In Search of Lost Time Patterns.

How Class, Gender and Social Contexts Structure our Daily Lives.

Giacomo Vagni

Thesis submitted for the degree of Doctor of Philosophy in Sociology

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UNIVERSITY OF OXFORD

Department of Sociology
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Thesis abstract

In this thesis, I investigate sequential patterns of time use in 23 countries during the period 1961- 2015, progressively moving down the level of analysis from a cross-national level to focus on the UK, and then on UK couples. This contribution to the literature comprises three empirical studies.

The first study explores the different daily time use sequences structuring 23 contemporary societies across 50 years. The analyses reveal eight common everyday sequence patterns; including different paid work, unpaid work, and leisure clusters. This set of patterns shows similar distributions across the different countries and time periods.

The second study investigates socio-demographic differences in time use patterns in the UK over the period 1983-2015. Important differences exist between men and women regarding the distribution of paid and unpaid work, and the time patterns of working class men and women are also very different from those of middle/upper class men and women. The social stratification of time use is also revealed by the unequal distribution of patterns between weekdays and weekends.

The last study explores gender inequalities at the level of couple time use patterns in the UK in 2015. I take an innovative approach by analysing diaries from partners of the same couple simultaneously. I find that, when together with their partner, men are much more likely to watch TV and enjoy leisure while women do domestic chores.

The thesis proposes new ways to explore time use diaries and contributes to several areas of sociology, such as social stratification research and the domestic division of labour literature. The thesis concludes by reflecting on potential explanations as to why and how time use patterns can at the same time be highly stratified by class and gender while also being relatively stable across time and country.

– Michael: “We are here because there is something wrong with society.”

– Jim: “See, you’re always saying there’s something wrong with society, maybe there’s something wrong with you?”

– Michael: “If it’s me, then society made me that way.”

— The Office. S05E01.

This thesis is dedicated to Sonny, Cinnamon, Sierra, Donatella & Katy

Contents

List of Figures

List of Tables

Chapter 1

Introduction

"While economics is about how people make choice,
sociology is about how they don't have any choice to make."
— Bertrand Russell

1.1 General Introduction

Everything we do takes time. Everything we do takes place in time. Time is a fundamental dimension of social life. In looking at what people do all day we can learn how inequalities are created and how they are reproduced. We can learn about the social structure of a society. Because time is a universal currency understood by everyone, we can also meaningfully compare societies across time and across space.

We learn about what people do all day thanks to time use *diaries*. Time use diaries are collected in large-scale *Time Use Surveys* generally by universities or government agencies. In a time use diary, an individual is asked to record every activities she is engaged in during the past 24 hours. Nowadays, millions of time use diaries exist from countries around the world, such as Korea, the US, Italy, India, Poland, Canada, Japan, Hungary, Finland, China, and many more. The Multinational Time Use Survey (MTUS) is the largest harmonised freely available database for studying time-use [1]. It is the primary data source I am using in this thesis.

Time-use data provides a unique look into the social world. The data possess both qualitative and detailed information on micro-processes as well as the generalizability of large-scale quantitative surveys. This source of data is ideal for quantitative *micro-sociology*. However, the many great details offered by time-use diaries are often reduced to the study of average time spent in activities (Bianchi et al., 2006; Sayer et al., 2009; Bittman et al., 2003; Robinson & Godbey, 2010; Cornwell et al., 2019).

This thesis proposes innovative ways to look at three classical sociological areas of research.

Chapter 2 revisits one of the oldest area of time use research: cross-countries time use comparison (Szalai, 1972). The main research questions of chapter 2 are: Is there a set of common time use patterns shared by all societies? And if so, what are these patterns? The

[1] `https://www.timeuse.org/mtus`

main innovation of chapter 2 is to go beyond average time spent in activities and explores *patterns* of time use. Chapter 3 looks at the social stratification of time use patterns in Britain during the period 1983-2015. Its main contribution is to look at how patterns are distributed by class and gender. Finally, chapter 4 looks at a very different type of patterns; patterns of activities shared together. It contributes to the division of household labour literature in looking at what partners do when both report being together.

This thesis starts by analyzing time use patterns at the most global level. Then move on to analyze the specific case study of Britain in more details. Finally, the analysis explore the micro-interactions of couples in their daily activities.

Time Use Research

Time use research has a long history in sociological research and it is one of the oldest source of quantitative data about the social world (Cornwell et al., 2019). Time diaries have been particularly influential in the sociological areas of paid work, domestic work and leisure. One of the strength of time use diaries is the high reliability and high precision of the estimates thanks to lower recall bias and lower desirability bias compared to stylized questions (Robinson & Godbey, 2010). Because quality surveys exist for many countries spanning over several decades, time use surveys have been extensively used to traces social change in daily life (Gershuny & Sullivan, 2019).

Figure 1.1 and 1.2 shows two examples of time use diaries. Time diaries generally collect several fields of information such as primary activities, secondary activities, who else was present during the activity and where the activity took place. The 2014/2015 survey also collected the enjoyment of time and the use of electronic devices (see Figure 1.2)

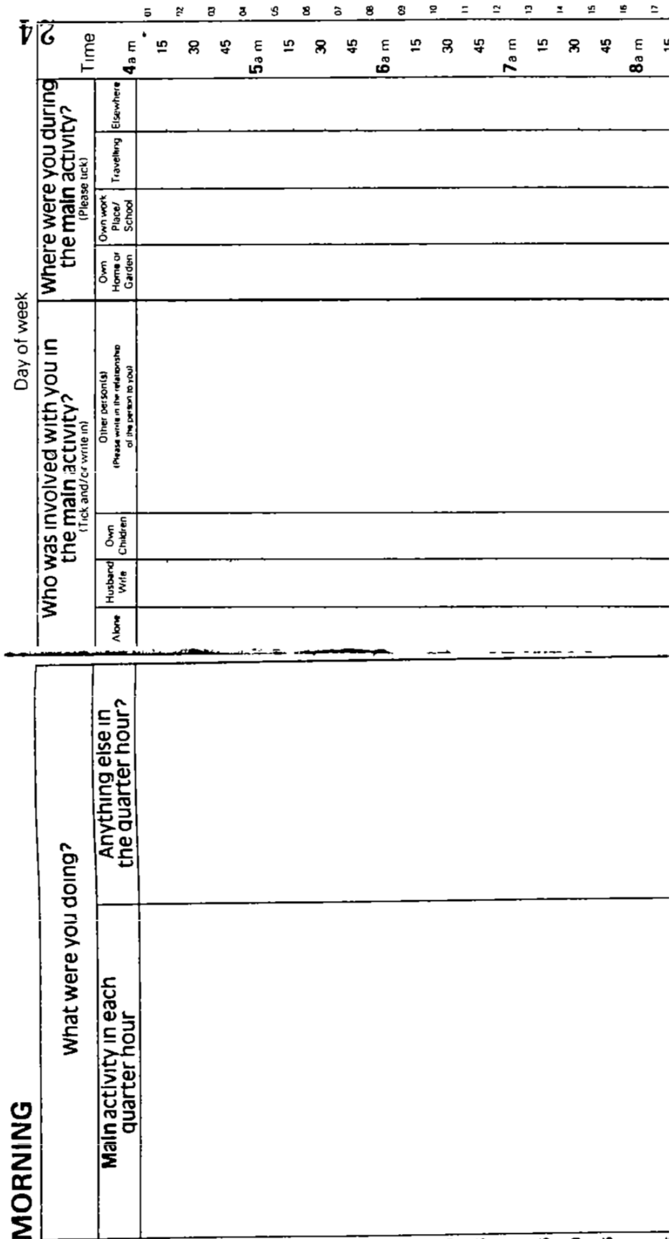

Figure 1.1: The UK Time Use Survey 1983 Diary

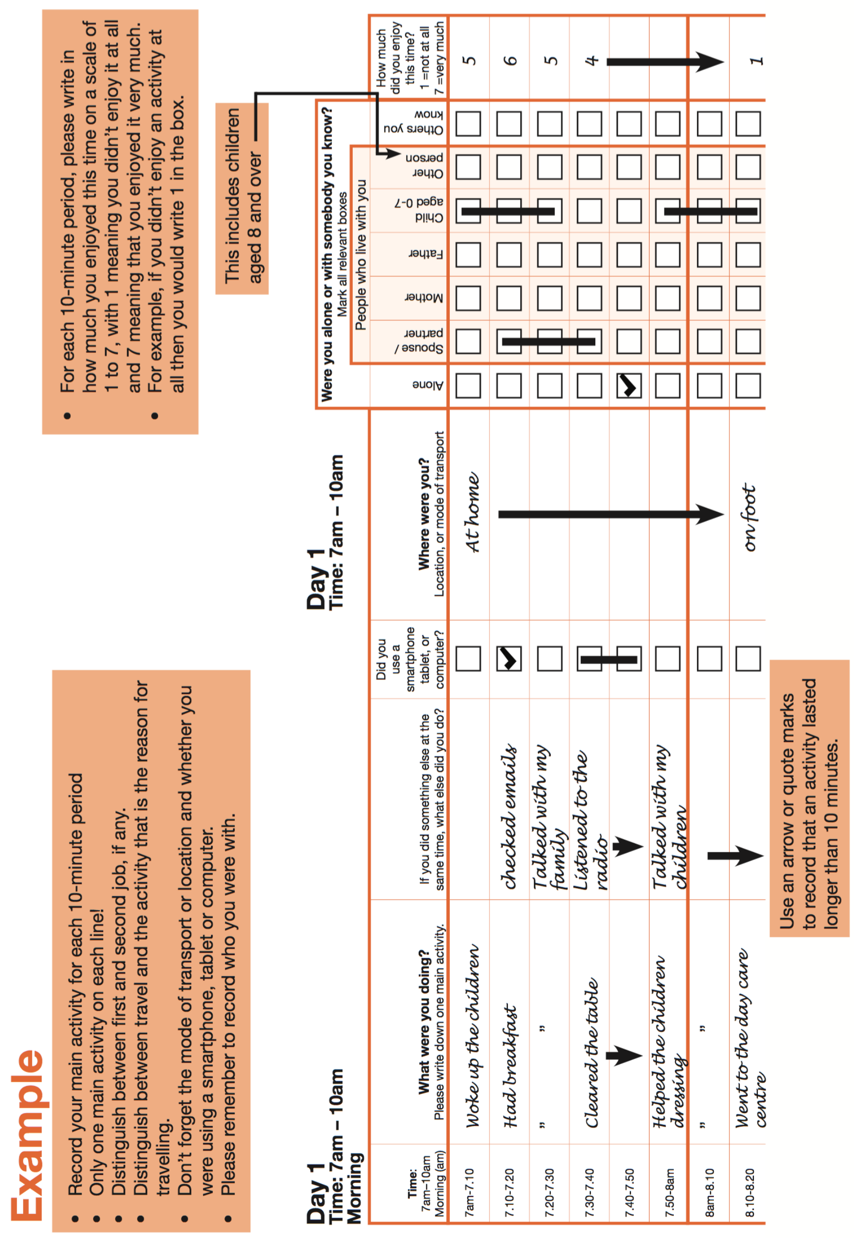

Figure 1.2: The UK Time Use Survey 2015 Diary

Figure 1.3 and Figure 1.4 shows what is called a “sequence distribution plot” also known as “chronogram”. It shows time use activities over 24 hours starting from 4 a.m. to 4 a.m. the next day[2].

The x-axis shows the time of day, while the y-axis shows the proportion of people engaged in a specific activity during that time interval. Figure 1.3 shows the sequence distribution plot for weekdays and Figure 1.4 for weekends with men on the upper panel and women on the bottom panel for the years 1974, 1983, 2000 and 2015 in the UK.

These two figures illustrate some of the general trends in activities in the UK (Gershuny & Sullivan, 2019). Paid work has declined on weekdays and has slightly increased on weekends. Unpaid work (i.e. domestic chores, childcare, etc.) has declined over the years, especially for women. Readers can explore for themselves the other trends in activities during this period of time. What is also remarkable is the general level of consistency of these chronograms. This population-level stability is explored in details in Chapter 2.

[2]The UK time use surveys generally starts at 4 a.m. but starting time can vary between surveys

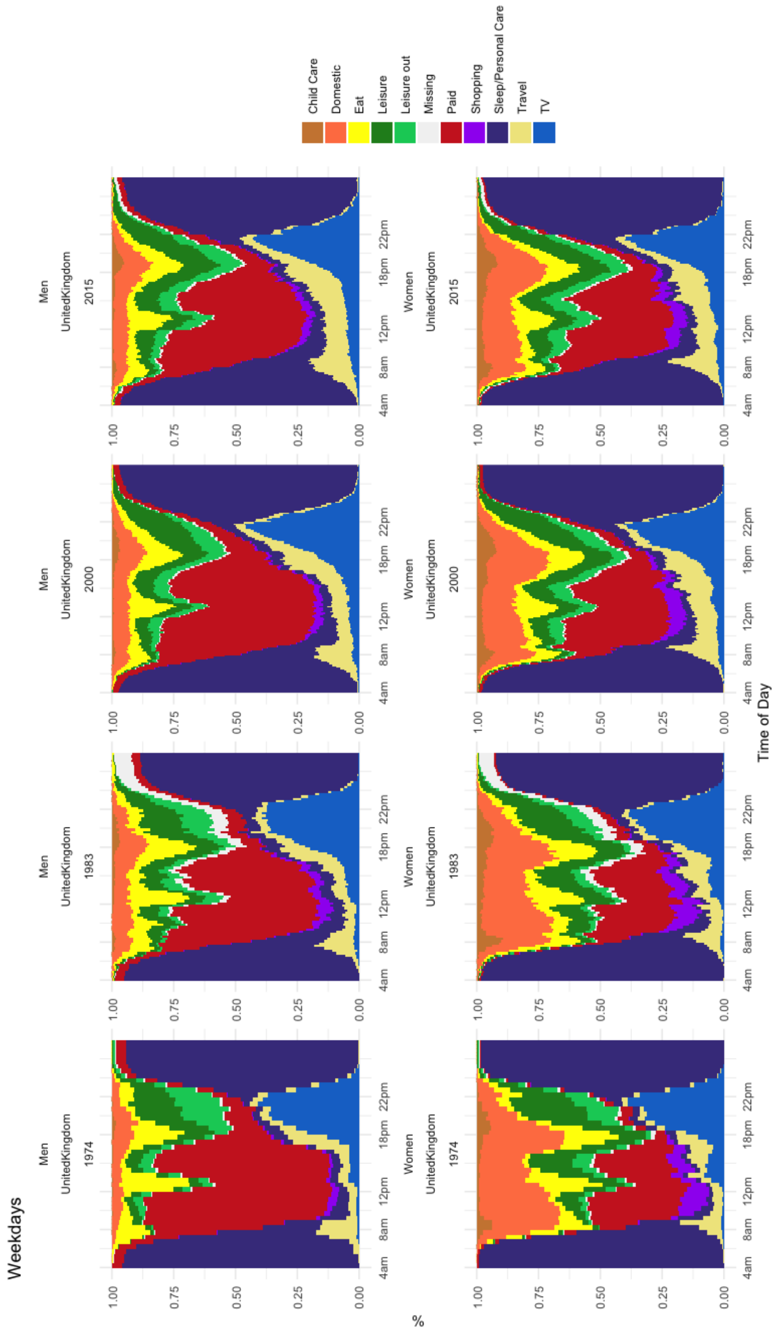

Figure 1.3: Sequence Distribution Plots Showing Time-Specific Activity Sequences On Weekdays by Gender

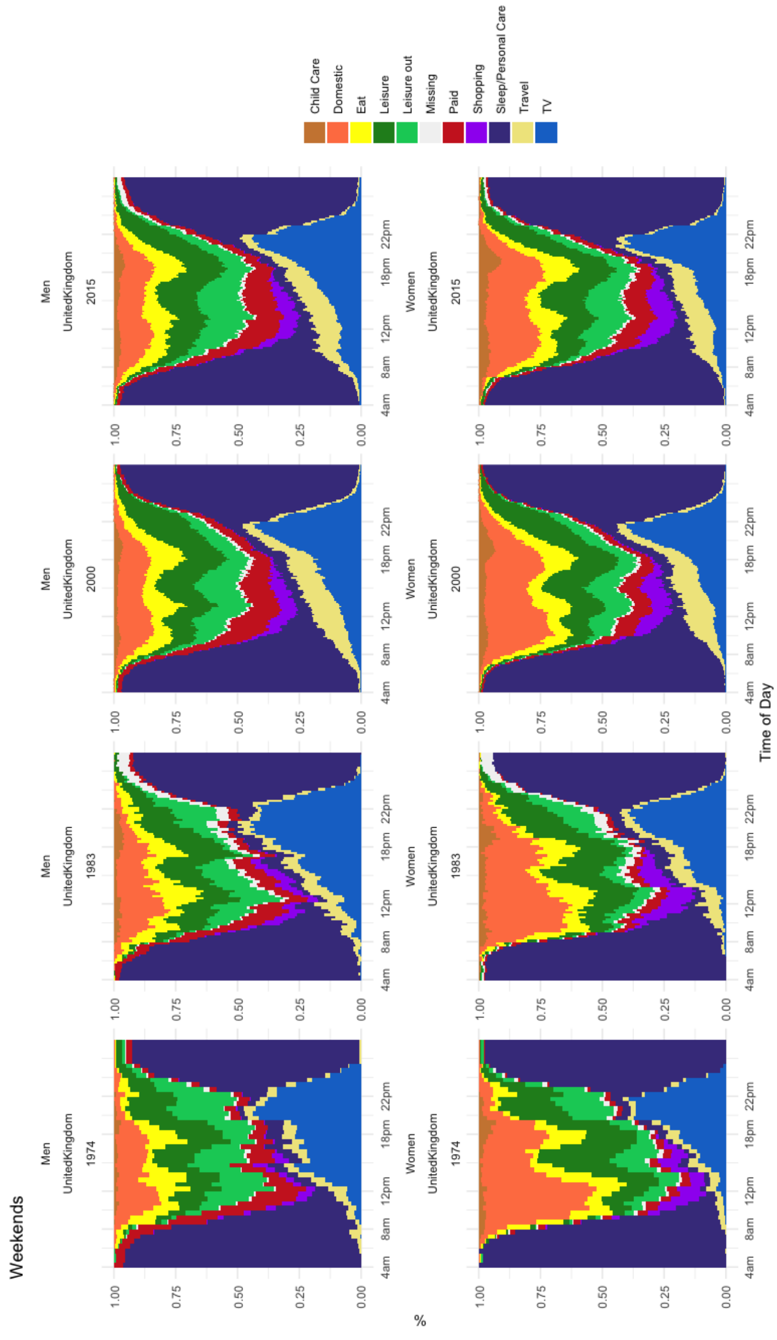

Figure 1.4: Sequence Distribution Plots Showing Time-Specific Activity Sequences On Weekends by Gender

However, population-level estimates can mask important heterogeneity. Searching for patterns is about discovering hidden structures. The use of time is not just heterogeneous, in the sense that every individuals allocate their time in different ways. There is a structure behind this heterogeneity. This heterogeneity is not random. This is a case of "structured heterogeneity". Sequence analysis is a tool for uncovering just that.

Sequence Analysis

Sequence analysis was introduced in sociology in the early work of Abbott 1995. Since then the method has been widely successful in life course studies and in demography (Aisenbrey & Fasang, 2010; Billari, 2001; Billari & Piccarreta, 2005; Elzinga & Liefbroer, 2007; Van Winkle, 2018). Sequence analysis has been less prominent in time use research. Lesnard was the first to introduced the method in time use research with his landmark study of work schedules and family time in France (2008; 2004). He also invented and popularized a new sequence matching algorithm that is theoretically tailored for time use research (Lesnard, 2010). We will discuss it in chapter 3. However, since then few studies have really contributed to time use research using sequence analysis. Chapter 2 and chapter 3 are two of the most recent contributions to the time use literature using this methodology.

Sequence analysis is about sequence of events. In life course research, events can be employment trajectories, fertility trajectories and so on. In time use research, events can be the activities (e.g. cooking, playing, cleaning, etc.).

Sequences have different interesting properties. The most important properties are the *duration* of sequence, the *order* of events and the *timing* of events (Zerubavel, 1985). Averages only focus on duration, and leave out ordering and timing. Sequence analysis was coined "holistic" because the method takes the whole sequence as the unit of analysis (Billari & Piccarreta, 2005). It distinguishes itself from other longitudinal method such as "Survival analysis" focusing on one discrete event and not on the entirety of the sequence (Helske et al., 2014). This is particularly meaningful in time use research as the entire day is the unit of analysis. Conceptually, time use activities cannot be describe by simple Markov Processes. Activities later in the day do not generally depend on activities earlier that day. Days are routinized and generally planned in advance. For some people the organization of daily routine is planned months in advance. Of course some people have more routinized schedules than others but the immediate past does not necessarily impact the immediate future. In time use, it is also the case that the *future influences the past*. We do things now in anticipation of the future. This is exemplified for instance in the fact that people on average work longer hours on Thursdays, hoping that they can leave earlier for the weekends the next day.

Sequence analysis can be simply illustrated as follow. Take 2 sequences (i, j) with three states $\{A, B, C\}$. States are the discrete components of the sequences (also known as the *alphabet*).

i	A	B	C
j	C	B	A

Duration-wise, sequence i and sequence j spend the same amount of time in the same states. But you can see that the ordering and timing of the states are different.

The goal of running a sequence analysis is to find the closest pair of sequences regarding a particular dimension of interest (timing, duration, ordering, etc.). Sequence analysis uses different "distance measures" to capture different dimensions of time.

Different algorithms use different distance measure and thereby will give different proximity between sequences. But the goal of all distance measure is to search for the pairs of sequences with the smallest distance. Sequence analysis works by comparing pairs of sequences. The natural way to "store" pairs of sequence is in what is called a "dissimilarity matrix" which provides the relationship in terms of distance between all sequences.

The core idea behind the most used algorithm, the Optimal Matching, is to find the minimal number of operation to transform sequence *i* into sequence *j* (or vice versa) (Abbott & Forrest, 1986). This algorithm uses three main operations: substitution, insertion and deletion. Substitution refers to the fact that a state is simply "substituted" with another one to make the sequence more similar. Insertion and deletion, also called "indel", refer to addition and subtraction. The idea is then to count how many operations are needed to make the two sequences similar. If you only need 1 operation, then the two sequences are fairly similar. If you need 10 operations, then they are more dissimilar. Many different algorithms exist in sequence analysis, all trying to capture different dimensions of sequences (for a comprehensive review, see Studer & Ritschard (2016)).

The natural step from this procedure is to group similar sequences together. This as been done generally by way of clustering (Kaufman & Rousseeuw, 1990). A clustering algorithm is applied to the distance matrix and it is then possible to retrieve a set of finite clusters. The goal of clustering is to find the optimal number of homogeneous groups that meaningfully summarize the data. This is not always easy and time use diaries are particularly challenging because of the high number of states (i.e. activities) and the high number of episodes (generally 24 hours decomposed in 10 minutes intervals which equals to 144 episodes). Life course has in general less states and much shorter sequences. The clustering is the way to retrieve the patterns of time use, which constitute the core of this thesis.

Patterns of Time

The word "pattern" comes from the French word *patron*: "something serving as a model" (Oxford Dictionary). A pattern is a model, which can generates an infinite number of structured outputs. In our case the outputs under scrutiny are sequences of activities. The scientific program of "pattern searching" can be traced to fields such as linguistics and anthropology. For instance, the generative grammar of Chomsky or the study of myths of Claude Levi-Strauss is part of a similar research program; the searches for structured patterns in myths or in human languages, and the universal rules generating these patterns.

This paradigm can also be linked to Pierre Bourdieu's vision of sociology. In his famous study of taste, Bourdieu showed that taste was patterned, and that these "patterns of tastes" were linked to social class in the French society (1984). The research program of the pattern paradigm is to detect a *structure* among the infinite numbers of seemingly unrelated tastes, ideas, actions, choices and activities. Furthermore, the goal is not simply to find patterns but also to show that they are linked to the social structure. Bourdieu went a step further to show how these patterns emerged through socialization and how social agents then went on to reproduce the social structure through patterned life choices 1972.

Social stratification generally refers to social class but it should refers more generally to anything that stratifies a society: gender, race, age, etc. Gender stratifies society as much as social class. Social structure refers to the hidden, latent or unobserved structure that generates the observed differences between groups[3].

Each societies face the issue organising the general division of labour but also to distribute the outputs of labour. Societies need to allocate individuals to productive activities and to rewards these activities. This differential in allocation and rewards is generated by the social structure and it is what we observe with social stratification. In other words, social stratification is the manifest or observed expression of the social structure. It is the system of gender stratification that allocates women in certain sphere of activities and men in others, and rewards women less for working in these spheres [4]

[3]The concept of social structure has been defined in many different ways in sociology (Bruce & Yearly, 2006; Boudon & Bourricaud, 2006). Here I sketch my own concept of social structure.

[4]Think of the unpaid labour of mothers. Children are not just private goods, but ultimately public goods.

Time use diaries have an important contribution to make to sociological science in showing how social life is structured in real time and space. From childhood to old age, individuals allocate their time and resources according the context they found themselves in. Time allocated to paid work, unpaid work, leisure and childcare have both impact in the immediate present and in the long run. With childcare, parents start a long process of cultural and human capital accumulation embodied in their children. Early capital accumulation dictates future choices and transitions often reinforcing initial difference and accumulation. Time use is a window from which one can observe the cause and effect of inequalities.

We are very far to have achieve this level of description of the social world. But we can start to see how a full sociological science program would like. How initial circumstances pushes individual towards different allocation of their time, which in turn will either change these circumstances or reinforce them and in turn will lead to further endogenous choices of time allocation.

Contributions of the Thesis

My contribution with this thesis is to simply show that time use is patterned, that these patterns are heterogeneous and that this heterogeneity is linked to the social structure through social class and gender. This thesis is rather the beginning of a research program rather than the conclusion of such program. This thesis raises more questions than answers. Many questions are left for future research, the most salient being: How do these time use patterns emerge and evolve throughout the life course?

Chapter 2 is the very first general attempt to use the gigantic Multinational Time Use Study (MTUS) sequence file in a comprehensive way. The MTUS sequence file provides time use information throughout the day for 23 different countries. Chapter 3 is the first paper to reveal the time use patterns in Britain during 1983-2015 in a social stratification perspective. Chapter 4 is the first paper to explore what activities couples do together using multiple time use diaries.

Substantially, this thesis unveils how patterns actually look like for a range of primarily Western countries. One of the substantial finding of Chapter 2 is to show that once we account for the several ideal-typical time use patterns present in each country, very different societies are in fact quite similar. However, Chapter 2 does not explore individuals or group-level variations. Chapter 3 undertakes this work for the UK. It reproduces the methodology of Chapter 2 and disaggregate the patterns by social class, gender, year, and day of the week. It shows that even though clear time use patterns exist at the general population level in Britain, these time use patterns are highly stratified. Chapter 4 opens the door to another great potential of time use diaries too often overlooked: couple time use diaries. Chapter 4 compares diaries for partners from the same households. Time use surveys often collect multiple diaries per households and it is therefore possible to analyze simultaneous time diaries from different members of the same household. In this chapter I show that partners do not necessarily report the same activity when reporting being together.

Acknowledgments

This thesis would not be what it is without the great generosity of so many people. Many different voices have influenced me and challenged me during my time as a PhD student. First, I would like to thank my supervisors, Oriel Sullivan and Jonathan Gershuny, who gave me the opportunity to study under their guidance at Oxford. Most of my time during my PhD was split between the Centre for Time Use Research and Nuffield College. I want to thank all the members of the Centre for Time Use Research.

Nuffield College was an extraordinary place to study. I am grateful to many of my

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1.2 Abstract of Chapters

Patterns of everyday activities across social contexts

Abstract

Social-scientific theory and research give rise to conflicting expectations regarding the extent to which individuals' everyday lives in modern society follow predictable patterns of behavior. Much previous research has addressed this issue implicitly by documenting widespread trends in patterns of "time use" or "time allocation," including trends in time devoted to paid work, unpaid work, and leisure. This study expands on this research by examining common patterns with respect to not how much time individuals spend on certain everyday activities (e.g., leisure), but rather how those activities are sequenced throughout the day. Using sequence methods and cluster analysis, we analyze a large collection of harmonized time diaries from the Multinational Time Use Study (MTUS), including diaries from 23 countries and dating back to 1961. Our analysis of these diaries reveals eight common everyday sequence patterns—including different paid work, unpaid work, and leisure clusters. This same set of patterns reappears in a generally similar distribution across the different countries and time periods that are included in the MTUS sequence data. This study has implications for how analysts study time diary data and raises important questions about the causes and consequences of individuals' experiences with particular behavioral sequences.

The Social Stratification of Time Use Patterns

Abstract

Time use is both a cause of social inequality and a consequence of social inequality. However, how social class stratifies time-use patterns is seldom studied. In this paper, we take a holistic approach in describing time-use patterns over the period of 1983-2015 by social class, gender and day of the week in the British context. Using sequence analysis methods, we go beyond the average time spent doing activities to show how the diversity of time-use patterns in British society is socially stratified. We find that 13 clusters capture the heterogeneity of time-use patterns and that these clusters are associated with social class, gender and day of the week. We find that working-class men and women are more likely to be doing shift work, such as working the morning, evening and night on weekdays and weekends. We find that paid work has been increasing on weekends for working-class households. We discuss how time-use research can further our understanding of social stratification.

Alone Together: Gender Inequalities in Couple Time

Abstract

An important body of research has used time diaries to assess the transformation of gender relationships at home. However, little is known about how partners perceive time shared together. While the household division of labor still remains heavily gendered, it can be expected that what partners do, even when they are together, is also gendered. The aim of this paper is to address the question of the discrepancy (or mismatch) in couples' reporting of time together as well as the potential discrepancy in the activities engaged in during shared time. Using the 2015 UK Time Use Survey, I show that there is no gender difference in how partners report being together; however, important gender imbalances exist in what partners do when together. In particular, I find that, when together with their partner, men are much more likely to watch TV and enjoy leisure while women do domestic chores. I conclude by discussing different concepts of time together and the usefulness of couple-level diary data for studying gender relationships at home.

Chapter 2

Patterns of everyday activities across social contexts

"Even the most casual glance at our environment would already reveal a certain degree of orderliness. One of the fundamental parameters of this orderliness is time— there are numerous temporal patterns around us."

— Eviatar Zeruvabel

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Acknowledged author contributions: G.V. and B.C. designed research; G.V. performed research; G.V. analyzed data; and G.V. and B.C. wrote the paper.

Data deposition: The data and analyses related to this study are deposited on GitHub (https://github.com/giacomovagni/patterns-of-everyday-activities-across-social-contexts).

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2.1 Introduction

Everyday life sometimes seems unpredictable and disorganized. The difficulty of coordinating the seemingly chaotic flow of everyday obligations has been documented, for example, in a vast body of research on the challenges associated with maintaining household divisions of labor and in managing work-family role conflict (Cornwell & Warburton, 2014; Liu et al., 2011; Milkie et al., 2010, 2004; Presser, 2000; Strazdins et al., 2006; Major et al., 2002; Bianchi et al., 2000; Greenhaus & Beutell, 1985; Kelly et al., 2011). Several scholars have even commented that the pace of everyday life is “speeding up,” thus adding to the sense of everyday life’s tumultuousness (Wajcman, 2008). There are several reasonable explanations for this. It is possible, for one, that the expansion of non-standard work arrangements – including shift work and temporary work arrangements – has complicated individuals’ efforts to coordinate their everyday activities and obligations (Kalleberg, 2009; Presser, 2005; Wight et al., 2008; Allen et al., 2013).

At the same time, some scholars would argue that this sense of unpredictability and disorganization belies the highly structured organization of time in modern society. These scholars have argued that there are several common, normalized patterns or routines of behavior that characterize everyday life, making it much more predictable and therefore manageable for individuals (Giddens, 1984; Nadel, 1957; Parsons, 1937, 1951; Sorokin & Berger, 1939; Zerubavel, 1985). Indeed, the simultaneous operation of several different predictable, interlocking patterns of activity is the hallmark of divisions of labor across all societies, at the household level, in markets, and elsewhere.

To what extent individuals’ everyday lives in today’s society are characterized by predictable behavioral patterns remains an open question. To be sure, many social scientists have documented some evidence of temporal patterning in individuals’ everyday behavior. That different individuals tend to spend similar amounts of time doing certain things (e.g., paid work) is a dominant finding in the large body of research on time use or time allocation (Aguiar & Hurst, 2007; Gershuny, 2000; Gimenez-Nadal & Sevilla, 2012; Robinson & Godbey, 2010; Szalai, 1972). Scholarly interest in common behavioral patterns is also reflected in recent work that uses new technologies like smartphones to identify similar durable patterns of activity (Kung et al., 2014; Mucelli Rezende Oliveira et al., 2016; Simini et al., 2012; Song et al., 2010). Such analyses of time-stamped daily activity data seem to provide evidence that everyday behavior is more highly patterned than it sometimes seems.

We argue, though, that evidence regarding the prevalence of common patterns of everyday behavior is incomplete. Many studies have examined time "allocation" or time "use", but few have examined how and when individuals' behaviors unfold over the course of the day. The regularization of behavior into common predictable activity patterns should manifest not only in terms of the widespread normalization of the amount of time people spend on given activities, but also in terms of the sequential patterning of those activities during the course of the 24-hour day. Analyses of aggregate time use statistics cannot address this issue. For one, recent research shows that there is substantial variation in the rate at which individuals transition, or switch, between activities during the course of the day, even after controlling for how much time they spend on certain tasks (Southerton, 2003; Cornwell, 2013). Related work documents variation in the extent to which individuals engage in certain types of activities (e.g., leisure) in a "fragmented" manner, as opposed to consolidated chunks of time (Bittman & Wajcman, 2000; Mattingly & Blanchi, 2003).

Together, this growing body of work highlights the need for a direct examination of patterns in the sequencing of everyday behaviors, as a complement to existing research on how much time individuals spend doing those behaviors. Therefore, in this paper, we present an exploratory analysis which aims to shed light on: (1) the extent to which everyday behavior unfolds in common patterns that reappear across social contexts; and, more fundamentally, (2) what those patterns are.

Temporal Patterning of Everyday Life

Our goal is to analyze data from diverse social contexts to assess the extent to which everyday human activities – such as working, eating, and leisure – are patterned in some set of typical, predictable temporal sequences. It remains to be seen how many common behavioral patterns exist, or how common they are both within and across social contexts.

Many scholars have argued that *there exist certain widespread, archetypal behavioral sequence patterns that characterize everyday life across otherwise very different societies* (Nadel, 1957; Parsons, 1937; Sorokin & Berger, 1939; Zerubavel, 1985; Durkheim, 1997 [1893]). Indeed, there are reasons to expect that there will be several behavior patterns that are common both within and between societies. For one, much of everyday social life is organized around institutions – such as families and households – which tend to give rise to common divisions of labor (Becker, 1981; Coltrane, 2000). These divisions of labor rely on different individuals ordering their activities such that their activities link together in a coordinated fashion. It is often advantageous for the different members of a group to engage in different but complementary, or interlocking, activities (Carriero et al., 2009). For example, in households where two parents are working, it is often easier to ensure that someone is with the children when those parents work different shifts (Presser, 2005; Lindsay et al., 2009; Liu et al., 2011). An implication is that some sets of individuals are likely to exhibit different sequences of everyday behavior – with some individuals engaged in one activity pattern and others engaged in another. That common patterns exist is also suggested by general time use research. This work has shown that various types of consumption (e.g., eating, television watching) tend to occur at certain times of the day for most people. However, this work has also shown that different temporal patterns of consumption hold for different groups of people (Glorieux et al., 2010).

