Levy Income Measure of Time and Income Poverty: United States

Sources, Methods and Assessment

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Abstract

In this paper, we present the match quality assessment of the statistically matched data used to construct the LIMTIP estimates for the United States, specifically for 2022. Using a statistical matching procedure, we construct a synthetic dataset by combining the American Time-Use Survey (ATUS) 2021 with the Annual Social and Economic Supplement (ASEC) 2022. First, we examine the alignment of the ATUS (weekday and weekend) and both datasets across important demographic characteristics. Next, we briefly describe the results from the matching algorithm. We conclude by comparing the marginal distributions of time use between the ATUS and the synthetic dataset. Our results suggest that our statistical matching procedure yielded a high-quality match, and the constructed synthetic dataset is appropriate for time poverty analysis. While not presented here, similar assessments were constructed for the ASEC matching from 2005 to 2021.

1 Introduction

In this paper, we describe the methodology behind the construction of the Levy Institute Measure of Time and Income Poverty (LIMTIP) for the United States.

The construction of the synthetic dataset created for use in estimating the LIMTIP requires a combination of information at the household and individual level. In addition to demographic characteristics, the estimation process requires data on income and time use. However, no single dataset contains comprehensive information of this type for all household members across time. To produce LIMTIP estimates, we first construct a synthetic data file by employing a statistical matching procedure to combine two source datasets: the base or recipient data (ASEC), which contains detailed demographic, income, and consumption data for households and individuals; and the donor data (ATUS), which contains individuals' time allocation in a range of daily activities, including paid work, unpaid care, domestic chores, leisure, self-care, and socializing. Using variables common to both datasets, we employ statistical matching to create a unique synthetic dataset that combines information from both sources. This dataset allows us to extract patterns of time use and income/consumption for all household members, which is useful for studying gender differences in the sharing of household production and other activities.

2 The Nature of Time Poverty and Income Poverty

2.1 Accounting for Time in Poverty Measurement

Poverty is a multidimensional concept that goes beyond the simple lack of income. In addition to income, poverty can be understood as a lack of access to resources, including time. From the LIMTIP perspective, time poverty refers to the lack of time people may have to engage in activities that are essential for taking care of the household, its members, self-care, and work.

As with any other measures of poverty, it is necessary to identify a threshold to determine if the resources available to a person or household should be classified as poor or non-poor. In the case of time, however, thinking about a threshold is less appropriate because all individuals have the same amount of time available to them.

The approach we have taken for the construction of the LIMTIP has been to identify the time balance people face after considering the time spent on essential activities. People with a negative balance are considered time-poor. We express the weekly time balance of individual i in household j, X_{ij}, as:

$$X_{ij} = 168 - M - \alpha_{ij} R_j - D^0_{ij}(L_{ij} + T_{ij}) \tag{1}$$

where 168 is the number of hours in a week, M is the sum of personal care and non-substitutable household production requirements, R_j is the required time of household production that a family

j needs to maintain the household, α_{ij} is the share of individual i in the household production requirements, D_{ij} is a dummy variable that takes a value of 1 if the person is employed and zero otherwise, L_{ij} are the hours of employment, and T_{ij} the hours of commuting.

To implement this measure, we need a dataset that contains information on time use, in addition to standard information required for poverty analysis. As mentioned earlier, the main source of information for time use comes from the American Time Use Survey (ATUS), which only provides information for a single person in the household and a single day. As described in Section 3, it is necessary to combine the ATUS with the ASEC data to construct a synthetic dataset that contains information on time use for all household members, which will allow us to impute all required variables for Equation 1.

2.2 Time Balance Implementation

Even with the synthetic dataset, it is necessary to impose some restrictions for the proper identification of the elements in Equation 1. First, R_j represents the required hours that a family with a specific household structure needs (number of adults, children, and elderly). To better identify the requirements of a typical household, R_j is estimated as the expected number of hours, given the family structure, that a family with income around the poverty-level (75-150%), with a fallback person, engages in household production. The requirements may reflect some extent of outsourcing of household responsibilities, which may include consumer purchases of substitutes that they can afford.

To calculate the actual share of household production requirements that each individual is responsible for, we use the estimated R_j multiplied by α_{ij}, which is the effective share of household production requirements that each individual is responsible for. This is estimated as the ratio of the individual's (imputed) time spent on household production to the total time spent on household production by all household members.

M represents the time required for personal care and non-substitutable household production requirements, which can be typically obtained by assumption or using average hours based on a particular year's data.

