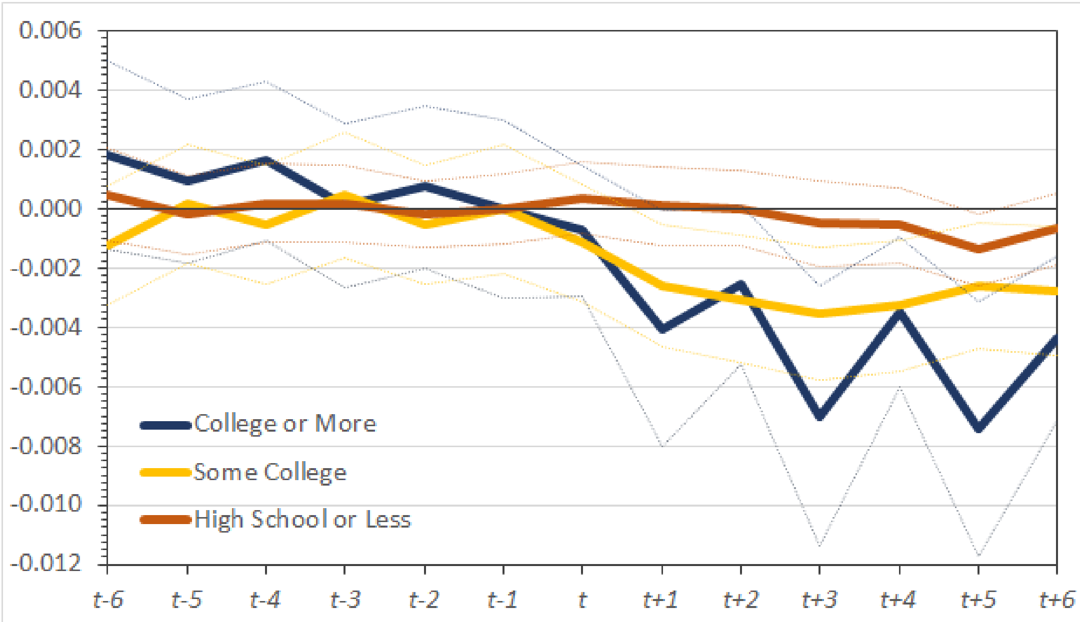
$$Q_{j(i)st} = \sum_{k=-n}^{n} \alpha_{s,t+k} + X_{it}\beta + \gamma_s + \delta_{st} + \eta_\tau + \epsilon_{ist},$$

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 fixed effects for the k years prior to, during, and after the incidence of the individual's first child in the household. We show results for 6 years of lead and lag. The vector of demographic controls, X_{it}, includes indicators for gender, marriage, gender $\times$ marriage, and four race categories; γ_s represents a set of dummies for each educational attainment category; $\delta_s t$ represents a set of dummies for educational attainment interacted with 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.

The results in Figure 8 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 causes households to migrate to lower quality-of-life metropolitan areas over time, particularly for the college educated. In the six years prior, the quality of life changes little across education groups. Following the first child, quality of life 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 points 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 points lower on impact and about 0.7 log points lower after three years (relative to its value prior to the first child). Thus, the arrival of children drives migration towards more affordable, lower quality-of-life areas, especially for the most educated. This is the most direct evidence of how children drive migration decisions.[15]

[15] Notably, our results provide an important caveat to the migration patterns studied by Kennan and Walker (2011). They find that relatively high implicit migration costs tend to reduce the flow of individuals across locations, and those that do move do so because of high expected returns to their lifetime income, driven partly by their match quality with their new location. Our results suggest there is also a countervailing push factor that may encourage migration. Having children causes a reassessment of the housing costs and returns to local amenities of one's current location. Individuals in costly, high-amenity locations will likely move somewhere else to avoid paying for amenities (through housing costs) that they are unlikely to enjoy. For them, there is an implicit cost to *not* moving. To the extent that high-cost, high-amenity cities tend to be denser and larger, this will have a de-agglomerating effect on the sorting of individuals across locations.

Figure 8: Estimated Changes in Metro Area 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 × marriage, race, highest education attained, education × age, and NLSY cohort × calendar year. Dashed lines represent 95 percent confidence intervals based on standard errors clustered by Metropolitan Statistical Area.

4 A Model of Life-Cycle Amenity Consumption

This section develops a general equilibrium model of wages, amenities, and housing prices, where households choose their consumption, leisure, and location, taking the housing costs and wages in each location as given. Workers differ in their type, defined by their demographics and household composition. The latter determines their leisure and expenditure preferences over their life cycle. 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 a tradable goods and local nontradable (i.e., housing) sector while nontradable prices are determined in equilibrium through competition in the nontradable sector. In equilibrium, utility is equalized across locations of differing amenity levels for individuals of a given type and 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 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. The nontraded good refers to housing and related expenditures, to the extent that their price varies by location, and has price p_{jt}. The traded good refers to expenditures on all other goods and services, and acts as the numeraire, i.e., with a price of one everywhere. Local amenities vary by location but cannot be purchased directly.

Leisure time is split into time spent enjoying local amenities, a_{it}, and all other forms of leisure, l_{it}, which we refer to as "leisure at home." The latter generates the same utility regardless of where one lives, and comes at no cost other than time. Time spent enjoying local amenities requires additional market expenditure $p^a(z_{it})$ per unit of a_{it}.

Besides leisure, time is allocated to nonleisure activities—i.e., market work, n_{it}, and home production, $\tau(z_{it})$, where the latter is exogenous and depends on household composition, z_{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 $I_{it} + s_{it}$. Since our data are for a single household respondent, the nonwage income represents spousal earnings plus any unearned income in our estimation.

Households maximize their lifetime utility given their type, k, their household composition, z_{it}, and the quality of amenities at their location, Q_{jt}. We interpret z_{it} as capturing the effects of household composition—and children in particular—on required home production time, goods demand, and leisure demand over the life cycle. Specifically, it determines available time through $\tau(z_{it})$, the price of "going out," $p^a(z_{it})$, as well as the preference shifters for goods and leisure demand, $\phi^x(z_{it})$, $\phi^y(z_{it})$, and $\gamma_0(z_{it})$. Formally, the household's utility maximization problem is:

$$\begin{aligned}
V(s_{it},\cdot;k,z_{it}) \quad &= \max_{\{x_{it},y_{it},a_{it},l_{it},n_{it}\}} \exp\{\phi^x(z_{it})\}\ln x_{it} + \exp\{\phi^y(z_{it})\}\ln y_{it} + \mu_0 Q_{jt} + h(Q_{jt},a_{it}) \\
&\qquad + \left(\tfrac{\gamma_1}{\gamma_1-1}\right)\exp\{\gamma_0(z_{it})\}(a_{it}+l_{it})^{\frac{\gamma_1-1}{\gamma_1}} + \beta V(s_{i,t+1},\cdot;k,z_{i,t+1}), \\
\text{subject to} \quad & s_{i,t+1} = (1+r)\left[I_{it} + w_{j(k)t}n_{it} - x_{it} - p_{jt}y_{it} - p^a(z_{it})a_{it}\right], \\
\text{and} \quad & n_{it} + \tau(z_{it}) + a_{it} + l_{it} = 1 \text{ for all } t.
\end{aligned}$$

The household's discount rate is β and the real interest rate is r. The household receives utility from total leisure time, i.e., the time spent on leisure at home or out. The function $h(Q_{jt}, a_{it})$ defines the additional utility derived from the time spent consuming amenities in a location with amenity value Q_{jt}. So long as the cross-partial derivative is positive, $h_{Qa}(Q_{jt}, a_{it}) > 0$, the value of local amenities and the time spent enjoying them will be complements. Except for the introduction of this new component, our functional form shares much in common with other characterizations of the consumption-leisure trade-off, which assume separable utility, and imply an elasticity of leisure with respect to wages equal to γ_1.

The household's problem simplifies by substituting the time constraint into the lifetime budget constraint to derive a "full-income" budget constraint, in the spirit of Becker (1965):

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

The full-income budget constraint in (1) highlights several features of the model. First, as in a standard consumption-leisure model, the opportunity cost of leisure time spent at home is the wage. Second, the opportunity cost of leisure time spent on local amenities is higher since it includes both the wage and the additional market cost of going out, $p^a(z_{it})$. Finally, home production activities affect full income by changing the time available for leisure and market work.

This simplification reduces the problem to one with a single constraint and four endogenous choice variables: the two consumption expenditures and the two measures of leisure time. The first-order conditions for this problem are

$$\begin{aligned}
\frac{\exp\{\phi^x(z_{it})\}}{x_{it}} &= \lambda_{it}\left[\beta(1+r)\right], && \text{(2a)}\\
\frac{\exp\{\phi^y(z_{it})\}}{y_{it}} &= \lambda_{it}\left[\beta(1+r)\right] p_{jt}, && \text{(2b)}\\
h_a(Q_{jt}, a_{it}) + \exp\{\gamma_0(z_{it})\}(a_{it}+l_{it})^{\frac{-1}{\gamma_1}} &= \lambda_{it}\left[\beta(1+r)\right]\left(p^a(z_{it}) + w_{j(k)t}\right), && \text{(2c)}\\
\exp\{\gamma_0(z_{it})\}(a_{it}+l_{it})^{\frac{-1}{\gamma_1}} &= \lambda_{it}\left[\beta(1+r)\right] w_{j(k)t}, && \text{(2d)}
\end{aligned}$$

where λ_{it} is the Lagrange multiplier on the lifetime budget constraint. Furthermore, combining equations (2c) and (2d) implies that the additional marginal utility of leisure spent going out equals the marginal cost of the market expenditures associated with it:

$$h_a(Q_{jt}, a_{it}) = \lambda_{it}\left[\beta(1+r)\right] p^a(z_{it}). \tag{2e}$$

4.2 Equilibrium

In equilibrium, the supply of the tradable and nontradable goods equals their demand, labor supply equals labor demand, and type-specific 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 and 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, assuming migration is costless, households' utility must be equal across locations and for a given individual's type, k, and household composition, z. Letting the value of this utility be $\kappa(k, z)$, we have that

$$V(s_{it}, \cdot; k, z) = \kappa(k, z). \tag{3}$$

This free mobility condition is useful in estimation, as it implies that $dV/dQ = 0$.

5 Model Estimation and Quantitative Analysis

5.1 Identification

Synthetic panel data constructed from the NLSY, ATUS, and CEX provide us with the variables necessary to identify the key parameters in the model. They also allow us to identify the preference shifts due to changes in household composition, z_{it}, over the life cycle. Specifically, the ATUS provides the time spent on home production, $\tau(z_{it})$, and leisure going out, while the CEX provides a market cost of going out, $p^a(z_{it})$, from expenditures on local amenities in the CEX. The preference shifters depend on an individual's marital status and their children, so that

$$\begin{aligned}
\phi^x(z_{it}) &= \phi_t^x + \phi_{mt}^x z_{it}^m + \phi_{ct}^x z_{it}^c + \phi_k^x + \sum_r \phi_r^x s_{kt}^r \\
\phi^y(z_{it}) &= \phi_t^y + \phi_{mt}^y z_{it}^m + \phi_{ct}^y z_{it}^c + \phi_k^y + \sum_r \phi_r^y s_{kt}^r \qquad (4) \\
\gamma_0(z_{it}) &= \gamma_t^0 + \gamma_{mt}^0 z_{it}^m + \gamma_{ct}^0 z_{it}^c + \gamma_k^0 + \sum_r \gamma_r^0 s_{kt}^r,
\end{aligned}$$

where z_{it}^m indicates marriage and z_{it}^c indicates the presence of children. The preference shifters also vary by type k through additive effects, ϕ_k^x, ϕ_k^y, or γ_k^0. They also control for changes in the composition of each synthetic cell, s_{kt}^r (described in more detail below). The ATUS provides leisure at home, l_{it}, and leisure spent going out, a_{it}. 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. The NLSY provides earnings per unit of work time, n_{it}, so that earnings, hours, and the hourly wage are internally consistent. The NLSY geocode data identify location over the life cycle, giving estimates of the value of local amenities, Q_{jt} (estimated as the local quality-of-life index) and the corresponding local price index, p_{jt}.

We assume the functional form $h(Q_{jt}, a_{it}) = \mu_1 Q_{jt}^{\eta} \ln a_{it}$, so that $h_a(Q_{jt}, a_{it}) = \frac{\mu_1 Q_{jt}^{\eta}}{a_{it}}$. Substituting this into equation (2e) and taking logs gives an elasticity of time spent going out with respect to the value of local amenities equal to η.

5.2 Moment Construction

We generate estimates of the necessary moments from the data for three education groups (high school or less, some college, college or more), gender, marital status, and presence of any children under 18 in the household, providing 24 types for k. We cover the life-cycle t using 19 two-year age bins from 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 a synthetic panel, we must address 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 to merge into the NLSY panel. The predicted measures are out-of-sample estimates of each expenditure or time use category.[16]

For expenditures, we estimate the relationship between each CEX expenditure category (in 2019 dollars) and observable demographic and labor market characteristics: three education categories, gender, marital status, as well as indicators for zero, one, or two or more children, 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 also include a rich set of interactions for all of these variables.[17] For time use, we use the same approach, regressing ATUS time-use categories, measured in minutes, on the same set of observable demographic and labor market characteristics.[18] In both cases, we take the coefficients from each regression and interact them with matching variables in the NLSY data to generate the predicted expenditure and time-use estimates for each individual-year observation.

The expenditure and time-use estimates for the synthetic panel across its k demographic groups and t age categories are the sample-weighted means of their predicted values. We also generate predicted estimates of income, hours, wages, and the quality-of-life index (along with its components) for each cell using the NLSY respondent data. We use the same approach and empirical specifications, but the estimates are within-sample in this case. Consequently, our quality-of-life estimates are comparable to those reported in Figures 2 and 3, except that we

[16]We take a similar approach to Blundell, Pistaferri, and Saporta-Eksten (2018), who match estimates from the ATUS and CEX to PSID data at the micro level. 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 via a synthetic panel.

[17]Specifically, we interact gender with marital status, 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, children, and education. We interact household adults with gender, marital status, and age. We interact race with gender, marital status, children, and education. We interact own and spouse's full-time employment status each with gender, children, and education. Finally, we interact school enrollment status with gender and education.

