Time Use Trends and Reallocation Decisions: An Exploration Using the American Time Use Survey

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a thesis submitted to the Faculty of Emory College of Arts and Sciences
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Abstract

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This thesis looks at time use data from the American Time Use Survey (ATUS). The ATUS tracks how many hours each day a person spends on a particular activity. The years this data has been recorded are 2003 to 2022, excluding 2020 and 2021. With this data, there are a couple of research objectives. It will track trends in time use over time. It will look at how lost work hours are reallocated. These objectives will also be done with respect to demographic groups like gender and generation. The analysis of reallocation decisions is done using Ordinary Least Square regressions. The data that will be used in this regression is a panel dataset at the state year level with first differencing. A finding of interest is that reallocation decisions change over time, for example, there is a higher preference to reallocate time to education in 2009 and 2010. Another interesting result is that there are increases in leisure time use for the American population between 2003 and 2022. Additionally, Baby Boomers reallocate more of their lost work hours to nonmarket work than Millennials or Generation X. Understanding these reallocation preferences can be incorporated into models of welfare loss from reduced work hours.

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Time Use is not only relevant to economic patterns but also day to day work habits. Thank you to everyone who helped this thesis reach the finish line.

Contents

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1 Introduction

Time use is how individuals allocate their time across different activities during a specific period. Time use can be measured in various ways, but all generally describe the amount of time used in a period. For example, minutes in an hour or days in a year. This paper will focus on how time is spent in terms of hours in a week when it addresses tracking time use. It will shift into measurement in terms of minutes in an hour when discussing reallocation decisions.

Since time use is just how people choose to allocate their time, it can be understood that time use is relevant in almost all aspects of life. Even reading this thesis is relevant to time use, since to read it, a person has decided to allocate time to the task. This means questions surrounding how time is spent are essential in understanding how people make decisions every day. Additionally, understanding not only trends in time use but how that time use is reallocated. Specifically, how lost market work hours are reallocated shows how people prefer to use their time if they are not working.

This thesis asks how time use has changed over time. Understanding these trends in time use reveals how people allocate time between their activities because relative levels of time use between activities can be shown. For example, trends in time use can show if a population spends more time on leisure than work. This thesis is similarly interested in how time use trends differ between genders and generations. Answers to this question reveal how different types of people behave differently. For example, if women spend more time on childcare than men, that reveals something about the differences between those groups. Another application of this question also reveals how events affect time use preferences. If there is a spike in an activity's time use in a given year, potentially there is an event that occurred in that period affecting time use preferences.

This thesis also asks how lost market work hours are reallocated to other activities. This would reveal the comparative importance of different activities. If lost work hours are reallocated to one activity over another, it may be because people prefer one activity more. In addition, this thesis asks about how reallocation decisions vary across different demographic groups. How do preferences change with a person's gender, generation, or marital status? Looking at how reallocation changes between groups reveals differing preferences between those groups. Having a better understanding of work time reallocation decisions gives economic models more depth. Rather than lost labor hours being only an economic loss, the increases in time use of other activities through reallocation of lost labor hours can be looked at alongside the labor hours loss. This thesis asks how lost work hours are reallocated differently if the source of lost work hours is from losing a job or from a cut in hours. This can give depth to models that estimate the economic impact by not only showing spillover effects of lost work hours into other time uses but also by delineating how reallocation differs based on the type of reduction in work hours. Lastly, this thesis asks how reallocation decisions vary across time, this can be used to see whether the aggregate economic situation impacts not only the levels of time use in a particular activity but how lost work hours are reallocated to other activities.

2 Literature and Motivation

Time Use has been discussed in a variety of ways across the literature. Time is compared to itself, Aguiar et al. (2013) tracks time use over time and how lost work hours are reallocated into other categories of time use. Time use is an outcome variable, Campaña (2023) looks at how social attitudes and institutions affect gaps in time use between men and women. Time use is an explanatory variable, Gibson and Shrader (2018) look at how the level of sleep time affects labor productivity. Each is a different way time use can be used to understand a phenomenon, and there are many phenomena time use brings understanding to. As previously stated, Campaña (2023) applies time use to the topic of gender. Neidell (2021) discusses the impact of climate change in terms of time use. Enam and Konduri (2018) applies time use to generational behavior differences. The wide set of use cases for and topics relevant to time use reveals the wide applicability and relevance time use has.

For the purposes of this thesis, previous research that is relevant to this thesis will be segmented into four broader themes: general research on time use, gendered time use, generational time use, and contemporary phenomena relating to time use. The reason for the division into these four themes is because each theme shows a different contribution of this thesis to the time use literature. General research on time use includes works that apply time use to broader economic principles like labor productivity in Gibson and Shrader (2018) or welfare losses in recessions in Aguiar et al. (2013). Gender refers to papers whose primary thrust is gender divisions in time use. Generational time use papers look at differing time use across generations. Lastly, contemporary phenomena discuss topics in which newer time use data becomes more relevant e.g. COVID-19 like in Hupkau and Petrongolo (2020) or climate change like in Neidell (2021). This thesis contributes to general research through the analysis of the reallocation of lost work hours. It contributes to the gender subsection of the literature through continued tracking of time use gaps between the genders as well as looking at differences in reallocation decisions between the genders. It contributes to generational time use literature through its application of lost work hour reallocation to understanding behavior preferences. It contributes to contemporary phenomena in time use through looking at new time use data that looks to post pandemic time use. These contributions will be expanded in relation to specific discussion of the literature throughout this section of the thesis.

While time-use literature has various niche applications, as will be discussed later, some papers push the general literature for time-use forward. These papers, while to some extent discussing topics of gender or recent phenomena, focus on the more general application of time-use data to economics. Aguiar et al. (2013) is a brilliant example of this since it both tracks trends in time use for the American population, as well as measures how lost work hours are reallocated to other types of time use. To do this trend graphs are generated for time use, and regressions exploiting cross-state variation in time use are run. In doing this, insights are gained into the welfare losses from recessions, because Aguiar et al. (2013) can quantify how time is reallocated due to losses in work hours from the Great Recession. Aguiar et al. (2013) is the inspiration for this thesis. Many of the analytical methods used in Aguiar et al. (2013) are similarly used for analysis done in this thesis, as well as the data for this thesis comes from the same source as Aguiar et al. (2013)'s data source which is the ATUS data. There are two main departures this thesis makes from Aguiar et al. (2013). This thesis extends analysis into generation differences. The other is the extension of the period for the data from between 2003 and 2010 to between 2003 and 2022. This extension of the period is relevant to understanding whether the time use patterns described in Aguiar et al. (2013) persist into the 2010s as well as giving insight into the post-Great Recession recovery which Aguiar et al. (2013) does not have.

Like Aguiar et al. (2013), Gibson and Shrader (2018) leverages time use data to discuss more general economic phenomena. Rather than focusing on the effect of recession as in Aguiar et al. (2013), Gibson and Shrader (2018) leverages time use data to understand labor productivity. Their goal is to measure how the level of sleep time affects labor productivity by using indicators for labor productivity such as wages. This paper rather than comparing time use categories, uses time use as an independent variable to determine effects on wages. Like this work and many other papers, the ATUS is their source of time-use data. Gibson and Shrader (2018) uses an instrumental variable approach to estimate the causal effect of sleep on productivity, with the exogenous source of variation being sunset time. It finds that sleep time is a determinant of wages and, that a one hour increase in weekly average sleep is associated with the same effect a one year increase in education has on wages. The findings in this thesis can supplement the work done in this paper through the increased understanding of how changes in another time use category, market work, can affect sleep time. Thus contributing to a more comprehensive economic model of the relationship between sleep and labor productivity.

Ramey and Francis (2009) departs from previous papers in this category by discussing economic history. It tracks trends in time use over the 20th century and specifically looks at tracking differences in gender for that period. The main problem Ramey and Francis (2009) must overcome is parsing through the various measures of time use throughout the 20th century. Having successfully overcome that challenge Ramey and Francis (2009) finds that larger declines in market work hours per worker over the 20th century are attributed to the decline of work hours for those aged 14 to 24 and those above the age of 55. Additionally, there has been a decline in male work hours that to some extent has been offset by the increase in female work hours. Ramey and Francis (2009) is relevant to this thesis, because they both are interested in tracking trends in time use for the broader American population and its gendered subsets. Like the contributions this thesis makes to Aguiar et al. (2013), this thesis will be an extension into the 21st century to see if the patterns found persist. It will also expand the discussion of demographic distinctions in time use from gender into generational differences.

While there is a varied set of topics time use papers cover, a common theme that is discussed is gender differences in time use. Even if it is not the focus of a paper, there typically is a discussion of gender differences in time use. In Aguiar et al. (2013) and Ramey and Francis (2009) time use trends are not only discussed for the American population but also sub-sectioned into trends in American men's and women's time use. The papers in this genre of literature do not only just touch on gender differences in time use, but gender differences are their primary focus. Hupkau and Petrongolo (2020) and Olmstead et al. (2020) use time-use data to discuss how COVID-19 and the recession associated with it affect the disparities in labor market outcomes for men and women. Hupkau and Petrongolo (2020) tracks the labor outcomes of men and women and develops an understanding of how COVID-19 changes those outcomes. Special attention is paid to two drivers of decreases in market work time: layoffs due to the recession and decreased access to child care due to distancing during COVID-19. This paper's time use categories of interest are market and nonmarket work. The data to track this variation in time use in Hupkau and Petrongolo (2020) are the COVID-19 supplement for the Understanding Society (Usoc) longitudinal study, and UK time use data. Hupkau and Petrongolo (2020) finds that pandemic recessions are qualitatively different than previous recessions because different sectors are impacted. Women work more in contact-based industries like hospitality, service, and travel and thus a pandemic has a larger impact on women's jobs. Additionally, the increased unavailability of childcare options increases the need for home production which disproportionally affects women's time use. Olmstead et al. (2020) continues the delineation between types of recession based on their gender outcomes but it brings discussion into the American context.

