Working Paper No. 1104

Levy Institute Measure of Time and Income Poverty: United States, 2007–2022 Sources, Methods, and Assessment

by

Fernando Rios-Avila
Universidad Privada Boliviana and London School of Economics

Ajit Zacharias
Levy Economics Institue

Thomas Masterson
Levy Economics Institute

and

Aashima Sinha
Levy Economics Institute

January 2026

Levy Economics Institute
P.O. Box 5000
Annandale-on-Hudson, NY 12504-5000
http://www.levyinstitute.org

ISSN 1547-366X

ABSTRACT

In this paper, we present the empirical methodology used to estimate the Levy Institute Measure of Time and Income Poverty (LIMTIP) for the United States over the period 2007–2022. We provide a step-by-step account of the statistical matching procedure employed to construct a synthetic dataset by combining the American Time Use Survey (ATUS) for year t with the Annual Social and Economic Supplement (ASEC) for year t + 1. We describe in detail how records were matched using a combination of principal component analysis, propensity score, and clustering methods. We then assess the quality of the match, focusing on the 2022 data. Specifically, we examine the alignment of the ATUS weekday and weekend samples with the synthetic dataset across key demographic characteristics and summarize the performance of the matching algorithm. Finally, we compare the marginal distributions of time use between the original ATUS data and the synthetic dataset. Our findings indicate that the statistical matching procedure produced a high-quality match, rendering the synthetic dataset suitable for time poverty analysis. Although not discussed in detail here, we also evaluated match quality for each year from 2007 to 2021.

KEYWORDS: Time Poverty; Income Poverty; Statistical Matching; LIMTIP

JEL CODES: C14; C40; D12; D31; I32; J22

INTRODUCTION

The Levy Institute Measure of Time and Income Poverty (LIMTIP) was developed to address blind spots in official measures of income or consumption poverty (Zacharias 2011; Zacharias 2023). Official measures neglect the minimum requirements for household production (e.g., cooking meals for family members, laundry, caregiving) needed for the household to reproduce itself as a unit, so the impoverishing effects of not meeting these requirements are hidden. Moreover, time deficits may constitute an independent dimension of deprivation when considering their potential impacts (e.g., parental time poverty leading to child neglect).

The LIMTIP itself, along with the information base assembled for its construction, can be used to analyze the time constraints stemming from the overlapping domains of paid and unpaid work, which are central to debates surrounding gender inequality and economic well-being. In a series of studies, Levy Institute scholars, in collaboration with international counterparts, have developed estimates for a set of countries: Argentina (2005), Chile (2006), Ghana (2012–13), Korea (2009), Mexico (2008), Tanzania (2011–12), Turkey (2006), Ethiopia (2015), and South Africa (2015).

We have now completed estimates of the LIMTIP for the United States from 2007 to 2022, based on the methodological framework developed in previous studies, with improvements and adaptations suited for the US context. In this paper, we provide detailed information on the data, estimation methodology, and quality assessment of these estimates.

We start with a brief discussion of the measurement of time and income poverty in Section 2, which outlines the data requirements for constructing the LIMTIP. A key challenge is that constructing the LIMTIP requires joint information on time use, employment, and income, which is typically not available from a single source. Section 3 describes the methodology used to address this challenge—specifically, the statistical matching procedure employed to combine the time-use survey with the survey of employment and income. In Section 4, we detail the implementation of the matching procedure, including dataset alignment and assessment of match quality. Finally, Section 5 presents concluding remarks.

SECTION 2. THE NATURE OF TIME POVERTY AND INCOME POVERTY

Accounting for Time Constraints in Poverty Measurement

Poverty is a multidimensional concept that goes beyond the simple notion of lack of income. From the LIMTIP perspective, time poverty refers to cases where families experience time deficits in their household production requirements. The outputs of household production activities are not directly observed (e.g., square feet of area cleaned over a week) in household surveys. However, labor input into household production can be observed in time-use surveys that capture the time individuals allocate to various household production activities, which can serve as proxies for the outputs. Accordingly, we consider people encountering time deficits as those who may not have sufficient time left for household production requirements after accounting for minimal time requirements for personal care such as sleeping. For those employed, we also account for the time constraints imposed by their jobs and related commute.

Every individual faces a daily time constraint of 24 hours. The first step in translating these ideas into measurement is to define the time balance of an individual. We express the annual time balance of working-age (18–64 years) individual i in household j, X_{ij}, as:

$$X_{ij} = 8736 - M - \alpha_{ij} R_j - D_{ij}^{0}(L_{ij} + T_{ij}) \qquad (1)$$

where 8,736 is the total number of annual hours (168 hours per week multiplied by 52, the number of weeks in a year), M is the sum of personal care and non-substitutable household production requirements, R_j is the required amount of household production time that a family j needs to maintain the household with a poverty-level of income, and α_{ij} is the share of individual i in the household production requirements. Both time thresholds are arrived at by multiplying the weekly hours by 52. To account for the time constraints due to employment, we also include D_{ij}, a dummy variable that takes a value of one if the person is employed and zero otherwise. Thus, for those employed, we further subtract their annual hours of employment (L_{ij}) and commuting requirements (T_{ij}). The annual values of both are calculated by multiplying the usual weekly hours of employment and weekly commuting time requirements by the weeks employed during the year.

Since M is uniform across individuals, variations in time balance between individuals arise from differences in meeting household production responsibilities and employment commitments. The time balance will be negative for those who cannot meet both simultaneously. We define a time deficit as a negative time balance and designate individuals with time deficits as time-poor. In principle, even among the non-employed, extremely high household production requirements can lead to time poverty, though, in practice, such instances are rare. Therefore, time deficits primarily reflect the shortfall encountered by employed people in meeting their household production requirements, given their employment constraints.

To construct this measure, we require a dataset that includes information on individuals' time use as well as the standard variables used in poverty analysis. The primary source of time-use data is the American Time Use Survey (ATUS), which provides information for only one person per household for a single day. We obtained the ATUS data from the Integrated Public Use Microdata Series (IPUMS) (Flood et al. 2023). For information on employment and variables needed to measure income poverty, we use the Annual Social and Economic Supplement (ASEC) of the Current Population Survey, also extracted from IPUMS for each respective year (Flood et al. 2023). The ASEC is the source of the official poverty estimates produced by the US Census Bureau and the Bureau of Labor Statistics (BLS).

As described in Section 3, it is necessary to combine the ATUS and ASEC datasets to construct a synthetic dataset that includes time-use information for all household members. This, in turn, allows us to ascertain all variables required for equation (1).

Estimating Time Balance

Even with the synthetic dataset, it is necessary to impose some restrictions to properly identify the elements in equation (1). These restrictions essentially rely on a *reference group* used for defining thresholds, similar to the procedure followed in constructing income poverty lines. First, R_j represents the hours of household production needed by a family with a poverty level of income. The anchoring of thresholds to the poverty level of income is crucial because the main objective of the LIMTIP is to identify the biases in conventional poverty measures due to the neglect of the household production needs of low- and moderate-income families. Second, it is reasonable to suppose that the thresholds will vary according to household structure (i.e., the number of adults, children, and elderly). Further, to avoid understating the thresholds, it is important to exclude families with potential time deficits in the reference group.

Accordingly, we estimate R_j as the expected number of required household production hours, conditional on the family structure, using as our reference group a subsample of households with income around the poverty level (75–150 percent of the poverty line) and the presence of a fallback person. We impose the income restriction to ensure that the estimate reflects the time requirements of a family that is close to the income poverty line, as described above. We also restrict the reference group to households with a fallback person—i.e., someone who is not employed and is potentially "able" to take care of the household production responsibilities. The estimated requirements may reflect some extent of outsourcing of household responsibilities, which may include consumer purchases of substitutes they can afford (e.g., fast-food takeout meals). We estimate the household requirements using the following conditional expectation function:

$$\hat{R_j} = E(R_j|HH_j) = a_0 \times [\#Adults_j + \gamma_1\#Children\ (0-5)_j + \gamma_2\#Children\ (6-14)_j$$

$$+ \gamma_3\#Children\ (15-17)_j + \gamma_4\#Elderly_j)]^{\delta} \quad (2)$$

Equation (2) estimates the household production threshold as a function of household structure, specified by the number of persons in various age groups. The coefficient a_0 represents the baseline household production requirement for a single adult living alone. The coefficient γ_i is interpreted relative to the base category, number of adults. The parameters capture the additional requirement (or additional supply) of household production time as a result of adding younger and/or older children, as well as elderly, relative to adults. An increase in children in the 0–5 age group is expected to have a different impact on the required hours of production compared to an increase in number of children in the 6–14 age group. The latter would be in the school-going category and may start spending more time outside the home, requiring lower household production time. Moreover, the presence of older children as well as elderly may even increase the supply of household production time. Further, $\delta < 1$ would indicate economies of scale as a result of increasing household size. In other words, larger households experience economies of scale in household production, as additional members increase total household production requirements less than proportionally. After estimating the model, we use the parameters to predict the household production hours for all households in the sample. The resulting estimates are assumed to be the household production threshold for each household.

As is evident from equation (1), in households with more than one individual with a potential time deficit, the household production requirements impinging on the individual are mediated by the individual's share (α_{ij}) in their household's required hours of household production threshold (R_{ij}). For example, the shares in a married-couple family would represent the division of household production responsibilities between the husband and wife (assuming there is no one else in the family to engage in household production). Typically, the intrahousehold division of domestic labor is determined via a complex process driven by social and cultural factors as well as differential bargaining power, all of which are subject to the influence of economic forces (Agarwal 1997). We assume that the share of household production requirements that each individual is responsible for (α_{ij}) is equal to their observed share of the total hours of household production time. It is important to note that the total number of hours of household production used in our analysis is estimated from the synthetic data because household-level measures of household production are available neither in the ATUS or ASEC.

Next, we move on to M, which represents the time required for personal care and non-substitutable household production. This constitutes requirements that cannot be delegated to other household members. M includes time required for sleeping, personal maintenance, and eating, among others. While some of these components are typically defined by assumptions, others like time required for sleep, are obtained based on (national) averages in the data, as we describe below.

Finally, we consider employment-related activities, L_{ij} and T_{ij}. The latter (i.e., commuting time requirements) are calculated using the ATUS. They are assumed to be equal to average commuting time, estimated separately for people with full- or part-time employment, allowing for heterogeneity across regions and years, depending on data availability. The total time spent on the job is derived from the information reported by the respondents in the ASEC regarding the time constraints imposed by employment. The ASEC provides information on weekly hours of employment as well as the number of weeks worked in a given year, from which we estimate the annual hours of employment.

Household Production Activities (*R*): Definition

We include four main categories of activities in our definition of household production. Time allocated to all activities is reckoned inclusive of the associated travel times where applicable. The activity categories[1] are:

1. Domestic chores: These are activities that are essential for the maintenance of the household. They include cleaning, cooking, laundry, house care, etc.
2. Procurement: These are activities related to the procurement of goods and services for the household. They include shopping for household supplies and obtaining services.
3. Child care: These are activities related to the care of household and non-household children. They include feeding, bathing, teaching, and playing with children.
4. Adult care: These are activities related to the care of adults, in particular elderly, in or out of the household. They include feeding, bathing, and assisting adults in the household.

For the identification of the required time for household production activities, we estimate models following equation (2). As noted above, the models are based on the synthetic dataset constructed from the ASEC and ATUS data (see Section 4 for more details). The model is estimated for each year based on data for the latest five-year period, e.g., the requirements for 2022 are based on the parameters estimated from the data for 2018–22. The results of the model showing the estimated parameters for all years are presented in Table 1. The parameters are used to predict the household production requirements. The years correspond to the years of the ATUS data and the estimates are at the household level (family unit based on the Supplemental Poverty Measure (SPM), described later).

[1] See Appendix Tables A1-A4 for a detailed list of activities included in each category.

Based on the parameters, the baseline average for a single-person household is around 25 hours spent on household production activities per week. This estimate is quite stable across all years, with a lower bound of 24.4 hours in 2021 and an upper bound of 26 hours in 2007. Our estimates suggest that, on average, the incremental impact on total household hours of a young child (0–5 years of age) is only half as much as that of a non-elderly adult. The effect is even smaller when the child is between 6 and 14 years of age but increases to about 75 percent for older children (15–17 years). In contrast, the incremental impact of an additional older adult is approximately the same as that of an additional younger adult. In interpreting these estimates, it is important to bear in mind that the incremental impacts pertain to the total number of household hours for all individuals and not just of an individual within the household. Further, the household-level hours tend to increase with the number of individuals 15 years and older who are available to engage in household production. We also find that there is little evidence of economies of scale in household production requirements, as the estimates of δ are close to 0.9.