There may be both individual and systems-level reasons that common temporal patterns tend to emerge in different social contexts. At the individual level, circadian rhythm plays a major role in creating predictable behavior patterns, as they provide a foundation for the daily cyclical nature of sleeping and waking. Other biological needs (especially nourishment) likewise figure into the regularized timing of other forms of activities during waking hours. Beyond this, some scholars have argued that individuals benefit from engaging in predictable behavioral sequences not only because it plugs them into the larger social systems discussed above, but also because the greater predictability in everyday life that comes with this is more psychologically comforting and less cognitively taxing than is enacting completely different behavioral sequences every day (Milkie et al., 2004; Giddens, 1984). Beyond these endogenous individual-level forces, the presence of common behavioral sequences benefits larger social units, including market systems, as discussed above. For these and likely other reasons, regular patterns of behavior may emerge across societies as an intended or unintended consequence of the fact that individuals organize their actions between the dual constraints of inevitable biological needs and widespread social-institutional practices.

On the other hand, several relatively recent societal trends may pose a challenge to the maintenance of normalized behavioral patterns. For one, the growing use of new information and communication technologies makes it easier for people to engage in last-minute planning and coordination, which may have reduced the predictability of their activity sequences (Castells, 2009). Second, multiculturalism and globalization increase the diversity of markets, cultural practices, and rituals, thus potentially increasing variation in the prevalence of certain sequences both within and between societies (Milanovic, 2016; Appadurai, 1996). Finally, the rise of flexible production, 24-hour markets, and other macroeconomic developments have led to the emergence of more flexible, nonstandard work arrangements, which reduce the prevalence of once-common or canonical work/family schedule arrangements (Kalleberg, 2009; Presser, 2005; Wight et al., 2008). It remains an open question whether these developments, or any other individual or social factors, have precluded the development of regular patterns of everyday human activity.

To our knowledge, few if any attempts have been made to examine the extent of regularity of human behavior with respect to its sequencing across a variety of geopolitical and temporal contexts.

2.2 Methods

To examine this question, we examine the largest collection of time diary data compiled to date; the Multinational Time Use Study (MTUS). These data are the culmination of efforts by the Centre for Time Use Research (CTUR) at the University of Oxford to harmonize detailed time diary data from vastly different populations (Fischer & Gershuny, 2016). In these diaries, individuals indicated via either telephone or paper diaries which specific activities they were engaged in at specific times over the course of a given 24-hour period. This dataset includes time diaries provided by people in 23 different countries from 1965 to 2015, for a total of 48 surveys. (A full enumeration of the countries and years from which these diaries were collected is provided in the Appendix).

Our first goal is to use the information about individuals' behavior throughout the day from these diaries to determine the extent to which there are common patterns of behavior with respect to several key human activities. To do so, we treat individuals' reports of behaviors as incidences of sequential behavior. Each time diary reveals a behavioral sequence that contains some combination of a harmonized class of eight general types of behaviors – including Unpaid Work, Personal Care, Eating, TV, Paid Work, Leisure, Travel, and Missing. The CTUR harmonized the diary data such that there are equivalent reports of what each individual was doing in each of 288 5-minute activity episodes on the day in question. For consistency with previous time-use studies, we focus on diaries that were collected on weekdays for the working-age population (18-65 years old), which narrows the sample to 225,551 individuals' diaries. Diaries in some settings were collected from midnight of one day to midnight the following day, while others covered the period from 6am to 6am. To maximize comparability, we compare diary entries that cover the period from 6am to 10pm. For each diary, this includes 960 minutes (16 hours) of observations in five-minute intervals, or 192 activity episodes per day.

Identifying Common Activity Patterns

To identify common patterns with respect to how individuals sequenced their behavior, we use social sequence analysis methods (Cornwell, 2015) to categorize the timing and order of the various activities individuals reported in their diaries. This involves using a sequence-alignment method to quantify the degree of dissimilarity, or distance, between each pair of activity sequences in the dataset, then using all of this pairwise information (stored in a "dissimilarity matrix") to identify "clusters" of individuals who reported similar sequences. Sequence alignment algorithms employ a combination of three fundamental operations to determine the degree of distance between a given pair of sequences: Deletions, insertions, and substitutions (Abbott, 1995). When two individuals time and order their activities in a very different manner, the algorithm calculates a high dissimilarity score.

Sequence Comparison

We tested three approaches to quantifying the difference between sequences. The first – the Hamming distance – counts the number of substitutions that are required to transform one sequence into another sequence (Hamming, 1950). Because it does not use insertions/deletions, the Hamming distance primarily measures differences between sequences in terms of when their activities occur (i.e., activity timing). The second distance measure is a variant – called Dynamic Hamming (DH) (Lesnard, 2010) – which uses a time-varying transition matrix to weight substitutions in terms of how unusual they are at different times of day. The last distance measure is derived from classical Optimal Matching (OM) (Abbott & Forrest, 1986). This approach uses the substitution operation in conjunction with insertion/deletion operations. While the insertion/deletion costs are set to 1, the transition matrix between states is used to determine the substitution cost (Gabadinho et al., 2011). OM-based distances therefore quantify the distance between a given pair of sequences in terms of differences in both the timing and order of activities in those sequences. Note that in the main text of this paper, we present findings that are based on analyses using the more interpretable Hamming-based distance, the original Hamming distance, as these findings were broadly consistent with those derived from analyses that used the DH and OM measures (see the end of the results section below).

Hierarchical Cluster Analysis

We use these distance measures to identify clusters of sequences that have similar sequential features. Once the distances between sequences were calculated, we used the hierarchical Ward algorithm to identify homogeneous clusters of sequences (Gabadinho et al., 2011). This is an agglomerative hierarchical clustering technique that attempts to minimize within-cluster variance Kaufman & Rousseeuw (1990), which is commonly used in social sequence analysis and tends to identify commonly sized clusters and therefore avoids poorly populated clusters (Cornwell, 2015). This clustering is performed on the matrix of distances or dissimilarities between sequences. The result is a set of hierarchically nested clusters that contain cases that evince relatively similar day-long activity sequences. To assess the validity of cluster solutions, we calculate the cophenetic correlation coefficient, which measures the level of association between the level of dissimilarity between (sets of) sequences and the point at which the cluster analysis fuses those sequences together. We use the elbow graph (see Fig A.8) and consulted a battery of measures that assess the variation of sequences within and between clusters (available upon request) to help identify an acceptable number of clusters (Sokal & Rohlf, 1962). Virtually all of these criteria indicate that a very small number of clusters is ideal. For reference, we present the hierarchical solution that contains all nested clusters (see Appendix), but in this paper we focus on the eight-cluster solution. This solution achieves the best compromise between the clear need for a solution that contains few clusters but that maximizes face validity given existing research on common time-use patterns. Solutions that contain more than eight clusters achieve poor fit according to most indicators, and they result in substantively trivial distinctions in time-use patterns.

The MTUS consists of an unbalanced panel of diaries, as some countries had more respondents and contribute more years of diaries as well. Thus, to give equal weight to countries and to time periods, we sampled 1,000 individuals in each country and across two general time periods (1969-1994, 1995-2009). The final random subsample used in the main analysis is composed of 31,089 individuals. (This number is not round because a few surveys only cover one time period and two surveys have less than 1,000 individuals, see Appendix, Table A.13.) In order to test the stability of our solution, we reproduced the sequence analysis on 10 different random subsamples. Results of this robustness check are reported in the results text below. We also conducted supplemental analyses to assess the sensitivity of our main cluster solution to pooling cases from multiple countries rather than conducting separate country-specific analyses (see Appendix).

Assessing the Distribution of Activity Patterns across Contexts

After using cases from the analytical subsample to identify a set of behavioral sequences that possess similar temporal characteristics, our final goal is to determine the extent to which this set of clusters reappears across the different social contexts that compose the MTUS dataset. First, we assess the bivariate association between the cluster to which a sequence is assigned and the country of origin/time period in which that sequence was observed. We use a simple chi-square test to assess the significance of the association and Cramer's V to measure the magnitude of the association. The latter measure ranges from 0 and to 1, with 0 indicating no association and 1 indicating a perfect association.

Second, we conducted a dissimilarity-based discrepancy analysis. The method was developed by Studer et al. as an alternative to cluster analysis (2011). The goal is to measure the strength and the statistical significance of the association between sequences and a set of covariates. It is a generalization of an ANOVA analysis. The equivalent of a total sum of squares is decomposed in a between-sequence discrepancy component and a within-sequence discrepancy component. A Pseudo-R^2 measures the share of discrepancy explained by explanatory covariates. This approach allows us to directly quantify the share of sequence discrepancy that is explained by country of origin and time period. The purpose of both of these analyses is to assess the degree to which the distribution of common sequence patterns that we identify using the cluster analysis described above varies by geopolitical and/or period context. The greater the association, the less universal this set of common sequence patterns is.

2.3 Results

Overall Activity Levels

Before discussing the sequential ordering of everyday activities, we begin with a brief overview of the distribution of time spent on specific activities (Appendix, Table A.11). On average, the individuals in the overall sample (N = 225,551) spend most of their waking time either working for pay or doing unpaid work (domestic chores, childcare). More precisely, individuals spend about 4h24m working for pay (27.5% of the day) and 3h29m doing unpaid work (21.8% of the day). Following this, in order of prevalence, is leisure (14.4% of the time) and TV watching (8.3%). Individuals spend on average 2h18m on leisure and 1h20m watching TV. An average of 1h21m is spent eating. The rest of the time is spent traveling or sleeping. We do not capture patterns of sleep very well in our analysis because night time is excluded for data comparability reasons.

Typical Activity Sequence Patterns

We move beyond the question of how much time individuals typically allocate to certain activities to explore the potential presence of common patterns in the sequencing of these activities. This involves an analysis to assess the presence of clusters in the Hamming-based activity sequence dissimilarity matrix.

Our examination of the clustering quality measures (available upon request) combined with our assessment of the graphical depictions of the activity patterns within clusters (see Appendix, Figure A.8) suggests that an eight-cluster solution achieves a workable balance between internal cluster quality and the interpretability of the clusters. The dendrogram of the hierarchical clustering from the Hamming-based activity sequence distances is presented in the Appendix, Figure A.7. The left panel shows the dendrogram as a whole, while the right panel shows a re-scaled version of the same figure to make it clearer how the clusters are hierarchically arranged vis-a-vis each other. This panel illustrates which of the main clusters that are presented here may be combined into larger parent clusters while also showing how they may be split into smaller sub-clusters. The eight clusters we identified are boxed using red lines in the figure.

Our main goal in this section is to describe the common sequence patterns that the above cluster analysis revealed. There are several ways to do this. First, we examine state distribution graphs for each of the eight clusters (A thru H) that were revealed by the Hamming-based clustering solution (Figure 2.1). This will provide a sense of the aggregate distribution of activities individuals within each cluster engaged in at each point throughout the day. We will then examine sequence index plots that show how these activities were sequenced by specific individuals (Figure 2.2).

Regular Paid Work Patterns

Clusters A ("Paid I Standard"), B ("Paid II Long"), C ("Paid III Morning") group individuals engaged in paid work for most of the day. Clusters A, B, C differ in the total amount of paid work they do (see Appendix, Table A.5) as well as in the timing of paid work. Individuals in Cluster A work an average of 8 hours and 37 minutes during weekdays, those in Cluster B work 9 hours and 21 minutes, and those in Cluster C work 7 hours and 50 minutes, on average. Individuals in Cluster A, on average, start working at 7:50 am, while those in Cluster B start later, at 8:25 am, and those in Cluster C start much earlier, at around 6:44 am (Appendix, Table A.6). The proportion of individuals engaged in paid work at different times of the day also differs across clusters (see Appendix, Table A.6). For example, at 8am, about 65% of individuals in Cluster A are engaged in Paid work, compared to 43% in Cluster B and 95% in Cluster C. The end of the work day also differs across clusters. The average end of paid work is 17:29pm for Cluster A, 20:14pm for Cluster B, and 14:23pm for Cluster C. Thus, the cluster labels reflect the three types of a full paid workday. "Paid I Standard" reflects the eight-to-five "standard" work schedule. "Paid II Long" reflects a lengthier work day (about 9 hours 21 minutes, on average). And "Paid III Morning" reflects an early morning start and early afternoon end of the workday.

Before moving onto a general description of the five remaining clusters, we also want to highlight differences between clusters with respect to their sequencing of work and other activities in general. Figure 2.2 presents sequence index plots, each of which include about 100 specific individual-level sequences stacked on top of each other. These plots provide more precise, non-aggregated information about how representative individuals within each cluster sequenced their activities throughout the day. We choose the representative cases as follow. We first computed the cluster medoid (Gabadinho et al., 2011), which represent the most representative sequence of the cluster. We then picked the 50 individuals closest to the medoid. Finally, we chose several sets of sequence each time more distant from the medoid. Thereby, the individuals closest to the bottom of the figure are the sequences closest to the medoid and the individuals at the top of the figure at the ones most distant to it.

In Figure 2.2, we can see the different start of paid work time for individuals in Clusters A, B and C. Most individuals started their day either by eating (colored deep blue) or by doing some unpaid paid (colored yellow) – which often means preparing someone else breakfast, feeding a child, or doing housework. Most individuals then commute to work (colored deep red). In Cluster A, we can see for some individuals a clear lunch break (deep blue) around noon and a clear dinnertime (deep blue) around 7pm, followed by TV watching (colored purple). Eating time is more spread out in Cluster B. While we can see that for most individuals in this cluster lunch occurs at around noon, this is not the case for all, perhaps reflecting the fact that some individuals in this cluster might eat at their desk or while working. This pattern is even more striking in Cluster C, where very few people take a real lunch break. Very early in the morning some of these individuals engaged in unpaid work and then commuted to work. Around 3.30pm, most of the individuals in Cluster C stopped working and then engaged in unpaid work until about 18.30, where most of them ate and watched TV.

Shift Work Patterns

The next two clusters group individuals doing what is often termed "shift work". They work on average less time than individuals in Clusters A-C. Also, these tend to engage in paid work during non-standard hours, such as evenings. Individuals in Cluster D ("Shift I Morning") start work on average at 8.04 am finish work at 14.23pm (see Appendix, Table A.6). Individuals in Cluster E ("Shift II Evening") start work at 11.47pm and finish work around 19.11pm. At 7pm, about 42% of individuals in Cluster E are still at work (Appendix, Table A.7). The sequence index plots that display the sequences of representative individuals for these groups (see Figure 2.2) reveal that individuals in Cluster E tend to wake up at around 7am then either engage in unpaid work or eat breakfast. Their lunchtime is clearly visible between 11.45am and 13.30pm. After lunch, virtually all of these individuals engage in paid work. At around 18.30, some individuals take a break to eat. After work, individuals in Cluster D generally engage in unpaid work until 19.30pm. There is more heterogeneity in the sequencing of activity from here on out within this cluster. Some then watch TV, some enjoy leisure time, and some still continue to engage in unpaid work.

Leisure Patterns

One cluster, labeled Cluster F ("Leisure"), groups individuals engaged either in leisure activities or in personal care activities during most of the day. Individuals in this cluster engage in leisure activities on average 4 hours and 43 minutes, and 3 hours and 46 minutes on average in personal care. They also watch the most TV compared to the other clusters (about 2 hours and 8 minutes on average). The sequence index plot shows clearly the predominance of leisure time in this cluster as well as the greater period of sleep (personal care) in the morning. They also wake up much later on average compared to other clusters.

Unpaid Work Patterns

The two last clusters group individuals who do a substantial amount of unpaid work during the day. Cluster G ("Unpaid Work I") and Cluster H ("Unpaid Work II") differ mainly in the overall amount of unpaid work time. Individuals in Cluster G do about 6 hours and 16 minutes of unpaid work compared to 8 hours and 42 minutes for individuals in Cluster H. The sequence distribution plot (Figure 2.2) shows that individuals in Cluster G engage in unpaid work during the morning and after lunch and then typically engage in some form of leisure. The individual sequence index plot shows that some individuals in this cluster engage in some form of leisure activities around 16pm. In contrast, individuals in Cluster H engage in unpaid work for most of the day (see Figure 2.2). They wake up earlier and engage in unpaid work earlier compared to individuals in Cluster G. For instance, at 6am about 16% of individuals in Cluster H are engaged in unpaid work, compared to 4% for individuals in Cluster G (see Appendix, Table A.9). They also remain engaged in unpaid work later into the day. At 5pm, 60% of people in Cluster H are still doing unpaid work compared to 37% in Cluster G.

Sequential Similarities across Clusters

Even though the eight clusters differ greatly with regard to the timing as well as the amount of time spent in certain activities, we should note some similar features with regard to the sequencing of activities across clusters. Mornings are typically mainly dedicated to work (paid or unpaid). Few individuals engage in TV or other leisure activities during morning hours, and most individuals watch TV in the evening. While TV is mainly an evening activity, other forms of leisure are more of an afternoon activity. With the exception of Cluster E ("Shift II Evening"), most individuals are awake by 10am. In fact, the average "wake up" time is 7.14 am for the general population (see Appendix, Table

A.10). Even though the timing of eating is greatly different between clusters, the average eating time is similar across clusters.

More generally, the different clusters evince similar patterns with respect to rates of transitioning between specific types of activities. The first-order transition matrices for each of the eight clusters are available upon request. For example, across all clusters, periods of eating are more likely to be followed by some form of work (paid or unpaid) than anything else (even in the "Leisure" cluster).

Sequential Similarities across Country and Period Contexts

A key question that motivated this analysis is, if we do identify some typical behavioral sequence patterns: How similar is the distribution of those patterns across different social contexts? We examine two dimensions of social context; geopolitical and temporal. The cross-tabulation shows that while there is a significant association between the cluster assignments and country (χ^2 = 6288.6, df = 154, p $<$ 0.001), this association is very weak (Cramer's $V = .17$). Additional tests, including a discrepancy sequence analysis, showed that countries did not explain much of the sequence variance in cluster assignment (less than 3% of the sequence variance is explained by countries, as shown in Appendix, Table A.12). This suggests that a generally similar distribution of the eight clusters described above appears in different countries. The same is true for the association between cluster and period, where we see a Cramer's V of .12, and where a discrepancy sequences analysis reveals that period explains less than 1% of the variance of the sequence (see Appendix, Table A.12).

Nonetheless, some important differences in sequence patterns across these social contexts should be noted (Appendix, Table A.2). Cluster A ("Paid I Standard") is highly prevalent in most countries. The proportion of individuals grouped in this cluster is 25-35%, with the exception of Austria, India, Italy, Peru, Poland, Slovenia and Spain. Cluster

B ("Paid II Long") is slightly more prevalent in India, Italy, Peru and Spain than in other countries. In most other countries, about 10% of individuals evince this pattern. Cluster C ("Paid III Morning") seem to be more prevalent in the ex-socialist Eastern European countries, such as Czech Republic, East Germany, Slovenia, and Poland. The "Shift" clusters (D and E) are distributed more equally among countries, as 5-10% of individuals are engaged in these type of schedules across the board. Cluster F ("Leisure") is also found in similar proportion across countries, with the exception of the ex-socialist countries and Germany. Cluster G ("Unpaid Work I") ranges 15-20% in most countries, with a slightly greater proportion (23%) in Spain and in The Netherlands (19%). Finally, Cluster H ("Unpaid Work II") ranges from 10-20% in most countries, at the exception of India and Peru (34% and 27%).

Regarding the period, we can note that the distribution of clusters does not considerably vary by period (before 1995 and after 1995). The most notable exception is the lower prevalence of Cluster C ("Paid III Morning") from 14% before 1995 to 8% after 1995, and the increase in the prevalence of Cluster H ("Leisure"), from 10% to 17%, across these periods (Appendix, Table A.3).

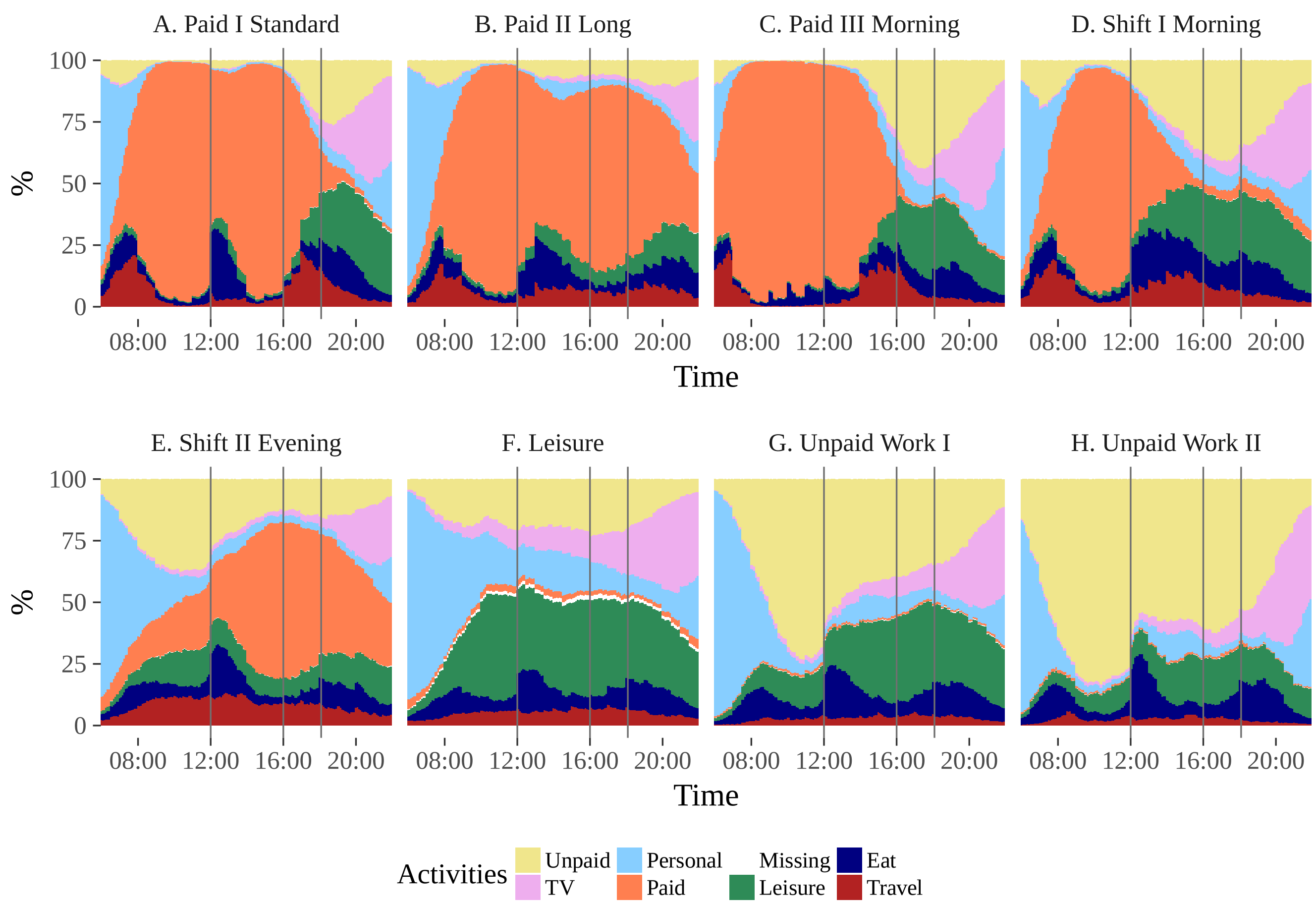

Figure 2.1: State Distribution Graphs Showing the Proportion of Members in Each Hamming-Distance-Based Cluster Engaging in Certain Activities at Each Time Point throughout the Day. N = 31,089.

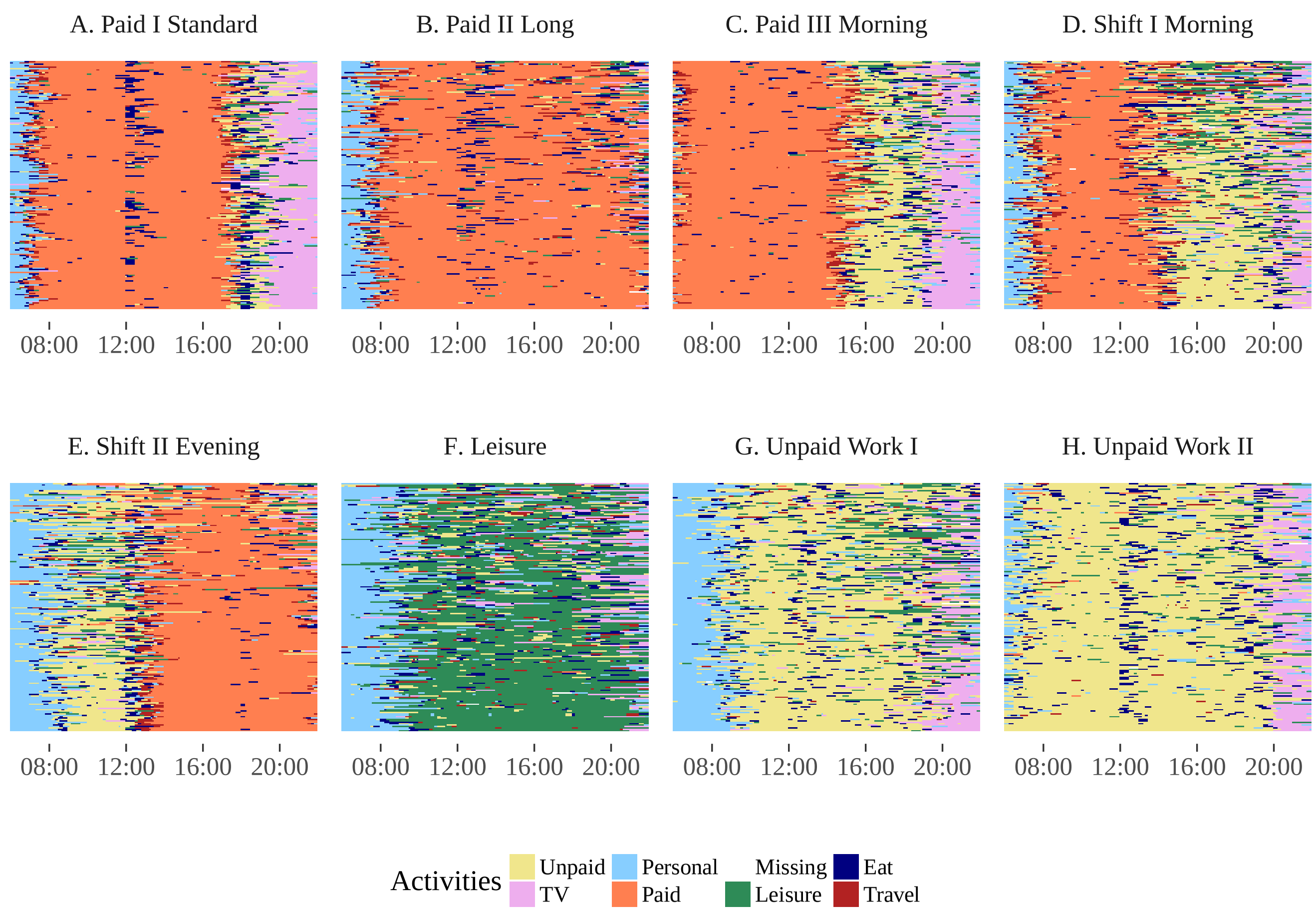

Figure 2.2: Sequence Index Plots Showing Time-Specific Activity Sequences for Medoids in Each Hamming-Distance-Based Cluster. N = 178 representative individuals per cluster.

2.4 Conclusion

To what extent do the complex activity sequences that compose individuals' everyday lives follow a regular, predictable pattern? Prior work shows that there are major similarities across societies with respect to how much time individuals spend, on average, engaging in certain activities such as paid work, unpaid work, and leisure (Aguiar & Hurst, 2007; Gershuny, 2000; Gimenez-Nadal & Sevilla, 2012; Robinson & Godbey, 2010; Szalai, 1972). The present study expands on this by revealing common patterns of behavior with respect to not only what people do during the course of the day, but also the sequential nature of those behaviors. In vastly different contexts, there reappears a common set of sequential activity patterns. These patterns involve important distinctions in the timing of several types of activities – relating not only to paid work (e.g., shift work), but also nuances in the timing of unpaid work and leisure. This set of findings is consistent with social science theories which have argued – but to date have not demonstrated empirically – that the simultaneous presence of several common routines of individual everyday behaviors are a hallmark of modern society (Giddens, 1984; Parsons, 1937; Sorokin & Berger, 1939; Zerubavel, 1985; Durkheim, 1997 [1893]).

This study provides some evidence in support of the idea that different societies exhibit similar diurnal behavioral patterns among their constituent members. But our study leaves some important questions unanswered. For one, what gives rise to these particular behavioral patterns? While some common patterns involve long hours of paid or unpaid work, others are characterized by short work shifts and considerable stretches of leisure. It is possible that these patterns reoccur due to some common macrosocial-structural forces, including the need for multiple interlocking activity patterns (Giddens, 1984; Parsons, 1937; Sorokin & Berger, 1939; Zerubavel, 1985) that enable household-level divisions of labor combined with the rise of non-standard work arrangements (Liu et al., 2011; Milkie et al., 2010, 2004; Presser, 2000; Strazdins et al., 2006).

At the same time, this set of patterns may arise partly as a byproduct of individual-level processes such as rational decision-making, routine-based behaviour and physiological processes like circadian rhythms. The origins of this recurring set of patterns is an important issue to consider in future work. And perhaps an even more important issue is to what extent which pattern or cluster individuals evince has consequences for them personally, such as with respect to social connectedness, social mobility, health and well-being. Existing work has examined the implications of work arrangements for individuals and their families (Lesnard, 2008; Flood & Genadek, 2016; White & Keith, 1990; Cornwell & Warburton, 2014; Fenwick & Tausig, 2001), but to our knowledge the consequences of other patterns has not been studied.

Regardless of the origins of these common patterns, future work should examine how they are distributed across social groups. Research on time use and the division of labor suggests that individual-level factors such as gender, race/ethnicity, social class, wealth, and life-course experiences shape individuals' exposure to these patterns. We know, for example, that there are substantial differences among individuals with respect to their exposure to factors that shape their control over when they engage in certain behaviors, including work scheduling constraints and access to flexible transportation (Grusky, 2014; Lin, 2000; Song et al., 2010). A promising direction for future work is to examine the extent to which the distribution of the sequence patterns we have identified here serve as a mechanism by which individual attributes affect longer-term individual outcomes, such as health and mobility.

This study has limitations. For one, the MTUS is a growing dataset, but it does not allow at the moment researchers to examine several potential sources of variation. The MTUS does not currently include harmonized sequence data on Asian, African or Latin American countries. A comparison with these countries could reveal important differences in daily activity patterns. Second, because we primarily report population-level patterns, it is beyond the scope of this paper to assess individual-level sources of variation in these patterns. As discussed earlier, individuals' activity sequences are likely shaped by a wide variety of life-course factors like gender, age, employment and marital status, aspects of social and material disadvantage, culture, as well as historical period (Robinson & Godbey, 2010; Szalai, 1972; Gershuny, 2000; Bourdieu, 1984; Sullivan, 2006). Finally, the vastness of the MTUS dataset makes a full-sample sequence comparison infeasible. Our analysis is therefore based on smaller, random subsets from within the larger data pool. Means of assessing the sensitivity of cluster solutions to random subsampling have not been developed. Until they are, scholars should exercise caution when generalizing results. This is a data analysis issue that other scholars who work with large-scape data will likely confront in coming years. These are all issues that need to be explored in future work that attempts to understand the origins of the extensive regularity and patterning of everyday activity that characterizes heterogeneous populations.

Chapter 3

The Social Stratification of Time Use Patterns

Unpublished Manuscript.

Data deposition: The data related to this study are deposited on the UK Data Archive.

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Time use is an effect of social inequality as much as a cause of social inequality. From the time spent at work or at school to the provision of childcare, time use is central to fully appreciating the extent of a society's stratification. Because everything we do takes time, inequality also must be temporally stratified. Time-use research often takes a narrow view on daily activities by focusing on one or two activities at a time (Altintas, 2016; Bianchi et al., 2000; Sullivan, 2010), making it difficult to grasp the overall structure and potential heterogeneous patterns of time use. A holistic approach is needed to better understand how activities in daily life are structured by gender, class or social contexts (Vagni & Cornwell, 2018). The aim of this study is to explore the link between time-use patterns and social stratification. We use the sequence analysis method to uncover time-use patterns in Britain during 1983-2015. We then describe the link between these emerging patterns and social class by gender. We start by reviewing some of the most important trends in time use over the last few decades and then move on to literature about time use and social stratification.

3.1 Prior Research

Time-Use Trends

Overall, paid work time has been declining over the last century. In 1870, it is estimated that people used to work about 57 hours a week (Huberman & Minns, 2007). In 1980, the number dropped to 40 hours a week. The UK has some of the longest working hours compared to other European countries. From a historical comparative perspective, the UK did not always have the longest working hours; in fact, in 1870, the UK had the lowest working hours in Europe (Huberman & Minns, 2007). However, from the 1950s onwards, the UK has been above average in terms of working hours compared to its

European counterparts and the US. During the Thatcher era, while working hours were either constant or in decline in continental Europe, working hours for men increased in the UK. It is only after New Labour came into power that working hours started declining and converging with those of the the US, while still been much above Germany, France and other European nations.

Women in the UK have lower working hours compared to women in other European countries, such as France and Sweden, as well as the US (see Figure 3.1), even though paid work has been increasing since WWII. Mothers in the UK have a relatively low level of employment, which can be partly explained by a very expensive private childcare system, and as a result, they experience one of the largest motherhood wage penalties in Europe (Grimshaw & Rubery, 2015).

