Measuring Inequality with Consumption Time

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Abstract

I construct a measure of consumption/leisure inequality from a model featuring Becker (1965) home production. Consumers simultaneously allocate liquid resources toward many different market purchases and time toward both market tasks (labor) and many different off-market activities. Each activity is uniquely associated with products purchased from the market. I use micro data on household time use and spending to quantify the degree to which households across the income distribution value the activities in which they spend time consuming. This measure is fundamentally different from a classic expenditure measure because it accounts for a household's simultaneous decision to allocate both liquid resources and time toward specific consumption activities. Model-implied dispersion is 3 to 7 times lower than that implied directly by expenditure data and over 2.5 to 5.5 times lower than that implied by wages.

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1 Introduction

A robust measure of consumption/leisure inequality is among the most elusive of pursuits in economics (Díaz-Jiménez, Glover, and Ríos-Rull 2011). Building on empirical evidence that households across the wage distribution spend their income and their off-market time in different ways, I construct a measure of consumption/leisure inequality that accounts for rich heterogeneity in consumption and time-use patterns for a broad partition of commodity groups across a diverse set of households. Owing to heterogeneity in consumption and time-use allocations across the income distribution, I find that different types of market products are complementary with off-market time inputs to varying degrees. By constructing utility and price indices that account for these differences, I show that welfare measures which account for time-use heterogeneity across product types are substantially less disperse than traditional wage, income, and expenditure measures of welfare.

Two fundamental questions motivate this paper. First, how do consumers' time allocations differ across the wage distribution, and what might such differences imply for inequality? Second, when accounting for both differences in the degree to which different consumption products are complementary with off-market time, how do inferences pertaining to welfare inequality change, especially when compared to measures of inequality derived from income and expenditure data? As a corollary to this question, I also explore how welfare measures differ between a model that accounts for product-level time-use heterogeneity (i.e., a model with multiple market products and multiple off-market time-use decisions) versus a model that features just a single consumption good and leisure.

To answer these questions requires a model that is flexible enough to capture the various consumption and time-use linkages associated with household decision-making. For this, I turn to the original home production conceptualization of Becker (1965) where every consumption decision is also associated with a joint time-use decision. That is, consumers cannot derive utility from a consumable market purchase unless they also simultaneously allocate some of their time toward *using* that purchase. The model implicitly treats households as singular, autonomous production units which generate non-tradable final consumption produced with the products they buy on the market and their own time. Indeed, for most households time is their most freely tradable asset. Households trade time for market resources and can substitute their off-market time for market services when engaging in certain activities. As wages rise, the opportunity cost of consumption activities also rises. That is, the value of engaging in off-market activities relative to work activities increases as the value of consumers' time rises. Yet, in order to enjoy off-market activities consumers must allocate market resources (income) toward procuring products that make those activities possible. In this paper I explore this classic consumption/leisure trade-off in a model where consumers may have preferences over not just a single consumption and a single leisure good, but a vector of heterogeneous consumption products and a vector of activities associated with those products to which they must allocate off-market time.

Attanasio and Pistaferri (2016) argue that to truly understand requires understanding the value consumers attach both to consumption and various off-market activities. To do this I deploy a Becker (1965) model, where every market purchase is also associated with a unique time-use decision. This model is also discussed in Aguiar and Hurst (2016) and explored in Fang, Hannusch, and Silos (2021) and Fang, Hannusch, and Silos (2022). The goal of this paper is most similar to the goals of Boerma and Karabarbounis (2021) and Fang, Hannusch, and Silos (2021) who each measure inequality through the lens of a Becker (1965) home production model. Fang, Hannusch, and Silos (2021) focus on the role that changes to relative prices of necessities versus luxuries play in driving the evolution of welfare inequality. Boerma and Karabarbounis (2021), in using a partially Beckerian model where home goods are produced using only time, so that explicit market-input and time-use complementarities are not considered, find that accounting for home production amplifies measures of inequality. I find the opposite, and by comparing my inequality results from a model with multiple off-market activities to one with strict consumption/leisure, I show how not accounting for multiple different linkages between market inputs and time-use can possibly lead to spurious inferences.

My findings appear to rhyme with results in Kopytov, Roussanov, and Taschereau-Dumouchel (2020) and Aguiar et al. (2021). Kopytov, Roussanov, and Taschereau-Dumouchel (2020) present strong evidence that increases in the allocation of time to leisure activities, which I call recreation, likely result from the declining relative price of leisure goods, suggesting consumption and time-use complementarities are at work. Aguiar et al. (2021) present a similar finding regarding the labor force participation decisions of young men. Engaging in a similar, but more general, exercise in spirit, I consider more dis-aggregated product and activity spaces, allowing for even richer relationships between price and income variation and the allocations of consumption and time.

Aside from a very new set of papers aimed at examining inequality and analyzing leisure time allocations through a home production lens, this paper is also in conversation with a series of papers that explore different aspects of consumption/leisure inequality. Krueger and Perri (2006) provide an explanation, rooted in the increasing efficiency of credit markets, for why the consumption distribution has fanned out slower than the income distribution. Heathcote, Perri, and Violante (2010) affirm their results. However, Aguiar and Bils (2015) break down expenditure by luxuries versus necessities and find that consumption inequality has more closely tracked income inequality than previously thought. I add to this literature by accounting for joint time-use and expenditure decisions over a relatively finer partition of activities.

Of course, the work featured here is also closely related to a long line of papers which grapple with topics under the umbrella of "home production." The term "home production" is often used to characterize a wide range of models with various features, though most models do not directly account for the time consumers must allocate toward the utilization of market services. Generally, it is assumed that only one particular type of market purchase is combined with time to yield final in-home consumption (Bernanke 1985; Greenwood and Hercowitz 1991; McGrattan, Rogerson, and Wright 1993; Greenwood, Rogerson, and Wright 1995; Rupert, Rogerson, and Wright 1995; Gomme, Kydland, and Rupert 2001; Greenwood, Seshadri, and Yorukoglu 2005; Goolsbee and Klenow 2006; Ngai and Pissarides 2008; Bridgman, Duernecker, and Herrendorf 2018; Boppart and Krusell 2020). An alternative set of papers features home production models where a subset of market products are inputs into some technological process that does not admit time as an input but often features an exogenous productivity component (Gronau 1977; Graham and Green 1984; Benhabib, Rogerson, and Wright 1991; Ingram, Kocherlakota, and Savin 1997; Boerma and Karabarbounis 2021). My set-up most closely follows the original Becker (1965) set-up, as well as the recent models in Fang, Hannusch, and Silos (2021) and Fang, Hannusch, and Silos (2022), and the more general set-up advocated for by Aguiar and Hurst (2016).

This paper proceeds as follows. In the next section i discuss some features in United States (U.S.) micro data which suggest that the degree to which consumption and off-market time use are complementary depends on the product and activity being considered. In Section 3 i then present and analyze a Beckerian model of home production that allows for differential consumption and time-use complementarities. In Section 4 I estimate a parameterized version of the model from Section 3. This yields inferences regarding how households across the wage distribution value their consumption activities differently. I then apply the model estimates to compare home-production-based measures of welfare dispersion with income and expenditure measures easily computed from publicly-available micro data.

2 Data

To understand how expenditure and time-use patterns vary across U.S. consumers, I turn to two widely-used and publicly-available data sources from the Bureau of Labor Statistics: 1) the Consumer Expenditure Survey's Public Use Micro Data (CEX-PUMD); 2) the American Time Use Survey (ATUS). The focus here is on measuring heterogeneity in expenditure and time-use patterns from 2003-2018, since the ATUS begins in 2003, and expenditure categories were partially re-classified in the CEX-PUMD after 2018, making comparison of data after 2018 to data before 2018 problematic.[1]

The goal in this section is to present a picture of how consumers of different incomes spend their money and their time. Given such data observations, I first examine whether consumption and time-use patterns for consumers at different implied hourly-wage quintiles changed over time from 2003-2018.[2] I then ask several questions. How do consumers at different income levels spend their money and their time? Specifically, are there differences across the income distribution with respect to the time and consumption shares associated with different activities? Given heterogeneity that may be observed with respect to expenditure and time-use behavior across broad consumption categories, how is variation across more granular components that comprise the broad categories' underlying activities driving this observed heterogeneity? Further, is there greater heterogeneity, and thus inequality, for certain types of consumption expenditure and for time spent engaged in certain types of off-market tasks than others?

Given the CEX-PUMD and ATUS are separate, independent surveys, I must construct a dataset of synthetic consumers with matched spending and time-use profiles.[3] Descriptions of the procedures used to both select a sample of working-age (age 25-65) consumers

[1]See the errata note listed here: https://www.bls.gov/cex/pumd_errata_2019_2020.htm. Despite the fact that the BLS claims the spurious expenditure classifications in the 2019 and 2020 surveys have been corrected, we find that expenditure share estimates for 2019 and 2020 are suspiciously different from those in all previous years. We thus choose to leave these years out from our sample. For more information contact the author: npretnar@ucsb.edu.

[2]The implied hourly-wage is the average hourly rate of pay for a consumer. For hourly consumers this is just their posted wage, but for salaried consumers we must compute this value by dividing weekly income by weekly hours.

[3]Boerma and Karabarbounis (2021), who also analyze joint expenditure and time-use decisions, rely on synthetically matched data from the CEX-PUMD and ATUS, though the process I use to match the data will be different. Boerma and Karabarbounis (2021) grapple with measuring inequality over the life-cycle (by age) rather than comparing measures of dispersion cross-sectionally over time.

and match the two datasets are in Technical Appendix A.[4,5] The analyses are conditioned on workers who earn positive weekly income. I abstract from accounting for adults out of the labor force or unemployed.[6] I do this because the productivity level of unemployed workers is unobservable, since their hourly wage rates are unobservable. As will become apparent, knowing a worker's market productivity via their hourly rate of income is important in order to quantify their opportunity costs of spending time participating in various off-market activities. This is true for both workers who are paid hourly and those who are salaried.

2.1 Broad Activity Category Classification

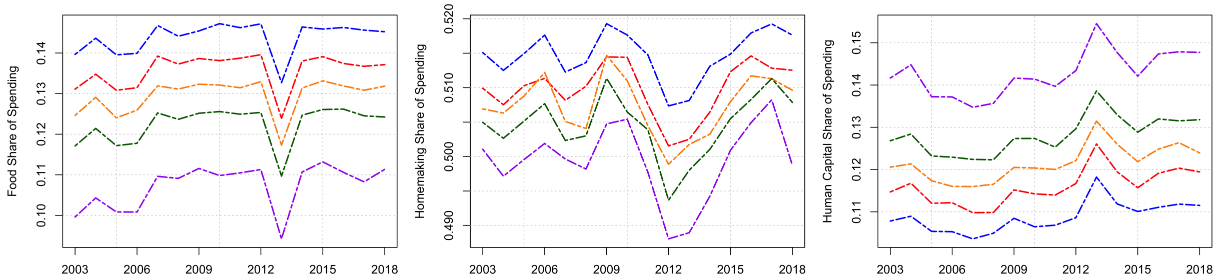
I consider two hierarchies of activity categories into which expenditure and time allocations are classified — 1) a broad-category classification; 2) a more dis-aggregated narrow category classification. Technical Appendix A contains a description of how the raw CEX-PUMD expenditure categories and the ATUS time-use categories are mapped into their respective categories. In the broad-category classification hierarchy we consider five expenditure bins: 1) Food; 2) Homemaking including Personal Care; 3) Human Capital including Childcare; 4) Recreation; 5) Travel. In addition to the five expenditure bins, I consider seven time-use bins: 1) Eating Food; 2) Homemaking including Personal Care Time; 3) Human Capital including Childcare Time; 4) Recreation; 5) Travel; 6) Sleep; 7) Work.

Figure 1 shows weighted average, broad-category expenditure shares by implied hourly-wage quintile in (a) through (e) and personal consumption expenditure (PCE) price in-

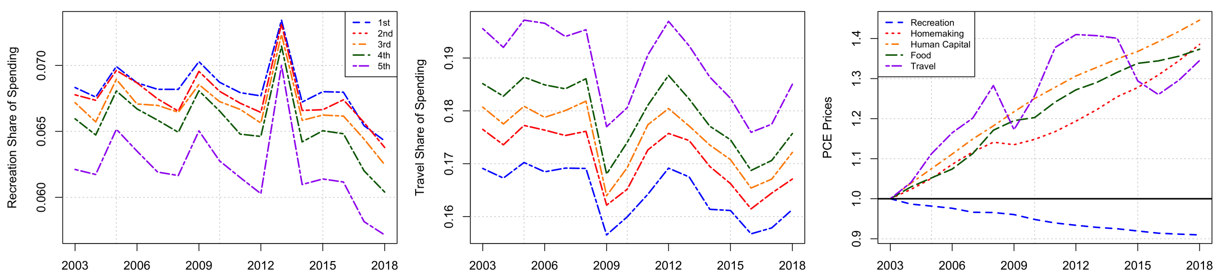
[4] All Technical Appendices are available at the author's website: https://www.npretnar.com/research.

[5] To summarize, I project household shares of income estimated from the CEX-PUMD into the ATUS for all of our activity-categories of interest. I then match consumers by income, hourly wages, fraction of time working, age, metropolitan-area indicator, geographic-region indicator, educational attainment, sex, race, family type, and year. Expenditure data is thus synthetic, while time-use data is raw data from the ATUS.

[6] Readers should thus be cautious when placing the results here in the context of how business cycles affect time-use and welfare outcomes, as is done in Aguiar, Hurst, and Karabarbounis (2013). Rather, when comparing the time-use and expenditure data, distributional changes should be interpreted as distributional changes to outcomes for employed workers of different human capital levels, *not* distributional changes for all working-age adults. This is because the selection procedure used here biases results toward workers who maintain at least part-time employment throughout the Great Recession. Such a bias should not be problematic and elicit skepticism with respect to the results in this paper, since ultimate goal is to measure the degree to which inequality, when accounting for time to consume, is simply different from measures which focus purely on spending and/or income.