Table 1: Estimated Parameters of the Model for Weekly Hours of Household Production Requirements: 2007–2022

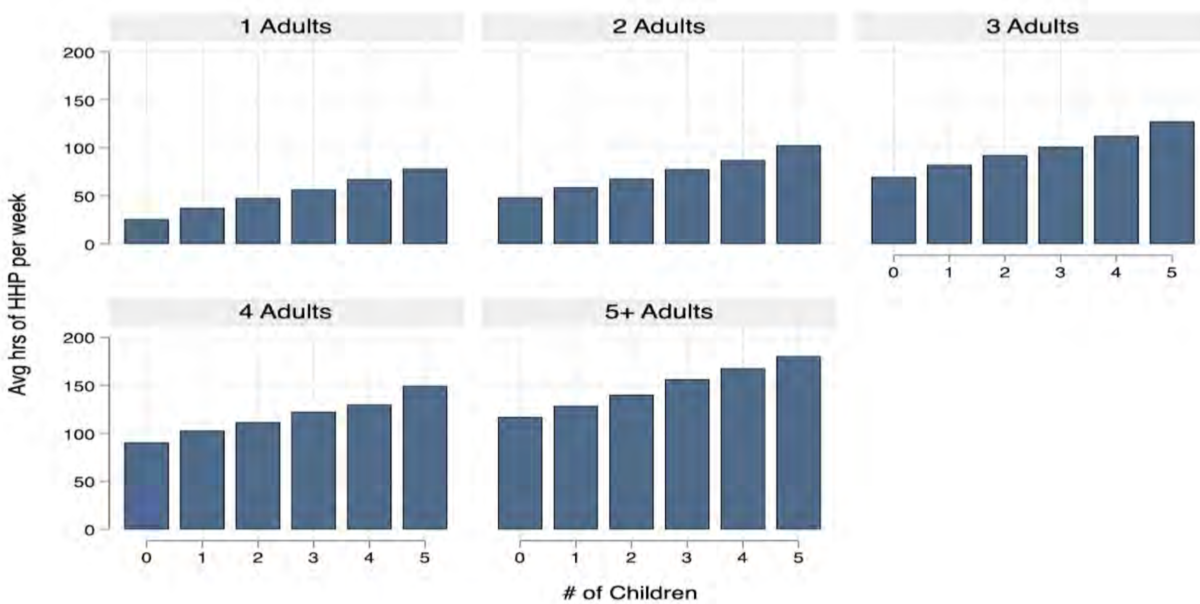
Year	2007	2008	2009	2010	2011	2012	2013
a_0	26.05	24.98	24.92	24.95	24.66	24.57	24.86
	-0.4	(0.36)	(0.35)	(0.32)	(0.32)	(0.34)	(0.36)
γ_1	0.5	0.49	0.50	0.48	0.52	0.51	0.50
	-0.02	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(-0.02)
γ_2	0.25	0.24	0.23	0.25	0.27	0.30	0.31
	-0.01	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
γ_3	0.75	0.72	0.68	0.65	0.67	0.73	0.80
	-0.04	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)
γ_4	0.98	1.01	1.01	1.01	1.02	1.04	1.02
	-0.01	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
δ	0.92	0.95	0.95	0.94	0.94	0.93	0.92
	-0.01	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	31737	33408	35194	36804	35767	35576	34431
Year	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
a_0	24.95	24.88	24.93	25.31	25.50	25.12	24.64

	(0.35)	(0.34)	(0.35)	(0.36)	(0.40)	(0.44)	(0.41)
γ_1	0.52	0.53	0.57	0.57	0.53	0.55	0.49
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
γ_2	0.32	0.33	0.33	0.31	0.32	0.34	0.38
	-0.02	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
γ_3	0.77	0.74	0.71	0.72	0.76	0.79	0.80
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
γ_4	1.04	1.07	1.07	1.03	1.00	1.01	1.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
δ	0.92	0.93	0.93	0.92	0.91	0.90	0.92
	-0.01	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	33199	32041	33222	31302	30049	28611	27847
Year	**2021**	**2022**					
a_0	24.42	25.06					
	(0.44)	(0.58)					
γ_1	0.48	0.43					
	(0.03)	(0.03)					
γ_2	0.39	0.40					
	(0.02)	(0.03)					
γ_3	0.89	0.92					
	(0.06)	-0.07					
γ_4	1.07	1.06					
	(0.02)	-0.02					
δ	0.93	0.92					
	(0.01)	-0.02					
N	21429	16078					

Note: Standard errors in parentheses

We illustrate the magnitude of the thresholds in Figure 1 using the data for 2022. While household production thresholds are estimated for different types of households, averages by number of total adults (18 years and above) and total number of children (0–17), are presented in the figure. As expected, there is a consistent positive slope across number of adults and number of children. Interestingly, as observed in Table 1, there is some evidence of economies of scale in household production requirements.

Figure 1: Threshold of Weekly Hours of Household Production, 2022



Note: The value 5 on the x-axis denotes households that have at least five children.
Source: Authors' calculation based on the synthetic dataset constructed from the ASEC and ATUS

Identification of Non-Substitutable Activities *M*

The component M represents the minimum time requirements for a set of activities that are considered non-substitutable. On the one hand, these are activities we consider to be basic requirements for the physical and mental health of the individual, and on the other hand, these cannot be delegated to others. The component M includes activities like personal care (sleeping, eating etc.; see Appendix Table A5 for the full list); and also, leisure and socializing.

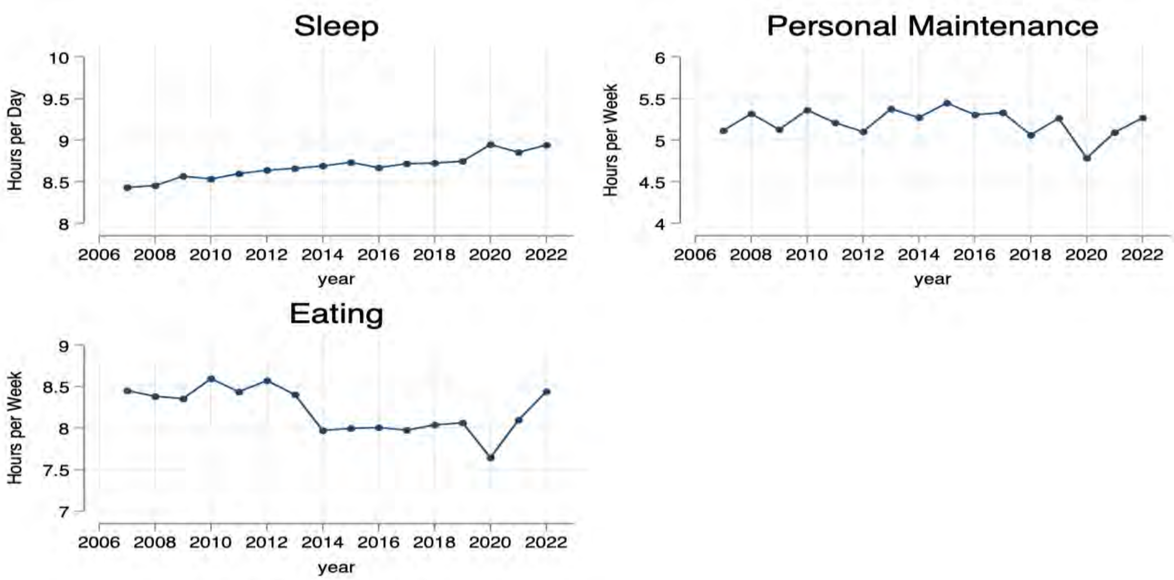
The amount of time required for leisure and socialization is determined by assumption, while others are based on the average values observed in the ATUS data for individuals in the 18–64 age group. We assume individuals require 10 hours minimum of leisure per week,[2] plus 7 hours

[2] In 2022, the median leisure time among 18-64 age group was about 4 hours per day (Flood et al., 2023), which would translate into a much higher weekly value than our presumed threshold for leisure.

weekly of non-substitutable household production that represents the minimum time for essential tasks of household management and socialization (including among household members). For personal care, we include average daily hours of sleep as reported in the ATUS data by year (8.9 hours a day in 2022) and the average hours dedicated to self-care activities like washing/grooming/dressing oneself daily, as well as eating or time spent waiting for these activities.

Figure 2 shows the trends in the main components of the personal care activities for the years 2007 to 2022. The figure shows that the time spent on sleep has been increasing steadily over the years, while personal maintenance and eating have been relatively stable. Interestingly, after 2012, the average time spent on eating has declined by about 30 minutes, while declining by an additional 30 minutes in 2020.

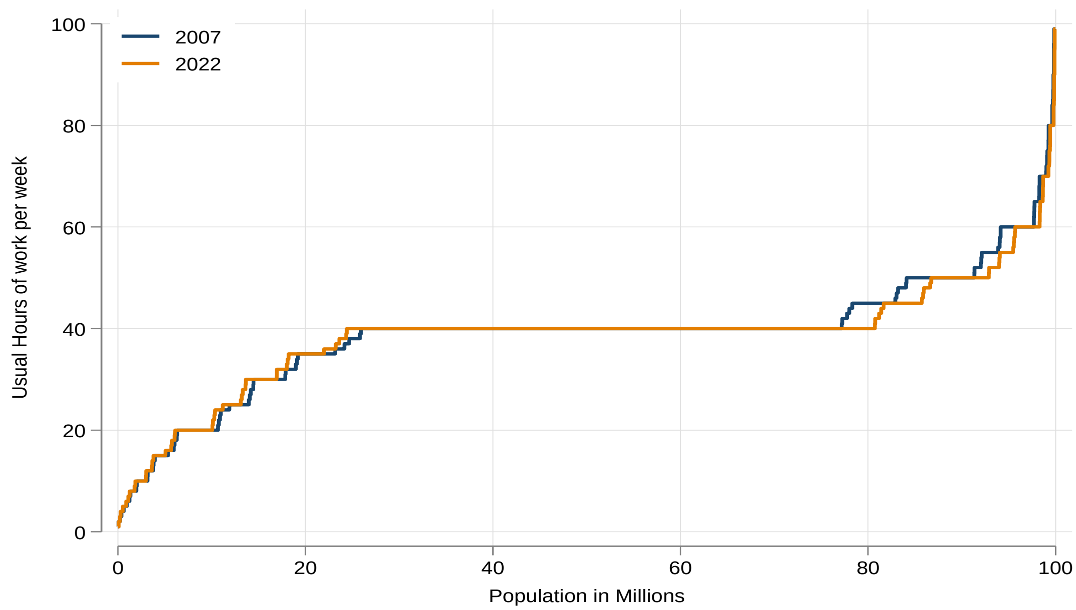
Figure 2: Thresholds of Personal Care, 2007-2022



Time Allocated to Employment and Commuting Time Requirements, *L* and *T*

For the identification of time commitments for employment and commuting time requirements, we use data from the ASEC and the ATUS. Specifically, for length of the workweek, we use the usual weekly hours worked last year reported in the ASEC data. Unsurprisingly, there have not been major changes in the average hours worked per week. In Figure 3, we show a Pen parade of the usual weekly hours of work across all years against the population in millions, highlighting the years 2007 and 2022. Based on the data, there have been very few changes in the number of individuals who work less than 40 hours a week, or more than 40 hours a week. However, the number of individuals who report to work exactly 40 hours has increased sharply over time.

Figure 3: Usual Weekly Hours Worked Last Year, 2007 and 2022



For the estimation of commuting time requirements, we use a two-step approach. First, we identify how much time people report commuting in the ATUS considering all individuals who had spent any time on income-generating activities. Next, we add this information to our synthetic dataset, and estimate the average commuting time by census division and year, differentiating between the full- and part-time employed. For full-time workers, we are able to estimate average commuting time across divisions and years. However, for part-time workers, due to data limitations, we only estimate average commuting time by division, pooling data across years.

Figure 4 shows average commuting time by region for full-time and part-time workers, across all years. As expected, time spent commuting for part-time workers is about half of that spent by full-time workers. We also observe some regional heterogeneity, with the highest commuting times for full-time workers observed in the Mid-Atlantic (5.2 hours per week) and South Atlantic (about 4.8 hours per week) regions. Similar patterns are observed for part-time workers. Figure 5 presents the trend of commuting time by region and year for full-time workers. While commuting time has been relatively stable across time, after the pandemic, we observe a decrease in commuting time in 2020–21 of over 1 hour per week. This may be related to the increased prevalence of remote work arrangements.

Figure 4: Average Commuting Time by Region and Employment Status, 2007–2022

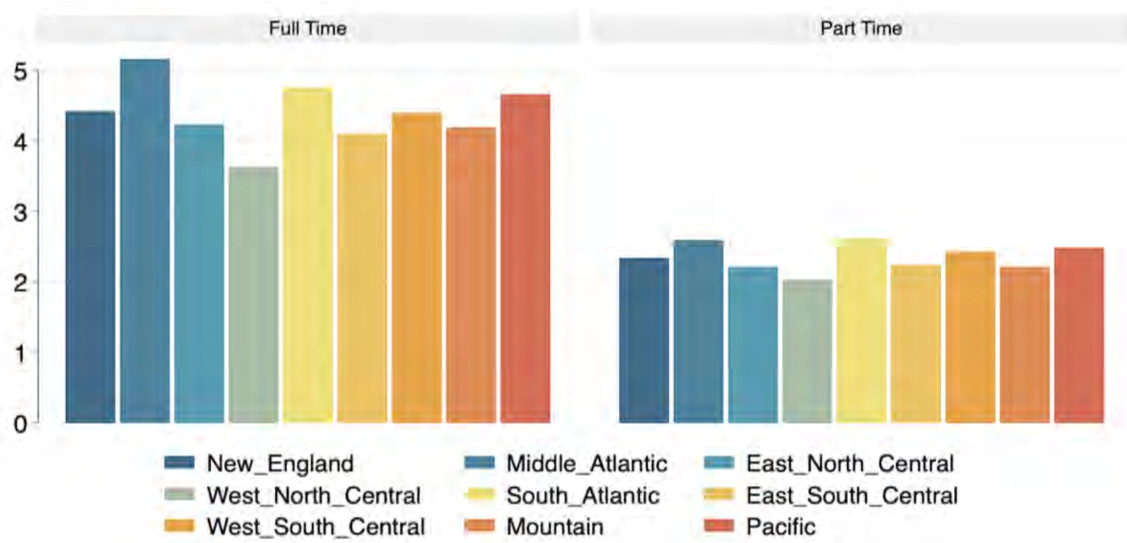
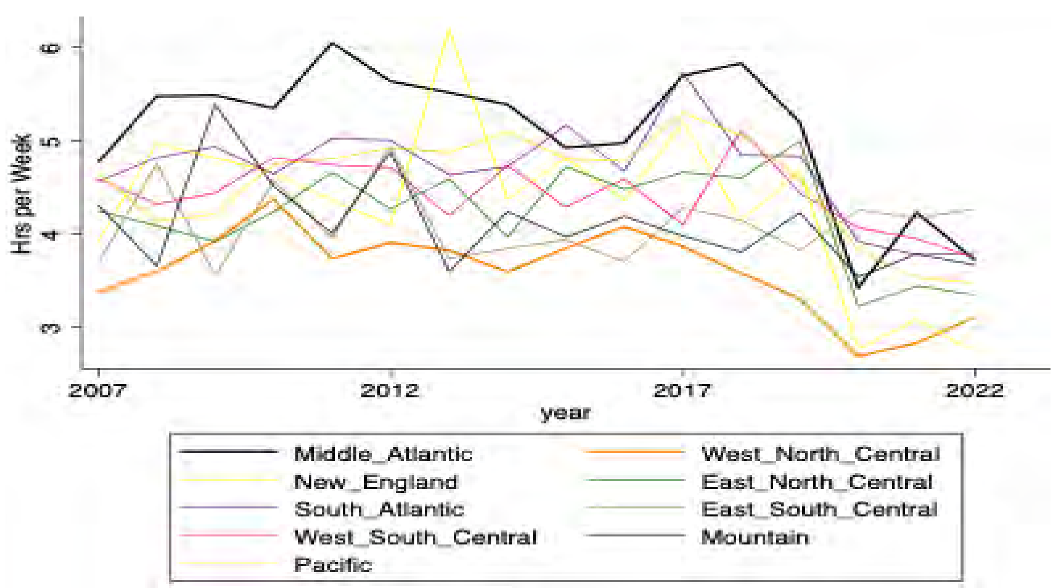


