Methodological Appendix to "Work Scheduling for American Mothers, 1990 and 2012"

Peter Hepburn

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Appendix A: Schedule Data and Analysis

This appendix provides a detailed account of (1) how schedule data were collected in the NCCS and NSECE and (2) how these data were used to develop the maternal schedule typology described in the main text of the paper. The level of detail provided is likely too great for the general reader but should prove helpful for those interested in replicating or extending this study. Most analysis is carried out in R. Sequence analysis is conducted using the TraMineR (Gabadinho, Muller, Ritschard, & Studer, 2015), TraMineRextras (Ritschard, Studer, Gabadinho, Muller, & Rousset, 2015), and WeightedCluster (Studer, 2014) packages; weighted logistic regression is carried out via the survey package (Lumley, 2016); and weighted, non-linear Blinder-Oaxaca decompositions are carried out via the Oaxaca package in Stata.

In the NCCS, the respondent was asked how many jobs they currently work. For each job, starting with the one in which they reported working the most hours in the previous week (Monday through Sunday), they were asked which days they worked in that previous week. The interviewer then asked what time they began and ended working on each of those days. The respondent was allowed to report two shifts per day per job, and reports on up to three jobs. Multiple shifts are rare. For instance, roughly 52.5% of respondents report the start time for a first shift on Monday, but only 0.31% report the start time of a second shift. Likewise, few respondents have multiple jobs. Of the 59.4% of respondents who report paid employment, 92.5% have only a single job. Respondents are then asked an identical set of questions about their spouse or partner, if present in the household.

The NSECE schedule data collection was somewhat more complicated. The respondent was asked if, in the last week, they did any work for pay; attended classes in a high school, college, or university; or attended any courses or training programs intended to help find a job, learn a skill, or learn a job. For each day of the previous week they were then asked if they participated in each of the reported activities (if any); there was no limit on the number of work, school, or training shifts reported in each day. The respondent was allowed to report that a given day of the week was identical to a previous day–thus reducing respondent burden–but if they did so they were asked a follow-up question confirming that the chosen day was indeed identical to the previously-described day. This set of questions was then repeated for the respondent's partner (if present in the household), any other parent of a child under age 13 in the household, and any other household members who provided more than five hours of childcare in the previous week. Respondent fatigue is a concern because this section comes after a similar, potentially more complex, childcare calendar section of the survey. The survey instrument was programmed to check parental work schedules for duplicated periods and to check against previously-collected childcare schedules for any periods of one hour or more in which children were not reported to be in care and parents were at work, school, or training. In such instances the respondent was prompted for more detail. It does not appear that the NCCS instrument included such checks.

The first difference between these two approaches is in the content of schedules. The NCCS functionally divides time into two categories: work and non-work. The NSECE allows for more states: work, school, training, and unclaimed time. For the sake of comparability, I was forced to collapse the school, training, and unclaimed categories in the NSECE into non-work (henceforth labeled "other").

The second difference is in the number of individuals whose schedules are recorded. In the NCCS, schedules are gathered only for the respondent and the spouse/partner; schedules for additional household members may be collected in the NSECE (if there are additional parents in the household or if other household members provided care in the previous week). Because my focus here is just on maternal schedules, I eliminate all schedules not associated with the focal mother.

Third, as discussed in the main text of the article, respondents to the NSECE were instructed to include time spent commuting to and from the given activity (work, school, or training) as part of the activity itself. There is no way to easily disentangle commuting time from working time, nor any way to confirm whether or not respondents to the surveys systematically followed the prompt to include commuting time. NCCS respondents were not instructed to include commute time in their responses nor does that survey collect data that would allow the analyst to add commuting time on to existing work reports.

Because the introduction of commuting time in the NSECE leads to a basic problem of commensurability with the NCCS, I trimmed working schedules in the former by taking into account three related variables: how far the individual's place of employment is from home (where individual is either the respondent or, as appropriate, the respondent's partner); the urbanicity of the area where the household is located; and whether the household has a car. Working off of American Community Survey numbers, I developed a simple rule to determine how much time to trim from the start and end of working periods. Table

A1 provides the numbers for households with a car; for those without a car I doubled all times. The resulting mean estimated commute among workers is 22.5 minutes, which is close to the 2009 national mean of 25.1 minutes traveled to work (McKenzie & Rapino, 2011).

