

*Working paper series*

**Schedule instability and unpredictability  
and worker and family health and wellbeing**

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### **Abstract**

The American labor market is increasingly unequal, characterized by extraordinary returns to work at the top of the market but rising precarity and instability at the bottom of the market. In addition to low wages, short tenure, few benefits, and non-standard hours, many jobs in the retail and food service industries are characterized by a great deal of instability and unpredictability in work schedules. Such workplace practices may have detrimental effects on workers. However, the lack of existing suitable data has precluded empirical investigation of how such scheduling practices affect the health and wellbeing of workers and their families. We describe an innovative approach to survey data collection from targeted samples of service- sector workers that allows us to collect previously unavailable data on scheduling practices and on health and wellbeing. We then use these data to show that exposure to unstable and unpredictable schedules is negatively associated with household financial security, worker health, and parenting practices.

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## Introduction

The American labor market is increasingly unequal, characterized by extraordinary returns to work at the top of the market but rising precarity and instability at the bottom of the market. This precarity is multi-dimensional, characterized by low-wages, few benefits, short tenure, contingent employment, and non-standard schedules. While the consequences of these dimensions of precarity have been studied, scholars, policy makers, workers, and advocates have recently documented a new set of precarious employment practices related to work scheduling that may have serious negative effects on workers and their families. However, very little research has traced how these scheduling practices affect health and wellbeing.

Many service-sector employers now use a combination of human resource management strategies to closely align staffing with demand. Under this system, workers receive their weekly work schedules as little as a few days in advance, their scheduled work hours and work days may change substantially week-to-week, and workers may have their shifts changed, cancelled, or added at the last minute (Golden, 2001; Appelbaum et al., 2003; Clawson and Gerstel, 2015). Recent estimates suggest that nearly 90% of hourly retail workers experience such instability (Lambert et al., 2014).

These scheduling practices have gained attention in the media with many journalistic accounts of the hardships imposed by unstable and unpredictable schedules (Singal, 2015; White, 2015; Kantor, 2014; Strauss, 2015). These accounts suggest, and related research supports the idea, that schedule instability may increase the volatility of household economic resources, increase stress and uncertainty, destabilize people's daily lives, interfere with combining work with schooling or secondary jobs, and prevent the establishment of regular schedules of personal and dependent care. Schedule and hours instability may then negatively affect workers' health behaviors and mental and physical health. These work scheduling practices may also transmit disadvantage across generations. Children whose parents work unstable and unpredictable schedules may be subject to inconsistent care arrangements and frequent disruptions to their routines and time with parents.

However, while there is evidence that other dimensions of precarious work – such as stable, but non-standard hours – negatively affect health and wellbeing, the evidence base on the effects of unstable and unpredictable scheduling practices is more limited. Data sources containing information on both work scheduling and health outcomes are rare and workers in low-wage unstable jobs are difficult to sample.

Nevertheless, policy makers have been actively pursuing changes to local labor regulations and, beginning in the Fall of 2016, four large cities are expected to pass local labor laws regulating unstable and unpredictable schedules (Ben-Ishai, 2015a). Large retailers, including Walmart, are independently making or contemplating changes to company policies.

We use an innovative survey method to collect data from 6,476 hourly non-managerial retail workers in the United States. Our study, the Retail Work and Family Life Study (RWAFLS), is unique in collecting detailed measures on schedule instability and unpredictability as well as measures of worker and family health, social wellbeing, and household financial security for a national sample of retail workers. This paper describes our unique data collection method and our methods for assessing and mitigating sample selectivity, then reports on the associations between work scheduling practices and worker health and wellbeing. We find that unstable and unpredictable work schedules are negatively associated with a number of dimensions of worker and family wellbeing including household economic insecurity, psychological distress, and reductions in parental time with children. These relationships have long been suspected but have not been systematically documented in large-scale empirical research.

The set of scheduling practices we examine – varying number of hours, variable schedules, and limited advance notice of work schedules – would likely be changed by proposed local legislation and proposed shifts in company practices. We conclude our paper by considering our findings in the context of proposed scheduling legislation and changes to company practice.

## **Background**

### **Employment Precarity**

One important dimension of socio-economic status is the nature of one’s paid work, and influential sociological research has shown increasing employment precarity since the 1970s, which has been defined as an increase in work that is “uncertain, unpredictable, and risky from the point of view of the worker” (Kalleberg, 2009, p. 2). While this increase in precarity has been widespread, those at the bottom of the income and occupational distribution have fared the worst. Fligstein and Shin (2004) report on a bifurcation of the labor market between the 1970s and 1990s in which workers with lower levels of educational attainment experienced declines in wages, declines in benefits such

as health insurance and pensions, and declines in job security and job satisfaction. Fligstein and Shin refer to this set of changes as the “insecuritization of work for those at the bottom” (p. 402).

These declines in job quality since the 1970s have been accompanied by a rise in non-standard work hours that encompass evenings, nights, and weekends - hours that are difficult to reconcile with parenting responsibilities. Presser (1999) documented the prevalence of these non-standard shifts two decades ago and was prescient in predicting that these non-standard shifts would continue to increase in their prevalence (McMenamin 2007).

### **Unstable and Unpredictable Work Schedules**

Scholars and policy makers have more recently identified a new form of employment precarity in the low-wage service sector rooted in a set of unstable and unpredictable scheduling practices. Under this system, workers receive their weekly work schedules as little as a few days in advance, their scheduled work hours and work days may change substantially week-to-week, and workers may then have their shifts changed, cancelled, or added at the last minute (Golden, 2001; Appelbaum et al., 2003; Clawson and Gerstel, 2015).

This set of practices allows employers to effectively transfer financial risk to their employees. Rather than commit to a set of stable employee schedules, employers now seek to maintain as lean staffing as possible and do so by scheduling workers for minimal regular hours, adding shifts at the last minute, asking workers to leave shifts early, and requiring “on call” shifts (Houseman 2001). Employers are thus able to avoid paying for idle staff time. In turn, employees encounter substantial uncertainty about when and how much they will work. In this way, unpredictable and unstable scheduling practices are yet another domain in which risk is transferred from large institutional actors to households (Hacker, 2006).

Unstable and unpredictable work schedules are now common in the service sector (Golden, 2001; Appelbaum et al., 2003; Enchautegui et al., 2015) and can be found among low-wage workers in other industries as well, such as health care (Clawson and Gerstel, 2015). Recent estimates show that 87% of early-career retail workers reported instability in their work hours from week to week over the past month. Of those retail workers who reported unstable work hours, the fluctuations were substantial, averaging almost 50% of their usual weekly hours (Lambert et al., 2014).

These arrangements are widespread and qualitatively distinct from low-wage stable non-standard

work. Early research has shown that this instability is highly salient for workers (i.e. Luce et al., 2014) and may even be a more important predictor of wellbeing than working non-standard hours (Henly and Lambert, 2014a). However, there is very little research that directly examines the social consequences of unstable and unpredictable work.