Figure 5: Commuting Time by Region and Years: Full Time workers, 2007-2022



Time Poverty

Time-poor individuals are identified as those with a negative time balance or time deficits. It is important to emphasize that the time deficits reflect the potential deficit individuals may face under typical time requirements for household production and personal maintenance, and do not account for how individuals may be currently allocating their time to these activities. For example, a parent in a household may choose to spend less time sleeping to take care of children, or he/she may be more efficient in household production activities than the average person.[3]

In addition to individual time poverty, we are also interested in the time deficits of households because standard income poverty thresholds are specified at the household level. We calculate the household-level time deficit as the sum of the time deficits of the members of the household. Our assumption is that there is no automatic mechanism that would offset the time deficits of some members with the potential time surpluses of other members. Thus, we consider a household to be time-poor if it has at least one member with a time deficit. The alternative would be to add up the time balances of the members of the household. This procedure would be tantamount to assuming that the time surplus available for household production for some household members will somehow be allocated automatically to offset the time deficit of other members. We consider such an assumption as less plausible compared to our assumption, in light of the observed widespread intrahousehold inequalities, primarily based on gender, in the division of household responsibilities.[4]

Formally, the time deficit experienced by a household j is defined as:

$$X_j = \sum_{i=0}^{j_n} min(X_{ij}, 0) \quad (3)$$

[3] This is in a similar vein as to how standard income-poverty measures classify a household as income non-poor if its income exceeds the official poverty threshold, regardless of the actual expenditure pattern which may not meet the minimal requirements of food, shelter, durable goods etc. For example, a household might prioritize certain expenses like spending more on housing to access better schools for their children at the expense of meeting minimal/adequate food requirements. The reasoning behind classifying the household as nonpoor is that the household can potentially meet the minimum poverty-level requirements, even if it chooses not to do so in practice.

[4] See Rios-Avila, Sinha, Zacharias, and Masterson (forthcoming), where we present the intrahousehold division of household production work and examine the potential impact of redistributing household production time to alleviate time and income poverty as well as gender inequality.

where j_n is the number of individuals in household j. A household is considered time-poor if $X_j < 0$, which indicates that at least one member of the household is time-poor.

Adjusting Income Poverty

Once household deficits have been calculated, we adjust the standard income poverty measure and create a new measure of income poverty threshold that accounts for the monetized value of time deficits. We use the Supplemental Poverty Measure (SPM) as the standard threshold, because compared to the official measure of poverty, SPM is a broader measure (Creamer and Burns 2024). It incorporates cash income, in-kind benefits, and necessary expenses. The SPM thresholds are based on expenditures for food, clothing, shelter, utilities, telephone, internet, and some in-kind benefits. Further, nondiscretionary expenses, such as taxes, work expenses, and medical out-of-pocket costs, are subtracted from family income.

The adjustment we make to the SPM involves monetizing the time deficits faced by a household, and using this value to adjust the poverty thresholds (Z_j). The adjusted poverty line Z_j^{adj} is used to determine income poverty status for household j[5] and is defined as

$$Z_j^{adj} = Z_j + \left(\left|X_j\right| * \ P_x \right)$$

where P_x represents the cost of buying an hour of services in the market that could be used to cover the time deficit due to household production. The new poverty threshold is used to calculate the time and income poverty status of the household.

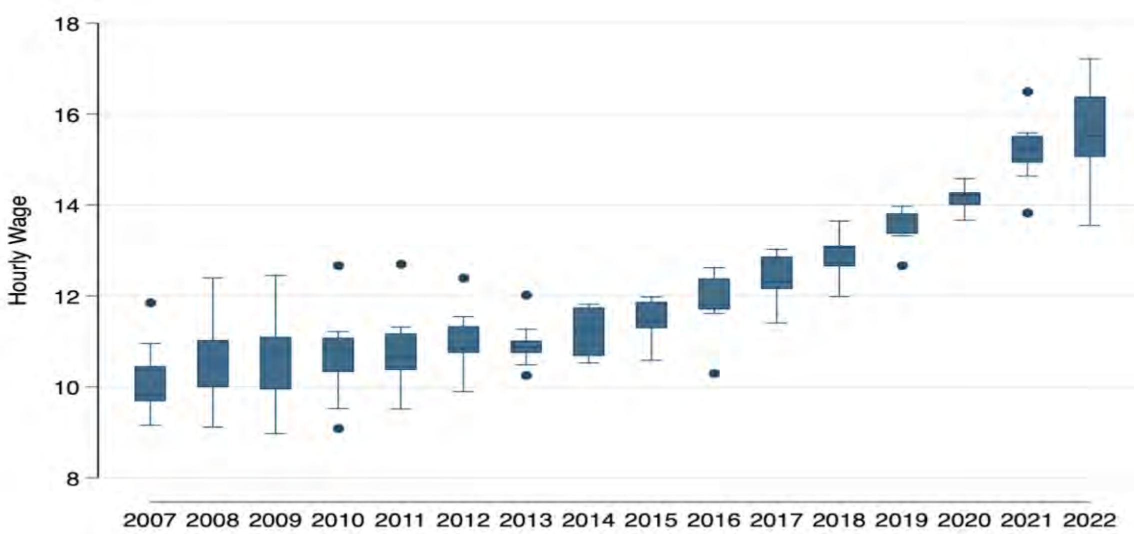
There are alternatives that could be used to monetize time deficits. For example, one could use minimum wage, or specialist wages (different occupational wages for different activities of

[5] We construct the LIMTIP estimates for SPM family units because they constitute a broader definition of family by including cohabitating partners and their relatives as well as foster children. In addition to the broader measure of poverty captured by the SPM poverty thresholds, the definition of family unit in SPM was an additional advantage to use SPM thresholds rather than the official poverty thresholds.

household production) (see Zacharias et al. [2024] for a discussion). For our present analysis, we use the average hourly wages for workers in the **private household** industry (census industry code 9290 from 2020 onwards) because that industry includes only workers employed in households performing various tasks of household production ranging from cooking to childcare. The source of our data is the monthly outgoing rotation group of the Current Population Survey (CPS), extracted from the National Bureau of Economic Research (NBER) (US Census Bureau & BLS 2007–2022).

To allow for spatial and time heterogeneity, average hourly wages are estimated using the nine census divisions, and a three-year average. In Figure 6, we present the trends of the hourly wages used to monetize the time deficits. We use a box-plot figure to show the spread of wages across the different census divisions. Perhaps the most outstanding case is the New England division, which had the highest average hourly wage in most periods, representing the outliers between 2007 to 2013. For the rest of the periods, wages are remarkably similar across divisions. In terms of levels, in 2007, the replacement cost of time was around $9.8 per hour, while in 2022, it was $15.2 per hour (not adjusted for inflation).

Figure 6: Average Hourly Wages for Private Household Workers, 2007–22



SECTION 3. STATISTICAL MATCHING METHODOLOGY

As described in the previous section, the construction of the LIMTIP requires household income, employment, and poverty data, along with time-use data. While the ASEC provides detailed information on income, employment, and demographic characteristics, in addition to the extended measure of income and poverty (the SPM), it does not have any information on time use. The ATUS, on the other hand, provides detailed information on time use, but only for a single individual in the household and for a single day. To construct the LIMTIP, it is necessary to impute the time allocated to household production by all household members in the ASEC survey, so that the methodology outlined in Section 2 can be implemented. In this section, we provide a brief description of the datasets used in the construction of the LIMTIP and the statistical matching procedure used to combine the datasets.

Data Sources

A summary of the main characteristics of the data can be found in Table 2, followed by a brief description of the ASEC and ATUS survey data. Both datasets were accessed through the Integrated Public Use Microdata Series (IPUMS) database (Flood et al. 2023).

Table 2: Surveys Used in Constructing the US-LIMTIP 2022

Survey	Survey Subject	Source	Sample Size	Year
American Time Use Survey (ATUS)	Time-use	IPUMS	8,136 Individuals	2022
Annual Social and Economic Supplement (CPS-ASEC)	Income, Demographics, Employment	IPUMS	116,571 Individuals	2023

Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS)

The CPS is a monthly survey administered by the US BLS. The survey collects comprehensive data on labor market situations, including statistics related to employment and unemployment, as well as detailed information on demographic characteristics (e.g., age, sex, race, and marital status), educational attainment, and family structure. Each household in the CPS is interviewed for four consecutive months, not interviewed for eight, and interviewed again for four additional months. In March of every year, the interviewed households answer additional questions as part of the ASEC supplement, formerly known as the Annual Demographic File. This supplement also collects data for an oversample, in order to increase the sample size and produce more reliable estimates for subpopulations.

In addition to the basic monthly information, this supplement provides data on work experience, income, poverty, noncash benefits, and migration.[6] The ASEC is used as the base dataset (the recipient), to which information from the donor dataset, ATUS, is imputed. We impute the time allocated to household production from the ATUS for every individual in the ASEC that is 15 years or older. As discussed below, a variety of individual-level data, such as age, are used in the imputation. We also use a set of variables that capture the household-level characteristics of the individual, e.g., the number of adults in the household.

American Time Use Survey (ATUS)

The ATUS is a survey sponsored by the BLS and collected by the US Census Bureau. It is the first continuous survey on time use in the US available since 2003. Its main objective is to provide nationally representative estimates of people's allocation of time among different activities, along with several context variables collecting information on what they did, where they were, and with whom they were over the course of a single day.

[6] In 2014, the ASEC supplement went through a redesign of the income-collection questions. As described in Semega and Welniak (2013), for the ASEC 2014, approximately one-third of the sample was randomly assigned to receive the redesigned income questions, while the remaining two-thirds were eligible to receive the set of ASEC income questions used in previous years, referred to as the "traditional income questions." For the statistical matching purposes, we use the second subsample.

The ATUS is administered to a random sample of individuals selected from a set of eligible households that have completed their final month's interviews for the CPS. Only one individual per household is selected to participate in the ATUS. This individual is at least 15 years old and is part of the civilian, non-institutionalized population in the US. To obtain a representative picture of time use across one year, data collection is spread over the entire year, and individuals are requested to report data for either a weekday or a weekend day, but not both.

Because the ASEC of any particular year collects information on income received during the previous year, the ATUS dataset used for the matching process is the one collected in the year prior to the ASEC data. That is, for the US-LIMTIP 2022, the ATUS data used are from 2022 and the corresponding ASEC data are from 2023. In addition, to improve on capturing the typical activities of individuals, we matched each record in the ASEC data with two ATUS observations based on the type of day of week, i.e., one for a weekday and one for a weekend day. This implies we are effectively treating the ATUS data as two separate datasets, ATUS weekdays and ATUS weekend days. This is done to account for the different patterns of time use between weekdays and weekends.

Statistical Matching

In order to create synthetic datasets that combine data from the different sources into a single dataset, we employ a methodology known as statistical matching. Statistical matching is a non-parametric imputation method that allows combining information from two (or more) independent datasets without imposing any distributional assumptions on the imputed variables. The basic idea of this methodology is to combine the information from two datasets, transferring information from one dataset (the donor) to another (the recipient). To do this, observations across surveys must be linked based on how similar they are (in a statistical sense). Similarity between the records is assessed on the basis of commonly observed characteristics and by taking into account how many individuals a survey observation represents in the population (using weights). Because of the peculiarities of the ATUS, we need to implement a double-matching procedure, where each ASEC observation is matched to two ATUS observations, one for a weekday and one for a weekend day, with the expectation that this would better represent their typical activities over a week, which can be further extrapolated into activities over one year.

The basic statistical matching setup consists of having access to two sources of data: survey A and survey B, which collect information from two independent samples of the same population. Survey A collects information Z, X, whereas survey B collects information Z, Y. Although both surveys collect common information Z (for example, demographics), they each contain information on variables that are not observed jointly: X (e.g., income) and Y (e.g., time use). The goal of statistical matching is to create synthetic data that will contain all information Y, X, Z, linking observations across the datasets based on their degree of similarity. We also constrain matches based on the weighted population each survey represents.