[18]For 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 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.

remove the residual component of the estimates that are not predicted by demographic and labor market characteristics.

We then rescale our measures so that they are internally consistent within the model's framework. All time-use estimates are given as a fraction of total "relevant" time in a given day, taken as the sum of work time, home production time, and leisure time at home and away from home. We add the amount of sleep time in excess of that reported at the 25th percentile of the sleep distribution to leisure time at home, assuming this additional sleep represents leisure. NLSY measures of total hours worked in the previous year, taken in average minutes per day, are used for work time, n_{kt}. This direct measure of work time is internally consistent with the NLSY wage and income estimates used to calibrate the model. We measure the share of time spent on leisure at home, l_{kt}, local amenity consumption, a_{kt}, and home production, $\tau(z_{kt})$, using the corresponding categories in Table 1. Expenditures on nontradable goods, $p_{jt}y_{kt}$, are taken as expenditures on housing rent or rental equivalence (for owned homes), utilities, and housing maintenance. Tradable goods include expenditures on every other category reported in Table 2 except local leisure. This last amount is equal to $p^a(z_{kt})a_{kt}$ in our calibration. I_{kt} is equated with all disposable household income in excess of the NLSY respondent's earnings. This includes the earnings of any spouse or partner, and total household nonwage income. The wage, $w_{j(k)t}$, is scaled to be consistent with the share of time devoted to work, n_{kt}. Finally, the per-unit market-cost of leisure spent going out $p^a(z_{kt})$ is taken as the ratio of local leisure expenditures to time spent going out.

Table 3 reports the mean predicted moment estimates identified directly from the data. About 40 percent of total expenditures are on nontradables. Just under half of income comes from the respondent's own earnings, i.e., the product of the daily wage and work time, with the remainder coming from spousal earnings or other sources. Nearly a quarter of relevant daily time is spent on home production, while 28 percent of it is spent working. The remaining time is spent on leisure, with 31 percent spent on leisure at home and 16 percent spent out enjoying local amenities.

Figure 9 reports the time-series behavior of estimated moments aggregated by education and age. The top row reports expenditures per day on tradable and nontradable goods. Both expenditure profiles are hump-shaped over the life cycle for each education group. Higher education groups have higher consumption profiles, with expenditures on tradable goods fanning out more

Table 3: Sample Means for Moments Used in Estimation

Variable	Sample Mean	Description	Data Source
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
$w_{j(k)t}$	353.12	Real daily wage	NLSY real annual earnings per hour worked in prior year
I_{kt}	104.87	Additional real household income (per day)	Total household disposable income net of wage earnings, $w_{j,st}n_{st}$
$\tau(z_{kt})$	0.242	Share of time spent on home production	Predicted ATUS time spent on home production (share of available time)
a_{kt}	0.162	Share of time spent on local leisure	Predicted ATUS time spent on leisure away from home (share of available time)
l_{kt}	0.313	Share of time spent on leisure at home	Predicted ATUS time spent on leisure at home (share of available time)
n_{kt}	0.284	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.

later in the life cycle (during one's mid-forties) compared to expenditures on nontradable goods.

In the second row, the left panel reports time spent on leisure at home; the right panel reports time spent enjoying local amenities, much like Figure 4. Those with a high-school degree or less spend the most time on leisure at home, while the college educated spend the least, with the difference between the two growing with age. The college educated spend the most time out enjoying local amenities, with the difference being greatest early in life.

In the third row, the left panel reports time devoted to home production. All three education groups exhibit similar hump-shaped patterns, though the peak amounts, between 26 and 29 percent of relevant time, occur later in life for more-educated individuals. The right panel reports work time, which is higher for the more educated at any given age. These profiles have a weaker hump shape, and by age 40 decline for every education group.

In the bottom row, the left panel reports per-unit amenity-time market costs, $p^a(z_{kt})$. These costs generally rise with both education and age, and rise most with age for the college educated. Much of the life-cycle variation is due to changes in household composition—e.g., going out to dinner, a married individual reports about twice the expenditure but the same time spent as a single individual, as the former likely dines more with their spouse. Finally, the right panel reports the daily wage, which is what individuals would earn if they devoted all relevant time to work. This wage rises over the life cycle for all education groups, but more so for the college 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 we 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 time in (2e) and total leisure demand in (2d). In each case we substitute 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, both with respect to nontradable goods demand. We use GMM to estimate these equations, in logs, from the synthetic panel.[19] As mentioned earlier, heterogeneity in k for the 24 categories of education $\times$ gender $\times$ marital status $\times$ the presence of children, both across and within synthetic cells, is accommodated through the preference shifters in (4). We control for changes in the composition of panel cells (due to sample attrition) using the s_{kt}^r variables in (4), which include the share of each cell that is Black, Hispanic, or other non-White, and the share of the college educated that are in school full-time. As a result, the model parameters are identified through life-cycle variation within demographic groups.

We can express the estimating equations from our first step with total leisure and leisure spent going out on the left-hand sides:

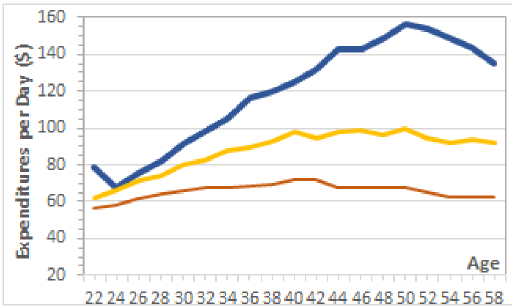
$$\ln\left(a_{kt}+l_{kt}\right) = -\gamma_1\left[\phi^y\left(z_{kt}\right)-\gamma_0\left(z_{kt}\right)-\ln p_{j(k)t}y_{kt}+\ln w_{j(k)t}\right]+u_{kt}^n, \tag{5a}$$

$$\ln a_{kt} = -\phi^y\left(z_{kt}\right)+\ln p_{j(k)t}y_{kt}-\ln p^a(z_{kt})+\ln\mu_1+\eta\ln Q_{j(k)t}+u_{kt}^a, \tag{5b}$$

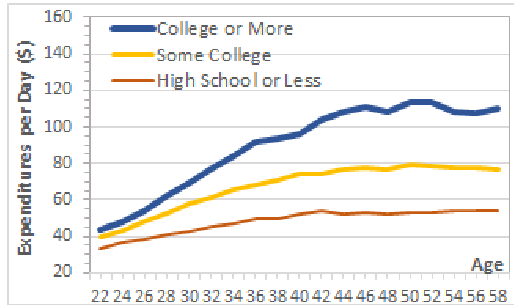
[19] We use the means of the log of each moment to deal with the aggregation biases in synthetic data highlighted by Attanasio and Weber (1993).

Figure 9: Life Cycle Behavior of Model Moments by Education

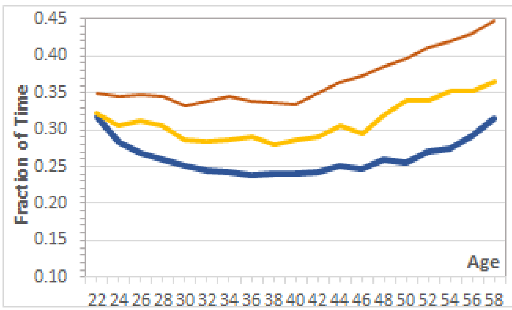
(a) Expenditures on Tradables, x_{kt}



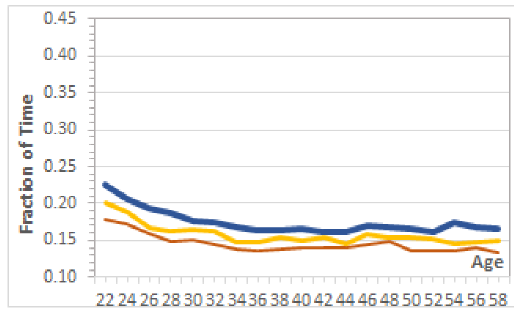
(b) Expenditures on Nontradables, $p_{jt}y_{kt}$



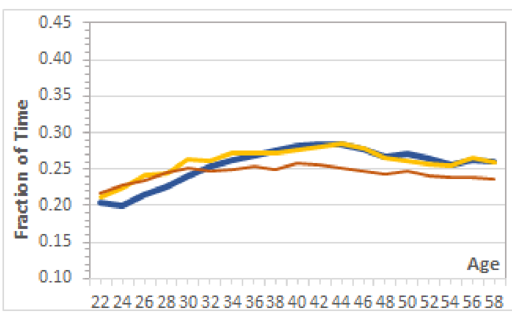
(c) Leisure Time at Home, l_{kt}



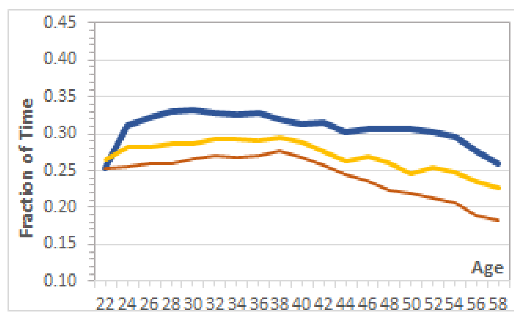
(d) Leisure Time on Local Amenities, a_{kt}



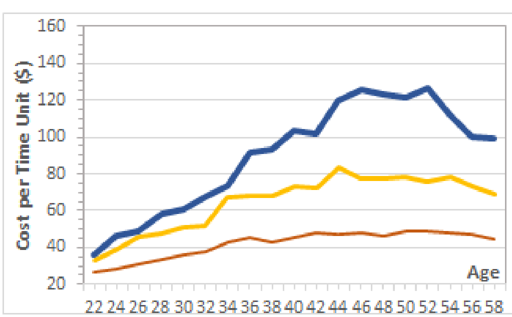
(e) Home Production Time, $\tau(z_{kt})$



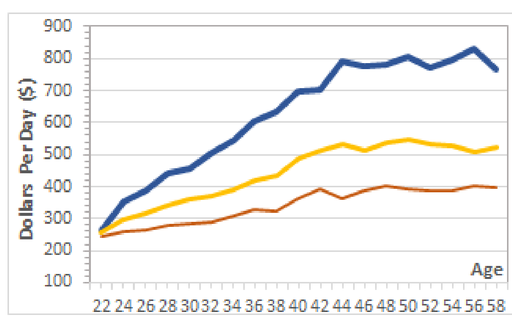
(f) Work Time, n_{kt}



(g) Amenity Time Cost, $p^a(z_{kt})$



(h) Daily Wage, $w_{j(k)t}$



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).

where u^n_{kt} and u^a_{kt} are error terms. The preference shifters specified in (4) use fixed effects for broad (six-year) age groups to identify the life-cycle variation in preferences independent of household composition. These age-group effects alone are interacted with the indicators for marriage and children.[20]

In the model, nontradable expenditures, $\ln p_{j(k)t} y_{kt}$ are endogenous. Furthermore, wages, $\ln w_{j(k)t}$, and amenity costs, $\ln p^a(z_{kt})$, while exogenous, are potentially subject to measurement error that is correlated with the error terms. This is because both are calculated using either the left-hand side variable or its complement in their denominators. To handle these endogeneity and measurement error issues, we introduce instrumental variables into the GMM framework. These instruments are the log of other household income, the share of the panel cell that has an employed spouse (and its interaction with gender), the share of the panel cell that has an additional adult (besides any spouse), and two-age bin (i.e., four-year) lags of log nontradable expenditures, log wages (in 5a), and log amenity costs (in 5b). The total leisure equation in (5a) additionally uses the log of the quality-of-life price component as an instrument.

In a second step, we estimate μ_0 using the free mobility condition in (3) evaluated at its optimum—i.e., where $dV/dQ = 0$. Specifically, given the synthetic panel data and GMM parameter estimates, the estimated value of μ_0 best fits this free mobility condition.[21]

The main parameter estimates are shown in Table 4. The estimate of $\hat{\gamma}_1$—interpreted as the (negative) elasticity of leisure with respect to the wage—is 0.33. It implies a labor supply elasticity of the same value, which is on the lower end of most micro labor supply estimates (see Chetty et al., 2011). This is consistent with its interpretation as a Marshallian elasticity. The estimate is also somewhat lower than estimates that account for extensive-margin employment adjustments and home production (e.g., Rupert, Rogerson, and Wright, 2000).

More uniquely, the point estimate of $\hat{\eta}$ implies a relatively large elasticity of time spent going out with respect to local quality of life. A 10 percent increase in the value of local amenities, as a fraction of income, increases the time individuals spend enjoying them by about 36 percent. To put this in perspective, consider that households spend 16 percent of their available time and

[20] In Online Appendix B.3, we report the parameter estimates obtained from alternative specifications of the preference parameters. We find qualitatively similar results to those reported in Table 4, though generally with a worse fit to the data.

[21] We describe our estimation procedure in more detail in Online Appendix B.2.

8 percent of their expenditures going out. If we factor in the time costs of going out (measured through their opportunity cost), this would amount to the equivalent of 45 percent of total market consumption. Thus, a 10 percent increase in quality-of-life, which reduces a household's purchasing power of market consumption by 10 percent, increases the total cost of going out by 16 percent of realized income (i.e., 45 percent of the estimate for $\hat{\eta}$), 87 percent of which is paid for in forgone earnings. The 95-percent confidence intervals of $\hat{\eta}$ include values that are always positive, but as low as 0.4, implying a much weaker mobility response.