(a) Food Expenditure (b) Homemaking Expenditure (c) Human Capital Expenditure

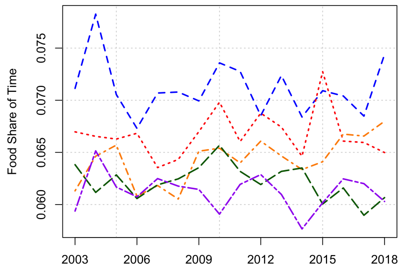


(d) Recreation Expenditure (e) Travel Expenditure (f) PCE Price Indices

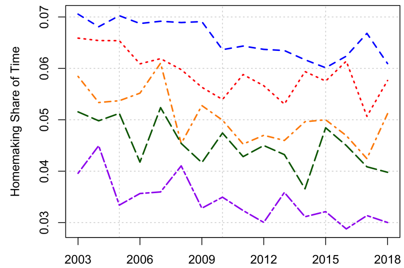
Figure 1: Panels (a) through (e) show weighted average expenditure shares by wage quintile from 2003-2018. The wage quintile legend is in panel (d), where "1st" corresponds to the lowest quintile. Panel (f) features broad-category price indices relative to a 2003 base year. Note, due to weighting the series may not sum exactly to one within each quintile and year pair.

dices for the corresponding expenditure categories in (f).[7] Figure 2 shows weighted average, broad-category time-use shares by implied hourly-wage quintile. There are three big takeaways to point out upon first observing both expenditure and time-use time series of micro data. First, expenditure and time-use shares are both subject to clear cross-sectional income effects. Further, for some categories the expenditure and time-use income effects are positively correlated and for others they are negatively correlated. Second, even for working-age adults who remain attached to the labor force the years around the Great Recession are associated with large swings in expenditure shares but not time-use shares. Third, higher-income workers spend more time working and less time doing everything else, including sleeping, than their lower-income counterparts. These facts suggest that

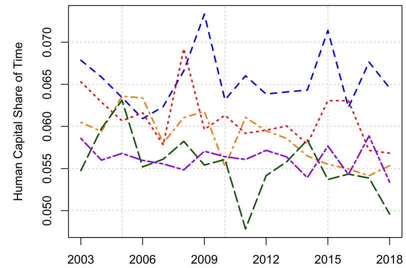
[7]Price indices are computed using expenditure and price data from the Bureau of Economic Association's (BEA) National Income and Product Accounts (NIPA). Specifically, I follow the procedures outlined in Whelan (2000) and Whelan (2002) and the appendices of Herrendorf, Rogerson, and Valentinyi (2013) and Bednar and Pretnar (2022) to unwind the chain-weighted price indices for categories in the underlying-details tables — NIPA Tables 2.4.4U and 2.4.5U. I then reconstruct aggregated category price indices for the five broad-category expenditure bins. Supplementary Materials available on the author's website contain a detailed NIPA/CEX-PUMD/ATUS task and consumption mapping table, which links the NIPA consumption categories with both the CEX-PUMD expenditure categories and ATUS task categories. See https://www.npretnar.com/research.



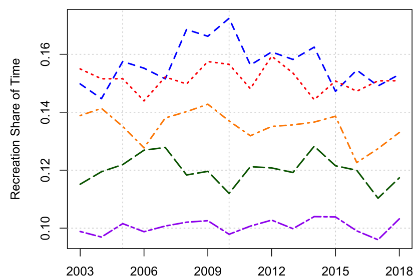
(a) Food Time (eating)



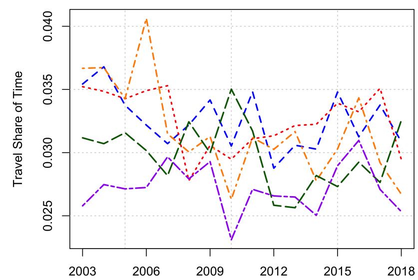
(b) Homemaking Time



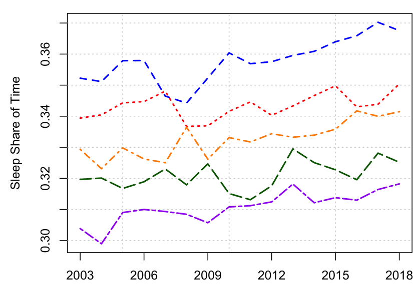
(c) Human Capital Development Time



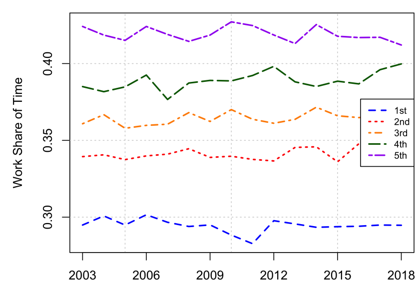
(d) Recreation Time



(e) Travel Time



(f) Sleep Time



(g) Work Time

Figure 2: Time shares are shown in all panels. Again, due to weighting, the series may not sum to one within each quintile and year pair. The wage quintile legend is in panel (g) where "1st" corresponds to the lowest quintile.

any model of joint consumption and time-use decisions will need to be flexible enough to accommodate differences in within-category elasticities of substitution between consumption and time use, as well as differences in the factor shares of market-purchase inputs (e.g., expenditure) versus time-use inputs in the separate production processes associated with the different activity categories.

Differences in patterns of cross-sectional heterogeneity with respect to expenditure and time use suggest that the rate of substitution between consumption and time use within activity category j is different than the rate of substitution between consumption and time use within activity category $j' \neq j$. Comparing the average (over time) levels of expenditure and time use across implied hourly-wage quintiles, notice that lower-income consumers spend a relatively (compared to higher-income consumers) lower share of expenditure on travel in Figure 1e but a relatively higher share of time on travel in Figure 2e. Human capital expenditure and time allocation follow the opposite pattern: higher-income consumers spend a relatively higher share of wallet on human capital development, but lower-income consumers spend a relatively higher share of time. Shares of food, homemaking, and recreation expenditure and time-use, however, have the same cross-sectional patterns: higher-income consumers spend a smaller share of wallet and time than their lower-income counterparts. In focusing on the years immediately preceding and following the Great Recession, notice that human capital and recreation shares of expenditure rose during the recovery period across all working quintiles, while travel, food, and homemaking shares of expenditure all fell. The drop in travel expenditure for working adults appears to be a leading recessionary indicator while falling food expenditure seems to lag. These facts make sense: travel and recreation are largely discretionary. The spikes in shares across all quintiles for travel and recreation in the years following the Great Recession suggest that perhaps consumers had pent up demand for these discretionary categories, after having pulled back on their expenditure during the recession.

Despite the apparent relationship between discretionary spending shares and business cycles, no such relationship seems to exist for time use.[8] Why might this be? Income shocks may affect consumption and time-use allocations in different ways, further highlighting the importance of allowing for heterogeneity in the degree to which spending is affected by income, while also allowing for cross-sectional differences in time-use shares across categories.

[8]Note that this relationship does not exist for *workers*, which suggests readers should be cautious making a direct comparison between the findings here and those in Aguiar, Hurst, and Karabarbounis (2013), who focus on how excess hours from foregone market work due to a recession are allocated to off-market tasks.

Table 1: Shares of Broad Category Expenditure and Time Use by Wage Quintile (2003)

		Expenditure					*Time Use*				
		1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Food	Eating Out incl. Alcohol Consumption	0.181	0.228	0.252	0.282	0.333	0.023	0.025	0.022	0.021	0.029
	Making & Eating Meals at Home incl. Alcohol Consumption	0.819	0.772	0.748	0.718	0.667	0.977	0.975	0.978	0.979	0.971
Homemaking	Caring for Pets incl. Using Pet Services	0.006	0.005	0.005	0.006	0.006	0.007	0.007	0.008	0.007	0.010
	Clothing & Footwear	0.064	0.063	0.062	0.066	0.070	0.023	0.016	0.013	0.008	0.006
	Household Cleaning, Maintenance, & Shopping for Household Products	0.056	0.067	0.071	0.074	0.070	0.068	0.070	0.062	0.062	0.043
	Household Financial Management	0.048	0.056	0.070	0.080	0.093	0.013	0.015	0.016	0.016	0.018
	Using Legal & Professional Services	0.009	0.011	0.013	0.017	0.019	0.000	0.000	0.000	0.000	0.000
	Using Professional Homemaking Services, Except Caring for Others	0.003	0.003	0.005	0.007	0.014	0.000	0.000	0.000	0.000	0.000
	Utilization of Housing Infrastructure incl. Furniture	0.815	0.795	0.774	0.751	0.728	0.889	0.893	0.901	0.907	0.923
Human Capital	Caring for Children incl. Paid Childcare Services	0.040	0.042	0.043	0.067	0.064	0.149	0.153	0.127	0.100	0.114
	Education incl. Helping Children w/ Educational Activities	0.057	0.049	0.054	0.077	0.117	0.051	0.038	0.028	0.028	0.035
	Health Care Activities for Self, Children, & Other Adults	0.548	0.649	0.683	0.649	0.594	0.030	0.029	0.024	0.021	0.017
	Personal Care Activities	0.257	0.189	0.157	0.142	0.155	0.675	0.680	0.708	0.740	0.702
	Reading & Writing, incl. with Children	0.097	0.070	0.064	0.065	0.070	0.096	0.100	0.113	0.111	0.132
Recreation	Arts, Crafts, & Non-paid Hobbies	0.008	0.011	0.013	0.018	0.020	0.003	0.003	0.006	0.002	0.006
	Attending Sporting Events, Plays, Museums, & Other Spectatorial Events	0.049	0.070	0.093	0.118	0.160	0.060	0.055	0.058	0.063	0.064
	Communicating with Others Remotely Using Technologies	0.413	0.380	0.351	0.315	0.273	0.029	0.034	0.036	0.027	0.035
	Engaging in Religious & Spiritual Activities	0.116	0.150	0.163	0.187	0.222	0.022	0.016	0.022	0.020	0.015
	Exercising & Other Physical Recreational Activities, incl. Boating & Flying	0.024	0.025	0.024	0.028	0.028	0.047	0.051	0.058	0.075	0.098
	Playing Games incl. Electronic Games	0.032	0.036	0.038	0.046	0.048	0.045	0.043	0.052	0.052	0.049
	Social Activities incl. Hosting Social Events	0.008	0.011	0.013	0.018	0.020	0.170	0.149	0.137	0.141	0.127
	Tobacco & Drug Use	0.140	0.096	0.087	0.062	0.036	0.006	0.007	0.003	0.003	0.003
	Watching Television & Listening to or Playing Music	0.210	0.221	0.217	0.207	0.195	0.618	0.643	0.628	0.619	0.602
Travel	Traveling for Non-work Activities incl. Maintenance & Public Transit	1	1	1	1	1	1	1	1	1	1

Table 2: Shares of Broad Category Expenditure and Time Use by Wage Quintile (2018)

		Expenditure					*Time Use*				
		1st	2nd	3rd	4th	5th	1st	2nd	3rd	4th	5th
Food	Eating Out incl. Alcohol Consumption	0.235	0.292	0.324	0.353	0.404	0.036	0.041	0.025	0.032	0.030
	Making & Eating Meals at Home incl. Alcohol Consumption	0.765	0.708	0.676	0.647	0.596	0.964	0.959	0.975	0.968	0.970
Homemaking	Caring for Pets incl. Using Pet Services	0.004	0.006	0.005	0.007	0.006	0.008	0.007	0.012	0.010	0.010
	Clothing & Footwear	0.040	0.040	0.043	0.042	0.046	0.020	0.017	0.013	0.008	0.008
	Household Cleaning, Maintenance, & Shopping for Household Products	0.069	0.080	0.087	0.083	0.080	0.053	0.056	0.050	0.037	0.030
	Household Financial Management	0.052	0.064	0.081	0.100	0.122	0.010	0.015	0.012	0.011	0.013
	Using Legal & Professional Services	0.018	0.018	0.021	0.024	0.030	0.000	0.000	0.000	0.000	0.000
	Using Professional Homemaking Services, Except Caring for Others	0.003	0.003	0.005	0.006	0.017	0.000	0.000	0.000	0.000	0.000
	Utilization of Housing Infrastructure incl. Furniture	0.815	0.789	0.759	0.739	0.699	0.909	0.904	0.913	0.933	0.939
Human Capital	Caring for Children incl. Paid Childcare Services	0.038	0.031	0.041	0.056	0.072	0.101	0.121	0.121	0.097	0.125
	Education incl. Helping Children w/ Educational Activities	0.052	0.046	0.058	0.065	0.098	0.046	0.030	0.035	0.017	0.037
	Health Care Activities for Self, Children, & Other Adults	0.665	0.744	0.763	0.752	0.698	0.023	0.028	0.019	0.015	0.023
	Personal Care Activities	0.229	0.168	0.126	0.116	0.118	0.769	0.765	0.748	0.814	0.712
	Reading & Writing, incl. with Children	0.016	0.012	0.012	0.011	0.014	0.061	0.056	0.077	0.058	0.102
Recreation	Arts, Crafts, & Non-paid Hobbies	0.006	0.009	0.011	0.014	0.018	0.001	0.004	0.002	0.007	0.001
	Attending Sporting Events, Plays, Museums, & Other Spectatorial Events	0.047	0.079	0.107	0.125	0.185	0.053	0.046	0.055	0.061	0.056
	Communicating with Others Remotely Using Technologies	0.455	0.398	0.376	0.348	0.283	0.026	0.022	0.027	0.015	0.025
	Engaging in Religious & Spiritual Activities	0.115	0.143	0.161	0.173	0.204	0.034	0.038	0.024	0.025	0.014
	Exercising & Other Physical Recreational Activities, incl. Boating & Flying	0.021	0.030	0.028	0.033	0.031	0.046	0.065	0.071	0.084	0.120
	Playing Games incl. Electronic Games	0.028	0.038	0.040	0.046	0.049	0.094	0.072	0.051	0.090	0.079
	Social Activities incl. Hosting Social Events	0.006	0.009	0.011	0.014	0.018	0.138	0.104	0.114	0.123	0.120
	Tobacco & Drug Use	0.114	0.084	0.061	0.042	0.021	0.007	0.014	0.010	0.000	0.001
	Watching Television & Listening to or Playing Music	0.206	0.210	0.205	0.206	0.191	0.600	0.636	0.645	0.597	0.585
Travel	Traveling for Non-work Activities incl. Maintenance & Public Transit	1	1	1	1	1	1	1	1	1	1

2.2 Expenditure and Time-use Shares for Narrow Categorization

For a granular understanding of consumer spending and time-use patterns, I turn to a more dis-aggregated partition of the expenditure and time-use set. While the broad-category classification features five main activity groups, our narrow-category classification contains 24 different expenditure and time-use activity groups. The narrow categorization is a proper partition of the broad categorization. For a specific list of the ATUS tasks and CEX-PUMD expenditure categories that belong to each of the narrow categories, see Technical Appendix A again.

Tables 1 and 2 present shares of expenditure and time use by the implied hourly-wage quintile within broad categories for years 2003 and 2018, respectively. For example, at the top of the table the broad category is "Food" which is associated with two narrower categories, "Eating Out including Alcohol Consumption" and "Making and Eating Meals at Home incl. Alcohol Consumption." Several facts can be gleaned from these tables. First, for all quintiles, some products which comprise substantial shares of wallet within a category comprise very small shares of time (e.g., health care in human capital, communicating using technologies, and religious or spiritual activities in recreation). However, for some categories it is the other way around (e.g., caring for children and engaging in personal care activities in human capital and both social activities and watching television in recreation). Second, some activities appear to be expenditure luxuries but less luxurious along the time-use dimension and/or vice-versa. For example, making and eating meals at home is a large fraction of food expenditure for low income households but a larger fraction of food time for higher income households. For religious and spiritual activities, the opposite is true. The results from the narrow-category break-down here lend further credence to the presence of heterogeneity in time-use and consumption complementarities which lead to both heterogeneity in the expenditure and time-use allocations cross-sectionally and over time as incomes rise and relative prices change.