## **Expected Effects of Unstable Schedules on Wellbeing**

Although there is little prior research that directly examines the relationship between schedule unpredictability and instability and health and wellbeing for service-sector workers, theory and prior research provide several reasons to expect that unpredictable and on-call scheduling for hourly employees will have a range of negative effects.

Most broadly, the positive relationship between socioeconomic status and health is robust and well established. Those with lower incomes and less education have shorter life expectancy, higher rates of morbidity, depression, and health risk behaviors, and socioeconomic status has been theorized to be a “fundamental cause” of health outcomes (Link and Phelan, 1995). To the extent that exposure to unstable and unpredictable work schedules is another dimension of socio-economic status, we might expect similar ill effects.

Scholars have also long been concerned with the effects of precarious work specifically on health and wellbeing. Prior research has carefully documented the effects of non-standard work schedules on adult wellbeing (i.e. Presser, 2003; Presser, 1999; Wight, Raley, and Bianchi, 2008) and on child outcomes and parenting (i.e. Joshi and Bogen, 2007; Han, 2005; Miller and Han, 2008; Morsy and Rothstein, 2015; Scott et al., 2004). Separate research in sociology and epidemiology has shown how limited flexibility in the workplace negatively affects the health and wellbeing of white collar workers (Marmot et al., 1997; Ala-Mursula et al., 2002; Hurtado et al., 2016; Olson et al., 2015; Davis et al., 2015; Moen et al., 2016).

But, the evidence base on the effects of unstable and unpredictable schedules on the wellbeing of hourly workers and their families is much thinner. A first order question relates to how workers perceive their schedules. While limited advanced notice and variable shift timing might, a priori, appear undesirable, some suggest that rather than embodying harmful instability, these scheduling practices are a reflection of employee desire for flexibility (Hatamiya, 2015). Qualitative research on workers with unstable and unpredictable schedules suggests that these practices are

perceived negatively (Henly, Shaefer, and Waxman, 2006). But, there is little large scale survey data demonstrating whether workers would prefer more stable schedules.

Second, unpredictable and unstable work schedules may have negative consequences for household economic security. Variable hours may, mechanically, lead to income volatility, especially if that variability makes it difficult for workers to hold secondary jobs that might otherwise be used to smooth earnings. Prior research has shown that schedule instability leads to economic insecurity (Ben-Ishai, 2015b; Golden, 2015, Haley-Lock, 2011; Luce et al., 2014; Zeytinoglu et al., 2004). In a 2013 survey of workers with low to moderate income, among those who reported income volatility, having an irregular work schedule was the most common reason given (Federal Reserve Board 2014). Similarly, in a financial diary study of 235 households, negative income shocks were common and a drop in work hours was one of the main culprits (Murdoch and Schneider 2014).

Unpredictable and unstable schedules may also have negative effects on worker and family health and wellbeing. These effects could be caused by economic instability. Additionally, such scheduling practices also appear to interfere with daily routines and causes chronic stress and uncertainty (Ben-Ishai, 2015b; Golden, 2015, Haley-Lock, 2011; Luce et al., 2014; Morsy and Rothstein, 2015; Zeytinoglu et al., 2004). These factors, in turn, have been shown to be negatively related to health and wellbeing. In terms of worker wellbeing, prior research indicates that income volatility negatively affects sleep and food sufficiency (Wight, Raley, and Bianchi, 2008; Leete and Bania, 2010). Elevated levels of work stress are also related to unhealthy behaviors such as smoking (Kouvonen et al., 2005) and alcohol consumption (Harris and Fennell, 1998). Research has found that income volatility and job insecurity are both associated with worse self-rated health (Halliday, 2007; Goh, Pfeffer, and Zenios, 2015).

In terms of child wellbeing and parenting, prior research has also found income volatility and economic uncertainty are associated with parenting stress (Wolf et al., 2014), harsh parenting (Gassman-Pines, 2013; Schneider et al., 2013), less parenting time (Wight et al., 2008), and poor child outcomes (Gennetian et al., 2015; Schneider et al., 2013; Miller and Han, 2008). In addition, several studies have documented a direct relationship between unstable work schedules and inconsistent and low quality child care arrangements (Ben-Ishai et al., 2014; Enchautegui, et al., 2015; Henly and Lambert, 2005; Luce et al., 2014; Morsy and Rothstein, 2015; Williams and Boushey, 2010) and between disrupted schedules at home for children and lower quality parental interactions

(Henley, Shaefer, and Waxman, 2006).

Although data on scheduling practices and health and wellbeing outcomes are limited, prior research provides indirect evidence to suggest that these scheduling practices are linked with a range of financial, health, and wellbeing outcomes. The prior research evidence leads us to the following set of hypotheses:

1. We hypothesize that workers exposed to unstable scheduling practices will be more likely to express a desire for stable work hours.
2. We expect that unstable and unpredictable schedules will be negatively related to household economic security as seen in income volatility and measures of financial strain.
3. We predict that exposure to these scheduling practices may interfere with sleep and depress self-rated health and emotional wellbeing.
4. For working parents, we hypothesize that unstable work schedules will reduce developmental time with children and increase parenting stress.

We propose an innovative approach to data collection and estimation that will allow us to directly examine the relationship between unstable and unpredictable schedules and worker attitudes, household financial security, health and wellbeing, and parenting.

## **Data and Methods**

The lack of existing research on how unpredictable schedules affect worker and family wellbeing stems from a lack of available data. There are three interrelated limitations of existing data: (1) few data sets include measures of scheduling practices, (2) data sets that include measures of scheduling practices rarely include measures of wellbeing, and (3) existing data cannot be used to describe the scheduling practices at the large retail firms that are at the center of policy debate and organizing activity.

First, few data sets actually measure scheduling practices. While scholars have developed an accepted set of survey items to measure unpredictable and unstable work schedules (Lambert and Henly, 2014b), these items are new and have not yet been included on the large scale governmental surveys that are the mainstay of social science research. For instance, the American Community Survey and the Decennial Census both contain large numbers of retail workers, but do not measure advance notice of schedules or variation in weekly hours. Other smaller-scale data sets such as the Panel Study of Income Dynamics, the National Health Interview Survey, the National Longitudinal



Study of Youth-79, and the National Longitudinal Study of Adolescent to Adult Health also contain little information on scheduling practices.

Second, those surveys that contain information on scheduling practices generally lack information on health and wellbeing - key outcomes of interest. For instance, the Current Population Survey included a set of scheduling measures in a special module in 2004 (and includes a recurrent question on hours worked that contains an option to report that hours vary), but does not include measures of worker or family health or wellbeing. A series of state and national surveys conducted by the Employment Instability Network contain detailed measures of scheduling instability and unpredictability, but no measures of health and wellbeing. Those surveys that do contain detailed outcome data – such as NHIS, Fragile Families, Add Health, and others – lack good measures of scheduling practices.