From the mobility condition, we estimate a relatively large utility value of local quality-of-life alone, $\hat{\mu_0}$. This serves mainly as a normalization for the other parameters and does not have much meaning in isolation. However, it pairs sensibly with the scaling parameter on leisure spent going out, $\hat{\mu_1}$.[22]

Table 4: Estimated Model Parameters

Parameter	**Estimate**
$\hat{\gamma_1}$, (negative) leisure elasticity	0.329
	(0.071)
$\hat{\eta}$, exponential parameter on quality of life (in complementarity)	3.57
	(1.62)
$\hat{\mu_0}$, utility from local quality of life	7.26
	(0.13)
$\hat{\mu_1}$, scaling parameter on leisure spent out preference	0.165
	(0.015)
Test for Overidentifying Restrictions, p-value	0.566

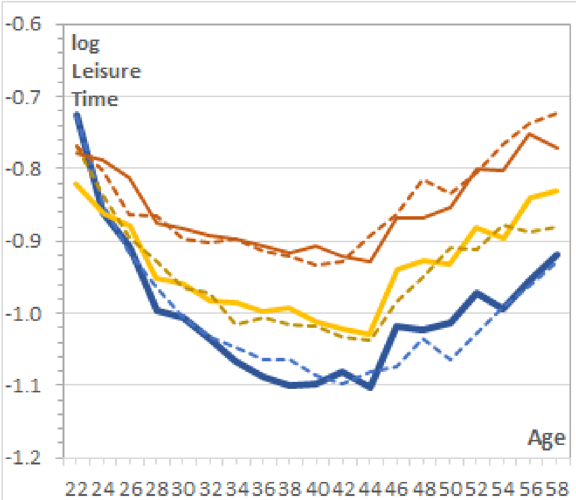
Notes: Table reports the parameter estimates from the GMM estimation of our model on a set of expenditure, time use, income, and local quality of life moments from a synthetic panel of 445 demographic $\times$ age cells. Standard errors are in parentheses. See text for details.

Figure 10 presents two evaluations of the model's fit of the data for education $\times$ age. The left panel compares the model's predicted log total leisure to log total leisure in the data, while the right panel compares the model's predicted log amenity time to log amenity time in the data. Overall, the model matches the shapes of these profiles rather closely. For total leisure time, the model captures 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.

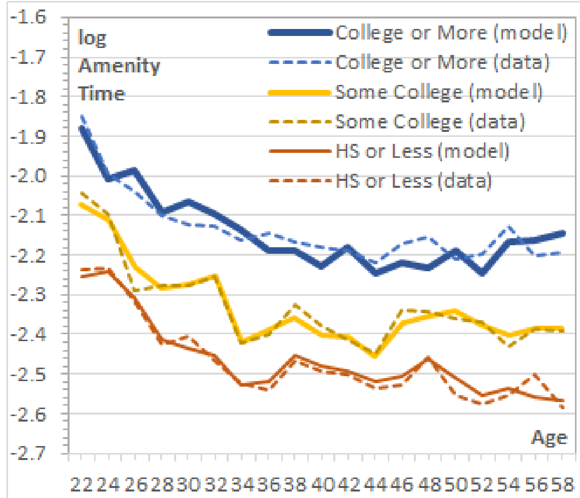
[22] In Online Appendix B.3, we present our estimates for the preferences shifters, $\phi^y(z_{it})$ and $\gamma^0(z_{it})$ aggregated into education $\times$ age bins and incidence of household children $\times$ age bins. In general, we estimate that preferences for nontradables rises over the life cycle, while the preference for leisure is U-shaped over the life cycle.

Figure 10: Evaluations of Model Fit

(a) Actual vs. Model-Implied Total Leisure Time



(b) Actual vs. Model-Implied Amenity Time



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.

5.4 Model Evaluation

Our final exercise involves evaluating the model's implications for household behavior in response to changes in their local quality of life, namely from moving to a new metro area. In doing so, we alter the households' environment along two dimensions. First, we move all individuals to a metro with a higher quality-of-life and have them face new nontradable prices and wages commensurate with this move. We then repeat the move removing the amenity–quality-of-life complementarity in the model—i.e., we set $\eta = 0$, leaving all other parameters the same as in the estimated baseline specification. We then compare how choices for goods and leisure change with this move with and without the complementarity. This exercise highlights and quantifies the importance of the complementarity for household behavior and sorting across locations. Note that the moves are partial equilibrium in the sense that households take prices and wages as given when they move, and their moves do not alter the equilibrium prices and wages across metro areas.

The new equilibrium demands for goods and time-use take the household's new location as given. Substituting the first-order conditions into the full-income budget constraint in equation (1), one obtains a nonlinear relationship between nontradables demand and the exogenous parameters and variables of the model,

$$w_{j(k)t}(1-\tau(z_{kt}))+I_{kt}+ds_{kt}= \qquad (6)$$
$$A_{j(k)t}(z_{kt})\left[e^{\phi^x(z_{kt})}+e^{\phi^y(z_{kt})}e^{\gamma_1\gamma_0(z_{kt})}w_{j(k)t}^{1-\gamma_1}A_{j(k)t}(z_{kt})^{\gamma_1-1}+\mu_1 Q_{j(k)t}^{\eta}\right]$$

where $ds_{kt} \equiv s_{kt} - \frac{s_{k,t+1}}{(1+r)}$ is the (negative) net change in savings, and $A_{j(k)t}(z_{kt}) \equiv p_{j(k)t}y_{kt}/e^{\phi^y(z_{kt})}$ is the inverse of the marginal utility of income. Note that nontradables demand, y_{kt}, only shows up through the marginal utility of income, and that the right-hand side of (6) is the expenditure function for our model. We have incomplete data on individuals' savings from the CEX, and no data on how it evolves over time. Consequently, the estimates of ds_{kt} equate the two sides of equation (6) in the baseline estimation, given each household's location, prices, expenditures, and time use observed in the data. We then keep that value constant throughout our exercise, essentially treating ds_{kt} as exogenous income. We can solve for y_{kt} using (6) and a nonlinear solver, and then recover the other equilibrium demands through the first-order conditions described in equations (2a)-(2e). We do this separately for each cell in our synthetic panel.

By construction, we recover the nontradable demand observed in the data for the household's current location by equating $\ln p_{j(k)t}$ to the quality-of-life index's price component. The first part of the exercise moves everyone to a location that has a one-standard deviation higher value of $\ln Q_{j(k)t}$ and $\ln p_{j(k)t}$, based on the distributions of quality-of-life and prices across metros seen in the data. These correspond to a 4.9 log point and a 25.1 log point increase in each, respectively. The wage data are a function of both observable characteristics and location. To deal with this, we calculate the corresponding increase in wages using the predicted wage relationship used to estimate μ_0 (which we describe in Online Appendix B.2). This relationship provides a predicted increase in wages conditional on individuals' observable characteristics, and implies a wage increase of 4.2 log points associated with this move. We solve for the new nontradables demand holding all other variables in (6) constant, and then derive the new demands for tradables and leisure time accordingly.[23]

For the second step of the evaluation, we repeat the exercise for the case without the leisure-location complementarity, where $\eta = 0$. To do so, we first re-estimate the baseline goods and

[23]Note that in the online appendix we report the results of repeating our exercises where we instead move households to a one-standard deviation *lower* quality-of-life location and reduce their (log) values of $Q_{j(k)t}$, $p_{j(k)t}$, and $w_{j(k)t}$ by the amounts listed above. This produces essentially symmetric results.

leisure demands for households in their current location, since eliminating the complementarity causes them to re-optimize their demands at their current location. We then move them to a one-standard deviation higher quality-of-life location, given the same quality-of-life, price, and wage changes used in the baseline evaluation. Finally, we solve for their demands at their new location.

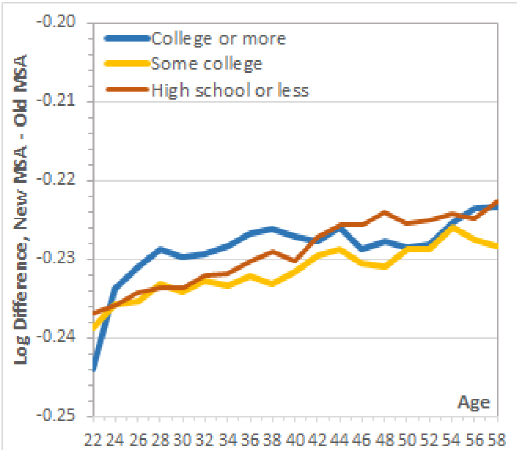
Figures 11 and 12 report how the (log) demands for nontradable goods, amenity time, and total leisure time change following the hypothetical move. Figure 11 reports the demand changes aggregated by age and education, while Figure 12 reports the changes aggregated by age and the presence of children.

Several results stand out from these figures. First, changes in goods and leisure demands are roughly similar by education group, though we remind readers that these demands by group still differ in levels. Second, all groups respond to moving to a higher quality-of-life metro by reducing their housing (nontradable) demand considerably. In the baseline exercise (left panels), the reduction is between 22 and 24 log points, with larger declines among the young and the less educated. By construction, the counterfactual move increases the nontradable price by 25 log points, so housing *expenditures* rise for all education groups. Third, there is a sharp increase in time spent enjoying local amenities that is roughly constant over the life cycle. In the baseline exercise, all education groups increase their amenity time by around 20 log points, with larger increases later in life. This increase in leisure time going out, however, coincides with a modest *decline* in total leisure time, i.e., a modest rise in work time. This is a response to the new higher wage. Together, these two results imply all types of individuals reduce their leisure time at home substantially.

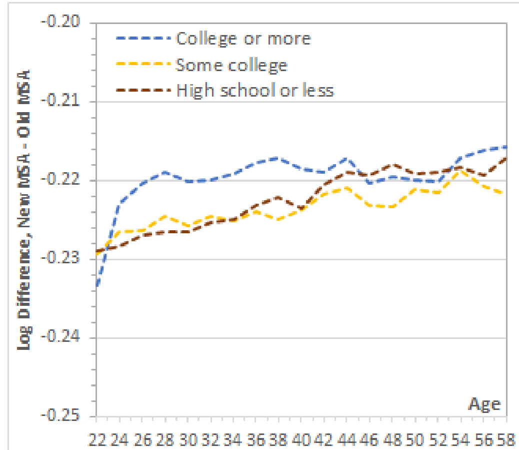
The distinction between leisure going out versus staying in, together with the location complementarity reveals how individuals substitute time use when the move to an area with higher quality-of-life: individuals will stay in less and go out more, boosting the utility they gain from the new area. Without the distinction between leisure types, the bottom-right panel of Figure 11 suggests one would infer a decline in all types of leisure time in response to the move, but panel (c) reveals that this would be incorrect. When we remove the complementarity, households only spend slightly more time enjoying leisure outside the home, as shown in panel (d), and have almost no change in total leisure, as shown in panel (f). They also consume slightly more housing,

Figure 11: Demand Changes in Response to Moves to Higher-Q_{jt} Metro Areas, by Education

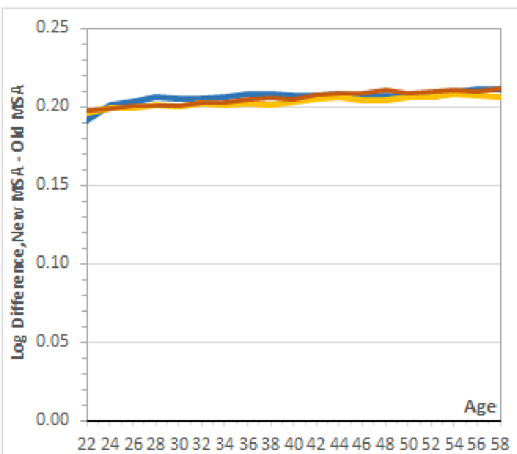
(a) Change in $\ln y_{kt}$, baseline η



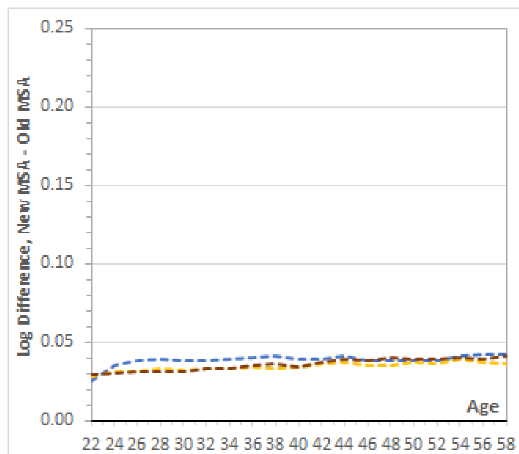
(b) Change in $\ln y_{kt}$, $\eta = 0$



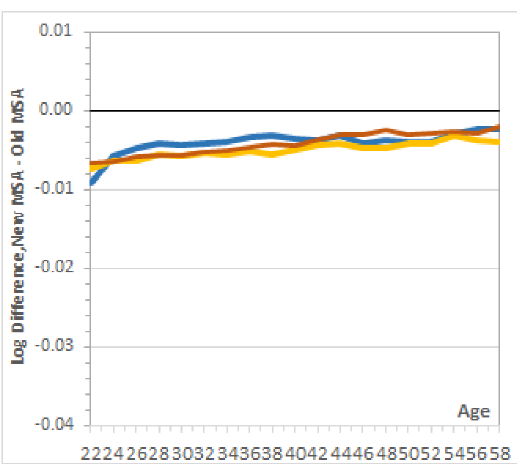
(c) Change in $\ln a_{kt}$, baseline η



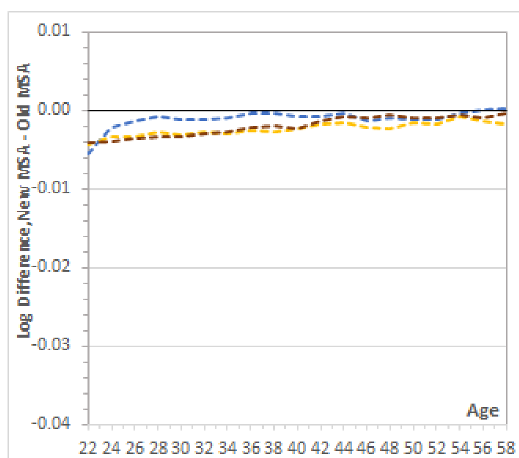
(d) Change in $\ln a_{kt}$, $\eta = 0$



(e) Change in $\ln (a_{kt} + l_{kt})$, baseline η



(f) Change in $\ln (a_{kt} + l_{kt})$, $\eta = 0$



Notes: Figure reports the (log) change in nontradable demand, amenity time, or total leisure time in response to a counterfactual move to a one-standard deviation higher-quality of life metro area. The moves represent a 4.9 log point increase in Q_{jt}, a 25.1 log point increase in p_{jt}, and a 4.2 log point increase in w_{jt}. Estimates are aggregated across all synthetic panel cells by education. The right panels report the demand changes in our baseline model, while the left panels report the demand changes where we shut down the complementarity between Q_{jt} and amenity time by setting $\eta = 0$.

as seen comparing panels (a) and (b).