2.3 Inequality

In this section I perform two main exercises. First, I assess inequality in terms of total expenditure and the total value of off-market (non-work) time and compare expenditure and time-use measures of inequality to wage and income dispersion. Second, I repeat these exercises focusing on expenditure and time use across the broad activity categories. In all of the analyses here, I take cues from Krueger and Perri (2006) and compute Gini coefficients, 90/10 ratios, and 50/10 ratios of spending, the value of off-market time, income, and wages, all using CEX-PUMD and ATUS sampling weights.[9]

2.3.1 Inequality of Income, Total Expenditure, and Total Off-market Time

How severe is inequality of total spending and the value of total off-market time in the raw expenditure and time-use data? Figure 3 panels (a) through (c) show three measures of inequality over time for expenditure, income, and wages in CEX-PUMD, while panels (d) through (f) show the same measures for total off-market time, income, and wages in ATUS. Income and wage data from CEX-PUMD are characterized by greater dispersion than the same series from ATUS. Further, expenditure dispersion is greater than dispersion with respect to the value of off-market time. Spending inequality between the top and bottom deciles is over twice as great as off-market time-use inequality. For the 50th and 10th percentiles expenditure inequality is twice as great as off-market time-use inequality.

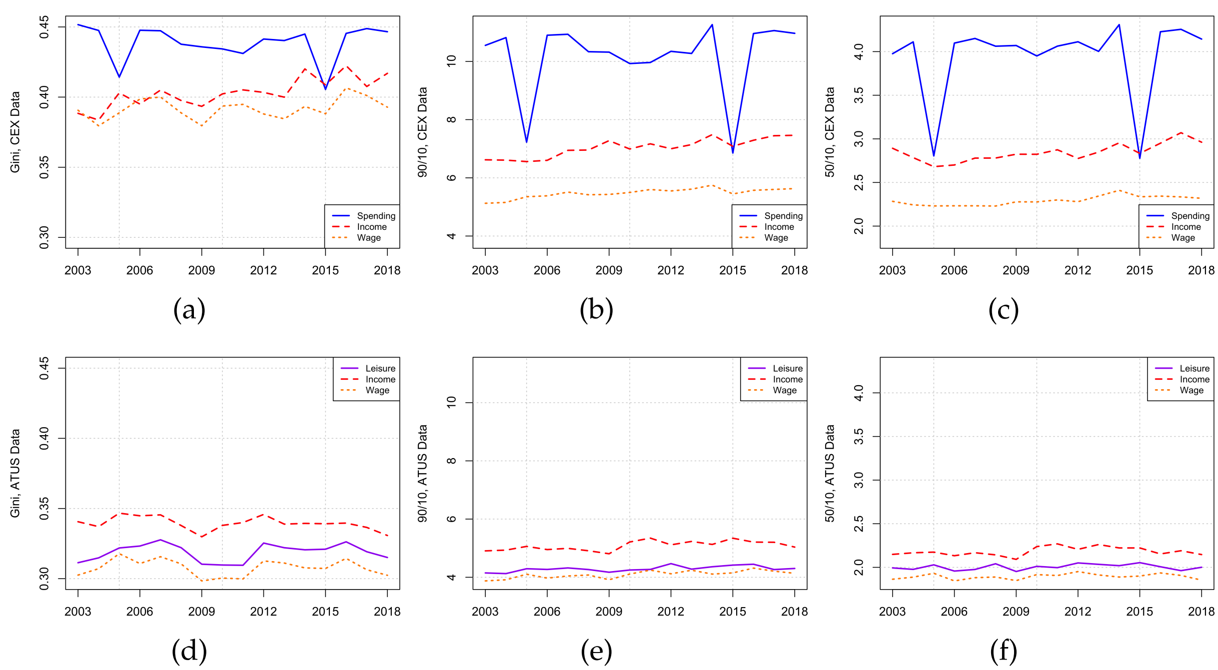


Figure 3: Panels (a) through (c) feature Gini coefficients, 90/10 ratios, and 50/10 ratios for data from the CEX-PUMD, while panels (d) through (f) feature the same dispersion summary statistics for data from ATUS. In (a) through (c) blue lines are measures of expenditure inequality, while in (d) through (f) purple lines are measures of off-market time inequality, where off-market time is weighted by the imputed hourly wage.

[9]The value of off-market time is just the consumer's imputed hourly wage multiplied by the number of hours they spend not working. All measures of income and wages are pre-tax.

2.3.2 Measuring Inequality by Activity Category

What might be driving expenditure and leisure inequality? That is, how do the raw measures of inequality differ if I focus just on inequality of expenditure and time-use in specific, broad activity categories, like recreation, food, and homemaking, amongst others? I find that within-category dispersion is substantially greater than category-aggregated dispersion described in Section 2.3.1. Further, inequality in expenditure in one category may either be less than or exceed inequality in time use in that same category.

Figure 4 features weighted Gini coefficients for income and wages (black lines), as well as broad-category spending and wage-weighted time use. Income and wage inequality are substantially less than category-specific expenditure and time-use inequality for all but food and homemaking spending and homemaking time use. Human capital and travel feature the most category-specific inequality for both expenditure and time use.

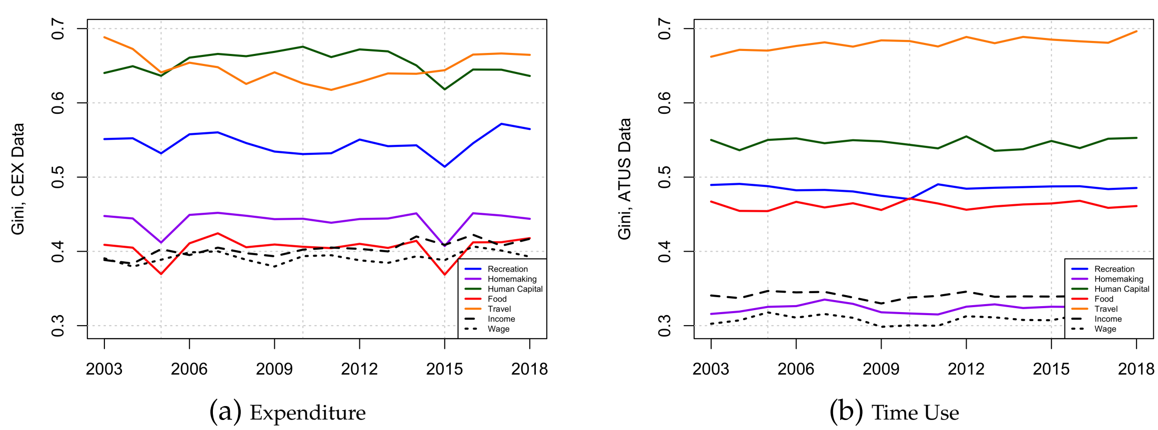


Figure 4: Panel (a) features Gini coefficient measures of income, wages, and broad-category expenditure from the CEX-PUMD, while panel (b) features Gini coefficients of income, wages, and wage-weighted broad-category time use from ATUS.

In addition to computing the weighted Gini coefficients, we also compute 90/10 and 50/10 ratios, but we do not plot their results here.[10] With respect to these ratios, recreation, human capital, and travel are associated with the greatest degrees of inequality. With respect to spending, the 90th percentile spent on average 24 times more than the 10th percentile over the 2003-2018 sample, while for travel this value is 34 times more. The 90/10 ratio for recreational time is 28, and for human capital time it is 25. With respect to the 50/10 ratios, the rank-order is preserved in terms of which categories are associated with the greatest degree of inequality.

[10]Note that for some categories (human capital expenditure and travel time use) the weighted 10th percentile is 0, so that 90/10 and 50/10 ratios are infinite.

3 Model

The model operates at the household level, where a household, regardless of composition, is a single, autonomous decision maker.[11] All households are assumed to be price takers on the market. To avoid notational clutter I dispense with household indices, i, for now but will introduce them in the estimation section later on, where it is more important to distinguish between household-level observations.

Let $\mathscr{J}$ be the set of market products available for purchase in the formal market. $\mathscr{J}$ is assumed countable and finite. Let $\mathcal{J}$ be a partition of $\mathscr{J}$. Each $\iota \in \mathcal{J}$ is a set of market products with similar characteristics and features. Thus, ι is a broad commodity aggregate with elements $j \in \iota \subseteq \mathscr{J}$ where each j is a unique good or service contained in the aggregate (i.e., if ι comprises all food and food-service market purchases, j could be a head of lettuce purchased at the grocery store or a take-out pizza from the local pizza parlor).[12]

Let P_j be the price of market product $j \in \mathscr{J}$ and q_j be the real quantity of market product j purchased by a household. In the spirit of Becker (1965) and Aguiar and Hurst (2016) households combine some amount of off-market time, n_j, with each q_j to engage in activity $g_j(\cdot,\cdot)$. The outputs of activity $g_j(\cdot,\cdot)$ are in-home, final consumption which is denoted by c_j:

$$c_j = g_j(q_j, n_j) \tag{1}$$

Assumption 1. *There exists exactly one and only one in-home consumption output, c_j, for each unique market input, q_j.*

Assumption 2a. *In-home production functions, $g_j(\cdot,\cdot)$, are continuously differentiable, strictly increasing, and strictly concave in all arguments. Further, $g_j(0,n_j)$, $g_j(q_j,0)$, and $g_j(0,0)$ are each well-defined and finite.*

Assumption 1 eliminates the possibility of in-home joint production, which would complicate model analysis and make estimation all but impossible. This is a commonly deployed assumption in home production models combining market inputs with off-market

[11] I do not distinguish between households comprised of multiple adult workers or single adult workers. I also do not distinguish between off-market tasks performed by different agents within the household. Just assume that the household operates as a perfectly egalitarian collective.

[12] Relative to the partitions of the CEX-PUMD and ATUS datasets I deploy, each ι is a broad aggregate and each $j \in \iota$ is one of the narrow categories featured in Table 1 and 2.

time to generate final consumption (Aguiar and Hurst 2016).[13] Assumption 2a ensures that consumers may choose not to use a product or spend their time participating in activity g_j.

Let $G_\iota(\cdot,\cdot)$ be an activity aggregator function for activities associated with commodity-group ι. Let q_ι be an index describing the total quantity of market products consumed from the set $\iota \subseteq \mathscr{J}$. Let n_ι similarly be an index describing the total time devoted to activities associated with products that comprise ι.[14] Consumers have final preferences over the vector of outputs of final consumption which can be represented using either a preference relation over $\boldsymbol{c}$ or a preference relation over the composite of utility and home production functions:

$$u(\boldsymbol{c}) \equiv u\big(\boldsymbol{G}(\boldsymbol{q},\boldsymbol{n})\big) \equiv \mathcal{U}(\boldsymbol{q},\boldsymbol{n}) \tag{2}$$

$u(\cdot)$ describes preferences over $\boldsymbol{c}$, while $\mathcal{U}(\cdot,\cdot)$ describes the composite utility function with preferences over the choices of $\boldsymbol{q}$ and $\boldsymbol{n}$.[15]

Assumption 2b. *Product-aggregated production functions, $G_\iota(q_\iota, n_\iota)$, are continuously differentiable, strictly increasing, and strictly concave in all arguments. Further, $G_\iota(0, n_\iota)$, $G_\iota(q_\iota, 0)$, and $G_\iota(0,0)$ are also each well-defined and finite.*

Assumption 2b is the analog of Assumption 2a for the product-aggregated production functions. Note that $\boldsymbol{q}$ and $\boldsymbol{n}$ have components q_ι and n_ι. $\mathcal{U}(\cdot,\cdot)$ is the transformation of $u(\cdot)$ that takes the commodity-group in-home consumption vector as inputs and yields the same utility level and preference ordering as the underlying utility function over the entire activity set. Following from Leontief (1947), for $\boldsymbol{G}(\cdot,\cdot)$ to be a valid aggregator over the partition $\mathcal{J}$ it must be the case that if $j, j' \in \iota$ and $k, k' \in \iota'$ where $\iota \cap \iota' = \varnothing$, then

$$\underbrace{\left(\frac{\partial g_j}{\partial q_j} \Big/ \frac{\partial g_{j'}}{\partial q_{j'}}\right)}_{MRS_\iota(q_j, q_{j'})} \perp \underbrace{\left(\frac{\partial g_k}{\partial q_k} \Big/ \frac{\partial g_{k'}}{\partial q_{k'}}\right)}_{MRS_{\iota'}(q_k, q_{k'})}$$

That is, the marginal rates of substitution for market products associated with activities in ι are independent of those for products associated with activities in ι'. Thus, the definition of $\mathcal{J}$ should be such that the sets of $\mathcal{J}$ are different enough that rates of substitution for

[13] See Barnett (1977) for a discussion regarding how the presence of joint in-home production effectively negates the possibility a model can be estimated.

[14] Note that the choice of index (i.e., j versus ι) is the only notational distinction we make between the products comprising a broad-commodity aggregate and the aggregate itself.

[15] Vectors are bold throughout this exposition.

products within a commodity-group do not depend on rates of substitution for products outside of that group. $\mathcal{U}(\cdot,\cdot)$ then contains all the information needed to describe the rate of substitution between q_j and q_k (or n_j and n_k), where $j \in \iota$ and $k \in \iota'$. Further, market purchases for a set of products, q_ι, can be represented as a single decision rather than as a collection of decisions to purchase each q_j for every $j \in \iota$. This structure will come in handy to simplify our quantitative exercises later on.

Assumption 3. *$u(\cdot)$, and thus $\mathcal{U}(\cdot,\cdot)$, is continufously differentiable, strictly increasing, strictly concave. Further, $\forall j$ as $c_j \to 0$, Inada conditions are satisfied, so that $u \to -\infty$.*

Assumption 3 forces activities, c_j, to always be positive. Further, if c_j are always positive then the components, c_ι, of the vector-valued aggregator, $\boldsymbol{G}(\boldsymbol{q},\boldsymbol{n})$, are always positive as well.

In addition to allocating time, $\boldsymbol{n}$, to off-market activities, consumers also work on the market, supplying labor time, ℓ, and earning wages, w. Depending on their labor contract consumers may either adjust their labor supply elastically or not adjust it at all. Let $\theta \in \{0,1\}$ be an indicator that describes the labor contract (i.e., salary versus hourly). We assume $\theta = 0$ if labor is supplied inelastically (i.e., salaried) and $\theta = 1$ if ℓ is elastic and adjustable by consumer choice (i.e., hourly). A consumer's time-use constraint is:

$$\sum_{j\in\mathscr{J}} n_j \equiv \sum_{\iota\in\mathcal{J}} n_\iota \leq \overline{n} - \ell(\theta) \tag{3}$$

$\ell(0) = \overline{\ell}$, which is constant and may be agent-dependent, while $\ell(1)$ freely varies as a function of a consumer's off-market time allocation decision.