Given its context shift, it uses different data from Hupkau and Petrongolo (2020). Olmstead et al. (2020) uses the American Community Survey (ACS), the ATUS, and the Current Population Survey (CPS), Olmstead et al. (2020) comes to a similar set of conclusions to Hupkau and Petrongolo (2020). Using the paths of labor time loss and home production time increases, it is found that pandemic recessions are unique in that they disproportionally hurt sectors that have more women and decrease the availability of market childcare options, thus shifting the time burden disproportionally onto women. While this thesis will not directly address time use data that was collected during the pandemic as Hupkau and Petrongolo (2020) and Olmstead et al. (2020) did, it supplements their work through comparisons between pre-COVID-19 time use and post-COVID-19. This is possible because the scope of data for this thesis includes the post-COVID-19 cross-section of data in 2022. There will also be an analysis of gendered reallocation preferences which adds to the discussion of time use differences between the genders. This also means that the aforementioned papers are relevant to this thesis through their shared interest in gender gaps in time use.

Campaña (2023) tackles gendered questions surrounding time use in a unique way as compared to Hupkau and Petrongolo (2020) and Olmstead et al. (2020). Rather than trying to understand the effects of contemporary phenomena, COVID-19, on time use, it uncovers how broader social and institutional features affect gendered disparities in time use. Campaña (2023) uses the heterogeneity in social attitudes and institutional features across different European countries, to understand their impacts on time use. To do this, they use trend analysis and multi-level regression analysis to parse out the impact of social attitudes and institutional features. The data used is the Harmonized European Time Use Survey (Hetus) and European Values Study (EVS). Campaña (2023) discovers that gaps between the genders exist and are closing to some extent, but more traditional social attitudes regarding women increase gaps in time use for market and nonmarket work. The uncovering of how losses in market work are reallocated into other time categories in this thesis can supplement the models made in Campaña (2023). Since Campaña (2023) is interested in gender gaps for both market and nonmarket work it is important to understand how those changes in market work get reallocated into nonmarket work. This thesis aids in that understanding by looking at the increased time reallocated to nonmarket work associated with a loss in market work hours.

Gender gaps in time use are not the only relevant demographic disparities for this thesis. A primary concern is understanding the differences between the time use habits of various generations. This topic is not unique in the literature, and several papers have asked why different generations allocate their time differently. Enam and Konduri (2018) attempts to isolate cohort effects (generational differences).

on heterogeneity between generational time use. They try to isolate cohort effects from those of age and period. In doing so, 4 waves of time use data are used from the years 1965, 1985, 2005, and 2010. The data comes from the American Heritage Time Use Study and the ATUS. To parse out the cohort differences both analysis of descriptive statistics over time, and multivariable modeling frameworks were used, with the intention of being able to control for age and minimize period effects. Enam and Konduri (2018) finds that the most prominent differences between cohorts are in travel time at early stages of individual's lives (18 to 34), the difference between cohorts is the lowest in middle aged groups, and that the biggest downward shift in travel was between Baby Boomers and Generation X. While this thesis is not as interested in travel time use, it is interested in different time use behaviors between the generations. This thesis can supplement analysis of different generation's time use preferences in Enam and Konduri (2018) through the analysis of continuous yearly data on trends in generations. Enam and Konduri (2018) takes four one year slices of data across a large period, whereas this thesis looks at trends for all years between 2003 and 2019 as well as 2022. To some extent, this can help deal with bias introduced from the period effect, since it introduces data for several years into one period rather than one year for a period.

Garikapati et al. (2016) narrows down the analysis done in Enam and Konduri (2018) by focusing on the age effect on time use within the Millennial generation. Garikapati et al. (2016) looks at in-generation age variation, so it can be found whether older Millennials allocate time in ways than younger Millennials. The findings of Garikapati et al. (2016) show that differences in time use between Millennials and previous generations close as Millennials increase in age. This may be due to Millennials reaching milestones like marriage and having children as they age, which makes their behavior more like prior generations. The analysis of data ends in the year 2013, while this thesis would add six years of data. This is marginal, but the addition of new data is relevant to these generational distinctions because there will be additions to the sample of older members of younger generations, and thus continue at improving cohort analysis that can reduce the age effect. Additionally, Garikapati et al. (2016) helps contextualize some of the reasons as to why age effects can bias cohort effects, a bias that is observable in the results of this thesis.

In addition to the general economic concepts, gender disparities, and generational distinctions that time-use data can uncover, time-use data can provide insight into contemporary phenomena that are relevant today and may continue to be relevant in the future. Whether this is the rise of internet use as discussed in Vilhelmson et al. (2018), COVID-19 as discussed in Hupkau and Petrongolo (2020) and Olmstead et al. (2020), or climate change as discussed in Neidell (2021). Each is unique in the phenomenon they discuss, but the unifying threads between these seemingly varied topics are that time use data will help better understand them, and these phenomena are not going away and will be continually relevant into the future.

Over the past two decades, the popularity of the Internet has risen tremendously. Vilhelmson et al. (2018) investigates the effects of this increase in internet use with respect to youth activity patterns. It asks about how personal time use trends in Swedish youth are affected by the increasing presence of the internet over time, how priorities in leisure time shift due to that phenomenon and do those preferences differ between subsets of the youth population. Using Swedish time use data in three different periods (1990/91, 2000/01, and 2010/11), Vilhelmson et al. (2018) finds that some offline free time activities tended to decrease, while others like sports and outdoor recreation have stayed the same. They do confirm that Swedish youth's free time habits have transformed over the span of their data. While this thesis does not contribute much to the discussion on youth time use or the rise of the internet, Vilhelmson et al. (2018) is illustrative that time use analysis must be continually updated, because of the varying societal contexts over time due to technological innovations. The importance of continual updates due to changes in time use from phenomena such as technology serves as evidence as to why the newer data used in this thesis is relevant.

Neidell (2021) uses time use data to uncover the effects on the economy from climate change. Over the past ten years and into the future climate change has become more relevant and will likely continue to become more relevant in the economy. Neidell (2021) uses market work time use as an outcome variable that will be explained by variations in temperature. It uses geographic and time-use data found in the ATUS paired with weather data to uncover how variance in a geographic area's temperature affects the quantity of labor hours in that area. This relationship is modeled using a nonlinear least squares method and uses data from 2003 to 2019. Neidell (2021) finds that there is no significant decrease in market work associated with an increase in temperature, but does find that there is a decrease in labor hours associated with a temperature above 90 degrees. Neidell (2021) uses this relationship to estimate the economic impact of climate change through the loss of market work hours. This thesis can help supplement Neidell (2021)'s analysis by adding information about the reallocation of lost market work time into the model. The lost market work hours are not absolute losses in welfare, because they will be redistributed to other activities. This reallocation information will give more depth to the estimate of economic losses from climate change.

3 Data

The data this thesis uses is the American Time Use Survey (ATUS) which is data created by the Bureau of Labor Statistics (BLS). The ATUS collects data through interviews done on the telephone. Eligibility for the interviews is determined by an individual's household completing the final month of the Current Population Survey (CPS), the individual from a household being at least 15 years of age, and the household being inside any of the 50 states or Washington D.C. Participants will use a 24 hour time diary to answer questions in the interviews conducted by the BLS. Respondents will use this time diary to track how much time they spend on various activities throughout the day. During the interview, respondents will then be asked how much time they spent on activities such as shopping, childcare, or sleeping. This process results in each observation being an individual level observation corresponding to a single household.

The ATUS has been conducted for the last twenty years, with available data spanning from 2003 to 2022. This thesis uses every existing year of the ATUS except for 2020 and 2021. 2020 is excluded from the sample, because of incomplete recording of the ATUS in 2020 due to the COVID-19 pandemic. Similarly, the inconsistent return to work policies in 2021, because of the COVID-19 pandemic, makes 2021 difficult to analyze such that it is better to exclude it from the sample.

The ATUS is excellent data to use for answering the proposed research questions about time use. The ATUS tracks time use in many categories. This is useful because its specific categories can be discussed, e.g., the ATUS asks questions about leisurely activities like TV watching or socializing that can be looked at individually rather than as components of a broader leisure category. Another benefit is the yearly recording of time use data, which allows for looking at every year in the period as compared to data that only looks at one or two years across a larger period. The literature seems to find the ATUS useful as well. Many other papers that look at American time use also use the ATUS. It is a data source for Aguiar et al. (2013) , Gibson and Shrader (2018), Enam and Konduri (2018), and Neidell (2021).

Activities as recorded by the ATUS have been grouped into seven primary categories of time use in this thesis, which are Market Work, Other income-generating activities, Job Search, Childcare, Nonmarket Work, Leisure, and Other. These categories are in line with previous research on trends in time use and reallocation decisions. The same activity categorization as this thesis is found in Aguiar et al. (2013).

- Market Work refers to time working in the market sector. This includes main jobs, second jobs, and overtime work.

- Other income-generating activities include activities like hobbies or cooking that generate income.
- Job search simply refers to the time spent by an individual looking for a job.
- Childcare measures time spent caring for, educating, or playing with children.
- Nonmarket work refers to home production. It can be thought of as four elements. Core home production, activities related to home ownership, obtaining goods and services, and care for other adults. Core home production entails cooking or cleaning. Activities related to home ownership entail home repairs or lawn maintenance. Obtaining goods and services entails time spent on shopping activities that exclude medical care, education, and restaurant meals. Care for other adults entails time spent on activities like preparing a meal for another adult or transporting an adult.
- Leisure refers to time spent on activities that do not generate income like reading, sports, television, or music.
- Other measures categories of time use that have not been incorporated into the above categories. This includes education, civic and religious activities, and one's own medical care.

Other than the categorization of activities, there have been several steps in cleaning the ATUS data. This thesis uses the multiyear files produced by the ATUS. Four original files are merged. The CPS file includes variables collected from the Current Population Survey, the roster file includes information such as age and sex, the respondent file has information such as earnings and statistical weights, and the activity file carries information about time spent on activities. Due to the data cleaning process, some observations from the ATUS data had to be dropped. First, observations that have missing information for activity times were dropped from the dataset. Next, this thesis restricts the sample provided by the ATUS to the working age population. That is, only those between the ages of 18 and 65 are included in the sample of data for this thesis. While this means there is limited generalizability to the elderly and children, the focus of this thesis is the working age population, so the inclusion of those outside that population would only harm internal validity. With these restrictions, the sample size of the data for this thesis is 174,794.