Figure 12 reports results aggregated by age and children rather than age and education. As this is a different aggregation of the same synthetic panel estimates, the overall changes are similar in magnitude to those in Figure 11. Those with children see a larger drop in housing than those without. They also do not increase their time going out as much. Their total leisure time falls by more. These differences stem partly from the higher home production demands on time for those with children.[24] This helps reconcile the sorting behavior of households with children away from high-amenity areas, since they do not have as much time to take advantage of the local amenities. They also suffer more from the higher costs, having to increase their work more than childless households. These changes are greater for households with children in the case with the location-leisure complementarity than without.

6 Conclusions

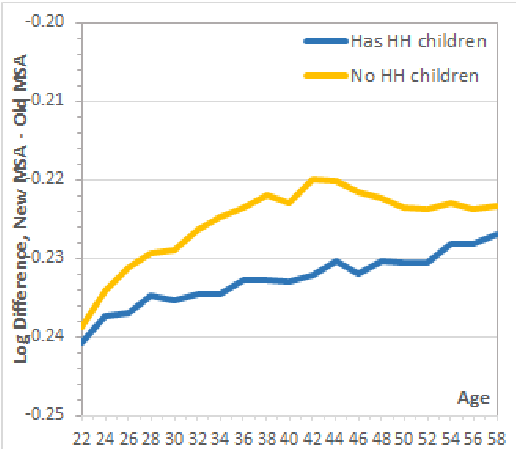
This paper examines the location choices of individuals over their life cycle, focusing on the amenity value of their locations, and variations by skill group. In a model of spatial equilibrium, places with greater amenities will be the least affordable, offering the highest costs-of-living paired with relatively low real wages. Individuals move to higher-amenity metro areas when young, with the college educated moving towards the highest-amenity locations. As a result, individuals enjoy the most amenity value around age 30, much earlier than peak consumption expenditures. Thereafter, individuals of all education groups tend to gradually move towards lower-amenity, but more affordable, metro 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 patterns consistent with these location choices. The more educated enjoy more leisure outside the home, while the less educated enjoy more leisure at home. Moreover, individuals of all education levels tend to enjoy local amenities most when young and at much-older ages. The resulting U-shaped pattern is most pronounced for the college educated. Using geographically coarse measures, we show that there is a direct, positive relationship between time spent enjoying local amenities and the quality of

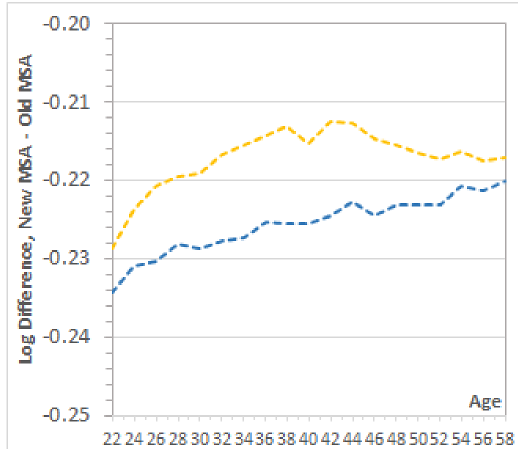
[24] For reference, we replicate the moment estimates reported in Figure 9 by the presence of children and age in the online appendix.

Figure 12: Demand Changes in Response to Moves to Higher-Q_{jt} Metro Areas, by Presence of Children

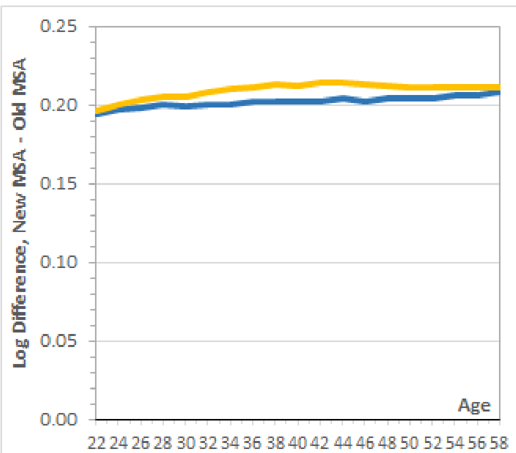
(a) Change in $\ln y_{kt}$, baseline η



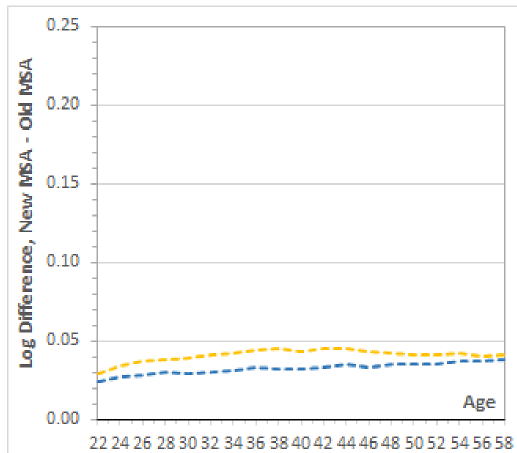
(b) Change in $\ln y_{kt}$, $\eta = 0$



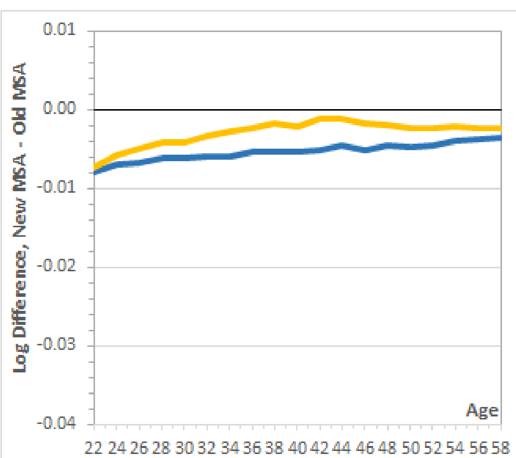
(c) Change in $\ln a_{kt}$, baseline η



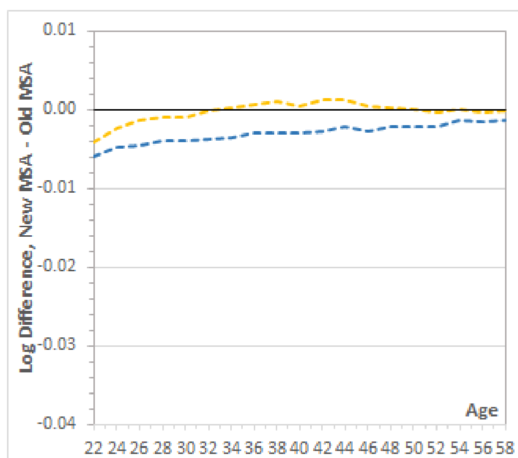
(d) Change in $\ln a_{kt}$, $\eta = 0$



(e) Change in $\ln(a_{kt} + l_{kt})$, baseline η



(f) Change in $\ln(a_{kt} + l_{kt})$, $\eta = 0$



Notes: Figure reports the (log) change in nontradable demand, amenity time, or total leisure time in response to a counterfactual move to a one-standard deviation higher-quality of life metro area. The moves represent a 4.9 log point increase in Q_{jt}, a 25.1 log point increase in p_{jt}, and a 4.2 log point increase in w_{jt}. Estimates are aggregated across all synthetic panel cells by presence of household children. The right panels report the demand changes in our baseline model, while the left panels report the demand changes where we shut down the complementarity between Q_{jt} and amenity time by setting $\eta = 0$.

life of where one lives.

These patterns are especially consistent with migration decisions in response to having children, which adds demands for housing and time. These reduce a household's demand for local amenities and causes households to move to more affordable, lower-amenity areas. A key mechanism behind this behavior appears to be a strong complementarity between local amenity value and time spent going out. Since amenity values are priced into housing costs, individuals seek more affordable areas to avoid paying for the amenities they no longer have time to enjoy. Individuals that never have children live in higher quality-of-life areas throughout their adult lives, and the gap between those with and without children is highest for the college educated. Furthermore, an event-study analysis suggests that individuals move towards lower-amenity areas when the first child arrives, especially for the college educated.

We develop a general equilibrium model of wages, amenities, and housing prices where households choose their consumption, leisure, and local amenities (through their location choice) to reconcile the theory with our findings. The key innovations of the model are that it distinguishes between leisure time spent at home and leisure time spent enjoying local amenities; a complementarity between this time going out and local amenity quality; and shifts in the cost of enjoying amenities that reflect changes in family composition over the life cycle. Our estimates suggest that the complementarity is not only statistically significant, but potentially large in how it affects leisure behavior.

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 local amenities. Since children increase housing demand and decrease available time to enjoy amenities, they reverse patterns effects in the middle of the life cycle.

We highlight the key features of our empirical evidence by evaluating a hypothetical move of individuals to a higher quality-of-life location. The evaluation reveals two additional insights. First, a Rosen-Roback framework that accounts for a simple labor-leisure time tradeoff would not capture changes in leisure time spent at home and leisure time spent going out, which can have important effects on the local economy and the potential production of local amenities. Second, ignoring the leisure-location complementarity would substantially underestimate how much individuals would go out in higher-amenity areas.

We conclude that examining migration and local amenities through a life-cycle lens uncovers an important age component for geographic sorting. Analogous to many studies of life-cycle labor supply, there is a strong role for children, and constraints on time influence where people want to live and how much they benefit from local amenities.

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ONLINE APPENDIX

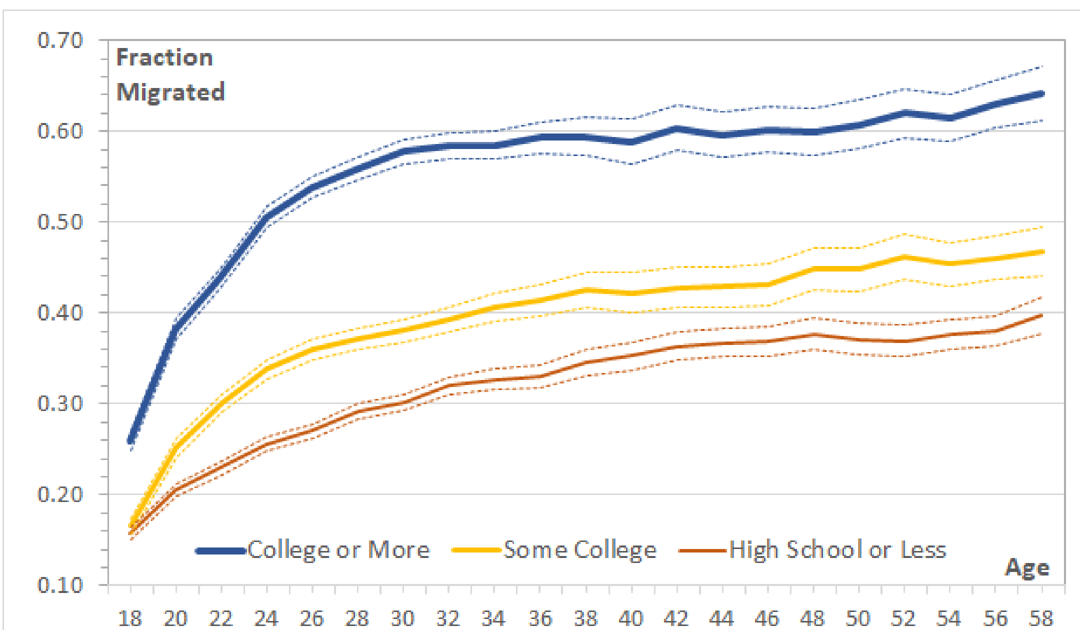
for "Skills, Migration, and Urban Amenities over the Life Cycle"
by David Albouy and R. Jason Faberman

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 our empirical results on migration.

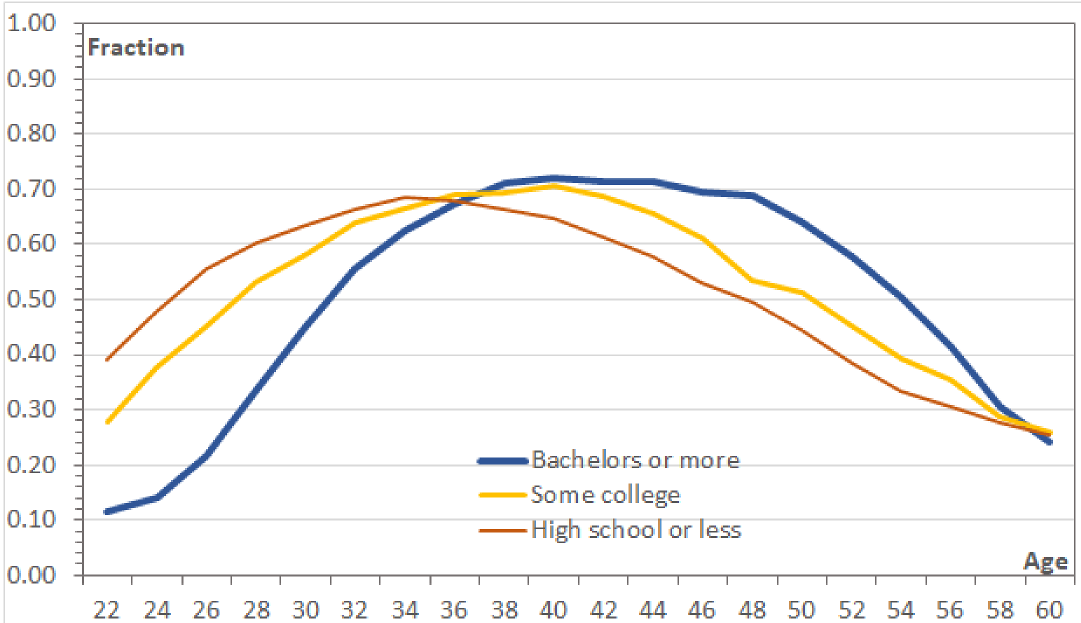
Figure A1: Permanent Migration Rates (Relative to Metro Area at Adolescence) by Education and Age



