Patterns of everyday activities across social contexts.

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Significance Statement

Everyday life in modern society often seems unpredictable and disorganized. Much research has demonstrated the structured nature of time, though, by documenting trends in individuals time use or allocation. We expand on this by using sequence analysis methods to identify and describe common patterns with regard to how individuals sequence their everyday activitieslike working, eating, and travelingduring the course of the day. Using a large collection of time diaries from different contexts, we identify eight common behavioral sequence patterns. The distribution of these patterns holds across a variety of countries and over time. This study provides additional evidence of the highly structured nature of everyday behavior and suggests future directions for time use research.

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 patternsincluding 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.

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Everyday life sometimes seems unpredictable and disorganized. The difficulty of co-ordinating the seemingly chaotic flow of everyday obligations has been documented, for example, in a vast body of research on the challenges associated with maintaining house-hold divisions of labor and in managing work-family role conflict (Cornwell & Warburton, , , , , , , , ,). Several scholars have even commented that the pace of everyday life is speeding up, thus adding to the sense of everyday lifes tumultuousness (Wajcman,). There are several reasonable explanations for this. It is possible, for one, that the ex-pansion of non-standard work arrangements including shift work and temporary work arrangements has complicated individuals efforts to coordinate their everyday activities and obligations (Kalleberg, , , ,).

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, , , , , ,). 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 todays society are characterized by pre-dictable 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 allo-cation (Aguiar & Hurst, , , , ,). 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, Greco, Sobolevsky, & Carlo, , , ,). 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 every-day 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, ,). 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, ,).

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, , , ,). 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, ,). 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, Ghysels, & van Klaveren,). 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, , ,). 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, Laurijssen, Minnen, & Tienoven,).

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., ,). 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,). 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, ,). 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, , ,). 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.

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,). 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 SI Appendix, Table S14).

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,) 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,). 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,). 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,) - 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,). 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, Ritschard, Mueller, & Studer,). 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 and SI Appendix).

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.,). This is an agglomerative hierarchical clustering technique that attempts to minimize within-cluster variance (Kaufman & Rousseeuw,), which is commonly used in social sequence analysis and tends to identify commonly sized

clusters and therefore avoids poorly populated clusters (Cornwell,). 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 Appendix) 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,). 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 Figs S2 and 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 SI Appendix.) 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 Cramers 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 (Studer, Ritschard, Gabadinho, & Müller,). 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.

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 (SI Appendix, Table S11). 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 travelling 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 combined with our assessment of the graphical depictions of the activity patterns within clusters (see SI) 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 SI Appendix, Figure S7. 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 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). Sequence index plot shows the complete sequence from 6am to 10pm for certain individuals. We selected the most representative as well as the most unrepresentative sequences for each clusters. The most representative sequences (relative to the "medoid" (Gabadinho et al.,) of the cluster) are displayed at the bottom and the most unrepresentative at the top of the figure (see SI).

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 SI Appendix, Table S4) 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 (SI Appendix, Table S6). The proportion of individuals engaged in paid work at different times of the day also differs across clusters (see SI Appendix, Table S7). 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 15:07pm for Cluster C (see SI Appendix, Table S6). 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 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.,), 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.

Here (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 SI Appendix, Table S6). 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 (SI Appendix, Table S7). The sequence index plots that display the sequences of representative individuals for these groups (see Figure 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 (see SI Appendix, Table S4). 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) 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). 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 SI Appendix, Table S9). 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 7.14am for the general population (see SI Appendix, Table S10). 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 ($\chi^2 = 6288.6$, df = 154, p < 0.001), this association is very weak (Cramers V = .17). Additional tests, including a discrepancy sequence analysis,

showed that countries did not explain much of the sequence discrepancy (less than 3% of the sequence discrepancy is explained by countries, as shown in SI Appendix, Table S12). 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 Cramers V of .12, and where a discrepancy sequences analysis reveals that period explains less than 1% of the sequence discrepancy (see SI Appendix, Table S12).