One important exception is the 2011 and 2013 waves of the National Longitudinal Survey of Youth - 1997 (NLSY-97). In those two waves, the NLSY-97 contained items that gauged amount of advance notice of schedules that the respondent received at work, the degree of control the respondent had over her schedule, and the week-to-week variability in the respondent's work hours. The NLSY-97 also contains useful measures of adult health and wellbeing. However, the NLSY-97 is limited to a specific cohort of workers - all of whom were born between 1975 and 1982 and were aged 29 to 36 in 2011. Because the NLSY-97 is designed to be nationally representative of that age cohort, the sample size of workers in the retail industry is limited, with 763 respondents working in retail in 2011.<sup>1</sup> Further, some portion of these retail industry workers are in managerial positions, and the employer name is not available in the data.

Finally, though policy attention and organizing is focused on regulating large chain retailers, there is no data that can be used to actually describe scheduling practices at these companies. Administrative data, which is at sufficient scale to describe practices at individual employers, does not contain measures of schedules or of worker health and wellbeing. Surveys that measure scheduling practices either do not collect information on the names of individual employers or lack any substantial number of cases within particular employers. In sum, there is an acute lack of data that contains measures of scheduling and outcomes of interest for sufficiently large samples of retail

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<sup>1</sup>From the NLSY-97 documentation of the industry codes for respondents' current or most recent job in Round 14. <https://www.nlsinfo.org/content/cohorts/nlsy97/topical-guide/employment/industry-occupation-tables>

workers. A significant challenge in collecting this data is the effective recruitment of large samples of retail workers at reasonable cost.

## Survey Methodology

We use an innovative method of collecting web-based surveys from a population of low-wage service-sector workers. We use audience-targeted advertisements on Facebook to recruit respondents to a survey. Facebook collects extensive data on its users by harvesting user-reported information and inferring user characteristics from activity. Facebook then allows advertisers to use this data at the group level to target advertisements to desired audiences. We take advantage of this infrastructure to target survey recruitment messages to active users on Facebook who (1) reside in the United States, (2) are between the ages of 18 and 50, and (3) list one of several large retail companies as their employer.

This approach to survey data collection departs from traditional probability sampling methods and some have raised reasonable questions about such approaches (Groves, 2011; Smith, 2013). One possible source of bias arises from our sampling frame – Facebook users. While earlier research noted selection into Facebook activity (Couper, 2011), recent estimates show that approximately 80% of Americans age 18-50 are active on Facebook (Perrin, 2015). Thus, the sampling frame is now on par with coverage of telephone-based methods (Christian et al., 2010).

Our approach is innovative, but not without precedent. Faced with declining response rates to traditional probability sample surveys, an emerging body of work has demonstrated that non-probability samples drawn from non-traditional platforms, in combination with statistical adjustment, yield similar distributions of outcomes and estimates of relationships as probability-based samples. This work has drawn data from Xbox users (Wang et al., 2015), Mechanical Turk (Goel, Raod, and Sroff, 2015; Mullinix et al., 2016), and Pollfish (Goel et al., 2015). Yet, of all of these platforms, Facebook is the most commonly and widely used by the public (Perrin, 2015). In recent prior work, Bhutta (2012) reports on using Facebook to recruit Catholic respondents to a survey. However, her approach differs starkly from ours. Rather than using targeted advertising, as we do, Bhutta (2012) issued survey invitations to members of Catholic affinity groups on Facebook and then relied on chain referrals to recruit additional respondents. This approach initially selects on the intensity of Catholic identity to recruit and then introduces problems of correlated errors

through the chained referrals.

Below, we discuss the logistics of our alternative approach using targeted advertising in greater detail, and then describe several steps that we take to guard against sample selection bias.

### **Detailed Survey Methodology**

We purchase advertisements on the Facebook platform, paying on a cost-per-click basis (meaning that we incur expenses against our daily advertising budget every time a user clicks on our advertisement, but not every time a user sees our advertisement).

We define our target audience by age (18-50) and employer and systematically vary the advertising message. Varying the messages accomplishes two important goals. First, by varying the messages, we increase our click-through-rate (CTR). Second, as described in detail below, we use pairs of distinct and opposing messages that are designed to appeal to respondents who differ on some unobserved characteristic that could influence our results.

Respondents who click on the link in our advertisement are redirected to an online survey hosted through the Qualtrics platform. The front page of the survey contains introductory information and a consent form. Respondents provide consent by clicking to continue to the survey instrument. The specific survey items are detailed below.

Each advertisement is targeted to the employees of a particular large retail company. We selected these companies from the top 15 largest retailers by sales in the United States (National Retail Federation, 2015). We first exclude Amazon.com (#8) and Apple Stores/iTunes (#13) from this list because their rank is the product exclusively or partially of internet sales rather than traditional brick-and-mortar retail operations. We then selected eight companies from the remaining 13.

We placed these survey recruitment advertisements on Facebook between January and June of 2016. We purchased advertisements on a cost-per-click basis. Our advertisements generated 1,284,428 views and 28,410 clicks through to our survey. We calculate our overall click-through-rate as 2.21%. Of those continuing through to our survey, 11,932 consented to begin the survey. Our most liberal response rate then is that 42% of those who clicked began the survey and that 0.9% of users who saw one of our advertisements began a survey. There was, however, some attrition over the course of the survey. Our adjusted response rate, taking only fully completed surveys (surveys where respondents advanced through to the end of the survey and provided their email

address for follow-up) as the numerator, is that 18% of users who clicked completed the survey and 0.4% of users who saw one of our advertisements completed a survey. These response rates are far lower than in traditional survey methods. However, a sample such as ours would be difficult if not impossible to reach through traditional methods. Nevertheless, we are attentive to issues of sample selectivity and address potential bias by weighting and testing for selection on unobservables.

## Methods of Mitigating Bias

As noted above, Facebook use is so widespread as to diminish concerns about its use as a sampling frame. However, a second source of bias arises from non-random non-response to the recruitment advertisement. We investigate and ameliorate such potential response biases using both accepted and more novel methods.

First, statisticians have developed a set of post-stratification and weighting methods that can be used to generate accurate estimates from this type of data (Wang et al., 2015; Goel et al., 2016). This approach allows us to adjust our data to account for discrepancies in the demographic characteristics of our sample compared with the characteristics of a similar target population of workers captured in the high-quality probability sample survey data collected by the American Community Survey (ACS) and the Current Population Survey (CPS). In particular, compared to a similar sample of workers in the ACS or CPS, our sample over-represents women and non-Hispanic whites. We construct weights that when applied allow our sample to more closely mirror the population of retail workers we are aiming to represent.

We post-stratify our data into a set of 40 cells defined by the characteristics of age, gender, and race/ethnicity. We construct weights by comparing distributions across these 40 cells in our data to distributions in the ACS and CPS data. We then construct weights such that within a group the sum of weights within the Facebook survey equals the total number of observations in that group in the ACS or CPS. We then adjust weights so that they sum to the original sample size in our survey sample so as not to affect standard errors. After applying the weights, the demographic composition of our sample on these three characteristics matches the composition of the corresponding samples in the ACS and CPS. Further details on our weighting approach are provided in the Appendix.