TABLE A1 HERE

Finally, fourth, data from these two studies are also stored differently. In the NCCS files these data are stored as collected: as start and end times by shift and job. In these NSECE they are stored as 15-minute blocks: each household member for whom a schedule was collected has a vector of 15-minute blocks starting from 12:00-12:14 am Monday and ending with 11:45-11:59 pm Sunday (15-minute blocks over a 7-day week results in 672 entries). Each block can take on one of four values: "work," "school," "training," or "no work/school/training" (essentially an open block). The blocks can also take on a "don't know/refused" status, but this is exceedingly rare, occurring in only 0.04% of all blocks across all schedules collected. I recoded these as open blocks. This states-sequence format is ideal for sequence analysis; I reformatted the NCCS to match. Because shifts in the NCCS were not constrained to 15 minute intervals, I was forced to round starting and ending times to the nearest quarter hour.

As discussed in the main text, I placed four restrictions on the data. First, I limited single-parent households to those headed by a woman. Second, I included only partnered mothers from heterosexual two-partner households. The exclusion was driven by the extremely small number of same-sex couple households available for analysis. Third, I removed male sex-sex two-partner households because they include no mothers. Fourth, for data quality reasons, I removed cases where the mother was listed as having worked the entirety of at least one 24-hour day. Each individual's schedule is stored as a 672-block vector running from 12 am Monday until 11:59 pm Sunday (four 15-minute blocks per hour * 24 hours per day * 7 days per week = 672). I modified both data sets such that each individual had seven day-level (96-block) sequences rather than one week-level (672-block) sequence. Once harmonized, I merged the two datasets. As noted above–and given these restrictions–schedule data were collected from 916 single-mother respondents and from 3,532 mothers in two-partner households in the NCCS. In the NSECE, schedule data were collected from 2,780 single-mother respondents and from 7,590 mothers in two-partner households.

Figure 1 is a sequence index plot that presents, as a set of horizontal bars, a simple visualization of the vectors of work and non-work for six selected person-days. In this case, each of the selected days is a Tuesday; time runs left-to-right from 12 am through 11:59 pm (23:59 military time). The bottom-most individual (individual 1) did no work on this particular Tuesday and thus all 96 of their 15-minute blocks are set to "other." Individual 2, by contrast, worked from 7:45 am to 4 pm (a standard work day, albeit one that both started and ended slightly early). Individual 3 worked an extended standard day, arriving to work at 6 am and staying through to 5 pm. Individual 4 also worked during standard hours, but only three and a half hours total. Individual 5 worked slightly less (two and a half hours) and in the evening (6-8:30 pm). Finally, the top-most individual shows the classic signs of working the evening/night shift: he or she reports having started work at 12 am (the shift in fact started on Monday evening) and their shift ends at 6 am. They then report work starting back up at 6 pm and running through the end of the day (the shift continues in the Wednesday report).

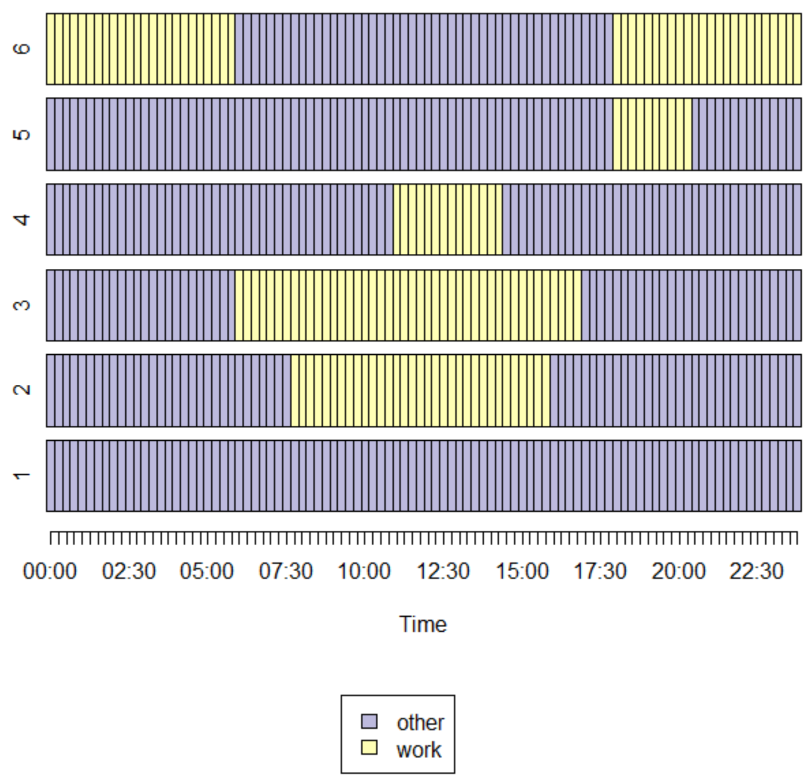

Figure 1: Sequence index plot of six selected Tuesdays.