Nonetheless, some important differences in sequence patterns across these social contexts should be noted (SI Appendix, Table S2). 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 (SI Appendix, Table S3).
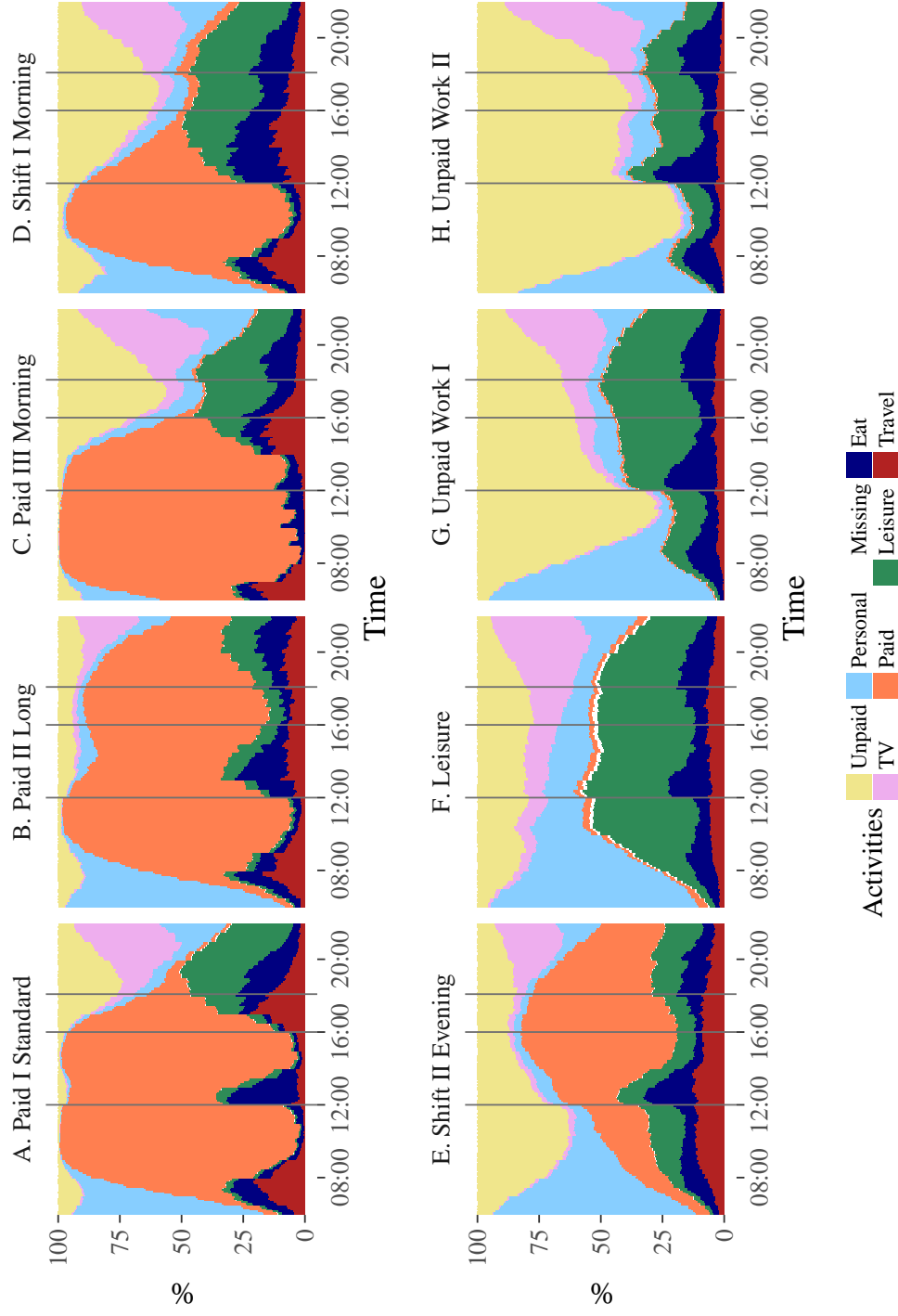
Figure 1. State Distribution Graphs Showing the Proportion of Members in Each Hamming-Distance-Based Cluster Engaging in Certain Activities at Each Time Point throughout the Day. N = 31,089.
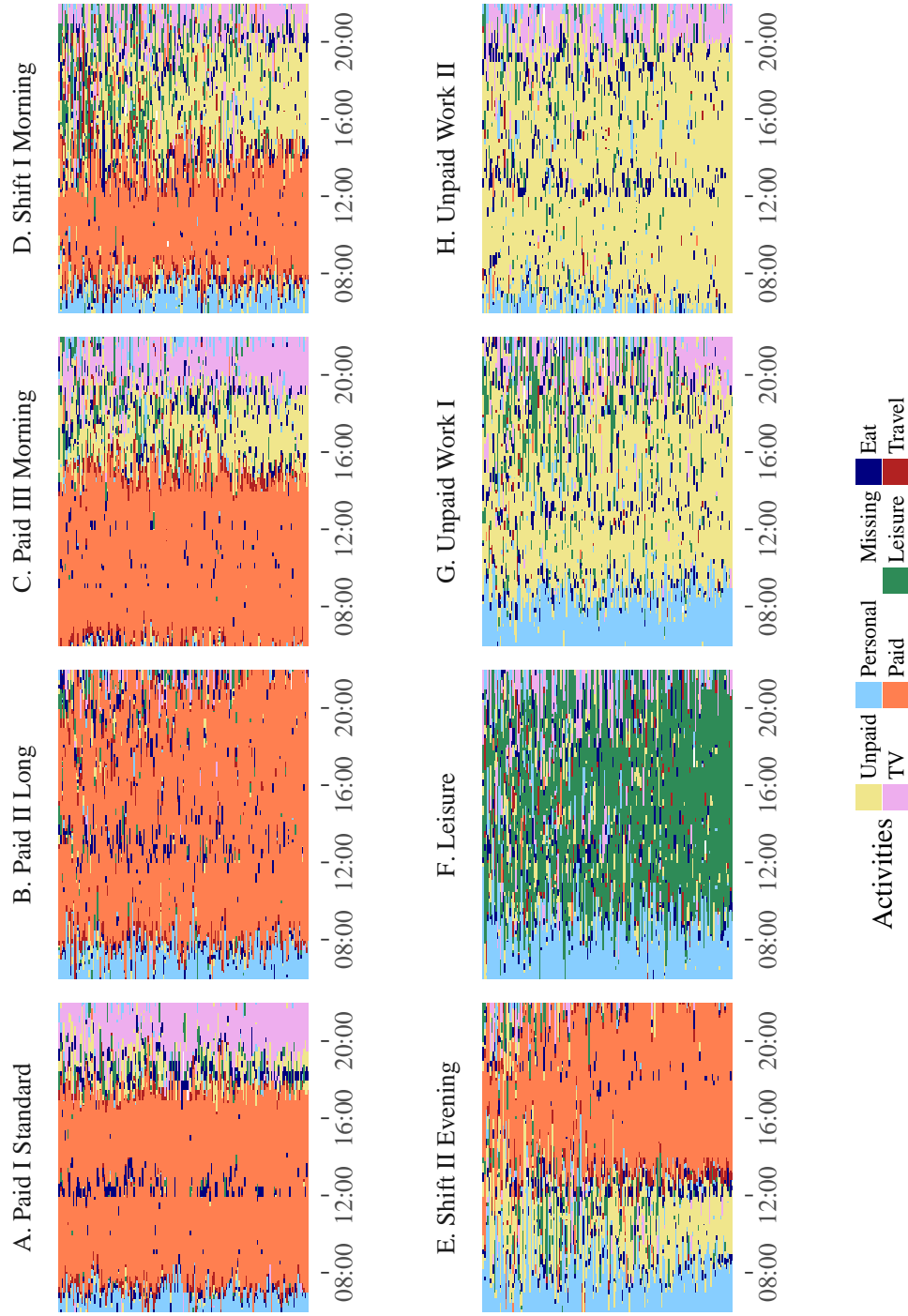
Figure 2. Sequence Index Plots Showing Time-Specific Activity Sequences for Medoids in Each Hamming-Distance-Based Cluster. N = 178 representative individuals per cluster.

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, , , , ,). 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, , , , ,).

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, , , ,) that enable household-level divisions of labor combined with the rise of non-standard work arrangements(Liu et al., , , , ,).

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, , , , ,), 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, , ,). 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, , , , ,). 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.

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