Notes: Figure reports fraction of individuals from the pooled sample of NLSY79 and NLSY97 respondents who reside in a different metro 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 ages 32 and 42, with the peak occurring later for more-educated individuals. Our evidence in the main text shows 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



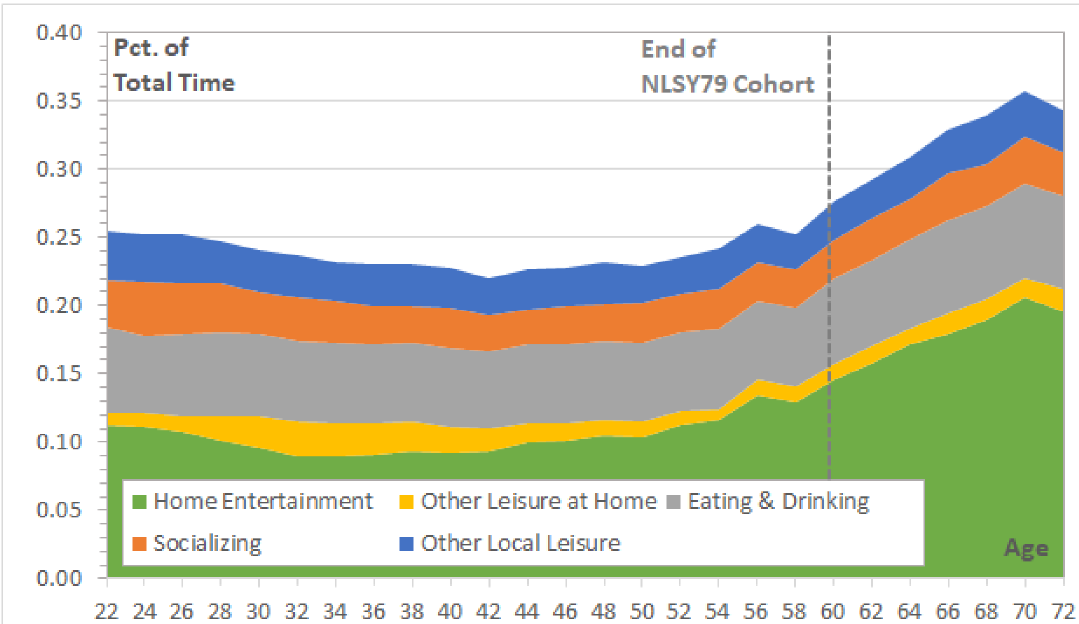
Notes: Figure reports mean number of children in the household by highest degree attained and two-year age bins. Sample is all individuals pooled from the NLSY79 and NLSY97 cohorts.

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 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.

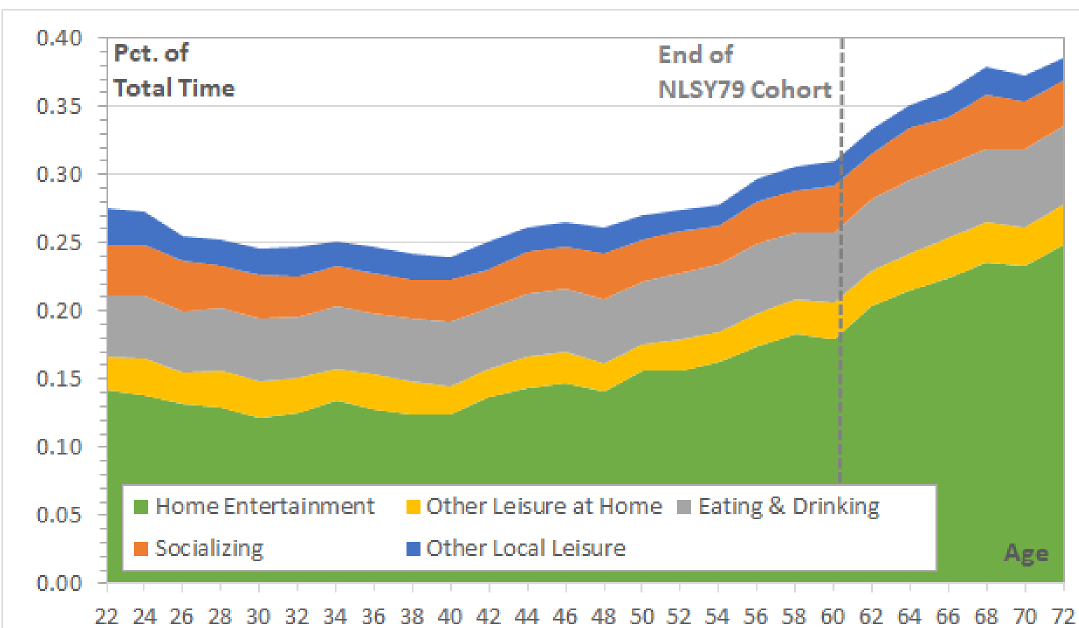
Figure A4 reports the share of expenditures dedicated to leisure activities by expenditures on food and drink at home, other leisure at home, food and drink consumed locally, other local leisure, and leisure on trips. The categories line up with those reported in Table 2 of the main text. Unlike time 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).

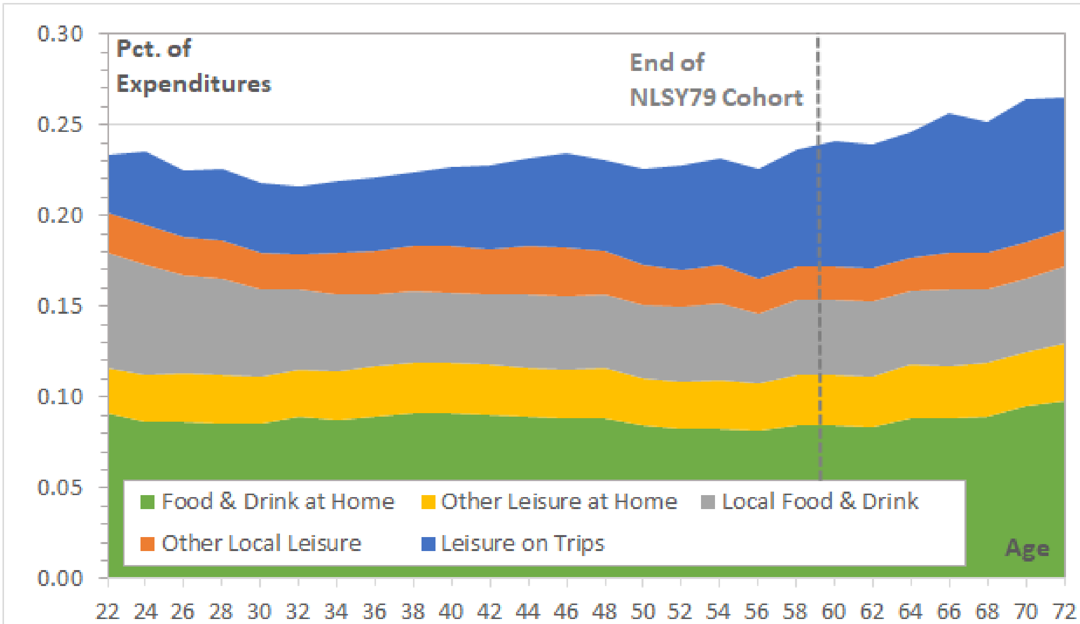
a slight U-shaped pattern with age, while total leisure expenditures for the college educated are roughly flat when they are young and then gradually increase over time starting in their forties, with larger increases after their mid-fifties. The difference is largely driven by a gradual increase in the share of expenditures spent on leisure during trips by the college educated. The expenditure 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 larger than the differences by education. 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 education, but after conditioning out average metro 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. 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 metros relative to the NLSY79 cohort in their 20s and 30s. Finally, the bottom right panel compares the estimates of

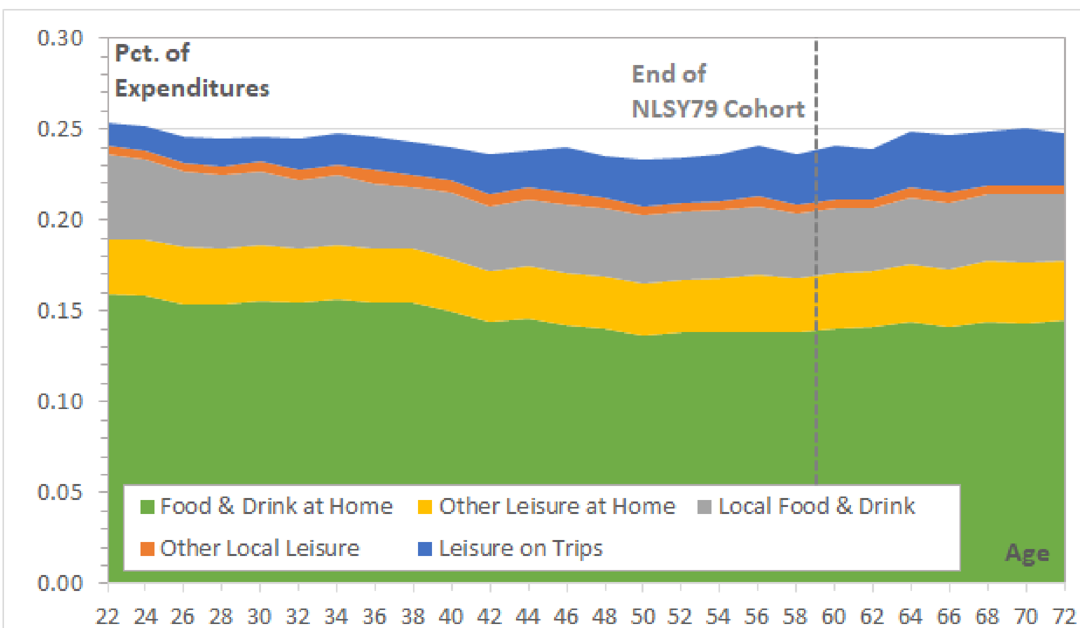
[2]We measure school quality using average reading and math scores from the Stanford Educational Data Archive (SEDA) at the county level, aggregated to our MSA definitions (available at: `https://exhibits.stanford.edu/data/catalog/db586ns4974`). We use data on mean violent and property crimes per capita 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).

quality of life based on data from 1980 and 2000. We restrict the sample to the NLSY79 since it is the only cohort where both years are relevant for their migration decisions. In short, both measures produce qualitatively similar results by education and age. 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 from Diamond (2016).

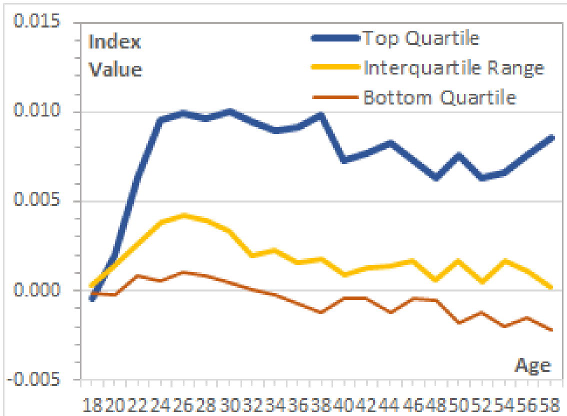
Finally, Table A1 reports the OLS coefficients from the regression of each listed time use category on an intercept term and the quality-of-life index. The top panel reports the results of estimating each regression on a sample of ATUS respondents from the 2003-2019 panel aggregated into the metropolitan or nonmetropolitan portions of each U.S. state. These results correspond to the trendline estimates reported in Figure 6 of the main text. The bottom panel reports the results of estimating each regression on a sample of ATUS respondents from a shorter period, 2016 to 2019, aggregated by Consolidated Business Statistical Area (CBSA). CBSAs represent the latest definitions of metros and are therefore most comparable to our main analyses using the NLSY. They are only available from 2016 forward, however. Reassuringly, we get very similar results for each time-use category across both samples. Compared to the estimates in the table and in Figure 6 of the main text, we find a slight decline in our coefficient estimates in absolute value, but the estimates for leisure away from home and leisure at home retain their sign and statistical significance. This is also true when we restrict our leisure measures to only include activities that one can identify as occurring within the local area (for leisure away from home), or within the home. In our state-metro area sample, the coefficient for the restricted measure of leisure away from home (which only includes time spent on local entertainment, sports, and recreation) is 0.045, compared to 0.075 for the full measure of leisure away from home. For the restricted measure of leisure at home (which only includes time spent on home entertainment, personal time, and relaxation time), the coefficient is essentially unchanged at -0.135.