Table 1 compares a set of descriptive statistics for the unweighted analysis sample (column 1), the analysis sample weighted based on the ACS (column 2), the analysis sample weighted based

on the CPS (column 3), and tabulations of the same characteristics for the target population from the ACS (column 4) and CPS (column 5). Before weighting, our sample is disproportionately female and White, non-Hispanic as compared to the ACS (column 4) and CPS (column 5) samples. However, the age distribution of our unweighted data is not notably different from that of the ACS or CPS samples. Our weighted sample (columns 2 and 3) is, by construction, identical to the samples from the ACS and CPS on gender, age, and race/ethnicity. We do not weight on education and we see that while the share of respondents with a BA or more matches that of the ACS and CPS, the share with some college is somewhat higher than in those data. However, the share enrolled in school is consistently about 25%.

This approach can effectively adjust for bias in observed characteristics, including for data with much more extreme demographic bias than we observe in our data (i.e. Wang et al., 2015). However, this approach assumes that within narrowly defined cells, the sample is drawn randomly. It is possible, however, that other unobserved biases exist in sample selection.

Second, rather than speculate about such forms of non-specific bias, we generate hypotheses about potential, specific unobserved characteristics that might both alter survey response and bias the relationship between schedule instability and health and wellbeing outcomes. We then run advertisements that elicit these “unobservable” characteristics in their messaging (for instance, contrasting an advertising message referencing insufficient work hours with one referencing overwork) and examine if the relationship between schedule instability and health and wellbeing varies for respondents recruited through these opposing channels.

## **Key Measures**

We fielded an online survey containing approximately 70 questions for workers without children, and 90 questions for working parents. The survey was divided into five modules. The first module contained information on job characteristics, the second on household finances, the third on worker health and wellbeing, the fourth on parenting and child wellbeing (asked only of parents with children in the home), and the fifth on demographics.

## **Independent Variables: Schedule Instability and Unpredictability**

We measure the instability of respondents' schedules with 3 key items. First, we ask respondents to classify their usual schedule as a regular day shift, a regular evening shift, a regular night shift, a variable schedule, a rotating shift, or some other arrangement. Second, we ask respondents for the amount of advance notice they are given of their schedule, differentiating one week of notice or less, 1-2 weeks, 2-3 weeks, 3-4 weeks, or 4 weeks or more (we collapse these last two categories into one since few respondents reported 4 weeks or more of notice). Third, we calculate a measure of hour volatility by asking respondents to report the most and the fewest weekly hours they worked over the past 4 weeks and taking the difference in hours divided by the maximum weekly hours. These items have been carefully developed and tested by the Employment Instability Network (Henly and Lambert, 2014b).

## **Dependent Variables**

We examine four groups of outcome variables: (1) work-related attitudes, (2) household financial security, (3) adult health and wellbeing, and (4) parenting. The questions used to measure outcomes in each of these domains are generally drawn from existing surveys, including the Behavioral Risk Factor Surveillance System and the Fragile Families and Child Wellbeing survey.

*Work-Related Attitudes.* We assess the relationship between our measures of schedule unpredictability and instability and three measures of attitudes. First, respondents are asked to indicate their agreement with the statement "I would like to work more hours," (Strongly Agree (SA), Agree, Disagree, or Strongly Disagree (SD)). Second, respondents are asked to indicate their agreement with the statement, "I would like to work more regular hours" (SA to SD). The first is designed to gauge satisfaction with the number of hours and the second with the regularity of those hours. For each of these measures, we create a dichotomous variable separating those who strongly agree or agree from those who disagree or strongly disagree.

*Household Financial Security.* We measure three dimensions of household financial security. First, we gauge household income volatility by directly asking respondents, "would you say that week to week your household income is basically the same or goes up and down." We treat this as a dichotomous variable. Second, we ask respondents, "in a typical month, how difficult is it for you to cover your expenses and pay all your bills" and ask respondents to rate it as very

difficult, somewhat difficult, or not at all difficult. We recode responses into a dichotomous variable contrasting “very difficult” with “somewhat” or “not at all difficult.” Third, we create an additive index of household economic hardships experienced in the 12 months prior to survey composed of the following indicators: using a food pantry, going hungry, not paying utilities, taking an informal loan, moving in with family or friends, staying in a shelter, or deferring needed medical care.

*Worker Health and Wellbeing.* We measure workers’ self-rated health using a five-category response scale (excellent, very good, good, fair, or poor) recoded to a dichotomous variable contrasting excellent or very good health with good, fair, or poor self-rated health. We gauge general emotional wellbeing by asking respondents, “taken all together, how would you say things are these days? Would you say you are, (1) very happy, (2) pretty happy, or (3) not too happy.” We recode responses into a dichotomous variable contrasting very or pretty happy with not too happy. We also measure self-rated sleep quality as very good, good, fair or poor and create a dichotomous variable contrasting very good or good sleep with fair or poor sleep. Finally, we use the Kessler-6 index of non-specific psychological distress, assessing both the total score as a continuous variable (ranging from 0 to 24) and creating a dichotomous measure of serious psychological distress that separates scores below 13 from those between 13 and 24 (Kessler et al., 2003).

*Parenting.* For working parents who live with children under the age of 15, we ask about time spent with children engaging in the following 6 activities: eating meals together, watching television together, playing video games with children, homework help or reading, active play indoors, and active play outdoors. Respondents rated each activity as occurring never (4), 1-2 times per month (3), once a week (2), several times a week (1), or everyday (0) and we created a summative index ranging from 0 to 24 to capture the intensity of parental time with children. Note that **higher values** on this index signal **less time** spent with children.

We also measure parenting stress. Respondents are asked their level of agreement, either strongly agree, agree, disagree, or strongly disagree, with four statements: (1) being a parent is harder than I thought it would be, (2) I feel trapped by my responsibilities as a parent, (3) I find that taking care of my children is much more work than pleasure, and (4) I often feel tired, worn out, or exhausted from raising a family. We then create a summative index of the responses that ranges from 0 (strongly disagree with all four statements) to 12 (strongly agree with all four statements), such that higher values indicate greater parenting stress.

## Controls

The rise in precarious employment involved declines in wages and worsening of employment conditions more generally, in addition to the changes in scheduling practices. Therefore, to isolate the effects of scheduling practices from other features of precarious employment, all of our models control for hourly wage, average work hours in the last month, household income, and job tenure. We also control for a set of demographic characteristics composed of age, race/ethnicity, gender, educational attainment, school enrollment, marital status, and presence of children in the household. These individual characteristics help to control for selection into jobs with particular attributes. Last, we include employer and state fixed effects in our models, which control for any time-invariant characteristics of employers and states.