The time required for employment and commuting is calculated as the total time spent on employment and commuting, also based on the time use survey. It may consider heterogeneity based on full-time and part-time employment, as well as heterogeneity across regions and years.

2.3 Time Poverty

Once the time balance is calculated, time-poor individuals are identified as those with a negative time balance or time deficits. It is important to clarify that these time balances reflect the theoretical deficit individuals may face under typical time requirements and do not account for how individuals may actually allocate their time.

In addition to individual time poverty status, we may also be interested in the time poverty status of the household. To measure the poverty status and poverty degree suffered by a household, we impose the assumption that the deficits or surpluses people face cannot be exchanged across household members. In this case, we may consider a household to be time-poor if at least one of its members is time-poor. This is a more conservative approach, as it may be the case that some members of the household are time-poor, while others are not.

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

$$X_j = \sum_{i=1}^{j_n} \min(X_{ij}, 0) \tag{2}$$

where j_n is the number of individuals in the household. The time poverty status of the household is then defined as if $X_j < 0$, which may indicate that at least one member of the household is time-poor.

2.4 Adjusting for Income Poverty

Once household deficits have been calculated, it is possible to adjust for the standard income poverty measure. This process is done by adjusting the income poverty threshold by monetizing the value of the time deficits. The adjusted poverty lines are then used to calculate the time and income poverty status of the household.

Call Z_j the poverty line used to determine time poverty status for a household j. The adjusted poverty that considers time poverty is then defined as:

$$Z_j^{adj} = z_j + (|X_j| * P_x) * \kappa \tag{3}$$

where P_x represents the cost of buying an hour of time (services) in the market to cover the time deficit in terms of household production, and κ is a parameter that adjusts the monetized value of the time deficit to the same time unit as the poverty line. For the case of the US-LIMTIP, we use a $\kappa = 52$, because the poverty line is defined as an annual threshold. The new poverty threshold is then used to calculate the time and income poverty status of the household.

2.5 Monetizing Time Deficits

How are wages estimated, and what are the sources of information?

3 Statistical Matching Methodology

As described in the previous section, the construction of the LIMTIP requires access to standard income, employment, and poverty data, as well as 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 Supplemental Poverty Measure, 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 use of all household members, so 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.

3.1 Main Data Sources

The measurement of time and income poverty requires microdata on individuals and households with information on time spent on household production, time spent on employment, as well as household income. Given the importance of the intrahousehold division of labor and the differences across single and dual-earning households, it is necessary to have information on the time spent on household production by household members. While the American Time Use Survey (ATUS) provides good information on household production, and the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS) provides good information regarding time spent on employment and household income, there is no single data source that has all the required information for the case of the US. Furthermore, while the ATUS does collect detailed information on time use, it only collects this information for a single day and a single individual within the household. Due to these limitations, further efforts are necessary to create a synthetic dataset that captures the time use of all household members and estimates a good approximation of activities for a typical week, rather than a single day.

A summary of the main characteristics of the data can be found in Table 1, with a brief description of the ASEC and ATUS survey data in the next subsections. Both datasets were accessed through the Integrated Public Use Microdata Series (IPUMS) database (Flood et al., 2023).

Table 1: Surveys used in constructing the LIMTIP for the United States

Survey	Survey Subject	Source	Sample Size	Year
American Time Use Survey	Time-Use	U.S. Census Bureau/IPUMS	8,136 Individuals	2021
Annual Social and Economic Supplement (CPS-ASEC)	Income, Demographics, Employment	U.S. Census Bureau/IPUMS	Full Sample: XXXX Restricted Sample: 118,990	2022

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

The CPS is a monthly survey administered by the US Bureau of Labor Statistics. The survey collects comprehensive data on labor market situations, including statistics related to employment and unemployment, as well as detailed information on demographic characteristics (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 previously interviewed households answer additional questions as part of the ASEC supplement, formerly known as the Annual Demographic File. In addition to the basic monthly information, this supplement provides data on work experience, income, noncash benefits, and migration. 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.

While we implement the statistical matching procedure for the ASEC from 2005 to 2022, the present document only describes the results for the ASEC 2022 match. The ASEC 2022 is used as the base dataset (recipient), as it contains rich information regarding demographics and economic status for every member of the household. For the matching process, we consider data for the household, rather than the family, as the aggregated level at which some demographics are constructed. The matching, however, is done at the individual level, considering only individuals who are directly or indirectly related to the household head. This implies that non-relatives living in the household are generally not considered in the matching process. Similarly, people not living in households, such as those living in institutions or group quarters, are not considered in the matching process either.