Let $y(\cdot,\cdot\,;\ \theta)$ be a consumer's total income net of savings which can be written to depend on their labor-contract type, θ. Let P_ι be a price index which describes the price level of the group of products, ι. The budget constraint can be written:

$$\sum_{j\in\mathscr{J}} P_j q_j \equiv \sum_{\iota\in\mathcal{J}} P_\iota q_\iota \leq y\big(w,\ell(\theta)\,;\,\theta\big) \tag{4}$$

Income net of savings is such that:

$$y\big(w,\ell(\theta)\,;\,\theta\big) = \begin{cases} w\,\overline{\ell} + I, & \theta = 0 \\ w\,\ell + I, & \theta = 1 \end{cases} \tag{5}$$

where I is capital income net of savings, which is exogenous to the decision problem we outline under both the assumption that preferences are time-separable and the invocation of two-stage budgeting (Deaton and Muellbauer 1980).[16]

3.1 Equilibrium Analysis

I focus on equilibrium allocations for the broad-category partition. Consumers take prices $\boldsymbol{P}$ and w as given. Salaried consumers are assumed to take $\bar{\ell}$ as given.[17] Conditional upon their type, θ, consumers choose a vector of consumption, $\boldsymbol{q}$, a vector of off-market time, $\boldsymbol{n}$, and their labor hours, $\ell(\theta)$, so as to maximize (2) subject to (3), (4), and (5).

Let $\mu(\theta)$ be the Lagrangian multiplier on (3). This value differs depending on the worker's type since there is one less choice variable when workers are salaried ($\theta = 0$). Let λ be the multiplier on (4). A home production equilibrium must satisfy the following first-order conditions and ensure that both the time-use and budget constraints hold:

$$\frac{\partial \mathcal{U}}{\partial q_\iota} \equiv \frac{\partial u}{\partial c_\iota}\frac{\partial G_\iota}{\partial q_\iota} = P_\iota \lambda, \qquad \forall \iota \in \mathcal{J} \tag{6}$$

$$\frac{\partial \mathcal{U}}{\partial n_\iota} \equiv \frac{\partial u}{\partial c_\iota}\frac{\partial G_\iota}{\partial n_\iota} = \mu(\theta), \qquad \forall \theta \in \{0,1\},\ \ \forall \iota \in \mathcal{J} \tag{7}$$

$$\mu(1) = w\lambda \tag{8}$$

Equation (8) is only valid for hourly workers, since it characterizes the trade-off between labor supply and consumption. Salaried workers do not face such a choice, however. This has implications for how the marginal products of in-home time use, as described by Proposition 1, are characterized.

Proposition 1. *(The Marginal Products of In-home Time Use)*

i. For hourly workers the marginal products of in-home time use in all processes, G_ι, are equal to the hourly wage, w.

ii. For salaried workers the marginal products of in-home time use in all processes, G_ι, are equal to $\mu(0)/\lambda > 0$, where $\mu(0)/\lambda \neq w$ except over a measure-zero set.

All proofs are in Technical Appendix B.

Proposition 1 says that the hourly wage pins down the marginal products of in-home time use exactly for hourly workers, but not for salaried workers. For salaried workers,

[16] Among other relevant models that focus on allocations while abstracting from consumption/savings dynamics are the structural change work of Herrendorf, Rogerson, and Valentinyi (2013) and Bednar and Pretnar (2022) and time-allocation models of Aguiar and Hurst (2007) and Aguiar and Hurst (2016), as well as the original Becker (1965) home-production model.

[17] I abstract from employment separation decisions, so that salaried workers are assumed to always work their contracted $\bar{\ell}$.

since y is exogenous to the allocation decision, $\mu(0)$ will vary in y via the equilibrium allocations of consumption and off-market time-use. Thus, for a panel of salaried consumers, the distribution of $\mu(0)$ will not identically correspond to the distribution of the effective hourly rate of pay, w. Further, $\mu(0)$ will be unknown to the econometrician, so that estimation of a demand system described above on a panel of salaried consumers will be plagued by unobserved heterogeneity, which the econometrician must tackle.

A consequence of Proposition 1 is that for hourly workers the budget constraint can subsume the time-use constraint to get the classic Becker (1965) maximum-possible-income budget constraint:

$$\sum_{j \in \mathscr{J}} (P_j q_j + w\, n_j) \equiv \sum_{\iota \in \mathcal{J}} (P_\iota q_\iota + w\, n_\iota) \leq w\, \overline{n} + I, \qquad \text{if} \qquad \theta = 1 \tag{9}$$

Given $\overline{\ell}$ is a constant we cannot subsume the time-use constraint into the budget constraint when labor is inelastically supplied. This has implications for the effective "prices" (or unit costs) of final consumption that the household faces when trading off whether to engage in one activity versus another. Lemma 1 addresses this.

Lemma 1. *(The Price of Final Consumption) Let ψ_ι be the internal household, Beckerian price of final consumption, c_j. This value is*

$$\psi_\iota = \begin{cases} \frac{P_\iota q_\iota}{c_\iota} + \frac{\mu(0)\, n_\iota}{\lambda c_\iota}, & \theta = 0 \\ \frac{P_\iota q_\iota}{c_\iota} + \frac{w\, n_\iota}{c_\iota}, & \theta = 1 \end{cases} \tag{10}$$

In the Becker (1965) set-up the internal household cost of producing one unit of final consumption, c_ι, is ψ_ι. Lemma 1 states that this is the sum of the value of market expenditure per unit of final consumption and the internal household value of off-market time per unit of final consumption. As Becker (1965) notes, ψ_ι represents the sum of "direct" and "indirect" costs, where "direct" costs are market expenditure per unit of final consumption (i.e., the outcome of activity ι) and "indirect" costs are the value of time per unit of final consumption. One can think of ψ_ι as the price a household of skill level w pays itself to achieve consumption of the outputs of activity ι. Of course, no markets exist for the sale of c_ι between households. If such markets did exist, though, households of skill level w would be willing to pay $\psi_\iota(w)$ for one unit of $c_\iota(w)$ to a household also of type w engaged in the production of $c_\iota(w)$.

The Beckerian price of final consumption is a function of the household's marginal product of labor. This relationship, however, is indirect since the marginal product of labor is embedded in the equilibrium choice functions associated with q_ι and n_ι and, therefore, c_ι and ψ_ι. The general model outlined thus far can say nothing about the sign of how ψ_ι varies in wages or market prices. The effective, internal household "price" a household pays to achieve one unit of final consumption, c_ι, may thus either rise or fall as wages and income rise. Variation in the price of market products, P_ι, could cause ψ_ι to rise or fall as well. Both income effects and substitution effects with respect to demand for market inputs and off-market time act simultaneously on the price of final consumption, ψ_ι, and the demand for final consumption itself, c_ι. Further, such effects depend on a complex set of jointly entangled underlying mechanisms. These mechanisms include, but are not limited to, whether the utility is homogeneous, the elasticities of substitution between c_ι and $c_{\iota'}$, the production intensities and factor shares of q_ι and n_ι in each $G_\iota(\cdot,\cdot)$, the elasticities of substitution between q_ι and n_ι in each $G_\iota(\cdot,\cdot)$, etc. Within-household heterogeneity with respect to the structures of production processes, $G_\iota(\cdot,\cdot)$, will further enrich the equilibrium responsiveness of the prices of final consumption to variation in market outcomes.

3.2 Parameterizations of $\boldsymbol{G}(\cdot,\cdot)$ and $u(\cdot)$

In this section I present parameterizations of $\boldsymbol{G}(\cdot,\cdot)$ and $u(\cdot)$ that satisfy Assumptions 2b and 3. Continuing to operate at the product-aggregated level, I take no stand on the structures of $g_j(\cdot,\cdot)$ nor the indexing functions that yield P_ι and q_ι as functions of each P_j and q_j, $\forall j \in \iota$. In fact, assume that price and quantity indices are simply available empirically from some statistical agency, so that eventually I will be able to pass the product-aggregated indices P_ι and q_ι directly to an estimator to recover structural parameters.

For $G_\iota(\cdot,\cdot)$ I choose Stone-Geary modified constant elasticity of substitution (CES) functions, where $G_\iota(\cdot,\cdot)$ are heterogeneous across product categories, ι (Geary 1950; Stone 1954):

$$c_\iota \equiv G_\iota(q_\iota, n_\iota) = \Big(\omega_\iota(q_\iota + \gamma_\iota^q)^{\nu_\iota} + (1-\omega_\iota)(n_\iota + \gamma_\iota^n)^{\nu_\iota}\Big)^{\frac{1}{\nu_\iota}} \\ \forall\iota,\ \omega_\iota \in (0,1), \quad \nu_\iota \in (-\infty, 0) \cup (0,1) \qquad \text{and} \qquad \gamma_\iota^q, \gamma_\iota^n > 0 \tag{11}$$

Forcing γ_ι^q and γ_ι^n to each be strictly positive allows for observations of zero quantities of market inputs and off-market time for activity group ι. By allowing for heterogeneity in ω_ι across product groups, I can capture the fact that activities associated with some types of market purchases are more or less time-intensive than others. Finally, by allowing for heterogeneity in the substitution elasticity, $\frac{1}{1-\nu_\iota}$, the model is flexible enough to account for differential rates of adjustment of q_ι relative to n_ι across categories as relative prices vary.

For $u(\cdot)$ I take the standard CES route:

$$u(\boldsymbol{c}) = \left(\sum_{\iota \in \mathcal{J}} \phi_\iota c_\iota^\rho \right)^{\frac{1}{\rho}}, \quad \forall \iota,\ \phi_\iota \in (0,1), \quad \sum_{\iota \in \mathcal{J}} \phi_\iota = 1, \quad \rho \in (-\infty, 0) \tag{12}$$

In (12) ρ governs the elasticity of substitution across final consumption. In Bednar and Pretnar (2022), when examining the long-run rise in the services share of expenditure through the lens of a home production model, we assume that $\rho < 0$ so that the outputs of final consumption activities are always complementary. This helps account for the fact that the data cannot be partitioned to explicitly handle for joint production. As an example, consider the activity of "wearing clothes," which is something that most people do most of the time (nudists being the exception). Therefore, someone may be wearing clothes while traveling or engaging in recreational activities, though the act of getting dressed is a personal care activity that would fall under the broad activity category "homemaking." Allowing for complementarities in preferences over the outputs of these activities thus accounts for the fact that certain components of some broad-activity aggregates are also cursorily associated with other activities in ways that are often impossible to account for in the dataset construction and cleaning process.[18]

Note that (12) is a CES utility aggregator over product-aggregated final consumption outputs, c_ι. Proposition 2 characterizes a household-specific final-consumption-aggregated price index that accounts for heterogeneity across households with respect to the degree to which they value the different components of final consumption. This endogenous price index embeds both differences across households in terms of the value of their off-market time and their resulting differences in expenditure and time-use allocations.

Proposition 2. *(Price Index of Final Consumption) Fix $\overline{u} = u(\boldsymbol{c})$ at a household's utility-maximizing allocation. Let $e^{\Psi}(\boldsymbol{\psi}, \overline{u})$ be the net value of household resources required to achieve fixed $\overline{u}$. Then, under CES final preferences, the price index of final consumption, Ψ, which satisfies the expenditure minimization dual problem, is defined as follows:*

$$\Psi = \left(\sum_{\iota \in \mathcal{J}} \phi_\iota^{\frac{1}{1-\rho}} \psi_\iota^{\frac{\rho}{\rho-1}} \right)^{\frac{\rho-1}{\rho}} \tag{13}$$

[18] Assuming $\rho < 0$ thus manages to avoid the problem of joint in-home production. If we wanted instead to allow explicitly for joint production, we would have to take a stand on the fractions of certain products used in one activity versus another when constructing the final dataset on which the estimator would be targeted.

where

$$e^{\Psi}(\boldsymbol{\psi}, \overline{u}) = \Psi\, \overline{u} \equiv \sum_{\iota \in \mathcal{J}} \psi_\iota c_\iota = y_{max} \tag{14}$$

$$\text{with} \quad y_{max} = \underline{w}\, \overline{n} + I \quad \text{and} \quad \underline{w} = \begin{cases} \frac{\mu(0)}{\lambda}, & \theta = 0 \\ w, & \theta = 1 \end{cases}$$

and y_{max} is the maximum-possible value of net resources.

Note that Ψ increases as each ψ_ι increases. Each ψ_ι can rise for different reasons — wage increases, price increases, or cross-price substitution effects driving decreased (i.e., more costly) production of c_ι. Cross-sectionally, larger ψ_ι are generally associated with higher incomes, though this is not always true if c_ι rises faster in wages than ψ_ι. Thus, cross-sectionally, composition effects with respect to how households allocate their resources and time across home-production activities can either dampen or enhance variation in the household-specific final price index, represented by Ψ, relative to wage or expenditure dispersion.

After estimating structural parameters I will perform several quantitative exercises to construct measures of purchasing power parity across households in order to quantify differences in the cost-of-living, which is a function of cross-sectional differences in Ψ. I will then compare measures of dispersion from such endogenous inferences to more traditional measures of inequality. Readers may find the results in this paper surprising because they challenge recent evidence in Boerma and Karabarbounis (2021) that dispersion, and thus inequality, is higher when accounting for home production tradeoffs in the household's decision set.

4 Estimation

In order to arrive at a quantitative measure of welfare inequality that accounts for heterogeneity across households with respect to how they use different kinds of market products, spend their off-market time, and thus value final consumption, estimates for the model's structural parameters are required. I estimate production and utility parameters directly from the equilibrium conditions in (6) through (8) using the synthetically matched ATUS/CEX-PUMD dataset. I construct matched data by projecting the CEX-PUMD into the ATUS, so that the sampling weights deployed are those for subjects of the ATUS. A full description of the procedure used to construct the synthetically-matched ATUS/CEX-PUMD dataset is outlined in Technical Appendix A, along with the sample selection assumptions. With parameter estimates in hand, I can compute ψ_ι and c_ι for each activity and household and construct price indices, Ψ, at the household-level which can be used to engage in different kinds of distributional comparisons.

The estimation strategy is of the Bayesian learning variety. Specifically, I form a likelihood function around (6) through (8), setting the Recreation good as the base good when the broad-category specification is estimated. I then form priors for the distributions of structural parameters using both theoretical intuition and reduced-form evidence from data. Finally, I estimate the full model's posterior distribution on our entire matched sample of households using a Hamiltonian Monte Carlo (HMC) integration procedure (Neal 2011; Betancourt and Stein 2011; Gelman et al. 2013b; Gelman et al. 2013a).[19] Note that two separate, independent estimations are performed. In the main specification the broad-category data is used to estimated structural parameters. An alternative specification is estimated with only one market good and one off-market time-use decision. I call this alternative specification the classic consumption/leisure model. This model is used as a comparison in the exercises exploring different measures inequality.