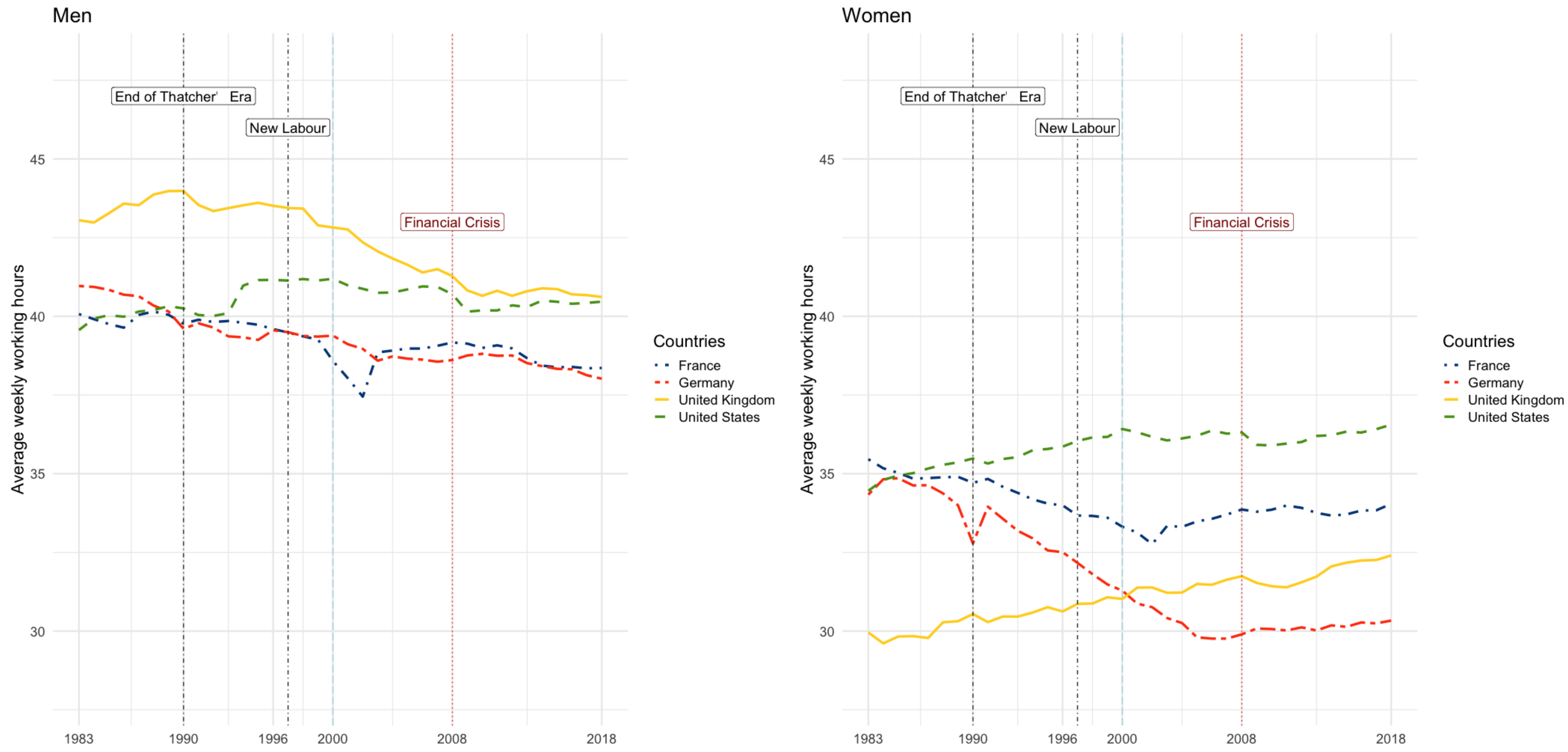

Figure 3.1: Trends in working in four countries by sex

Like working hours, unpaid work – in particular, domestic work – has been on the decline. Large-scale time-use studies show a clear, large average decline in domestic work for women since the 1960s for a range of countries (Altintas & Sullivan, 2016; Gershuny, 2000). The decrease in women's domestic time has been followed by a much smaller but still significant uptick in men's share of domestic work (Sullivan, 2000). Evidence suggests that at the population level, there is a gender convergence in time use (Sullivan, 2006). However, it is unclear if the convergence has stalled in recent years (England, 2010). While domestic chores have declined since the 1950s, childcare, which is another form of unpaid work, has been increasing for both mothers and fathers (Sani & Treas, 2016). Paid and unpaid work can also be combined to form a measure of "total work". Gershuny and Sullivan report that total work per day was 511 minutes for women and 573 minutes for men in 1961 (2019). They show that total work declined by 1 hour and 30 minutes for men and by 17 minutes for women since the 1960s. In proportion of time, this means that in 2015, women's unpaid work represents 50% of their total working time (compared to 63% in 1965), while unpaid work represents 30% of total work for men nowadays (compared to 16% in 1965) (Gershuny & Sullivan, 2019, p.37). Finally, leisure and other measures of free time have increased over the past few decades in the US context (Aguiar & Hurst, 2007), while these measure have been fairly stable in the UK (Gershuny & Sullivan, 2019).

The Social Stratification of Time

Population averages can mask important group-level heterogeneity. Aside from gender differences in time use, class- and education-based differences play an important role. Regarding paid work, historical differences in working time exist between the upper class and working class (Veblen, 1994 [1899]). While "idleness" was a symbol of status a century ago, "busyness" is the new sign of high status (Gershuny, 2011). Beyond the social status of working time, studies have pointed to a real emerging divide in working hours between white collar and blue collar occupations (Costa, 2000; Gershuny, 2011). Harriet Presser stressed that work was moving towards a "24-hour, 7-day-a-week economy" (1999, p.1778). The increase in the service sector, in the interconnectedness of global markets and the technological advancement and consumer demand for "on-call" work has changed the nature of the standard workweek and increased non-standard work schedules (Presser, 2005). Non-standard work schedules are socially stratified as members of the working class or lowly educated individuals have less control over their schedules (Breedveld, 1998; Lesnard, 2004). Even though, evidence suggests that families use non-standard work schedules to manage work–family responsibility (Presser, 2005), non-standard schedules can create negative externalities for families if imposed upon workers and families Lesnard (2008); Täht & Mills (2015). Work schedules can be an important mechanism of the creation or reinforcement of social inequalities (Lesnard, 2008). Working hours directly and indirectly impact the consumption of leisure. Non-standard work schedules affect the possibility of enjoying leisure in synchronicity with the rest of society and might therefore affect the enjoyment and quality of leisure (Cornwell, 2015). Time-use research has highlighted important gender differences in leisure, such as the fact that women's leisure is more fragmented and more likely to be shared with children (Bittman & Wajcman, 2000). Studies have documented a divergence of leisure time between educational groups and show that lower-class individuals are enjoying an increase in leisure over time compared to highly educated individuals (Aguiar & Hurst, 2007; Sullivan & Gershuny, 2004).

Regarding the content of leisure, Bourdieu's influential work highlighted the stratified nature of leisure consumption along the highbrow/lowbrow axis (1984). Even though the highbrow/lowbrow patterns might have moved towards a model of "omnivore" consumption patterns (Peterson & Kern, 1996), time-use research still shows that highly educated individuals spend less time watching TV and more time going to the cinema or theatre and reading (Gershuny, 2000). So, even though leisure time might be higher for low-income individuals, the content of that time might not necessarily contribute to their cultural and human capital. Another important leisure-related time-use activity that appears to be stratified is eating and, in particular, eating together in families (Putnam, 2016). Evidence for the UK shows that individuals in managerial and professional occupations spend significantly more time eating with partners and children compared to working-class families (Jarosz, 2019). Working-class individuals are also more likely to skip meals and spend less time eating on average. Shift work also plays a significant role in the propensity of skipping meals, which can create health risks (see (Jarosz, 2019)). Childcare appears to be a highly stratified time-use activity. Even though childcare has been increasing steadily over time, educated fathers and mothers spend more time doing childcare activities on average, even after controlling for other socio-demographic characteristics (Altintas, 2016; Sani & Treas, 2016; Sullivan et al., 2014). Some evidence suggests that in the US context, the educational gap in childcare has been increasing over time (Altintas, 2016; Putnam, 2016; Sani & Treas, 2016). Childcare is an important component of social stratification and inequality (Fiorini & Keane, 2014; Fomby & Musick, 2018; Schneider et al., 2018). Childcare, and more generally parental–child interactions, can have long-lasting consequences for a child's life course (Bono et al., 2016; Hsin & Felfe, 2014; Kalil & Mayer, 2016; Rowe & Goldin-Meadow, 2009). Childcare therefore might be an important mechanism in the creation of social inequality (Ermisch, 2008; Hoff-Ginsberg, 1998; Huttenlocher et al., 2010; Rowe, 2008). Even though, childcare is a heavily stratified activity, its determinants are less understood. While some researchers argue that resources and constraints are the main determinants of the provision of childcare (Bennett et al., 2012; Chin & Phillips, 2004), others show that class differences in parenting practices exist beyond resources and constraints (Weininger et al., 2015). Moreover, working time constraints alone do not fully explain a mother's involvement with her children, as full-time working mothers are capable of providing a similar level of childcare compared to other mothers who work part time or who do not work (Hsin & Felfe, 2014).

The Social and Political Context of this Study

The UK has often been described as belonging to the "liberal" welfare states regime, along with the US, characterized by free-market principles and means-tested benefits (Esping-Andersen, 1990). However, the UK would be best represented as more of a "between" European social-democracies and the US.

The US can be considered the epitome of a free-market capitalist society with low employment protections, low collective bargaining, and low social expenditure. France and Germany, on the other hand, would be closer to the ideal European-style "managed" capitalism or state capitalism (Schmidt, 2003, 2002) with a highly regulated labour market, high level of employment protections, high social expenditure and important coverage of social security benefits (e.g. unemployment, childcare, etc.). The UK lies somewhere between the US and continental Europe, represented by France and Germany, regarding the measure of social expenditures, employment regulation and protection, as well as collective bargaining (see Appendix for some illustrations). Since the 1980s, the UK has progressively shifted towards to a "workfare state" (Esping-Andersen et al., 2002). Unemployment benefits have diminished over time and means tests have become stricter, pushing individuals to seek employment rather than to rely on social benefits. Flexibility in the labour markets and deregulation became core principles for promoting growth and economic development for both Thatcher and New Labour. Important changes in the legislation regarding employment took place during the Thatcher era. I name a few that clearly highlight the shift towards more free-market solutions to economic problems: restricting industrial action (1980), limiting powers to set minimum wages (1986), tightening contribution conditions for unemployment benefits (1988), repealing working time controls (1989) and including an 'actively seeking work' requirement for unemployment benefits (1989)[1]. Collective bargaining was slowly dismantled towards more individual- or firm-wage bargaining. New Labour did not reverse collective bargaining or employment protection policies set by previous conservative governments. In some cases, New Labour furthered deregulations, such as with The Sunday Trading Act 1994, which gave shops the right to open on Sunday (Boulin & Lesnard, 2016). The Working Time European directive setting a limit on 48 hours a week was implemented in 1998 during the New Labour government, however the 48-hour limit is high above regular working hours. The implementation also introduced subtleties, such as the fact that it is not a 48-hour-weekly limit but an average of 48 hours of work per week over 17 weeks. It worth contrasting this figure with the French government's attempts to set a 35-hour workweek in 2000 (Pailhé et al., 2019). We can also compare this working time limit with the US's overall general lack of federal working time regulation, meaning the country mainly lets firms set their own regulations. Other important distinction and rapprochement is in regards to the childcare system. The law guarantees parents in the UK a certain amount of parental leave; such a guarantee is absent at the federal level in the US. However, parental leave is much more limited in the UK compared to other European countries (Daly & Ferragina, 2018; Gauthier, 2002; Thévenon, 2011). Once again, this is an example of the UK policies lying between the unregulated US model and the highly regulated one of continental Europe, this time in terms of childcare and gender equality. The cost of children is substantial for most British families, which translates into lower enrollment of children under 2 years old in formal childcare compared to other European countries, such as France, and a lower employment rate of mothers (Boeckmann et al., 2014). In conclusion, the UK is an interesting case study, as it seems to be standing "between" the US and Europe – more

[1]see (Deakin & Reed, 2000) for the full list and for a comprehensive review for the UK.

economically liberal than most European countries while still much more regulated than the US.

Summary and Research Questions

This paper aims to provide a general description of time-use patterns during the 1980s-2015 by social class and gender in the British context. We are interested in uncovering which time-use patterns exist in British society and how these patterns are stratified over time. Because past research never focused on time-use patterns but only on averages, it is difficult to make hypotheses about what kind of patterns we expect to find. However, we draw a general picture of the expected findings. Following previous literature, we can expect working hours to be lowering over time for working-class men compared to upper-class men. For women, we can expect a general increase in working hours between 1983 and 2015. We expect working-class individuals to be experiencing more and more non-standard working hours over time and during weekends in particular, during which time laws regarding working hours have relaxed over time. Because class is related to temporal autonomy, assuming that shift work and non-standard work schedules contain undesirable hours, we expect to see more working-class people in these types of schedules. We thus expect an increase in leisure time or free time during weekdays for working-class households. Finally, we expect men to increase and women to decrease their domestic time over this period, but we also expect upper-class households to increase their childcare time at a faster rate compared to working-class households.

3.2 Data

We use two time-use surveys for this study: the ESRC Time Budget Survey 1983/84 (UKTUS 1983) and the United Kingdom Time Use Survey 2014/2015. The UKTUS 1983 is a stratified national random sample of all households in the UK. The survey took place during autumn 1983 and winter 1984. It was collected by SCPR, the University of Bath and the University of Sussex. A total of 78% of households completed the household interview, and 51% of eligible members of returned diaries. The UKTUS 2015 was collected by NatCen for the Centre for Time Use Research between April 2014 and March 2015. It drew a random national sample of households in the UK with a response rate of about 40%. Our sample includes 1,501 individuals aged 30-69 years (for more information about the sample selection, see Appendix Table B.1 and Table **??**).

Harmonization process

We harmonized the time-use activities from the original codes for the two surveys, and we mapped the detailed activities into an 11-activity schema guided by the work presented in Vagni and Cornwell (2018). The 11 activity categories are: (1) childcare, (2) domestic work, (3) eating, (4) leisure, (5) leisure, (6) paid work, (7) sleep, (8) travel, (9) TV, (10) other and (11) unknown. More information about the recoding can be found in the Appendix. We harmonized social class using The National Statistics Socio-economic classification (NS-SEC) (Rose et al., 2005). The NS-SEC has become the standard socioeconomic classification used at the Office of National Statistics in the UK. One important theoretical distinction with this schema is the difference in employment relations between, on the one hand, the "service relationship" and, on the other hand, the "labour contract" (Rose et al., 2005, p.16). The service relationship concept is based on the idea that there is a long-term mutually beneficial relationship between employers and employees and that the amount of effort and work put forth by the employee is not directly commensurable by a "wage per hour" but rather by long-term, deferred, benefits, such as career opportunities, pension and so on. In the service relationship, the employment is stable, and employees look to future opportunities for career development. On the other hand, the labour contract captures the idea of a worker only being committed to the job for a certain number of hours, often with no long-term perspective. In contemporary society, one can think of the jobs generated by the new service economy (e.g. Deliveroo) and by seasonal workers (e.g. fruit picking). A continuum exists between these two ideal types of employment relations. Social class has been widely used in social science because it has been shown to be a good measure of economic condition in the long run (Goldthorpe, 2000). Class not only captures income differences but employment security (e.g. becoming unemployed) and, more generally, economic security. So, it is a natural stratifying variable to use in this study. We used the so-called "dominance model" proposed by Erikson to attribute social class to families or households rather than individuals (1984). Even though we analyse men and women separately, our social class variable is a household variable [2]. Therefore, it reflects the household social position rather than the individual social position. This is important, even though we did not conduct couple-level analyses, because time-use allocation, such as paid work or childcare time, is decided at the household level. Classifying individuals based on their own social class can also underestimate the total household resources at an individual's disposal; in particular, this is true for stay-at-home parents. We coded the original NS-SEC categories in a 3-class schema: Class I (managerial class), Class II (professional and intermediate class) and Class III (working class). We kept the managerial class separate, even though in the 1980s, the proportion of managerial households was rather small; we did this primarily because we are interested in comparing the behaviours of the most privileged social class (managerial or upper class [3]) to the most unprivileged class (working class) to capture potential divergence patterns.

[2] Single parents are attributed their own social class.

[3] To help the manuscript read more easily, we use the terms Class I, managerial class and upper class indistinguishably.

Control Variable

We will only use one control variable in our analysis: family status. We distinguish between couples with children, couples without children, single parents and single-person households. Family status will control for the fact that the distribution of these family forms is not even between social classes. Adding more control variables is tempting but ultimately can complicate the analysis. A growing body of research has stressed issues related to "collider bias" when adding control variables (Elwert & Winship, 2014). It is difficult to explain the collider bias without introducing the Directed Acyclic Graph (DAG) system, but in simple terms, controlling on a collider variable can open a "back-door path" and cause bias in the estimates (Breen, 2018; Morgan & Winship, 2015). This is also why we did not select only samples of parents, especially if we are interested in class patterns of time use, because such sub-selection might create sample selection bias (Elwert & Winship, 2014). Our approach is closer to a population approach, where we examine global patterns, even though the groups' composition might be heterogeneous. However, we believe that family status captures a large proportion of heterogeneity in time use (Gershuny, 2000). Moreover, in our model, we assume that family structure is not antecedent to social class. However, it could very well be the case that reverse causality applies here so that family structure causes class position. These questions of causality and bias are extremely difficult to address using cross-sectional surveys. The spirit of our analysis is descriptive, not causal, but readers must keep these limitations in mind.

Analytical Strategy

We take a holistic approach to considering how all daily activities have changed over time. Given the descriptive purpose of this paper, we use a sequence analysis to uncover time-use patterns (Lesnard, 2008; Vagni & Cornwell, 2018). Lesnard introduced sequence analysis in time-use research a decade ago, and we follow the standard steps of this method Lesnard (2010). The overall goal of the method is to create a finite set of clusters made of homogeneous sequences, not unlike a latent class analysis. However, it worth nothing that sequence analysis is much broader than the clustering approach we use (Aisenbrey & Fasang, 2010; Cornwell, 2015; Gabadinho et al., 2011). The first step is to run a matching algorithm to create a pairwise distance matrix between all sequences. We then apply a clustering technique on that distance matrix to create homogeneous groups. We used the matching algorithm proposed by Lesnard called Dynamic Hamming (Lesnard, 2010; Cornwell, 2015). The algorithm is build on the Hamming distance, which is a simple count of simultaneous events only using substitution costs (Hamming 1950). Lesnard introduced an important modification to the method related to the weighting of the substitution costs.

Lesnard's original empirical example has only two states: doing paid work ($e = 1$) and not doing paid work ($e = 0$). The sequences are strings of zeros and ones from $1, \ldots, T$ (T equals 24 hours in time use diaries). Distance algorithms are always applied to pairwise sequences (for instance, comparing sequence i to sequence j).

In the most basic Hamming model, each matched episode (or event) is counted 1, so that the Hamming distance between i and j is simply a sum of matched events or states (e) of pairwise sequences .

$$Ham(i, j) = \sum_{t=1}^{T} 1 - \mid e_t^i - e_t^j \mid \tag{3.1}$$

Dynamic Hamming reweights t according to the transition frequencies for each time period. The transition matrix is simply the probability of transitioning from one state to another from t_{-1} to t.

As Lesnard notes:

> "The strength of the flux between two different states, measured by transitions, can be used as an indicator of how close two different events are. A low transition rate between two states means that at that particular moment, these two states are not connected, hence they can be considered as being part of two distinct trajectories. On the contrary, a high transition rate between two states can be interpreted as a change of state within a single trajectory." (Lesnard, 2010, p.399)

Let us express the transition matrix between (t_{-1}, t) and (t, t_{+1}) as a transition weight (w), where t rather than denoting the starting and ending point of an episode (e.g. 10:00 a.m., 10:10 a.m.), represents an interval of time [10:00 a.m.,10:10 a.m.]. The low transition rate between states around the interval t would suggest that these states belong to different trajectories, while high transitions rate at a certain time would suggest similar trajectories.

We can then simply write the following:

$$DynHam(i,j) = \sum_{t=1}^{T} 1 - \mid e_t^i - e_t^j \mid \cdot \frac{1}{w_t} \tag{3.2}$$

The substitution costs are therefore time-varying and are inversely proportional to transition rates (Lesnard, 2010). We then use Ward hierarchical clustering to group the pairwise distances into a small number of homogeneous discrete groups (Gabadinho et al., 2011). Using the derived set of clusters, we investigate their distribution by year, social class, gender and weekdays/weekends. No consensus on how to best choose the optimal number of clusters exists. Time-use sequences are particularly difficult to group due to the high number of episodes and the often high number of states. We follow some heuristic criteria to determine the number of clusters (see Appendix).

We finally use multinomial logistic regressions to study cluster membership by social class and to control for family status.

3.3 Results

Before describing results from the clustering analysis, let us describe some general trends found when comparing the sequences by social class and gender (the figures are displayed in the Appendix B.1).

We find that on weekend days, leisure, domestic work and TV occupy most of the day, while paid work fills most of the time during weekdays. We find a decline in paid work on weekdays between 1983 and 2015 and a general increase in leisure time. We also find a small increase in childcare time. On weekends, we find that paid work seems to have slightly increased between the two periods. We can clearly see that childcare increased on weekends between the 1980s and 2015. TV and domestic chores have, on the other hand, decreased. Important class differences structure men's lives both on weekdays and on weekends. First, we see that men in Class I are working longer hours during weekdays compared to working-class men. They also travel more, eat at more structured times and watch less TV. Working-class men seem to be working at earlier times in the morning in 2015. We can see that they also do more domestic chores than upper-class men. Middle-class men have patterns that seem to lie between the two other classes. They work on weekdays more than working-class men but enjoy more leisure during the day compared to upper-class men. Over time, we see that men from all classes are enjoying more leisure and work less during weekdays. The patterns on weekends seem less stratified than those on weekdays; however, we note than upper-class men watch less TV and provide more childcare, especially in 2015. Overall, childcare increased for all men on weekends. Regarding women's time use, we first see that they are doing much more domestic work compared to men, regardless of their social class [4]. In 1983, working-class and upper-class women had fairly similar weekdays and weekends. However, it seems that time use on weekdays has diverged over time by class for women. Women in Class I are spending a

[4]Appendix Figure B.1 shows women's time-use patterns by class and by weekday/weekend.

much greater proportion of their day working for pay in 2015 than working-class women. Domestic work has reduced for all women between the two periods; however, it seems to have reduced at as faster rate for upper-class women. Overall, childcare increased between 1983 and 2015. However, we see that upper-class women are spending much more time providing childcare on weekdays compared to working-class women. Time spent traveling has also increased over time. We also find that working-class women have started to work more on weekends, while upper-class women barely spend any time working for pay on weekends. Weekend days were more similar between classes in 1983 than in 2015. For instance, upper-class women seem to have given up domestic work at a much faster rate than working-class women on weekends.

Typology of Daily Activities

The overall averages and distribution can hide heterogeneous patterns. This is why we turn to the clustering of sequences to reveal hidden sequence time-use trajectories. We derive 13 clusters that capture the patterns of activities found in the two time-use surveys. We found six clusters that capture paid work patterns (two clusters capture standard work schedules patterns, four capture shift work patterns); four clusters that capture unpaid work patterns; one cluster that captures leisure, TV and personal care activities; and one residual cluster (“Other”). Figure 3.2 shows the distribution of activities throughout the day by cluster.

Paid work clusters. Six clusters capture the patterns of paid work with two subgroups. One subgroup captures patterns of standard “full-day” work patterns while the second captures shift work and non-standard schedules patterns. Cluster 1, Paid Standard I, captures 8:00 a.m.-6:00 p.m. standard work schedules. Paid Standard II captures a slightly shorter working day with an earlier work ending point. The four shift work clusters capture morning shift, afternoon shift, evening shift and night shift, respectively.

Unpaid work clusters. Five clusters capture unpaid work patterns. The Unpaid Childcare cluster captures individuals spending a large proportion of their day providing childcare. The Unpaid Domestic I cluster is a mix of domestic work, childcare and afternoon leisure. Unpaid Domestic II captures mainly afternoon domestic work. Unpaid Domestic III captures individuals who spend most of their day doing housework. Finally, individuals in the Unpaid Domestic IV cluster have a morning housework shift.

Leisure and other clusters. The leisure cluster captures individuals who spend most of their day enjoying free time, leisure activities and personal care, with a bit of time still dedicated to domestic work.

These 13 clusters capture the most heterogeneous time patterns in the data. However, informed by the extent of the data's heterogeneity, we further reduced these patterns to study their association with class and gender. Informed by the similarities and qualitative differences between these clusters, we collapsed the Paid Standard working day into one cluster. We also collapsed the morning, evening and night shifts into a single cluster. We excluded the afternoon shift because we noticed that the association between afternoon shift and class is quite different from the one of the other clusters. We grouped the unpaid "shift" domestic clusters together (Unpaid I, II, and IV) and left the childcare cluster and the full day domestic work cluster separate. This results in 8 total clusters. Nonetheless, we present the complete regression tables with the 13 clusters in the Appendix.

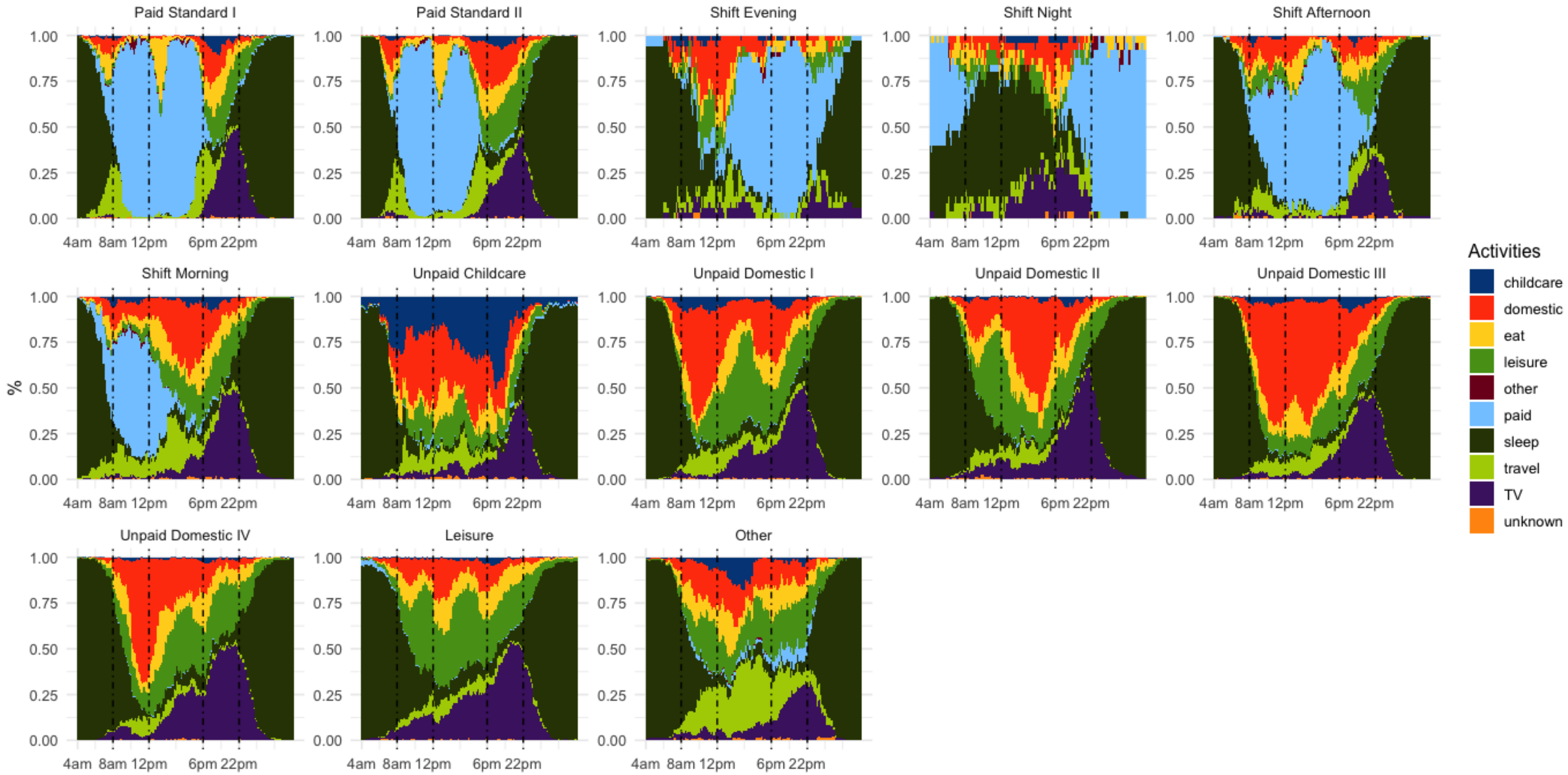

Figure 3.2: State Distribution Graphs Showing the Proportion of Members in Each Dynamic Hamming-Distance-Based Cluster Engaging in Certain Activities at Each Time Point throughout the Day.

Class and Clusters

In this section, we explore the distribution of clusters by social class and gender for weekdays and weekends. We present both the regressions tables (on the 8 clusters' schema) and the predicted probabilities of the multinomial models. The reference category for the regressions is managerial class, with family status set to couples with children and the year set to 1983. For weekdays, we took the paid standard work schedule as the reference category for the clusters and the leisure cluster on weekends.

Table 3.1 shows the multinomial regressions for men on weekdays; Table 3.2 shows the regressions for men on weekends. We can see that both middle-class and working-class men have more chances to work morning and evening shifts on weekdays ($p < 0.01$). We also find that working-class men are more likely to be found in the long domestic work cluster ($p < 0.05$) and the leisure cluster ($p < 0.05$) on weekdays. The regressions suggest that middle-class men ($p < 0.001$) and working-class men ($p < .10$) have fewer chances of being in the childcare clusters on weekends compared to upper-class men. Working-class men are also less likely to be in the long domestic work cluster on weekends ($p < 0.05$).

Figure 3.3 shows the predicted probabilities for men on weekdays in the upper panel and weekends in the bottom panel[5]. The predicted probabilities for men on weekdays show that men in the managerial class are found in greater proportion in the paid standard cluster (around 55% in 2015) compared to working-class men (28% in 2015). We note that the proportion of this cluster has been diminishing over time for all men on weekdays. The proportion is rather stable over time on weekends. We note the more important proportion of working-class men in this type of schedule on weekends. Middle-class men are right in the centre in terms of proportion of paid standard work schedules (7% in 2015). In 2015, about 15% of working-class men were found in the morning or evening shift cluster on weekdays, compared to only 6% of men in the managerial class. The

[5]The probabilities for the clusters "Shift Afternoon" and "Other" are not displayed.

third figure displays the proportion of the childcare cluster, and we can see that about 4% of upper-class men have this type of pattern on weekdays compared to less than 1% for working-class men. Looking at weekends, we see that the proportion of upper-class men in that cluster grew dramatically from less than 1% to almost 7%, compared to less than 1% to 2% for working-class men.

The long domestic work cluster seems to have declined during 1983-2015 for men on weekends while slightly increasing on weekdays. The proportion diminished from 26% to 14% for upper-class men and from 11% to 6% for working-class men. Finally, the proportion of men in the leisure cluster is highly stratified. On both weekdays and weekends, working-class men have more likelihood to be found in that cluster.

Table 3.1: Multinomial Regression - Men. Weekdays.

	Dependent variable:						
	Shift Morning/Evening	Shift Afternoon	Unpaid Childcare	Unpaid Domestic	Domestic Long	Leisure	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Middle Class	1.062^{**}	-0.286	-0.528	0.477	0.192	0.290	0.058
Working Class	1.478^{**}	-12.970	-1.316	0.744^{+}	1.171^{*}	1.072^{*}	1.291^{*}
Year 2015	0.360	0.469	0.464	0.093	0.576	0.245	0.535
Childless Couples	0.227	-0.138	-1.305^{*}	1.127^{***}	1.177^{**}	1.165^{***}	0.810^{+}
Single Person	-0.566	-0.592	-1.069	1.451^{***}	0.546	1.249^{**}	0.742
Constant	-2.459^{***}	-1.934^{***}	-2.133^{***}	-2.094^{***}	-3.055^{***}	-2.641^{***}	-3.421^{***}
Akaike Inf. Crit.	2,114.587	2,114.587	2,114.587	2,114.587	2,114.587	2,114.587	2,114.587

Note. Reference category of clusters is Paid Standard

$+$ p<0.1; $*$ p<0.05; $**$ p<0.01; $***$ p<0.001

Table 3.2: Multinomial Regression - Men. Weekends.

	Dependent variable:						
	Shift Morning/Evening	Shift Afternoon	Unpaid Childcare	Unpaid Domestic	Domestic Long	Leisure	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Middle Class	-0.200	-0.511	-2.451^{***}	-0.529	-0.846	-0.465	-0.819
Working Class	-0.635	-1.232	-1.853^{+}	-0.476	-1.432^{*}	-0.160	-1.294^{+}
Year 2015	-0.155	0.635	2.337^{*}	-0.083	-0.635	0.025	0.392
Childless Couples	-0.373	0.858	-2.088^{*}	0.526	0.055	0.563	0.184
Single Person	-0.099	2.035^{*}	-1.402	0.656	0.320	0.643	0.900
Constant	0.961	-1.657	-0.600	1.888^{***}	1.846^{**}	1.308^{*}	0.441
Akaike Inf. Crit.	2,177.498	2,177.498	2,177.498	2,177.498	2,177.498	2,177.498	2,177.498

Note. Reference category of clusters is Leisure $+$ p<0.1; $*$ p<0.05; $**$ p<0.01; $***$ p<0.001

Table 3.3: Multinomial Regression - Women. Weekdays.

	Dependent variable:						
	Shift Morning/Evening	Shift Afternoon	Unpaid Childcare	Unpaid Domestic	Domestic Long	Leisure	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Middle Class	0.431	−0.159	−0.521	−0.363	−0.178	−0.012	−0.541
Working Class	1.138^{*}	0.523	0.327	0.996^{**}	0.866^{*}	0.830^{+}	0.175
Year 2015	−0.349	−0.172	0.450	-0.575^{*}	-0.785^{**}	-0.575^{+}	−0.179
Childless Couples	−0.500	−0.287	-2.999^{***}	0.178	0.396	0.949^{+}	0.128
Single Parent	−0.214	−1.013	-2.021^{*}	−0.452	−0.386	1.029	0.389
Single Person	−0.474	−0.313	-3.043^{***}	0.300	0.334	1.839^{***}	0.334
Constant	-0.801^{+}	-1.205^{*}	0.190	0.389	−0.075	-2.006^{***}	-1.174^{*}
Akaike Inf. Crit.	2,887.747	2,887.747	2,887.747	2,887.747	2,887.747	2,887.747	2,887.747

Note. Reference category of clusters is Paid Standard

$+$ p<0.1; $*$ p<0.05; $**$ p<0.01; $***$ p<0.001

Table 3.4: Multinomial Regression - Women. Weekends.