## Analytic Models

We estimate associations between our three key measures of schedule instability (variation in weekly hours, schedule type, and advanced notice) and four domains of outcomes: work-related attitudes, household financial security, adult health and wellbeing, and parenting. While these estimates are not causal, we note that by design our sample has limited heterogeneity: everyone is a non-managerial hourly retail worker and we control for economic and demographic characteristics as well as for state and employer fixed-effects. We estimate the following model:

$$Y_i = \alpha + \beta X_i + \lambda J_i + \mu + \omega + \epsilon_i \quad (1)$$

where, our outcome of interest,  $Y$  for individual  $i$ , is regressed on a set of control variables,  $X$ , and a set of job scheduling characteristics,  $J$  described above. The coefficients of interest are represented by  $\lambda$  and summarize the relationship between work schedules and the wellbeing of workers and their families in terms of the dependent variables described above. The set of individual-level controls,  $X_i$ , will include respondent-level measures of race/ethnicity, age, education, nativity, marital status, hourly wage, average work hours in the past month, household income, job tenure, and household composition. The terms  $\mu$  and  $\omega$  represent employer and state fixed effects, which control for unobserved time-invariant characteristics of employers or states. Equation (1) shows the OLS model that we use for continuous outcomes. For dichotomous outcomes, we estimate logistic



regression models where the log odds of the dependent variable is regressed on the set of predictors shown in equation (1) and the error term drops out.

## **Analytic Sample**

The data contain responses from 6,476 non-managerial hourly workers employed at one of 8 large retail firms in the United States. In our main results, we use listwise deletion and analyze complete cases, an approach recommended in Allison (2001). We exclude 859 respondents who are missing data on at least one of our three main measures of scheduling unpredictability and instability. Of the remaining 5,617 respondents, we exclude an additional 1,343 who are missing data on the economic controls (hourly wage, household income, and tenure). We then drop 1,105 additional respondents missing data on any of the demographic controls (age, gender, race/ethnicity, educational attainment, school enrollment, marital status, living with children, or state of residence). Finally, we exclude 340 additional respondents who are missing data on any of the outcome measures.<sup>2</sup> Our final, balanced analysis sample for the models examining work attitudes, household financial security, and adult health is 2,829 cases.

Of the 4,274 respondents who report having children, 1,341 lived with his or her children and had at least one child under the age of 15. Of those, 54 cases were dropped because of missing data on the three key scheduling variables and another 87 cases were dropped because of missing data on economic variables. 205 more cases were dropped due to missing data on demographics. Finally, we drop 112 additional cases to limit the parent sample to those with non-missing data on all outcomes. Our final analysis sample for parenting outcomes is 883 cases.

## **Robustness**

We first test the sensitivity of our results to using list-wise deletion. Because we can only estimate our fully controlled model using the limited list-wise deleted sample, we first re-estimate our models without the control variables but using the same analysis sample of 2,829 complete cases. We then compare those estimates with results from models estimated on the full sample of all available data also without controls. We compare both of those sets of estimates with each other and to our

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<sup>2</sup>Here, we make an exception: economic hardship was only asked of a subsample of respondents. Rather than limit all analyses to that subsample, we examine this outcomes for the smaller subsample of respondents asked this set of questions.

preferred models.

In our main models, we present unweighted results for the regressions. To test robustness, we re-estimate each of the regression models using the weights derived from ACS and CPS data. The full details of the weighting procedures can be found in Appendix 1.

Third, we present the results of our analysis of the sensitivity of the estimates to unobserved factors that could shape survey response and bias our estimates of the key relationships. Our general approach is to define a dummy variable that represents one of a pair of opposing advertising messages through which respondents were recruited. Then, we interact our key predictor variables with the dichotomous indicator for advertising message. In cases where we find consistent, significant interactions, we show the implied upper and lower-bounds of our estimates.

## Results

### Descriptive Statistics

#### Scheduling Practices at Large Retailers

Table 2 describes the schedules of the retail workers in our main analytic sample. Schedule variability and short-notice are common. The plurality of workers, 45%, report having variable schedules with another 15% reporting a rotating shift. A smaller share, 21% has a regular day-time schedule, while another 8% has a regular evening schedule and 9% has a regular night shift. Over all then, less than a quarter work a regular standard time shift, another 15% work a regular non-standard shift, and almost 60% work some kind of variable schedule.

Workers also receive little advance notice of their weekly schedules. 19% receive less than one week of notice and 42% receive 1-2 weeks. A third receive their schedules between 2 and 3 weeks out and a small minority, 7%, have at least three weeks notice. Together, 60% of workers have less than two weeks of advance notice.

Finally, workers also experience substantial variation in the total hours they worked each week over the month prior to interview. We calculate this measure as the amount of hours in the week in which the respondent worked the most hours minus the amount of hours in the week the respondent worked the fewest hours divided by the number of hours worked the week the respondent worked the most hours. The mean percent variation is 33%, which implies that a worker that averaged

25 hours per week in the prior month likely worked as little as 20 hours at least one week of the month and as many as 30 hours in another week during the same past month.

### **Attitudes, Financial Security, Health and Wellbeing, and Parenting**

In Table 3 and Table 4, we present univariate statistics for our key outcomes, organized into the domains of attitudes, household financial security, health and wellbeing, and parenting.

Workers in our sample express a clear desire for more hours (with 70% agreeing or strongly agreeing that they would like more hours) and for more regular hours (with 86% agreeing or strongly agreeing). By that measure, there is evidence that these unstable schedules are not preferable for most workers, contrary to industry claims (Hatamiya, 2015).

There is also very low household financial security in our sample. Nearly half of workers report that their household incomes vary from week-to-week, which is a striking level of income volatility. One-third report that they have difficulty paying bills and meeting their expenses in a typical month and respondents also report a mean of two economic hardships over the prior twelve months.

In Table 4, we show that nearly two-thirds of respondents report only good, fair, or poor health, a third report “not being too happy,” three-quarters characterize their sleep quality as fair or poor, and, perhaps most strikingly, 43% cross the threshold to serious psychological distress on the Kessler 6 scale.

### **Sample Inclusion and Weighting**

The statistics described above characterize the un-weighted final analysis sample of 2,829 cases. The second columns of statistics in Table 2, Table 3, and Table 4 describe the full set of the 6,632 non-managerial hourly employees we surveyed, some of whom are missing data on one or more covariates. There are no notable differences in these descriptive statistics between the two samples. It does not appear that respondents who complete the entire survey instrument experience any real differences in scheduling as compared with respondents who skip items or do not complete the survey.

Neither of these columns of statistics are, however, weighted to correct for bias in the demographics of our sample as compared to the known characteristics of workers in the industries and occupations of interest. To adjust for such biases, we post-stratify our data by gender, age, and

race/ethnicity and re-weight our data to resemble the characteristics of workers in the industries and occupations corresponding to our target sample frame as reflected in the American Community Survey and the Current Population Survey. The full details of our weighting procedures are described in the Appendix.

The third column of statistics in Table 2, Table 3, and Table 4 are estimated after weighting our regression sample using weights constructed from the ACS. Column 4 weights the regression sample instead using the Current Population Survey. In both cases, the distributions are very similar to the unweighted means in columns 1 and 2.

## Regression Results

We now turn to our estimates of the relationship between three key indicators of unpredictable and unstable work schedules (week-to-week variability in hours worked, schedule type, and weeks of advance notice) and four sets of outcome variables that capture: (1) work attitudes, (2) household financial security, (3) worker health and wellbeing, and (4) parenting.