In turn, this synthetic dataset allows researchers to analyze otherwise unobservable relationships between X and Y or, as in our case, income and time use. However, inference on the relation between X and Y can only be done to the extent that Z explains the common variation between X and Y. In other words, the matching of the datasets is done using common information between the two surveys, while trying to preserve the distributional characteristics of the combined information under the assumption that both surveys represent the same population. There are numerous empirical works in economics and other disciplines that have applied this strategy (see for example, Rässler [2002] and D'Orazio, Di Zio, and Scanu [2006]).

Matching Algorithm

As described in Lewaa, Hafez, and Ismail (2021), statistical matching could be considered a non-parametric variation of the stochastic regression approach, where no specific distribution assumption is imposed, and the imputed values are drawn directly from the observed distribution in the donor file. In particular, we implement a variation of the rank-constrained statistical matching described in Kum and Masterson (2010), which employed stratification by matching variables chosen ahead of time for theoretical reasons (for example, using sex as a strata variable for a match of time-use data), and used the last observation matched by observation sample weight. We improve on previous implementations by using a weight-splitting approach in combination with clustering analysis for an automatic selection of strata groups.[7]

[7] This is in contrast with previous iterations of Statistical matching used for the estimation of the LIMEW, which was based on ex-ante ad-hoc stratification, last-match-unit approach

We use the following steps to implement the statistical matching procedure:

Step 1: Data harmonization and weight adjustment

The first step involves harmonizing all common variables that will be used in the matching process and survey balancing. This is a necessary step in all imputation methods because variables need to have consistent definitions before they can be utilized for imputation. Further, this step includes adjusting sample weights to ensure that the weighted population is the same across all surveys. The standard practice is to adjust the sample weights of the donor sample. Additionally, for technical reasons, the weights are adjusted to be whole numbers. While it is customary to adjust weights to match the total population, it may also be advisable to adjust weights to align with subpopulations based on selected strata variables.

Lastly, it is recommended to verify if both the donor and recipient files truly represent the same population by comparing the means, variances, and proportions of key variables across both surveys. In instances where significant imbalances are observed, reweighting methods can be employed to improve the balance between the surveys. However, there is no definitive rule to determine when a discrepancy in the distribution constitutes a substantial imbalance and researchers rely on rules of thumb.

We adjusted the ATUS sample weights to match the population of individuals 15 years or older in the ASEC based on the individual weight: `ASECWT`, excluding those not living in households and those not related to the head of the household. As noted above, we divided the ATUS sample into weekday and weekend day records, effectively matching each ASEC observation with two ATUS observations. Accordingly, weights are adjusted for each subsample separately, so that the weekday and weekend ATUS samples both match the recipient (ASEC) weighted population. These weights are further adjusted based on three strata variables: gender of the respondent, whether there is a child ($\leq$ 17 years of age) in the household, and whether the respondent is employed. The adjusted weights are used for matching, but not for the balance assessment.

Step 2: Strata and Cluster identification, and propensity score estimation

The second step involves identifying statistically similar records based on commonly observed characteristics. This is accomplished through a combination of three methodologies:

1. **Principal Component Analysis (PCA)**: PCA is utilized as a data-reduction technique to decrease the dimensionality of the *common* variables to a few linear combinations. While there are numerous suggestions on determining the optimal number of components, we select the first few components that explain approximately 50 percent of the data's variation. To construct the LIMTIP, we consider household characteristics, individual characteristics, and economic characteristics. We used variables related to household structure, the number of children of different ages, number of adults of different age groups and genders, employment status of the householder and spouse (if present), level of household income, and home ownership. We also consider individual demographic characteristics such as age, gender, race, and education level.

2. **Cluster analysis**: Once the principal components are estimated, they are employed to identify clusters within the dataset using a k-means cluster iterative partition algorithm. A brief description of the algorithm can be found in James et al. (2021). As this algorithm only discovers locally optimal clusters and their identification is influenced by random initial conditions, it has a tendency to generate suboptimal clusters. To mitigate this issue, we modify the algorithm by repeating the procedure a sufficient number of times and selecting the "optimal" cluster based on the largest Calinski-Harabasz pseudo-F index (Caliński and Harabasz 1974). This ensures that the chosen cluster maximizes intra-cluster similarity while minimizing inter-cluster dissimilarity. This procedure generates various sets of clusters of different sizes. The clusters with the highest numbers of groups are prioritized in the statistical-matching procedure since they represent the most similar records, while clusters with fewer groups are utilized in later stages of the matching process.

3. **Propensity score matching:** To improve the matching procedure, we estimate a propensity score using a logistic regression model. The dependent variable is a binary indicator denoting whether an individual belongs to the donor or recipient dataset, while the independent variables include all common variables Z (including interactions or transformations). In the

scenario where both surveys can be considered random samples from the same population, the expected coefficients on all variables should, in theory, be zero or be statistically insignificant. However, due to sampling variability and differences in survey design, some variation in the propensity scores is typically observed. The logit model and corresponding propensity scores can be estimated using the complete pooled dataset or stratified by the primary strata variables.

Step 3: Matching and weight splitting

Once the propensity score has been estimated and the clusters and strata have been defined, we proceed with our matching algorithm. We start by creating cells which combine the identified strata and clusters from the previous step. The cells that combine the most detailed strata and clusters will be used first, as they would identify the most similar records. In addition to the strata and clusters, this step may also consider using other variables that are not part of the main strata, but that are important for reinforcing the similarity of the records during the matching process.[8]

Starting with the most detailed sets of cells, records within each cell are ranked in increasing order using the propensity score. Within each cell, a record with the lowest propensity score from the donor file is matched or linked to a record with the lowest propensity score in the recipient file. If both records have the same weight, they are considered fully matched and removed from the donor or recipient pool. If the weights are different, the record (donor or recipient) with the lowest weight is removed from the pool, and the weight of the matched record is adjusted by subtracting the weight value of the excluded record. The record with the adjusted weight is retained in the pool for a subsequent match. This process of matching records and weight adjustment, if necessary, continues until there are no more donor or recipient records left in that cell. If there are unmatched records from the previous steps, the procedure is repeated using a less detailed cluster until all records from the donor and recipient files are matched.

[8] Specifically, variables that were used outside of the main strata, for eg: race and age were used, as they were found to be important in the matching process. These variables are only used for a few rounds of matching and are not part of the main strata.

Once the matching is completed, we obtain a synthetic dataset where all records in the donor file are matched to potentially multiple records in the recipient files, and vice versa. Records matched at an earlier stage are considered to be the best matches, while those matched at later stages are considered to be less similar. For the final synthetic dataset, we select the *best* matched records for all the donor and recipient files. In general, records that were matched in the earlier stages (most detailed clusters) are considered to be better than those at later stages. In case of ties, records matched with the largest split weight are preferred. If further ties exist, the match is randomly chosen.

Due to this step, some observations in the donor sample may not be used at all, while others may be used more frequently than their weight would suggest. However, if the sample sizes and weight structures are similar across both files, we can expect only minor discrepancies between the distribution of the imputed data in the donor and recipient datasets. Nevertheless, if the sample sizes differ significantly, it is advisable to use the largest file as the recipient file, which is our approach in the US-LIMTIP construction.

The statistical matching procedure described above aims to impute all missing values in the recipient file by transferring the observed distribution of the imputed values from the donor file. After the matching process is completed, and the best matches are selected, we obtain a dataset that contains unique identifiers for each record in the recipient and donor files. These identifiers allow us to link/transfer any information from the donor file to the recipient file. This is an advantage over more conventional imputation methods that require a separate imputation model for each variable that requires imputation.

4. MATCHING QUALITY IMPLEMENTATION AND ASSESSMENT

Data Alignment

A meaningful statistical matching process would require that the surveys which are to be statistically merged represent the same population with approximately similar characteristics across their weighted samples. In this section, we present the alignment of the ATUS weekday

2022 and ATUS weekend 2022 with the ASEC 2023 datasets across key demographic characteristics. The alignment is determined to ensure that the two datasets are comparable and that the matching procedure is appropriate.

Table 3 compares the distribution of individuals across selected characteristics, including the strata variables. Since both datasets were collected within one year of one another, we expect them to be well-aligned, as most of the variables used reflect structural characteristics that are rather stable across time. The majority of the statistics presented in Table 3 suggest that there is reasonably good alignment between the ASEC and ATUS. We found a similarly good alignment balance for our restricted sample of 18–64 years (see Appendix Table A6). We now turn our attention to the matching procedure and our main results.

Table 3: Data Alignment, ATUS Weekday, ATUS Weekend and Matched Data, 2022

	ATUS Weekday			ATUS Weekend			ASEC		
	Men	Women	Total	Men	Women	Total	Men	Women	Total
Race/Ethnicity									
Non-Hispanic White	61.8	61.8	61.8	63.2	62.5	62.8	61.1	60.4	60.8
Black	11.4	12.8	12.1	11.3	12.8	12.1	11.5	12.7	12.2
Hispanic	18.1	17.2	17.6	18.2	17.1	17.6	18.3	17.5	17.9
Other	8.7	8.3	8.5	7.2	7.6	7.4	9.0	9.4	9.2
Presence of young children (young = <=5yrs)									
None	89.1	85.6	87.3	86.8	86.0	86.4	87.9	86.5	87.2
One or more	10.9	14.4	12.7	13.2	14.0	13.6	12.1	13.5	12.8
Employment status									
Nonemployed	26.7	36.6	31.8	27.0	40.4	33.8	32.1	41.8	37.0
Employed	73.3	63.4	68.2	73.0	59.6	66.2	67.9	58.2	63.0
Number of children in HH									
None	66.4	63.4	64.9	66.5	63.9	65.2	66.3	63.3	64.7
One	14.4	13.3	13.8	13.8	16.3	15.1	14.5	15.9	15.2
Two	13.9	14.4	14.1	12.7	11.7	12.2	11.8	12.9	12.4
Three or more	5.3	8.9	7.2	7.0	8.1	7.5	7.4	7.9	7.7
Number of adults in HH									
One	17.8	20.6	19.2	19.1	18.8	18.9	14.6	19.0	16.8
Two	56.3	53.7	55.0	56.3	55.6	56.0	53.0	52.1	52.6
Three or more	25.9	25.7	25.8	24.6	25.6	25.1	32.4	28.9	30.6
Age									
15/24	16.7	15.7	16.2	16.7	15.2	15.9	16.7	15.7	16.2
25/39	24.8	24.1	24.4	25.2	23.9	24.5	25.5	24.0	24.7
40/54	23.1	22.4	22.7	23.0	22.4	22.7	22.9	22.3	22.6
55/64	15.6	15.5	15.6	15.5	16.0	15.8	15.2	15.3	15.2
65 and above	19.8	22.3	21.1	19.6	22.5	21.1	19.7	22.8	21.3
Fam Structure									
Single	31.2	35.5	33.4	31.1	31.8	31.4	31.7	36.2	34.0
Couple	68.8	64.5	66.6	68.9	68.2	68.6	68.3	63.8	66.0
Education									
Less than Hs	14.0	13.2	13.6	14.7	12.8	13.7	14.4	12.9	13.6
High School	29.6	25.8	27.7	29.3	25.9	27.6	29.4	25.7	27.5
Some College	21.8	22.4	22.1	19.2	22.5	20.9	24.2	26.1	25.2
College +	34.5	38.6	36.6	36.8	38.8	37.8	32.0	35.3	33.7
Fam Income Quintile									
Less than 35K	19.3	22.1	20.7	20.5	21.5	21.0	19.1	22.1	20.7
35k-60k	20.6	19.5	20.1	17.8	20.3	19.1	18.8	19.0	18.9
60k-100k	23.5	24.6	24.1	25.5	23.3	24.4	24.0	23.5	23.8
100k-150k	16.6	14.9	15.7	17.2	17.1	17.2	16.8	15.6	16.2
150k or more	20.0	18.8	19.4	19.0	17.8	18.4	21.2	19.7	20.5
Household size									
1	14.8	15.8	15.3	16.2	15.0	15.6	13.1	14.9	14.0
2	34.1	34.7	34.4	34.8	34.9	34.8	34.0	33.7	33.9
3	18.5	16.4	17.4	17.0	18.8	17.9	19.5	18.9	19.2
4	20.5	15.6	18.0	17.7	17.0	17.3	17.3	17.1	17.2
5 or above	12.0	17.5	14.8	14.5	14.3	14.4	16.0	15.3	15.6

Matching Procedure

As described above, our matching procedure involves various steps to help ensure that the distribution of the imputed/transferred data in the ASEC is as close as possible to the distribution of time use in the ATUS, using a large set of common characteristics. Following our proposed strategy, after all data have been harmonized and weights adjusted, we use PCA to reduce the dimensionality of the data, grouping the variables into three categories: household characteristics, individual characteristics, and economic characteristics.