	Dependent variable:						
	Paid Standard	Shift Morning/Evening	Shift Afternoon	Unpaid Childcare	Unpaid Domestic	Domestic Long	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Middle Class	0.906	0.631	0.567	−0.462	0.062	0.205	−0.239
Working Class	1.514^{+}	0.710	−0.043	0.253	0.455	0.704^{+}	−0.070
Year 2015	0.985	0.693	−0.325	0.654^{+}	-0.630^{**}	-0.730^{**}	0.132
Childless Couples	−0.803	−0.672	0.710	-3.888^{***}	−0.131	-0.863^{**}	-0.747^{+}
Single Parent	0.026	0.367	−10.577	−0.898	−0.555	−0.067	−0.252
Single Person	-1.607^{+}	−1.028	-14.967^{***}	-3.314^{***}	−0.308	-1.068^{**}	−0.433
Constant	-2.904^{**}	-2.101^{**}	-2.831^{**}	0.225	1.358^{***}	1.093^{**}	−0.222
Akaike Inf. Crit.	2,454.302	2,454.302	2,454.302	2,454.302	2,454.302	2,454.302	2,454.302

Note. Reference category of clusters is Leisure

$+$ p<0.1; $*$ p<0.05; $**$ p<0.01; $***$ p<0.001

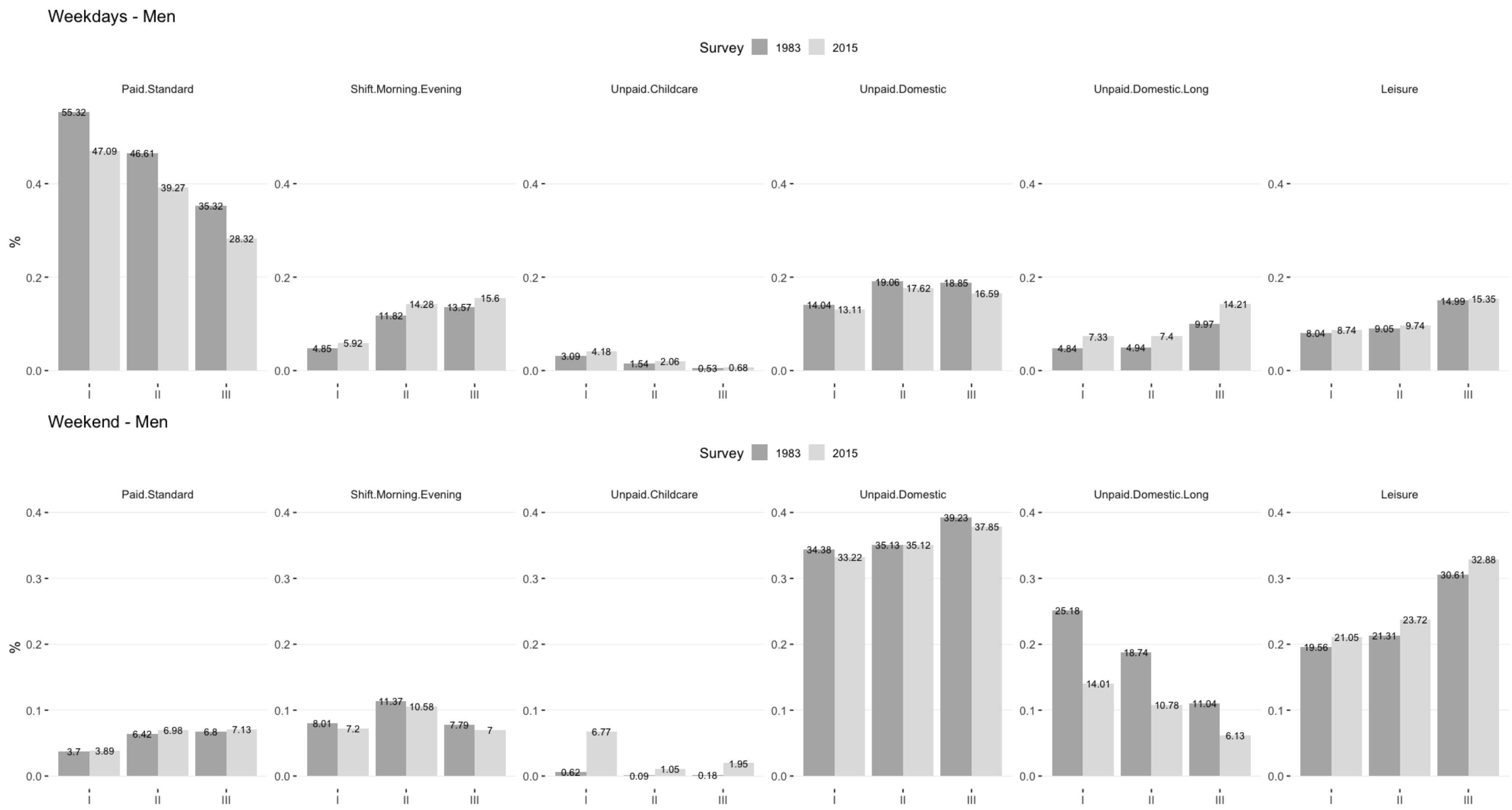

Figure 3.3: Predicted Probabilities from the Multinomial Regression Models for Men by Year on Weekdays and Weekends.

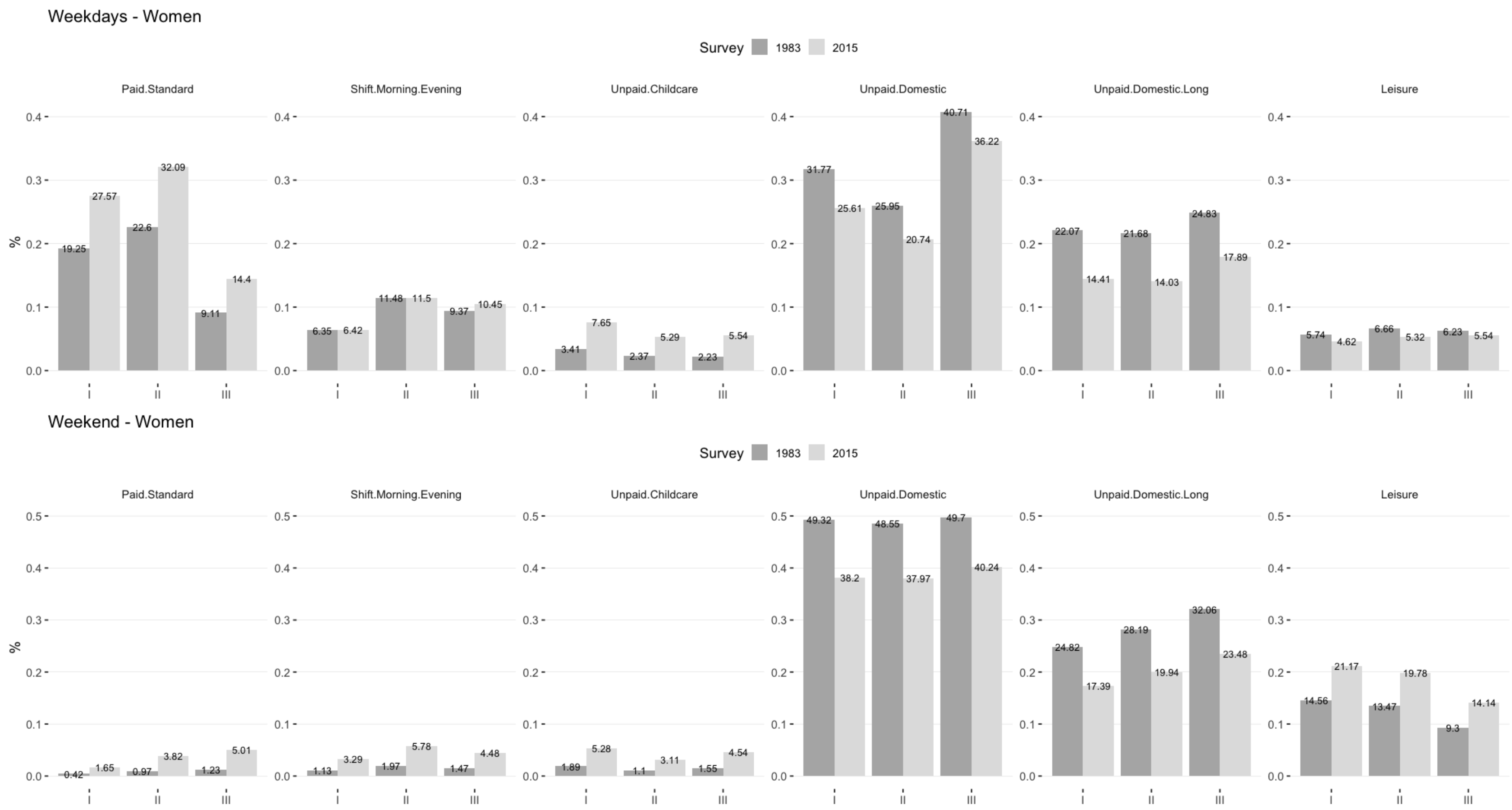

Figure 3.4: Predicted Probabilities from the Multinomial Regression Models for Women by Year on Weekdays and Weekends.

Table 3.3 shows the results for women on weekdays, and Table 3.4 shows the results for women on weekends. The regressions suggest that working-class women also have higher likelihood of being found in the leisure cluster on weekdays compared to upper-class women ($p < 0.10$). Working-class women have more chances of having morning or evening shifts on weekdays ($p < 0.05$). They also are more likely to be found in the two domestic clusters ($p < 0.01$) compared to upper-class women with standard work schedules on weekdays. On weekends, we find that working-class women are more likely to work full-day, standard work schedules ($p < 0.10$) and more likely to have long domestic work-type days ($p < 0.10$).

The predicted probabilities of women shows that all women have increased their time spent at work and diminished their domestic work time (Figure 3.4). However, important class differences still exist between working-class and upper-class women. As the regressions showed, upper-class women are more likely to have standard working days compared to working-class women on weekdays. The proportion increased from 20% to almost 30% for women in Class I, compared to 10% to 15% for women in Class III. However, working-class women are more likely to be working a standard, full-day schedule on weekends. The proportion rose from 1% to 5% for working-class women, but stayed constant (around 1%) for upper-class women. We can also see that working-class women are more likely to have a full day of housework on weekends compared to upper-class women. We do not find significant differences between women in the patterns of childcare between classes.

3.4 Discussion

In this paper, we explored time-use patterns structuring British society during 1983-2015. We found meaningful patterns that capture the heterogeneity in daily time use. This paper is one of the first efforts bridging time-use research and social stratification research. The "sequence pattern approach" offers insights that average time spend in activities cannot provide. For instance, the average time spent at work cannot distinguish the multitude of shift work schedules (Lesnard, 2008). Linking these heterogeneous patterns to class, we found an important cleavage between social classes. We first found that upper-class men and women have a higher likelihood of standard work schedules during weekdays and a lower likelihood of working for pay during weekends. We found that non-standard work schedules, such as morning, evening and night shifts, were more prevalent in working-class households. We also found that working-class men have experienced an important reduction in their standard work schedule and in paid work more generally and have experienced an increase in "leisurely" and non-working days over that period. Working-class women were more likely to be clustered in the housework clusters, both during weekdays and on weekends. Over time, we found a higher propensity of working-class women working for pay on weekends. Finally, we found that the childcare cluster (i.e. a full day spent providing childcare) has been increasing over time, but our model suggests that the increase has been particularly important for upper-class households. The reduction of paid work and unpaid work during 1983-2015 is in line with the literature (Gershuny, 2000; Robinson & Godbey, 2010). Our results suggest that the class divide in working hours is a real phenomenon and not simply a "social status" question (Gershuny, 2005). We found strong gender differences in the distribution of time-use clusters. Gender is an important factor of time stratification. We found that women are more likely to be in the domestic/housework clusters and less likely to be in the standard work schedule cluster compared to men (Gershuny & Sullivan, 2019). We also found a general large propensity of women to be working shifts. Working-class women are particularly overrepresented in these types of schedules. Our study took place in the British context from 1983 to 2015. Our goal was not to analyse a particular policy, but we can wonder about the role of social policy in shaping time patterns. We can only speculate on this issue. Vagni and Cornwell compared time-use patterns from 23 different countries and found minimal differences between them (2018). In their study, the UK had very comparable time-use patterns to the US and France. They identified a similar set of clusters and found no differences in the distribution of the free time, paid work and unpaid work clusters. However, their study did not account for gender and class differences and only focused on weekdays. Nevertheless, their result suggests that at the population level, socio-political institutions might play a small role in shaping time-use patterns. A different design from theirs is needed to truly understand the role of policy and time use. We can still speculate how institutions and policies in affecting inequalities might impact time patterns. Scheduling work is an obvious area where policies can matter. For instance, a study focusing on the French 35-hour workweek reform showed how an exogenous change in working hours affected general time-use allocation (Pailhé et al., 2019). Gershuny and Sullivan note that "it appears that public policy regimes involving the kinds of state regulatory activity on production and consumption [...] have a greater effect on the time that people spend in paid work" (2003, p.223). They do not find differences in domestic work and leisure across regime. Domestic work is more strongly associated with individual characteristics, such as education, than with welfare regime (Gershuny & Sullivan, 2003). Even though, to our knowledge, no study has shown how work-related policy reforms affect inequality in daily time-use patterns, we can speculate that the distribution of the paid work clusters might show that they are the ones most affected by policies and institutional contexts. Our results support that working-class individuals, especially women, have proportionally more shift work schedules on weekends compared to upper-class women. Obviously, it is unclear if shift work is the result or the cause (or both) of inequality, but it is nonetheless an important dimension of inequality because it is stratified. Work schedules are not randomly assigned to people according to class but are structured by class. Temporal autonomy and control over schedules are important dimensions of social stratification and therefore should be understood in that context. A comparison between the stratification of time-use patterns in the UK with more regulated economics, such as in France, Germany or the Scandinavian countries, could be informative in our understanding of the link between inequality and time patterns.

As pointed out by Goodin et al. (2008), social institutions matter depending on household types (e.g. dual-earning families, lone parents, etc.). To fully understand the role of welfare regime, one should explore how social stratification and family status interact. In our study, we simply controlled for family status. The next natural step will be to explore the interaction of family structure and class. Different regimes will impact the temporal autonomies of single households, dual-earning parents and lone parents differently. In their study of temporary autonomy, Goodin et al. find that individuals in a welfare/gender regime like Sweden have more discretionary time (i.e. "free time") compared to those in liberal regimes (Goodin et al., 2008) [6]. Because working-class households are the most affected by single parenthood, political regimes will affect inequalities in different ways, and thus will impact time-use patterns differently. Further research should try to combine a social stratification approach of time-use patterns with a cross-country comparison approach focusing on the different family status.

The limitations of this study should be highlighted. One limitation is that the analyses focused on individual time use rather than accounting for household time-use patterns. Further work should investigate this issue using multiple diaries per household. Another limitation is the lack of a longitudinal link between time use and the life course. Linking life course to time-use patterns will offer researchers a more complete picture and a better understanding of these patterns.

[6] The idea of discretionary time is slightly different from that of free time, as discretionary time is the time left after the *necessary* time in paid, unpaid and personal care activities is used. For the technical definition of discretionary time, please see (Goodin et al., 2008).

This study is exploratory and descriptive in nature. Our aim was to establish associations between time-use patterns and social class stratification. Further work should tackle the question of mechanisms and causality. How do these patterns emerge, and what causes them? Time is a crucial component of everyday social contexts. Everything takes place in time. The time to commute to work, to the nursery or to school, as well as the time spent at work and to sustain basic needs – all these spatio-temporal issues are intimately linked to differential opportunities that are socially stratified. Embodied time in the context of human capital accumulation is an important link between time use, life course and social stratification, as well as gender inequalities (Becker, 1994; Gershuny & Sullivan, 2019). More effort is needed to understand how the class of origin shapes time use and how time use shapes class destination from a longitudinal point of view. The same can be said about the life course. How do life course events interact with time-use patterns and social stratification? In this paper, we controlled for family status, but it is likely that family status or different stages of the life course interact differently with class and time-use contexts.

Despite these limitations, this study is the first to explicitly explore the heterogeneity in time-use patterns for men and women in a social stratification context. We showed how the sequential pattern approach can help unveil hidden patterns (Lesnard, 2010; Vagni & Cornwell, 2018). This paper contributes to this field by showing what these patterns looked liked, how they changed over time and how they were stratified by class and gender.

Chapter 4

Alone Together: Gender Inequalities in Couple Time

Love Is Just a Four-Letter Word
— Joan Baez

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Data deposition: The data related to this study are deposited on the UK Data Archive.

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Gender relationships have dramatically changed since WWII. Intimate relationships have progressively shifted towards a model where love, equality and intimacy have become core values of partnership and marriage (Cherlin, 2010; Coontz, 2005). Gains from marriage have shifted from household specialization, with complementary in production, to a model of complementarities in consumption and in particular in the joint consumption of leisure (Mansour & McKinnish, 2014; Stevenson & Wolfers, 2007).

The search for intimacy and fulfilling partnerships is thought to have heightened the need for time shared in leisurely activities (Voorpostel et al., 2009). Research on togetherness often emphasizes that time shared between partners, or couple time, is important for partnerships (Hill, 1988). Indeed, studies have found a positive association between time shared with partners and well-being and marital quality (Flood & Genadek, 2016; Gager & Sanchez, 2003; Sullivan, 1996).

However, little attention has been paid in time use research onto how partners differ in the way they perceive time together and into the potential gender inequalities during time together. Most time use research, based on individual diary data, have to assume that partners share the same activity when together (Genadek et al., 2016). Little is known about how partners' actually divide their activities during shared time.

The aim of this study is twofold. The first aim is to establish if partners systematically differ according to their gender in the way they report time together. The second aim is to explore what partners do when together and if gender inequalities do persist during shared time.

To answer these questions, I use the latest United Kingdom Time Use Survey (UKTUS) 2014/2015. Time use diaries offer a unique micro-sociological account of couple and family life. The UKTUS collected diaries from both partners enabling a true comparison of partners' activities during shared time, in contrast with some other time use surveys, notably the American Time Use Survey, that collects only one diary per household.

4.1 Prior Research

Time Together and Families

Family sociologists have long hypothesized the importance of time together for couples' solidarity and for family cohesion. Berger and Kellner (1964) stressed the importance of daily contacts in the making of a relationship. Studies have generally found a positive association between time shared with the partners and relationship quality and well-being (Crawford et al., 2002; Flood & Genadek, 2016; Sullivan, 1996; Zuo, 1992). Studies have also shown that partners actively coordinate their schedules to spend time together, stressing the importance of time together for couples (Carriero et al., 2009; Hallberg, 2003; Hamermesh, 2000; Klaveren & Brink, 2007), and adding evidence for the hypothesis that togetherness is a crucial mechanism for the functioning of contemporary relationships (Buswell et al., 2012; Hill, 1988; Lesnard, 2004). The centrality of time shared with the partners can be placed in the general context of the transformation of personal relationships in Western societies (Beck & Beck-Gernsheim, 1995; Buswell et al., 2012; Giddens, 2013; Schwartz, 1995). The importance of time together for relationships is also reflected in the fact that time spent together with the partners has been increasing over time (Genadek et al., 2016; Voorpostel et al., 2009; Neilson & Stanfors, 2018).

Gender Differences in Time Use

A large body of research has analyzed gender differences in time use activities (Bianchi et al., 2000; Gershuny, 2000; Sullivan, 2000). Differences can be found between men and women not only in the average time spent in different activities, but also in the way activities are carried out. For instance, women's leisure time is more fragmented, more often spent in the presence of children and more often combined with other less enjoyable activities (Bittman & Wajcman, 2000; Mattingly & Blanchi, 2003). Men also tend to engage in more leisure activities while women are at work than vice versa (Dush et al., 2017, p. 12).

Combining several activities, also known as "multitasking", is an important strategy for parents trying to gain time in their busy lives (Bianchi et al., 2006). Mothers in particular are more prone to multitasking compared to fathers, which can create an extra sense of time pressure and negatively affect their subjective well-being (Craig, 2006; Offer & Schneider, 2011). Multitasking in an important component to consider when studying the division of household labor (Craig, 2006, 2007; Sayer et al., 2009).

Time Together and Gender

Bernard (1972) argued that experiences within a marriage are fundamentally different for men and women. Men and women do not perceive, experience, or share the same expectations about relationships (Ferree, 2010; West & Zimmerman, 1987). Women are more often dissatisfied with their relationship than men, more often think about separation, and more often initiate divorce (Thompson & Walker, 1989). This dissatisfaction has several complex causes, such as differences in expectations, inequalities in the division of labor, as well as differences in perceptions of fairness and justice (Wilkie et al., 1998; Thompson, 1991).

Gager and Sanchez studied how couples perceive the amount of time they spend together (2003). They did not find strong gender differences in the reporting of time together (even though they found evidence that shared time increased marital solidarity but only for women). However, the study did not measure time together using time diaries. Evidence of differences in the reporting of time together using time use diaries is mixed. Lesnard found that in the French Time Use Survey about 76% of couples "have converging statements of being together", questioning if the rest of the discrepancies are "mistakes or reveal diverging gendered views on being together" (2008: 465). Using the American Time Use Survey, Flood and Genadek (2016) as well as Dew (2009) found that women reported less time with their partner, on average, compared to men. Pooling time use surveys from the United States, France and Spain, Garcia-Roman et al. also found that women on average reported less total time with the partner (2017). On the other hand, Neilson and Stanfors did not find evidence of discrepancy in the reporting of time together by gender in Sweden (2018). Freedman et al. (2012) using couple-level time diaries did not find systematic differences between partners in the report of time together.

The time use literature is ambivalent regarding the relationship between time together and gender. On the one hand, the literature often describes time together as an important mechanism for couples to enhance their relationship while on the other hand acknowledging the potential gendered discrepancy between partners. Given the persistence of gender inequalities in contemporary societies, often revealed in time use research by the unequal distribution of activities between partners, it is unlikely that time together itself is not affected by gender.

Source of Variation in Time Use

One important source of variations in couple time use stems from the economic resources deriving from employment that are available to partners. Marital bargaining theories predict that unpaid work is a function of the economic resources possessed by each partner (Bittman et al., 2003; Deutsch, 2007; Gupta, 2006; Sullivan, 2011). Economists have been interested in how working hours affect the joint consumption of leisure (Hallberg, 2003; Mansour & McKinnish, 2014). Mansour and McKinnish finds that "couples who are less specialized in hours of work spend more joint time together" (2014, p.1143). So, the labor market position not only impacts the division of household work, but also the propensity of couples to spend more or less time in joint activities. More generally, employment status also affects time together in simply reducing the opportunities for partners to be together. Several studies have shown for instance that dual earners spend on average less time together than single earner couples (Flood & Genadek, 2016; Glorieux et al., 2011; Neilson & Stanfors, 2018). Non-standard working hours also affect the opportunity for togetherness Lesnard (2008); Presser (2005).

Another important source of variations affecting couples' time use is the presence of children and in particular of young children (Berk, 1985). The transition to parenthood negatively affects women's labor market participation, and increases their housework time (Budig & England, 2001; Mattingly & Blanchi, 2003; Sanchez & Thomson, 1997). Research on togetherness shows that children reduce the time that partners spend together as a couple (Flood & Genadek, 2016), and directly impact the jointness of leisure consumption (Hamermesh, 2000).

Research Questions

Most time use studies use independent samples of men and women to study household interactions or the household division of labor (Bianchi et al., 2000; Wight et al., 2008). Including both partners' activities can shed new light on the gender dynamics at play during shared intimate moments (Dush et al., 2017; Smith et al., 1998; Szinovacz & Egley, 1995).

The aim of this paper is to address the question of the discrepancy (or mismatch) in couples' reporting of time together as well as the potential discrepancy in the activities engaged in during shared time. Partners' shared activities are an opportunity to look more closely at the gendered dimension of intimate life in a micro-sociological way (Kellerhals et al., 1993).

Expectations are mixed regarding how activities are distributed during shared time. On the one hand, given the persisting gendered division of intimate life, we can expect to see differences between men and women in activities even during time together. On the other hand, because time together has been described as a particularly important way for a couple to (re)connect, we can expect that most couples share the same activity when together, and most particularly, to share leisure activities.

I focus mainly on the two sources of variation in couple time use discussed in the literature overview, the presence of children and the employment status. I expect that having children would reduce the jointness of activities during shared time and deepen the gender gap in activities. Similarly, I hypothesize that couples who are less specialized in terms of their work arrangements would have a more equal distribution of activities during shared time when compared with other working arrangements where men have higher market resources than women. However, it is not entirely clear if resource theory can be applied to the distribution of shared activities.

4.2 Data

The UK 2014–2015 Time Use Survey

The UK Time Use Survey 2014–2015 (UKTUS) is a nationally representative, stratified random sample of UK households that forms the latest contribution of the UK Office of National Statistics to the Harmonized European Time Use Study (HETUS). The survey collected over 16,500 diaries from 9388 people in 4238 households. The survey has a response rate of 40.5%, comparable to the American Time Use Survey or the Swedish Time Use Survey (Neilson & Stanfors, 2018).

Time use diaries have been used extensively to trace social change, and to estimate daily activities such as working hours, leisure time, domestic chores, eating behavior, and childcare (Gershuny, 2000; Robinson & Godbey, 2010; Vagni & Cornwell, 2018). Diaries differ from stylized survey questions, which ask respondents to recall and estimate the time they spend on different activities. Stylized questions generally take the following form: "How many hours did you spend doing . . . ?" However, these sorts of questions have been criticized because of desirability and memory bias (Juster et al., 2003). Instead of asking respondents to estimate average time spent in different activities, time use diaries ask respondents to record all of their activities during a given day. This method has been shown to reduce bias (Juster et al., 2003).

The UKTUS 2014–2015 was collected using paper diaries. A face-to-face interview was conducted first, and time use diaries were given to each member of the household to fill out. The UKTUS includes two time use diaries for each respondent: one weekday diary and one weekend diary. Each household member older than 8 years old was requested to fill out a time use diary. The diaries are structured in 10-min intervals starting at 4 a.m. The respondents had to fill out 144 time intervals (144 $\times$ 10 equals 24 hours). The diaries enabled the respondents to write down their main activities, their secondary activities, their location, and other persons who were present (with whom) during each 10-min time interval. The with whom information collected information about the spouse/partner, the child, and others. In this paper, I am primarily interested in the information related to the presence of the partner/spouse. The exact wording of the question was: "Were you alone or with somebody you know?" The respondent could then tick a box indicating "spouse/partner".

Checking the quality of the with whom information, I found that less than 1% of respondents had complete missing information, and 45% had no missing at all. About 85% of the couple sample had less than 25% of missing copresence information. I also analyzed missing information by gender and found no differences. I chose to remove couples with more than 50% of missing copresence information from my analyses. (For a full discussion see Online Supplement). In effect, the missing copresence information of the partner in the analytical sample is counted as 0 (not present). This limitation should be kept in mind.

Sample

Table 4.1 shows the final sample used in this paper. The analytical sample used in this paper is composed of 1427 heterosexual couples (2854 individuals) in which both partners filled two time use diary during the same 2 days.

The analyses presented in this paper were run on both the complete sample of couples and the subsample of parents to detect if some of the results were conditioned on having young children living in the household. A full description of the sample characteristics can be found in "Appendix C". The subsample of parents is composed of 333 couples (666 individuals) with at least one child under 8 years old and where at least one parents is employed.

Because I restricted my analysis to couples where both partners filled a diary, I was concerned about possible selection bias. In order to address this question, I compared the UKTUS to a much larger survey, the UK Labor Force Survey,1 and find little differences in key socio-characteristics between the two surveys (see C). Therefore, I did not use the survey weights for the analyses.

Measures and Analytical Strategy

The main variable of interest in this paper is time spent together, as indicated in the "with whom" field of the diary. The exact wording of the question in the time use diary was "Were you alone or with somebody you know?" from which the respondent could indi-

Table 4.1: Characteristics of the sample. UK 2015.

	N	%
Number of children		
1 child	173	12.12
2 children	263	18.43
More than 2 children	72	5.05
No children	919	64.40
Employment status		
Both full-time	430	30.13
Both Not Working	70	4.91
Both Retired	340	23.83
Female Breadwinner	95	6.66
Man full-time, woman not working	194	13.59
Man full-time, woman part-time	229	16.05
Other arrangement	69	4.84
Age		
18–44 years old	567	39.73
44–64 years old	469	32.87
More than 64 years old	391	27.40

cate if his or her partner/spouse was present. The measure of time together is a dummy variable, with 1 indicating the partner/spouse being present during an activity and 0 indicating absent. The measure excludes paid work and sleeping periods. Therefore, partners reporting being together during these activities were not counted.

The first measure of interest indicates when *both* partners report being together (when their responses match). It can be defined as:

$$Match_{jt} = (p^{m}_{jt} \cdot p^{w}_{jt}) \tag{4.1}$$

where t represents the time interval (10 min), with $t = (1, \ldots, 144)$, pt (for partner presence) is a binary variable $(0,1)$ indicating if the partner is present or not during an interval t, and p^{m}_{jt} denotes the men's response at time t, and p^{w}_{jt} represents the women's response at time t (from the same couple j). Conversely, a mismatch measure would be defined as:

$$Match_{jt} = |p^{m}_{jt} - p^{w}_{jt}| \tag{4.2}$$

The mismatch measure can be decomposed into a men's discrepancy component ($DMen_j$) and a women's discrepancy component ($DWomen_j$). For instance, the men's discrepancy measure denotes when the (male) partner indicates being with the partner but the partner does not indicate being together (and vice versa).

The total time together can be thus defined as:

$$Total_{jt} = Match_{jt} + DMen_{jt} + DWom_{jt} \tag{4.3}$$

$Total_{jt}$ is therefore the sum of the agreement of being together plus the disagreement of the male and female partners.

The activities considered in this paper have been recoded into six categories: (1) childcare (abbreviated CH), (2) domestic chores (abbreviated DM), (3) eating meals (abbreviated EA), (4) leisure (abbreviated LE), (5) TV watching (abbreviated TV), and (6) other (abbreviated OT). Childcare includes both routine childcare (e.g. feeding the child) and developmental childcare (e.g. playing with the child, reading). Domestic chores include all domestic tasks such as cleaning the house and preparing meals. Leisure is a broad category that includes going to a museum or the cinema and attending sport events but excludes TV watching, which has its own category. Finally, the "other" category groups all other activities: paid work, travelling, shopping, sleeping, personal care, and missing activities

The second main measure I am interested in is the level of agreement about activities done when partners are together. The agreement in activities means simply that partners are doing the same thing when together. This is more simply illustrated by a cross-table of partners' activities when together, as shown in 4.1

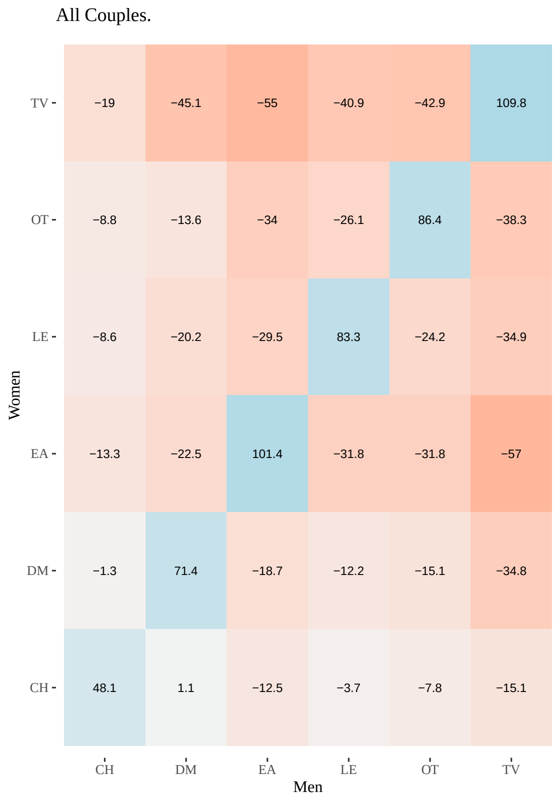

Figure 4.1: Illustrative cross-tabulation of partners' activities. Chisquare Standardised Residuals. CH childcare, DM domestic, EA eat, LE leisure, OT other

The percentage of agreement about activities when together is calculated by dividing the sum of the matched activities (agreement) by the total of activities (both matched and mismatched). This index measures the agreement within couples of activities when together. In a stylized form, this can simply be expressed as:

$$\frac{\sum_i \sum_j n_{ij} \text{ for } i = j}{\sum_i \sum_j n_{ij}} \tag{4.4}$$

where n_{ij} is the observed frequency for cell (i, j). One limitation of this measure is that couples that did not spend at least one episode together and that did not have at least one matched activity are excluded. In effect this concerns only a small number of couples $(n = 49)$. Otherwise, the measure is insensitive to the total time spent together.

I use OLS regression to study the association between a range of covariates and the diagonal measure described above. However, I use a multilevel approach when I analyze the time spent in different activities by gender. The diagonal activity measure is a "couple-level" measure (each row represents a couple), but the time spent in activities is an individual measure, and because I am dealing with individuals nested in couples, multilevel modeling is an appropriate approach to account for this form of non-independence (Goffette, 2016). The samples slightly differ between the OLS and the multilevel models. The multilevel models include couples that do not have at least one matched activity episode. Both models however exclude couples that did not spend any time together.

All the analyses presented in this paper are weighted so that the days of the week are represented equally.

I used two main explanatory variables: Household with a child under 8 years old and Couple employment status. Household with a child under 8 years old is a dummy variable indicating if a child younger than 8 years old is currently living in the household. The couple employment status is a categorical variable with seven categories: (a) Both Full-time earners, (b) Men Full-time, Women Not Working, (c) Men Full-time, Women Part-time (d) Female Breadwinner, (e) Both Not Working, (f) Both Retired, (g) Other Arrangements. I used the mean age of the couple as control variable, with three categories: (a) Less than 44 years old, (b) 44–64 years old, (c) More than 64 years old.

4.3 Results

Table 4.2 shows total time reported as together disaggregated by the matched responses and the discrepancies in matching for men and women. The daily total time together is 408 min for parents and 502 min for all couples. The partners' responses matched (i.e. both partners report being together at the same time, $Match_j$) 64.55% of the time for all couples, although the proportion is lower for parents (57.44%). The discrepancy in partners' responses is not skewed toward women or men as shown in Figure 4.2. For all couples, $DWomen_j$ is 17.79%, while $DMen_j$ equals 17.66%, meaning that in about 18% of cases partners' report the presence of the other, but the other does not. For parents the discrepancy is higher, at $DWomen_j$ 22%, and $DMen_j$ 20.59%.

Figure 4.2 shows the average report of time with the partner for man and woman belonging to the same couple. The two distributions are very similar confirming that the report of time with the partner is not bias according to gender. The yellow points indicate that male and female partners are reporting on average the same time with the partner. The blue crosses indicate when the female partner is reporting more time and the green squares when the male partner is reporting more time.

Figure 4.3 shows how time together varies throughout the day. The solid line indicates total time together, the long dashed line the $Match_j$ index, the "mismatched" lines at the bottom indicate the women's discrepancy ($DWomen_j$) and the men's discrepancy ($DMen_j$) respectively. The trends in men and women's mismatches closely follow each other during the day. It visually seems that parents have more mismatches compared to all couples.