3.1.2 American Time Use Survey (ATUS)

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

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 United States. 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.

The ATUS 2021, which contains a total of **xx** observations, is used as the donor dataset to obtain information regarding time use, which will be transferred to the ASEC 2022.

3.2 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 kind of non-parametric imputation method that allows combining information from two independent datasets, without imposing any distributional restrictions on the outcome 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 paired/linked based on how similar (statistically similar) they are based on common and observed characteristics, 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 one year, which means treating the ATUS collected for a weekday and weekend day as two separate surveys.

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 (Consumption) and Y (Time use). In this case, 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 how close they are based on observed characteristics. It is also possible to constrain matches based on the weighted population each survey represents.

In turn, this synthetic dataset should allow researchers to analyze otherwise unobservable relationships between X and Y, or as in our case, income and time use (D'Orazio et al., 2006; Rässler, 2002). Thus, inference on the relation between X and Y can only be done to the extent that Z explains most of the common variation between X and Y.

3.2.1 Matching Algorithm

As described in Lewaa et al. (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 improves on the approach by using a weight splitting approach in combination with clustering analysis for an automatic selection of strata groups.^[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 strat

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3.2.2 Matching Algorithm (continued)

The statistical matching procedure applied for the paper is a multi-step process that can be explained as follows:

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.

Furthermore, 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, reweighted 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.

For the case of the US-LIMTIP, the ATUS sample weights are adjusted to match the population of 15 years or older individuals in the ASEC based on the individual `ASECWT`, excluding those not living in households and those not related to the head of the household. To improve the quality of the imputed data, we consider dividing the ATUS sample into two groups: one from weekdays and one from weekend days, effectively matching each ASEC observation with two ATUS observations. This is done to account for the different patterns of time use that are observed.

For the matching implementation, weights are adjusted for each subsample separately, so that the weekday/weekend ATUS samples 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 (17 years of age) in the household, and whether the respondent declares to be working. The adjusted weights are used for the 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 ***common*** 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% of the data's variation. For the construction of the LIMTIP, we consider variables related to household structure, number of children of different ages and adults of different age groups and gender in the household, employment status of the household head 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 number 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 enhance the matching procedure, we estimate a propensity score using a logit model. The dependent variable in the model is a binary indicator that determines whether an observation belongs to the donor or recipient file, while the independent variables consist of 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 for all variables should be zero or statistically insignificant. However, due to sampling variability and variations in survey design, it is common to observe variation in the propensity score. The logit model and propensity score can be estimated for the entire pooled survey or using the primary strata variables.

3.2.3 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.[1]

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 as 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 adjusting weights, 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. 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 "best" 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 across both files are similar, 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.

[1] Specifically, one variable that was used outside of the main strata has been race and age, as it was 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.

3.3 Estimation of Time Deficits

[This section should describe how the time deficits are estimated using the synthetic dataset created through the statistical matching process.]

4 Statistical Matching Quality Implementation and Assessment

4.1 Data Alignment

In this section, we present the alignment of the ATUS (weekday and weekend) and the ASEC 2022 datasets across important demographic characteristics. The alignment is done to ensure that the two datasets are comparable and that the matching procedure is appropriate.

[This section should include tables and analyses comparing the key demographic characteristics between the ATUS (weekday and weekend) and ASEC 2022 datasets.]

5 Matching Procedure

Briefly describe the Matching and the table for matching (Rounds, number of matches, etc).

[This section should provide details on the matching procedure, including the number of rounds, the number of matches at each round, and any other relevant statistics.]

6 Matching Quality Assessment

Here we present the results for Matching Quality.

[This section should assess the quality of the matching procedure, potentially including comparisons of the marginal distributions of key variables between the original and synthetic datasets.]

7 Conclusions

This paper presents the quality assessment of the statistical matching procedure used to combine the household survey data and time use data for the United States to obtain comprehensive estimates on time and income poverty.

Overall, the two datasets are well aligned, which warrants the implementation of the statistical matching. Based on the statistics presented here, the matching quality is good, showing strong balance across different household characteristics. There are, however, a few large imbalances that are isolated in small groups. Overall, we conclude that the statistical matching procedure employed has precisely imputed time-use estimates for the household survey, which in turn contributed towards producing an insightful measure of poverty for the US-LIMTIP.

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