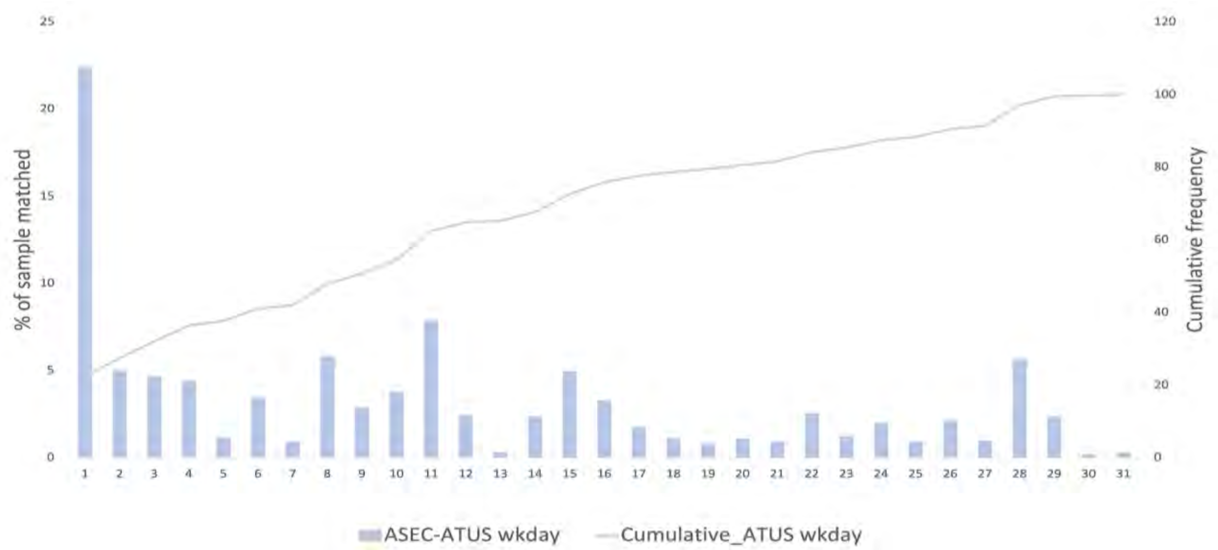
Once the PCA scores have been obtained, we use a partition cluster algorithm to identify groups of individuals of similar characteristics based on the first few components within PCA category. Specifically, we use a modified k-means algorithm to identify sets with 20, 10, 5, 3 and 2 groups, within each category. For the ranked matching, we estimate a propensity score using a logit model based on race, age, spouse's age, education, key employment variables including full-time employment status and class of worker indicating self-employment, private, or public employment, and household characteristics including number of adults, number of children, relation to household head. We also add to the model the first components of the 3 categories of principal components to further improve matching using different variations of common characteristics. The propensity scores are estimated separately based on the combinations of gender, employment status, and the presence of a child in the household.

Using a combination of the cluster sets, the strata variables, and other aggregated characteristics we considered important, we create 31 sets of matching cells. In the first round, in addition to strata variables, we include age group, family income, number of adults and number of kids, and three sets of the largest size clusters (size 20). The last set of matching cells are created using only the strata variables.

Matching Rounds

We start by examining the distribution of matched records by matching rounds. While one would prefer to have a larger share of the observations be matched during the first steps of the matching algorithm to ensure a higher quality match, the rate at which observations are matched can vary based on the restrictions that can be imposed on matching cells. Figure 7 presents the share of observations in the sample that are matched during each round and the corresponding cumulative shares for ATUS weekday. We find that 22.4 percent of the sample is matched in the first round. This is a good match given the extensive set of variables and clusters used for matching in the first round. Further, by round 16, 75 percent of the ATUS weekday sample has been matched to ASEC, and finally by the round 31, all observations in the recipient files are matched to a donor from the time-use data. While the first round of the match is somewhat lower than in other time-use matches (see, for example, Masterson [2010]) this is due to a higher than usual number of variables and larger cluster sizes used in the first round. We find similar matching trends across rounds for ATUS weekend matches (see Appendix Figure A1).

Figure 7: Share of Matched Observations by Round, ATUS Weekday, 2022



Matching Quality Assessment

In this section, we discuss the match quality for the year 2022. Some of the key criteria to assess the quality include the ability of the match to preserve the true individual values of the distribution (strongest test), the joint distribution of the transferred data, the correlation of the data, and the marginal distributions (weakest test) (Rässler (2002), (2004)). We apply statistical matching since the true values of the transferred data—as well as the joint distribution or correlations—are unknown. We then assess the quality of the match based on comparisons of the marginal distribution of the transferred data (time-use) across various selected household characteristics.

While there are different strategies that have been developed to assess the quality of the transferred data, including the comparison of the coefficients of potential explanatory econometric models (for example, Rios-Avila [2015]), in this paper, we focus on comparing three distributional statistics: the mean, the median and the standard deviation, of household production in minutes per day across strata variables and selected characteristics for the sub-sample of 18 to 64-year age group. For easy comparison, we report the ratios of the statistics across the ASEC imputed data and ATUS (weekend and weekday).

First, we compare the time spent in minutes per day on household production, which is obtained by adding up time spent on childcare, adult care, domestic chores, and procurement. Table 4 provides a comparison of the distribution of daily minutes of household production in the donor and matched file, specifically looking at different percentiles of the unconditional distribution and the Gini coefficient of the time spent on household production for the year 2022. As expected, we observe a close matching of the overall distribution, because the matching process guarantees an almost-perfect transfer of the overall distribution from the time-use to the household survey data.

Table 4: Distribution of Household Production, Gini and Percentiles, 2022

	Gini coeff	p10	p25	p50	p75	p90
Panel A						
ATUS Weekday	0.55	0	32	115	246	465
ASEC	0.55	0	31	115	251	470
Ratio	0	-	-0.03	0	0.02	0.01
Panel B						
ATUS Weekend	0.49	0	57	180	360	510
ASEC	0.49	0	55	180	355	510
Ratio	0	-	-0.04	0	-0.01	0

Note: Ratio is defined as imputed data divided by donor data, minus 1.

Next, in Table 5 we present the mean time-use estimates (daily minutes) of total household production along with its sub-components, namely childcare, adult care, domestic chores (e.g., cooking, cleaning, laundry, etc.), and procurement (shopping, etc.), for ATUS weekday and ATUS weekend matches. The tables compare the donor–recipient ratio of averages. We see that, for all the time use variables, the differences in the averages of the synthetic and original file variables are very small: less than or equal to 4 percent, and for most variables less than 2 percent.

Table 5: Comparison of Mean Time-use Variables (daily minutes), ATUS and Imputed Data, 2022

Survey	Core	Childcare	Adult care	Procurement	HouseholdProduction
Weekday					
ATUS	97.1	39.0	9.0	29.3	174.3
ASEC	100.3	37.5	9.2	28.9	176.0
Ratio ASEC/ATUS-1	-0.01	-0.04	0.03	-0.01	0.01
Weekend					
ATUS	139.3	31.9	10.6	44.5	226.3
ASEC	137.9	30.6	11.0	43.9	223.4
Ratio ASEC/ATUS-1	-0.01	-0.04	0.02	-0.01	-0.01

Note: Ratio is defined as imputed data divided by donor data, minus 1.

In Figures 8 and 9, we present boxplot representations of the distribution of time spent on household production during weekdays and weekends by number of adults and number of children. A visual inspection of these data suggests the quality of the match data is high, but the distribution observed in the recipient files seems smoother compared to the distribution from the donor data.

Figure 8: Boxplot of Household Production by Number of Adults and Children, ATUS Weekday, 2022

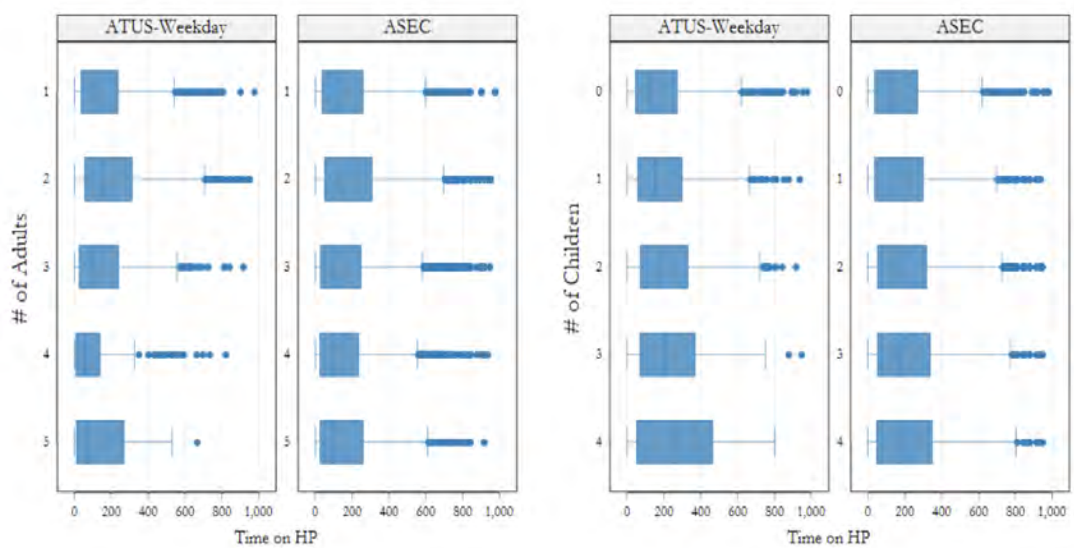
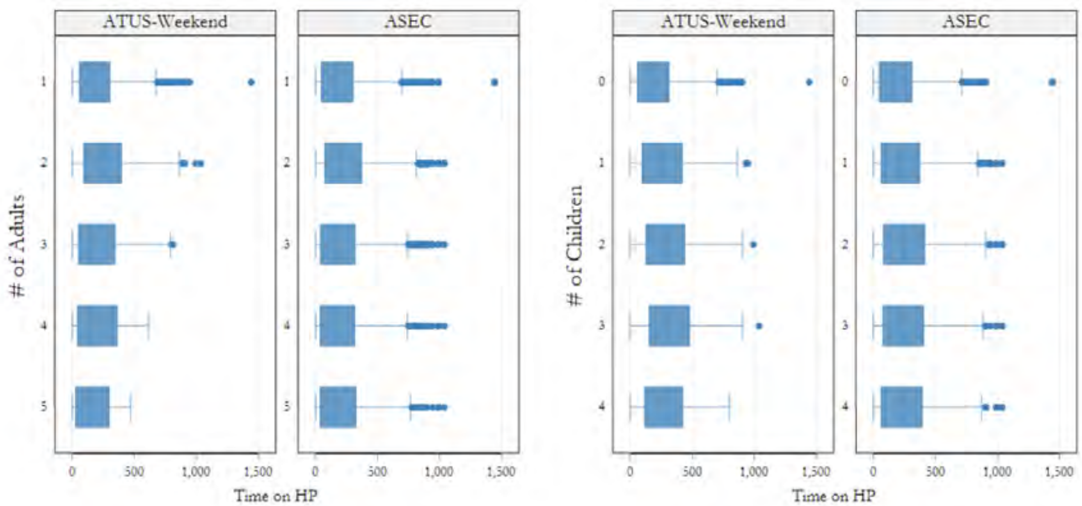


Figure 9: Boxplot of Household Production by Number of Adults and Children, ATUS Weekend, 2022



We now turn to assessing the match quality of household production time for the year 2022, comparing the matched data with ATUS weekday and ATUS weekend. We compare the imputed and real distributions of time use, in terms of mean, median, and standard deviations, based on the original survey weights.

In Table 6 we present the mean estimates of time allocation in household production for the sample aged 18 to 64 years for men, women, and the combined sample from ATUS weekday, and ratios of mean estimates comparing the matched data with ATUS weekday, for the main subgroups. Most of the ratios of ASEC to ATUS weekday mean values across selected variables fall within a narrow band of under 10 percent, and almost all the ratios fall within the 15 percent difference, with only a few exceptions. These include (i) the non-employed sample with children present in the household, such that the difference is 23 percent for the combined sample and 57 percent among men; (ii) the 15–24 age category, wherein the differences are 22 percent for the combined sample and 28 percent for women; and (iii) for education less than high school, the difference is slightly over 15 percent among women.

Table 6: Mean Daily Minutes of Household Production by Selected Variables, Weekday, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	Women	Total	Men	Women	Total
Race/Ethnicity						
Non-Hispanic White	138.7	221.4	180.0	0.0	0.0	0.0
Black	112.6	181.4	149.3	0.0	0.1	0.1
Hispanic	99.1	260.5	180.4	0.1	-0.1	0.0
Other	130.7	184.2	157.6	0.0	0.2	0.1
Presence of young children (young <=5yrs)						
None	119.7	194.9	156.7	0.0	0.1	0.0
One or more	173.4	341.7	269.9	-0.1	-0.1	-0.1
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	172.8	314.2	244.9	0.0	-0.1	0.0
Nonemployed children	369.2	455.1	442.2	-0.6	-0.1	-0.2
Employed no children	97.1	141.8	118.3	0.0	0.0	0.0
Employed children	146.9	233.9	189.4	0.0	0.0	0.0
Number of children in HH						
None	109.5	173.5	140.3	0.0	0.1	0.1
One	131.4	250.9	193.1	0.1	0.0	0.1
Two	182.9	284.6	235.5	-0.1	0.0	0.0
Three or more	157.2	345.1	278.9	0.0	-0.1	-0.1
Number of adults in HH						
One	122.5	170.8	147.3	-0.1	0.0	0.0
Two	144.6	248.4	196.7	0.0	0.0	0.0
Three or more	96.4	198.8	148.1	0.1	0.1	0.1
Age						
15/24	71.3	149.5	110.1	0.1	0.3	0.2
25/39	129.2	235.6	182.9	0.0	0.0	0.0
40/54	131.3	234.0	183.1	0.0	0.0	0.0
55/64	156.3	226.8	192.3	-0.1	0.0	0.0
Fam Structure						
Single	100.6	184.2	144.2	0.1	0.0	0.0
Couple	139.0	239.5	188.9	0.0	0.0	0.0
Education						
Less than HS	111.3	326.2	214.4	0.0	-0.2	-0.1
High School	115.7	222.2	161.3	0.1	0.1	0.1
Some College	132.0	222.0	178.2	-0.1	0.0	0.0
College +	137.7	199.5	172.1	0.0	0.0	0.0
Fam Income Quintile						
Less than 35K	133.0	248.9	195.2	0.0	0.0	0.0
35k-60k	117.6	248.4	179.8	0.1	0.0	0.0
60k-100k	125.5	208.0	167.8	0.0	0.0	0.0
100k-150k	127.0	183.8	155.4	-0.1	0.1	0.0
150k or more	132.0	216.1	173.8	0.0	0.0	0.0

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

Next, we present the median values in Table 7, which show similar trends. Median values across most variables fall within a narrow band of under 10 percent, and almost all ratios differ by less than 15 percent, with only a few exceptions which belong to relatively small subgroups. For example, in the age variable, the 15–24 category shows differences of 17 percent for the combined sample and among men, and 47 percent among women; however, the 15–24 age subgroup constitute only about 16 percent of the sample. Larger differences were observed for Hispanic men (71 percent) and Black women (25 percent), corresponding to relatively smaller subgroups of 18 and 13 percent, respectively. Further, for the interaction variable of employment status and number of children, households comprising non-employed members with children the difference for the overall sample is 29 percent and for men it is much higher (92 percent) whereas for single men households the difference is 33 percent. Households with three or more children showed a difference of 31 percent for men sample, whereas households with three or more adults showed a difference of 50 percent for men sample. For education level less than high school, the difference is 75 percent among men and 19 percent among women. Finally, for income quintile $35k–$60k, the difference is 22 percent for the overall sample and 27 percent among men. While some differences in median household production exist between the ATUS weekday and ASEC samples, these subgroups are either small in size or involve relatively little time. Therefore, we do not consider these differences to bias our main results, which pertain to much larger subgroups.