Table 4.2: Total time, matched time and discrepancy in partners' responses of time together by parental status

	Total	$Match$	$DMen$	$DWom$	$Match$	$DMen$	$DWom$
	(min)	(min)	(min)	(min)	(%)	(%)	(%)
All	502.06	324.06	88.67	89.33	64.55	17.66	17.79
Parents	408.08	234.38	83.9	89.79	57.44	20.56	22

Women's discrepancy ($DWomen_j$) is slightly higher during the morning, while men's discrepancy ($DMen_j$) is a bit higher during the afternoon and evening. Tables 4.3 and 4.4 show the diagonal of activities (being together and doing the same thing). First, the sum of the diagonal is around 60%; this means that partners, when together, are doing the same

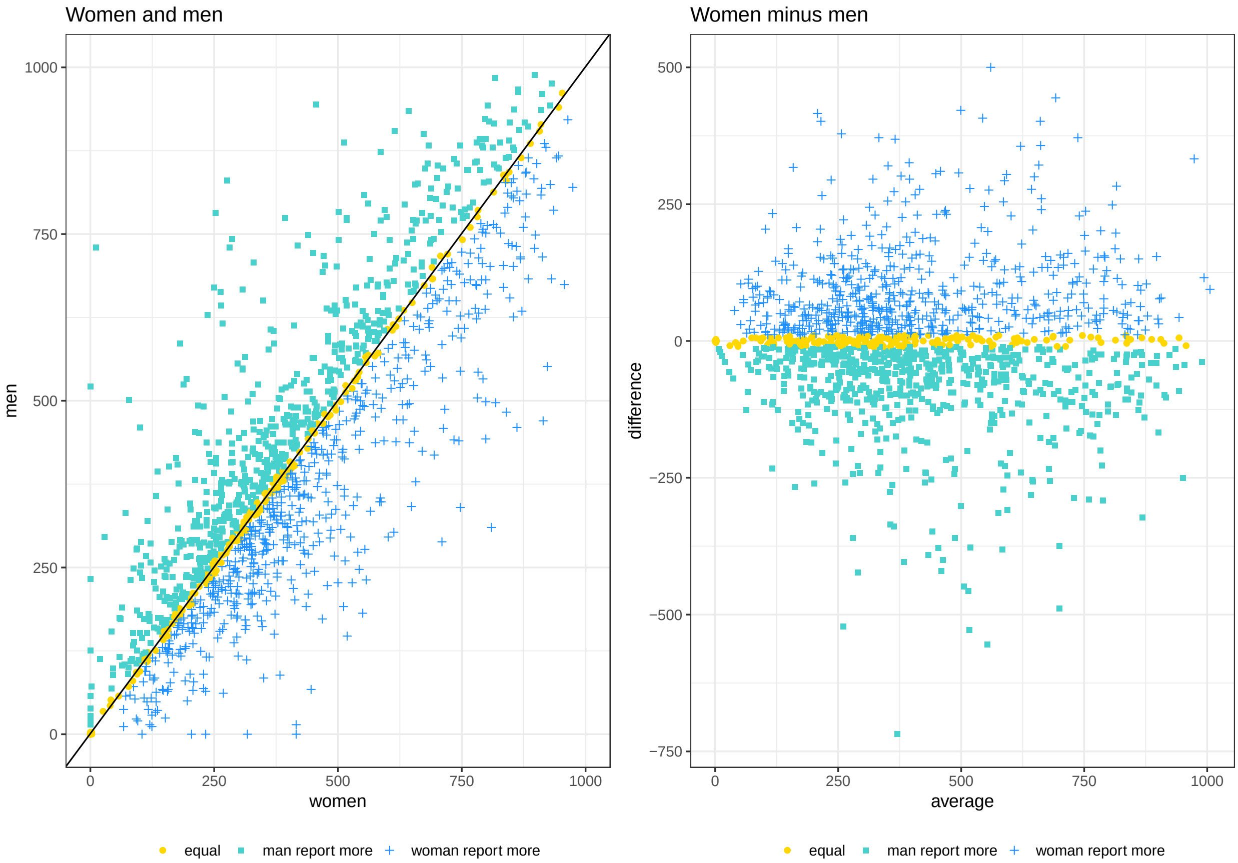

Figure 4.2: Average reporting of time together by gender (within couples comparison)

activities about 60% of the time. In 62% of cases, partners do the same activities when together (for all couples). The distribution of the diagonal itself shows that when together and reporting the same activity, couples are mainly watching TV, eating together, and even doing domestic chores together. Table 4.4 shows the diagonal for different couple employment configurations. Looking at the total agreement (diagonal), we can note that full-time working couples, as well as female breadwinner couples, are more likely to agree on activities than other couples. Again, it is important to understand that this is not the overall distribution of activities, but the distribution of activities done together. The picture could be very different when looking at the overall distribution.

Figure 4.4 shows the sequence of activities for men and women over the course of the day (left hand side) as well as the aggregate distribution of activities when together (right hand side). The way to read these figures is to compare the men's distribution of activities to the women's distribution of activities and to look for differences in activities.

At first glance we can see that couples in general do the same activities when together. We can see a "spike" in eating time around 13 pm. TV time slowly increases from 4 pm until peaking around 22 pm. Gender differences are noticeable, as we can see that women perform more housework (when together) than men during the day (color red). This is more visible on the right-hand side figure showing the aggregate proportion of joint activities. TV is the activity most likely to be shared between partners. But we can clearly see that women do more domestic work and more childcare than men during shared time, while men watch more TV than women during shared time. This could be thought to be an artifact of analyzing only primary activities. However, I looked at secondary activities (Appendix), and I did not find any evidence that men report more domestic work as a secondary activity (or women more TV) when together. Even if we look at activities when partners disagree about being with one another ($Mismatch_j$), we do not see that women tend to report more TV or men more domestic work (see C).

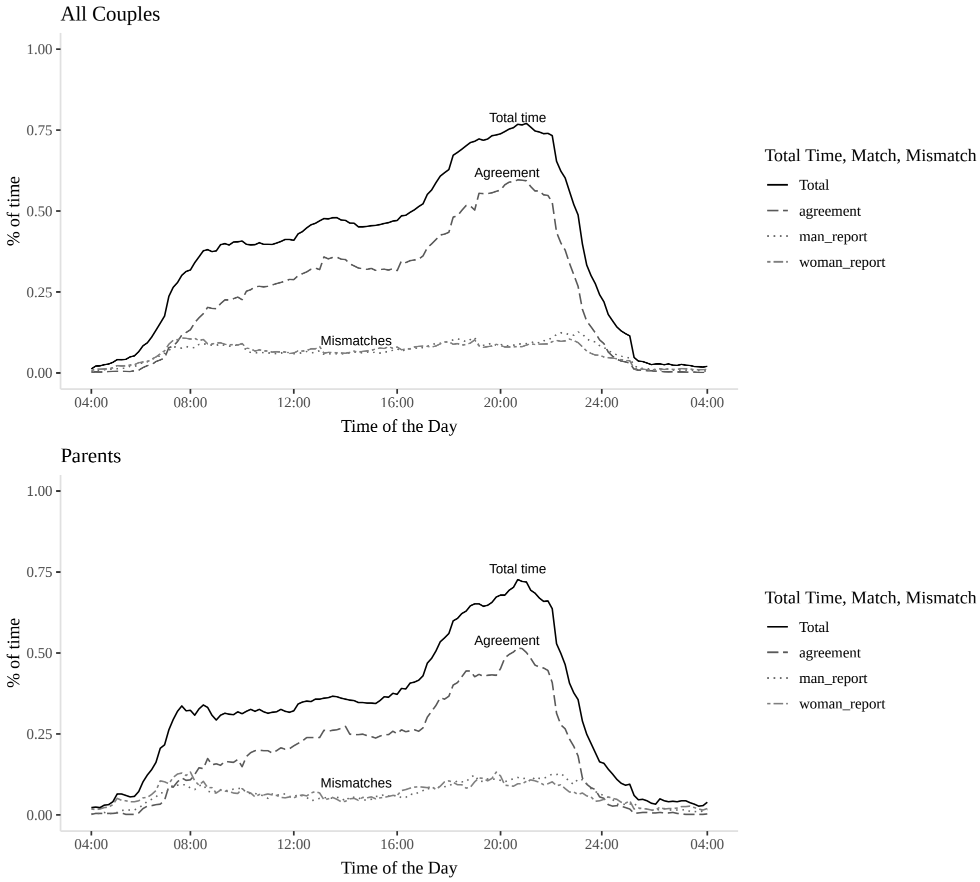

Figure 4.3: Total time, matched time and discrepancy in partners' responses of time together by parental status

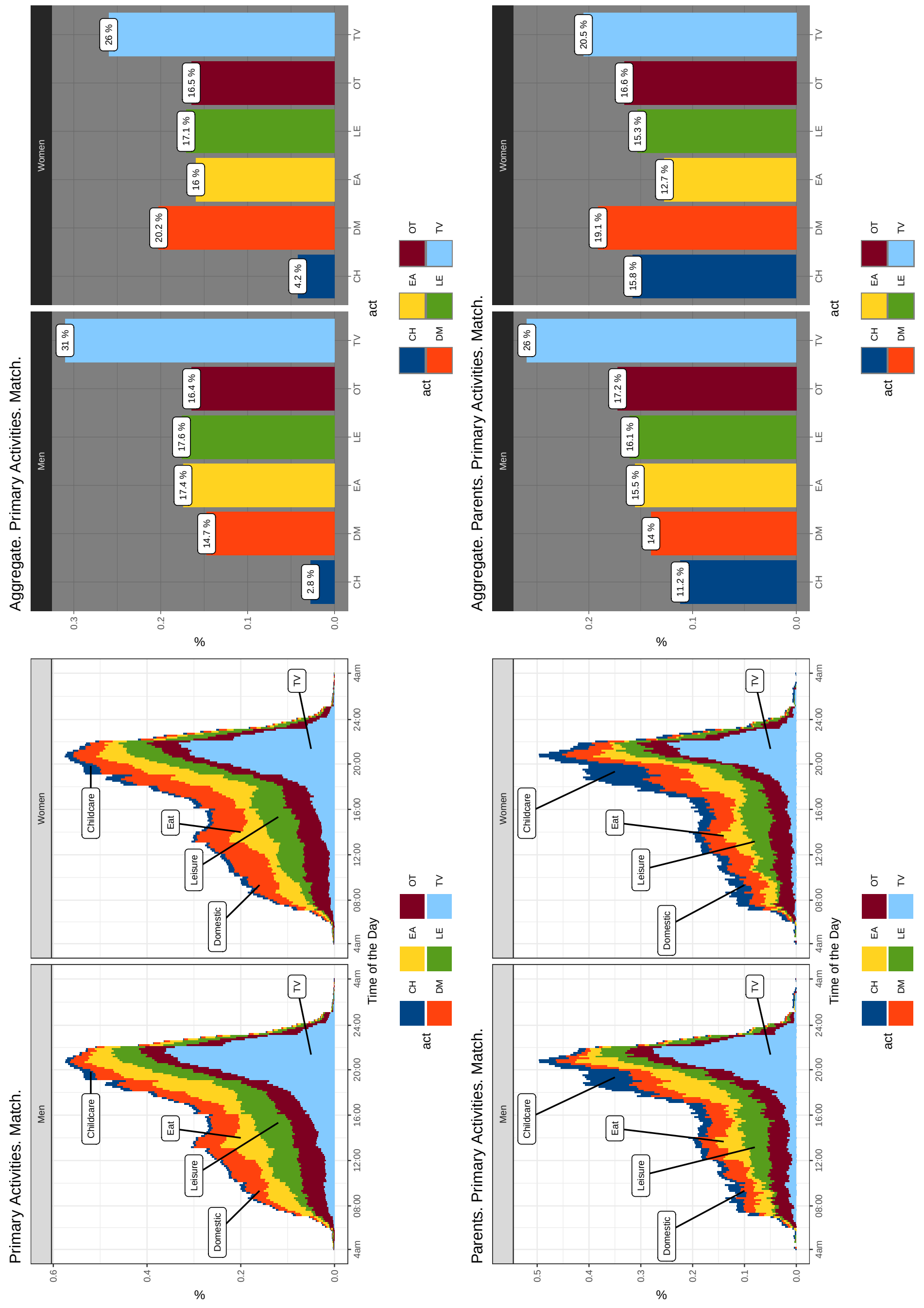

Figure 4.4: Distribution of individuals' activities by gender over the day. Primary activities. All couples.*CH* childcare, *DM* domestic, *EA* eat, *LE* leisure, *OT* other

Table 4.3: Total diagonal and share of the diagonal for each activity by parental status (presented in %)

	CH	**DM**	**EA**	**LE**	**OT**	**TV**	**diagonal**
All couples	0.01	0.09	0.12	0.1	0.1	0.2	0.62
Parents	0.06	0.08	0.09	0.1	0.1	0.16	0.59

Table 4.4: Total diagonal and share of the diagonal for each activity by employment status (presented in %)

	CH	**DM**	**EA**	**LE**	**OT**	**TV**	**diagonal**
Both full-time	0.02	0.09	0.11	0.11	0.12	0.2	0.65
Man full-time, woman not working	0.03	0.07	0.12	0.1	0.09	0.19	0.61
Woman full-time, man not working	0.01	0.09	0.1	0.11	0.1	0.23	0.64
Man full-time, woman part-time	0.03	0.08	0.1	0.1	0.11	0.2	0.63
Both not working	0.01	0.08	0.1	0.1	0.09	0.26	0.63
Retired	0	0.1	0.12	0.09	0.09	0.2	0.61

The sequence for parents also shows that mothers report more domestic work and more childcare during shared time compared to fathers. Looking at the sequence figure (left hand side), we note, in particular, the greater proportion of childcare done by mothers around 18 pm and the greater proportion of TV watching for fathers at this time.

Figure 4.5 shows the distribution of the partners' activities when the respondent is doing a certain activity. In Figure 4.5 , the figures on the left hand side ("Agreement. Men. Primary Activities.") show what women are doing when men are doing certain activities, and vice versa for the figures on the right hand side ("Agreement. Women. Primary Activities."). For instance, when men are doing childcare, 53% of the time women are also doing childcare. However, when women are doing childcare, men are doing childcare for only 34% of the time. When women are doing childcare, 17% of the time men watch TV, compared to only 7% of the time for women when men report doing childcare. Even though eating and watching TV are the most "agreed upon" activities, women do still more domestic chores and childcare while men eat or enjoy leisure. When men report leisure, about 16% of the time women are doing housework, compared to only 8% of the equivalent time for men. I looked at secondary activities to see if men were less likely to report domestic chores or childcare as primary activities, but this is not the case (see Appendix C). If anything, the inclusion of secondary activities increases the gap in housework between the partners.

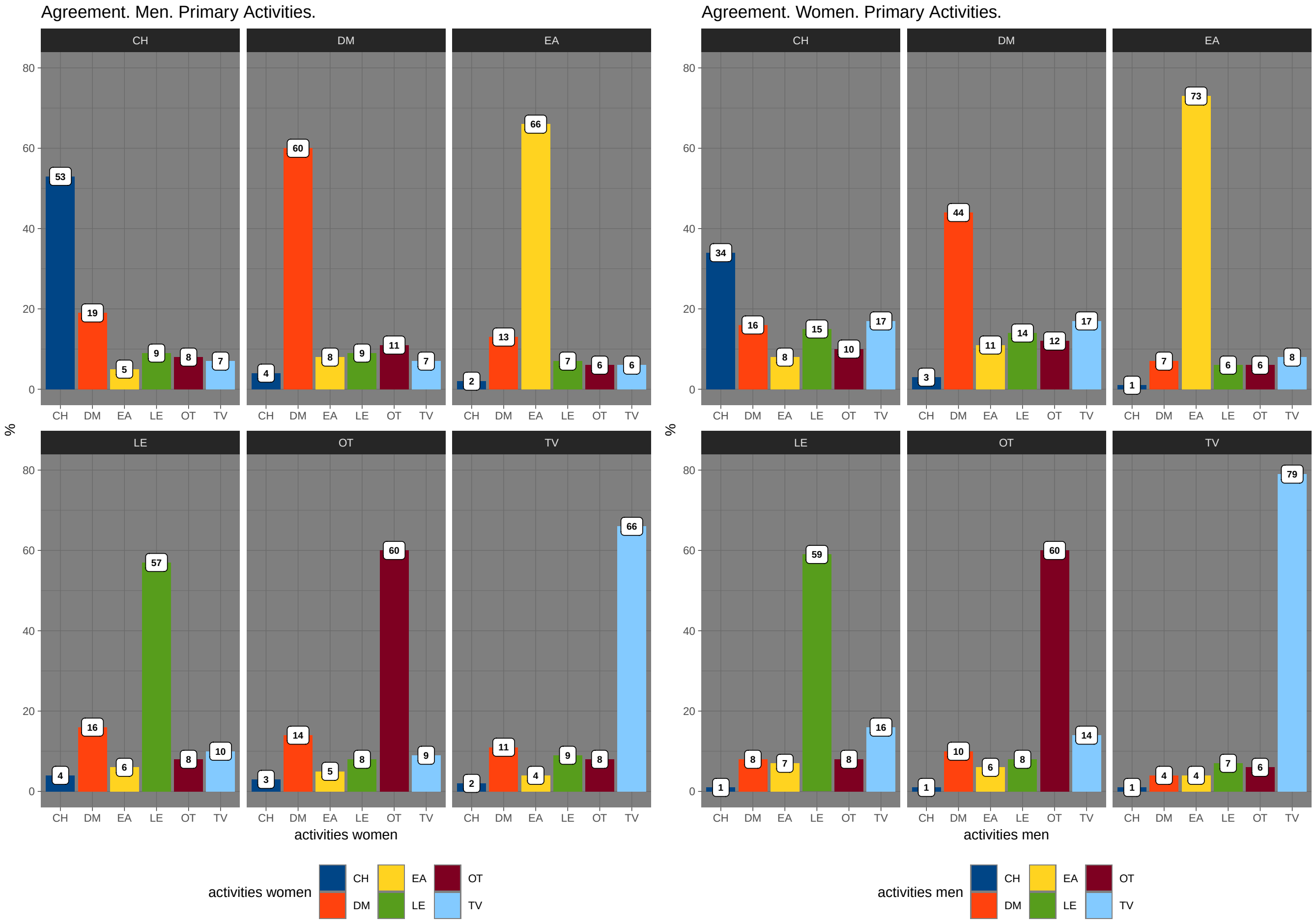

Figure 4.5: Distribution of joint activities by gender. All couples. *CH* childcare, *DM* domestic, *EA* eat, *LE* leisure, *OT* other

The OLS regression on the diagonal is presented in Table 4.5. I present four models, including the following variables: Household with a child under 8 years old (ref=no children under 8 years old), Employment status (reference = Both Working Full Time), and Mean age of the partners (ref=less than 44 years old). The constant is 0.63, meaning that partners report doing the same thing while together 63% of the time when together. A score of 1 indicates no mismatches in activity when together. We can see that children reduce the jointness[1] of activities by about 6% ($p<0.001$). Regarding the employment status of the couple, we see that the categories "Men working full-time and Women part-time", "Both Retired" and "Other arrangement", have all lower agreement about activities compared to "Full-time dual-earners". However, employment status does not explain very much of the variance ($R^2 = 0.007$). The coefficients for the presence of young children are stable across models, suggesting that children do negatively impact on the jointness of activities. I omitted the model for parents because none of the variables used here were significantly related to the diagonal (results available upon request).

[1] I use the concept of jointness throughout the results section and in the discussion. However, I want to draw attention to the fact that I am using it in a very specific manner, referring to when partners are both together and doing the same activity.

Table 4.5: OLS Regression on the Diagonal when Partners report Being Together (all couples)

	Dependent variable:			
	Diagonal (%)			
	(1)	(2)	(3)	(4)
Child under 8 (ref = No)				
Child Under 8	-0.059^{***} (0.012)		-0.071^{***} (0.013)	-0.102^{***} (0.016)
Employment status (ref = Both FT)				
Male Breadwinner		-0.035^{+} (0.018)	-0.020 (0.018)	-0.007 (0.018)
Female Breadwinner		-0.011 (0.023)	-0.025 (0.023)	-0.005 (0.023)
Man full-time, woman part-time		-0.042^{*} (0.017)	-0.029^{+} (0.017)	-0.022 (0.017)
Both Not Working		-0.020 (0.026)	-0.024 (0.025)	-0.005 (0.026)
Both Retired		-0.035^{*} (0.015)	-0.055^{***} (0.015)	-0.009 (0.023)
Other Arrangement		-0.058^{*} (0.027)	-0.062^{*} (0.026)	-0.046^{+} (0.027)
Couple's age (ref = Less than 44)				
44-64 years old				-0.046^{**} (0.015)
More than 65 years old				-0.078^{***} (0.023)
Constant	0.630^{***} (0.006)	0.639^{***} (0.010)	0.659^{***} (0.011)	0.687^{***} (0.014)
Number of Couples	1378	1378	1378	1378
R^2	0.019	0.007	0.028	0.034
Note:		+ $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$		

Tables 4.6 and 4.7 present the multilevel regression models on time spent doing different activities while being together. The coefficients are expressed in minutes.

I show the models for Domestic Work, Childcare (for parents only), TV, Leisure and Eating. We can see that men, on average, do 18 min (p < 0.001) less domestic work, and watch 16 min ($p < 0.001$) more TV while together with their partner. Women also tend to report less eating while together (-4.87 min, $p < 0.001$). There were no significant gender differences in joint leisure. We can note that unemployed and retired couples watch on average more TV together compared to Full-time dual earners. The presence of children reduces time watching TV together (minus 16.721 min), leisure time (minus 8.86 min) and eating together (minus 8.48 min). Table 4.7 shows the results for parents only. We can see here that women are doing more domestic chores, more child care, watch less TV and eat less often than men, when both partners are reporting being together. Overall, the results for parents are very similar to the results for all couples.

Table 4.6: Multilevel Regression on Activities by Gender when Partners report Being Together (all couples)

	Dependent variable:			
	Domestic	TV	Leisure	Eating
	(1)	(2)	(3)	(4)
Sex (ref = Man)				
Woman	18.25***	−16.85***	−1.76	−4.87***
Child under 8 (ref = No)				
Child Under 8	7.04	−16.71**	−8.86+	−8.48*
Employment status (ref = Both FT)				
Male Breadwinner	−0.72	4.89	3.12	8.32*
Female Breadwinner	0.05	9.53	9.67	−5.00
Man full-time, woman part-time	−5.74	3.61	−4.92	−4.04
Both Not Working	25.68***	73.35***	24.50**	11.59*
Both Retired	33.42***	41.28***	38.89***	23.39***
Other Arrangement	2.85	−10.54	13.20	8.48
Couple's age (ref = Less than 44)				
44–64 years old	14.01**	15.11*	5.29	7.41*
More than 65 years old	24.46***	29.50**	−2.65	25.23***
Constant	28.82***	80.99***	49.37***	45.55***
Number of Couples	1396	1396	1396	1396
Number of Individuals	2792	2792	2792	2792

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Table 4.7: Multilevel Regression on Activities by Gender when Partners report Being Together (Parents)

	Dependent variable:				
	Domestic	Childcare	TV	Leisure	Eating
	(1)	(2)	(3)	(4)	(5)
Sex (ref = Man)					
Woman	14.47***	12.70***	−15.17***	−1.77	−6.93***
Employment status (ref = Both FT)					
Male Breadwinner	1.12	−8.36+	1.25	8.31	5.46
Man full-time, woman part-time	−2.25	−6.30	1.02	−1.41	1.68
Couple's age (ref = Less than 44)					
44-64y	1.08	−12.58+	16.63	5.16	−1.75
Constant	37.53***	34.61***	67.70***	39.61***	37.69***
Number of Couples	320	320	320	320	320
Number of Individuals	640	640	640	640	640

Note: + $p<0.1$; * $p<0.05$; ** $p<0.01$; *** $p<0.001$

4.4 Discussion

This paper explored the agreement and disagreement in time together, as well as the distribution of activities during shared time, between partners. I find that overall when partners report being together, they are sharing the same activity. This is consistent with the study of (Freedman et al., 2012).

The most prevalent activities performed together in a couple are watching TV, eating and sharing leisure. In this sense, this paper is in line with studies arguing that shared time and shared leisure appear as fundamental components structuring contemporary relationships (Beck & Beck-Gernsheim, 1995; Berger & Kellner, 1964; Mansour & McKinnish, 2014). I also did not find any clear gender differences in the average reports of time together. Female partners do not report more or less time together than their male partners. This is in line with other studies (Freedman et al., 2012) and (Neilson & Stanfors, 2018). The number of mismatches within a couple, on average, balances each other's. One of the implication is that time use researchers interested in estimating time together could either use men's or women's reports of time together for the estimation of togetherness. However, the issue with individual diary data is that, overall, time together is likely to be either underestimated or overestimated, depending on one's interpretation of what constitutes time together. For instance, consider the results presented in Table 4.2 for parents. The total time together was 408 min (100%), of which 57% was matched and about 20.6% was a mismatch for men and 22% for women. With data from both members of a couple, it is possible to present the different estimates based on men and women, or both. But with data only from one individual, about 20% of mismatched time together will be missing. Imputing partners' responses cannot solve this issue.

This leads to the question of what constitutes time together. Should both partners agree on being together, or is only one partner's report sufficient for counting time together? What I called the total time together constitutes the sum of agreement between partners plus the sum of disagreements. It is reasonable to assume that when only one partner reports being together, the other partner is physically present, even if he/she does not recognize that they are together. However, it is impossible to say if the activity is necessarily shared when only data from one individual of the couple is available; thus, time use researchers should be cautious in assuming that partners are doing the same activity when only one partner's diary is collected.

Following from these observations, I would like to propose two new broad concepts of time together: shared presence and time engaged. Shared presence should be counted as the total time together, including the disagreements or mismatches. This concept can be viewed as a record of the partner's presence. The mismatches are likely to represent the fact that the partner is present but not truly engaged in a shared activity. The time engaged measure should be restricted to the times when both partners report being together. We can assume that when both partners report being together, they must agree to some extent about what is going on and how a particular situation should be interpreted. One could go a step further and restrict the engaged time together to when both partners report being together and when both report doing the same activity. Only data collection from both partners can fully account for these complexities. The results presented in the second part of the paper clearly show the gendered dimension of time together. These findings bring together the disparate time use literature on time together (Genadek et al., 2016; Neilson & Stanfors, 2018) and on the division of household labor (Bianchi et al., 2000; Gupta, 2006; Sullivan, 2000). I showed that, when men and women reported spending time together, men were doing more leisure activities, while women performed more unpaid activities. This result confirms previous research (Dush et al., 2017).

This finding can be put into perspective with Bernard's idea of the two marriages (1972) (1972). To some extent, men and women sometimes have contradictory everyday experiences of their shared time. The traditional division of household labor still exists even during shared moments—moments which some of the literature describes as a time when partners can work on the relationship and potentially improve their marital quality (Berger & Kellner, 1964). However, the gendered component of time together indicates that we must be cautious in interpreting time together as a necessarily homogeneous and agreed-upon time. In this sense, the utility of couple time or family time is not the same for men and women. Women still are doing more housework than men during shared time. The analysis of secondary activities did not change this picture.

This imbalance in the utility of time can be related to studies suggesting that women are generally more often dissatisfied with their relationship than men (Fowers, 1991). We can assume that doing unpaid work while one's partner is enjoying leisure activities (e.g., preparing dinner while one's partner is watching TV) could affect the perception of fairness and equity, which in turn could affect partnership satisfaction. More research is needed in this area. It would be possible, for instance, to use some time diary data to explore how the discrepancy in responses and activities affects partners' enjoyment of time. A comparison of partners' enjoyment using couple data would shed light on these issues and inform contemporary debate about persisting gender inequalities.

Another contribution of this paper is the analysis of what I referred to as the "activity diagonal". With or without looking specifically at shared time, the diagonal is a simple way to summarize the division of activities within couples. One advantage of the cross-tabulation of partners' activities is that cross-tables integrate the 24 h-constraints of everyday life. The analysis of the diagonal also enables us to detect more complex activity interactions, such as men watching TV while women are doing chores. Log-linear models applied to cross-tabulations of couples' activities could be an interesting avenue for future research on partners' shared activities (Hout et al., 1987; Smith et al., 1998). Nonetheless, the precise meaning of the diagonal identified here is open to interpretation. The diagonal can be interpreted as a measure of equality. The division of labor between partners is generally studied from the broader point of view of paid versus unpaid work, market versus non-market work. Studies are generally concerned about the overall distribution of activities within couples, and resource-based theories have been generally applied to the average total time spent in certain activities (Bittman et al., 2003; Gupta, 2006; Sullivan, 1996). Looking at activities during shared time gives another look at the power dynamic taking place inside the household. This paper provided evidence that even during reported shared time, partners did not divide their activities equally. Men overall still enjoyed more free time than women during shared time. However, I failed to show clear evidence that resources influenced the way partners divided their activity during time together. I did not see that more equal couples (less specialized) in terms of employment status were more prone to do the same activity during shared time compared to more specialized couples. Future research could examine other measures, such as income (relative and absolute) to see if the jointness of activities during shared time is influenced by partners' resources.

Some limitations of this study should be noted. An important limitation is that it is impossible to disentangle the difference in perception of a situation from objective situational differences. For instance, when partners are both caring for a child together, women could perceive and report this situation as shared childcare or shared domestic chores, while men might report it as shared leisure. This difference in perception could be rooted in the fact that mothers bear a more general responsibility concerning the supervision of children and their childcare time is therefore more stressful and less associated with leisure (Milkie & Peltola, 1999). However, in other instances, like when women report doing domestic work while men are watching TV, we can reasonably believe that an objective difference in activities is occurring. In this situation, we can assume that the man is physically lying on the couch watching TV while the woman is physically up and doing domestic chores. This is the principal difficulty with the study of social phenomenon like time together. Social actors constantly interpret, reinterpret and misinterpret everyday situations. They also negotiate the meaning of situations and social interactions, contemporaneously and in retrospect. This is particularly true for intimate relationships, which Berger and Kellner describe as "nomos-building" 1964 (1964: 220). Not only do couples create their own "couple subculture", but the set of norms and meanings they create is not necessarily agreed upon between partners themselves at all times. In that sense, time together is very difficult to study because of the strong phenomenological component at the core of interpersonal relationships (Berger & Luckmann, 1991). So, one can wonder what time use diaries actually captures when recording time together. How do we get to the actual situation, is an important question however unlikely to receive a satisfactory answer because there is no "objective" benchmark regarding what is going on during a particular interaction between family members. Perhaps with the introduction of so-called "camera diaries" in time use research, scientists will be able to disentangle the subjective/interpretative component from the actual/objective component of a situation (Gershuny et al., 2017).

Can social desirability play a part in the reporting of time together? It is unlikely that social desirability bias is playing a role here, even though desirability does seem to play a role when men report their domestic work in stylized questionnaires (Kamo, 2000). For instance, it could be that men who do a lot of domestic work would either under-report or even not perceive their involvement in unpaid work as fitting in the "domestic work" category, in order to preserve their self-image (Hochschild, 2012; West & Zimmerman, 1987). This possibility seems unlikely in this case because time use diaries are considered to be much freer of these sorts of biases than stylized survey questions (Kan, 2008). In order to better understand patterns of activity reporting, two possible solutions could be considered using time use diaries. The first one would be to use the location information.

Unfortunately, the location information in the UKTUS 2014–2015 is not precise enough to distinguish the different rooms in a house where activities are taking place, for instance.

Moreover, location reports did not differ much between partners, so there is little variation to exploit. The second solution would be to use the enjoyment information provided by the diaries. Future research could address the discrepancy in enjoyment when partners are together and correlate it with the reported activities.

In this paper I looked at a particular social context: the UK in 2014–2015. However, comparing the diagonal of activities over time, both when partners are together but also when they are apart, will be greatly informative for future understanding of the transformation of gender relationships at home. Comparing the diagonal of activities between partners across different countries (where couple time use diaries exist) will also be of great interest in the study of gender and family relationships.

Chapter 5

Conclusions

Time is an ocean but it ends at the shore.
— Bob Dylan

This thesis has explored the multifaceted nature of time use in different social contexts. It has explored time patterns from a global perspective as well as from a micro-level one. This thesis was not guided by one single general research question but was rather motivated by describing and explaining the complexity of time allocation in modern societies. The aim of this thesis was to establish the set of social regularities in order to contribute to our understanding of contemporary societies, social inequalities and couple relationships.

This thesis has established a few key facts. In Chapter 2, I established the very high level of consistency in time patterns across countries and across time. I used sequence analysis methods and clustering to analyse one of the largest collection of time diaries: 48 time use surveys covering 23 countries and spanning more than 50 years. This study is one of the largest and most comprehensive sequence analysis of time diaries. It revealed eight common everyday sequence patterns—including different paid work, unpaid work, and leisure clusters. I found that this set of patterns reappears in a generally similar distribution across the different countries and time periods. This study is a step forward in time use research, who has mainly focused on average time spent in activities. In this chapter, for the first time I was able to show how these sequential patterns actually look like for a large set of countries. This paper provides the foundations for future research using sequence analysis in time use research.

In Chapter 3, I showed that within a specific social context, time use patterns were highly stratified by class and gender. This chapter contributes directly to the limitations of Chapter 2. It is the first study to incorporate organically sequence analysis, time use and stratification research. Social class is seldom used in time use research and time use diaries are seldom used in stratification research. In this study, I bridge this gap and proposes new avenues of research for the study of social inequality and time use. One important contribution of this chapter is to analyse the time use activities together. This enables to truly have a “holistic” approach to the stratification of time use. It is my hope that it will inspire other studies incorporating sequence analysis and time use in this way.

Finally, in Chapter 4, I compared in great detail the time use diaries from partners of the same couple. To my knowledge, no study really dedicated an entire study to this issue[1]. This chapter fills an important gap in recognising that time together is also gendered. While I find that it is the case that when partners report being together, they spend a large proportion of their time doing the same activities (mainly leisurely activities), in about 20% of the time their activities do not match. The important finding is that when they do not report the same activities (while reporting being together), women tended to do more domestic work while men were more likely to be enjoying leisure. This is the first empirical study really demonstrating that even during shared moment together, the unequal division of labour still persists. This is an important contribution to the gender division of labour literature and to the gender inequality literature more generally.

How do the chapters inform each other and what picture are they sketching once taken together?

We could start by reflecting a little deeper on the consistency in time use patterns across countries established in Chapter 2. What could explain this stability of patterns?

First, this stability could be due to the fact that most of the countries analyzed in Chapter 2 are developed countries. Would the picture be radically different with the inclusion of more developing countries? A hint that patterns might be different in these countries is given in Chapter 2 itself. India and Peru[2] seem to have much more unpaid work patterns than other countries. As the Multinational Time Use Study dataset keeps growing, time will tell if these patterns are truly universal or not or if this stability is a feature of "developed" nations.

Could the activity schema affect the level of stability across contexts? It is clear

[1]While other studies have noticed this discrepancy between partners in activities when together, none really dedicated too much attention to it (Lesnard, 2008; Freedman et al., 2012).

[2]Peru in the 1960s

that the smaller the activity schema, the more general the classification (thus the more comparable). But a very general schema might mask subtle differences between contexts. This is certainly true, but the aim of sequence analysis is to detect the signal from the noise. Even if my classification of activities is very general, this does not change the fact that the three fundamental categories of time paid work, unpaid work and free time are still distributed evenly between social contexts.

Of course, some activities are more comparable across countries and over time than others. Which are the most comparable activities? Is it sleeping, paid work or eating? It is difficult to say. But the reader can immediately note here how already general are the time use activities. Time use surveys rarely collect the content of activities (e.g. What do people eat? What kind of work are they doing?). Paid work in Peru in the 1960s is certainly very different from Paid work in the UK in 2015. The time use activities are already general, abstract, classification of time. However, these categories have clear definition in the literature. For instance, the definition of work is well established in time use research. It uses the so-called "third person criterion": "Work is anything that you might ask a third party to do on your behalf without losing the direct utility that derives from it." (Gershuny, 2018, p.4).