Looking at how demographic distinctions are made in the data. Gender is coded through a binary variable for if the individual is male. If the binary variable for male is equal to one then the individual's gender is men, else gender is women. The only variable for race used in this thesis is a binary variable for whether the individual is Black. This binary variable was created through a categorical variable for race in the ATUS data. If the race of an individual in the categorical variable is Black then the binary variable in this thesis is coded as a one, else the binary variable is a zero and the individual is non-Black. This demographic variable for race is included to help account for differences in socioeconomic status or labor market discrimination of Black people. This is supported through Neumark (2018) which finds evidence that hiring and wage discrimination exists on racial and ethnic lines in America.

Lastly, this thesis is interested in answering questions about differences in behavior between generations. This means it is essential to show which generations are being discussed and define them. The three generations that will be discussed are Baby Boomers (birth years 1946−1964), Generation X (birth years 1965−1980), and Millennials (birth years 1981−1996). No other generations were selected, because Generation Z was still being born during the span ATUS data was being recorded, and there are few in the Silent Generation (birth years 1928−1945) who were working while the ATUS data was being recorded. Regarding specific cleaning processes for the analysis done about different generations, observations for individuals outside of those generations are dropped. E.g. there are no older generations than Baby Boomers and no younger generations than Millennials in any data that is used to measure differences in generational behavior.

4 Methodology

Having gone over the data being used in this thesis, there will be a discussion of the research methods used. It is important to note that the methods used in this thesis are inspired by and similar to those of Aguiar et al. (2013) which this paper is in part extending. There are three primary methods used in this thesis. The first is the series of graphs used to reveal time use trends between 2003 and 2022. Second, are the aggregate tables used to show average levels of time use amongst various groups. Lastly, are the regressions used to find how lost market work time is reallocated into other time use categories. Since the first two methods mentioned are relatively straightforward the main focus in this section will be explaining the regression equations used in this thesis.

For the graphs and aggregate tables in this thesis, individual-level data is used. For the graphs tracking time use over time, weighted means with weights provided by the ATUS were calculated. The same weighted mean calculation was done for each observation in the aggregate tables section. Focusing on the methods for the analysis of generational differences, the graphs tracking time use over time are not separated into age subgroups. While doing so would deal with the age effects biasing results, they create comparisons of younger middle-aged Millennials in 2017 to older middle-aged Baby Boomers in 2004, for example. This creates more of a period effect bias, as well as still not fully resolving the age effect bias introduced. It also means that for many of the comparisons only two generations can be compared, rather than all three, which is the interest of this thesis. That means there will be age effect bias that is observable in these graphs. There are tradeoffs in mitigating period effects and age effects. This thesis sacrifices the mitigation of age effects for better mitigation of period effects.

For the regressions data, a first differencing approach is used, and data is aggregated at the state by year level. The first differencing approach means that instead of the level of time use in an observation being the input for the regression, it is the difference between the level in the base year minus the level of the previous year. While this approach does make the interpretation of estimated coefficients less straightforward, it allows for controls of cyclical economic trends across states. This control of state-specific fixed effects can reduce bias if, for example, one state is going through a recession while another's economy is booming in the same period. State year level data is used rather than individual-level data. The states included are all fifty states and Washington D.C. This aggregation is important to the ability to do a first differencing approach. First differencing is done with panel data. The ATUS is not panel data, the same individuals are not interviewed repeatedly from 2003 to 2022. There is a different cross section of the population interviewed each year. Aggregating at the state by year level turns the ATUS into panel data because the aggregation would track the average of each state throughout the period of data. State by year aggregation also helps control for low-frequency trends in the data, which are gradual patterns in the data over the period of interest. These trends can be seen in this thesis results with the consistent rise in leisure time, for example. By aggregating at the state-year level, we can compare the relative variance between states to help reduce the influence of these low-frequency trends.

All regressions in this paper are ordinary least squares regressions. The standard errors used in this paper are clustered standard errors with state-level clustering. This will help reduce the effect of correlation between observations from the same state.

Having explained the procedure used to prepare the regressions, the regression equations are as follows.

Base Equation:

$$\Delta\tau_j = \alpha_j - \beta_j \Delta\tau_{market} + \epsilon_j$$

Equation with Demographic Controls:

$$\Delta\tau_j = \alpha_j - \beta_j \Delta\tau_{market} + \beta_1 \Delta\tau_{male} + \beta_2 \Delta\tau_{Black} + \beta_3 \Delta\tau_{married} + \beta_4 \Delta\tau_{haschild} + \beta_{5-10} \Delta\tau_{AgeDummies} + \beta_{11-14} \Delta\tau_{EducationDummies} + \epsilon_j$$

Equation with Time Controls:

$\Delta\tau_j = \alpha_j - \beta_j\Delta\tau_{market} + \beta_{1-9}\tau_{TimeDummies} + \epsilon_j$

Equation with Demographic and Time Controls:

$\Delta\tau_j = \alpha_j - \beta_j\Delta\tau_{market} + \beta_1\Delta\tau_{male} + \beta_2\Delta\tau_{Black} + \beta_3\Delta\tau_{married} + \beta_4\Delta\tau_{haschild} + \beta_{5-10}\Delta\tau_{AgeDummies} + \beta_{11-14}\Delta\tau_{EducationDummies} + \beta_{15-24}\tau_{TimeDummies} + \epsilon_j$

$\Delta\tau_{market}$ is the independent variable of interest in the regression. It is the change in market work hours between the baseline year and the prior year. Since it is essential for there to be variation in the independent variable it is important to note some sources of variation in market work hours for the period of interest. One source of variation is the natural fluctuation in employment throughout the business cycle. Another is the Great Recession, which led to losses of employment and employment hours for many. Both result in variations in changes in market work hours. At the individual level these variations can look like cut hours or layoffs. At the state level these variations can look like factory closures.

$\Delta\tau_j$ represents the dependent variables of interest for each time use category j. Each time use category j is one of the seven main categories of time use as described in the data section or one of the subcategories of time use comprising the larger category. Similar to $\Delta\tau_{market}$, $\Delta\tau_j$ shows the change in hours of time use for category j between the baseline year and the prior year. α_j corresponds to the intercept parameter of regressions for each time use category j. β_j is the slope parameter that represents the association between change in market work hours and change in time use for category j. Notably, unlike other slope parameters in these equations. β_j has a minus sign rather than a plus sign in front of it. This is because this thesis is interested in a loss of work hours, so β_j must be multiplied by negative one to make the interpretation of tables more intuitive. Additionally, β_j is multiplied by one hundred to make reading the tables easier. ϵ_j represents the error term for each regression involving time use category j.

Demographic controls are the same for all j time use categories. At the individual level of data they would be binary variables, but at the state level, they are the proportion of that state's sample with that demographic characteristic. Including the first differencing, the demographic controls are the difference between the proportion of the state's sample with that demographic characteristic in the base year and the prior year. There is a demographic control for if someone is male, Black, married, or has a child. There are age controls for five different age groups within the data. Those are individuals between 18 and 27, 28 and 37, 38 and 47, 48 and 57, and 58 and 65. The youngest age group was removed from the regression equations to avoid collinearity in the data. There are also four education level groups used as demographic control. Those are individuals with less than a high school degree, high school graduates, some college education, and college graduates and above. The lowest education level was removed from the regression equation to avoid collinearity in the data.

Time controls are the same for all j time use categories. Notice, unlike all other variables in the regression time controls do not have a Δ in front of them. This is because the time controls are binary variables that correspond to the two-year periods that the observation is in. The interpretation of the estimate of the coefficient is as follows: A one unit decrease in market work hours is associated with a β_j unit increase in time use for category j.

There is a modification of the above regression specifications for regressions relating to changes in market work on the intensive and extensive margins. Work hours lost on the extensive margin refers to work hours lost from unemployment. Work hours lost on the intensive margin refers to lost work hours of employed people. With this change in work hours and its corresponding slope parameter for time use category j can be decomposed into the following equation.

$$\beta \Delta \tau_{market\text{ work}} = \beta_i \Delta \tau_{intensive\text{ work}} + \beta_e \Delta \tau_{extensive\text{ work}}$$

This equation allows for the calculation of intensive and extensive slope coefficients for time use category j. These are β_i and β_e respectively. For this thesis, the changes in work are calculated as the difference in the 2009 to 2010 period from the 2006 to 2008 period. This choice of period is due to them being before and during the Great Recession, a major source of work hours variation in this thesis. Using change from a set of two year periods, rather than one year periods, has the benefit of increased sample size, which helps mitigate noise in the data. $\Delta\tau_{marketwork}$ is calculated as the difference between average market work in the two periods. $\Delta\tau_{intensivework}$ is calculated as the average fraction of the population that is employed between the two periods multiplied by the change in market work hours between the two periods. $\Delta\tau_{extensivework}$ is calculated as the average market work hours between the two periods multiplied by the change in the fraction of the population that is employed between the two periods. β is the coefficient β_j in the baseline regression with demographic controls. β_i is found the same way as β except using data for the regression that only includes employed individuals. β_e is found by solving the above equation for β_e since all other terms can be found in the data.

5 Trend Analysis

Figures 1, 2, and 3 show trends in time use for the sample of the American population, American men, and American women. Additionally, figures 4, 5, and 6 show trends in time use across different generations. In the aggregate tables sub section there will be tables displaying the heterogeneity in time use of the different demographic groups discussed in this thesis.

The trend for market work has been relatively consistent between 2003 and 2022. However, there have been fluctuations in average market work hours throughout the period. From 2003 to 2007 there were steady increases in average market work hours. There was a large decline in average market work hours until 2010, associated with the Great Recession. Afterward, there have been steady increases in market work hours, and they have returned to a similar level compared to 2003.

Nonmarket work has experienced a pattern of consistent decline in hours per week between 2003 and 2019. Every period except for 2008 to 2009, 2012 to 2013, and 2014 to 2015 experienced a decline in nonmarket work hours. Additionally, the increases in nonmarket work hours for the aforementioned periods are offset by the decreases in nonmarket work hours for the following periods. Between 2019 and 2022 nonmarket work level stays relatively consistent for the American population. Leisure time use tells a different story. The trend for leisure is an increase throughout the period of 2003 to 2019. Like nonmarket trends in time use, this pattern for leisure is not consistent. There are decreases in leisure time from 2005 to 2007, 2009 to 2010, 2012 to 2016, and 2018 to 2019. Despite the numerous periods in which there are decreases in leisure time, the increases in leisure time in periods leisure increases are relatively large. Additionally, between 2019 and 2022 there is a large spike in leisure time by roughly 2 hours per week.