### Worker Attitudes and Scheduling Practices

We first examine the relationship between work schedules and two indicators of worker attitudes – the desire for more hours and the desire for more regular hours. Our estimates of these relationships are presented in the first two columns of Table 5, for Models 1 and 2. These columns contain coefficients from logistic regression models. We only present the key coefficients of interest, but all models contain the full set of controls as well as employer and state fixed-effects, as shown in Equation (1).

We find the expected relationship between unstable schedules and work-related attitudes. Respondents who reported greater variation in their weekly work hours over the month prior to interview were significantly more likely to agree or strongly agree with the statement that they would prefer to work more hours. Working a variable shift or a rotating shift was also associated with a higher likelihood of wanting to work more hours, relative to working a regular day shift. Notably, there were no statistically significant differences in the desire for more hours between regular day shift workers and workers assigned to non-standard (night or evening), but regular shifts. Variability rather than non-standard scheduling appears to be the more salient factor, a pattern

that holds across our models.

We see some similar patterns when we take desire to work more regular hours as the outcome. There are strong and significant associations between working a variable or rotating schedule and wanting more regular hours. Notably, these effects are larger than the effects on wanting more hours. Taking predicted probabilities of each outcome by schedule type, we see that 72% of workers with a variable shift and 74% of workers with a rotating shift wanted more hours compared with 66% of regular day shift workers – about 10% more. But, 91% of workers with a variable shift and 92% of workers with a rotating shift wanted more regular hours compared with 78% of regular day shift workers – 15% more.

In contrast, advanced notice of work schedules was not related to either outcome.

### **Household Financial Security and Scheduling Practices**

Unstable and unpredictable work schedules are negatively associated with household financial security, even after controlling for hourly wage, household income, and other control variables. The relationships between work schedules and household financial security are shown in Models 3-5 of Table 5.

The most pronounced effects are on volatility in weekly household income. Recent week-to-week variation in hours and working a variable or rotating (vs. stable day) schedule are all significantly and positively related to reporting week-to-week income volatility. Having less than two weeks' advance notice of one's work schedule is also associated with income volatility. Compared to having less than one week of advance notice, having 2-3 weeks or more than 3 weeks of advanced notice significantly reduces the likelihood of experiencing income volatility. Interestingly, there is no difference between having less than 1 week and 1-2 weeks of advance notice. Having more advance notice of one's work schedule may make it easier for workers to maintain a second job, which could help with income smoothing and reduce volatility.

The top panel of Figure 1 plots the predicted probability of experiencing income volatility by recent week-to-week variation in hours, schedule type, and amount of advance notice. Approximately 34% of respondents who report very little variation in weekly hours report experiencing income volatility. A significantly larger share, 47% of respondents with the median level of variation (30%) report volatility and 63% of respondents with variation at the 90th percentile report

income volatility. There are also large differences by schedule type – with about 42% of workers with regular shifts (day, evening, or night) reporting volatility compared with 53% of workers with variable schedules and 49% of workers with rotating shifts. Similarly, while 53% of workers with less than a week of advance notice and 50% of workers with 1-2 weeks of notice experience income volatility, that share drops to 44% and 42% for workers with 2-3 weeks or more than 3 weeks of notice, respectively.

Having a variable schedule also significantly increases the risk of having difficulty paying bills and covering expenses and increases the number of household economic hardships. Though the coefficients are positively signed, there are not significant relationships between recent week-to-week variation in hours and these outcomes. Advance notice is not associated with difficulty paying bills but there is some evidence that greater advance notice (2-3 weeks) reduced reported hardships.

### **Worker Health and Wellbeing and Scheduling Practices**

Unstable and unpredictable work schedules are also negatively associated with worker health and wellbeing. Models 1-5 of Table 6 present the regression results for our measures of worker health and wellbeing. With the exception of self-rated health, we find significant negative associations between working a variable schedule (vs. a stable day schedule) and between having at least two weeks of advance notice and our outcome measures. Those who work a variable schedule are less likely to report being very or pretty happy or to report their sleep quality as very good or good. They are more likely to score higher on the Kessler-6 measure of psychological distress and are more likely to be in serious psychological distress.

It is notable that neither working a regular evening shift nor a regular night shift is significantly associated with lower happiness or psychological distress. It is variability rather than non-standard timing that seems to matter for these measures of wellbeing. The important exception here is that working a regular night shift is significantly negatively associated with sleep quality and with self-rated health.

Respondents who have at least two weeks notice are more likely to report being very or pretty happy and more likely to report very good or good sleep quality. They also score lower on the Kessler 6 and are less likely to cross the threshold to serious psychological distress. For each of these outcomes, there is no significant difference between having less than a week and 1-2 weeks

of notice. The meaningful threshold appears to be at 2 weeks of notice, with some evidence of accumulating benefits of greater notice.

To size these effects, in the bottom panel of Figure 1 we plot the predicted probability of experiencing serious psychological distress by each of our three main measures of schedule unpredictability and instability. There is a positive relationship with recent week-to-week hour variation. But, we see more dramatic differences by schedule type: 46% of those with a variable schedule are so classified as compared with 38% of those with a regular day-time schedule - a substantively large and significant difference. Greater advance notice also matters – 49% of those with less than 1 week of notice are in serious psychological distress as compared with about 37% of those with greater than 2 weeks of notice.

## **Parenting and Scheduling Practices**

Our key measures of scheduling exhibit consistent and sizable associations with work-related attitudes, household economic security, and adult health and wellbeing. Variable work schedules are also associated with parenting outcomes, but hours varying and advance notice are not. For parenting stress, working a variable schedule or working an evening shift both raise parental stress. For parenting time, working a variable schedule is significantly associated with spending less time with co-resident children under the age of 15, but week-to-week hourly variation and advanced notice are not. We see similar negative and significant relationships for those who work a rotating schedule as opposed to a regular day shift. Notably, while there is no significant difference in time spent with children between those who work a day shift and those who work a night shift, we do see that working an evening shift, a time when children are likely to be home from school and awake, has the largest negative association with time spent with children.

## **Robustness**

We report on three types of robustness tests: (1) to the exclusion of missing data and the inclusion of controls, (2) to post-stratifying and weighting the data to retail workers in the CPS, and (3) to accounting for likely unobserved factors that affect sample selection and could bias the estimates.

## Missing Data

The results reported above are based on models estimated with demographic and economic controls on the sub-set of respondents who had complete information on each of those variables (as well as key predictors). Here, we assess the sensitivity of our results to using list-wise deletion to handle missing data compared with using more parsimonious regression models for a larger analysis sample.

To do so, we compare our preferred estimates (M1), which are run on the sub-sample of cases with complete data on all controls and which include controls, with two alternatives. First, we similarly restrict our analysis sample to those with complete data on all controls, but we do not include any of the controls in our model (including dropping the state fixed effects, but not the employer fixed effects) (M2). Second, we again do not include control variables, but we also do not restrict our analysis sample to those with complete data on all controls (M3). M2 might differ from M1 because we do not control for possible confounders. M3 might differ from M1 because we do not include controls, but also because we include cases that are otherwise deleted. M2 might differ from M3 because of the inclusion of these additional cases. By comparing all three estimates, we can assess the importance of excluding cases with missing data from our analysis.