To analyze these data I made use of a set of sequence and cluster analysis tools. I began by running a variant of Optimal Matching (OM) over all person-day reports from single mothers. OM yields a measure of how dissimilar each sequence is from every other sequence; given n sequences it produces an n x n symmetrical matrix (called a dissimilarity matrix) wherein each (i,j) off-diagonal entry is the dissimilarity between sequence i and j. Functionally, it provides the “cost” of transforming–through insertions, deletions, and substitutions–any one observed sequence into another observed sequence. More similar sequences cost less to transform into one another whereas such transformation is more "expensive" between dissimilar sequences. The costs associated with each substitution are presented as a substitution-cost matrix which is generated using either theory, intuition, the observed transition rates between the various states, or some combination of those methods (Abbott, 1995; Abbott & Tsay, 2000; Aisenbrey & Fasang, 2010; Elzinga & Studer, 2015). Following Lesnard (2008, 2010; Lesnard & Kan, 2011), I employed Dynamic Hamming Distance (DHD) matching, a variant of OM in which the cost of transitioning between states varies with time. Rather than rely on a single substitution-cost matrix (as in standard OM), there is one for each contiguous pair of blocks. Functionally this means that the cost of substituting "non-work" for "work" at 9 am (when such a transition is relatively common and thus "cheap") will be different than doing so at 9 pm (when the transition is rare and thus "expensive"). DHD matching is well-suited to a time-varying process like employment. It is also worth noting that DHD matching relies solely on substitutions and does not allow insertions or deletions. Given that all sequences in these data are of equal length, this poses no serious problem. In addition to the papers cited above, those interested in the particulars of DHD matching and its use should refer to Lesnard & de Saint Pol (2009); Raab, Fasang, Karhula, & Erola (2014); Fasang & Raab (2014). To establish the multi-dimensional substitution matrix I relied solely on the transition rates between states at each point in time.

Because of the number of comparisons involved, OM can be a computationally intensive process. To streamline it, I aggregated such that each unique person-day appears only once in the data and weighted these cases according to their frequency. The 103,684 total person-days from single mothers were reduced to 2,369 unique lines; each line represented, on average, 43.8 person-days (minimum of 1, maximum of 67,300). I carried out DHD matching on these unique lines. Because the process took into account the frequency weights associated with each unique sequence, the multi-dimensional substitution cost matrix that resulted was identical regardless of whether it was produced with the full or the aggregated data set.

I used the resulting dissimilarity matrix and employed the non-hierarchical Partitioning Around Medoids (PAM) algorithm to derive clusters from the data. Studer (2013) makes a strong case for PAM, which seeks to maximize a global rather than local criterion, as an alternative to hierarchical clustering. I did, however, test alternative clustering options: Ward's Minimum Variance Method and the Weighted Pair Group Method with Arithmetic Mean (WPGMA, which is advocated by Lesnard (2008)). The former derived very similar clusters with slightly lower average silhouette widths; I used the Ward clusters as the initial medoids in the PAM algorithm. WPGMA, by contrast, yielded lower-quality and often quite sparse clusters. This process resulted in each person-day being allocated to a cluster; the reader should refer to Figure 1 and associated text in the main text for description of these day-level clusters. The final selection of clusters involved weighing both fit statistics and the descriptive potential of each additional group. This was, admittedly, a somewhat subjective process, but a necessary one. Adjudicating number of clusters by fit statistics alone would have led to a clearly-inadequate two-cluster solution: workers and non-workers. I attempted to select more clusters where (a) the additional cluster offered a qualitatively new pattern relative to those already selected and (b) the additional cluster did not result in significantly worse average silhouette width across all clusters

I then re-configured the data into a week format; each mother had a sequence of seven days where each day is represented by the cluster to which it was assigned in the previous step. I run a second sequence analysis and clustering exercise, again using the PAM algorithm, across this set of person-week sequences. The end result is to categorize each individual's week. Figure 2 provides state distribution plots that correspond to the seven week-level clusters. As is evident, each week-level cluster is primarily but not exclusively made up of days of the associated type; weekends are particularly likely to be non-working regardless of cluster.

The week-level specification allowed me to observe the extent of variability in schedule type across days. I recorded the total number of different work-type clusters that a given individual falls into over the course of the observed week (i.e., the count of unique clusters omitting the non-work cluster). I marked mothers as experiencing within-week schedule variability if they experienced more than one working schedule over the course of the seven-day sequence. This measure is discussed in greater detail in Methodological Appendix B.