5.1 Gender Differences

Having discussed more general trends of time use, investigation into differences in market work time use trends between men and women can be discussed. Investigating the years after Aguiar et al. (2013)'s scope, 2010 to 2019, we can observe that men's market work hours increased by 3.32 hours per week and women's market work hours by 0.61 hours per week. This is a 10.93 percent and 2.63 percent increase respectively. The gendered subset analysis is in line with the broader increase in market work hours after 2010 despite not reaching the same levels of work hours in 2006 and 2007 before the Great Recession. Having looked at post-recessionary increases in market activity we see an increase in work hours, but is that trend the same when looking at changes from 2003 up until before COVID began in 2020? When it comes to men there has been a small decline in market work hours by about 0.02 hours per week between 2003 and 2019. This is a percent decrease of 0.05, which indicates that market work between then and the last pre-covid year in this data is minimal for men. This is different when looking at the change in market work for women over the

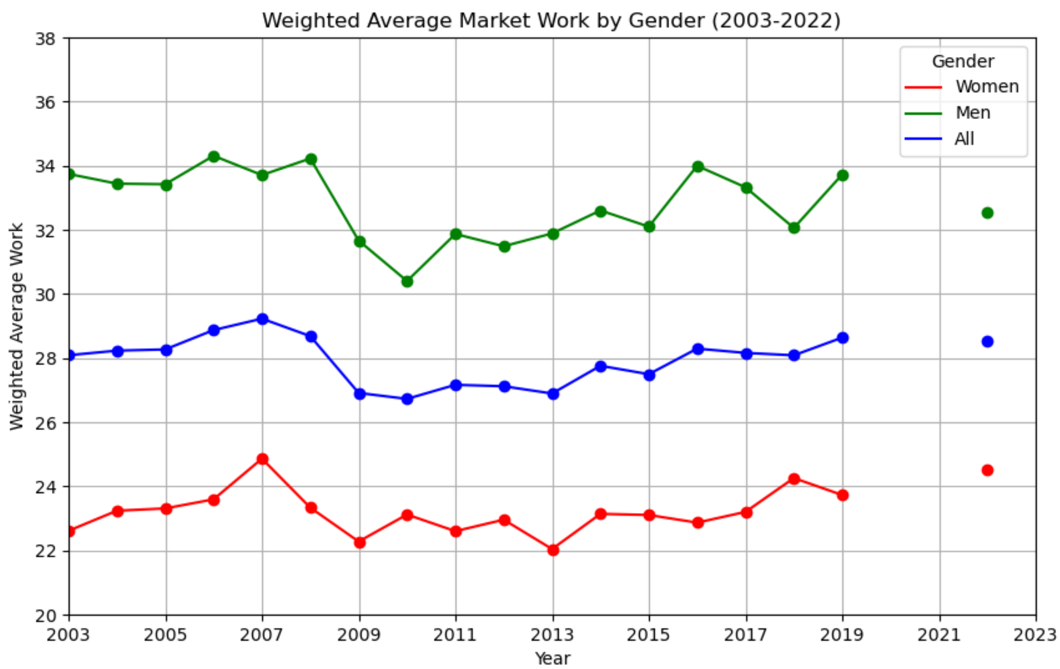

Figure 1: In this figure market work over time is displayed for the broader American population (Blue), American men (Green) and American women (Red). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

same period. Women, on average, worked 1.12 hours more in 2019 than in 2003 resulting in a 4.94 percent increase in work hours. This shows that for men an increase in market work hours from 2010 to 2019 is mostly attributed to a decline in market work hours during the Great Recession.

Looking at differences between pre and post-pandemic market work hours, an interesting disparity between men's and women's market work hours is revealed where men have decreased their average work hours by 1.18 hours per week, but women have increased their average work hours by 0.79 hours a week. This is interesting because it is inconsistent with the results on disparities in the effect of COVID-19 on men and women. This might suggest that since 2020, when Hupkau and Petrongolo (2020) and Olmstead et al. (2020) were published, women's work hours have rebounded from their decline due to the pandemic. This could be due to the reduction of stay-at-home orders which may have increased the demand for service and hospitality workers as well as increased the supply of market child care services. Each change is about a 3 percent decrease and increase respectively, which may indicate a continuing trend of the closing of a market work hours gap between the two genders. The respective decreases and increases in market work hours generally balance out, with a small 0.42 percent decrease in total market work hours between 2019 and 2022.

Regarding gender differences in nonmarket work and leisure, the pattern for nonmarket work is similar to that of market work because the gap in time use between men and women is closing. However, regarding nonmarket work women have higher levels of time use than men. This means that the gap in market work is from higher men's time use and the gap in nonmarket work is from higher women's time use as compared to the opposite gender. Moving onto leisure trends over the past decade. A similar trend of increasing leisure persists in the later half years of the data as compared to its earlier years. Likewise, throughout the sample years of 2003 to 2022 leisure time use between men and women moves together. There are only some exceptions to this like in 2019 or 2004. Between 2019 and 2022 the patterns for leisure time use also persists.

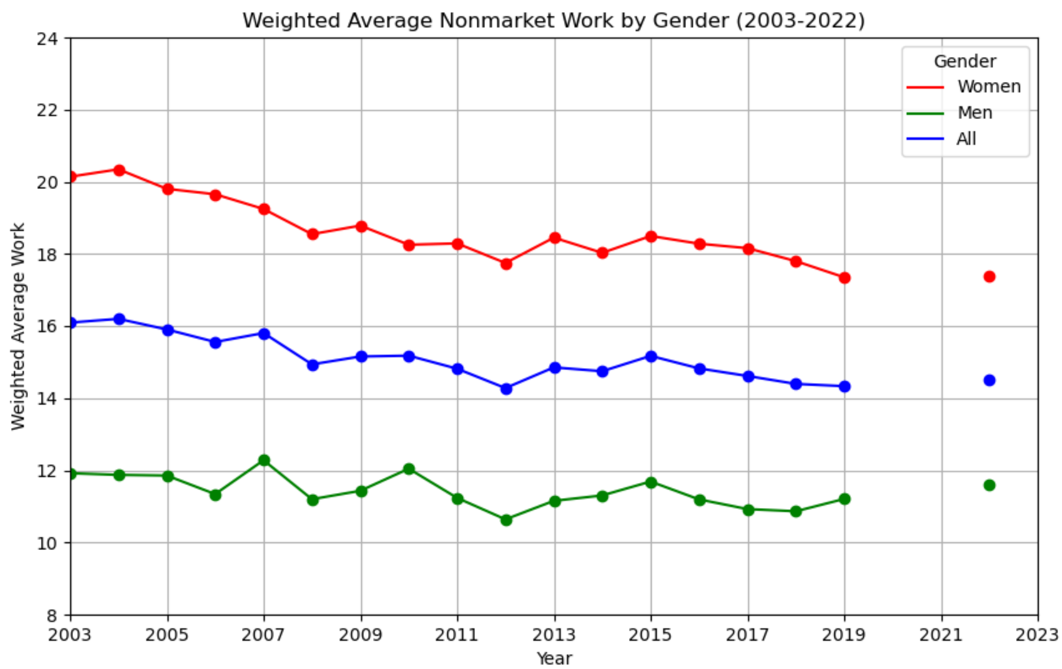

Figure 2: In this figure nonmarket work over time is displayed for the broader American population (Blue), American men (Green) and American women (Red). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

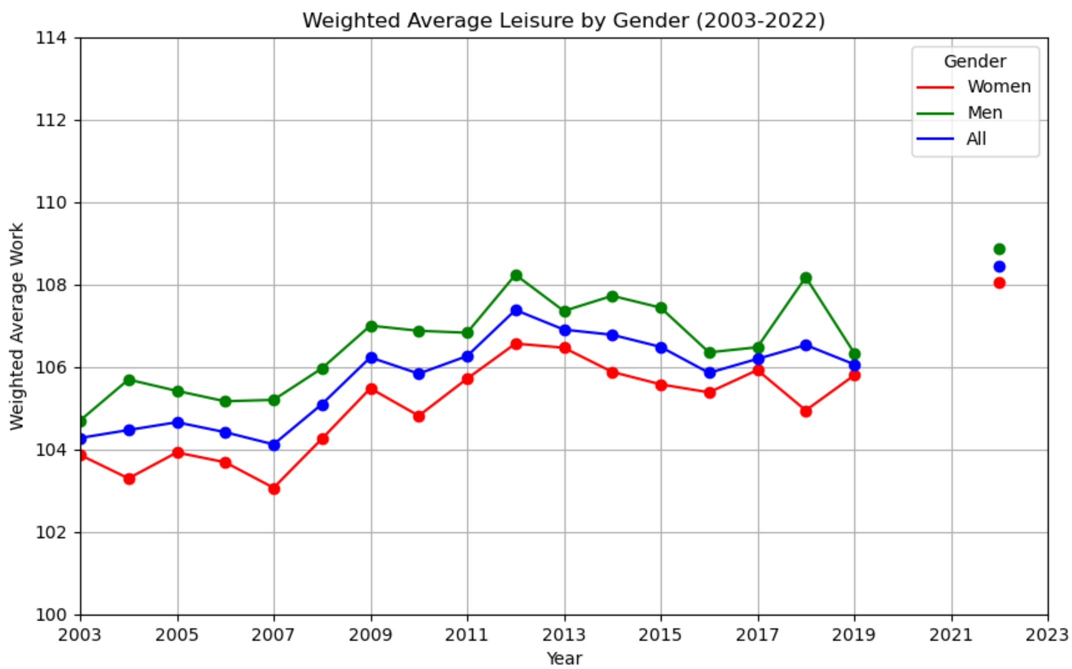

Figure 3: In this figure nonmarket work over time is displayed for the broader American population (Blue), American men (Green) and American women (Red). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

5.2 Generational Differences

Figures 4, 5 and 6 depict the average time used by generation for market work, nonmarket work, and leisure time use respectively. The trend for Generation X is relatively consistent for each of the primary time use categories with only a larger spike in leisure time between 2019 and 2022 (before and after the pandemic). Market work and leisure time use have an opposite relationship over time for Millennials and Baby Boomers. Between 2003 and 2019 Millennial leisure time decreased and Baby Boomer leisure time increased. Conversely, in the same period, Millennial market work time increases while Baby Boomer's market work time decreases. These inverse relationships between Millennials and Baby Boomers may indicate a tradeoff in the composition of the aggregate workforce between the two generations. Additionally, Baby Boomers consistently have the highest nonmarket work hours of all three generations, followed by Generation X and then Millennials.