A.2 Additional Results from the American Community Survey

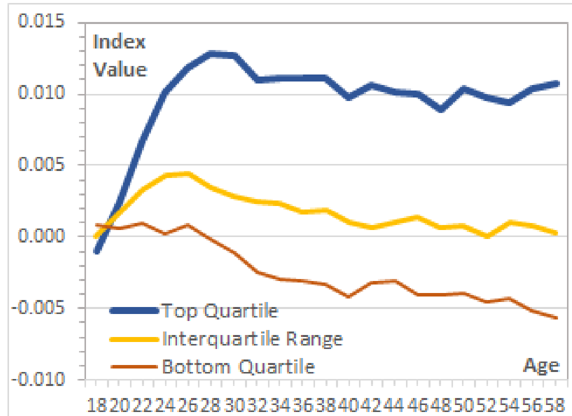
We also replicate our results using pooled microdata from the American Community Survey (ACS). We use the 1 percent Public-Use Micro Sample (PUMS) data for 2005 to 2021. The ACS asks a rich set of questions on demographics, income, and location to the households in its sample,

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

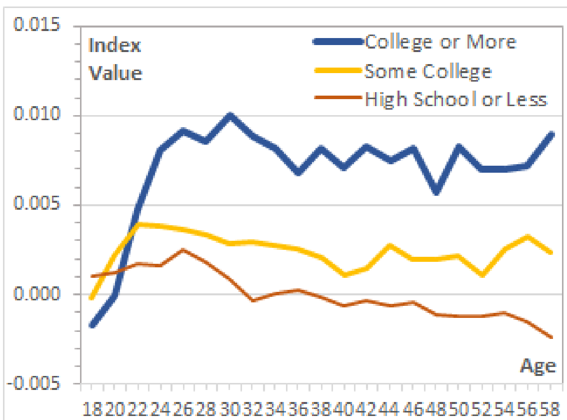
(a) By AFQT Score



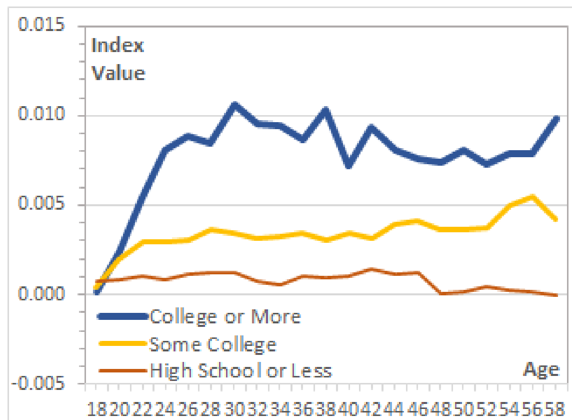
(b) By Avg. Income per HH Member



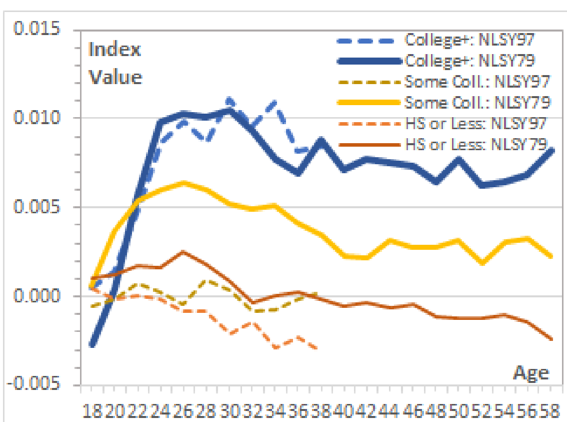
(c) Balanced NLSY Panels



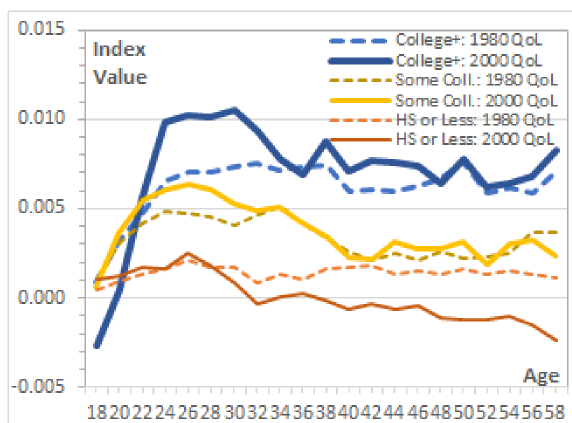
(d) Controlling for School Quality, Crime



(e) NLSY97 vs. NLSY97 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 metro-area 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 metro data.

Table A1: Regression Estimates for Local Quality of Life and Time Use

Dependent Variable:	Leisure Away from Home *All*	Leisure Away from Home *Restricted*	Leisure at Home *All*	Leisure at Home *Restricted*	Home Production	Work Time
Sample: *State metropolitan & nonmetropolitan areas (2003-19)*						
QoL	0.075	0.045	−0.135	−0.136	−0.013	0.053
coefficient	(0.012)	(0.006)	(0.025)	(0.025)	(0.018)	(0.044)
R^2	0.256	0.325	0.265	0.273	0.006	0.028
N			100			
Sample: *Metropolitan CBSAs (2016-19)*						
QoL	0.064	0.030	−0.118	−0.115	−0.026	0.051
coefficient	(0.014)	(0.012)	(0.024)	(0.023)	(0.013)	(0.038)
R^2	0.116	0.124	0.124	0.121	0.011	0.016
N			296			

Notes: The table reports the estimated coefficients from the OLS regressions of the listed dependent variables on our quality-of-life index (using 2000 population as weights). The restricted leisure time away from home only includes time spent on local entertainment, sports, and recreation, and the restricted leisure time at home only include time spent on home entertainment and personal and relaxation time. The top panel reports the estimates using the 2003-2019 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. The bottom panel uses the ATUS sample for 2016 to 2019 matched to quality-of-life estimates by CBSA (the only years for which we have CBSA data in ATUS). Robust standard errors are in parentheses.

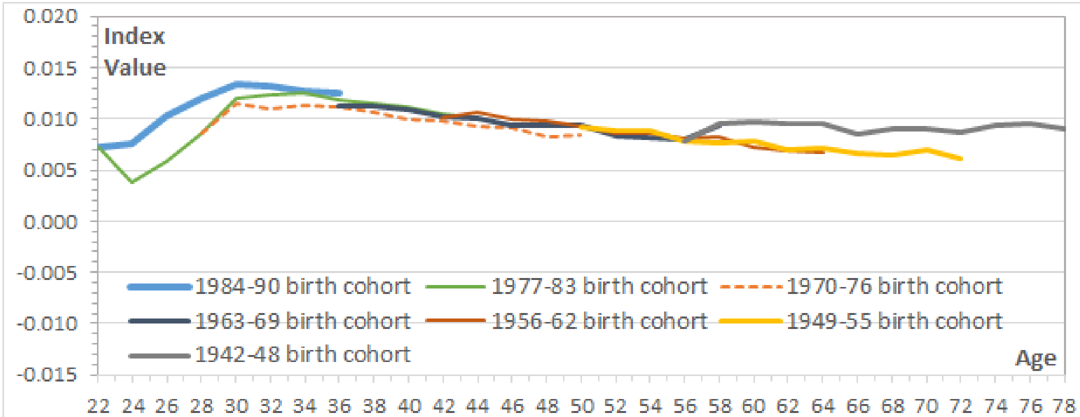
including their location in the current and prior year. The ACS is an imperfect comparison to our NLSY results in that the data are not longitudinal, only follow the location of individuals over a short horizon, and only have information on their household characteristics at the time of the survey interview. 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 our quality-of-life estimates 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, which accounts for cohort-specific differences over the life cycle.

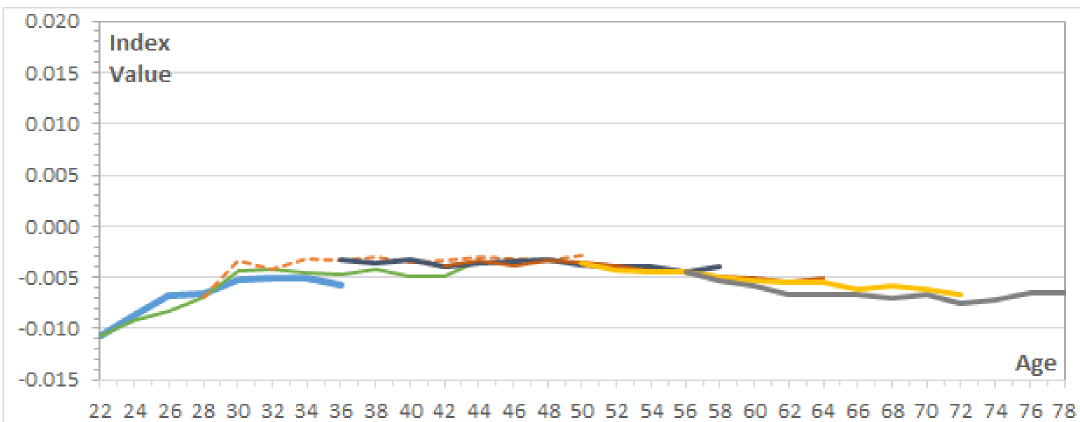
Our results are in Figure A6. The top panel shows the life cycle behavior for those with at least a college degree, the middle panel shows the behavior for those with some college, and the bottom panel shows the behavior for those with a high school degree or less. In short, the figures show very similar patters 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 time, with the hump peaking in their thirties. The estimates are highest 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 A6: Quality of Life over the Life Cycle: American Community Survey Data

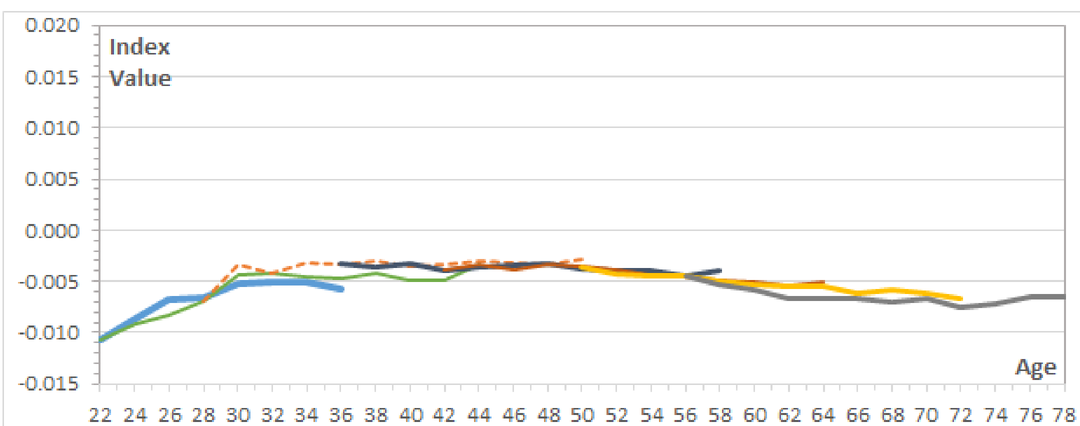
(a) Education: College or More



(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.

B Additional Model Derivations and Results

B.1 Moment Estimates by the Presence of Children

Figure B1 presents the moment estimates used in our model estimation from Figure 9 of the main text aggregated by the presence of children rather than by education. The aggregated moments correspond to the baseline expenditures (in levels) and leisure time in our model evaluation results in Figure 12 of the main text and Appendix Figure B5.

Figure B1 shows roughly similar patterns as those in Figure 9, with some notable variations by the presence of children that are not observed by education. First the hump-shape in tradable and nontradable goods expenditures over the life cycle is present only for those with children. Second, the U-shaped pattern of home leisure time observed in Figure 9 is generally only present for those with children, while the high and declining time spent on local amenities observed in Figure 9 is much more prevalent among those without children. As one might expect, home production time is consistently higher for those with children. Those without children tend to work relatively more earlier in life, while those with children tend to work relatively more later in life. Amenity time costs rise to a relatively higher level for those with children, but level out for those without children in their mid-thirties. Finally, wages rise similarly for both groups, but are somewhat higher for those with children later in life.

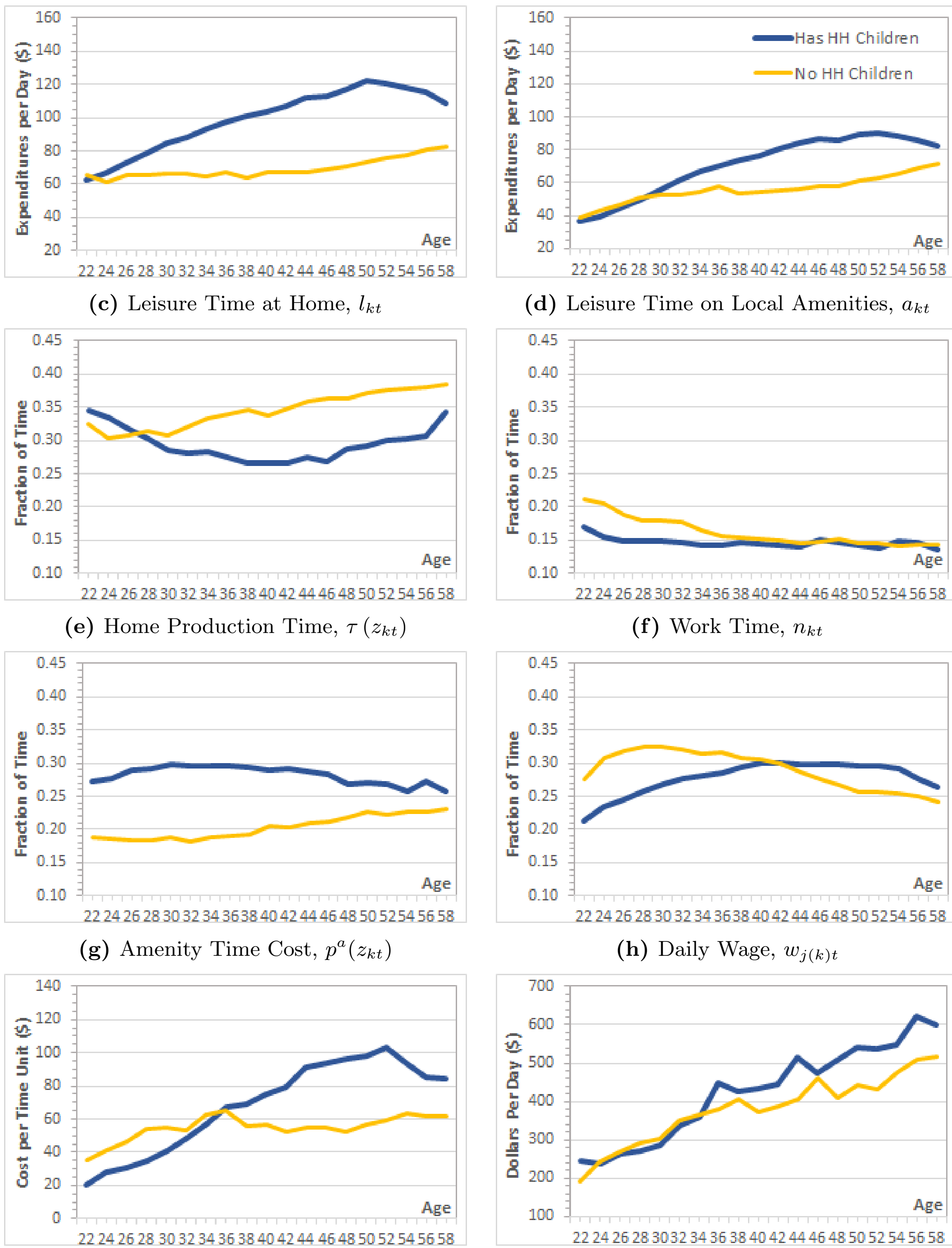
B.2 Estimation of μ_0

We estimate μ_0 in a second step following our GMM estimation. We obtain our estimates of μ_1, γ_1, and η, along with our estimated preference shifters, $\phi^y(z)$ and $\gamma^0(z)$ from the GMM estimation described in the main text. We then use these estimates along with the required data moments to estimate μ_0 using the free mobility condition implied by the indirect utility function of our model. We can express this utility function in closed form as a function of the nontradable goods expenditure, $p_{jt}y_{kt}$,

$$\begin{aligned} V(s_{kt},\cdot;k,z_{kt}) = \phi^x(z_{kt})e^{\phi^x(z_{kt})} + \phi^y(z_{kt})e^{\phi^y(z_{kt})} + \left[e^{\phi^x(z_{kt})} + e^{\phi^y(z_{kt})}\right]\ln A_{j(k)t}(z_{kt}) \\ -e^{\phi^y(z_{kt})}\ln p_{j(k)t} + \mu_0 Q_{j(k)t} + \mu_1 Q^{\eta}_{j(k)t}\left[\ln\mu_1 + \eta\ln Q_{j(k)t} + \ln A_{j(k)t}(z_{kt}) - \ln p^a(z_{kt})\right] \\ + \left(\frac{\gamma_1}{\gamma_1 - 1}\right)e^{\gamma_1\gamma_0(z_{kt})}w^{1-\gamma_1}_{j(k)t}A_{j(k)t}(z_{kt})^{\gamma_1 - 1} + \beta V(s_{k,t+1},\cdot;k,z_{k,t+1}) = \kappa(k,z), \end{aligned} \quad \text{(B1)}$$

where $A_{j(k)t}(z_{kt}) \equiv p_{jt}y_{kt}/e^{\phi^y(z_{kt})}$ is the inverse of the marginal utility of income. The free mobility condition is where all individuals are in their optimal location, given their k and z, which