Within each person-week I also calculated how many standard hours (8 am - 5:59 pm, Monday through Friday), nonstandard weekday hours (12 am - 7:59 am; 6 pm - 11:59 pm, Monday through Friday), and weekend hours (at any hour, Saturday and Sunday) each individual works. I also designated each day as either non-working (if no work was reported), part-time (if less than seven hours of work are reported), or full-time (if seven or more hours of work are reported). These measures are used in Table 3.

Finally, it bears noting that the NCCS and NSECE were collected over slightly different calendar periods. The NCCS was collected between October, 1989 and June, 1990; the NSECE was collected between January and June, 2012. In both cases the majority of cases were collected between January and April. I carried out a series of regressions to check whether month of interview was a predictor of week-level schedule cluster. I found no evidence of seasonality in work schedules; results are available upon request.

Appendix B: Schedule Variability

Unstable schedules–those that vary from day-to-day or week-to-week or that may be changed in the course of a shift–have the potential to be more disruptive

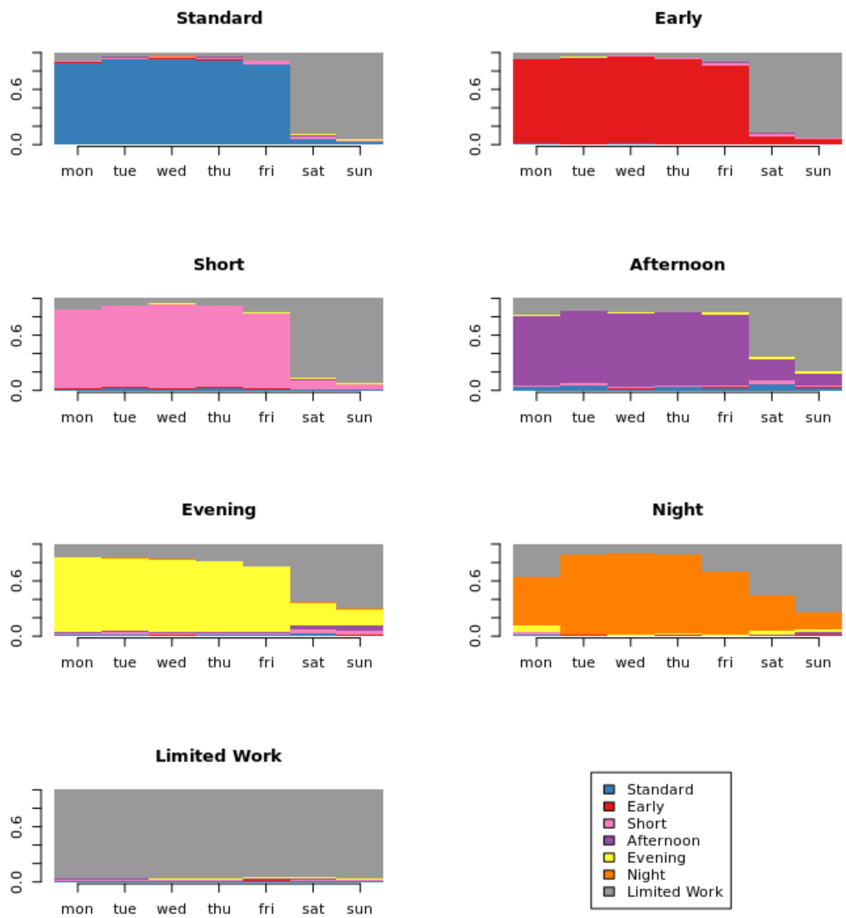

Figure 2: State distribution plot of person-week work schedules.

than nonstandard shifts. A predictable nonstandard shift can be planned for; an unpredictable working schedule may make organizing other arrangements (including childcare) especially problematic (Bohle, Quinlan, Kennedy, & Williamson, 2004; Gerstel & Clawson, 2014; Henly, Shaefer, & Waxman, 2006; Zeytinoglu, Lillevik, Seaton, & Moruz, 2004). In this paper I was unable to offer a measure of schedule instability that got at all four components instability that have been highlighted in the literature: worker control, advance notice, and within- and between-week variability. I was, in fact, able to measure only within-week schedule variability: were individuals working the same type of schedules each working day or did their working schedules vary? To do so, I counted the number of unique work-type schedules (omitting non-working days) over the seven observed days. Individuals who took on more than one unique working-type cluster were marked as holding variable schedules. This definition raised two questions. First, how did this measure of within-week schedule variability relate to other components of schedule instability? Second, was this measure driven by part-time employment?