Figure 2a and Figure 2b show these comparisons. For each outcome, we plot the coefficients for our key scheduling variables, comparing the coefficient estimate from M1, M2, and M3. Each outcome has its own panel. All of the models are estimated with OLS regression to facilitate comparisons across models with different predictors (Mood, 2010). Note that the OLS coefficients plotted in the figures will not match the logistic regression coefficients previously presented in tables. The direction of the relationship being depicted is consistent whether OLS or logistic regression coefficients are presented.

The large red dot captures our preferred estimates. In general, dropping the controls (represented by the blue diamond) increases the effect sizes for our attitudinal and economic outcomes (farther to the right for week-to-week variation in hours and having a variable schedule and farther to the left for more advanced notice), which is expected. Without controlling for hourly wages, income, and other control variables, we are likely to overestimate the relationship between scheduling practices and outcomes.

Dropping the controls and including all cases (represented by the orange triangle) generally



produces estimates that are either as large or larger than either of the two alternatives (though not without exception).

Our preferred estimates for self-rated health are not significant and so we do not remark on variation in those effects. For happiness, sleep-quality, and psychological distress, the patterns are generally similar to those for the attitudinal and economic outcomes – the coefficients are as large or larger without controls and without controls and with all cases as in the preferred models. This robustness test suggests that omitted cases are unlikely to bias our estimates upward and imply that some of our estimates of the relationships between scheduling practices and outcomes may be conservative.

## **Weighted Results**

The regression results above are estimated on unweighted data. We can also re-estimate the key models with weights to adjust the sample demographics (age, race, and gender) to resemble the target population’s characteristics as tabulated from the American Community Survey or the Current Population Survey.

Table 7 presents an alternative set of regression estimates that use the weights derived from the American Community Survey. When weights are applied, the overrepresentation of women and non-Hispanic whites in our sample is adjusted for. In general, there are few differences between the weighted and unweighted regression results.

For the two attitudinal outcomes, the results are similar. The relationship between week-to-week hour variability and desiring more hours remains significant and is slightly stronger. However, having a variable or rotating (vs. regular day) is no longer significantly associated with preferring more work hours. Working a variable or rotating schedule remains significantly associated with preferring more regular hours, though the coefficients are about 30% smaller in size.

For the economic outcomes – income volatility, difficulty paying bills, and economic hardship – the results are largely unchanged after weighting. Week-to-week variability in hours remains significantly positively associated with income volatility, working a variable schedule is significantly positively associated with all three measures, and working a rotating schedule significantly increases the risk of income volatility and hardship. Having at least two weeks of advance notice of schedules is, as before, significantly associated with lower levels of income volatility.

In the unweighted models of worker health and wellbeing, we did not find any significant associations with self-rated health, but for working the night shift. In Table 7, we see that after weighting, this remains true. For happiness, the associations with scheduling practices reported in Table 6 remain or are strengthened after weighting. For sleep quality, weighting attenuates the relationship with having a variable schedule, but the beneficial effect of greater advance notice remains. Greater week-to-week variation in hours, having a variable or rotating schedule, and having less than two weeks of advance notice are all still negatively and significantly associated with psychological distress and with serious psychological distress.

Finally, the relationship between schedule type and both parenting stress and time remains largely unchanged, with working a variable schedule or an evening shift associated with more parental stress and less parental time with children.

These results are substantively unchanged if we use the weights derived from the Current Population Survey rather than the American Community Survey.

### **Bounding the Effect of Sample Selection on Potentially Confounding Unobservables**

The weighted results above give us confidence that any demographic biases in our sample composition in terms of age, gender, and race/ethnicity are not skewing our estimates of the relationship between unstable and unpredictable scheduling practices and worker and family health and wellbeing. However, it remains possible that workers select into our survey sample on the basis of some unobserved characteristic and that same characteristic confounds the relationship between scheduling practices and worker health and wellbeing.

We cannot definitively rule out the possibility that this sort of selection on a confounder is occurring. But, we propose and test a method for assessing the presence of a specified confounder. To do so, we first chose one such likely confounder – time pressure. Here, it is certainly possible that workers who feel that they are time constrained would both be less likely to take our survey and that time constraint could also bias the relationship between scheduling practices and health and wellbeing.

We next developed a pair of advertising recruitment messages designed to elicit responses by workers who were either “high” or “low” on this “unobserved” factor. For time pressure, we one of two advertising messages to recruit respondents: either “Not getting enough hours at [EM-

PLOYER]?” or “Overworked at [EMPLOYER]?”

We then compare respondents recruited to the survey through each message channel. We first conduct a manipulation check to determine if the messages actually serve to elicit responses from different groups of potential respondents. For time-pressure, we compare respondents recruited through the over-work message versus the insufficient hours message in terms of their stated desire for more work hours. There is a large and significant difference between the two groups with 84% of those who were recruited through the insufficient hours message channel desiring more work hours versus 68% of those who were recruited through the over-work message channel.

We next re-estimate each of our preferred models, now including an interaction between recruitment message and each of our three key predictors – week-to-week hour variability, schedule type, and weeks of advanced notice. If the unobserved variable “time pressure” confounds our key relationships between scheduling practices and health and wellbeing, then we would expect that the interaction terms would be significant. Of the 96 interaction terms across the twelve models, only 7 were significant at the  $p < 0.05$  threshold. By chance, we would expect about 5 significant coefficients across 96 models.

Figure 3a and Figure 3b chart the predicted values of each outcome by predictor x message. In these figures, each mini-figure plots the predicted values based on the interaction of a particular predictor and message. There are then three mini-figures for each outcome (week-to-week variability in hours, schedule type, and weeks of notice). In almost all cases, the 90% CI are overlapping, indicating no difference in the relationship by message type. The one interesting exception is the desire for more hours. There, the relationship between unstable and unpredictable schedules and desiring more hours is significantly weaker for those who are recruited through the over-work channel versus the insufficient hours channel.

## Discussion

The Retail Work and Family Life Study collected data from a national sample of hourly retail workers at eight large employers. We used a novel method of data collection, in which respondents were recruited via targeted advertisements on Facebook. Using this approach, we address the lack of data on scheduling practices available alongside data on economic, health, and wellbeing outcomes. Our focus on a large sample of hourly retail workers is purposeful, allowing us to limit

sample heterogeneity on extraneous and potentially confounding variables such as socioeconomic status and human capital and to examine a segment of the labor force acutely affected by unstable and unpredictable work schedules.