4.1 Broad Category Estimation

4.1.1 Likelihood Function

The likelihood function for the broad category specification is formed around a system of relative demand and time-use equations. Let $J > 1$ be the cardinality of the partition $\mathcal{J}$. Let i index individual households. Let $\iota = 1$ denote the base activity category (i.e., Recreation) around which we construct our system of relative demand and time-use equations. Let $\boldsymbol{\varepsilon}_i$ be a $2(J-1)$-dimensional vector of model errors. The $2(J-1)$ system of estimating equations is

$$q_{i,\iota} = \Pi^{q}_{\iota,1}(\boldsymbol{P}, \underline{w}_i\,;\, \boldsymbol{\phi}, \boldsymbol{\omega}, \boldsymbol{\nu}, \rho) q_{i,1} + \Pi^{q}_{\iota,0}(\boldsymbol{P}, \underline{w}_i\,;\, \boldsymbol{\phi}, \boldsymbol{\omega}, \boldsymbol{\nu}, \rho)\gamma^{q}_{1} - \gamma^{q}_{\iota} + \varepsilon_{i,\iota} \tag{15}$$

$$n_{i,\iota} = \Pi^{n}_{\iota,1}(\boldsymbol{P}, \underline{w}_i\,;\, \boldsymbol{\phi}, \boldsymbol{\omega}, \boldsymbol{\nu}, \rho) n_{i,1} + \Pi^{n}_{\iota,0}(\boldsymbol{P}, \underline{w}_i\,;\, \boldsymbol{\phi}, \boldsymbol{\omega}, \boldsymbol{\nu}, \rho)\gamma^{n}_{1} - \gamma^{n}_{\iota} + \varepsilon_{i,\iota+J-1} \tag{16}$$

I let $\underline{w}_i$ be equal to the type-specific value of off-market time. This value is $\mu_i(0)/\lambda_i$ for salaried workers and the wage rate, w_i, for hourly workers. The parameterized functions $\Pi^{n}_{\iota,1}(\cdot,\cdot\,;\,\cdots)$ and $\Pi^{q}_{\iota,1}(\cdot,\cdot\,;\,\cdots)$ are defined in Lemma B1 of Technical Appendix B.

[19] For a high-level overview of how HMC routines work, see Technical Appendix C of Bednar and Pretnar (2022).

I assume $\boldsymbol{\varepsilon}_i$ is normally distributed with variance/covariance matrix $\boldsymbol{\Omega}$:

$$\boldsymbol{\varepsilon}_i \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}) \tag{17}$$

When the likelihood is evaluated, the model errors are weighted according to normalized weights derived from the ATUS representation weights which sum to unity each year.

The variance/covariance matrix, $\boldsymbol{\Omega}$, can be decomposed into its diagonal and off-diagonal components in order to implement a computationally-efficient LKJ prior distribution (Lewandowski, Kurowicka, and Joe 2009). The prior assumptions on $\boldsymbol{\Omega}$ are

$$\begin{gathered}\boldsymbol{\Omega} = \Xi(\boldsymbol{\sigma}\mathbb{I})\Xi^\top \\ \Xi \sim \mathrm{LKJ}(2) \\ \sigma_k^2 \sim \mathcal{N}_{(0,\infty)}(0, 2^2), \quad 1 \leq k \leq 2(J-1)\end{gathered}$$

Ξ is lower triangular with a unit diagonal, $\mathbb{I}$ is a $2(J-1) \times 2(J-1)$ identity matrix, and $\boldsymbol{\sigma}^2$ is the vector of diagonal components of $\boldsymbol{\Omega}$. The components of $\boldsymbol{\sigma}^2$ follow independent, truncated normal priors.

4.1.2 Prior Distributional Assumptions on Structural Parameters

Priors on the home production and utility structural parameters follow both from theory and preliminary, reduced-form regression estimates. Moderately flat priors are chosen for $\boldsymbol{\phi}$, $\boldsymbol{\omega}$, $\boldsymbol{\gamma}^q$, and $\boldsymbol{\gamma}^n$:

$$\boldsymbol{\phi} \sim \mathrm{Dirichlet}\big(\mathrm{vec}_{J-1}(1)\big), \qquad \omega_\iota \sim \mathcal{U}[0,1], \qquad \gamma_\iota^{q \wedge n} \sim \mathcal{N}_{(0,\infty)}(0, 10^2)$$

Truncated normal priors are given to the quasi-intercept parameters $\boldsymbol{\gamma}^q$, and $\boldsymbol{\gamma}^n$, which allow for zero consumption and time use. For the elasticity of substitution between final consumption activities, parameterized as $\frac{1}{1-\rho}$, we specify a log-normal prior as follows:

$$-\rho \sim \mathcal{LN}(-0.5, 1)$$

It only remains to specify priors for ν_ι. To do this I independently estimate separate weighted OLS regressions on the within-category marginal rate of technical substitution conditions and back out implied estimates for ν_ι from the following:

$$\begin{aligned}&\ln(P_\iota n_\iota + \gamma_\iota^n) - \ln(P_\iota q_\iota + \gamma_\iota^q) = \beta_0 + \beta_1 \ln(w_i/P_\iota) + \delta_{i,j} \\ &\widehat{\nu}_\iota = 1/\widehat{\beta}_1 + 1\end{aligned} \tag{18}$$

To isolate prior estimates for ν_ι, I preliminarily set $\gamma_\iota^n = \gamma_\iota^q = 1$. I find that $\widehat{\nu}_\iota < 0$ for all j, suggesting that time and market purchases are complements in all of the broad consumption categories. The priors are then:

$$\nu_\iota \sim \mathcal{LN}\left(\ln(-\widehat{\nu}_\iota) - \frac{1}{2}, 1 \right)$$

Results from the reduced-form regressions in (18) are featured in Table 3. All reduced-form coefficients are significant at the 1% level.

Table 3: Reduced-form Regressions for Prior Estimates of $\widehat{\nu}_\iota$

	Broad Activity Category				
	Recreation	Homemaking	Human Capital	Food	Travel
$\widehat{\beta}_0$	1.447	1.176	0.991	0.264	0.179
	(0.015)	(0.008)	(0.011)	(0.009)	(0.011)
$\widehat{\beta}_1$	-0.623	-0.783	-0.793	-0.496	-0.725
	(0.005)	(0.003)	(0.004)	(0.003)	(0.004)
R^2	0.207	0.568	0.395	0.272	0.363
$\widehat{\nu}_\iota$	-0.606	-0.277	-0.261	-1.017	-0.379

Observations: $57,918$

4.1.3 Estimating the Value of Off-market Time for Salaried Workers

Recall that the value of off-market time for hourly workers is just the wage w_i. For salaried workers $\mu_i(0)/\lambda_i$ must be estimated. To do this, I specify a prior on $\mu_i(0)/\lambda_i$ that's centered around the salaried worker's implied hourly wage, w_i, and which allows for $\frac{\mu_i(0)}{\lambda_i} = \frac{1}{2}w_i$ to be two standard deviations from the mean, w_i:

$$\mu_i(0)/\lambda_i \sim \mathcal{N}_{(0,\infty)}(w_i, 0.5\, w_i^2)$$

The normal prior is truncated below at zero to avoid negative off-market time valuations.

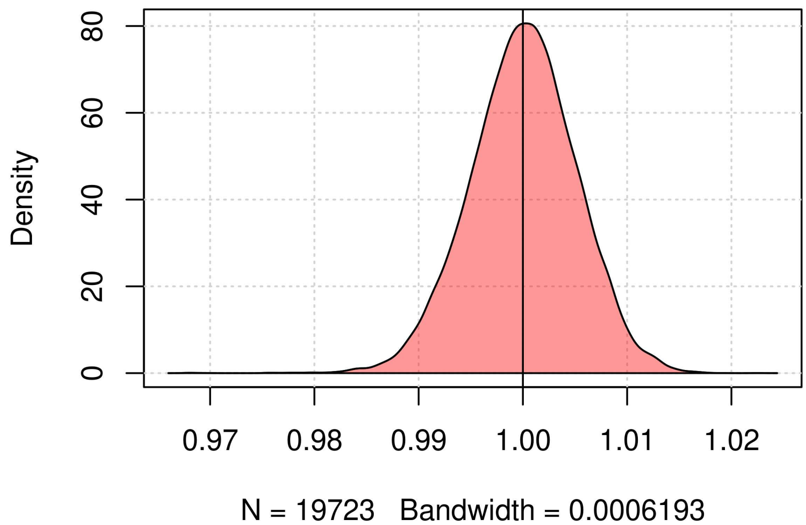


Figure 5: The kernel density estimate of the posterior means of $(\widehat{\mu_i(0)/\lambda_i})/w_i$ for type $\theta = 0$ consumers is centered around one, suggesting there is no identifiable difference between salaried consumers' value of off-market time and their imputed hourly wage. Note that approximately 34.1% of our sample are salaried consumers (19,723).

4.1.4 Estimation Results for Structural Parameters of Broad-category Model

In cardinal order the broad categories are 1) Recreation; 2) Homemaking;[20] 3) Human Capital excluding Working; 4) Food; 5) Travel.[21] Table 4 presents the posterior distributions of structural parameters associated with utility and home production. Human capital development, eating, and travel have the highest weights, ϕ_ι, in the preference set, while homemaking, surprisingly, has the lowest. When looking at the home production factor shares, ω_ι, time has a higher factor share in eating and traveling, while market products have higher factor shares in all other activities. Skipping down to the bottom of Table 4, recall that the prior estimates suggest that market products and time are complementary in all production processes (i.e. $\nu_\iota < 0$). These complementarities are strongest

[20]For the structural estimates I fold sleep time into the homemaking category. I do this because there is substantial heterogeneity both cross-sectionally and over time in terms of how households across the wage distribution allocate time toward sleep. I do not wish to eliminate such variation from informing our structural estimates. I choose to fold sleep time into the homemaking category because most people sleep in their homes most of the time and in doing so utilize housing infrastructure and furniture, which are included in calculations of resources allocated to the homemaking broad category group.

[21]The numbers corresponding to these categories are those associated with the subscripts on the parameters listed in Table 4.

in activities associated with recreation and weakest in activities associated with human capital development.

Table 4: Parameter Estimates — Broad Category Model

Parameter	Mean	S.D.	2.5%	25%	50%	75%	97.5%
ρ	-0.6686	0.3061	-1.4207	-0.8332	-0.6170	-0.4541	-0.2098
ϕ_1	0.1614	0.0638	0.0567	0.1152	0.1548	0.2019	0.2991
ϕ_2	0.0337	0.0154	0.0110	0.0227	0.0312	0.0419	0.0711
ϕ_3	0.2740	0.1011	0.1169	0.2003	0.2615	0.3317	0.5108
ϕ_4	0.2951	0.0959	0.1352	0.2265	0.2842	0.3519	0.5141
ϕ_5	0.2358	0.0988	0.0912	0.1644	0.2214	0.2909	0.4687
ω_1	0.9424	0.0592	0.7842	0.9209	0.9617	0.9832	0.9976
ω_2	0.5221	0.1940	0.1437	0.3798	0.5295	0.6614	0.8684
ω_3	0.4736	0.2027	0.0938	0.3227	0.4713	0.6263	0.8492
ω_4	0.4699	0.2219	0.1124	0.2949	0.4418	0.6219	0.9244
ω_5	0.3581	0.2032	0.0508	0.1898	0.3332	0.5060	0.7864
ν_1	-0.7227	0.3540	-1.5289	-0.8967	-0.6695	-0.4697	-0.2112
ν_2	-0.2579	0.1707	-0.6562	-0.3486	-0.2209	-0.1279	-0.0348
ν_3	-0.1754	0.1297	-0.5201	-0.2335	-0.1395	-0.0839	-0.0256
ν_4	-0.5855	0.3315	-1.3958	-0.7561	-0.5400	-0.3493	-0.0999
ν_5	-0.2659	0.1835	-0.7021	-0.3624	-0.2287	-0.1305	-0.0375
γ_1^q	2.3862	1.1160	0.7159	1.6321	2.2142	2.9585	5.0254
γ_2^q	5.3528	3.7261	0.3561	2.4804	4.6020	7.5739	14.4795
γ_3^q	3.3941	1.3791	0.9701	2.4446	3.2520	4.2046	6.4333
γ_4^q	0.9655	0.8719	0.0356	0.3174	0.7080	1.3537	3.2107
γ_5^q	3.5448	1.8832	0.5884	2.2007	3.3103	4.6320	7.7678
γ_1^n	20.9224	5.8925	11.1519	16.5368	20.4201	24.6196	33.9465
γ_2^n	1.8569	1.8408	0.0499	0.5165	1.2472	2.6383	6.6673
γ_3^n	1.4930	1.2604	0.0610	0.5766	1.1948	2.0574	4.6790
γ_4^n	1.7717	1.4007	0.0718	0.6990	1.4537	2.4596	5.4182
γ_5^n	2.4818	1.6021	0.2637	1.3190	2.2192	3.2904	6.3809

Figure 5 plots a kernel density estimate for the distribution of estimated off-market time valuations ($\mu_i(0)/\lambda_i$) relative to wages (w_i) for salaried workers ($\theta = 0$). Specifically, letting the posterior mean of $\mu_i(0)/\lambda_i$ be denoted with a hat as follows $\mu_i\widehat{(0)/}\lambda_i$, I plot the density over i of $(\widehat{\mu_i(0)/\lambda_i})/w_i$.[22,23] The standard deviation of the distribution of posterior means is 0.0051. In pre-estimation benchmarking exercises I found that the posterior distributions of $\mu_i(0)/\lambda_i$ appear to be, at most, weakly identified. In multiple benchmarking simulations the estimated posterior variances of the distributions of $\mu_i(0)/\lambda_i$ were always close to the prior variances, which were varied independently to test identification.

The estimation results pertaining to the value of off-market time for salaried workers thus indicate that simply using such workers' imputed hourly wage is a reasonable approximation to the value of off-market time. This is because benchmarking suggests these values cannot be strongly identified in a hierarchical set-up such as that which is estimated, nor is there any reason to believe empirically that these values should be significantly different from the underlying, imputed hourly wage.

4.1.5 Likelihood Variance/Covariance and Model Fitness

In Table 6 I present estimates of $\boldsymbol{\sigma}$ (the standard deviation of the likelihood, *not* the variance). Estimates of the off-diagonal components of $\boldsymbol{\Xi}$ (likelihood covariances), which is the Cholesky factorization of the variance/covariance matrix, $\boldsymbol{\Omega}$, are relegated to Technical Appendix C.1. I index the components of $\boldsymbol{\sigma}$ by abbreviating the broad category and appending either q or n to the subscript to denote to which likelihood equation the estimate refers. In Technical Appendix C.1 I reference the Cholesky-factored off-diagonal terms in a similar manner. Note that the units of σ_k are each real-2003 dollars of consumption per day for quantities and hours per day for time use. Thus, the mean value of $\sigma_{\text{Home q}}$ of 4.7266 says on average over all atomic posterior epochs, $m \in \{1, \ldots, \mathcal{M}\}$, \$4.73 is the weighted-average one-standard deviation boundary which envelops 68% of observations in any *given* epoch m. Similarly, for the mean estimate of $\sigma_{\text{Home n}}$, on average over all atomic posterior epochs, $m \in \{1, \ldots, \mathcal{M}\}$, 3.16 hours is the weighed-average one-standard deviation boundary which envelops 68% of observations in any *given* epoch m.

Note that interpretations pertaining to the values of standard deviations are different from interpretations of standard deviations for a frequentist model. This is because every epoch (i.e., atomic draw) of the HMC sampler is associated with a unique draw of $\boldsymbol{\sigma}_m$ which is correlated with draws of all other structural parameters. Therefore, to put these estimates into context I compute several weighted quantiles of the ratios $\sigma_{\iota\,\text{q}}/q_{i,\iota}$ and $\sigma_{\iota\,\text{n}}/n_{i,\iota}$ across the sample. For quantities of market purchases, the standard deviations for

[22]Hats are used to denote all posterior means.