Table 7: Median Daily Minutes of Household Production by Selected Variables, Weekday, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	**Women**	**Total**	**Men**	**Women**	**Total**
Race/Ethnicity						
Non-Hispanic White	82.0	165.0	120.0	0.0	0.0	0.0
Black	70.0	115.0	95.0	0.0	0.3	0.1
Hispanic	35.0	190.0	95.0	0.7	-0.1	0.0
Other	90.0	116.0	95.0	0.0	0.3	0.3
Presence of young children (young <=5yrs)						
None	70.0	135.0	95.0	0.0	0.1	0.1
One or more	140.0	302.0	215.0	-0.1	-0.1	-0.1
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	120.0	290.0	195.0	0.0	-0.1	0.0
Nonemployed children	452.0	485.0	482.0	-0.9	-0.1	-0.3
Employed no children	55.0	90.0	75.0	0.0	0.0	0.0
Employed children	100.0	194.0	150.0	0.0	0.0	0.0
Number of children in HH						
None	60.0	120.0	85.0	0.1	0.1	0.1
One	90.0	192.0	130.0	-0.1	0.1	0.1
Two	130.0	235.0	190.0	-0.2	0.0	-0.1
Three or more	130.0	305.0	215.0	-0.3	0.0	-0.2
Number of adults in HH						
One	65.0	130.0	95.0	0.0	0.0	0.0
Two	90.0	180.0	129.0	0.0	0.1	0.0
Three or more	40.0	135.0	85.0	0.5	0.1	0.1
Age						
15/24	30.0	85.0	60.0	0.2	0.5	0.2
25/39	80.0	163.0	120.0	-0.1	0.0	0.0
40/54	88.0	170.0	125.0	0.0	0.0	0.0
55/64	85.0	195.0	127.0	-0.1	0.0	-0.1
Fam Structure						
Single	45.0	129.0	90.0	0.3	0.0	0.0
Couple	87.0	180.0	125.0	-0.1	0.0	0.0
Education						
Less than Hs	40.0	259.0	140.0	0.8	-0.2	-0.2
High School	65.0	150.0	90.0	0.1	0.1	0.2
Some College	75.0	160.0	120.0	-0.1	0.0	0.0
College +	87.0	145.0	119.0	-0.1	0.1	0.0
Fam Income Quintile						
Less than 35K	82.0	179.0	135.0	0.0	0.1	0.0
35k-60k	51.0	180.0	98.0	0.3	0.0	0.2
60k-100k	77.0	136.0	105.0	-0.1	0.1	0.0
100k-150k	80.0	134.0	100.0	-0.2	0.0	-0.1
150k or more	76.0	175.0	120.0	0.0	0.0	0.0

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

Next, we assess the match quality for **ATUS weekend and ASEC** in Table 8 based on mean estimates of time allocation in household production for the sample aged 18 to 64 years and find a more or less similar match quality as ATUS weekday. Once again, the mean values across selected variables fall within a narrow band of under 10 percent, and nearly all the ratios fall within the 15 percent difference with a handful of exceptions. There are only two cases with over a 20 percent difference: among the sample of Black men, the difference is 21 percent and for the age group variable, among men in the 15–24 age category the difference is 26 percent. Moreover, when we look at the median estimates in Table 9, we observe that the difference for the majority of variables again falls within 10 percent and nearly all the ratios fall within the 15 percent difference. In a few exceptional cases, larger differences were observed such as for the Black sample, the difference is 29 percent overall, 80 percent for Black men and 28 percent for Black women; whereas for 15–24 age category the difference for the men sample is 50 percent and overall, in this age category, the difference is 29 percent. Further, for an education level less than high school the difference is 24 percent for the women sample. As noted above, this group is small, hence insignificant to be considered to affect overall match quality. Therefore, while a few subgroups show some differences between the actual and imputed values, the overall match quality can be considered high across the majority of subgroups. Finally, we also examined the standard deviation estimates in Tables 10 and 11 and found that nearly all the ratios of ASEC to ATUS weekday and ASEC to ATUS weekend fall within a narrow band of under 10 percent. Overall, in terms of the ratios of averages and dispersion, we observe narrow gaps for most variables, again suggesting high match quality between ATUS weekday and ASEC.

Table 8: Mean Daily Minutes of Household Production by Selected Variables, Weekend, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	**Women**	**Total**	**Men**	**Women**	**Total**
Race/Ethnicity						
Non-Hispanic White	216.1	265.4	240.4	0.0	0.0	0.0
Black	130.2	191.7	162.7	0.2	0.1	0.2
Hispanic	187.8	260.4	224.0	-0.1	0.0	-0.1
Other	177.3	271.1	225.7	0.1	0.0	0.0
Presence of young children (young <=5yrs)						
None	183.7	231.6	207.4	0.0	0.0	0.0
One or more	267.4	361.7	317.2	-0.1	-0.1	-0.1
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	150.8	200.6	181.3	0.1	0.0	0.0
Nonemployed children	141.3	336.6	293.3	0.0	0.0	-0.1
Employed no children	183.3	224.6	201.9	0.0	0.0	0.0
Employed children	237.5	296.6	265.8	0.0	0.0	0.0
Number of children in HH						
None	178.6	218.7	197.9	0.0	0.0	0.0
One	219.2	292.4	258.4	0.0	0.0	0.0
Two	255.3	319.8	288.3	-0.1	0.0	-0.1
Three or more	200.3	313.8	263.3	0.1	0.0	0.0
Number of adults in HH						
One	194.5	216.0	204.1	0.0	0.0	0.0
Two	223.9	275.6	250.0	0.0	0.0	0.0
Three or more	147.1	236.2	193.7	0.1	0.0	0.0
Age						
15/24	97.2	179.3	136.8	0.3	0.0	0.1
25/39	207.6	268.8	238.0	0.0	0.0	0.0
40/54	218.4	286.6	252.6	0.0	0.0	0.0
55/64	221.4	238.5	230.3	0.0	0.0	0.0
Fam Structure						
Single	163.8	207.3	184.4	0.0	0.0	0.0
Couple	212.4	273.7	243.7	0.0	0.0	0.0
Education						
Less than HS	185.1	220.7	201.6	-0.1	0.1	0.0
High School	173.8	221.5	194.3	0.0	0.1	0.1
Some College	188.4	252.6	222.9	0.0	-0.1	0.0
College +	225.1	281.7	255.5	0.0	0.0	0.0
Fam Income Quintile						
Less than 35K	168.0	226.2	196.4	-0.1	0.0	0.0
35k-60k	196.1	252.6	225.7	-0.1	0.0	0.0
60k-100k	198.6	246.9	223.0	0.0	0.0	0.0
100k-150k	189.8	277.5	233.0	0.1	0.0	0.0
150k or more	230.1	272.8	251.2	0.0	0.0	0.0

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

Table 9: Median Daily Minutes of Household Production by Selected Variables, Weekend, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	Women	Total	Men	Women	Total
Race/Ethnicity						
Non-Hispanic White	180.0	240.0	200.0	-0.1	0.0	0.0
Black	50.0	135.0	105.0	0.8	0.3	0.3
Hispanic	120.0	222.0	175.0	0.0	-0.1	-0.1
Other	140.0	206.0	180.0	0.0	0.0	0.0
Presence of young children (young <=5yrs)						
None	135.0	190.0	164.0	0.0	0.1	0.0
One or more	252.0	360.0	310.0	-0.1	-0.1	-0.1
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	95.0	180.0	135.0	-0.1	-0.1	0.0
Nonemployed children	77.0	335.0	285.0	-0.2	0.0	-0.1
Employed no children	135.0	184.0	150.0	0.0	0.0	0.0
Employed children	205.0	275.0	240.0	0.0	0.0	0.0
Number of children in HH						
None	122.0	180.0	150.0	0.0	0.0	0.0
One	150.0	270.0	215.0	0.2	0.0	0.1
Two	240.0	315.0	275.0	-0.2	0.0	-0.1
Three or more	150.0	320.0	235.0	0.2	-0.1	0.0
Number of adults in HH						
One	150.0	170.0	160.0	-0.1	0.0	-0.1
Two	180.0	245.0	210.0	0.0	0.0	0.0
Three or more	75.0	200.0	146.0	0.4	0.0	0.0
Age						
15/24	40.0	135.0	70.0	0.5	-0.1	0.3
25/39	150.0	233.0	190.0	0.0	0.0	0.0
40/54	180.0	270.0	222.0	0.0	-0.1	-0.1
55/64	167.0	205.0	185.0	-0.1	0.0	0.0
Fam Structure						
Single	105.0	161.0	135.0	0.0	0.1	0.0
Couple	174.0	250.0	204.0	-0.1	0.0	0.0
Education						
Less than Hs	110.0	161.0	135.0	-0.2	0.2	0.0
High School	105.0	190.0	125.0	0.1	0.1	0.3
Some College	150.0	205.0	180.0	-0.1	0.0	0.0
College +	185.0	270.0	222.0	0.0	-0.1	-0.1
Fam Income Quintile						
Less than 35K	90.0	180.0	125.0	-0.1	0.0	0.0
35k-60k	145.0	205.0	182.0	-0.2	0.1	0.0
60k-100k	160.0	210.0	187.0	0.0	0.0	0.0
100k-150k	140.0	250.0	180.0	0.1	0.1	0.1
150k or more	205.0	248.0	220.0	-0.1	0.0	-0.1

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

Table 10: Standard Deviation of Daily Minutes of Household Production by Selected Variables, Weekday, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	Women	Total	Men	Women	Total
Race/Ethnicity						
Non-Hispanic White	162.4	198.9	186.2	0.0	0.0	0.0
Black	144.5	180.2	167.8	0.0	0.1	0.1
Hispanic	141.8	236.8	211.3	0.0	0.0	0.0
Other	160.3	170.3	167.3	0.0	0.1	0.1
Presence of young children (young <=5yrs)						
None	153.5	187.0	174.9	0.0	0.0	0.0
One or more	170.7	234.3	225.3	0.0	0.0	0.0
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	185.8	224.3	217.8	0.0	0.0	0.0
Nonemployed children	253.8	245.7	248.1	-0.1	0.0	0.1
Employed no children	133.9	145.6	141.3	0.0	0.0	0.0
Employed children	157.2	184.0	176.2	0.0	0.0	0.0
Number of children in HH						
None	146.2	176.0	164.3	0.0	0.0	0.0
One	149.2	218.3	197.2	0.1	0.0	0.0
Two	189.6	201.0	201.9	-0.1	0.1	0.0
Three or more	153.2	246.5	235.7	0.1	0.0	0.0
Number of adults in HH						
One	157.7	154.3	157.7	-0.1	0.0	0.0
Two	167.8	218.4	201.6	0.0	0.0	0.0
Three or more	128.4	193.6	172.2	0.1	0.1	0.1
Age						
15/24	113.8	169.3	148.9	0.0	0.2	0.2
25/39	151.5	216.4	194.4	0.0	0.0	0.0
40/54	153.5	207.7	189.9	0.0	-0.1	0.0
55/64	185.3	190.7	191.2	0.0	0.0	0.0
Fam Structure						
Single	139.9	174.7	164.3	0.0	0.0	0.0
Couple	162.8	215.1	197.0	0.0	0.0	0.0
Education						
Less than Hs	153.7	259.3	236.3	0.0	-0.1	-0.1
High School	149.8	214.4	187.7	0.0	0.0	0.0
Some College	159.7	199.3	186.6	0.0	0.0	0.0
College +	161.7	182.1	176.0	0.0	0.0	0.0
Fam Income Quintile						
Less than 35K	162.3	232.0	210.6	0.0	0.0	0.0
35k-60k	161.7	215.0	199.8	0.0	0.0	0.0
60k-100k	143.3	202.7	180.9	0.0	0.0	0.0
100k-150k	153.1	173.2	165.7	0.0	0.1	0.1
150k or more	166.0	184.2	180.1	0.0	0.0	0.0