5.3 Aggregate Tables

The following tables show the averages for various subsections of the data. This gives insights into the heterogeneity of time use based on various demographic categorizations. These include Table 1 which shows differences amongst men and women. Table 2 shows differences between Black and non-Black people. Table 3 shows differences across marital status. Lastly, Table 4 shows differences in pre-COVID and post-COVID time use for the gender gaps in time use between men and women.

Men have more market work hours on average which is consistent with literature like Aguiar et al. (2013) and Ramey and Francis (2009). Women spend 2.9 hours more per week on child care and 7.15 hours more on nonmarket work than men. This gap is similar to those found in Hupkau and Petrongolo (2020) and Olmstead et al. (2020). Uniquely men spend more time on home ownership activities than women. Moving away from work, leisure time

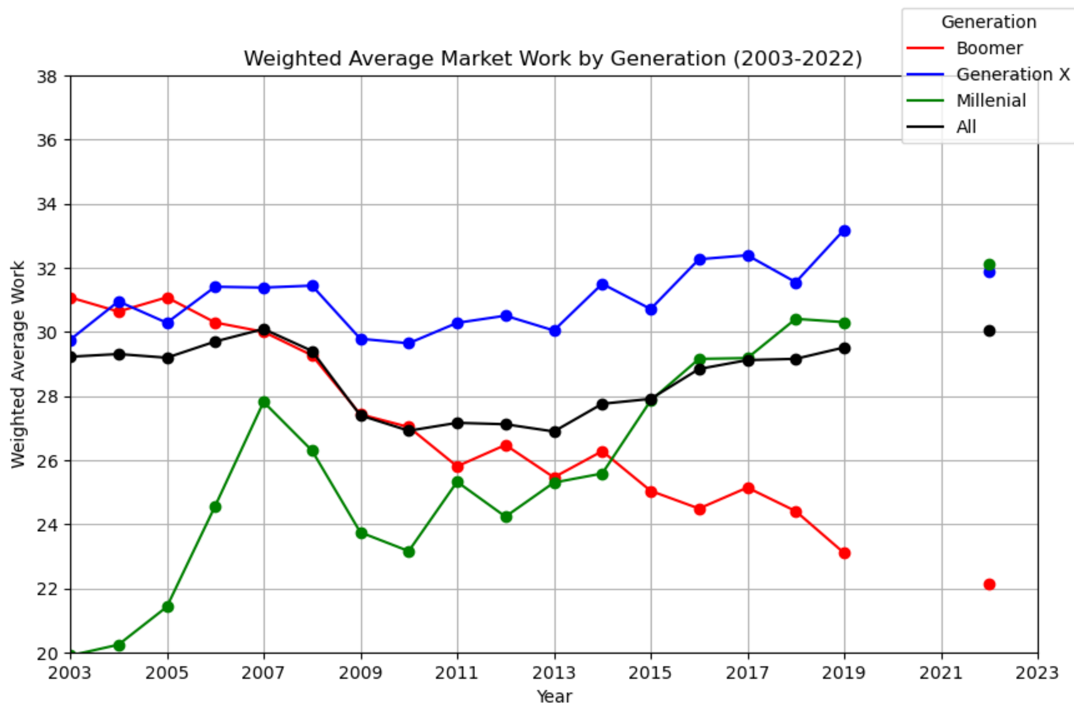

Figure 4: In this figure market work over time is displayed for the broader American population (Black), Baby Boomers (Red), Generation X (Blue), and Millennials (Green). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

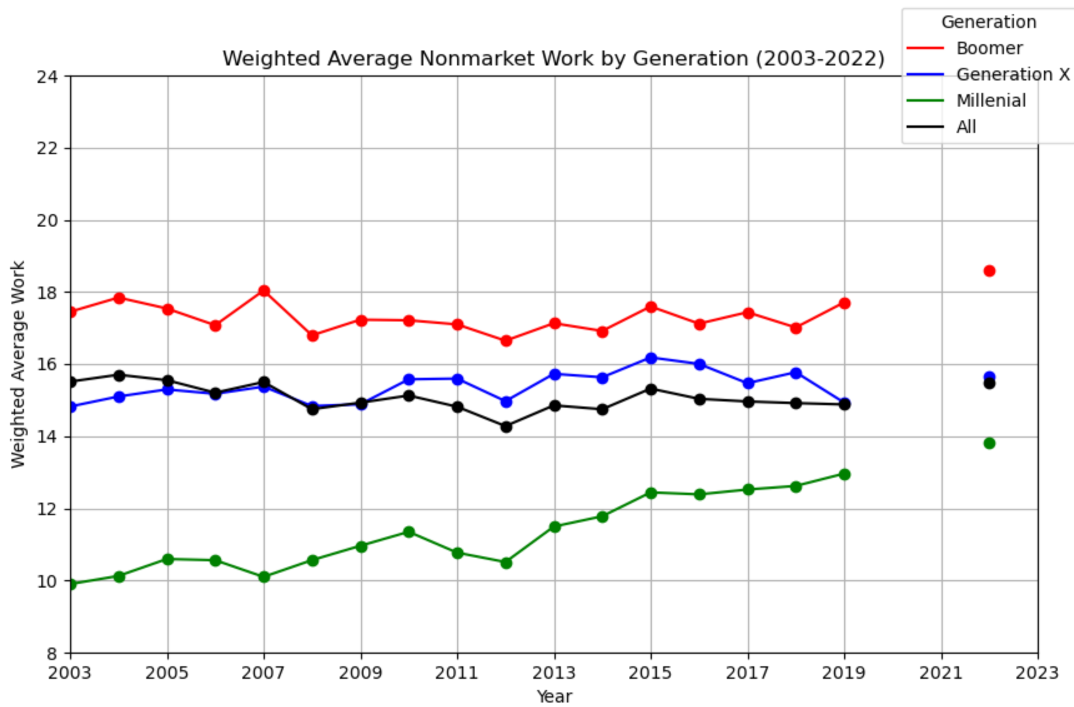

Figure 5: In this figure nonmarket work over time is displayed for the broader American population (Black), Baby Boomers (Red), Generation X (Blue), and Millennials (Green). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

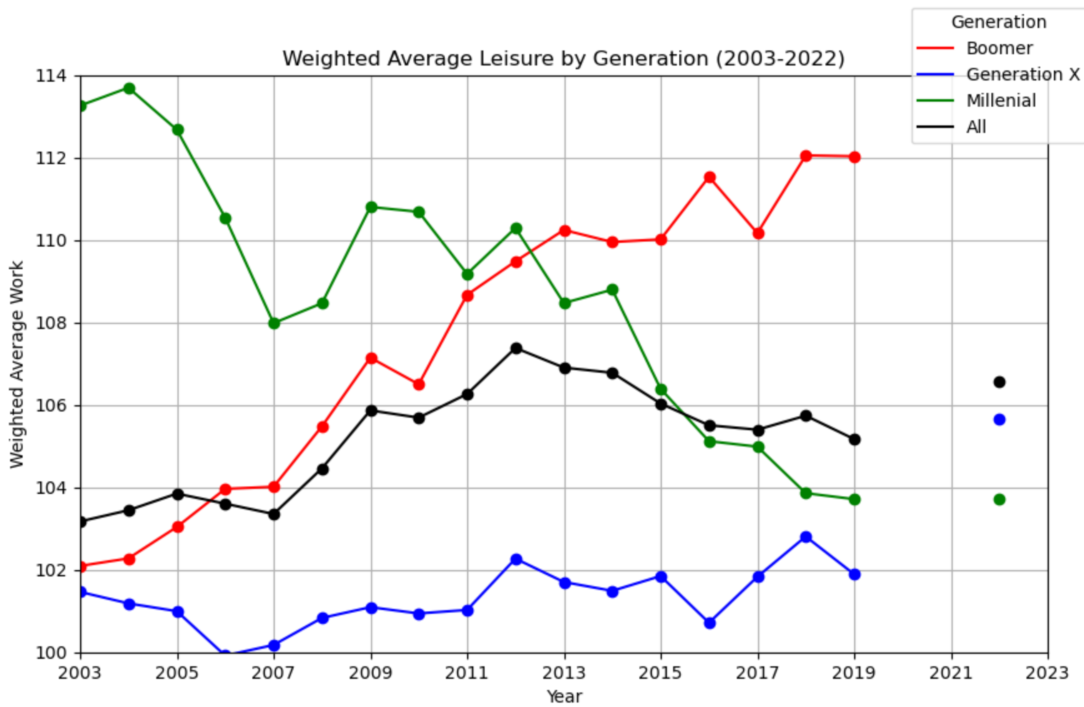

Figure 6: In this figure leisure over time is displayed for the broader American population (Black), Baby Boomers (Red), Generation X (Blue), and Millennials (Green). It is important to note that there is no data for the years 2020 and 2021, so the trend from 2019 to 2022 is only reflective of the differences between those two periods.

Time Use Category	Men	Women
Market work	32.79	23.27
Other income-generating activites	0.17	0.19
Job search	0.34	0.21
Child care	2.35	5.25
Nonmarket work	11.42	18.57
Core home production	5.71	12.85
Home ownership activities	2.67	1.24
Obtaining Goods and Services	2.31	3.65
Other leisure	9.57	8.62
Obtaining Goods and Services	2.31	3.65
Others care	0.74	0.82
Leisure	106.7	105.19
TV watching	18.99	15.77
Socializing	6.82	6.88
Sleeping	59.59	61.03
Eating and personal care	11.73	12.88
Other	5.05	6.42
Education	1.81	2.14
Civic and religious activities	1.46	1.94
Own medical care	0.62	0.95

Table 1 shows average time use for Men (Left) and Women (Right) for each time use category

Time Use Category	Black People	Non Black People
Market work	24.87	28.38
Other income-generating activites	0.2	0.17
Job search	0.49	0.24
Child care	3.02	3.94
Nonmarket work	12.22	15.46
Core home production	7.84	9.55
Home ownership activities	0.88	2.09
Obtaining Goods and Services	2.75	3.03
Other leisure	8.18	9.21
Obtaining Goods and Services	2.75	3.03
Others care	0.75	0.78
Leisure	111.28	105.18
TV watching	22.25	16.67
Socializing	7.31	6.79
Sleeping	62.13	60.07
Eating and personal care	11.42	12.44
Other	7.02	5.57
Education	2.09	1.97
Civic and religious activities	2.48	1.6
Own medical care	1.09	0.74

Table 2 shows average time use for Black people (Left) and non-Black people (Right) for each time use category

between the two genders is relatively similar across the board.