To answer the first question, I explored the relation between within-week schedule variability several questions from the NCCS and NSECE. In both surveys, work schedules were complemented by questions on schedule variability. Unfortunately, these are not the same questions. In the NCCS, respondents were asked (of each job), "Do you usually work the same or fixed hours every week or do your hours vary from week to week, such as rotating from days to evenings or nights?" An equivalent question was asked of their partner's schedule (as appropriate). In the NSECE they were asked, "Did (you/she/he) work (your/his/her) usual schedule last week, is there no usual schedule, or was last week's schedule not the usual one?" These two questions can both be understood as measures of between-week variability. There was an additional question in the NSECE that asks the respondent how far in advance they (or the other individual whose schedule they are describing) usually knew what days and hours they would need to work. Neither survey included any questions on worker control over schedules.

I cross-tabulated within-week schedule variability with mother-specific reports from these three questions. If my measure was indeed capturing something about schedule variability, I expected that those mothers who I categorized as having variable schedules would be more likely to have worked varying schedules (in the NCCS), that they would have had no usual schedule or that last week's would not have been usual (in the NSECE), and that they would have had less advance notice of scheduling (in the NSECE). From the NCCS I developed a variable that indicates whether the respondent reported maternal schedule variability in any job. Results are displayed as column percentages in Table A2.

TABLE A2 HERE

In the NCCS, mothers marked as having within-week schedule variability were far more likely to report between-week variability in hours (40.1% compared to 14.2%). In the NSECE only 24.4% of mothers who I categorized as having within-week stable schedules reported either "No Usual" or an "Unusual" week, whereas 41.1% of those with variable schedules did so. Almost twice as many mothers displaying within-week schedule variability reported having less than a week of advance notice of their schedule (17.2% compared to 9.4%).

These results generally supported the idea that this measure of within-week schedule variability was related, in the expected ways, with other components of schedule instability. Those with within-week variability in their schedules did self-report *more* of the factors that characterize unstable or contingent work than their counterparts with observed stability in schedule. But it was also clear that it would be a mistake to treat within-week variability as a direct proxy for schedule instability. 14.2% of mothers displaying within-week stability in working schedules reported in the NCCS that their working schedules varied from week to week. That sort of between-week variation should be accounted for in measuring instability. At the same time, 59.9% of mothers with within-week variability *did not* report between-week variability. It may not be appropriate to include these significant sub-populations in any analyses of schedule instability.

The second question posed above was whether within-week variability was driven by part-time employment. If this was the case, then the observed increase in within-week schedule variability between 1990 and 2012 may simply have been a function of the across-period growth in part-time employment. To check this possibility, I cross-tabulated weekly working hours (none, less than 35, or 35 hours or more) and within-week variability. The results are in Table A3, split by household type and year, presented as row percentages.

TABLE A3 HERE

Amongst single mothers working some hours in 1990, the difference in within-week variability between part-time and full-time workers was 1.1 percentage points (a non-significant difference according to a weighted chi-square test). By 2012 this gap had grown to 2.8 percentage points and, interestingly, it is full-time workers who demonstrate greater within-week schedule variability.

Partnered mothers working part-time did have significantly higher rates of within-week variability in 1990 relative to their peers working full-time (14.5% compared to 11.0%; $p=.036$ for a weighted chi-square test). This difference shifted in the 2012 data: here mothers working full-time had significantly higher observed variability (22.4% compared to 18.7%; $p=.049$). A simple weighted logistic regression model predicting maternal within-week schedule variability in two-partner households on the basis of (1) a dummy variable for survey year (1990 as the reference group), (2) a dummy variable for mother's part-time work (with full-time as the reference group), and (3) the interaction between these two provided some further illumination (results available upon request). Both survey year (being in the 2012 sample) and part-time work status significantly increased the odds of within-week variability. The interaction, however, is significantly negative, suggesting a weakening of the association between maternal part-time work and schedule variability in such households.

Appendix C: Supplementary Tables and Analyses

Table A4 provides results from the three logistic regression models that underlie Figures 2 and 3 in the main text. The models are presented with the main effects (and significance indicators) in the first two columns; interaction terms (and significance indicators) are in the next two columns. In the main text, average marginal effects based on these models are presented in Figure 2 and predicted probabilities from the third model are presented in Figure 3.