Figure B1: Life Cycle Behavior of Model Moments by Presence of Children



(a) Expenditures on Tradables, x_{kt}

(b) Expenditures on Nontradables, $p_{jt}y_{kt}$

(c) Leisure Time at Home, l_{kt}

(d) Leisure Time on Local Amenities, a_{kt}

(e) Home Production Time, $\tau\left(z_{kt}\right)$

(f) Work Time, n_{kt}

(g) Amenity Time Cost, $p^{a}\left(z_{kt}\right)$

(h) Daily Wage, $w_{j(k)t}$

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).

occurs where $dV/dQ = 0$. We derive the free mobility condition for our model by totally differentiating equation (B1) with respect to Q and substituting in the full-income budget constraint from equation (1) where appropriate. Keep in mind that our closed-form equation includes y_{kt} is endogenous. Premultiplying the free-mobility condition by Q, we get

$$
\begin{aligned}
Q\frac{dV}{dQ} = w_{j(k)t}\left(1-\tau(z_{kt})\right)A_{j(k)t}(z_{kt})^{-1}\left(\frac{d\ln w}{d\ln Q}\right) - e^{\phi^y(z_{kt})}\ln p_{j(k)t}\left(\frac{d\ln p}{d\ln Q}\right) \\
+\mu_0 Q_{j(k)t} + \eta\mu_1 Q^{\eta}_{j(k)t}\left[\ln\mu_1 + \eta\ln Q_{j(k)t} + \ln A_{j(k)t}(z_{kt}) - \ln p^a(z_{kt})\right] \\
-e^{\gamma_1\gamma_0(z_{kt})}w^{1-\gamma_1}_{j(k)t}A_{j(k)t}(z_{kt})^{\gamma_1-1}\left(\frac{d\ln w}{d\ln Q}\right) = 0.
\end{aligned}
\tag{B2}
$$

We assume that our synthetic panel observations are at their optimum in terms of location choice and goods and time demands. Consequently, we use our data moments to identify the wage, $w_{j(k)t}$, home production time, $\tau(z_{kt})$, local quality of life, $Q_{j(k)t}$, amenity costs, $p^a(z_{kt})$, and nontradable expenditures, $p_{jt}y_{kt}$. We use the price component of our quality-of-life index to identify (log) $p_{j(k)t}$. We use our GMM estimates for the relevant parameters, and identify $\phi^x(z_{kt})$ using our data moments for $\ln p_{jt}y_{kt}$ and $\ln x_{kt}$, our estimates for $\phi^y(z_{kt})$, and their relationship implied by the first-order conditions in equations (2a) and (2b) of the main text. This leaves us with the $\frac{d\ln p}{d\ln Q}$ and $\frac{d\ln w}{d\ln Q}$ terms unidentified. We obtain estimates for both of these by estimating the (log-linear) relationships between the wage and price moments in our synthetic panel and the quality-of-life value in separate regressions. Specifically, we estimate

$$
\begin{aligned}
\ln p_{j(k)t} &= \pi^p_0 + \pi^p_1 \ln Q_{j(k)t} + u^p_{kt} \\
\ln w_{j(k)t} &= \pi^w_{gmc} + \pi^w_{gst} + \pi^w_1 \ln Q_{j(k)t} + u^w_{kt},
\end{aligned}
$$

where π^w_{gmc} is a set of interacted gender $\times$ marital status $\times$ children fixed effects and π^w_{gst} is a set of gender $\times$ education $\times$ age fixed effects. We include these fixed effects to account for the fact that our daily wage estimates depend on demographic and other characteristics that are uncorrelated with location (since they come from the NLSY data and not the wage component of the quality-of-life index). We weight observations in each regression by the sum of their NLSY sample weights. The slope terms in each regression, π^p_1 and π^w_1, give us our estimates for $\frac{d\ln p}{d\ln Q}$ and $\frac{d\ln w}{d\ln Q}$, respectively.

With these in hand, we obtain an estimate of μ_0 with a least-squares fit of equation (B2), again weighting each panel observation by the sum of its NLSY weights.

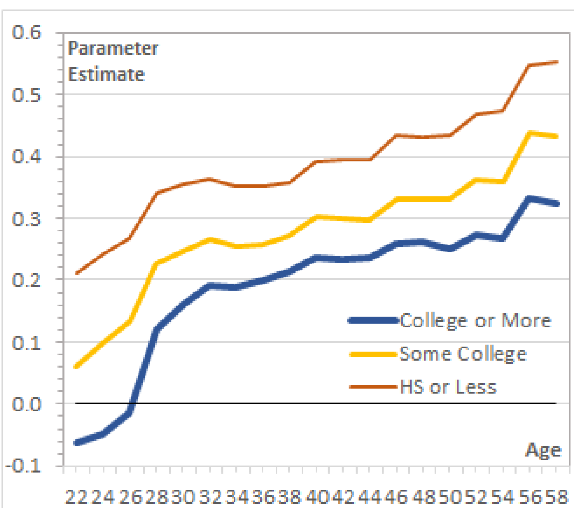
B.3 Additional GMM Estimates and Robustness

B.3.1 GMM Estimates of Preference Shifters

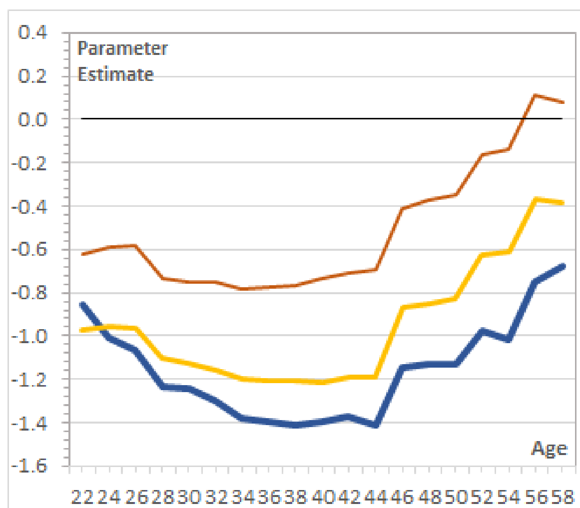
Figures B2 and B3 present our estimated preference shifters aggregated by and and education or the presence of children, respectively. We identify these estimates through the controls for demographics in our GMM estimating equations (equations (5a) and (5b) in the main text). Specifically, let $\hat{a}(z)$ be the vector of predicted estimates from the demographic controls included in (5a) and let $\hat{b}(z)$ be the vector of predicted estimates from the demographic controls included in (5b). Under this notation, our estimated preference shifters are $\phi^y(z) = -\hat{b}(z)$ and $\gamma^0(z) = \frac{1}{\gamma_1}\hat{a}(z) - \hat{b}(z)$. By construction, we recover an estimate of these preference shifters for each observation in our synthetic panel. The figures report the mean preference shifter estimates by education $\times$ age and children $\times$ age, respectively, where the means are weighted by the sum of the NLSY sample weights within each panel cell.

Figure B2: Preference Shifter Estimates by Education

(a) Nontradables Preference, $\phi^y(z)$



(b) Leisure Preference, $\gamma^0(z)$

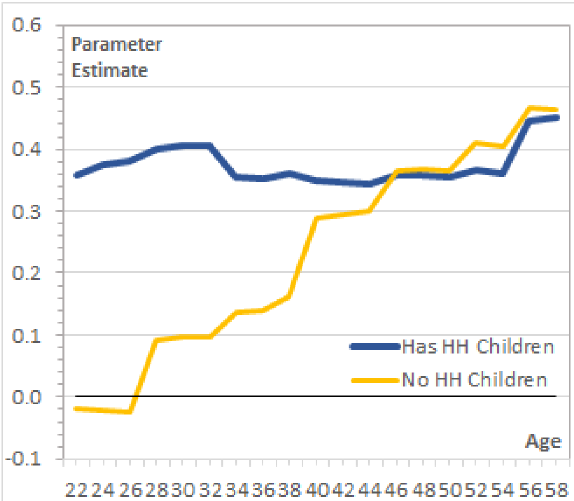


Notes: Figure reports the estimated preference shifters for nontradable goods demand, $\phi^y(z)$, and (total) leisure demand, $\gamma^0(z)$, aggregated into education $\times$ age cells. Estimates are identified through the demographic controls and fixed effects included in our GMM estimation as described in Section 5.1 of the main text.

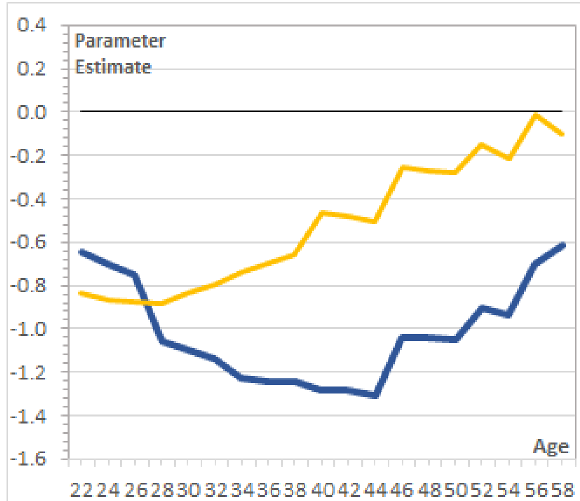
Figure B2 shows that demand for housing (nontradables) is generally rising over the life cycle and decreasing with education. The latter is driven mostly by the fact that housing is a higher *share* of total expenditures for the less educated. The demand for leisure is U-shaped for each education group, with a steady rise from one's mid-forties through age 59. Leisure demand is also decreasing with education. The observed patterns are driven by lower overall work hours for the less educated and by the fact that hours tend to fall later in life despite rising wages.

Figure B3: Preference Shifter Estimates by Presence of Children

(a) Nontradables Preference, $\phi^y(z)$



(b) Leisure Preference, $\gamma^0(z)$



Notes: Figure reports the estimated preference shifters for nontradable goods demand, $\phi^y(z)$, and (total) leisure demand, $\gamma^0(z)$, aggregated into incidence-of-household-children $\times$ age cells. Estimates are identified through the demographic controls and fixed effects included in our GMM estimation as described in Section 5.1 of the main text.

Figure B3 shows that demand for housing is rising over the life cycle for those without children, but is higher and relatively constant for those without children. Preferences for housing for the two groups converge by their mid-forties. The demand for leisure is U-shaped over the life cycle for those with children, but consistently rising over the life cycle for those without children. For all but their early twenties, those without children demand more leisure than those with children. This is partly accounted for by the fact that those without children devote less time to home production, and therefore have a greater time endowment to allocate to both work and leisure time.

B.3.2 GMM Estimates Under Alternative Model Specifications

The preference shifters reported in the previous subsection come from the interaction of martial status and the presence of children with a set of broad age-category fixed effects, along with those fixed effects alone and other demographic controls (described in the main text). We experimented with alternative specifications for these preference shifters, using various combinations of age trends interacted with an dummy variable and/or a break in the trend for those aged 40 or more. The specification we use in our baseline estimation (and described in the main text) generally provides a better fit of the data, with more precise parameter estimates. Table B1 reports the results of our GMM estimation using these alternative preference-shifter specifications. All specifications include a time trend in age with a break for those aged 40 or more and a dummy variable (i.e., level effect) for those aged 40 or more. The first column additionally interacts marital status and the presence of children with the dummy variable for those aged 40 or more. The second column includes this interaction plus an interaction with the time trend for those aged 40 or more. The third column includes their interaction with the time trend for all ages, including the break in the trend for those aged 40 or more. The fourth column includes their interaction with the full time trend (including the break) and the dummy variables for ages 40 and over. While all specifications generally perform worse than the specification used in the main text, all also generally produce comparable parameter estimates to those for our baseline model.