Non-Black people spend about three and a half hours more on market work than Black people. Conversely, Black people spend about double the time on job searches than non-Black people. There is a similar size gap between Black people and non-Black people for nonmarket work hours, with non-Black people spending 3.24 hours more. Many categories of time use between non-Black people and Black people are similar, but across the board, Black people spend more time on leisure, TV watching, and sleeping.

Married people spend 2.64 more hours per week on market work than their single counterparts, but singles spend more time on both other income generating activities and job

Time Use Category	Married	Single
Market work	29.13	26.49
Other income-generating activites	0.14	0.22
Job search	0.17	0.4
Child care	5.21	2.12
Nonmarket work	17.27	12.32
Core home production	10.75	7.6
Home ownership activities	2.52	1.24
Obtaining Goods and Services	3.19	2.74
Other leisure	8.61	9.67
Obtaining Goods and Services	3.19	2.74
Others care	0.81	0.74
Leisure	102.11	110.67
TV watching	16.19	18.8
Socializing	5.96	7.96
Sleeping	58.71	62.32
Eating and personal care	12.64	11.92
Other	4.73	7
Education	0.66	3.62
Civic and religious activities	2.02	1.31
Own medical care	0.78	0.8

Table 3 shows average time use for married people (Left) and single people (Right) for each time use category

Time Use Category	Men-Women Gap 2019	Men-Women Gap 2022
Market work	10	8.03
Other income-generating activites	0.18	0.05
Job search	-0.04	0.16
Child care	-2.69	-2.62
Nonmarket work	-6.15	-5.75
Core home production	-6.07	-6.08
Home ownership activities	1.33	1.21
Obtaining Goods and Services	-1.24	-0.58
Other leisure	0.68	-0.54
Obtaining Goods and Services	-1.24	-0.58
Others care	-0.17	-0.3
Leisure	0.54	0.81
TV watching	1.98	3.61
Socializing	1.04	1.04
Sleeping	-1.77	-2.17
Eating and personal care	-1.38	-1.13
Other	-1.72	-1.04
Education	-0.34	-0.05
Civic and religious activities	-0.5	-0.43
Own medical care	-0.36	-0.36

Table 4 Shows the gap between men and women in time use for a each time use category. The gap before COVID, in 2019, is on the left and the gap after COVID, in 2022, is on the right

searches than married people. This may suggest higher job stability for married people than singles. Intuitively, married people spend over double their time on child care than single people. There are also large gaps in nonmarket work between the two groups, with married people spending 4.95 hours more on nonmarket work and 3.15 hours more on core home production. Leisure time is where singles spend significantly more time than their married counterparts; spending 8.56 more hours on leisure, 2.61 more hours on tv watching, 2 more hours on socializing, and 3.61 more hours sleeping each week. Other categories of time use have relatively small gaps between the two groups.

The main finding of interest regarding the change in the gaps between Men and Women's time use during the pandemic is in market work. The gap between men's and women's market work shrank between 2019 and 2022. This is an opposite finding as compared to Hupkau and Petrongolo (2020) and Olmstead et al. (2020) which investigate gaps in time use during the COVID-19 pandemic. This may suggest there was a rebound in women's work hours after stay-at-home protocols decreased.

6 Regression Analysis

6.1 Base Results

Table 5 shows the base results of the regression for the broader American sample. The regression equations used to derive these estimates are in the methods section of this thesis.

Before entering explicit discussion of the base results it is important to note how these tables are interpreted. The size of the coefficient estimate determines the level at which a time use category is associated with a loss in work hours. A larger number is a stronger correlation. A positive coefficient for a time use category indicates that increases in time use for that category are associated with a loss of work hours. This may indicate that the time

Time Use Category	Other Income generating activities	Job search	Childcare	Nonmarket Work	Core home production	Home ownership activities	Obtaining goods and services	Others Care	Leisure	Socializing
Base Estimates (1)	0.39	1.32	4.32	16.55	7.91	3.7	3.37	1.57	59.31	8.8
Base Standard Errors (2)	0.51	0.55	1.46	2.56	2.16	1.28	0.69	0.95	2.99	2.17

Time Use Category	Other Leisure	TV	Sleeping	Eating and personal care	Other	Education	Civic and Religious Activities	Own Medical Care
Base Estimates (1)	12.27	21.49	16.19	0.56	14.03	5.56	2.6	1.92
Base Standard Errors (2)	2.05	2.9	2.19	1.23	2.07	1.72	0.98	0.76

Table 5: Row 1 shows the base regression estimate with no controls. Row 2 shows the standard error for the base estimate. Each column is a time use category j.

use category is a substitute to work hours. A negative coefficient for a time use category indicates that decreases in time use for that category are associated with a loss of work hours. This may indicate that the time use category is a complement to work hours. Coefficients can be interpreted as a loss of one hour of work being associated with a hundredth of the coefficient increase in hours of that time use category. For example, if a category's coefficient is 50, then a loss of one work hour is associated with an increase of 0.5 hours, 30 minutes, of that activity.

It is interesting to note that there are no negative coefficients for any time use category in the base results table. This means that the average American would increase their time use for every category of activity listed if their work hours decreased. This is interesting, because it may indicate that for the average American none of the listed time use categories are complements to market work. Additionally, it can be seen that the largest two categories of time use that the average American would reallocate time to are nonmarket work and leisure. Each hour of lost market work hours is associated with a roughly 10 and 40 minute increase in nonmarket work and leisure respectively.

6.2 Extensive and Intensive Margin Results

With the base results discussed, a discussion about the difference in losses in market work hours on the intensive and extensive margin arises. The restricted change in those margins refers to the assumption that a change in either of those margins would have the same effect on the reallocation of time to other categories as each other and general losses in market work hours. This means that the restricted changes assume βs for change in work hours, extensive and intensive change are equal. This assumption does always hold, because there are observable differences in the coefficients for market work hours, the extensive margin, and the intensive margin. The unrestricted change in those margins lifts that assumption and expresses the change in market work hours through the equation on extensive and intensive margins in the methods section. This unrestricted change in the margin allows for the

Time Use Category	Base est. with demo. controls (1)	Base s.e. with demo. controls (2)	Work hours change (3)	Restricted intensive change (4)	Restricted extensive change (5)	Intensive estimated coef. (6)	Intensive coef. s.e. (7)	Extensive estimated coef. (8)	Extensive coef. s.e.(9)	Unrest. intensive change (10)	Unrest. extensive change (11)
Other Income generating activities	0.63	0.54	0.01	0.01	0.01	1.07	0.52	0.19	0.01	-0.01	0
Job search	1.62	0.61	0.03	0.02	0.02	0.64	0.37	2.61	0.01	-0.01	-0.03
Childcare	4.48	1.35	0.09	0.05	0.05	4.81	1.47	4.14	0.09	-0.05	-0.04
Nonmarket Work	16.96	2.70	0.36	0.18	0.18	18.9	2.46	14.99	0.56	-0.19	-0.15
Core home production	8.3	2.06	0.18	0.09	0.09	9.66	1.98	6.92	0.22	-0.1	-0.07
Home ownership activities	4.26	1.40	0.09	0.05	0.04	4.92	1.64	3.59	0.08	-0.05	-0.04
Obtaining goods and services	2.9	0.72	0.06	0.03	0.03	3.4	0.62	2.4	0.03	-0.03	-0.02
Others Care	1.5	0.88	0.03	0.02	0.02	0.92	0.75	2.08	0.02	-0.01	-0.02
Leisure	58.92	3.28	1.25	0.63	0.62	59.58	2.77	58.25	2.27	-0.6	-0.58
Socializing	8.99	1.97	0.19	0.1	0.09	9.73	1.74	8.24	0.22	-0.1	-0.08
Other Leisure	11.55	1.79	0.24	0.12	0.12	11.06	2.53	12.05	0.29	-0.11	-0.12
TV	20.95	3.10	0.44	0.22	0.22	24.73	2.91	17.12	0.78	-0.25	-0.17
Sleeping	17.03	2.23	0.36	0.18	0.18	15.24	2.50	18.85	0.49	-0.15	-0.19
Eating and personal care	0.4	1.29	0.01	0	0	-1.18	1.05	1.99	0.01	0.01	-0.02
Other	14.13	2.06	0.3	0.15	0.15	10.62	1.77	17.68	0.36	-0.11	-0.18
Education	6.3	1.76	0.13	0.07	0.07	3.75	1.58	8.89	0.14	-0.04	-0.09
Civic and Religious Activities	2.51	1.05	0.05	0.03	0.03	2.13	1.01	2.89	0.04	-0.02	-0.03
Own Medical Care	1.49	0.72	0.03	0.02	0.02	1.27	0.69	1.72	0.02	-0.01	-0.02

Table 6: Column 1 shows the base regression with demographic control estimates, and column 2 shows its corresponding standard errors. Column 3 shows change in average work hours. Column 4 shows change in the restricted intensive margin. Column 5 shows change in the restricted extensive margin. Column 6 shows the estimated coefficient for the intensive margin and column 7 shows its corresponding standard error. Column 8 shows the estimated coefficient for the extensive margin and column 9 shows its corresponding standard error. Column 10 shows the change in the unrestricted intensive margin and column 11 shows the change in the unrestricted extensive margin.

understanding that an association with a change in the intensive margin or extensive margin can be different from each other and the association with the change in a general loss in market work hours.

When comparing the differences between the coefficients for intensive and extensive change in market work it can be observed that there is a larger coefficient for the extensive margin for job searches than the intensive margin, a roughly 0.02 hour reallocation difference. This makes sense because someone will likely look for a job if unemployed, but someone with work loss due to the intensive margin already has a job. Additionally, there is almost no reallocation of time into other income-generating activities from the extensive margin, while there is about a 0.01 hour reallocation associated with the intensive margin. This might make sense if a person who has been moved to part-time work then looks for other income generating activities to supplement lost income while remaining at their current job. Education also has a much larger extensive coefficient than intensive. This similarly makes sense because if a person loses their job, they may increase their education level to increase their job prospects. Conversely, the intensive coefficient is larger than the extensive coefficient for home ownership and core home production activities, roughly a 0.01 and 0.03 hour reallocation respectively. A possible explanation for this is if someone is working part-time they could be more focused on nonmarket activities like home care.