TABLE A4 HERE

The counterfactual standardization exercise that I present in Figure 4 and associated text is, in effect, a simple form of decomposition. I also conducted Blinder-Oaxaca decompositions to assess the relative importance of structural shifts and relational changes in explaining observed differences (Hlavac, 2018; O'Donnell, Doorslaer, Wagstaff, & Lindelow, 2008). In each case the change in the given outcome between 1990 and 2012 was modeled on the basis of the same variables used in logistic regression analysis: mother's occupation; mother's education (a dummy variable indicating a college diploma or higher); respondent's race (a dummy variable indicating that the respondent is non-white); log of family income; and, as appropriate, household type (a dummy variable indicating single mother). Because the dependent variables in these cases were binary (i.e., holding a nonstandard schedule or not), I employed a non-linear extension of Blinder-Oaxaca models using logistic regression and the weighting method outlined by Yun (2004). I calculated two-fold decompositions; the reference coefficients were set, following Jann (2008), using a pooled regression model including group indicator as an additional regressor. Results were substantively equivalent regardless of selected reference category (results available upon request). I computed decompositions based on normalized effects across categorical predictors (Yun, 2005).

Figure 3 presents simplified results from these decompositions. Essentially, these models break the observed differences between 1990 and 2012 rates of the given schedule characteristic into a component attributable to changes in structural characteristics and a component attributable to shifting relationships between characteristics and the given outcome measure. Because of missing values in some of the covariates, the absolute differences in the schedule characteristics modeled in the decompositions does not perfectly match the differences reported in Table 3.

In the top panel, we see that changes between 1990 and 2012 in population characteristics–in the occupational distribution, in educational attainment, in the racial distribution, and in income–would have led, ceteris paribus, to a small (0.44 percentage point) increase in single mothers doing evening work. Changes to the relationships between these characteristics and the likelihood of evening work account for the remaining 1.11 percentage points. Put differently, 71.6% of the observed change is accounted for by relational shifts and the remainder by

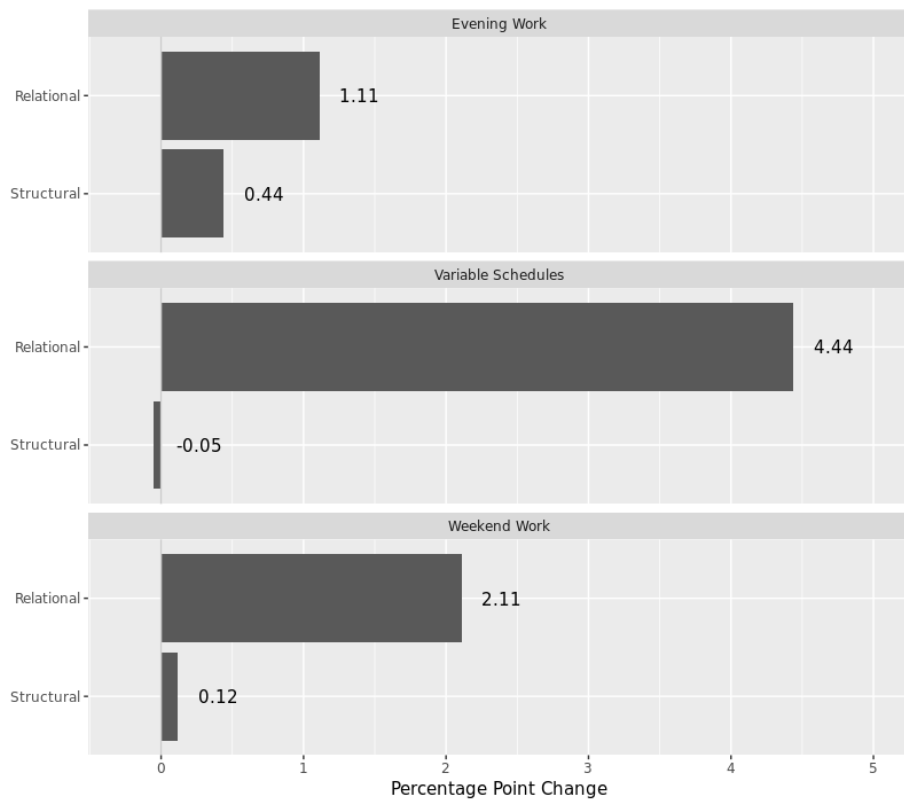

Figure 3: Results from Blinder-Oaxaca Decompositions.

population shifts. The pattern is in the same direction but more stark in the other two panels. The entirety of the increase in within-week variability and 94.6% of the increase in weekend work is due to relational changes. Taken as a whole, these analyses confirm the patterns observed in Figure 4 of the main text.