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

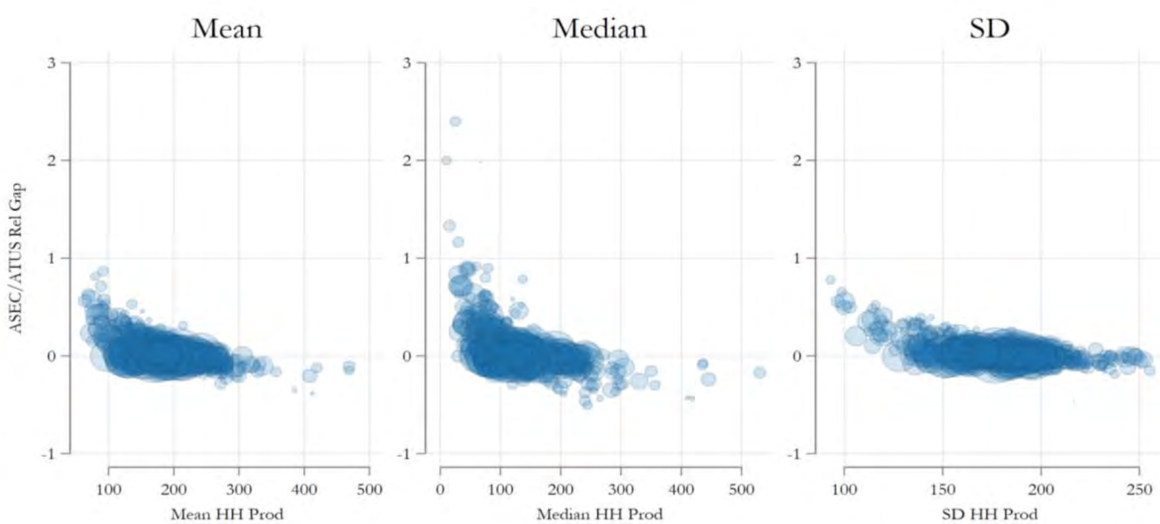
Table 11: Standard Deviation of Daily Minutes of Household Production by Selected Variables, Weekend, 2022

	ATUS			Ratio [(ASEC/ATUS)-1]		
	Men	Women	Total	Men	Women	Total
Race/Ethnicity						
Non-Hispanic White	198.8	205.1	203.4	0.0	0.0	0.0
Black	172.3	177.3	177.3	0.0	0.1	0.1
Hispanic	187.3	206.5	200.2	0.0	0.0	0.0
Other	158.1	206.1	189.9	0.1	-0.1	0.0
Presence of young children (young <=5yrs)						
None	183.4	192.4	189.4	0.0	0.0	0.0
One or more	220.8	217.2	223.7	0.0	0.0	0.0
Employed/Nonemployed Child presence (5-18)						
Nonemployed no children	165.0	162.6	165.1	0.1	0.0	0.0
Nonemployed children	152.4	219.6	221.6	0.0	0.0	0.0
Employed no children	181.9	184.9	184.3	0.0	0.0	0.0
Employed children	211.3	223.1	218.9	0.0	0.0	0.0
Number of children in HH						
None	179.8	179.8	180.9	0.0	0.0	0.0
One	224.3	223.3	226.4	-0.1	0.0	0.0
Two	198.7	218.7	211.4	0.0	0.0	0.0
Three or more	187.5	228.4	218.2	0.1	0.0	0.0
Number of adults in HH						
One	182.6	186.2	184.4	0.0	0.0	0.0
Two	199.6	211.5	207.2	0.0	0.0	0.0
Three or more	173.7	191.4	188.3	0.1	0.0	0.0
Age						
15/24	124.3	180.4	159.0	0.2	0.0	0.1
25/39	193.4	208.0	202.9	0.0	0.0	0.0
40/54	192.1	208.4	203.2	0.0	0.0	0.0
55/64	209.6	189.9	199.6	0.0	0.0	0.0
Fam Structure						
Single	181.9	187.3	185.6	0.0	0.0	0.0
Couple	195.2	206.3	203.2	0.0	0.0	0.0
Education						
Less than Hs	194.5	222.9	208.3	-0.1	-0.1	-0.1
High School	191.9	188.7	191.8	0.0	0.1	0.0
Some College	185.2	203.7	197.8	0.0	0.0	0.0
College +	193.4	203.9	201.0	0.0	0.0	0.0
Fam Income Quintile						
Less than 35K	188.8	200.2	196.4	0.0	0.0	0.0
35k-60k	189.5	190.2	191.7	0.0	0.0	0.0
60k-100k	186.6	196.7	193.1	0.0	0.0	0.0
100k-150k	184.0	219.5	206.8	0.0	0.0	0.0
150k or more	208.0	207.2	208.5	0.0	0.0	0.0

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

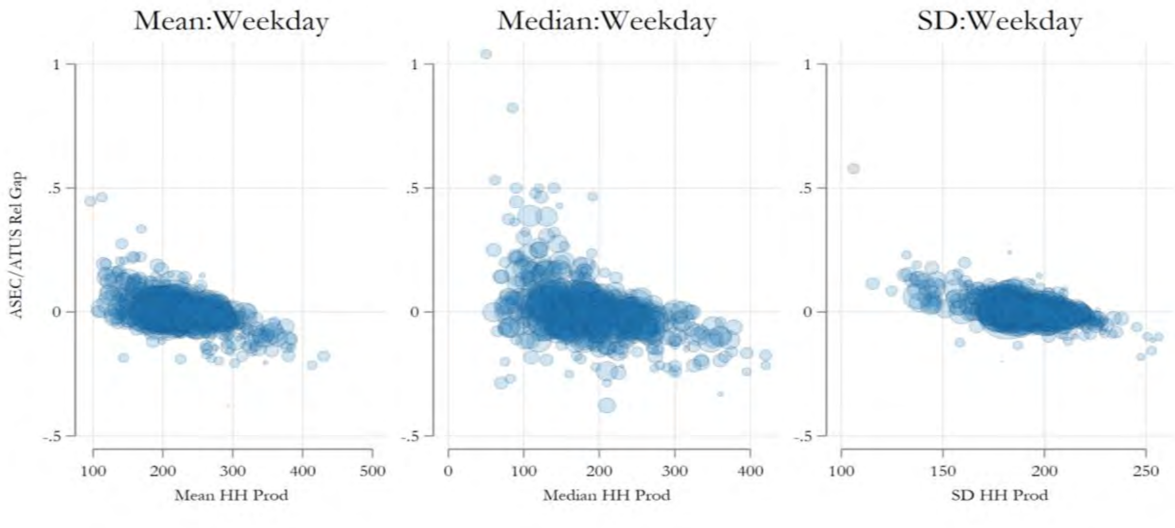
To provide a more comprehensive overview of the marginal distribution across all categorical variables involved in the matching process, we present a scatter plot of the relative ratios against the ATUS mean, median, and standard deviation values. The sizes of the points are proportional to the weighted number of observations in each category. These are shown in Figures 10 and 11 for the year 2022. We use all combinations across variables presented in Table 3. As can be observed from the scatter plots, most of the combinations show relative gaps concentrated around zero, with a few outliers. Most outliers are observed either among small groups, or where the statistic of interest was small in magnitude. For example, for weekday data, we observe very large gaps when the median of household production is below 50 minutes per day. Interestingly, the ASEC imputation tends to be understating the time use in cases where the mean or the median is high.

Figure 10: Relative Gap in Time Use Estimates: Weekday, 2022



Note: Each point is weighted by the relative importance of the Combination. Larger Cells represent more information. The x-axis shows the value observed in the Donor File (ATUS) which can be the mean, median or Standard error

Figure 11: Relative Gap in Time Use Estimates: Weekend, 2022



Note: Each point is weighted by the relative importance of the combination. Larger Cells represent more information. The x-axis shows the value observed in the Donor File (ATUS) which can be the mean, median or Standard error

CONCLUSIONS

In this paper, we discuss the empirical methodology used to estimate the US LIMTIP for the period 2007–2022 and highlight key limitations in existing datasets that hinder the development of a poverty measure accounting for time deficits. We provide a detailed overview of the statistical matching methodology employed to combine US household survey data from the Annual Social and Economic Supplement (ASEC) with time-use data from the American Time Use Survey (ATUS). After describing the step-by-step matching procedure, we present a quality assessment of the matched data. Overall, we find that the two datasets are well aligned, supporting the validity of the statistical matching approach. The estimates indicate that the matching quality is strong, showing good balance across different household characteristics. A few imbalances exist in small groups, but these have minimal impact on the overall matching quality. We conclude that the statistical matching procedure effectively imputes time-use estimates for the ASEC survey, enabling the development of a more informative, time-adjusted measure of poverty for the US.This augmented measure provides an improved metric of the poverty challenges that individuals and households face and can help inform policies that are inclusive, sensitive to time deficits, and gender equitable.

REFERENCES

Agarwal, B. 1997. "'Bargaining' and Gender Relations: Within and Beyond the Household." *Feminist Economics*, *3*(1), 1–51. https://doi.org/10.1080/135457097338799

Caliński, T., and J Harabasz. 1974. "A Dendrite Method for Cluster Analysis." *Communications in Statistics* 3 (1): 1–27. https://doi.org/10.1080/03610927408827101.

Creamer, J., & Burns, K. 2024. "Comparing Poverty Measures: Development of the Supplemental Poverty Measure and Differences with the Official Poverty Measure. Social, Economic, and Housing Statistics Division." US Census Bureau. Retrieved from https://www.census.gov/newsroom/blogs/random-samplings/2024/09/difference-supplemental-and-official-poverty-measures.html

D'Orazio, Marcello, Marco Di Zio, and Mauro Scanu. 2006. *Statistical Matching: Theory and Practice*. 1st ed. Wiley. https://doi.org/10.1002/0470023554.

Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. 2023. *Integrated Public Use Microdata Series, Current Population Survey: Version 11.0 [dataset]* Minneapolis, MN: IPUMS, 2023. IPUMS. https://doi.org/10.18128/D030.V11.

James, G., D. Witten, T. Hastie, and R. Tibshirani. 2021. *An Introduction to Statistical Learning: With Applications in R*. Second edition. Springer Texts in Statistics. New York, NY: Springer. https://doi.org/10.1007/978-1-0716-1418-1.

Kum, H. and T. Masterson. 2010. "Statistical Matching Using Propensity Scores: Theory and Application to the Analysis of the Distribution of Income and Wealth." *Journal of Economic and Social Measurement* 35 (3-4): 177–96. https://doi.org/10.3233/JEM-2010-0332.

Lewaa, I., M. S. Hafez, and M. A. Ismail. 2021. "Data Integration Using Statistical Matching Techniques: A Review." *Statistical Journal of the IAOS* 37 (4): 1391–1410. https://doi.org/10.3233/SJI-210835.

Masterson, T. 2010. "Quality of Match for Statistical Matches Used in the 1992 and 2007 Limew Estimates for the United States." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1680409.

Rässler, S. 2002. *Statistical Matching: A Frequentist Theory, Practical Applications, and Alternative Bayesian Approaches*. Lecture Notes in Statistics 168. New York: Springer.

———. 2004. "Data Fusion: Identification Problems, Validity, and Multiple Imputation." *Austrian Journal of Statistics* 33 (1&2): 153–71. https://doi.org/10.17713/ajs.v33i1&2.436.

Rios-Avila, F. 2015. "Quality of Match for Statistical Matches Using the Consumer Expenditure Survey 2011 and Annual Social Economic Supplement 2011." Levy Economics Institute Working Paper. Rochester, NY: Levy Economics Institute of Bard College. https://doi.org/10.2139/ssrn.2554089.

Rios-Avila, F., Sinha, A., Zacharias, A., and Masterson, T. (Forthcoming). *Redistribution and Time Poverty: Balancing Responsibilities in Couple Households*. Levy Economics Institute of Bard College.

Semega, Jessica L, and Edward Welniak. 2013. "Evaluating the 2013 CPS ASEC Income Redesign Content Test," Census bureau income statistics working paper,. https: //www.census.gov/content/dam/Census/library/working-papers/2013/demo/semega-01.pdf.

US Census Bureau and US Bureau of Labor Statistics. 2007–2022. Current Population Survey, Merged Outgoing Rotation Groups (CPS MORG) [microdata]. Retrieved from the National Bureau of Economic Research (NBER): https://www.nber.org/research/data/current-population-survey-cps-merged-outgoing-rotation-group-earnings-data

Zacharias, A. 2011. *The Measurement of Time and Income Poverty* (Working Paper No. 690). Levy Economics Institute of Bard College. http://www.levyinstitute.org/pubs/wp_690.pdf

———. 2023. "Poverty of time," in *Research Handbook on Measuring Poverty and Deprivation,* edited by J. Silber. Edward Elgar Publishing.

Zacharias, A., F. Rios-Avila, N. Folbre, and T. Masterson. 2024. "Integrating Nonmarket Consumption into the Bureau of Labor Statistics Consumer Expenditure Survey," A Study Conducted in Support of the BLS Research-Based Consumption Measure,

Zacharias, A., R. Antonopoulos, and T. Masterson. 2012. "Why time deficits matter: Implications for the measurement of poverty." Informe de Proyecto de Investigación. Programa de las Naciones Unidas para el Desarrollo (UNDP)/Levy Economics Institute of Bard College.

Zacharias, A., T. Masterson, and E. Memiş. 2014. "Time deficits and poverty: the levy institute measure of time and consumption poverty for Turkey." *Ekonomik Yaklasim* 25(91): 1–28.

Zacharias, A., T. Masterson, F. Rios-Avila, K. Kim, and T. Khitarishvili. 2018. "The measurement of time and consumption poverty in Ghana and Tanzania." Research Project Report, August. Annandale-on-Hudson, NY: Levy Economics Institute of Bard College.