[23]Note that $\widehat{\mu_i(0)/\lambda_i}$ is agent-specific, so that each salaried agent is associated with their own posterior distribution with atomized draws $\mu_i(0)/\lambda_i$ and agent-specific mean $\widehat{\mu_i(0)/\lambda_i}$.

Table 5: Likelihood Standard Deviation Estimates

Parameter	Mean	S.D.	2.5%	25%	50%	75%	97.5%
$\sigma_{\text{Home q}}$	4.7266	0.6834	3.6007	4.2440	4.6655	5.1233	6.2626
$\sigma_{\text{Human q}}$	1.0758	0.2335	0.7227	0.9112	1.0368	1.2000	1.6131
$\sigma_{\text{Food q}}$	1.0309	0.2193	0.7041	0.8757	0.9956	1.1495	1.5258
$\sigma_{\text{Travel q}}$	1.4020	0.2891	0.9654	1.1927	1.3565	1.5707	2.0940
$\sigma_{\text{Home n}}$	3.1605	0.5573	2.2349	2.7669	3.1061	3.4886	4.3729
$\sigma_{\text{Human n}}$	1.7431	0.3373	1.2212	1.5148	1.6971	1.9155	2.5855
$\sigma_{\text{Food n}}$	1.2847	0.2625	0.8852	1.0928	1.2480	1.4327	1.9011
$\sigma_{\text{Travel n}}$	1.2217	0.2552	0.8410	1.0477	1.1866	1.3487	1.8392

homemaking, human capital, food, and travel are at the weighted medians 5.7%, 26.1%, 22.8%, and 18.4% of real market purchases. For time use these values are 12.8%, 56.2%, 52.4%, and 40% respectively. The estimated standard deviation at the 90th percentile is 21.5% of homemaking consumption, 98.2% of human capital consumption, 86.6% of food consumption, and 68.7% of travel consumption. The corresponding time-use values at the 90th percentile are 23.2%, 116.6%, 86.3%, and 78.2%. By this measure the model performs better at fitting the synthetically-projected expenditure data than it does the raw ATUS data.

By other measures of fitness, however, this is not as clear cut. For each agent I compute the average vector of model errors, $\widehat{\varepsilon}_i$, and then measure the correlation of each component of this vector with $\underline{\widehat{w}}_i$ to understand if posterior-average deviations from predicted outcomes are systematically correlated with implied wages. For the time-use equations absolute Pearson's correlation coefficient estimates are all less than 0.08. For market-quantity equations these absolute values range from 0.14 to 0.41, which could signal that some systematic bias is present, but such values could be by-products of the fact that the quantity data are synthetically constructed, where income and wages are key predictors contributing to the projections. Technical Appendix C.1 includes scatter plots of $\widehat{\varepsilon}_i$ against $\underline{\widehat{w}}_i$ for each component of $\widehat{\varepsilon}_i$. The scatter plots show that the non-zero correlations appear to be driven by the increasing variance of each component of $\widehat{\varepsilon}_i$ as $\underline{\widehat{w}}_i$ increases, so that the scatter plots fan out as $\underline{\widehat{w}}_i$ goes up, but the relationship appears centered near zero for each $\underline{\widehat{w}}_i$ and each component of $\widehat{\varepsilon}_i$.

4.2 Production Parameter Estimates in Classic Consumption/Leisure Model

Table 6: Parameter Estimates — $J = 1$ Model

Parameter	Mean	S.D.	2.5%	25%	50%	75%	97.5%
ω	0.1019	0.0286	0.0613	0.0819	0.0967	0.1160	0.1735
ν	-0.6272	0.2025	-1.0763	-0.7404	-0.6062	-0.4867	-0.2979
γ^q	4.0444	3.6181	0.0858	1.3050	3.1092	5.7554	13.6306
γ^n	24.2782	6.2280	12.5540	20.0128	24.1836	28.1129	37.0803
σ	10.7564	0.9312	9.0791	10.0841	10.7296	11.3854	12.6768

Assume now that $J = 1$, and all market inputs are embedded in a single market quantity, q_i, while all off-market time use (including sleep) is captured by a single time-use value, n_i. Production of the single final consumption good, c_i, still happens according to (11), however, in this set-up utility is linear in final consumption, since $\phi = 1$ and $u(c)$ is homogeneous of degree one (i.e., $u(c_i) = c_i \equiv G(q_i, n_i)$, and ρ cannot be identified). I estimate this model off of a likelihood functions formed around the following first-order condition, which describes the marginal rate of technical substitution between q_i and n_i:

$$n_i = \Gamma(P, \underline{w}_i)q_i + \Gamma(P, \underline{w}_i)\gamma^q - \gamma^n + \varepsilon_i \tag{19}$$

The function $\Gamma(P, \underline{w}_i)$ contains parameters ν and ω and is again described in Lemma B1 of Technical Appendix B. I, again, use a weighted set-up, letting ε_i be normal:

$$\varepsilon_i \sim \mathcal{N}(0, \sigma^2), \quad \text{with} \quad \sigma^2 \sim \mathcal{N}_{(0,\infty)}(0, 2^2) \tag{20}$$

Priors for ω, γ^q, and γ^n are the same as in the broad-category model. For ν I engage in the same pre-estimation procedure as before, first targeting (18) in OLS to arrive at a prior mean, finding that, again, q_i and n_i are complements (i.e., $\nu < 0$). I get a prior value of $\widehat{\nu} = -0.237$, which is backed out of reduced-form coefficients that are all significant at the 1% level.[24]

Table 6 presents the posterior distribution of parameters, estimated using HMC from the one good consumption/leisure model. q_i and n_i are weak complements, and n_i dominates in the production of final consumption (ω near 0). The mean standard deviation is approximately \$10.76 real 2003 dollars per day. The posterior distribution around all

[24]The pre-regression results of this model are omitted here due to space constraints.

parameters is tight, suggesting a well-identified model where estimates are driven substantially more by variation in the data rather than prior assumptions. Finally, the posterior distribution of $\mu_i\widehat{(0)/}\lambda_i$ is almost identical to the distribution estimated in the broad category model, and I do not present this distribution here due to space constraints. I will use the parameter estimates from this model strictly for comparison purposes later in the paper.

4.3 Resource Allocation to Activities Across the Wage Distribution

Let us return now to the broad-category model. Recall the discussion in Section 3.1 pertaining to how variation in observable market outcomes affects both the internal price/cost of engaging in activities and the willingness of a household to devote resources toward pursuing such activities. In this section I show how the degree to which households engage in and value different activities varies across the imputed-wage distribution.

First, I seek a high-level understanding of how households at different wage quintiles allocate their resources toward different broad activities. For a cursory gauge of differences in household production I compute the average shares of internal production associated with the five broad categories by wage quintile. Specifically, index the epochs of the HMC sampler by m, where $\mathcal{M}$ is the total number of independent iterates computed over the entire HMC procedure. Let $\alpha_{i,\iota}$ be the share of internal household outlay devoted to the production of final consumption output, $c_{i,\iota}$. For each agent I compute:[25]

$$\widehat{\alpha}_{i,\iota} = \frac{1}{\mathcal{M}} \sum_{m=1}^{\mathcal{M}} \frac{\psi_{i,\iota,m} c_{i,\iota,m}}{\sum_{j \in \mathcal{J}} \psi_{i,j,m} c_{i,j,m}} \tag{21}$$

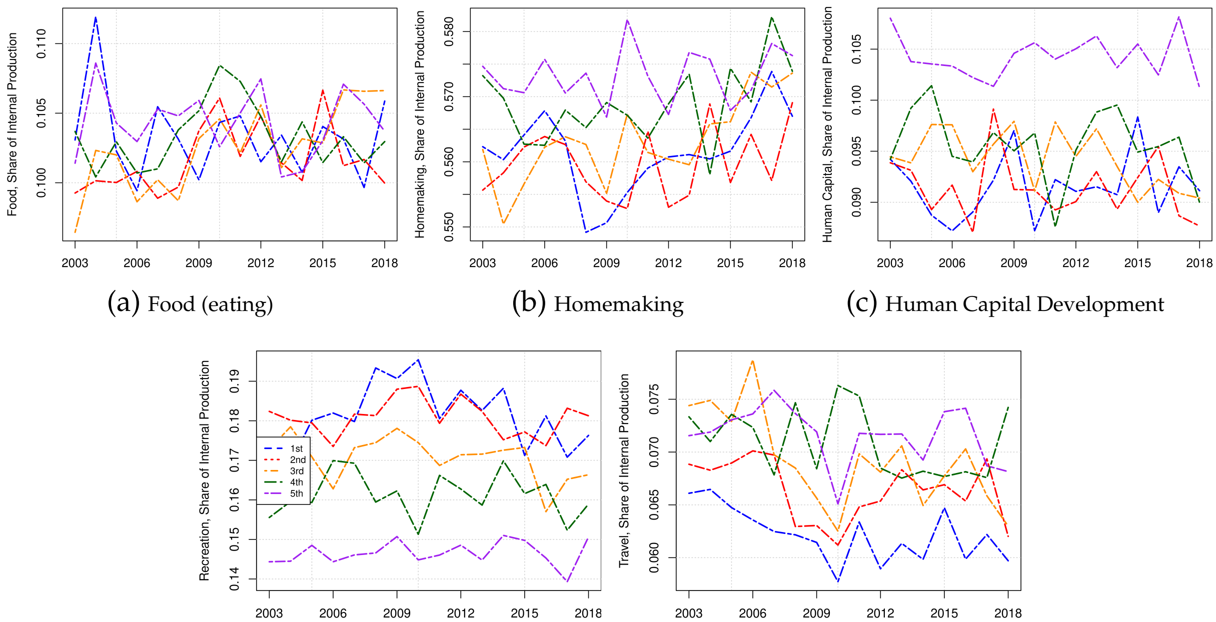
where $\psi_{i,\iota,m}$ is the m^{th} element of the computed posterior array for $\psi_{i,\iota}$. The shares are computed at each epoch for each agent with the average taken over all agents. I then compute the weighted average shares by broad category and quintile and plot these values in Figure 6.[26,27]

Amongst consumers across the wage distribution, homemaking comprises the largest share of in-home economic activity at greater than 50% for all quintiles, followed by recre-

[25]Hats are used to denote posterior means.

[26]In addition to the internal outlay shares, I also plot posterior estimates for $\psi_{i,\iota}$, $c_{i,\iota}$, and $\psi_{i,\iota}c_{i,\iota}$ for each category across wage quintiles in Technical Appendix C.2.

[27]Note that when computing $\widehat{\psi}_{i,\iota}$ I pass the synthetic data observations for $\boldsymbol{q}_i$ and $\boldsymbol{n}_i$ through the function $\boldsymbol{G}_{\iota,m}(\boldsymbol{q}_i, \boldsymbol{n}_i\,;\, \boldsymbol{\omega}_m, \boldsymbol{\nu}_m, \boldsymbol{\gamma}^q_m, \boldsymbol{\gamma}^n_m)$ at each epoch of the posterior distribution to get $\boldsymbol{c}_{i,m}$. I then compute each epoch of $\psi_{i,\iota,m}$ and take averages thereafter. Estimates of both $\widehat{\psi}_{i,\iota}$ and $\widehat{c}_{i,\iota}$ thus embed the likelihood errors and by extension unobserved preference heterogeneity that is implicit in the data.



(a) Food (eating)

(b) Homemaking

(c) Human Capital Development

(d) Recreation

(e) Travel

Figure 6: We plot the weighted-average posterior estimates of the internal shares of household expenditure, $\widehat{\alpha}_{i,\iota}$, for each category, as described in (21), by wage quintile. The legend is in panel (d).

ation, then both food and human capital development, and finally traveling. While over time the share estimates are noisy there do not appear to be any discernible long-run increases or decreases to these shares for any wage quintile since 2003. High-wage consumers (purple line) consistently spend a greater share of their total resources on homemaking and human capital development, while low-wage consumers (blue and red lines) consistently spend a greater share on recreational activities.

When breaking down the rate at which category-specific outlay grew for consumers across the wage distribution and compare these rates both to total outlay growth and implied-wage growth, several things can be observed. First, inspecting Table 7 there is less heterogeneity between consumers in the bottom and top of the wage distribution, in terms of both overall growth rates and how growth in outlay is distributed across categories versus heterogeneity between those in the third quintile and the bottom and top quintiles. Both the lowest and highest earners saw growth in recreational, homemaking, and food outlay which exceeded implied-wage growth, while those in the second and third quintiles saw only growth in homemaking and food outlay which exceeded implied-wage growth. Growth in the amount of nominal resources devoted to recreation and travel was the lowest for middle earners, while travel was at most second-lowest for

Table 7: Measured Average Annual Growth Rates by Wage Quintile, 2003-2018

	Wage Quintile				
$\psi_{i,\iota}c_{i,\iota}$	1st	2nd	3rd	4th	5th
Recreation	0.025	0.020	0.019	0.022	0.026
Homemaking	0.024	0.023	0.023	0.021	0.023
Human Capital	0.019	0.016	0.017	0.020	0.017
Food	0.026	0.022	0.029	0.021	0.023
Travel	0.018	0.014	0.009	0.023	0.020
Total Outlay	0.023	0.021	0.022	0.022	0.023
$\underline{w}_i$	0.023	0.022	0.022	0.022	0.022

everyone but those in the fourth quintile.

Table 8 presents the weighted-average factor shares of outlay by imputed-wage quintile. The top half shows the nominal share, $P_\iota \widehat{q_{i,\iota}/\psi_{i,\iota}}c_{i,\iota}$, by quintile, while the bottom half shows $\underline{w}_i \widehat{n_{i,\iota}/\psi_{i,\iota}}c_{i,\iota}$ by quintile. Note that expenditure and time shares are mostly stable over time across consumer units, so Is only present the intertemporal averages here, not the whole time series.[28] Consumers, generally speaking, have the highest expenditure shares for travel, followed by human capital accumulation, then food, recreation, and homemaking. Comparing shares across the top and bottom imputed-wage quintiles, notice that the top quintile has, on average, higher market-product factor shares in the production of all consumption experiences except food. The time input appears relatively more important for lower wage earners, especially for recreation and travel.

One of the main takeaways from this section is that higher wage earners appear to value human capital relatively more than everyone else, while lower wage earners appear to value recreational activities relatively more than everyone else, as measured by the shares of total outlay each type of household devotes to internal production. Viewing the first result through the lenses of Kopytov, Roussanov, and Taschereau-Dumouchel (2020) and Aguiar et al. (2021), who both suggest that leisure goods have improved in quality and also become relatively less expensive possibly driving certain consumers to spend greater amounts of their time engaging in leisure activities, our results suggest that one should expect such a phenomenon to mostly impact the ways in which low-income consumers allocate resources toward various activities. However, there is no evidence that, since 2003, consumers at any particular wage-quintile have significantly changed their

[28]The time series are featured in Technical Appendix C.3.