Paid work is then work that is paid for and unpaid work (domestic work, childcare) is work that is unpaid. The way work is collected across country is unlikely to be affected by country differences and by historical changes. This definition of work, especially paid work, is clear. Unpaid work might vary more over time and across contexts, but the range of variation is limited. Activities such as eat and sleeping are also very easy to define and directly comparable across contexts. Sub-categories of leisure are probably the most difficult categories to compare and broad categories of leisure might hide important differences. Technological changes here play an important role because it is sometime hard to predict how the future of leisure would look like. A recent example is the substitution of the TV by the laptops, smart-phones, tablets and other devices (Gershuny & Sullivan, 2019). It was difficult to imagine what would replace the TV back in the 1990s and how it would have affected things like family time (Vagni, 2019c). Of course, all these new categories of leisure can be grouped into a general category of "leisure at home" or simply "leisure" but one can see immediately that the nature itself of leisure has changed. But the categorization of leisure is still pretty clear: it is what is *left* after personal care (e.g. sleeping) and work (paid and unpaid) have been accomplished. Using the third person criterion, nobody would pay someone to go for them to a concert to enjoy music. As mentioned above, the aim of search for patterns is to detect a structure, not contents. So, it might be the case that social contexts affect the specific contents of paid work (working in a factory or working at home on a laptop) or leisure (playing video games or reading a book). This is something worth exploring in the future but does not invalidate our analyses.

Chapter 4 also revealed the potential subjective element at play in time use interactions (Vagni, 2019b). Partners do not always agree on what is going on during an interaction. This is worth exploring further too but this does not change the fact that most people know when they are working or not[3] and when they are enjoying time for themselves. In other words, it is unlikely that our classification of activities really had any impact on our results. Moreover, time use is probably one of the most easiest and meaningful things to compare across countries and across time. Contrast this with the difficulties of comparing values and norms across contexts (Inglehart & Baker, 2000). Ultimately, time is a universal benchmark. It does not devalue or inflate like money. It is a perishable good and, in general, people cannot save time for later. Its currency is constant and immediately comparable[4].

[3]The exception here might be academics or artists.

[4]This is not entirely true in the context of differential life expectancy for instance. Somehow the "price" of time should be different for contexts where life expectancy is 95 years compared to 30 years old. However, I am not aware of empirical evidence demonstrating that.

So, it seems truly remarkable that the same patterns are found in countries often clustered in different welfare regime or different variety of capitalism (Schmidt, 2002).

Our study is not an outlier in time use literature. We are not the only one puzzled by this stability. Gershuny writes:

> "How does it come to be that the eight hours of work per day [...] should hold so nearly constant, for some of the richest countries in the world, over a period of the three or more decades that must be remarkable for containing as much of more technical advance as any other period in human history? And how does it come about that a range of culturally diverse societies, widely separated in geographical terms [...] still all come to just a few minutes away from that 480 minutes total of paid and unpaid work?" (Gershuny, 2018, p.13)

In a recent study, Gershuny, also using the MTUS, looked at total work over 25 countries during the period 1960-2015 and finds that "the total of minutes of paid plus unpaid work seems to be stabilizing, in all the countries, within a fairly narrow range between 400 and 500 minutes per day" (Gershuny, 2018, p.12). He also shows that total work between men and women did not change much over time. It is important to understand that looking at total working time hides the obvious gendered nature of the distinction between paid and unpaid work.

This fact might be part of the explanation regarding the consistency of patterns across countries. The analyses in Chapter 2 are not disaggregated by gender. What Chapter 3 shows is that the distribution of paid and unpaid work between men and women (as well as between social class) is not equal. If total work is pretty much constant across contexts, this means then that when we look at patterns with no attention to gender, we should in fact expect this stability across countries. As chapter 3 suggests, a *stratified* cross-country analyses accounting should show that the distribution of these patterns are not equal between gender and class, even though when aggregated at the population level, they are equally distributed. This is an important insight. Future work should attempt to combine the methodology of Chapter 2 and 3 in combining the large cross-national comparison approach with the stratification approach.

But, the question of the stability of overall (or aggregate) patterns still needs an explanation.

I propose here a few potential explanations. The first explanation might be related to our biology. Circadian rhythms are internal 24-hours clock. The human body therefore has specific needs, such as an average of 8 hours a day. So, $1/3$ of time is taken by sleep. Another couple of hours must be dedicated to other biological functions such as eating and personal grooming. These personal activities must take between 2 to 3 hours. The rest of the day—about 13 hours—is therefore left for "non-biological" activities, such as work and leisure. A large proportion of the day must then be either dedicated to "productive" activities" (either paid or unpaid work) or leisure. Based on empirical evidence from time diaries we can speculate that total work must fill at least 10 hours a day. Then, between 3 to 5 hours can be dedicated to leisure and free time. It is not difficult to imagine that these 13 "non-biological" hours left, could be allocated in many different ways. But this is not what we have observed in Chapter 2. It seems that the whole range of contextual factors (institutions, policies, etc.) that is known to vary between countries do not affect this allocation much. Why? This is an interesting conundrum. How could France, the UK and the US have such similar time patterns?

One explanation could lie in the issue of *coordination*. Time has been described as a "network-good" (Young & Lim, 2014).

> "Network goods are things that increase in value as more and more people have them: whenever someone new acquires the good, it creates a positive externality for others." (Young & Lim, 2014, p.12)

So, coordination is essential to be able to make the best of free time. Coordination is about timing. Given our biological constraints, we can speculate natural daylight plays an important role in regulating the timing of when we wake up and when we go to bed. So, we can assume the time we wake up is given to us by these biological constraints. The coordination explanation argues that individuals would pick the time that is most likely to be synchronized with the rest of society. This could explain why the 13 hours left for work and leisure are not randomly assigned across societies. The average sunrise time around the world is between 6am and 8am. This is the starting point of the sequencing of daily activities. If most individuals need to accomplish 8-10 hours of total work to meet their social needs, then it is expected that they will on average coordinate these hours with the rest of society in order to enjoy time with others. This is a simple but powerful mechanism. It would be possible to test empirically if individuals with flexible schedules choose or not to coordinate their schedules with others. This would be interesting to really understand if people want to be in synchronicity or not with the rest of society.

Another related but slightly different explanation would have to do with *temporal norms*. It is likely that normative aspects of time (and especially timing) play an important role in determining general timing allocation of time use. There is evidence that individuals enjoy more certain hours of the day compared to others without specific observable reasons (Vagni, 2019a). Not all hours of the day have been created equal. On average people do prefer certain specific hours, without any real observable reasons. We can then speculate that a normative element is at play in explaining this phenomenon. I noticed for instance when analyzing data in Chapter 2 that certain activities at certain time on certain days had low probability of occurrence for no observable reasons. For instance, watching TV on a Monday at 10 a.m. was uncommon beyond what was expected from randomness. We can easily imagine the negative stereotype of watching TV alone at 10 a.m. on a Monday. Different moments of the day have different social connotations. It is not difficult to imagine hidden norms predicating when it is acceptable to enjoy leisure, when one should work and when one should be in bed. This normative component of daily time use is still largely unexplored empirically but seems a powerful mechanism explaining the stability in time use – especially because these norms are invisible and unconscious. It is likely that these norms were established long ago for some productive reasons and have simply persisted over time. For instance, the social world is still largely skewed in favour of "morning owl" individuals. To some certain extent, the rigidity of working times[5] reflects these norms. Qualitative studies could investigate this phenomenon to see if workers who arrive early as perceived more favourably, holding constant individual productivity. So, if there is a hidden positive stereotype about early working time, then it is not hard to see how society will converge towards certain types of schedules. Especially, because these norms are invisible, they are very hard to change. What I claim here is that there must exist a general normative culture about the timing activities that all the countries studied seem to share. This matter should be explored in more details. Fortunately, there exist cross-national time use surveys who also collected daily enjoyment information. This could be used to test if certain hours are more enjoyed than others, for no observed reasons.

Time use research has been a very descriptive field [6] but more general theory is needed to fully understand these patterns. Research should also now try to combine panel data and time use diaries. This is possible to a certain extent with the PSID, BHPS, the BCS 70 and the Millennium Cohort. The link between time use and the life course will offer invaluable insights on the mechanisms generating time use patterns.

Even though, this thesis raises a lot of questions, it still contributes in important ways to both time use research and to our general understanding of modern societies.

[5]When people *choose* to get to work and when they choose to leave work.

[6]Some general theories of time allocation do exist though, see Becker (1965); Gershuny (2000)

Appendices

Appendix A

Appendix. Patterns of Everyday Activities Across Social Contexts

Sequence Comparison

Sequence alignment algorithms employ a combination of three fundamental operations to determine the degree of distance between a given pair of sequences: Deletions, insertions, and substitutions Abbott (1995). When two individuals time and order their activities in a very different manner, the algorithm calculates a high dissimilarity score.

We tested three approaches to quantifying the difference between sequences. The first – the Hamming distance – counts the number of substitutions that are required to transform one sequence into another sequence Hamming (1950). Because it does not use insertions/deletions, the Hamming distance primarily measures differences between sequences in terms of when their activities occur (i.e., activity timing). The second distance measure is a variant – called Dynamic Hamming (DH) Lesnard (2010) – which uses a time-varying transition matrix to weight substitutions in terms of how unusual they are at different times of day. The last distance measure is derived from classical Optimal

Matching (OM) Abbott & Forrest (1986). This approach uses the substitution operation in conjunction with insertion/deletion operations. While the insertion/deletion costs are set to 1, the transition matrix between states is used to determine the substitution cost Gabadinho et al. (2011). OM-based distances therefore quantify the distance between a given pair of sequences in terms of differences in both the timing and order of activities in those sequences. Note that in the main text of this paper, we present findings that are based on analyses using the more interpretable Hamming-based distance, the original Hamming distance, as these findings were broadly consistent with those derived from analyses that used the DH and OM measures (see the end of the results section below).

Hierarchical Cluster Analysis

Once the distances between sequences were calculated, we used the hierarchical Ward algorithm to identify homogeneous clusters of sequences (Gabadinho et al., 2011). This is an agglomerative hierarchical clustering technique that attempts to minimize within-cluster variance (Kaufman & Rousseeuw, 1990), which is commonly used in social sequence analysis and tends to identify commonly sized clusters and therefore avoids poorly populated clusters (Cornwell, 2015). This clustering is performed on the matrix of distances or dissimilarities between sequences. The result is a set of hierarchically nested clusters that contain cases that evince relatively similar day-long activity sequences. To assess the validity of cluster solutions, we calculate the cophenetic correlation coefficient, which measures the level of association between the level of dissimilarity between (sets of) sequences and the point at which the cluster analysis fuses those sequences together. We use the elbow graph and consulted a battery of measures that assess the variation of sequences within and between clusters (available upon request) to help identify an acceptable number of clusters (Sokal & Rohlf, 1962). Virtually all of these criteria indicate that a very small number of clusters is ideal. For reference, we present the hierarchical solution that contains all nested clusters (see Fig A.2), but in this paper we focus on the eight-cluster solution. This solution achieves the best compromise between the clear need for a solution that contains few clusters but that maximizes face validity given existing research on common time-use patterns. Solutions that contain more than eight clusters achieve poor fit according to most indicators, and they result in substantively trivial distinctions in time-use patterns.

In order to test the stability of our solution, we reproduced the sequence analysis on 10 different random subsamples (see Fig A.1). Results of this robustness check are reported in the results text below. We also conducted supplemental analyses to assess the sensitivity of our main cluster solution to pooling cases from multiple countries rather than conducting separate country-specific analyses (see below "Pooled versus country-specific cluster analysis").

Robustness and Sensitivity of the Cluster Solution

Comparison of Distance Measures

To what extent the primary cluster solution may be shaped by our decision to use Hamming-based distances in the dissimilarity matrix and by the fact that we had to conduct the analysis using random subsets from the larger data?

Different solutions may emerge either by adopting different sequence alignment procedures (e.g., those that give weight to the order and not just the timing of activities) or distances or by drawing a random set of subsamples that just happen to be very different from those analyzed here. We approached the problem of the robustness and sensitivity of our cluster solutions by: (1) using different distance measures in the dissimilarity matrix submitted to clustering; and (2) performing the analysis on different randomly selected subsamples.

First, a comparison of the solutions produced by using the Hamming distance measure to the solutions produced by using the dynamic Hamming and OM-based distance measures (see Figures A.3, A.4, A.5, and A.6 show that the choice of distance measures does not drastically affect which clusters are identified. These approaches identified similar clusters (see Figures A.3, A.4, A.5, and A.6). Also, note that the cophenetic correlation coefficient ranges from .65 to .70 for each of these, indicating a moderate correlation between the fitted hierarchical dendrogram and the original pairwise dissimilarity measures on which it is based.

With regard to the sensitivity of these solutions to the particular random subsets we drew for the main analysis, Figure A.1 shows 10 different sequence analyses on 10 different random subsamples. Note that most of the clusters are stable and reappear in each of the eight-cluster solutions. Looking across the clusters reveals that the "Paid Work" clusters—Paid I Standard, Paid II Long, Paid III Morning, Shift I Morning—are stable across solutions. The cluster "Shift II Evening" is not consistent across solutions, however. Specifically, some solutions split this cluster into an afternoon shift cluster and an evening shift cluster. This is confirmed in Figure A.2, if one examines the ten-clusters solution (Cluster 6 and 7 split).

We finally tested alternative clustering algorithms such as the Beta-Flexible and the Partition around the Medoids. The results were highly consistent with the Ward solution and we decided to retain the Ward criterion because of consistency with most sociological sequence analysis research (upon requests).

Pooled versus country-specific cluster analysis

To ensure that the main sequence patterns we identified are not an artifact of the fact that we conducted the cluster analysis on a sample that contains cases pooled from all countries and time periods simultaneously, we conducted supplemental analyses in which clusters are identified in each country separately. We executed each of the country-specific cluster analyses using the same sequence alignment and clustering procedures as were used in the main pooled analysis.

These supplemental analyses classified cases in a similar manner as did the current analysis. In the separate and pooled cluster solutions, a given pair of cases in a given country were placed relative to each other the same way (i.e., they were placed in the same cluster in both solutions or they were placed in different clusters in both solutions) 83% of the time, on average. This suggests a high level agreement between country-specific and pooled cluster solutions. For reference, the level of agreement in the classification of within-country case pairs between the pooled analysis and each country-specific analysis are presented in Table A.1. Country-specific tempograms for the eight-cluster solutions are available upon request.

Note on the Sequence Index Plot

While the sequence distribution plot shows the percentage of individuals engaged in certain activities at a certain time, the index plot simply displays the individual sequences throughout the day Gabadinho et al. (2011). In order to keep the sequence index plot simple, we simply sorted the sequences according the cluster's medoid. The medoid is the most central sequence (the one with the minimal sum of distances to all other sequences) Gabadinho et al. (2011); Kaufman & Rousseeuw (1990). For each clusters, we ordered each sequences according to their distance to the medoid. In order to give a good representation of the sequences included in each clusters, we chose the 50th sequences closest to the medoid (including the medoid), then the 200th to the 250th sequence, then the 500th to the 550th and finally the 1000th to the 1025th sequence. These numbers, though arbitrary, decomposed best the different clusters.

Supplemental Tables

Table A.1: Pairwise Cluster Agreement by Country, Pooled versus Separate Country Analysis

	Countries	Cluster Agreement
1	AU	0.816
2	AT	0.848
3	BE	0.82
4	BL	0.812
5	CA	0.804
6	CZ	0.825
7	DE	0.845
8	DE East	0.854
9	DE West	0.847
10	DK	0.812
11	FI	0.825
12	FR	0.85
13	IN	0.791
14	IL	0.849
15	IT	0.883
16	NL	0.827
17	PE	0.85
18	PL	0.844
19	SI	0.812
20	ZA	0.832
21	ES	0.846
22	US	0.83
23	UK	0.811
	average	0.832

Table A.2: Distribution of Hamming-Based Clusters across Countries in the Harmonized MTUS Data (Row Percentage).

	A	B	C	D	E	F	G	H
Australia	0.32	0.07	0.06	0.04	0.10	0.13	0.14	0.14
Austria	0.14	0.03	0.07	0.28	0.08	0.11	0.16	0.13
Belgium	0.40	0.11	0.05	0.04	0.08	0.06	0.12	0.16
Bulgaria	0.38	0.05	0.11	0.03	0.08	0.14	0.11	0.10
Canada	0.35	0.06	0.09	0.04	0.09	0.18	0.11	0.09
Czech	0.17	0.05	0.36	0.06	0.10	0.06	0.07	0.12
Germany	0.26	0.05	0.16	0.10	0.09	0.09	0.13	0.12
Germany East	0.13	0.03	0.34	0.04	0.13	0.07	0.07	0.20
Germany West	0.27	0.09	0.09	0.04	0.10	0.07	0.15	0.18
Denmark	0.32	0.06	0.05	0.05	0.09	0.17	0.16	0.10
Finland	0.23	0.05	0.19	0.05	0.10	0.17	0.13	0.07
France	0.30	0.09	0.04	0.04	0.10	0.15	0.17	0.12
India	0.16	0.15	0.02	0.05	0.10	0.09	0.09	0.34
Israel	0.21	0.08	0.11	0.11	0.06	0.17	0.13	0.13
Italy	0.19	0.18	0.06	0.10	0.08	0.09	0.16	0.15
Netherlands	0.26	0.06	0.03	0.07	0.10	0.18	0.19	0.11
Peru	0.12	0.22	0.03	0.04	0.08	0.09	0.16	0.27
Poland	0.14	0.07	0.23	0.05	0.10	0.10	0.15	0.15
Slovenia	0.07	0.05	0.36	0.04	0.11	0.06	0.15	0.16
South Africa	0.31	0.04	0.08	0.06	0.06	0.18	0.12	0.14
Spain	0.11	0.24	0.09	0.05	0.08	0.14	0.23	0.06
USA	0.32	0.06	0.12	0.03	0.10	0.16	0.13	0.09
United Kingdom	0.34	0.05	0.03	0.05	0.10	0.17	0.16	0.09
Overall	0.25%	0.08%	0.12%	0.06%	0.09%	0.13%	0.14%	0.13%

χ^2 = 6288.6, df = 154, p.value $<$ 0.001, Cramer V = 0.169

Clusters: *A* = Paid I Standard, *B* = Paid II Long, *C* = Paid III Morning, *D* = Shift I Morning *E* = Shift II Evening, *F* = Leisure, *G* = Unpaid Work I, *H* = Unpaid Work II

Note: N = 31,089

Table A.3: Distribution of Hamming-Based Clusters across Time Periods in the Harmonized MTUS Data (Row Percentage).

	A	B	C	D	E	F	G	H
before 1995	0.24	0.08	0.14	0.07	0.09	0.10	0.14	0.13
after 1995	0.26	0.08	0.08	0.05	0.09	0.17	0.15	0.12
Overall	0.25%	0.08%	0.12%	0.06%	0.09%	0.13%	0.14%	0.13%

χ^2 = 660.6, df = 7, p.value $<$ 0.001, Cramer V = 0.145
Clusters: *A* = Paid I Standard, *B* = Paid II Long, *C* = Paid III Morning, *D* = Shift I Morning *E* = Shift II Evening, *F* = Leisure, *G* = Unpaid Work I, *H* = Unpaid Work II
Note: N = 31,089

Table A.4: Average Amount of Time Spent in Certain Activities, by Hamming-Based Cluster

	Clusters	Eat	Leisure	Missing	Paid	Personal	TV	Travel	Unpaid
1	A. Paid I Standard	01:12	01:26	00:01	08:37	01:21	01:01	01:04	01:14
2	B. Paid II Long	01:13	01:01	00:00	09:21	01:48	00:30	01:03	00:59
3	C. Paid III Morning	01:02	01:34	00:00	07:50	01:07	01:15	00:54	02:15
4	D. Shift I Morning	01:37	02:14	00:00	04:58	01:38	01:13	01:11	03:05
5	E. Shift II Evening	01:11	01:37	00:01	05:24	02:20	00:52	01:21	03:11
6	F. Leisure	01:20	04:43	00:12	00:22	03:46	02:08	00:49	02:36
7	G. Unpaid Work I	01:31	03:21	00:01	00:08	02:44	01:27	00:28	06:16
8	H. Unpaid Work II	01:27	01:51	00:00	00:07	01:53	01:32	00:23	08:42

Note: N = 31,089

Table A.5: Average Amount of Time Spent Doing Paid and Unpaid Work, by Hamming-Based Cluster.

	Clusters	Paid	Unpaid	Total Work	Ratio $\frac{Paid}{Total}$
1	A. Paid I Standard	08:37	01:14	09:51	0.87
2	B. Paid II Long	09:21	00:59	10:21	0.90
3	C. Paid III Morning	07:50	02:15	10:05	0.78
4	D. Shift I Morning	04:58	03:05	08:04	0.62
5	E. Shift II Evening	05:24	03:11	08:35	0.63
6	F. Leisure	00:22	02:36	02:58	0.12
7	G. Unpaid Work I	00:08	06:16	06:24	0.02
8	H. Unpaid Work II	00:07	08:42	08:50	0.01

Note: N = 31,089

Table A.6: Average Paid Work Starting and Ending Time, by Hamming-Based Cluster.

Clusters	Average start	Average end
A. Paid I Standard	07:50	17:29
B. Paid II Long	08:25	20:14
C. Paid III Morning	06:44	15:07
D. Shift I Morning	08:04	14:23
E. Shift II Evening	11:47	19:11
F. Leisure	11:45	15:37
G. Unpaid Work I	12:34	15:39
H. Unpaid Work II	11:12	15:39

N = 31,089
Note: Computed on the first episode of work.
Analysis restricted for individuals engaged in paid work.

Table A.7: Proportion of Individuals Engaged in Paid Work at Different Times of the Day Across Clusters

	Clusters	value	06:00	08:00	17:00	19:00
1	A. Paid I Standard	Paid	5.57%	65.44%	46.97%	6.22%
2	B. Paid II Long	Paid	3.46%	43.45%	73.8%	57.15%
3	C. Paid III Morning	Paid	34.24%	95.77%	1%	1.08%
4	D. Shift I Morning	Paid	6.79%	55.15%	3.61%	5.18%
5	E. Shift II Evening	Paid	5.7%	13.27%	57.71%	42.81%
6	F. Leisure	Paid	4.02%	1.4%	1.91%	1.52%
7	G. Unpaid Work I	Paid	0.72%	0.79%	0.95%	0.7%
8	H. Unpaid Work II	Paid	0.67%	1.2%	1.31%	0.41%

N = 31,089

Table A.8: Average Unpaid Starting and Ending Time, by Hamming-Based Cluster.

	Clusters	Average start	Average end
1	A. Paid I Standard	11:50	18:55
2	B. Paid II Long	10:50	17:26
3	C. Paid III Morning	13:12	19:31
4	D. Shift I Morning	09:59	19:23
5	E. Shift II Evening	09:01	17:15
6	F. Leisure	09:50	17:47
7	G. Unpaid Work I	08:18	19:24
8	H. Unpaid Work II	07:10	20:03

N = 31,089
Note: Computed on the first episode of unpaid work.
Analysis restricted for individuals engaged in unpaid work.

Table A.9: Proportion of Individuals Engaged in Unpaid Work at Different Times of the Day Across Clusters

	Clusters	value	06:00	08:00	17:00	19:00
1	A. Paid I Standard	Unpaid	5.43%	5.17%	12.85%	24.36%
2	B. Paid II Long	Unpaid	2.55%	9.4%	5.93%	9.12%
3	C. Paid III Morning	Unpaid	9.47%	0.42%	42.71%	32.66%
4	D. Shift I Morning	Unpaid	7.87%	13.21%	40.59%	30.62%
5	E. Shift II Evening	Unpaid	6.12%	27.19%	13.93%	14.72%
6	F. Leisure	Unpaid	4.19%	16.61%	21.76%	16.15%
7	G. Unpaid Work I	Unpaid	4.44%	34.78%	37.4%	31.51%
8	H. Unpaid Work II	Unpaid	16.07%	63.99%	60.35%	47%

N = 31,089

Table A.10: Average Wake-Up Time, by Hamming-Based Cluster.

	Clusters	Average
1	A. Paid I Standard	06:51
2	B. Paid II Long	07:21
3	C. Paid III Morning	06:14
4	D. Shift I Morning	06:52
5	E. Shift II Evening	07:40
6	F. Leisure	08:07
7	G. Unpaid Work I	07:51
8	H. Unpaid Work II	06:57
	Average	07:14

Note: Computed on the last episode of personal care.
N = 31,089

Table A.11: Average Amount of Time Spent in Certain Activities for the Full Sample.

	variable	mean	hours	error	CI 95% lower	CI 95% upper	%
1	Eat	81.36	01:21	0.23	81.13	81.58	8.50
2	Leisure	138.63	02:18	0.52	138.11	139.16	14.40
3	Missing	2.52	00:02	0.12	2.40	2.64	0.30
4	Paid	264.11	04:24	1.00	263.11	265.12	27.50
5	Personal	129.21	02:09	0.41	128.80	129.62	13.50
6	TV	80.04	01:20	0.37	79.68	80.41	8.30
7	Travel	54.60	00:54	0.27	54.33	54.88	5.70
8	Unpaid	209.52	03:29	0.79	208.73	210.32	21.80

N = 225,551

Note: Unweighted analysis.

Table A.12: Dissimilarity-based Discrepancy Analysis

	Country	p.value
Pseudo F	39.635	0.001
Pseudo R2	0.027	0.001
	Period	**p.value**
Pseudo F	77.859	0.001
Pseudo R2	0.002	0.001

Note: Number of Permuations = 1,000

Supplemental Figures

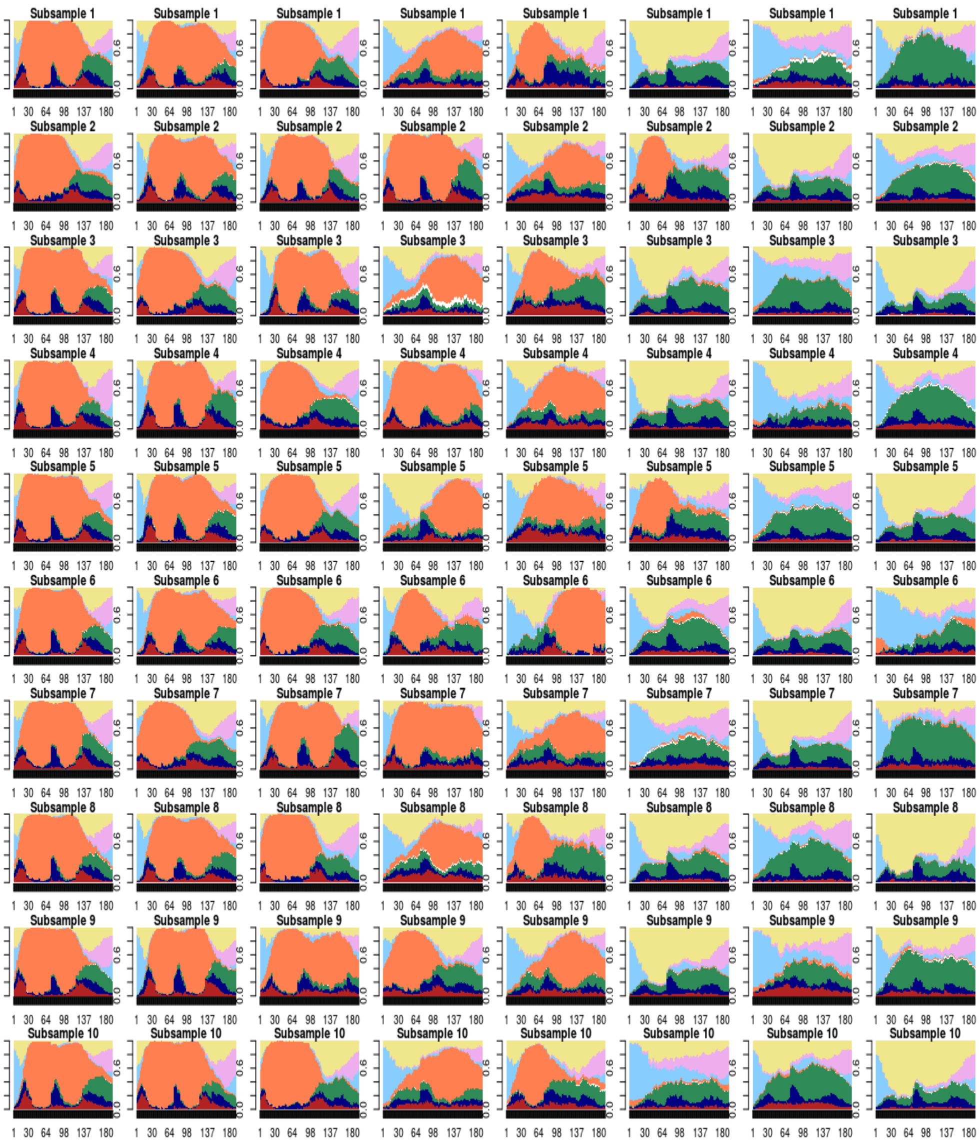

Figure A.1: State Distribution Graphs of Ten Hamming-Distance based Clusters Performed on Ten Different Independent Subsamples. Subsamples N = 3,700

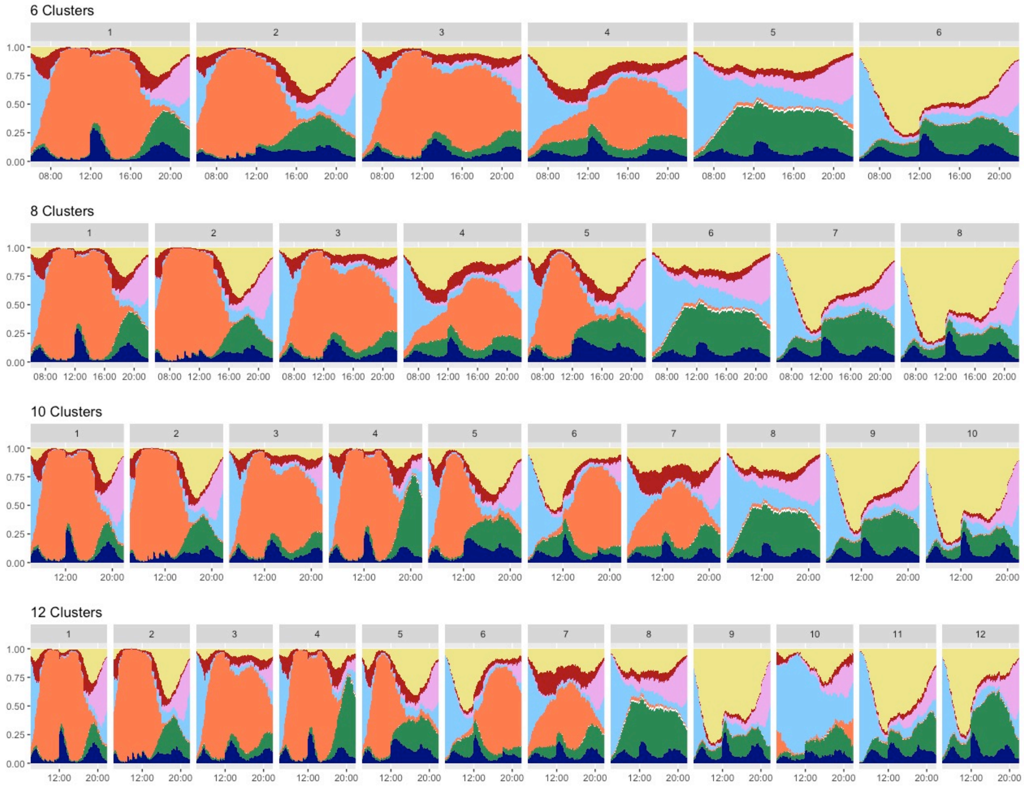

Figure A.2: State Distribution Graphs Showing Different Clustering Solution. Hamming-Distance-Based Clusters. N = 31,089

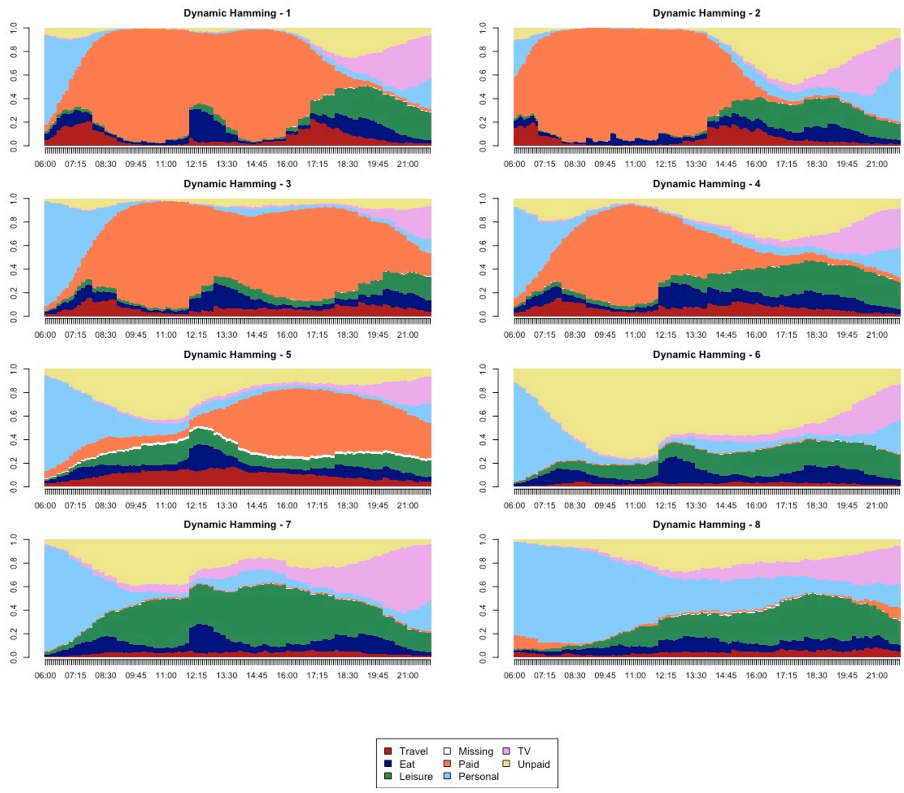

Figure A.3: State Distribution Graphs of Eight Dynamic Hamming-Distance-Based Cluster.