6.3 Period Results

Moving on from looking at intensive and extensive coefficients it is important to verify the consistency of these results across time. Aguiar et al. (2013) highlights the importance of breaking down the analysis into year subsets, because each period may be associated with different aggregate economic environments. For example, during the Great Recession, the aggregate economic environment looks different than in non-recessionary years like 2005 or 2015. It is then important to understand whether individual time use preferences change across these different periods. Table 7 subsections results into two-year periods. It uses

Time Use Category	2005 2006 coef. (1)	2005 2006 s.e. (2)	2007 2008 coef. (3)	2007 2008 s.e. (4)	2009 2010 coef. (5)	2009 2010 s.e. (6)	2011 2012 coef. (7)	2013 2014 s.e. (8)	2013 2014 coef. (9)	2013 2014 s.e. (10)	2015 2016 coef. (11)	2015 2016 s.e. (12)	2017 2018 coef. (13)	2017 2018 s.e. (14)
Other Income generating activities	-0.05	0.71	-1.34	0.36	0.65	0.44	0.97	0.82	2.79	2.82	-1.21	1.40	-1.37	1.60
Job search	0.35	0.50	0.63	0.56	1.02	0.67	0.33	0.51	1.25	0.82	2.56	1.71	1.32	1.43
Childcare	3.07	2.75	3.99	2.77	5.24	4.46	-0.34	2.69	-1.53	2.69	8.97	2.74	0.9	2.91
Nonmarket Work	19.66	10.58	18.3	4.49	2.27	10.35	20.18	4.11	1.6	7.68	25.33	8.03	21.79	10.59
Core home production	2.03	4.87	9.19	5.69	-3.58	4.11	11.11	4.85	-2.83	3.82	15.63	6.74	10.14	7.04
Home ownership activities	8.66	10.38	3.23	2.97	3.55	8.24	-1.7	2.89	3.3	3.91	5.27	2.87	4.19	2.93
Obtaining goods and services	7.57	3.40	5.07	2.34	-0.32	2.69	5.66	2.11	0.5	3.11	3.24	1.85	4.83	2.73
Others Care	1.4	2.86	0.76	1.55	2.62	1.26	5.12	2.13	0.63	1.56	1.19	1.00	2.63	2.65
Leisure	54.24	7.86	54.4	10.01	44.9	7.80	77.07	10.75	84.9	7.02	57.77	11.10	60.06	11.70
Socializing	8.69	4.50	10.6	6.67	4.55	4.21	12.77	11.60	8.18	4.47	0.79	6.87	12.92	6.17
Other Leisure	12.72	5.28	1.88	7.40	9.42	6.27	24.73	12.13	21.7	7.83	12.09	4.20	7.99	6.53
TV	20.29	8.20	14.8	8.46	10.9	4.67	22.72	5.26	38.6	6.23	37.13	7.31	11.73	9.91
Sleeping	3.34	4.20	29.3	6.37	22	3.81	15.42	5.55	13.2	3.97	5	6.62	26.96	6.55
Eating and personal care	9.2	3.51	-2.19	3.17	-1.9	2.97	1.43	4.41	3.33	2.46	2.76	2.75	0.45	3.99
Other	12.28	6.06	17.2	6.88	28.1	4.41	11.47	6.10	6.48	4.33	7.03	8.48	15.08	6.67
Education	13.15	5.68	10.7	6.97	18.1	5.33	-5.66	3.44	3.12	4.65	-2.61	5.19	8.29	5.71
Civic and Religious Activities	-0.81	3.04	2.82	3.08	2.9	2.24	7.27	2.54	-2.66	1.67	0.46	2.22	5.73	3.02
Own Medical Care	0.2	1.94	2.99	2.70	3.95	1.75	-0.72	1.55	1.8	1.79	3.98	3.58	-1.35	2.01

Table 7: Column 1 shows the estimated coefficient for 2005 and 2006, and column 2 shows its corresponding standard error. Column 3 shows the estimated coefficient for 2007 and 2008, and column 4 shows its corresponding standard error. Column 5 shows the estimated coefficient for 2009 and 2010, and column 6 shows its corresponding standard error. Column 7 shows the estimated coefficient for 2011 and 2012, and column 8 shows its corresponding standard error. Column 9 shows the estimated coefficient for 2013 and 2014, and column 10 shows its corresponding standard error. Column 11 shows the estimated coefficient for 2015 and 2016, and column 12 shows its corresponding standard error. Column 13 shows the estimated coefficient for 2017 and 2018, and column 14 shows its corresponding standard error.

the ordinary least squares method with no demographic or time controls which is the base specification regression. Additionally, it is important to note that since there are an odd number of years in the data the year 2019 was removed from Table 7.

It is found that there are several statistically significant differences from the recessionary period of 2009 and 2010 in a few areas. The first difference of note is that other income-generating activities had a negative coefficient in 2007 and 2008, and became a positive coefficient in the following period. This indicates that for a brief period immediately before the Great Recession other income generating activities were a complement to market work hours, which they are not for most other periods. A possible explanation for this is that the tightened economic landscape after 2008 resulted in less people being able to afford goods and services produced by hobbyists, thus lowering the demand for and quantity of other income generating activities. After the 2009 to 2010 period, in 2013 and 2014, there was almost a doubling of the amount of time allocated to leisure activities in the later period. This may indicate that people were more willing to participate in leisure activities as economic recovery from the Great Recession occurred. If a person feels more economically secure, they may be more likely to indulge in their hobbies. Conversely, there was a significantly larger reallocation of lost work hours to education in the recessionary period of 2009 to 2010 as compared to the next period. This suggests that people took advantage of the reduced job market to strengthen their career prospects through education.

6.4 Gender Subset Results

In this subsection, this paper follows the same procedure as Aguiar et al. (2013) to see if there are differences in the coefficient estimates by either gender or marital status subgroups. This analysis has been a prime concern for previous literature. A large focus of Aguiar et al. (2013) is on the differences in time allocation of lost work hours for singles and married individuals. Similarly, a major finding in Ramey and Francis (2009) is the varying trends in men and women for work time. Likewise it is the prime concern of Hupkau and Petrongolo

Time Use Category	demo. time control coef.(1)	demo. time control s.e. (2)	Men coef. (3)	Men s.e. (4)	Women coef. (5)	Women s.e. (6)	Married coef. (7)	Married s.e. (8)	Married and spouse employ coef.(9)	Married and spouse employ s.e. (10)	Singles coef. (11)	Singles s.e. (12)
Other Income generating activities	-0.94	0.71	-1.06	0.77	1.01	0.51	-0.35	0.53	0	0.44	0.49	0.48
Job search	1.19	0.62	0.81	0.54	0.58	0.27	0.72	0.24	0.43	0.38	1.19	0.45
Childcare	3.49	1.58	3.63	1.64	2.24	2.16	3.87	1.40	3.49	1.71	1.52	0.96
Nonmarket Work	18.11	2.30	19.7	2.40	17.98	3.41	24.71	2.14	22.46	2.49	19.55	2.20
Core home production	7.49	1.51	8.02	1.55	10.02	2.98	10.59	2.15	12.01	2.04	12.88	2.01
Home ownership activities	3.21	1.47	3.72	1.40	1.86	1.47	5.5	1.34	4.97	1.84	0.14	0.84
Obtaining goods and services	4.77	0.78	5.24	0.82	4.56	1.04	7.29	1.58	4.97	1.08	4.16	1.05
Others Care	2.64	0.87	2.7	0.96	1.54	0.77	1.33	0.95	0.5	0.94	2.37	0.97
Leisure	60.61	3.75	59.6	4.10	57.7	6.30	53.98	3.88	62.57	2.58	57.71	2.93
Socializing	8.62	2.58	8.2	2.80	7.76	2.32	7.14	1.29	9.18	1.99	11.91	2.09
Other Leisure	13.17	2.60	13.2	2.68	12.02	2.73	12.05	2.51	15.57	1.77	9.91	3.41
TV	22.6	3.61	23.3	3.82	15.93	3.42	18.39	3.29	18.34	2.37	22.27	2.63
Sleeping	16.34	2.75	15	2.28	21.97	4.79	15.46	2.28	17.85	2.50	12.31	3.03
Eating and personal care	-0.13	0.98	-0.09	0.91	0.03	1.31	0.92	1.55	1.64	1.31	1.32	1.34
Other	15.26	3.76	14.6	3.88	17.5	4.07	9.34	2.19	10.2	2.05	14.96	2.28
Education	10.35	2.89	10.2	2.95	7.34	3.29	2.35	0.76	2.01	0.84	9.51	2.06
Civic and Religious Activities	1.32	0.99	1.46	1.12	4.89	1.00	3.71	1.25	5.72	2.01	1.89	0.94
Own Medical Care	1.04	0.92	0.24	0.75	3.01	2.43	0.98	1.05	0.18	0.66	1.43	0.92

Table 8: Column 1 shows the base coefficient estimates with demographic and time controls, and column 2 shows the corresponding standard errors. Column 3 shows the coefficient estimate for men, and column 4 shows the corresponding standard errors. Column 5 shows the coefficient estimate for women, and column 6 shows the corresponding standard errors. Column 7 shows the coefficient estimate for married people, and column 8 shows the corresponding standard errors. Column 9 shows the coefficient estimate for married people with spouse employment, and column 10 shows the corresponding standard errors. Column 11 shows the coefficient estimate for singles, and column 12 shows the corresponding standard errors.

(2020) and Olmstead et al. (2020).

Amongst other minor differences in the current data, women are more inclined to allocate their lost market work hours to civic and religious activities than men. This potentially can show that women are more willing to engage in their communities than men. These minor differences in allocation preference despite the gaps in time use between the genders may indicate that the levels of these time use gaps are satisfactory for Americans on average. This story of similarity does not carry over to the comparison of married people and their single counterparts. There are many differences. Singles have a stronger preference to allocate their time to other income generating activities, leisure (except for sleeping), and education. Married people have allocated more of their time to child care, non-market work, and home ownership activities than their single counterparts. Most of these differences are intuitive, due to marriage being a major life milestone that would carry with it a modified set of responsibilities as compared to the single life.