Table 8: Average Factor Shares of Outlay by Imputed-wage Quintile

Nominal Expenditure Share by Wage Quintile, $P_\iota \widehat{q_{i,\iota}/\psi_{i,\iota}} c_{i,\iota}$					
Activity	1st	2nd	3rd	4th	5th
Recreation	0.152	0.158	0.166	0.178	0.189
Homemaking	0.154	0.165	0.169	0.173	0.168
Human Capital	0.328	0.352	0.350	0.356	0.344
Food	0.300	0.300	0.292	0.280	0.248
Travel	0.590	0.598	0.609	0.620	0.632
Nominal Time Share by Wage Quintile, $\underline{w}_i \widehat{n_{i,\iota}/\psi_{i,\iota}} c_{i,\iota}$					
Activity	1st	2nd	3rd	4th	5th
Recreation	0.848	0.842	0.834	0.822	0.811
Homemaking	0.846	0.835	0.831	0.827	0.832
Human Capital	0.672	0.648	0.650	0.644	0.656
Food	0.700	0.700	0.708	0.720	0.752
Travel	0.410	0.402	0.391	0.380	0.368

behavior: total outlay shares appear stable over the entire sample as are activity-specific factor input shares, which can be seen in Technical Appendix C.3. Regarding resources allocated to human capital development, higher-income consumers indeed spend a greater share of their total resources on human capital development, but this is stable over time, and, in fact, for such consumers, total resources allocated for human capital development have grown slower than the amount of resources such consumers allocate to recreational activities. On average, higher-income consumers spend relatively more market resources on human capital than others, but only by a couple of percentage points.

The lack of heterogeneity with respect to resource allocation is actually a striking takeaway from this exercise. While I have documented heterogeneity with respect to how consumers allocate resources to recreation and human capital, and to a lesser extent travel, on the margin the differences in behavior are small. Further, the stability of such behavior over the last two decades, across the wage distribution, is also striking. Such low variances and such stability will help inform results when measuring dispersion and inequality through the model's lens in the forthcoming pages of this paper.

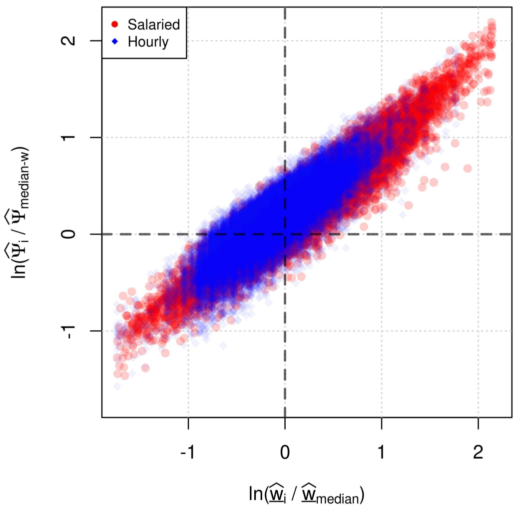
4.4 Constructing Price Indices to Measure Model-implied Inequality

A primary goal of this paper is to measure welfare heterogeneity when accounting for different ways in which households allocate resources toward consumption and time use across the wage distribution. Recall the household-specific final-consumption-aggregated price index, Ψ_i, from Proposition 2. This object is endogenous and depends on the time allocation, $\boldsymbol{n}_i$, and market expenditure allocation, $\boldsymbol{q}_i$, which are decisions of each agent i in our sample. Indeed, this object, indexed by i, is just a price index which describes the price-level of activities, $\boldsymbol{c}_i$, ultimately consumed by household i. This object can be used to measure differences in the cost-of-living (COL) across households with classic purchasing-power parity (PPP) analyses similar to those used to compare living standards across countries in international macroeconomics.

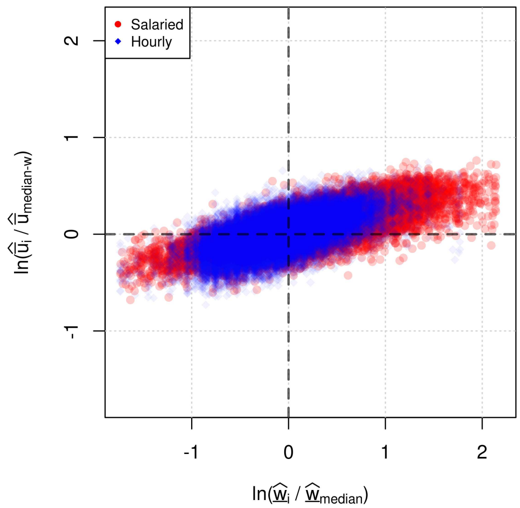
From (14) in Proposition 2 it can be seen that while Ψ_i is a household-specific price index, $\overline{u}_i$ describes a utility index which is heterogeneous across households, accounting for cross-sectional variation in $\boldsymbol{c}_i$. Note that by the CES structure of final preferences, the utility index is also an aggregated quantity index in a model with $J > 1$, describing the total quantity of all final consumption in household i. To understand how price levels and utility indices vary across households of different wages, I let the median implied-wage earner (i.e., median $\widehat{\underline{w}}_i$) be the base/numeraire household then compare the natural logs of $\widehat{\Psi}_i/\widehat{\Psi}_{\text{median-w}}$ and $\widehat{\overline{u}}_i/\widehat{\overline{u}}_{\text{median-w}}$ to the natural log of the ratio $\widehat{\underline{w}}_i/\widehat{\underline{w}}_{\text{median-w}}$. Scatterplots of these comparisons are featured side-by-side in Figure 7.[29] Dispersion across households with respect to relative internal prices is clearly higher than dispersion with respect to relative utility. In fact, relative price dispersion is almost perfectly correlated with relative implied-wage dispersion, while relative utility (quantity) dispersion is significantly lower. Using Pearson's correlation coefficient, correlation between $\ln(\widehat{\Psi}_i/\widehat{\Psi}_{\text{median-w}})$ and $\ln(\widehat{\underline{w}}_i/\widehat{\underline{w}}_{\text{median-w}})$ is 0.905, while the correlation between $\ln(\widehat{\overline{u}}_i/\widehat{\overline{u}}_{\text{median-w}})$ and $\ln(\widehat{\underline{w}}_i/\widehat{\underline{w}}_{\text{median-w}})$ is just 0.696. This suggests that differences between measures of inequality will come not from heterogeneity in the ultimate unit-cost of final consumption (i.e., Ψ_i) but from heterogeneity in outcomes (i.e., quantities of final consumption and utility).

Table 9 demonstrates how dispersion with respect to model-implied objects differs. The top third of the table contains measures of dispersion from the consumption/leisure model with $J = 1$. The bottom two-thirds contains measures from the broad-category model, where the middle third are aggregates over categories, and the bottom third are

[29] Note that I first compute the agent-level posterior means of the targeted indices then divide the agent-level posterior means by the posterior means of those same indices for the median implied-wage earner in the sample.



(a) Price Indices Relative to Wages



(b) Utility (Quantity) Indices Relative to Wages

Figure 7: Panel (a) shows a scatterplot of the log of relative internal price indices against the log of relative wages. Panel (b) shows a similar scatterplot, projected on the same scale, of the log of relative utility (i.e., internal-household aggregated quantity) indices against the log of relative wages.

within-category measures of model-implied total outlay. In this table I present distributional summary statistics of raw, non-logged agent-level means, *not* values relative to the median implied-wage earner. The units of each statistic are slightly different, though most are in real 2003 dollars. $\widehat{\Psi}_i$ is dollars per unit of final consumption, $\widehat{\overline{u}}_i$ is unit-less, though each posterior mean is a model-implied CES-aggregated quantity index, $\underline{\widehat{w}}_i$ is dollars per hour, $\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$ is the value of all resources (market resources plus time) expended on all activities in a given day, and each $\widehat{\psi_{i,\iota} c_{i,\iota}}$ is the value of all resources expended on a particular activity, ι, in a given day.[30]

Table 9 shows the standard deviation of each statistic as well as posterior quantiles, means, and the difference between the 90th and 10th percentiles. To understand how to read the values in Table 9, focus first on the 90-10 differential for $\widehat{\Psi}_i$, which is \$38.41 in the broad category set-up. This says that the value of one unit of final, aggregated consumption is \$38.41 more for a household in the 90th wage percentile than a household in the 10th wage percentile. Looking at the 90-10 differential for $\underline{\widehat{w}}_i$, the implied hourly wage of a household in the 90th percentile is \$28.59 more than a household in the 10th percentile. Similarly, the 90-10 differential for $\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$ suggests that the value of

[30]Note that $\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$ is the posterior-mean of model-implied daily expenditure, which is the empirical analog of (14). We compute $e_{i,m}^{\Psi}(\boldsymbol{\psi}_{i,m}, \overline{u}_{i,m})$ at each epoch, m, of the posterior and then take the mean.

daily market expenditure plus the value of time used in off-market activities is \$516.62 more for households in the 90th percentile relative to those in the 10th percentile. Comparing the broad category estimates with those of the single good consumption/leisure model, in-home price dispersion is less when only one good is included, but in-home consumption/utility-index dispersion is greater. Accounting for activity-specific market-input and time-use heterogeneity (i.e., heterogeneity across processes in ω_ι and ν_ι) thus appears to affect the welfare calculations.

Table 9: Distributions of Model-implied Outcomes

	One Good, Consumption/Leisure Model					
Object	S.D.	25%	Median	Mean	75%	90% - 10%
$\widehat{\Psi}_i$	5.846	6.156	8.495	9.994	12.019	12.254
$\widehat{\overline{u}}_i$	3.849	39.403	41.057	41.908	44.026	10.323
$\widehat{\underline{w}}_i$	13.974	12.204	17.544	21.486	26.030	29.649
$\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$	268.188	246.735	350.619	419.125	509.193	549.603
	Broad Category Model					
Object	S.D.	25%	Median	Mean	75%	90% - 10%
$\widehat{\Psi}_i$	17.494	25.613	33.440	37.221	44.364	38.410
$\widehat{\overline{u}}_i$	0.820	3.721	4.236	4.304	4.815	2.094
$\widehat{\underline{w}}_i$	13.359	12.220	17.360	21.099	25.568	28.594
$\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$	248.405	238.315	336.265	399.710	485.331	516.615
	$\widehat{\psi_{i,\iota} c_{i,\iota}}$ by Broad Category					
Category	S.D.	25%	Median	Mean	75%	90% - 10%
Recreation	67.422	26.167	51.638	68.870	90.199	136.063
Homemaking	140.379	131.734	186.431	223.334	272.996	296.164
Human Capital	42.761	14.683	26.172	38.676	47.455	71.565
Food	35.618	19.236	31.522	41.085	51.139	68.132
Travel	33.124	11.306	18.686	27.745	32.189	47.870

Focusing on the broad category model, notice that, at first glance, the median, mean, and 90-10 differential for $\widehat{e}_i^{\Psi}(\boldsymbol{\psi}_i, \overline{u}_i)$ may seem to be very large. However, note that these values are mostly driven by homemaking which includes the daily rental-equivalent value of housing and sleep time. For example, in the bottom half of the table, the 90-10 differential is \$296.16 in total outlay for the homemaking category. Turning back to Figure 1, note that homemaking comprises over 50% of total expenditure. Observe also that homemaking is generally associated with the largest values of $\psi_{i,\iota}$ as well as the biggest absolute gap between top and bottom quintiles: specifically, the difference between top and bottom quintiles for $\psi_{i,\text{Homemaking}}$ was \$12.68 in 2018. The homemaking production level, $c_{i,\iota}$, also has the widest absolute gap between top and bottom quintiles — \$7.99 in 2018. Thus, inequality as measured by dispersion with respect to total outlay (market spending plus time) is heavily driven by the homemaking category, which embeds housing values and the value of sleep, which is presumably higher for higher wage earners, and by extension higher human capital households.

Second to homemaking is the 90-10 differential in total outlay attributable to recreational activities — \$136.06 on average over the entire 2003-2018 period. But the 2018 in-home price of recreational activities, $\psi_{i,\text{Recreation}}$, is only \$3.85 more for those in the fifth versus first quintiles. Recall that excluding sleep time from homemaking consumers of all quintiles spend the largest fraction of their off-market time on recreational activities. In 2018 those in the first quintile spent about 1.2 hours more per day on recreational activities than those in the fifth quintile. This suggests that the 90-10 differential for recreational activities is driven mostly either by gaps in total spending and the value of time (i.e, $\underline{w}_i$) but not the number of hours.

5 Counterfactuals to Measure Welfare Dispersion

I engage in several counterfactual exercises. The first two counterfactuals take the entire sample over our entire time series of data as given and examine the model implications for inferences regarding inequality and dispersion across the entire cross-section of agents; that is, I do not distinguish between an agent living in 2005 versus 2015, grouping all households in our sample together, measuring real data-observable (i.e., total spending and wage) inequality (\$2003) over the 2003-2018 period, and then comparing these measures to the model-implied measures. In the third and fourth counterfactuals, I then repeat these two exercises for each period in the sample to understand how the comparative measures of dispersion may have changed over time. I find, again, that broken down year by year, the model-implied measures of dispersion are smaller than those implied by wages and total Beckerian outlay. Further, all measures of dispersion have changed at roughly the same rates.

5.1 Counterfactual #1: Living with the Median Wage Earner's $\Psi_{\text{median-w}}$

The first counterfactual measures the agent-level posterior-predicted differences in total outlay that would be implied if all consumers lived with final prices characterized by those of the median wage earner, $\Psi_{\text{median-w}}$, but experienced the same final utility, $\overline{u}_i$. This exercise is analogous, for example, to measuring the difference in total outlay of a U.S. consumer who wants to maintain his U.S. standard of living but moves to Mexico City where the unit-cost of all consumption is lower. The difference is that instead of engaging in cross-country PPP analyses, we are supposing such a consumer's unit costs of final consumption were those of the median wage earner. For a higher wage earner, I then ask what is the value of their left-over resources, and for a lower wage earner, I ask how much would be needed to compensate them to live with higher unit costs. This exercise is not necessarily equivalent to one measuring consumption equivalent variation in equilibrium. Rather, I estimate each consumer's utility at each posterior parameter draw, $\overline{u}_{i,m}$, fixing this value then at the same parameter draw, I compute the counterfactual outlay implied by forcing household i to experience price-level, $\Psi_{i,m}$:

$$\widetilde{e}^{\Psi}_{i,m}(\boldsymbol{\psi}_{\text{median-w},m}, \overline{u}_{i,m}) = \Psi_{\text{median-w},m}\overline{u}_{i,m} \tag{22}$$

Tildes are used to denote counterfactual variables. (22) describes a singular, atomic realization of the counterfactual outcome for agent i at parameter draw m. We let $D^{\Psi}_{i,m}$ be implied left-over outlay at posterior realization m, where the Ψ superscript denotes that we are fixing Ψ in this counterfactual:

$$D^{\Psi}_{i,m} = e^{\Psi}_{i,m}(\boldsymbol{\psi}_{i,m}, \overline{u}_{i,m}) - \widetilde{e}^{\Psi}_{i,m}(\boldsymbol{\psi}_{\text{median-w},m}, \overline{u}_{i,m}) \tag{23}$$

This value is generally positive for higher wage earners and generally negative for lower wage earners.