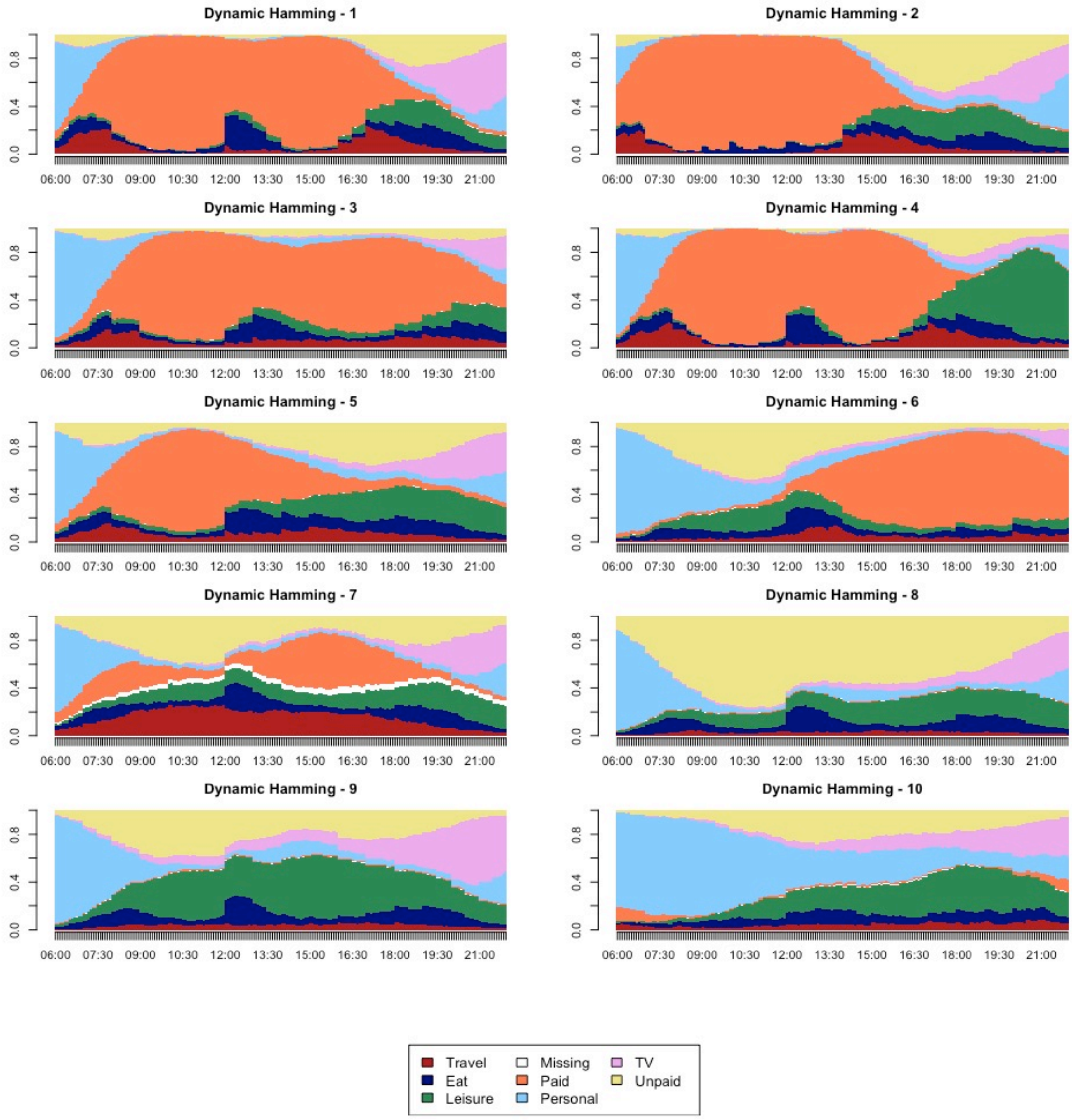

Figure A.4: State Distribution Graphs of Ten Dynamic Hamming-Distance-Based Cluster.

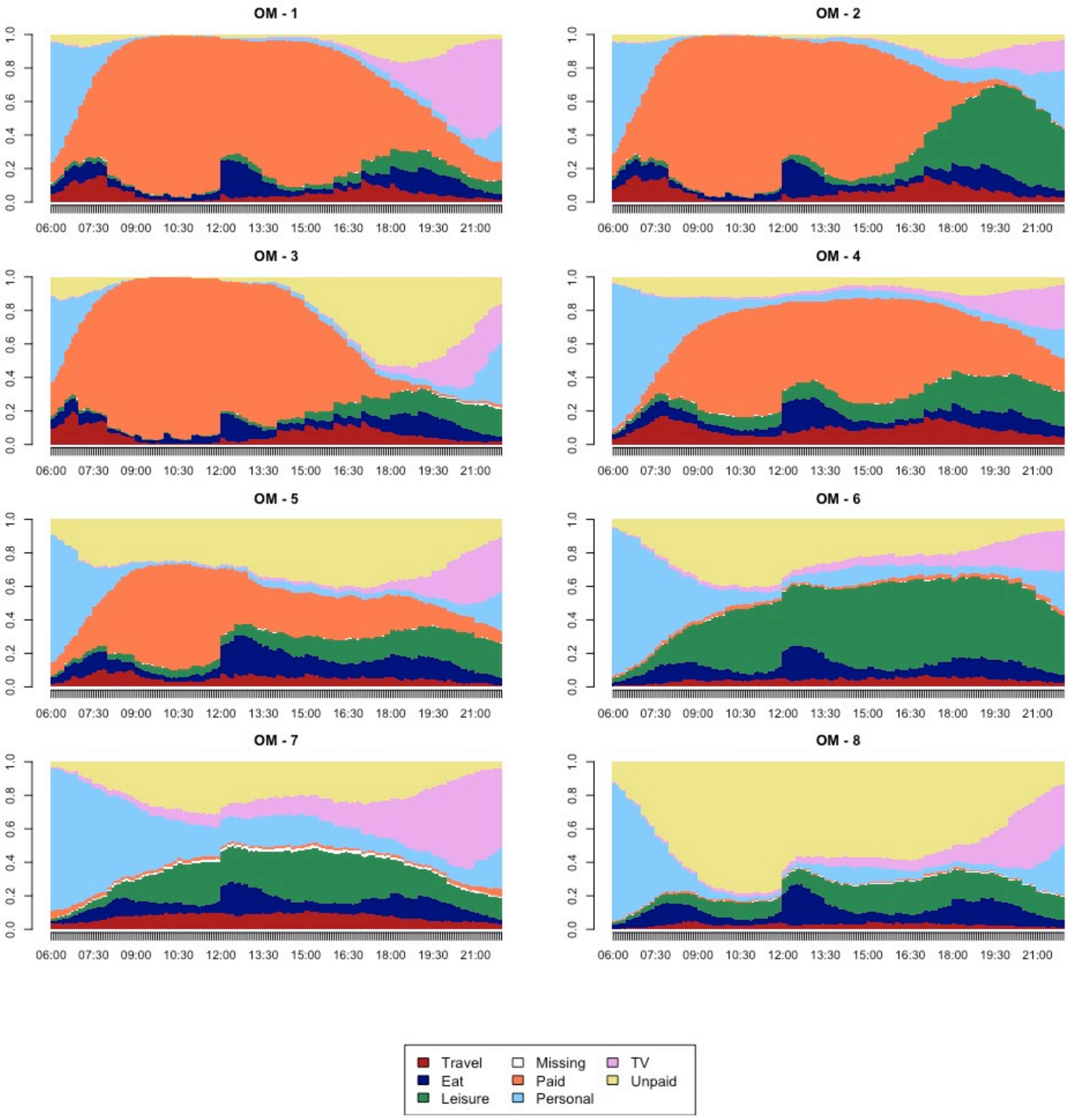

Figure A.5: State Distribution Graphs of Eight OM-Distance-Based Cluster.

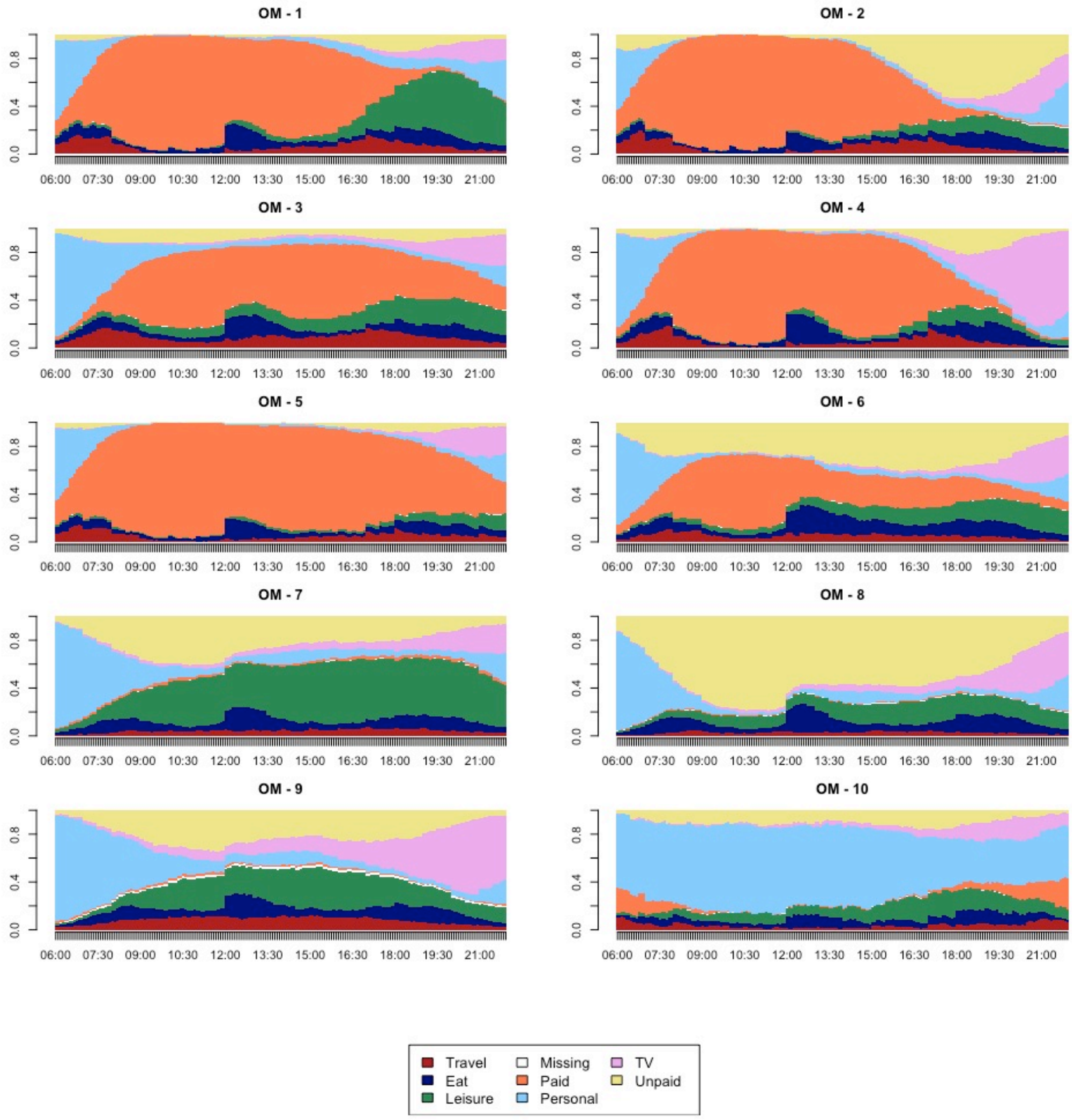

Figure A.6: State Distribution Graphs of Ten OM-Distance-Based Cluster.

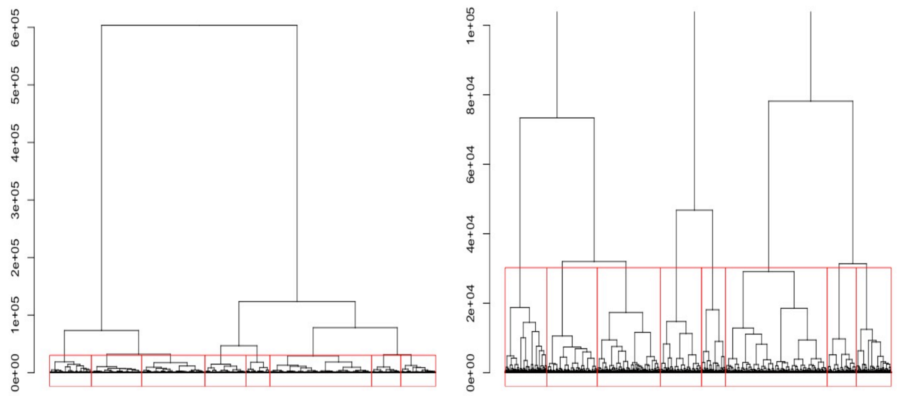

Figure A.7: Dendrograms Showing the Hierarchical Clustering from Hamming-Based Activity Sequence Distances. (a) Full Dendrogram, (b) Bottom of the Tree. N = 31,089.

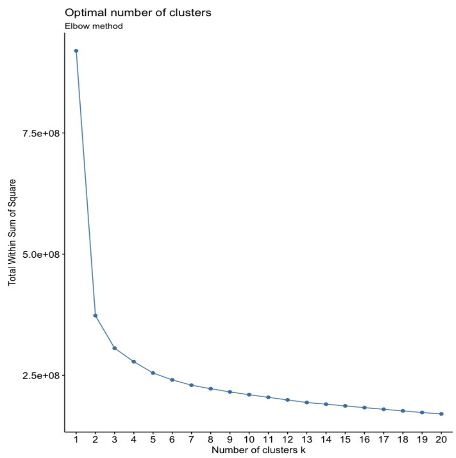

Figure A.8: Elbow criterion of the Ward Hierarchical Clustering. Within Sum of Squares. Performed on a random subsample of 1,000 cases.

]

Data Information

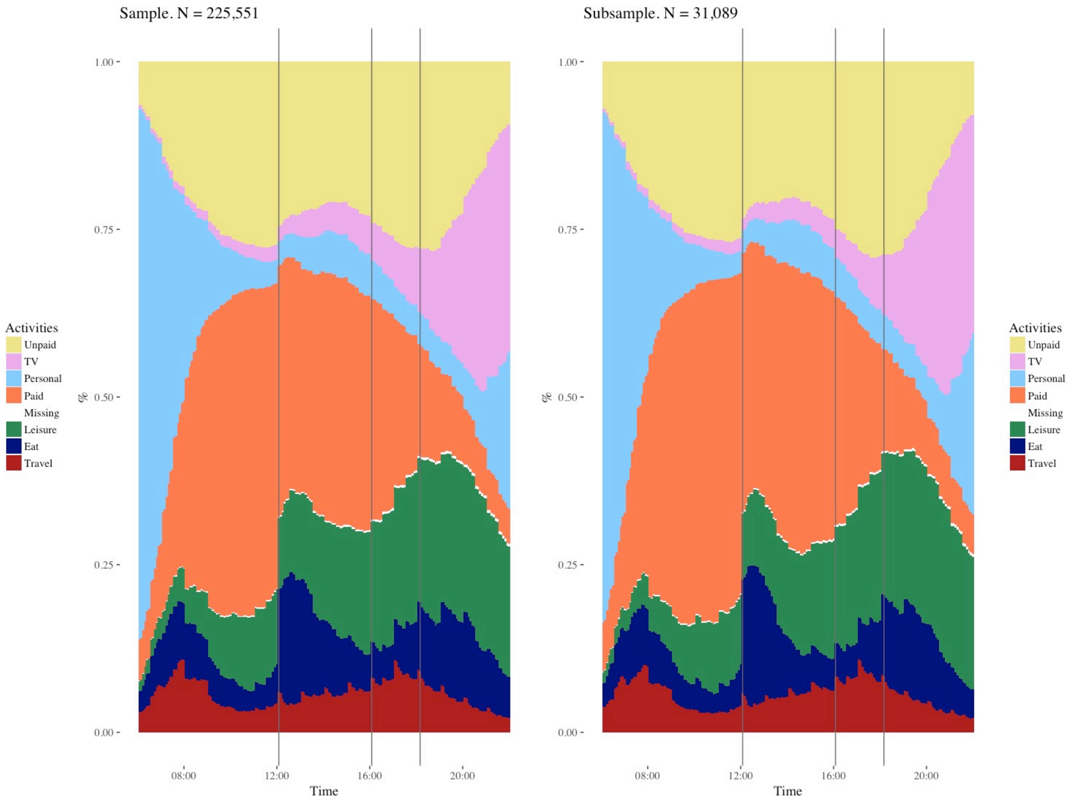

Figure A.9: State Distribution Graphs Showing the Proportion of Individuals Engaging in Certain Activities at Each Time Point throughout the Day Comparing the Original Sample and the Analytical Subsample.

Table A.13: Number of Cases in the Sample and Subsample

	Sample		Subsample	
Country	after 1995	before 1995	after 1995	before 1995
Australia	3575	926	1000	926
Austria	0	14349	0	1000
Belgium	0	1551	0	1000
Bulgaria	5204	1438	1000	1000
Canada	7329	0	1000	0
Czech	0	894	0	894
Denmark	7174	0	1000	0
Finland	2678	4209	1000	1000
France	11553	11034	1000	1000
Germany	0	8916	0	1000
Germany East	0	1429	0	1000
Germany West	0	1358	0	1000
India	17440	0	1000	0
Israel	0	1586	0	1000
Italy	0	8642	0	1000
Netherlands	5833	8687	1000	1000
Peru	0	269	0	269
Poland	16591	1617	1000	1000
Slovenia	0	1420	0	1000
South Africa	7403	0	1000	0
Spain	36905	1965	1000	1000
USA	9558	3666	1000	1000
United Kingdom	12739	7613	1000	1000
N	225,551		31,089	

Table A.14: Description of the Survey Characteristics.

country		survey	Szalai*	N
UnitedKingdom	UK	1961	0	2373
UnitedKingdom	UK	1974	0	2351
UnitedKingdom	UK	1987	0	1490
UnitedKingdom	UK	2000	0	7162
UnitedKingdom	UK	2015	0	5577
UnitedKingdom	UK	1983	0	1399
Australia	AU	1974	0	926
Australia	AU	2006	0	3575
India	IN	1998	0	17440
Poland	PL	1965	1	1617
Poland	PL	2003	0	16591
Czech	CZ	1965	1	894
Israel	IL	1991	0	1586
USA	US	1965	1	896
USA	US	1975	0	1440
USA	US	1985	0	1330
USA	US	2003	0	5954
USA	US	2012	0	3604
Denmark	DK	2001	0	7174
Belgium	BE	1966	1	1551
Slovenia	SI	1965	1	1420
Italy	IT	1989	0	8642
South Africa	ZA	2000	0	7403
Finland	FI	1979	0	4209
Finland	FI	2009	0	2678
Bulgaria	BL	1965	1	1438
Bulgaria	BL	2001	0	5204
France	FR	1966	1	1932
France	FR	1985	0	9102
France	FR	2010	0	11553
Germany West	DE West	1965	1	1358
Germany East	DE East	1966	1	1429
Germany	DE	1991	0	8916
Spain	ES	1992	0	1965
Spain	ES	1997	0	1963
Spain	ES	2002	0	23938
Spain	ES	2008	0	2452
Spain	ES	2009	0	8552
Austria	AT	1992	0	14349
Netherlands	NL	1975	0	1050
Netherlands	NL	1980	0	2193
Netherlands	NL	1985	0	2669
Netherlands	NL	1990	0	2775
Netherlands	NL	1995	0	2724
Netherlands	NL	2000	0	1456
Netherlands	NL	2005	0	1653
Peru	PE	1966	1	269
Canada	CA	2010	0	7329

N = 225,551

Note: Information about the surveys can be found at **https://www.timeuse.org/mtus/surveys**. *Szalai** indicates the surveys part of the Szalai comparative study, see Szalai (1972).

Table A.15: Average Amount of Time Spent in Certain Activities, by Country and Time Period.

Country	Period	Unpaid	TV	Personal	Paid	Missing	Leisure	Eat	Travel
Australia	before 1995	03:36	01:27	01:59	04:23	00:00	02:04	01:27	01:01
Australia	after 1995	03:27	01:35	02:05	04:44	00:01	01:58	01:02	01:04
Austria	before 1995	03:39	01:40	01:24	03:53	00:00	02:45	02:06	00:30
Belgium	before 1995	03:19	01:12	01:42	05:56	00:00	02:00	01:39	00:08
Bulgaria	before 1995	02:27	00:29	01:26	06:55	00:00	02:17	01:20	01:02
Bulgaria	after 1995	03:23	01:54	02:13	03:51	00:00	02:00	01:39	00:57
Canada	after 1995	03:12	01:28	02:00	04:51	00:00	02:33	00:57	00:54
Czech	before 1995	03:59	00:53	01:31	06:05	00:00	01:45	00:59	00:44
Germany	before 1995	03:41	01:12	01:34	05:12	00:00	02:18	01:08	00:51
Germany East	before 1995	04:26	01:03	01:40	05:33	00:00	01:30	01:00	00:43
Germany West	before 1995	03:41	01:00	01:51	04:45	00:00	02:19	01:34	00:44
Denmark	after 1995	03:05	01:41	02:18	04:26	00:00	02:02	01:13	01:12
Finland	before 1995	03:00	01:02	01:34	05:31	00:01	02:51	01:16	00:40
Finland	after 1995	03:01	01:28	02:08	04:26	00:05	02:44	01:11	00:53
France	before 1995	03:27	01:09	02:10	04:36	00:00	02:11	01:26	00:57
France	after 1995	02:55	01:13	02:10	04:11	00:05	02:23	01:36	01:24
India	after 1995	04:55	00:48	02:02	03:42	00:00	02:35	01:20	00:34
Israel	before 1995	03:15	01:30	02:25	04:38	00:10	02:07	00:54	00:57
Italy	before 1995	03:32	01:09	02:08	04:23	00:00	02:22	01:41	00:42
Netherlands	before 1995	04:12	01:04	02:19	03:18	00:00	02:56	01:18	00:49
Netherlands	after 1995	03:26	01:03	02:18	04:13	00:11	02:28	01:12	01:06
Peru	before 1995	04:43	00:46	02:36	04:03	00:00	01:24	01:39	00:45
Poland	before 1995	04:07	00:59	01:40	05:41	00:00	01:32	01:06	00:52
Poland	after 1995	03:54	01:49	01:59	03:57	00:00	02:00	01:23	00:55
Slovenia	before 1995	03:47	00:38	01:58	04:48	00:00	02:45	01:14	00:46
SouthAfrica	after 1995	03:15	01:25	02:34	04:10	00:00	02:18	01:06	01:08
Spain	before 1995	03:15	00:59	02:39	04:16	00:00	02:24	01:24	01:00
Spain	after 1995	03:13	01:05	02:36	04:28	00:00	02:13	01:21	01:00
USA	before 1995	03:05	01:29	02:17	05:06	00:01	01:51	01:16	00:50
USA	after 1995	02:56	01:49	02:15	05:14	00:01	02:04	00:50	00:49
UnitedKingdom	before 1995	02:59	01:39	02:02	04:27	00:30	02:14	01:23	00:43
UnitedKingdom	after 1995	03:03	01:40	02:21	04:19	00:09	02:07	01:07	01:11

N = 225,551. Unweighted Analysis.

Table A.16: Activity Schema

Activity Schema	Activities MTUS
Eat	(meals at home, meals at work, . . .)
Leisure	(general indoor leisure, general out-of-home leisure, reading, cinema, sport event, walking. . .)
Paid	(paid work, paid work at home, main job, second job, . . .)
Personal	(selfcare, sleep and naps, wash, dress, . . .)
TV	(TV, radio)
Travel	(travel to . . . , travel to work, etc)
Unpaid	(child care, adult care, cooking, cleaning, laundry, . . .)

Note: All relevant information about activities can be found in the Multinational Time Use Study User's guide and documentation.

Software Acknowledgment

This research would not have been possible without the open-source community that provided the statistical tools used in this paper. All the statistical analyses have been conducted in R. The sequence analyse used the library TraMineR. The graphics have been produced using ggplot2 and TraMineR. The clustering analyses have been performed using the libraries fastcluster, factoextra and WeightedCluster. Data manipulation have used the following libraries: data.table, dplyr, reshape.

Appendix B

Appendix. The Social Stratification of Time Use Patterns

Sample selection

Table B.1: Original Sample by Year and Family Status

	hhtype	1983	2015
1	couple w/ dep. kids	366	1354
2	couple without children	360	1806
3	single parent w/ dep. kids	13	210
4	single person	114	713
5	couple w/ dep + adult kids	123	307
6	other	334	979
	Total	1310	5369

The sample was filtered in several ways for the study. In order to run the sequence analysis clustering, I had to make the number of observation in the two samples more alike. The 2015 survey is a much larger survey, so I first took a random subsample of 1000 observations. Then, I discarded two household types: the “other” category and the couples with a mix of dependents and independents children. The other category grouped all complex households.

I finally removed all individuals under 30 years old and over 70 years. The reason was to capture individuals once their social class is pretty much fixed (after 30 years old).

Table B.2: Final Sample Size

	survey	N
1	1983	634
2	2015	867

Table B.3: Characteristics of the Sample (N)

	Sex	Social Class	1983 N	2015 N
1	Man	I Managerial Class	53	115
2	Man	II Middle Class	148	224
3	Man	III Working Class	63	66
4	Woman	I Managerial Class	90	109
5	Woman	II Middle Class	176	263
6	Woman	III Working Class	104	90

Table B.4: Characteristics of the Sample (%)

	Sex	Social Class	1983 %	2015 %
1	Man	I Managerial Class	0.20	0.28
2	Man	II Middle Class	0.56	0.55
3	Man	III Working Class	0.24	0.16
4	Woman	I Managerial Class	0.24	0.24
5	Woman	II Middle Class	0.48	0.57
6	Woman	III Working Class	0.28	0.19

Table B.5: Characteristics of the Sample (%) by Sex, Class and Family Status

	Sex	Social Class	Year	Couple with kids	Childless couples	Single parents	Singles
1	Man	I Managerial Class	1983	0.42	0.51	0.00	0.08
2	Man	I Managerial Class	2015	0.42	0.46	0.00	0.12
3	Man	II Middle Class	1983	0.41	0.52	0.00	0.07
4	Man	II Middle Class	2015	0.35	0.50	0.01	0.14
5	Man	III Working Class	1983	0.44	0.38	0.00	0.17
6	Man	III Working Class	2015	0.30	0.32	0.00	0.38
7	Woman	I Managerial Class	1983	0.34	0.38	0.01	0.27
8	Woman	I Managerial Class	2015	0.37	0.48	0.03	0.13
9	Woman	II Middle Class	1983	0.47	0.44	0.01	0.09
10	Woman	II Middle Class	2015	0.32	0.42	0.06	0.21
11	Woman	III Working Class	1983	0.32	0.42	0.03	0.23
12	Woman	III Working Class	2015	0.23	0.33	0.12	0.31

Supplemental Regression

Table B.6: Multinomial Regression on 13 clusters schema - Men. Weekdays.

	Dependent variable:											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Middle Class	0.571^{*}	17.976^{***}	1.155	−0.019	1.121^{*}	−0.254	1.651^{**}	0.208	0.451	0.467	0.553	0.320
Working Class	0.397	17.192^{***}	1.045	−13.147	1.765^{**}	−1.148	0.887	0.503	1.366^{**}	1.302^{*}	1.267^{**}	1.483^{*}
Year 2015	-0.572^{*}	0.076	-1.425^{*}	0.173	0.560	0.161	−0.045	−0.057	0.291	−0.416	−0.041	0.248
Childless Couples	0.004	0.169	−1.044	−0.137	0.613^{+}	-1.299^{+}	0.460	1.008^{*}	1.196^{**}	2.021^{***}	1.179^{**}	0.833^{+}
Single Person	0.394	0.239	-15.026^{***}	−0.391	−0.086	−0.865	1.259^{*}	1.739^{**}	0.755	2.168^{***}	1.457^{**}	0.954
Constant	−0.060	-20.156^{***}	-1.934^{*}	-1.232^{*}	-2.610^{***}	-1.432^{*}	-2.782^{***}	-2.338^{***}	-2.370^{***}	-2.824^{***}	-1.954^{***}	-2.737^{***}
Akaike Inf. Crit.	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512	2,824.512

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Ref = Paid I. (1) = Paid II, (2) Shift Evening, (3) Shift Night, (4), Shift Afternoon, (5) Shift Morning, (6) Childcare, (7) Unpaid I, (8) Unpaid II, (9) Unpaid III, (10) Unpaid IV, (11) Leisure, (12) Other

Table B.7: Multinomial Regression on 13 clusters schema - Men. Weekends.

	Dependent variable:											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Middle Class	0.754	0.079	1.062	−0.416	−0.047	0.234	−1.983**	−0.212	0.334	−0.383	−0.156	−0.352
Working Class	−0.554	0.562	−0.061	0.291	−1.118	−0.692	−1.702*	−1.021*	−0.071	−1.270**	0.094	−1.156*
Year 2015	0.491	−0.523	−0.229	1.430	0.617	−0.365	2.315*	−0.010	0.360	−0.654*	−0.457	0.371
Childless Couples	−0.436	−0.684	−1.774*	−0.807	0.291	−0.787*	−2.655***	−0.279	0.009	−0.509+	0.155	−0.382
Single Person	−0.050	−1.480	−11.793	−12.038	1.423+	−0.233	−2.025+	0.342	−0.105	−0.303	−0.271	0.281
Constant	−2.501**	−1.595*	−2.465*	−3.388**	−2.967**	−0.620	−1.910+	−0.215	−1.424**	0.533	−0.298	−0.868+
Akaike Inf. Crit.	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682	2,806.682

Note: + p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Ref = Leisure. (1) Paid I, (2) = Paid II, (3) Shift Evening, (4) Shift Night, (5), Shift Afternoon, (6) Shift Morning, (7) Childcare, (8) Unpaid I, (9) Unpaid II, (10) Unpaid III, (11) Unpaid IV, (12) Other

Table B.8: Multinomial Regression on 13 clusters schema - Women. Weekdays.

	Dependent variable:											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Middle Class	0.086	18.605***	15.459	−0.099	0.298	−0.456	−0.098	−0.734	−0.120	−0.256	0.039	−0.485
Working Class	1.856*	21.555***	17.517	1.967*	2.198*	1.804*	2.767***	2.071*	2.302**	2.144*	2.246**	1.603+
Year 2015	−0.623+	1.219	−2.054	−0.604	−0.948*	0.012	−1.014**	−0.462	−1.213***	−1.451***	−1.009*	−0.608
Childless Couples	−0.665+	0.320	11.495	−0.743	−1.299**	−3.449***	−0.867*	0.213	−0.067	1.070+	0.489	−0.327
Single Person	−1.571*	−0.823	−6.416***	−1.952+	−1.190	−2.959***	−2.073*	−0.134	−1.347+	−20.601***	0.083	−0.544
Constant	−0.439	−17.695***	12.019	−0.630	−0.764	−3.361***	−0.782	0.601	0.015	1.478*	1.523*	0.023
Constant	1.325**	−21.548***	−28.481	0.363	0.974+	1.752***	1.511**	0.024	1.498**	−0.259	−0.424	0.395
Akaike Inf. Crit.	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213	3,596.213
Note:												+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Ref = Paid I. (1) = Paid II, (2) Shift Evening, (3) Shift Night, (4), Shift Afternoon, (5) Shift Morning, (6) Childcare, (7) Unpaid I, (8) Unpaid II, (9) Unpaid III, (10) Unpaid IV, (11) Leisure, (12) Other

Table B.9: Multinomial Regression on 13 clusters schema - Women. Weekends.