References

Abbott, A. (1995). Sequence Analysis: New Methods for Old Ideas. *Annual Review of Sociology*, *21*(1995), 93–113.

Abbott, A., & Tsay, A. (2000). Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect. *Sociological Methods & Research*, *29*(1), 3–33.

Aisenbrey, S., & Fasang, A. F. (2010). New Life for Old Ideas: The "Second Wave" of Sequence Analysis Bringing the 'Course' Back Into the Life Course. *Sociological Methods & Research*, *38*(3), 420–462. https://doi.org/10.1177/0049124109357532

Bohle, P., Quinlan, M., Kennedy, D., & Williamson, A. (2004). Working Hours, Work-Life Conflict and Health in Precarious and "Permanent" Employment. *Revista de Saude Publica*, *38*, 19–25. https://doi.org/10.1590/S0034-89102004000700004

Elzinga, C. H., & Studer, M. (2015). Spell Sequences, State Proximities, and Distance Metrics. *Sociological Methods & Research*, *44*(1), 3–47. https://doi.org/10.1177/0049124114540707

Fasang, A. E., & Raab, M. (2014). Beyond Transmission: Intergenerational Patterns of Family Formation Among Middle-Class American Families. *Demography*, *51*(5), 1703–1728. https://doi.org/10.1007/s13524-014-0322-9

Gabadinho, A., Muller, N. S., Ritschard, G., & Studer, M. (2015). TraMineR: a toolbox for exploring sequence data. Geneva: Institute for Demographic; Life Course Studies (IDEMO), University of Geneva. Retrieved from http://traminer.unige.ch/

Gerstel, N., & Clawson, D. (2014). Class Advantage and the Gender Divide: Flexibility on the Job and at Home. *American Journal of Sociology*, *120*(2), 395–431. https://doi.org/10.1086/678270

Henly, J. R., Shaefer, H. L., & Waxman, E. (2006). Nonstandard Work Schedules: Employer- and Employee-Driven Flexibility in Retail Jobs. *Social Service Review*, *80*(4), 609–634. https://doi.org/10.1086/508478

Hlavac, M. (2018). *oaxaca: Blinder-Oaxaca Decomposition in R*. https://doi.org/10.1007/s10645-016-9288-x

Jann, B. (2008). The Blinder-Oaxaca Decomposition for Linear Regression Models. *The Stata Journal*, *8*(4), 453–479. Retrieved from www.socio.ethz.ch

Lesnard, L. (2008). Off-Scheduling within Dual-Earner Couples: An Unequal and Negative Externality for Family Time. *American Journal of Sociology*, *114*(2), 447–490. https://doi.org/10.1086/590648

Lesnard, L. (2010). *Setting Cost in Optimal Matching to Uncover Contemporaneous Socio-Temporal Patterns* (Vol. 38, pp. 389–419). https://doi.org/10.1177/

0049124110362526

Lesnard, L., & de Saint Pol, T. (2009). Patterns of Workweek Schedules in France. *Social Indicators Research*, *93*(1), 171–176. https://doi.org/10.1007/s11205-008-9384-7

Lesnard, L., & Kan, M. Y. (2011). Investigating Scheduling of Work: A Two-Stage Optimal Matching Analysis of Workdays and Workweeks. *Journal of the Royal Statistical Society. Series A: Statistics in Society*, *174*(2), 349–368. https://doi.org/10.1111/j.1467-985X.2010.00670.x

Lumley, T. (2016). Survey. Retrieved from http://r-survey.r-forge.r-project.org/survey/

McKenzie, B., & Rapino, M. (2011). *Commuting in the United States: 2009* (No. September). Washington, DC: U.S. Census Bureau.

O'Donnell, O., Doorslaer, E. van, Wagstaff, A., & Lindelow, M. (2008). Explaining Differences Between Groups: Oaxaca Decomposition. In *Analysing health equity using household survey data* (pp. 147–157). Washington, DC: The World Bank. https://doi.org/10.1596/978-0-8213-6933-3

Raab, M., Fasang, A. E., Karhula, A., & Erola, J. (2014). Sibling Similarity in Family Formation. *Demography*, *51*(6), 2127–2154. https://doi.org/10.1007/s13524-014-0341-6

Ritschard, G., Studer, M., Gabadinho, A., Muller, N., & Rousset, P. (2015). TraMineRextras. Geneva: Institute for Demographic; Life Course Studies (IDEMO), University of Geneva. Retrieved from http://traminer.unige.ch/