Zacharias, A., T. Masterson, and K. Kim. 2014. "The measurement of time and income poverty in Korea." Informe de Proyecto de Investigación. Programa de las Naciones Unidas para el Desarrollo (PNUD)/Levy Economics Institute of Bard College/Korea Employment Information Service.

APPENDIX

Table A1: List of Activities under Domestic Chores

Code	Activity
20101	Interior cleaning
20102	Laundry
20103	Sewing, repairing, and maintaining textiles
20104	Storing interior hh items, inc. food
20199	Housework, n.e.c
20201	Food and drink preparation
20202	Food presentation
20203	Kitchen and food clean-up
20299	Food and drink prep, serving and clean-up, n.e.c
20301	Interior arrangement, decoration, and repairs
20302	Building and repairing furniture
20303	Heating and cooling
20399	Interior maintenance, repair, and decoration, n.e.c
20401	Exterior cleaning
20402	Exterior repair, improvements, and decoration
20499	Exterior maintenance, repair and decoration, n.e.c
20501	Lawn, garden, and houseplant care
20502	Ponds, pools, and hot tubs
20599	Lawn and garden, n.e.c
20601	Care for animals and pets (not veterinary care)
20602	Care for animals and pets (not veterinary care) (2008+)
20603	Walking, exercising, playing with animals (2008+)
20699	Pet and animal care, n.e.c
20701	Vehicle repair and maintenance (by self)
20799	Vehicles, n.e.c
20801	App, tool, toy set-up, repair, and maint (by self)
20899	Appliances and tools, n.e.c

20901	Financial management
20902	Household and personal organization and planning
20903	Hh and personal mail and messages (except e-mail)
20904	Hh and personal e-mail and messages
20905	Home security
20999	Household management, n.e.c
29999	Household activities, n.e.c
180201	Travel related to housework
180202	Travel related to food and drink prep
Code	Activity
180203	Travel related to int. maint, repair, and decoration
180204	Travel related to ext. maint, repair, and decoration
180205	Travel related to lawn, garden, and houseplants
180206	Travel related to care for animals (not vet care)
180207	Travel related to vehicle care and maint (by self)
180208	Trvl rel to app, tool, toy set-up, repair, and maint
180209	Travel related to household management
180299	Travel related to household activities, n.e.c

Table A2: List of Activities under Procurement

Code	**Activity**
70101	Grocery shopping
70102	Purchasing gas
70103	Purchasing food (not groceries)
70104	Shopping, except groceries, food and gas
70105	Waiting associated with shopping
70199	Shopping, n.e.c.

Code	Activity
70201	Comparison shopping
70299	Researching purchases, n.e.c.
70301	Security procedures rel. to consumer purchases
70399	Sec procedures rel. to cons purchases, n.e.c.
79999	Consumer purchases, n.e.c.
80201	Banking
80202	Using other financial services
80203	Waiting associated w/banking/financial services
80299	Using financial services and banking, n.e.c.
80301	Using legal services
80302	Waiting associated with legal services
80399	Using legal services, n.e.c.
90101	Using interior cleaning services
90102	Using meal preparation services
90103	Using clothing repair and cleaning services
90104	Waiting associated with using household services
90199	Using household services, n.e.c.
90201	Using home maint/repair/décor/construction svcs
90202	Waiting assoc w/home main/repair/décor/constr
90299	Using home maint/repair/décor/constr svcs n.e.c.
90301	Using pet services
90302	Waiting associated with pet services
90399	Using pet services, n.e.c.
90401	Using lawn and garden services
90402	Waiting assoc with using lawn and garden svcs
90499	Using lawn and garden services, n.e.c.

Code	Activity
90501	Using vehicle maintenance or repair services
90502	Waiting assoc with vehicle maint. or repair svcs
90599	Using vehicle maint. and repair svcs, n.e.c.
99999	Using household services, n.e.c.
100101	Using police and fire services
100102	Using social services
100103	Obtaining licenses and paying fines, fees, taxes
100199	Using government services, n.e.c.
160104	Telephone calls to/from salespeople
160106	Phone calls to/from household services providers
180701	Traveling to/from the grocery store
180702	Travel related to other shopping
180703	Travel related to purchasing food (not groceries)
180704	Travel related to shopping, ex. groc, food, gas
180705	Traveling to/from gas station
180799	Travel related to consumer purchases, n.e.c.
180802	Travel related to using financial svcs and banking
180803	Travel related to using legal services
180901	Travel related to using household services
180902	Travel rel. to using home maint. etc. svcs
180903	Travel related to using pet services (not vet)
180904	Travel related to using lawn and garden services
180905	Travel rel. to using vehicle maint. and repair svcs
180999	Travel related to using household services, n.e.c.
181001	Travel related to using government services

Table A3: List of Activities under Child Care

Code	Activity
30101	Physical care for household (hh) children
30102	Reading to/with hh children
30103	Playing with hh children, not sports
30104	Arts and crafts with hh children
30105	Playing sports with hh children
30106	Talking with/listening to hh children
30107	Helping or teaching hh children
30108	Organization and planning for hh children
30109	Looking after hh children (as a primary activity)
30110	Attending hh children's events
30111	Waiting for/with hh children
30112	Picking up/dropping off hh children
30199	Caring for and helping hh children, n.e.c.
30201	Homework (hh children)
30202	Meetings and school conferences (hh children)
30203	Home schooling of hh children
30204	Waiting associated with hh children's education
30299	Activities related to hh children's education, n.e.c.
30301	Providing medical care to hh children
30302	Obtaining medical care for hh children
30303	Waiting associated with hh children's health
30399	Activities related to hh children's health, n.e.c.
40101	Physical care for nonhh children
40102	Reading to/with nonhh children

Code	Activity
40103	Playing with nonhh children, not sports
40104	Arts and crafts with nonhh children
40105	Playing sports with nonhh children
40106	Talking with/listening to nonhh children
40107	Helping or teaching nonhh children
40108	Organization and planning for nonhh children
40109	Looking after nonhh children (as a primary activity)
40110	Attending nonhh children's events
40111	Waiting for/with nonhh children
40112	Dropping off/picking up nonhh children
40199	Caring for and helping nonhh children, n.e.c.
40201	Homework (nonhh children)
40202	Meetings and school conferences (nonhh children)
40203	Home schooling of nonhh children
40204	Waiting associated with nonhh children's education
40299	Activities related to nonhh children's education, n.e.c.
40301	Providing medical care to nonhh children
40302	Obtaining medical care for nonhh children
40303	Waiting associated with nonhh children's health
40399	Activities related to nonhh children's health, n.e.c.
80101	Using paid childcare services
80102	Waiting associated with purchasing childcare services
80199	Using paid childcare services, n.e.c.
160107	Phone calls to/from child or adult care providers
180301	Travel related to caring for and helping hh children
180302	Travel related to caring for and helping hh children (2005)

Code	**Activity**
180303	Travel related to hh children's education
180304	Travel related to hh children's health
180401	Travel related to caring for and helping nonhh children, inclusive
180402	Travel related to caring for and helping nonhh children
180403	Travel related to nonhh children's education
180404	Travel related to nonhh children's health
180801	Travel related to using childcare services

Table A4: List of Activities under Adult Care

Code	**Activity**
30401	Physical care for household (hh) adults
30402	Looking after hh adult (as a primary activity)
30403	Providing medical care to hh adult
30404	Obtaining medical and care services for hh adult
30405	Waiting associated with caring for hh adults
30499	Caring for household adults, n.e.c.
30501	Helping hh adults
30502	Organization and planning for hh adults
30503	Picking up/dropping off hh adult
30504	Waiting associated with helping hh adults
30599	Helping household adults, n.e.c.
39999	Caring for and helping hh members, n.e.c.
40401	Physical care for nonhh adults

Code	Activity
40402	Looking after nonhh adult (as a primary activity)
40403	Providing medical care to nonhh adult
40404	Obtaining medical and care services for nonhh adult
40405	Waiting associated with caring for nonhh adults
40499	Caring for nonhh adults, n.e.c.
40501	Housework, cooking, and shopping assistance for nonhh adults
40502	House and lawn maintenance and repair assistance for nonhh adults
40503	Animal and pet care assistance for nonhh adults
40504	Vehicle/appliance maintenance/repair assistance for nonhh adults
40505	Financial management assistance for nonhh adults
40506	Household management and paperwork assistance for nonhh adults
40507	Picking up/dropping off nonhh adult
40508	Waiting associated with helping nonhh adults
40599	Helping nonhh adults, n.e.c.
49999	Caring for and helping nonhh members, n.e.c.
180305	Travel related to caring for hh adults
180306	Travel related to helping hh adults
180307	Travel related to caring for and helping hh adults
180399	Travel related to caring for, helping hh members, n.e.c.
180405	Travel related to caring for nonhh adults
180406	Travel related to helping nonhh adults
180407	Travel related to caring for, helping nonhh adults
180499	Travel related to caring for, helping nonhh adults, n.e.c.

Table A5: List of Activities under Personal Care/Maintenance

Code	Activity
10101	Sleeping
10102	Sleeplessness
10199	Sleeping, n.e.c.
10201	Washing, dressing, and grooming oneself
10299	Grooming, n.e.c.
10301	Health-related self care
10399	Self care, n.e.c.
10401	Personal/private activities
10499	Personal activities, n.e.c.
19999	Personal care, n.e.c.
110101	Eating and drinking
110201	Waiting associated with eating and drinking
110299	Waiting associated with eating and drinking, n.e.c.
119999	Eating and drinking, n.e.c.
181101	Travel related to eating and drinking
181199	Travel related to eating and drinking, n.e.c.

Table A6: Data Alignment, ATUS Weekday, ATUS Weekend and Matched Data, 18-64 years, 2022

	ATUS Weekday			ATUS Weekend			ASEC		
	Men	**Women**	**Total**	**Men**	**Women**	**Total**	**Men**	**Women**	**Total**
Race/Ethnicity									
Non-Hispanic White	58.8	57.6	58.2	60.6	58.8	59.7	58.1	57.1	57.6
Black	11.2	12.5	11.9	11.7	13.2	12.4	12.0	13.5	12.7
Hispanic	20.5	20.5	20.5	19.5	19.4	19.5	20.3	19.3	19.8
Other	9.5	9.4	9.4	8.1	8.6	8.3	9.6	10.1	9.9
Presence of young children (young <=5yrs)									
None	86.6	82.3	84.4	83.7	81.8	82.7	85.1	82.6	83.9
One or more	13.4	17.7	15.6	16.3	18.2	17.3	14.9	17.4	16.1
Employment status									
Nonemployed	12.3	20.7	16.5	12.2	24.9	18.5	17.9	27.1	22.5
Employed	87.7	79.3	83.5	87.8	75.1	81.5	82.1	72.9	77.5
Number of children in HH									
None	64.1	58.2	61.1	63.2	58.5	60.9	63.2	57.8	60.5
One	14.5	15.2	14.9	15.6	17.9	16.8	16.2	18.6	17.4
Two	15.9	16.7	16.3	14.3	14.9	14.6	13.0	14.8	13.9
Three or more	5.5	9.9	7.7	6.9	8.6	7.8	7.6	8.8	8.2
Number of adults in HH									
One	16.2	16.8	16.5	17.6	14.0	15.8	12.7	14.6	13.6
Two	54.5	54.0	54.2	54.6	55.5	55.1	50.6	52.6	51.6
Three or more	29.3	29.3	29.3	27.8	30.4	29.1	36.7	32.9	34.8
Age									
15/24	14.9	14.3	14.6	14.9	13.8	14.3	15.5	15.0	15.2
25/39	33.2	33.2	33.2	33.7	33.1	33.4	33.8	33.2	33.5
40/54	31.0	31.0	31.0	30.8	30.9	30.9	30.5	30.7	30.6
55/64	20.9	21.5	21.2	20.7	22.2	21.4	20.2	21.1	20.7
Fam Structure									
Single	31.5	33.7	32.6	30.9	27.7	29.3	32.5	33.0	32.8
Couple	68.5	66.3	67.4	69.1	72.3	70.7	67.5	67.0	67.2
Education									
Less than Hs	9.3	8.4	8.9	9.5	8.2	8.8	10.1	8.1	9.1
High School	31.7	23.3	27.5	32.2	24.3	28.3	31.4	25.0	28.2
Some College	23.1	24.0	23.5	20.3	23.5	21.9	25.4	27.7	26.6
College +	35.8	44.3	40.1	38.0	44.0	41.0	33.1	39.2	36.1
Fam Income Quintile									
Less than 35K	17.4	19.8	18.6	19.0	18.1	18.5	17.1	18.8	18.0
35k-60k	19.8	17.6	18.7	16.3	17.9	17.1	17.7	17.8	17.8
60k-100k	24.1	24.9	24.5	24.2	24.7	24.4	24.0	23.9	24.0
100k-150k	17.1	16.7	16.9	19.3	18.7	19.0	17.8	17.1	17.5
150k or more	21.7	21.0	21.3	21.2	20.7	20.9	23.3	22.3	22.8
Household size									
1	13.4	11.2	12.3	15.0	10.3	12.6	11.7	10.2	10.9
2	29.4	31.6	30.5	29.7	31.2	30.4	28.9	30.5	29.7
3	19.6	19.6	19.6	19.0	21.0	20.0	22.1	21.8	21.9
4	23.6	17.3	20.4	20.2	20.8	20.5	19.8	20.3	20.1
5 or above	13.9	20.3	17.2	16.1	16.7	16.4	17.4	17.2	17.3

Note: Ratio estimates are defined as imputed data divided by donor data, minus 1. Family income intervals are the quintile cutoffs

Figure A1: Share of matched observations by round, ATUS Weekend, 2022