Table B1: Estimated Model Parameters Using Alternate Preference Specifications

Parameter	(1)	(2)	(2)	(4)
$\hat{\gamma}_1$, (negative) leisure elasticity	0.151	0.136	0.455	0.626
	(0.077)	(0.076)	(0.138)	(0.181)
$\hat{\mu}_0$, utility from local quality of life	11.58	10.86	8.72	9.21
	(0.16)	(0.16)	(0.18)	(0.17)
$\hat{\mu}_1$, scaling parameter on amenity complementarity	0.245	0.238	0.217	0.214
	(0.024)	(0.024)	(0.019)	(0.019)
$\hat{\eta}$, exponential parameter on quality of life	5.96	5.16	2.12	3.39
	(1.99)	(2.12)	(1.53)	(1.57)
Test for Overidentifying Restrictions, p-value	0.460	0.448	0.432	0.337
Interactions w/ marital status, children	Dummy for age 40+	Dummy & time for age 40+	Time trend w/ break	Dummy for age 40+, time trend w/ break

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 × age cells. All specifications include an age trend with a trend break for those aged 40 or more and a dummy variable for those aged 40 or more, in addition to the listed interactions by marital status and presence of children. Standard errors are in parentheses. See text for details.

B.3.3 Baseline Model Estimates by Selected Demographic Groups

In this section, we present estimates from our model estimated separately for each gender and education category. Specifically, we estimate our baseline model on subsets of our synthetic panel using GMM to obtain our initial set of parameters and the free-mobility condition, evaluated at $dV/dQ = 0$, to obtain μ_0. Our results are in Table B2. In general, we obtain similar parameter estimates by gender and by education, with some notable differences for our complementarity estimates. In particular, we find that women have a higher estimate of the elasticity of amenity time with respect to quality of life than men, though the difference is not statistically significant. We also find that the elasticity estimate rises with education, though only the college educated have an estimate that is significantly different from zero.

Table B2: Estimated Model Parameters for Selected Demographic Subsamples

	Gender		Education		
Parameter	**Men**	**Women**	**High School**	**Some College**	**College**
$\hat{\gamma_1}$, (negative) leisure elasticity	0.328	0.317	0.201	0.365	0.150
	(0.112)	(0.068)	(0.106)	(0.104)	(0.070)
$\hat{\mu_0}$, utility from local quality of life	7.02	9.53	7.12	8.79	8.77
	(0.13)	(0.09)	(0.11)	(0.20)	(0.20)
$\hat{\mu_1}$, scaling parameter on amenity preference	0.176	0.170	0.164	0.223	0.193
	(0.024)	(0.014)	(0.017)	(0.016)	(0.030)
$\hat{\eta}$, exponential parameter on quality of life (complementarity)	4.17	6.62	1.35	1.84	6.17
	(1.76)	(2.72)	(2.54)	(1.58)	(3.68)
Test for Overidentifying Restrictions, p-value	0.540	0.357	0.896	0.574	0.821
N	217	228	152	151	142

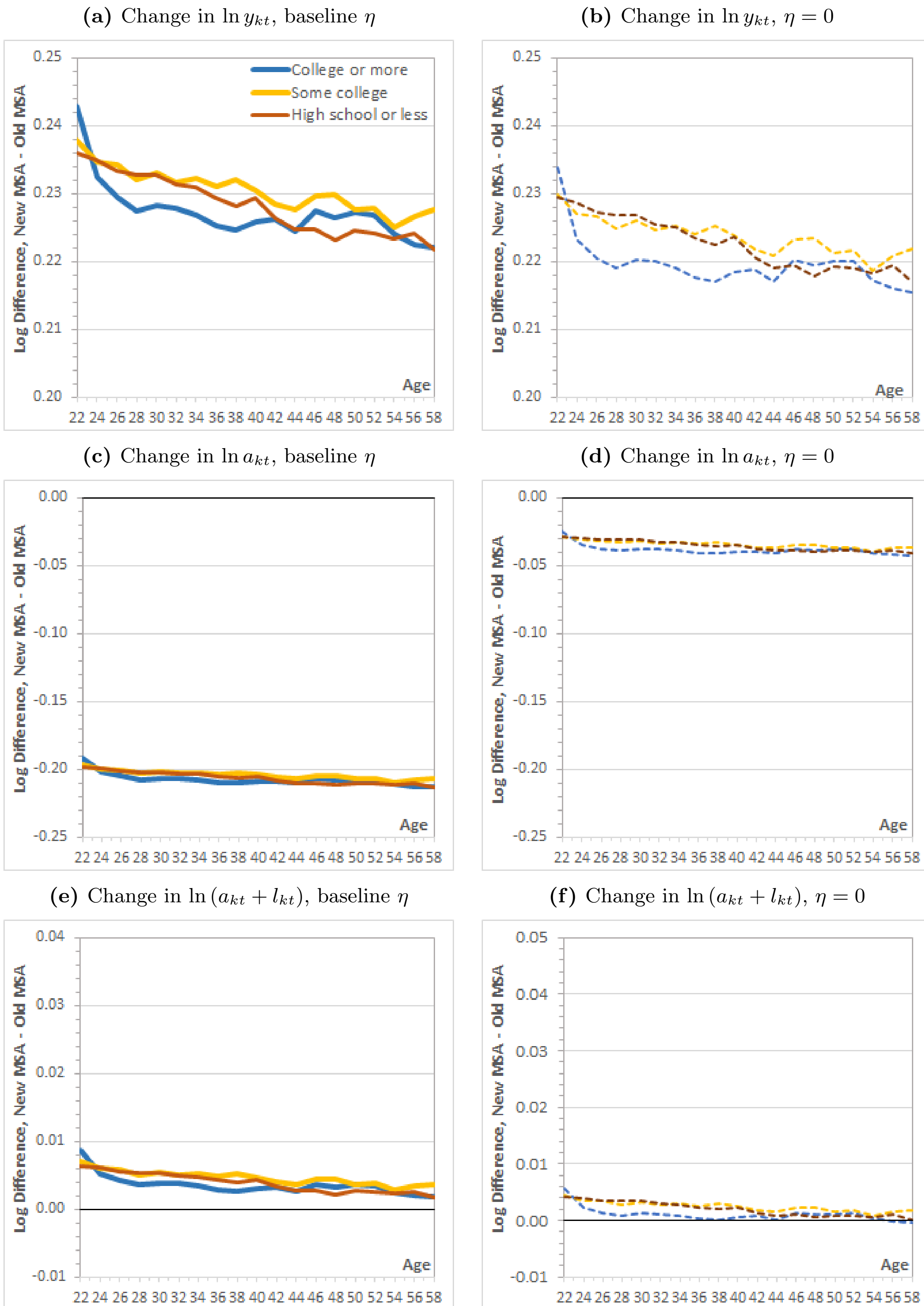
Notes: Table reports the parameter estimates from the GMM estimation of our model on a set of expenditure, time use, income, and local quality of life moments from subsets of a synthetic panel of demographic × age cells. Standard errors are in parentheses. See text for details.

B.4 Additional Results for Model Evaluation

This section reports the results of moving households to a one-standard deviation lower quality-of-life metro area. The exercise is the same as the one described in the main text, save that individuals now move to a worse location, in terms of its quality of life. In this exercise, we impose a 4.9 log point decrease in Q_{jt}, a 25.1 log point decrease in p_{jt}, and a 4.2 log point decrease in w_{jt}. We then re-estimate the goods and leisure demands, given these values, in versions of our model with and without the complementarity between quality-of-life and amenity time.

The results are in Figures B4 and B5. The results show symmetrical patterns to the demand changes reported in Figures 11 and 12 in the main text. Individuals respond to the move by increasing their housing (nontradable) demand, though their total housing expenditure falls somewhat. They consume slightly more total leisure, implying a reduction in labor supply, and reallocate their leisure time away from going out towards enjoying leisure at home. For the latter, they do so much more in our baseline model where the complementarity is included than in the counterfactual model where we set $\eta = 0$.

Figure B4: Demand Changes in Response to Moves to Lower-Q_{jt} Metro Areas, by Education



(a) Change in $\ln y_{kt}$, baseline η

(b) Change in $\ln y_{kt}$, $\eta = 0$

(c) Change in $\ln a_{kt}$, baseline η

(d) Change in $\ln a_{kt}$, $\eta = 0$

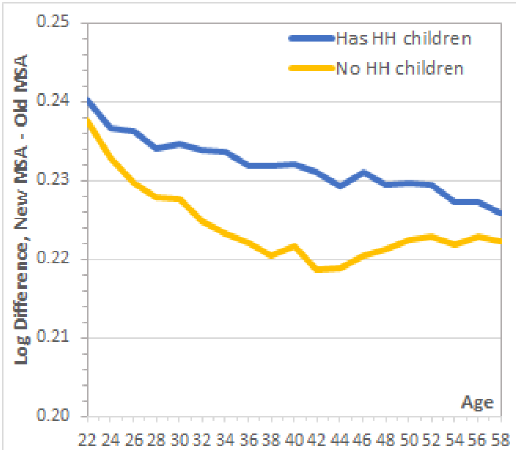
(e) Change in $\ln (a_{kt} + l_{kt})$, baseline η

(f) Change in $\ln (a_{kt} + l_{kt})$, $\eta = 0$

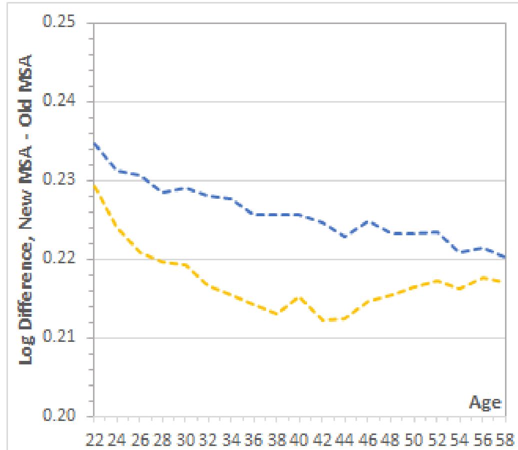
Notes: Figure reports the (log) change in nontradable demand, amenity time, or total leisure time in response to a counterfactual move to a one-standard deviation lower quality-of-life metro area. The moves represent a 4.9 log point decrease in Q_{jt}, a 25.1 log point decrease in p_{jt}, and a 4.2 log point decrease in w_{jt}. Estimates are aggregated across all synthetic panel cells by education. The right panels report the demand changes in our baseline model, while the left panels report the demand changes where we shut down the complementarity between Q_{jt} and amenity time by setting $\eta = 0$.

Figure B5: Demand Changes in Response to Moves to Lower-Q_{jt} MSAs, by Presence of Children

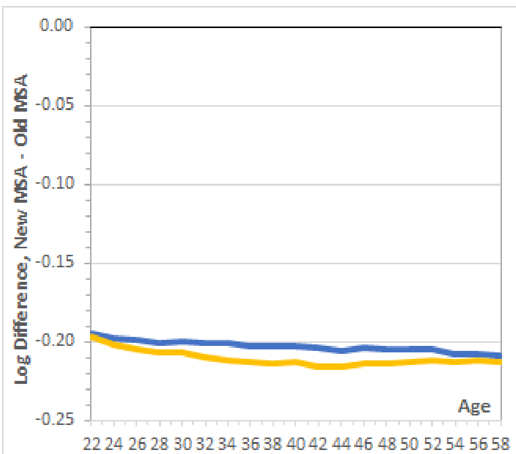
(a) Change in $\ln y_{kt}$, baseline η



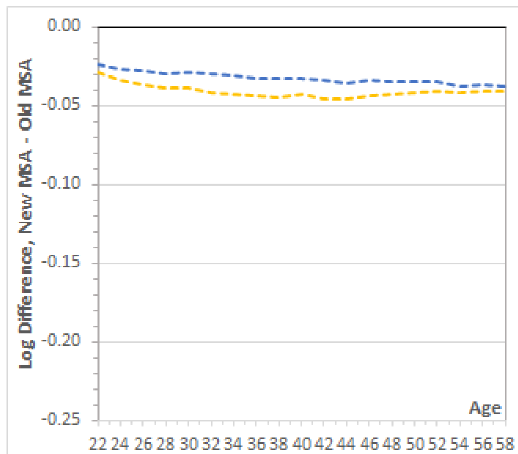
(b) Change in $\ln y_{kt}$, $\eta = 0$



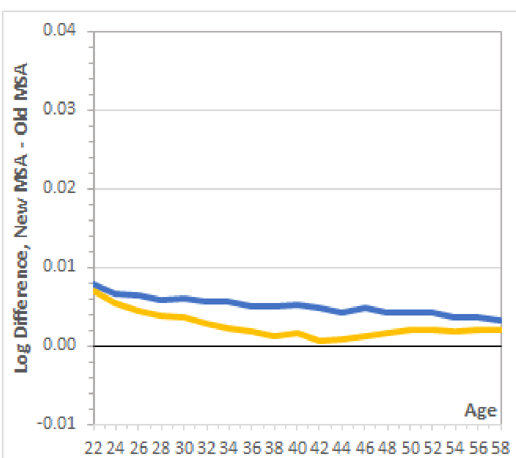
(c) Change in $\ln a_{kt}$, baseline η



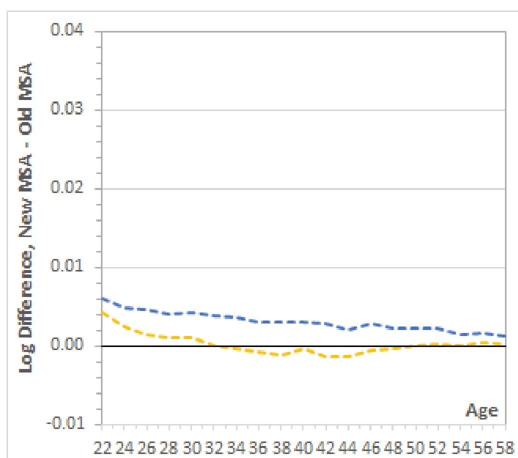
(d) Change in $\ln a_{kt}$, $\eta = 0$



(e) Change in $\ln (a_{kt} + l_{kt})$, baseline η



(f) Change in $\ln (a_{kt} + l_{kt})$, $\eta = 0$



Notes: Figure reports the (log) change in nontradable demand, amenity time, or total leisure time in response to a counterfactual move to a one-standard deviation lower quality-of-life MSA. The moves represent a 4.9 log point decrease in Q_{jt}, a 25.1 log point decrease in p_{jt}, and a 4.2 log point decrease in w_{jt}. Estimates are aggregated across all synthetic panel cells by presence of household children. The right panels report the demand changes in our baseline model, while the left panels report the demand changes where we shut down the complementarity between Q_{jt} and amenity time by setting $\eta = 0$.