Studer, M. (2013). *WeightedCluster Library Manual: A Practical Guide to Creating Typologies of Trajectories in the Social Sciences with R.*

Studer, M. (2014). WeightedCluster: Clustering of Weighted Data. Geneva: Institute for Demographic; Life Course Studies (IDEMO), University of Geneva. Retrieved from https://cran.r-project.org/web/packages/WeightedCluster/index.html

Yun, M.-S. (2004). Decomposing Differences in the First Moment. *Economics Letters*, *82*(2), 275–280. https://doi.org/10.1016/j.econlet.2003.09.008

Yun, M.-S. (2005). A Simple Solution to the Identification Problem in Detailed Wage Decompositions. *Economic Inquiry*, *43*(4), 766–772. https://doi.org/10.1093/ei/cbi053

Zeytinoglu, I. U., Lillevik, W., Seaton, B., & Moruz, J. (2004). Part-Time and Casual Work in Retail Trade. *Industrial Relations*, *59*(3), 516–544. https://doi.org/10.7202/010923ar

Table A1. Summary of Time Trimmed from Working Schedules by Distance to Work and Urbanicity

	High-Density Urban	Moderate-Density Urban	Rural
0 Miles	0 mins	0 mins	0 mins
<3 Miles	15 mins	15 mins	15 mins
3-8 Miles	30 mins	30 mins	30 mins
>8 Miles	45 mins	45 mins	30 mins

Table A2. Observed Work Schedule Variability and NCCS/NSECE Scheduling Questions

	Within-Week Schedule Variability	
	No (%)	Yes (%)
Varying Schedule (NCCS)		
No	85.8	59.9
Yes	14.2	40.1
Usual Schedule (NSECE)		
None	14.8	26.5
Unusual	9.6	14.6
Usual	75.5	58.9
Advance Notice (NSECE)		
<1 Week	9.4	17.2
1-2 Weeks	23.3	27.6
3 Weeks+	67.3	55.3

Table A3. Observed Work Schedule Variability and Hours Worked in the Recorded Week

		Within-Week Schedule Variability	
		No	Yes
	Maternal Working Hours (1990)		
	None (%)	100	0
	<35 (%)	83.7	16.3
Single Mother Households	>=35 (%)	84.8	15.2
	Maternal Working Hours (2012)		
	None (%)	100	0
	<35 (%)	80.2	19.8
	>=35 (%)	77.4	22.6
	Maternal Working Hours (1990)		
	None (%)	100	0
	<35 (%)	85.5	14.5
Two-Partner Households	>=35 (%)	89	11
	Maternal Working Hours (2012)		
	None (%)	100	0
	<35 (%)	81.3	18.7
	>=35 (%)	77.6	22.4

Table A4. Logistic Regression Models Predicting Work Schedule Characteristics

	Model 1: Evening Schedules (Single Mothers)				**Model 2: Variable Schedules (All Mothers)**				**Model 3: Weekend Work (All Mothers)**			
	Main Effect		Interaction w/ Time		Main Effect		Interaction w/ Time		Main Effect		Interaction w/ Time	
	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig	Coef	Sig
2012			0.516				-0.402				-2.028	+
Mother's Occupation												
Administrative (ref)									n/a		n/a	
None recorded	-16.257	***	0.835		-17.489	***	-0.478	*	-18.145	***	-0.068	
Magerial/Professiol	0.839		2.021		0.022		0.179		0.285		-0.219	
Technicians/Support/Sales	-16.468	***	18.696	***	0.819	***	-0.188		0.746	***	0.149	
Service	2.399	**	0.844		1.007	***	-0.555	*	1.147	***	-0.169	
Production/Manufacturing	1.849	*	1.264		-0.017		0.011		0.418	+	-0.039	
Other	1.726	+	-1.6		0.44		-0.329		0.375	+	-0.316	
Mother has College+	0.461		-1.944	+	0.26		-0.533	*	-0.155		-0.294	
Non-White Respondent	-0.433		0.917		-0.647	***	0.326		-0.395	**	0.417	*
Log Income	0.1		-0.147		-0.088		0.125		-0.37	***	0.229	*
Single Mother					0.442	*	-0.402	+	0.313	+	-0.409	*
# Obs	3,570				14,300				14,300			
Weighted	10,600,000				48,400,000				48,400,000			
Pseudo R2	0.226				0.199				0.246			
AIC	830				6,990				8,030			

significance levels: +<.1, *<.05, **<.01, ***<.001