	Dependent variable:											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Middle Class	0.052	19.225***	18.510***	11.698	0.557	0.309	−0.455	−0.072	0.356	0.203	−0.003	−0.237
Working Class	0.484	19.972***	20.119***	−0.800	−0.001	−0.400	0.282	0.613+	−0.443	0.731*	0.594	−0.070
Year 2015	20.997***	0.186	0.451	10.772	−0.327	0.783	0.641	−0.621*	0.348	−0.737**	−1.151***	0.131
Childless Couples	−0.183	−1.264	−1.505+	11.110	0.708	−0.441	−3.889***	−0.108	−0.280	−0.864**	−0.092	−0.746+
Single Person	0.541	−0.297	−21.467***	−3.554	−14.051***	1.109	−0.917	−0.771	−0.022	−0.094	−0.836	−0.253
Constant	−0.370	−21.324***	−22.381***	−6.869***	−18.402***	−0.328	−3.325***	−0.358	−0.044	−1.091**	−0.487	−0.433
Constant	−23.205***	−20.902***	−20.908***	−36.741	−2.828**	−2.426**	0.228	0.561	−0.917+	1.099**	0.582	−0.222
Akaike Inf. Crit.	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995	3,179.995
Note:												+ p<0.1; * p<0.05; ** p<0.01; *** p<0.001

Ref = Leisure. (1) Paid I, (2) = Paid II, (3) Shift Evening, (4) Shift Night, (5), Shift Afternoon, (6) Shift Morning, (7) Childcare, (8) Unpaid I, (9) Unpaid II, (10) Unpaid III, (11) Unpaid IV, (12) Other

Supplementary Figures

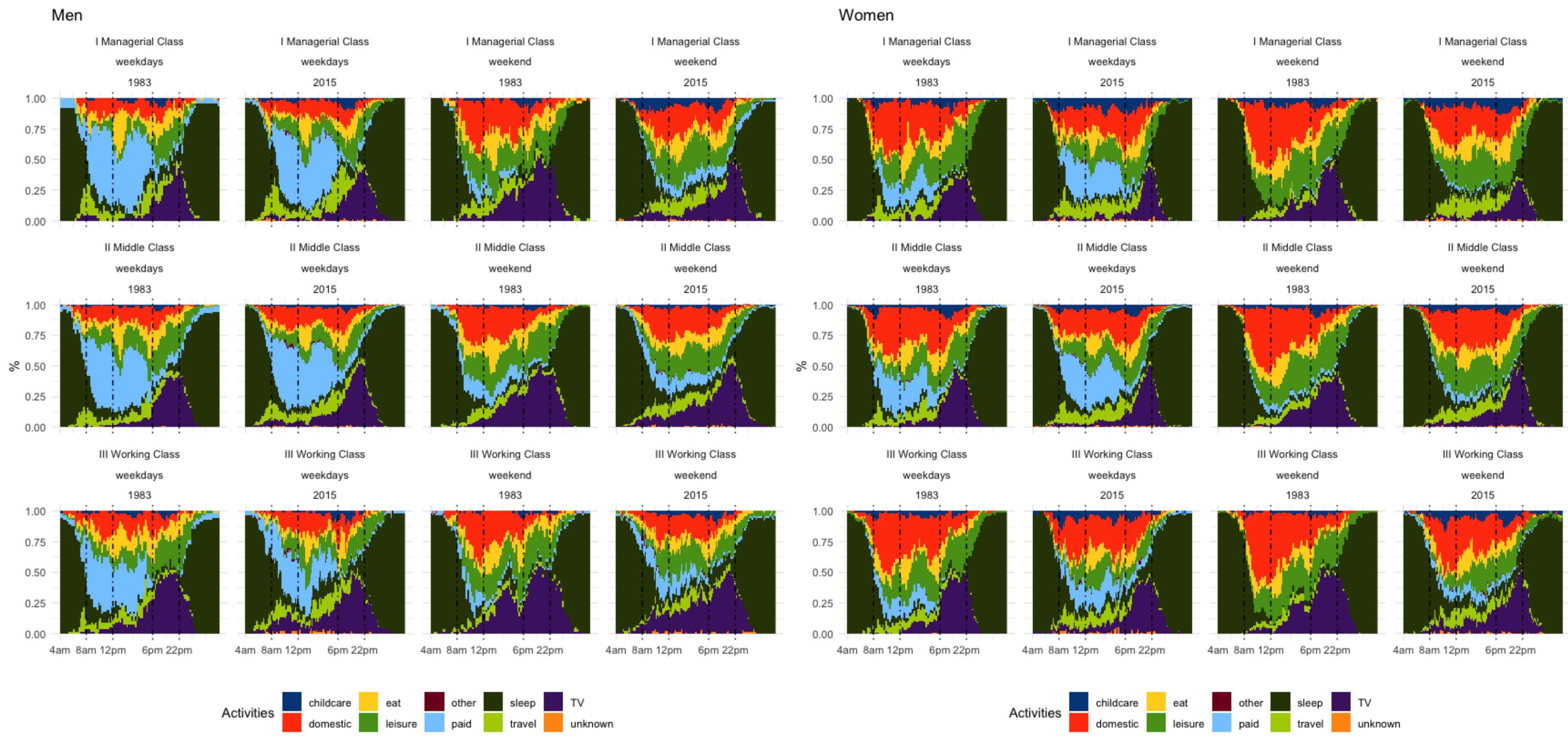

Figure B.1: State Distribution Graph Showing the Proportion of Individuals Engaging in Certain Activities at Each Time Point throughout the Day, by Class and Gender for the UK 1983-2015

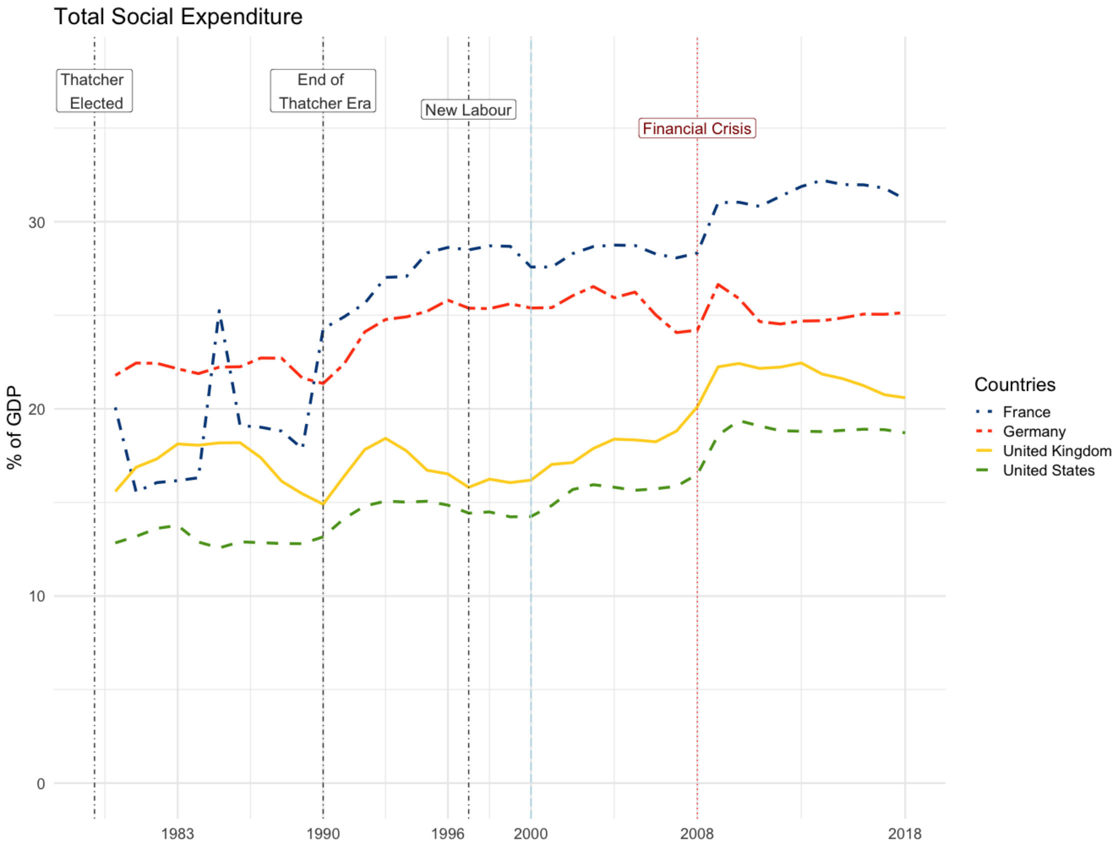

Figure B.2: Total Social Expenditures for 4 Countries. Computed from `stats.oecd.org`

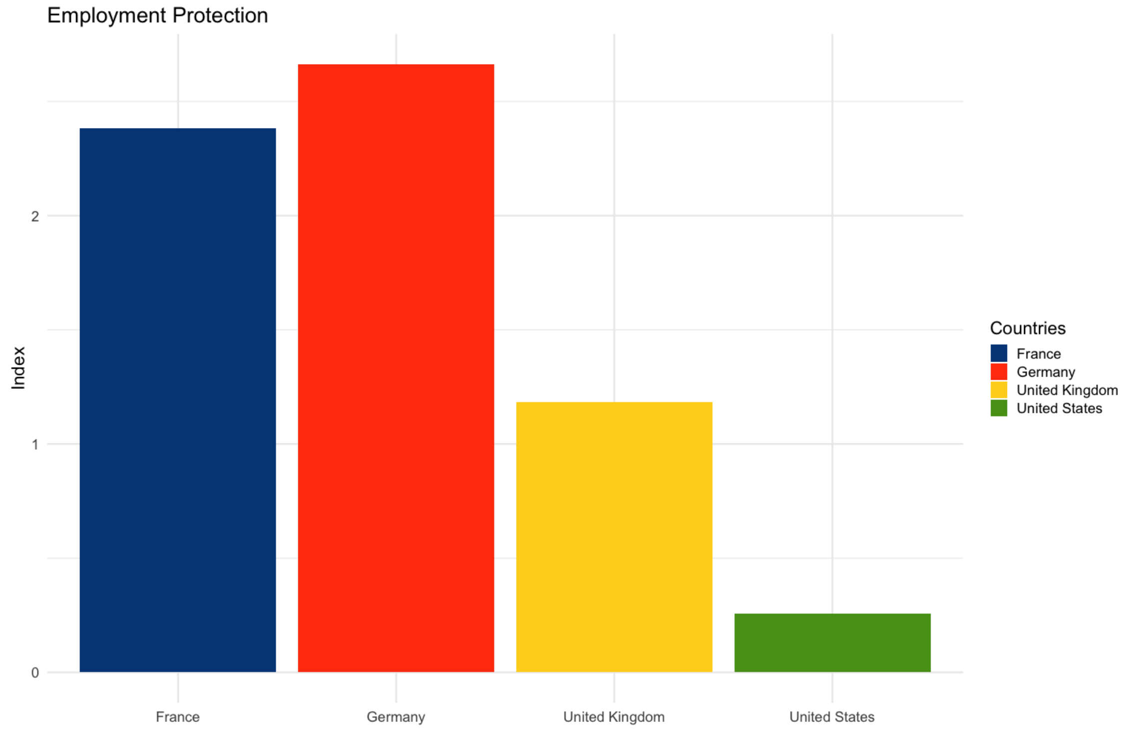

Figure B.3: Employment Protection Index for 4 Countries. Computed from `stats.oecd.org`

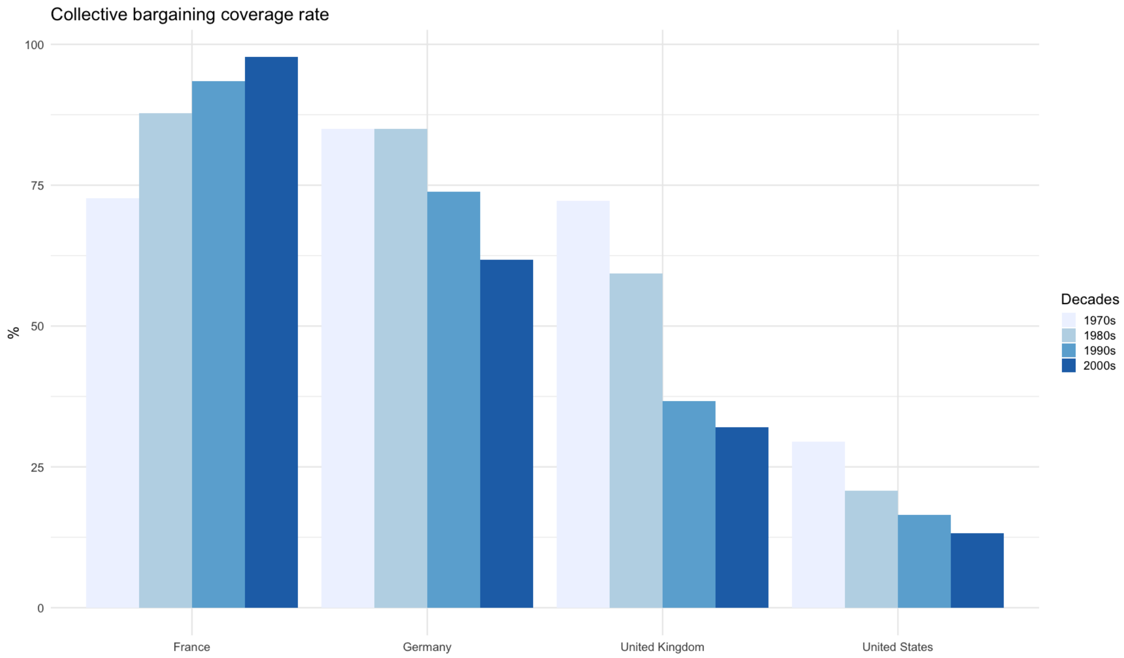

Figure B.4: Collective Bargaining Coverage Rate over Time. Computed from `stats.oecd.org`

Appendix C

Appendix. Alone Together: Gender Inequalities in Couple Time

Appendix C1. Characteristics of the Samples

The couple diary dataset used in the paper focuses on couples (adult) where both partners filled a time use diaries during the same day. We first selected all the individuals currently in a partnership (cohabiting or married), removing all the single person households as well as the "complex" households. We removed bad activity diaries (following the standard Multinational Time Use Study definition). There was 1840 women and 1771 men in a partnership. We then merged the male and female partners belonging to the same couple, with the condition that they filled their time use diaries during the same day. This reduced the number of male and female to 1654 couples. We removed couples with more than 50% of missing regarding the with whom information (detailed below), reducing the sample to 1522 couples. This is the basic sample with no age restriction. In the paper, this number is slighly reduced as we subset certain age categories.

Table C.1: Sample Selection UK 2015.

Household Type	Women Sample	Men Sample	Couple Sample	Couple Sample*
No children under 15 years old	1142	1146	1053	972
No children under 15 years old	698	625	601	550
Total	1840	1771	1654	1522

Note. * refers to the sample after removing the missing "with whom" (see below).

Appendix C2. Missing "with whom" information in the UK Time Use Survey 2015.

The missing "with whom" (copresence) information is measured by a dummy variable indicating if the respondent did not filled **any** of the with whom information (alone, spouse, children, other household member and other). If the respondent did not fill any of these info at time *t*, then the copresence information is missing during that interval of time.

Figure 1 shows the distribution of missing "with whom" information. We can see that about 85% of men and women have less than 25% of missing data. About 45% have no missing at all. About 5% of couple have between 25-50% missing copresence information. Less than 1% of men and women have complete missing.

Figure 2 shows the distribution of missing "with whom" throughout the day (4am to 4am). 0 on the y-axis means *no missing* and 1 means complete missingness. We can note that the missing information varies around 10% throughout the day, though stable. The men and women missing information closely follow one another.

Appendix C3. Sociodemographic characteristics of the Couple Time Use Diaries in the UK Time Use Survey 2015. A comparison with the Labour Force Survey.

The response rates for voluntary surveys have been steadily declining since the 1980s, reaching for most surveys a response rate between 40% to 60%. The UKTUS 2014-2015 reached a response rate of 40.4%. However, a substantial number of diaries were lost in the post, which would have yield a response rate of 45.5% (NatCen report).

In order to (partially) address the concern of selection bias in the sample of UKTUS couples, we decided to compare the survey with the Labour Force Survey. We use the

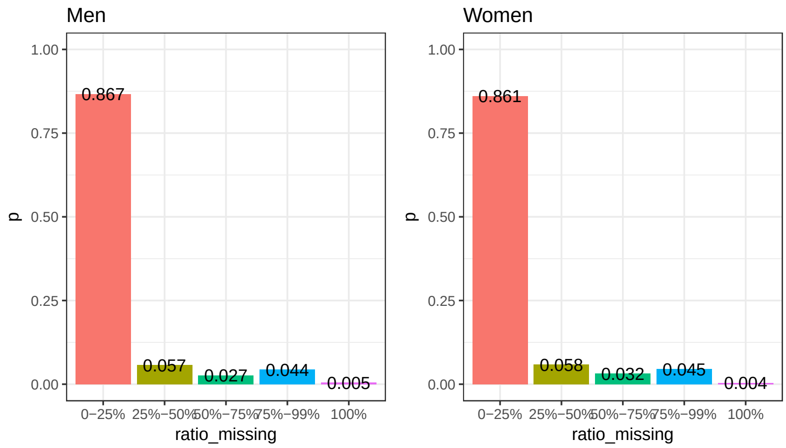

Figure C.1: Distribution of Missing WithWhom Information, Quartiles + Complete Missing (100)

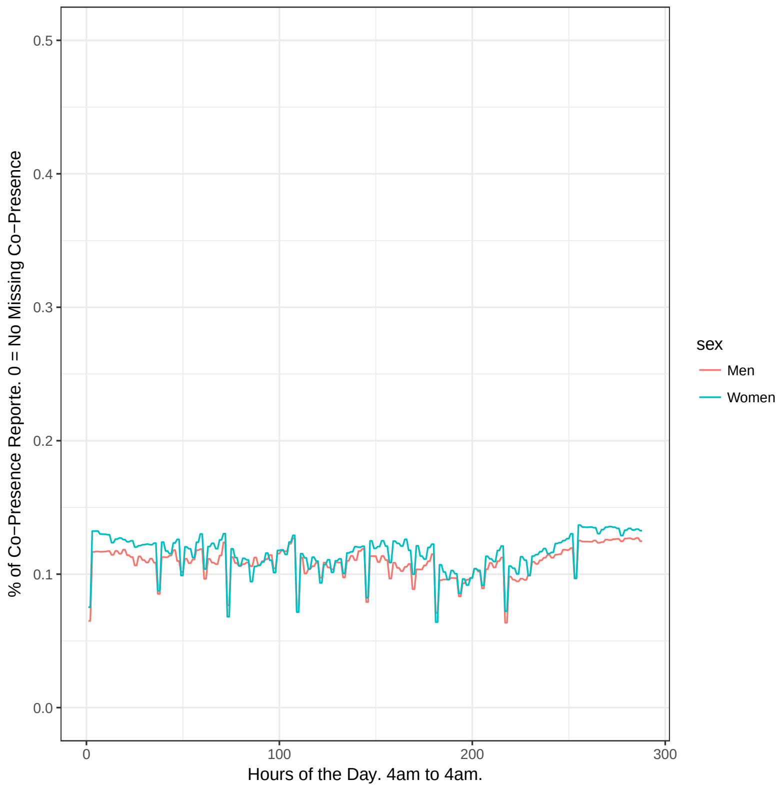

Figure C.2: Missing With Whom Information over the Day by Gender

Quarterly Labour Force Survey, July - September, 2014[1].

We are comparing the sample of heterosexual married men and women age between 19-70 years old. Althought, the UKTUS identifies cohabiting couples, this is not the case for the LFS, so we had to subset the sample of married individuals. The sample size is 1,040 men and women (belonging to the same couple) for the UKTUS and 16,746 married respondents for the LFS. We will compare 5 core characteristcs between the two samples separately for men and women: (1) age, (2) number of children, (3) education, (4) employment status, (5) occupations.

[1] Office for National Statistics. Social Survey Division, Northern Ireland Statistics and Research Agency. Central Survey Unit. (2017). Quarterly Labour Force Survey, July - September, 2014. [data collection]. 3rd Edition. UK Data Service. SN: 7570, http://doi.org/10.5255/UKDA-SN-7570-3

Results. Men. LFS vs UKTUS (couple sample)

The results for men show no fundamental differences in the distribution of characteristics between the two samples. The age distribution (quartiles) do not show outstanding differences between the two samples, despite men being slightly younger in the third quartile (Q 0.25) in the UKTUS. The distribution of children is however not entirely comparable. There is slighly more childless couples in the UKTUS (57% compared to 54%) than in the LFS. Regarding the education level of men, highly educated individuals are present in similar proportion in both surveys (29%). This is a good result suggesting that the time use sample is not skweded towards highly educated individuals. The employment status distribution is also very comparable with, in both surveys 59% of respondents "in paid employment" and about 2% "unemployed". However, there are slighly more retired individuals in the UKTUS and less self-employmed. Regarding occupations, the two distributions look very similar. We can however note that managers are slightly less represented in the UKTUS (13% vs 15%). Finally, Table 5 shows the quartiles distribution for the reported working hours in the two samples. The distribution is almost identical.

In conclusion, from this basic comparison of observed sociodemographics characteristics, the men in the UKTUS 2015 *couple sample* are good candidates to represent to general population of married men.

Table C.2: Men. Age Distribution

quartiles	xLFS	names	xUKTUS
0	19.00	0%	19.00
0.25	41.00	25%	39.00
0.5	51.00	50%	51.00
0.75	61.00	75%	62.00
1	70.00	100%	70.00

Table C.3: Men. Number of Children

var	% LFS	% UKTUS
1child	17.10	12.83
2children	20.14	23.17
>2children	8.11	5.90
NoChildren	54.65	58.09

Table C.4: Men. Education

var	% LFS	% UKTUS
Degree	29.17	29.40
other	70.83	70.60

Table C.5: Men. Employment Status

var	% LFS	% UKTUS
Employee	59.57	59.12
ILO unemployed	1.73	1.25
Other	7.89	5.09
Retired	13.84	20.09
Self employed	16.97	14.46

Table C.6: Men. Occupations. Employed Only.

var	% LFS	% UKTUS
Administrative	4.56	5.59
Assoc. professionals	16.62	16.30
Caring & Leisure	3.18	2.56
Elementary occupations	8.62	6.78
Machine Operatives	11.22	10.71
Managers	15.27	12.36
Professionals	23.50	26.83
Sales & cust services	3.28	4.03
Skilled Trade	13.67	14.56

Table C.7: Men. Working Hours. Employed Only.

quartiles	x hours LFS	x hours UKTUS
25%	37.00	37.00
50%	40.00	40.00
75%	48.00	47.00

Results. Women. LFS vs UKTUS (couple sample)

The results for women are broadly in line with what we observed for men. We can also see that more childess women are present in the UKTUS sample compared to the LFS sample. Regarding education, women in the UKTUS sample are more educated compared to the LFS one, with about 32% of women holding a degree in the UKTUS versus 28% in the LFS. This might reflect a selection bias for women in the UKTUS. Regarding employment, there are less women employed in the UKTUS with 50% of women in employment compared to 54% in the LFS. However, the main reason for this lower proportion of women employed is the greater proportion of retired women in the UKTUS sample. This issue of lower women's employment can be simply solved in subsetting the "working age population" or the employed women population. Regarding occupations, we can note minor differences in managerial occupations (8.15% in the UKTUS vs 6.83% in the LFS) and elementary occupations (8.05% in the UKTUS vs 6.79% in the LFS). Finally, the comparison of working hours between the two samples show nearly identical distribution.

Beside the slightly greater proportion (3-4% more) of highly educated women, the women UKTUS sample can be considered as a good sample of the married women population.

Table C.8: Women. Age Distribution

quartiles	xLFS	names	xUKTUS
0	19.00	0%	19.00
0.25	39.00	25%	37.00
0.5	50.00	50%	49.50
0.75	60.00	75%	62.00
1	70.00	100%	70.00

[1] "

Table C.9: Women. Number of Children

var	% LFS	% UKTUS
1child	16.33	11.99
2children	19.20	21.66
>2children	7.75	5.62
NoChildren	56.72	60.73

Table C.10: Women. Education

var	% LFS	% UKTUS
Degree	28.31	32.95
other	71.69	67.05

Table C.11: Women. Occupations

var	% LFS	% UKTUS
Employee	54.10	50.46
ILO unemployed	1.90	1.42
Other	19.47	15.84
Retired	16.92	24.95
Self employed	7.61	7.34

Table C.12: Women. Occupations. Employed only.

var	% LFS	% UKTUS
Administrative	20.67	18.66
Assoc. professionals	11.64	15.35
Caring & Leisure	14.57	13.44
Elementary occupations	8.05	6.72
Machine Operatives	1.50	1.00
Managers	6.83	8.93
Professionals	25.91	26.08
Sales & cust services	9.05	8.63
Skilled Trade	1.72	0.80

Table C.13: Women. Working Hours. Employed only.

quartiles	x hours LFS	x hours UKTUS
25%	20.00	21.00
50%	30.00	30.00
75%	39.00	37.00

Appendix D. Supplementary Tables and Analyses

Table C.14: Cross-tabulation of Partners' Primary Activities when Together. Row Percentage. Men.

	CH	DM	EA	LE	OT	TV
CH	0.52	0.19	0.05	0.10	0.08	0.07
DM	0.04	0.59	0.08	0.09	0.12	0.07
EA	0.02	0.13	0.66	0.07	0.06	0.06
LE	0.03	0.15	0.06	0.57	0.08	0.10
OT	0.03	0.14	0.05	0.08	0.60	0.09
TV	0.02	0.11	0.04	0.09	0.08	0.66

Table C.15: Cross-tabulation of Partners' Primary Activities when Together. Row Percentage. Women.

	CH	DM	EA	LE	OT	TV
CH	0.34	0.16	0.08	0.14	0.11	0.17
DM	0.03	0.43	0.11	0.13	0.12	0.18
EA	0.01	0.07	0.72	0.06	0.06	0.08
LE	0.02	0.08	0.07	0.59	0.08	0.16
OT	0.01	0.10	0.06	0.08	0.60	0.14
TV	0.01	0.04	0.04	0.07	0.06	0.78

Table C.16: Cross-tabulation of Partners' Primary Activities when Together. Row Percentage. Parents. Men.

	CH	DM	EA	LE	OT	TV
CH	0.54	0.18	0.04	0.08	0.09	0.07
DM	0.16	0.58	0.05	0.07	0.09	0.04
EA	0.08	0.14	0.59	0.06	0.06	0.07
LE	0.11	0.11	0.04	0.58	0.09	0.08
OT	0.10	0.14	0.04	0.07	0.58	0.08
TV	0.10	0.11	0.03	0.07	0.09	0.59

Table C.17: Cross-tabulation of Partners' Primary Activities when Together. Row Percentage. Parents. Men.

	CH	DM	EA	LE	OT	TV
CH	0.39	0.15	0.08	0.11	0.11	0.17
DM	0.11	0.42	0.11	0.09	0.13	0.15
EA	0.04	0.06	0.73	0.05	0.05	0.07
LE	0.06	0.06	0.06	0.61	0.08	0.13
OT	0.06	0.07	0.05	0.08	0.59	0.14
TV	0.04	0.03	0.05	0.06	0.07	0.75

Secondary Activities and Mismatch Activities

We used two measures of secondary activities: *Secondary* and *Secondary*$*$. The *Secondary* is simply the secondary field of the time use diary, so there will be a lot of missing information/not reported (NA) and in *Secondary*$*$ we simply filled the missing information by the primary activity.

Table C.18: Illustration of the two secondary activities measures.

ID	Time	Primary	Secondary	Secondary*
1	1	A	*NA*	A
1	2	A	*NA*	A
1	3	A	B	B
1	4	C	A	A

Table C.19 shows the distribution of secondary activities by gender. We can note that in 83% for men and in 81% for women, a secondary activty was not reported. Secondary activities are similarly distributed for men and women, with slighly more domestic work and childcare for women.

Table C.20 confirms that if primary activities were replaced by secondary activities when reported, the overall distribution would not dramatically change.

Table C.21, C.22, C.23, C.24 show how the cross-tablutions for different combinations of primary and secondary activities. The findings presented in the paper do not change if we account for secondary activities. Table S 13 and Table S 14 are the tables discussed in the paper (Figure 5), and are taken as references.

Figure S 3 shows the distribution of joint activities for the primary activities of the reference respondent and the secondary activities of the partner. For instance, the figure on the top shows what are the male partners doing the female partners are doing Childcare, Housework and so on. Looking at primary activities could have distorted our findings if men or women were to systematically under/over-reporting certain activities, such as housework or leisure as **primary** activities. But this figure clearly shows that men are not doing more housework as secondary activities.

Table C.19: Distribution of Secondary Activities by Gender.

	v	% men	% women
1	CH	0.50	1.40
2	DM	0.90	1.80
3	EA	1.50	1.30
4	LE	6.50	7.40
5	OT	1.90	2.00
6	TV	4.70	5.00
7	*NA* *	83.90	81.00

Note. * No secondary activity reported.

Table C.20: Comparison of the Primary Activities and Secondary Activities by Gender.

		Primary		Secondary*	
	v	% men	% wom	% men	% wom
1	CH	1.60	4.00	1.70	4.20
2	DM	9.00	13.60	7.80	11.60
3	EA	6.60	6.60	5.10	4.60
4	LE	9.90	9.70	14.00	14.50
5	OT	60.90	56.60	57.20	52.90
6	TV	12.00	9.50	14.10	12.20

Note. * replacing primary activities by secondary.

Table C.21: Men Primary Activities and Women Secondary Activities. Rows (Men) Percentage

	CH	DM	EA	LE	OT	TV
CH	0.45	0.15	0.03	0.18	0.08	0.10
DM	0.04	0.49	0.06	0.18	0.10	0.13
EA	0.02	0.10	0.38	0.27	0.05	0.16
LE	0.03	0.13	0.05	0.60	0.07	0.12
OT	0.03	0.13	0.04	0.19	0.45	0.16
TV	0.02	0.11	0.04	0.19	0.07	0.57

Table C.22: Woman Primary Activities and Men Secondary Activities. Rows (Women) Percentage.

	CH	DM	EA	LE	OT	TV
CH	0.31	0.16	0.10	0.15	0.13	0.17
DM	0.03	0.42	0.11	0.13	0.12	0.19
EA	0.01	0.08	0.65	0.08	0.07	0.11
LE	0.02	0.10	0.17	0.38	0.12	0.21
OT	0.02	0.11	0.07	0.09	0.56	0.16
TV	0.01	0.07	0.10	0.08	0.09	0.65

Table C.23: Both Partners' Secondary Activities. Rows (Men) Percentage

	CH	DM	EA	LE	OT	TV
CH	0.47	0.15	0.04	0.17	0.09	0.09
DM	0.04	0.52	0.06	0.15	0.10	0.13
EA	0.03	0.12	0.49	0.18	0.06	0.12
LE	0.03	0.11	0.06	0.59	0.07	0.14
OT	0.03	0.14	0.04	0.15	0.52	0.13
TV	0.02	0.12	0.04	0.16	0.07	0.59

Table C.24: Both Partners' Secondary Activities. Rows (Women) Percentage

	CH	DM	EA	LE	OT	TV
CH	0.33	0.13	0.07	0.20	0.09	0.17
DM	0.03	0.38	0.09	0.18	0.11	0.22
EA	0.01	0.07	0.57	0.16	0.06	0.13
LE	0.02	0.07	0.08	0.58	0.07	0.18
OT	0.02	0.09	0.05	0.15	0.52	0.16
TV	0.01	0.06	0.05	0.14	0.06	0.68

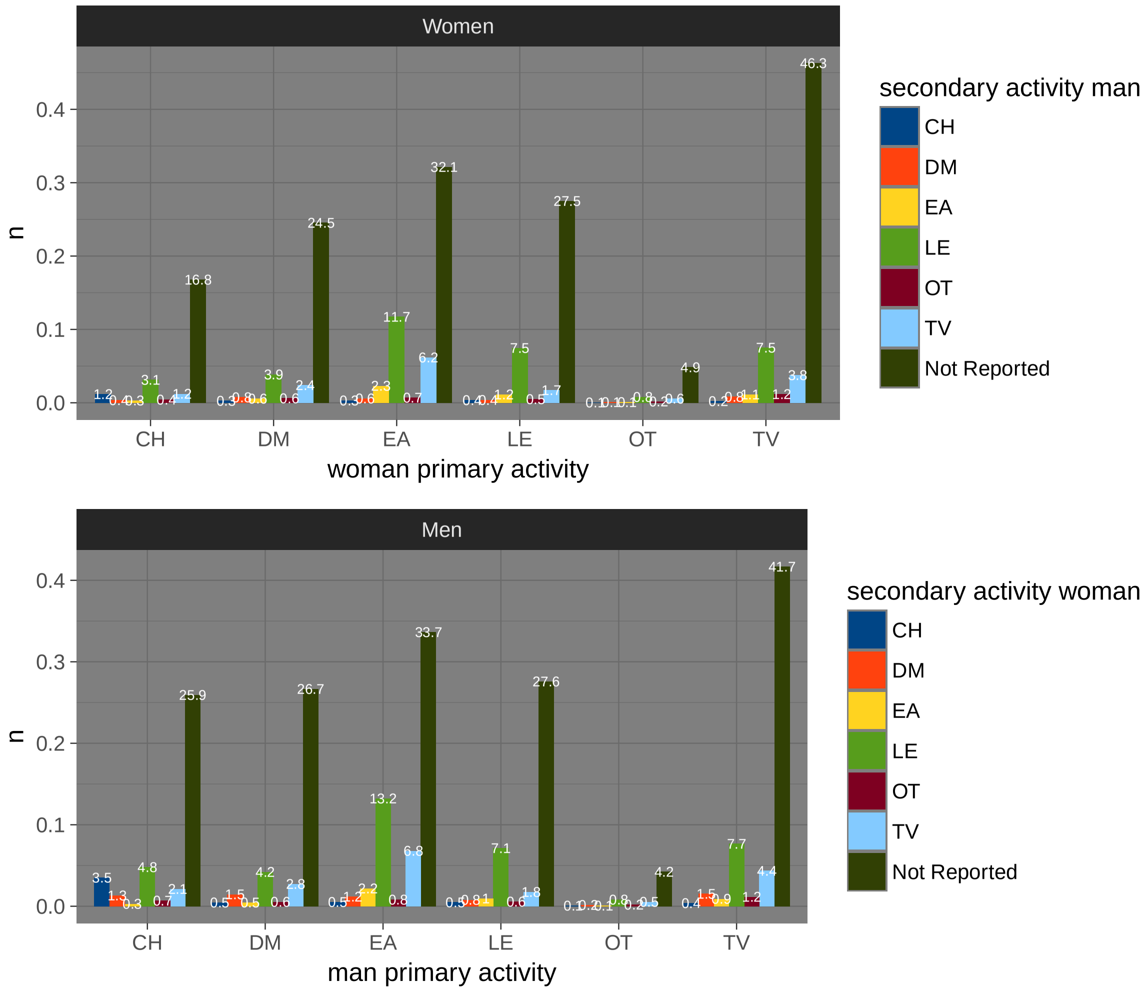

Figure C.3: Missing With Whom Information over the Day by Gender

Figure C.4: Distribution of Joint Activities by Gender. All couples. What the partner is doing when the other partner is doing X,Y,Z.

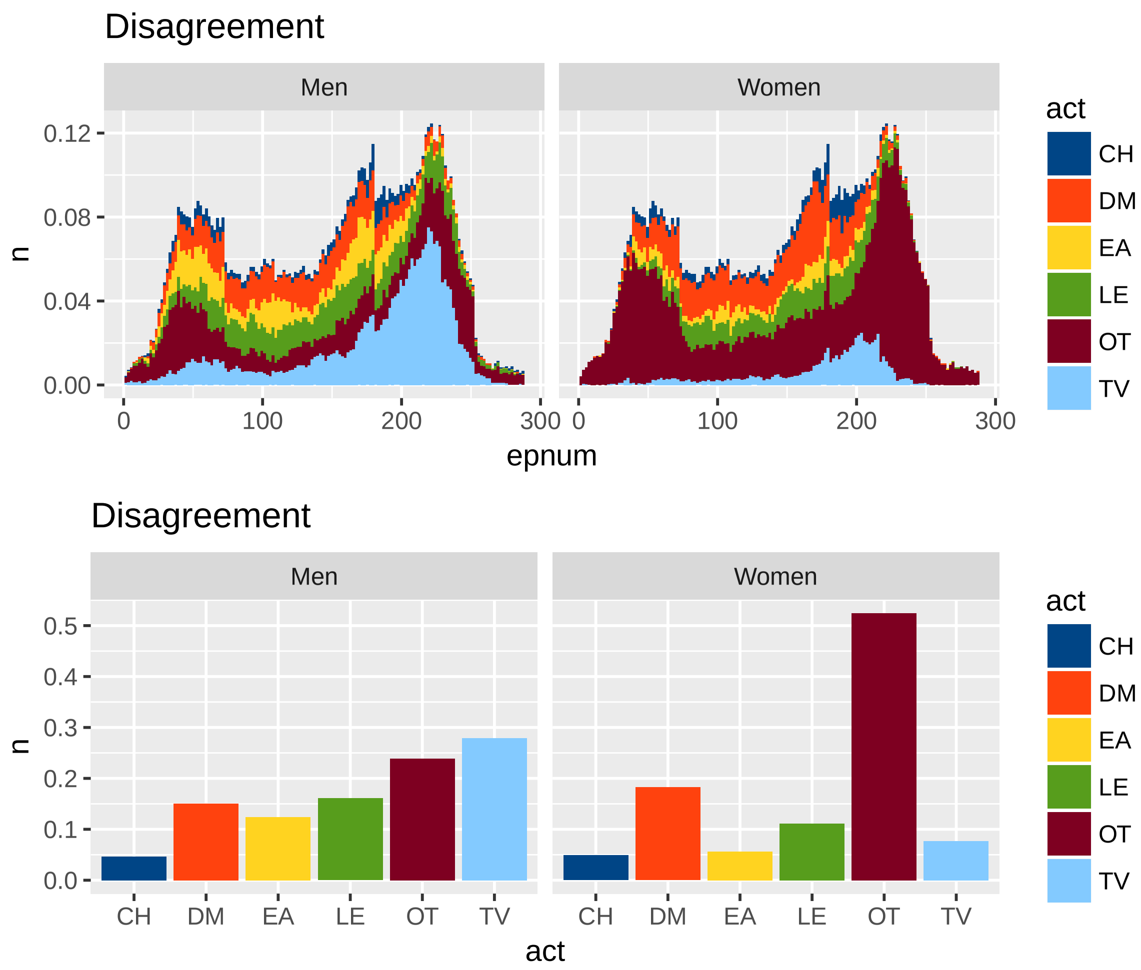

Figure C.5: Disagreement (Mistmaches). Primary Activities by Gender. (CH = Childcare, DM = Domestic, EA = Eat, LE = Leisure, OT = Other). This figure shows the activities for the Mismatched report of time together. The Childcare and Domestic activities are not affected if we consider the mismatched instead of the Match time together. Eat, Leisure and Other are the most prevalent categories.

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