Finally, to understand how differences in the valuations associated with particular activities may be driving the counterfactual results, I also recompute Ψ_i, fixing all but one of the values $\psi_{i,\iota}$ one at a time and substituting $\psi_{i,\iota}$ for $\psi_{\text{median-w},\iota}$. This yields a counterfactual value of $\widetilde{\Psi}_i$ which depends on four of the broad-category prices for consumer i and one of the broad-category prices of the median wage earner.

5.2 Counterfactual #2: Living at the Median Wage Earner's Utility Level

In the second counterfactual I examine what would happen if all households were mandated to have the same final utility (i.e., final aggregate consumption), $\overline{u}_{\text{median-w}}$, despite heterogeneity in their unit costs of in-home production, Ψ_i. This counterfactual amounts to taking households' abilities with respect to transforming time and market goods into final consumption as given and then forcing all of them to experience the same final utility. In some sense this exercise is akin to achieving final consumption egalitarianism, where, despite heterogeneity in ability, as captured by $\underline{w}_i$ via Ψ_i, all consumers have the same final consumption experience. This exercise demonstrates how much higher income consumers would need to be compensated to live at a relatively lower utility level versus how much lower income consumers would be willing to pay to increase their welfare.

For this exercise the counterfactual measure of expenditure at each posterior parameter draw is

$$\widetilde{e}^{\Psi}_{i,m}(\boldsymbol{\psi}_{i,m}, \overline{u}_{\text{median-w},m}) = \Psi_{i,m}\overline{u}_{\text{median-w},m} \tag{24}$$

The difference in predicted outlay is

$$D^{u}_{i,m} = e^{\Psi}_{i,m}(\boldsymbol{\psi}_{i,m}, \overline{u}_{i,m}) - \widetilde{e}^{\Psi}_{i,m}(\boldsymbol{\psi}_{i,m}, \overline{u}_{\text{median-w},m}) \tag{25}$$

where the u superscript on $D^{u}_{i,m}$ denotes that we are fixing utility in this exercise rather than the CES price index. Again, this value is positive for high wage earners and negative for low ones. The results of counterfactual exercises #1 and #2 are presented in Table 10 and discussed below in Section 5.4. Note that for the more granular, category-specific decomposition, I replace $c_{i,\iota}$ with $c_{\text{median-w},\iota}$ one by one and recompute $\widetilde{\overline{u}}_i$ accordingly, which is analogous to the procedure described in Section 5.1 that targets the category-specific contributors to variation in Ψ_i.

5.3 Counterfactuals #3 and #4: Variation in Dispersion Over Time, 2003-2018

In the third and fourth counterfactual exercises, I simply repeat counterfactuals #1 and #2 separately for each year in the sample, 2003-2018. I thus bin agents by the year in which their observations occurred, find the median implied-wage earner in that year, and then compute separate values of $D^{\Psi}_{i,m}$ and $D^{u}_{i,m}$ for each agent in that particular year's sample. The goal of these exercises is to see if there are trends over time in the model-predicted measures of dispersion, and, if so, how inferences pertaining to inequality have changed. For these two exercises I discuss both how period-by-period mean differences and 90-10 differences in differences have grown over time, comparing the counterfactual values to period-by-period wage and expenditure dispersion.

5.4 Discussion of Counterfactual Results

I summarize the compensated differentials from (23) and (25) in Table 10 for both the single good consumption/leisure model and broad category model. The table also contains two additional statistics that convey differences from the median consumer for their implied value of time, $\widehat{D}_i^{\underline{w}}$, and implied total outlay, $\widehat{D}_i^{e}$.[31] Table 10 thus represents the distribution of differences in outcomes relative to outcomes associated with the median wage earner.

Two things stand out from the counterfactual estimates. First, model-implied dispersion in welfare, as measured by counterfactual $\widehat{D}_i^{\Psi}$ and $\widehat{D}_i^{u}$, is higher for the single good consumption/leisure model than the broad category model. Again, activity-level heterogeneity with regards to the intensity of time use and substitutability of time and market inputs seems to matter. Second, model-implied dispersion as measured in Counterfactuals #1 and #2 is less than dispersion in imputed hourly wages and expenditure, though dispersion is substantially less when accounting for activity-level home production heterogeneity.

I will focus discussion of the counterfactuals on the broad category model. Looking first on Counterfactual #1, the value associated with the mean of $\widehat{D}_i^{\Psi}$ in Table 10 says that on average consumers would spend \$45.70 per day less to achieve the same utility if they lived in a household characterized by $\Psi_{\text{median-w}}$ compared to their own. For the same statistic the 90-10 difference says that consumers in the 90th percentile, with respect to compensated differentials, would spend \$170.74 less than a consumer in the 10th percentile, who would need to increase spending to live in the $\Psi_{\text{median-w}}$ household.

The second rows of both the top and bottom halves of Table 10 present the distribution of compensated differentials under Counterfactual #2. Under this counterfactual if

[31] These statistics are not counterfactual in nature but simply average differences relative to estimated outcomes of the median wage earner as follows:

$$\widehat{D}_i^{\underline{w}} = \overline{n}(\underline{\widehat{w}}_i - \underline{\widehat{w}}_{\text{median-w}})$$
$$\widehat{D}_i^{e} = \widehat{e}_i^{\Psi} - \widehat{e}_{\text{median-w}}^{\Psi}$$

I weight the wage differential by $\overline{n} = 24$ to place it in the same units (dollars per day) as the other counterfactual values.

Table 10: Distributions of Differences for Counterfactuals #1 and #2

	One Good, Consumption/Leisure Model					
Object	S.D.	25%	Median	Mean	75%	90% - 10%
$\widehat{D}_i^{\Psi}$	255.313	-74.084	19.968	89.612	168.127	513.589
$\widehat{D}_i^{u}$	47.881	-13.297	-3.465	12.510	26.768	93.208
$\widehat{D}_i^{w}$	335.376	-116.310	11.866	106.468	215.522	711.580
$\widehat{D}_i^{e}$	268.188	-79.094	24.791	93.296	183.365	549.603
	Broad Category Model					
Object	S.D.	25%	Median	Mean	75%	90% - 10%
$\widehat{D}_i^{\Psi}$	90.025	-9.282	20.007	45.699	69.978	170.738
$\widehat{D}_i^{u}$	45.362	-11.150	2.240	14.912	26.091	83.347
$\widehat{D}_i^{w}$	320.607	-115.905	7.451	97.187	204.441	686.255
$\widehat{D}_i^{e}$	248.405	-52.166	45.784	109.229	194.850	516.615

the value is positive then we would have to compensate consumers to live in $\overline{u}_{\text{median-w}}$, whereas if this value is negative consumers would be willing to pay to live in $\overline{u}_{\text{median-w}}$. We observe that on average (broad category model) consumers would need to be compensated \$14.91 to live with the utility of the median wage earner. However, the difference in compensation for the 90th percentile less negative compensation charged to the 10th percentile is only \$83.35 per day, which is less than the 90-10 differential under Counterfactual #1 for the broad category model. The interpretation of these values between counterfactuals is different, though: obviously, higher wage earners would prefer to reduce their unit costs of final consumption to live in a household with price level $\Psi_{\text{median-w}}$, but they would need to be compensated to reduce their utility and live in a household that experiences $\overline{u}_{\text{median-w}}$.

Discussing the results in Table 10 in the context of cross-sectional inequality, notice that differences in implied wages and differences in implied total expenditure are far more disperse than differences implied by counterfactual outcomes where we force everyone to face the same unit cost of final consumption or to experience the same final utility. For example, on average consumers would need to be paid \$97.19 per day to live with the median wage and \$109.23 to live with the median wage earner's total Beckerian outlay. While $\widehat{D}_i^{w}$ and $\widehat{D}_i^{e}$ are not exactly analogous to measures of wage and expenditure dispersion in the literature, this exercise demonstrates that when accounting for complementarities in final consumption, heterogeneity across home production activities with respect to time intensities, and elasticities of substitution with respect to using market products versus time, the distribution of welfare outcomes compresses relative to the wage and expenditure distributions. This result thus suggests that accounting for how households across the wage distribution spend their time using different products may dampen inferences regarding the degree of inequality present in the U.S. economy. Further, this result contrasts starkly with results in Boerma and Karabarbounis (2021) who suggest that dispersion increases when accounting for home production. The difference between my approach and theirs is that I account for time-to-consume across multiple categories, which appears here to be driving differences in dispersion between the broad category model and the single good consumption/leisure model. Thus, more broadly speaking, these results showcase the importance of accounting for activity-level heterogeneity with respect to consumption time when making inferences pertaining to equilibrium outcomes generated by consumer behavior.

Table 11: Counterfactuals #1 and #2, Decompositions by Broad Category

	Counterfactual #1, $\widehat{D}_i^{\Psi}$ with Fixed $\psi_{\text{median-w},\iota}$ by Category					
Category	S.D.	25%	Median	Mean	75%	90% - 10%
Recreation	34.493	10.630	24.574	31.060	43.554	71.930
Homemaking	7.659	-3.512	-1.750	0.500	1.616	12.603
Human Capital	31.099	-6.066	2.556	11.899	18.750	55.573
Food	27.527	-21.923	-15.960	-8.390	-4.652	43.861
Travel	27.201	-1.914	4.799	13.023	17.809	44.274
	Counterfactual #2, $\widehat{D}_i^{u}$ with Fixed $c_{\text{median-w},\iota}$ by Category					
Category	S.D.	25%	Median	Mean	75%	90% - 10%
Recreation	8.388	-3.615	-1.359	0.737	2.483	15.206
Homemaking	0.688	-0.398	-0.182	-0.144	0.051	1.087
Human Capital	23.854	-1.107	5.895	11.758	18.252	44.079
Food	16.042	-17.000	-9.657	-10.630	-3.751	29.892
Travel	20.693	1.822	7.568	13.948	18.199	35.118

How sensitive are inferences regarding inequality to category-specific variation in $\psi_{i,\iota}$ and $c_{i,\iota}$ across households? To answer this question I separately fix $\psi_{\text{median-w},\iota}$ and $c_{\text{median-w},\iota}$ for each category, then recompute each agent's counterfactual aggregate price index, $\widetilde{\Psi}_i(\psi_{\text{median-w},\iota})$, and aggregate utility index, $\widetilde{\overline{u}}_i(c_{\text{median-w},\iota})$. With counterfactual indices in hand, I then compute the differences described in (23) and (25). The distributions of these differences are featured in Table 11.

Technical Appendix C.2 features activity prices, $\psi_{i,\iota}$, and final consumption levels, $c_{i,\iota}$, broken down by income quintile: all are increasing in income. Recall the interpretations of Counterfactuals #1 and #2. Looking first at the top half of Table 11 and fixing the price of recreational activities at that of the median wage earner, on average consumers would spend \$31.06 less per day to participate in the same level of recreational activities and achieve the same utility. One shortcoming of this exercise is that it *cannot* account for final consumption cross-price effects, but rather it is designed simply to understand to which categories inequality measures are most sensitive. For food, focusing again on Counterfactual #1, a negative value at the mean (-\$8.39) is due to the fact that there is a lot of cross-sectional dispersion in the internal household price of food faced by consumers, so that many high-income consumers actually face a relatively lower unit cost for food activities than lower income consumers.

By unit costs (Ψ_i) inequality appears most sensitive to variation in the unit costs of recreational activities. By utility ($\overline{u}_i$) inequality appears most sensitive to human capital. The average consumer would need to be compensated \$11.76 to live with the median wage earner's final consumption of human capital activities ($c_{\text{median-w,HumanCapital}}$). Variation in the final consumption of recreational activities, however, is comparatively miniscule. The same is true for homemaking in terms both of unit costs and utility. Thus, depending on how dispersion is decomposed, it appears that variation in the unit cost or final price of recreation contributes strongest to variation in Ψ_i across households, while variation in the final consumption level of human capital activities contributes strongest to variation in $\overline{u}_i$. One can conclude from Table 11 that high earners would like to live with lower earner's unit costs of recreation, but low earners appear to benefit from higher final consumption levels for food and human capital, consistent with those of the median wage earner.

How do inferences regarding inequality change from 2003 to 2018? In Table 12 I present means and 90-10 differences for Counterfactuals #3 and #4 to compare years 2003 and 2018. Readers should be cautious comparing the magnitudes of means and 90-10 differences between Table 10 and Table 12: the former treats the entire sample as a single unit and computes weighted statistics therefrom, while the latter separates agents across periods and computes period-by-period weighted outcomes. Across these counterfactuals one can still observe that wage and expenditure inequality, especially at the tails, exceed model-implied inequality in welfare outcomes and the effective cost-of-living. In terms of rates of change over time, at the mean the expenditure and wage differentials grew fastest at average annual rates (2003-2018) of 2.94% and 2.71%, while cost-of-living differentials (fixed $\Psi_{\text{median-w}}$) and utility differentials (fixed $\overline{u}_{\text{median-w}}$) grew at 2.63% and 2.68% respectively. When looking at how the 90-10 differentials have changed, however, the fastest rate of growth was with respect to utility outcomes (2.66% annually), while the slowest was with respect to total, model-implied expenditure (2.18% annually). 90-10 wage differentials grew at a rate of 2.46% annually, while the cost-of-living differentials grew at a rate of 2.23% annually. Differences in the amount required to compensate consumers to lower their utility and consume a less preferable bundle have grown faster at the tails, despite the mean of the distribution fanning out the slowest. By this measure welfare dispersion as implied by the home production model has increased faster over time, even though absolute welfare dispersion remains lower than measures of wage and expenditure dispersion, a result that is consistent with findings in Fang, Hannusch, and Silos (2021).

Table 12: Mean and 90-10 Difference for Counterfactuals #3 and #4, 2003 & 2018

	One Good, Consumption/Leisure Model			
	2003		*2018*	
Object	Mean	90% - 10%	Mean	90% - 10%
$\widehat{D}^{\Psi}_{i,t}$	277.373	434.934	433.329	641.602
$\widehat{D}^{u}_{i,t}$	53.192	110.227	133.470	224.635
$\widehat{D}^{\overline{w}}_{i,t}$	76.949	572.311	121.841	840.025
$\widehat{D}^{e}_{i,t}$	288.069	446.616	451.510	651.733
	Broad Category Model			
	2003		*2018*	
Object	Mean	90% - 10%	Mean	90% - 10%
$\widehat{D}^{\Psi}_{i,t}$	93.337	162.661	141.401	231.442
$\widehat{D}^{u}_{i,t}$	47.616	96.239	72.685	146.520
$\widehat{D}^{\overline{w}}_{i,t}$	67.158	550.185	102.943	811.339
$\widehat{D}^{e}_{i,t}$	267.455	417.488	424.936	589.817

6 Conclusion

This paper presents a home-production-based model of consumption/leisure to show that, when accounting for rich, product- and activity-specific consumption and time-use complementarities, society-wide welfare dispersion is substantially less than what income and spending would suggest. This result appears driven by changes to patterns of consumption and time use involving recreational products and activities, as well as dispersion across the wage distribution regarding expenditure and time spent on human capital development.

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