6.5 Generational Subset Results

Table 9 primarily shows if there are differences in time allocation preferences amongst the three main working generations from 2003 to 2019. Those three generations are Baby Boomers, Generation X, and Millennials. The following coefficient estimates uses the base regression specification with time and demographic controls. It is important to include demographic controls like whether the individual has children or marital status because it is found that some time-use tendencies in generations are influenced by major life milestones Garikapati et al. (2016). Demographic controls for age are important to include, to help control for the age effect. Additionally, time controls are important to help control for the period effect.

Baby Boomers out of all generations reallocate proportionally more of their lost work hours to nonmarket work (0.26 hours reallocated), core home production (0.11 hours reallocated),

Time Use Category	Baby Boomers coef. (1)	Baby Boomers s.e. (2)	Generation X coef.(3)	Generation X s.e. (4)	Millennials coef (5)	Millennials s.e.(6)	Baby Boomers vs Generation X pvalue (7)	Baby Boomers vs Millennials pvalue (8)	Generation X vs Millennials pvalue (9)
Other Income generating activities	0.08	1.09	0.63	0.32	0.61	0.34	0.63	0.65	0.96
Job search	0.17	0.27	1.52	0.61	0.88	0.29	0.04	0.07	0.34
Childcare	1.88	0.92	6.28	1.77	7.69	1.92	0.03	0.01	0.59
Nonmarket Work	26.38	2.66	18.64	4.20	18.44	2.46	0.12	0.03	0.97
Core home production	11.32	2.83	8.16	2.32	10.92	1.79	0.39	0.91	0.35
Home ownership activities	8.47	3.44	6.07	3.23	2.08	1.06	0.61	0.08	0.24
Obtaining goods and services	5.93	1.04	3.44	0.89	4.49	1.07	0.07	0.33	0.45
Others Care	0.66	0.80	0.97	0.59	0.95	0.37	0.75	0.74	0.98
Leisure	65.98	3.68	56.92	2.90	54.93	4.24	0.05	0.05	0.7
Socializing	6.45	2.07	4.74	2.00	9.7	3.04	0.55	0.38	0.17
Other Leisure	12.9	2.29	14.31	1.84	14.4	2.06	0.63	0.63	0.97
TV	30.63	4.64	17.51	3.13	15.31	3.54	0.02	0.01	0.64
Sleeping	16.42	1.75	18.15	2.37	16.27	2.35	0.56	0.96	0.57
Eating and personal care	-0.42	1.28	2.2	2.00	-0.76	0.97	0.27	0.83	0.18
Other	5.99	2.54	9.66	2.10	16.42	4.81	0.27	0.06	0.2
Education	0.59	0.35	1.51	0.85	13.65	4.45	0.31	0	0.01
Civic and Religious Activities	1.85	1.14	2.62	1.25	1.27	1.21	0.65	0.73	0.44
Own Medical Care	0.79	1.45	1.75	0.63	0.11	0.24	0.55	0.64	0.01

Table 9: Column 1 shows the coefficient estimate for Baby Boomers, and column 2 shows the corresponding standard errors. Column 3 shows the coefficient estimate for Generation X, and column 4 shows the corresponding standard errors. Column 5 shows the coefficient estimate for Millennials, and column 6 shows the corresponding standard errors. Column 7 shows the pvalues associated with the Difference between Baby Boomers and Generation X. Column 8 shows the pvalues associated with the Difference between Baby Boomers and Millennials. Column 9 shows the pvalues associated with the Difference between Millennials and Generation X.

home ownership activities (0.08 hours reallocated), and shopping (0.06 hours reallocated). This may make sense because as Baby Boomers lose market work hours due to retirement, unlike other generations, they are able to spend more time at home. This may also indicate that these differences in behavior are not only due to cohort affect but also age effects. Millennials reallocate proportionally more of their lost work hours to education (0.14 hours reallocated) and socializing (0.10 hours reallocated). This increased preference towards education may make sense since Millennials are more likely to be earlier in their careers where education could be more beneficial. This similarly may indicate that cohort effects are not fully isolated and some age effects can be seen in the coefficent estimates. Generation X almost completely across the board, reallocates their time between the levels the other two generations allocate their time. This could be because Generation X is the middle ground between the two other generations, and thus is caught in the middle of time use allocation preferences across generational cohorts.

7 Conclusion

This paper investigated trends in time use amongst the broader population of Americans between 2003 and 2022, as well as investigating those trends for specific subsets of the American population. Those subsets are separated by gender, generation, race and marital status. Several regressions were run to understand which activities absorbed forgone market work hours. This regression analysis leveraged cross-state variation in time use to do these regressions. These results were separated into differing time periods to understand whether unique aggregate economic contexts changed time allocation preferences amongst Americans. The forgone market work hours were separated into extensive and intensive margins to understand how differing ways of reducing market work hours affect the allocation of time to other activities. Lastly, similarities and differences in time allocation preferences based on gender, marital status, and generation were leveraged to better understand how different subsets of the American population use their time and how they allocate forgone market work hours. Going forwards, it is important to continually update the analysis done in this paper and in Aguiar et al. (2013). A twenty-year span in data may not be sufficient to answer questions about generational splits, and a longer span of data may be needed to better understand those differences. Additionally, new societal contexts like aggregate economic environment or the introduction of new technologies may impact how future Americans spend their time, so updates to this analysis are necessary.

8 Appendix

Below is a table that shows what activities comprise each time use category. The first column is major time use category. These include the seven time use categories mentioned in the data section. Those are Market Work, Other Income Generating Activities, Job Search, Child Care, Nonmarket Work, Leisure, and Other. The center column consists of subcategories that comprise the major time use category. The right most columns are the specific activities that are included in each time use category. Note, some activities have the code n.e.c at the end. N.e.c stands for not elsewhere classified.

Category	Sub Category	Activity
Market Work	Market Work	Travel related to work
		Work-related activities
		Other Income-generating Activities
		Work and Work-Related Activities, n.e.c.

Category	Sub Category	Activity
		Working
		Socializing, relaxing, and leisure as part of job
		Eating and drinking as part of job
Other Income Generating Activities	Other Income Generating Activities	Other Income-generating Activities
Job Search	Job Search	Job Search and Interviewing
Child Care	Child Care	Physical care for household children
		Organization and planning for household children
		Looking after household children (as a primary activity)
		Attending household children's events
		Waiting for/with household children
		Picking up/dropping off household children

Category	Sub Category	Activity
		Caring for and helping hosuehold children, n.e.c.
		Activities Related to household Children's Health
		Physical care for nonhousehold children
		Organization and planning for nonhousehold children
		Looking after nonhousehold children (as a primary activity)
		Attending nonhousehold children's events
		Waiting for/with nonhousehold children
		Picking up/dropping off nonhousehold children

Category	Sub Category	Activity
		Caring for and helping nonhosuehold children, n.e.c.
		Activities Related to nonhousehold Children's Health
		Travel Related to Caring For and Helping household children
		Travel Related to Caring For and Helping nonhousehold children
		Reading to/with household children
		Talking with/listening to household children
		Helping/teaching household children (not related to education)
		Activities Related to household Children's Education

Category	Sub Category	Activity
		Reading to/with nonhoushold children
		Talking with/listening to nonhousehold children
		Helping/teaching nonhousehold children (not related to education)
		Activities Related to Nonhousehold Children's Education
		Playing with household children, not sports
		Arts and crafts with household children
		Playing sports with household children
		Playing with nonhousehold children, not sports
		Arts and crafts with nonhousehold children

Category	Sub Category	Activity
		Playing sports with nonhousehold children
Nonmarket Work	Core Home Production	Food and Drink Preparation, Presentation, and Clean-up
		Housework
		Vehicles
		Appliances and Tools
		Household Management except mail and email
		Household Activities, n.e.c.
		Travel related to household activities
	Home Ownership Activities	Exterior Maintenance, Repair, and Decoration
		Interior Repair and Decoration
		Lawn, Garden, and Houseplants
	Obtaining Goods and Services	Consumer Purchases

Category	Sub Category	Activity
		Professional and Personal Care Services excluding medical
		Household Services
		Goverment Services and Civic Obligations
		Travel related to consumer purchases
		Travel related to Professional and Personal Care Services except medical
		Travel related to household services
		Travel Related to Using Government Services and Civic Obligations
	Others Care	Caring For Household Adults
		Helping Household Adults
		Caring For and Helping household Members, n.e.c.

Category	Sub Category	Activity
		Caring For Non-household Adults
		Helping Nonhousehold Adults
		Caring For and Helping nonhousehold Members, n.e.c.
		Travel Related to Caring For and Helping household adults
		Travel Related to Caring For and Helping household members, n.e.c.
		Travel Related to Caring For and Helping Nonhousehold adults
		Travel Related to Caring For and Helping nonhousehold members, n.e.c.
Leisure	Other Leisure	Animals and Pets

Category	Sub Category	Activity
		Socializing, Relaxing, and Leisure
		Sports, Exercise, and Recreation
		Telephone Calls
		Travel related to socializing, relaxing, and leisure
		Travel related to sports, exercise, and recreation
		Travel related to telephone calls
		Household and personal mail
		Household and personal email
	Eating and Personal Care	Eating and Drinking
		Travel Related to Eating and Drinking
		Personal Care minus sleeping and health
		Travel Related to Personal Care

Category	Sub Category	Activity
	Socializing	Socializing and Communicating
		Attending or Hosting Social Events
		Playing games
		Waiting Associated with Socializing and Communicating
		Waiting Associated with Attending or Hosting Social Events
		Telephone Calls
		Travel Related to Socializing and Communicating
		Travel Related to Attending or Hosting Social Events
		Travel related to telephone calls
	TV watching	Television and movies (not religious)
		Television (religious)
	Sleeping	Sleeping
Other	Education	Education

Category	Sub Category	Activity
		Travel Related to Education
	Civic and Religious Activities	Religious and Spiritual Activities
		Volunteer Activities
		Travel Related to Religious/Spiritual Activities
		Travel Related to Volunteer Activities
	Own Medical Care	Health-related Self Care
		Medical Care Services
		Travel related to medical services

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