We focus on three scheduling practices that are expected to have negative effects on workers and their families: total work hours that vary from week to week, work schedules that vary, and short advance notice of work schedules. Using our novel data, we estimated the associations between each of these scheduling practices and economic, health and wellbeing, and parenting outcomes. By and large, we find evidence that these scheduling practices have a range of negative effects on workers and their families. These types of associations have been reported in journalistic accounts (Kantor, 2014; Singal, 2015) and in case studies (Haley-Lock, 2011; Henly and Lambert, 2014a), and are consistent with findings on broader low and moderate income samples (Federal Reserve, 2014; Golden, 2015). We build upon this prior research and provide systematic evidence that these practices are indeed associated with a range of negative outcomes for hourly workers employed in the retail sector. Jobs in the retail sector are characterized not only by unpredictable and unstable schedules, but also by low wages. Yet, even after adjusting for wages, incomes, and a range of other control variables, unstable and unpredictable scheduling practices were still related to financial insecurity, worse health outcomes, and parenting stress and reduced time with children for working parents.

Because we rely on a non-probability sample, we are attentive to issues of potential sample selectivity. We address selection issues in two ways. First, using post-stratification weighting, we adjust the demographic characteristics of our sample to reflect the broader national population of retail workers in the Current Population Survey and American Community Survey. Such post-stratification weighting approaches have been shown to successfully address selectivity in samples far more skewed than our own (Wang et al., 2015). This weighting procedure does not address potential selectivity on unobserved characteristics, which we instead attempt to assess using targeted advertisements with intentionally polarized recruitment messages, designed to attract workers on both ends of a continuum with respect to potential confounding characteristics. Using this strategy, we show that workers recruited by a message about “too many work hours” versus “insufficient work hours” yield a similar pattern of results with respect to the relationship between work schedules and wellbeing outcomes. Our test of polarized recruitment messages provides some reassurance

that sample selectivity does not threaten our results.

Although our data provide novel evidence on how work scheduling practices affect workers and their families, some limitations and cautions should be kept in mind. Our analyses are cross-sectional, and unobserved characteristics of individuals could lead some workers to sort into jobs with particular scheduling practices or to be subject to certain scheduling practices within jobs and to experience worse outcomes for reasons unrelated to those scheduling practices. We also cannot eliminate the possibility of a reverse causal relationship between scheduling practices and worse outcomes. Certainly, more research on how scheduling practices affect workers and their families would be desirable. While we have taken steps to guard against sample selectivity, particularly on potentially confounding variables, future work should investigate other possible sources of sample selection and seek to weight the data against employer-specific benchmarks.

Our research comes against the backdrop of a rapidly changing policy landscape, San Francisco has recently implemented legislation that requires chain stores to provide two weeks of advance notice of work schedules and access to more work hours, and several large cities including Seattle, Washington D.C., and San Jose are considering similar legislation. Our research provides support for the notion that requiring two weeks of advance notice would improve the lives of retail workers, specifically, improving workers' happiness, mental health, and economic security. Advance notice of at least two weeks seems likely to improve workers' ability to plan their child care, to combine work with schooling or a second job, and in turn may reduce stress and improve mental health.

Our study also documents a robust and widespread relationships between variable work schedules and economic, health, and parenting outcomes. Notably, local scheduling legislation does not directly prohibit variable work schedules, but rather requires advance notice and access to full-time hours before additional part-time workers are hired. These levers may well reduce variable work schedules by providing workers with the ability to plan ahead and reduce variability via voluntary shift trades, by reducing employer incentives to make last-minute schedule changes, and by providing workers with a greater number of expected hours. Still, whether these legislative changes, if approved and implemented, will reduce variable work schedules remains to be seen. New, targeted data collection will be necessary to answer this question.

The imminent changes in scheduling law and company practice provide an opportunity to study the effects of an exogenous change in work scheduling practices. Future research, capitalizing on

these exogenous changes, would represent an important step forward in understanding the causal link between work schedule practices and financial security, health, and wellbeing of workers and their families. Although our results are not definitive, they add to a growing body of evidence that scheduling practices have substantial effects on the lives of workers and their families and that an increase in the stability and predictability of work schedules would be likely to have a range of beneficial effects.

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## Tables

Table 1: Comparison of Demographics of Unweighted and Weighted Survey Data with Characteristics of ACS and CPS Samples

	(1) Analysis Sample Unweighted	(2) Analysis Sample ACS Weights	(3) Analysis Sample CPS Weights	(4) ACS Sample	(5) CPS Sample
<b>Gender</b>					
Male	24%	44%	44%	44%	44%
Female	76%	56%	56%	56%	56%
<b>Age</b>					
18-19	13%	14%	12%	14%	12%
20-29	42%	38%	38%	38%	38%
30-39	22%	18%	20%	17%	20%
40-49	20%	18%	19%	18%	19%
50+	4%	12%	10%	13%	11%
<b>Race/Ethnicity</b>					
White, Non-Hispanic	75%	64%	57%	63%	55%
Black, Non-Hispanic	6%	11%	13%	12%	14%
Hispanic	12%	16%	21%	16%	21%
Other or Two or More Races, Non-Hispanic	7%	8%	9%	8%	9%
<b>Educational Attainment</b>					
High School or Less	42%	44%	44%	62%	56%
Some College (including AA)	50%	48%	47%	29%	35%
BA or more	8%	8%	9%	8%	9%
<b>Enrolled in School</b>	25%	26%	25%	26%	27%
<b>N</b>	2829	2829	2829	154451	10527

Table 2: Work Scheduling Measures: Unweighted and Weighted Survey Data

	(1) Analysis Sample Unweighted	(2) Full Sample Unweighted	(3) Analysis Sample ACS Weights	(4) Analysis Sample CPS Weights
<b>Schedule Type (%)</b>				
Variable Schedule	45%	42%	44%	43%
Regular Daytime Schedule	21%	22%	20%	21%
Regular Evening Schedule	8%	8%	9%	8%
Regular Night Shift	9%	9%	10%	10%
Rotating Schedule	15%	17%	15%	16%
Other	2%	2%	2%	2%
<b>Advanced Notice (%)</b>				
1 week or less	19%	22%	20%	20%
Between 1 and 2 weeks	42%	40%	42%	42%
Between 2 and 3 weeks	32%	31%	31%	30%
3 Weeks or More	7%	7%	7%	7%
<b>Week-to-Week Hours Variation</b>				
Mean	33%	33%	33%	33%
Median	29%	29%	29%	29%
N	2829	varies	2829	2829

Table 3: Attitudinal and Household Economic Security Measures: Unweighted and Weighted Survey Data

	(1) Analysis Sample Unweighted	(2) Full Sample Unweighted	(3) Analysis Sample ACS Weights	(4) Analysis Sample CPS Weights
<b>Would Like More Hours</b>				
Strongly Agree/Agree	70%	69%	71%	71%
Disagree/Strongly Disagree	30%	31%	29%	29%
<b>Would Like More Regular Hours</b>				
Strongly Agree/Agree	86%	85%	86%	86%
Disagree/Strongly Disagree	14%	15%	14%	14%
<b>Week-to-Week Income Volatility</b>				
Yes	48%	46%	47%	46%
<b>Difficulty Paying Bills/Expenses</b>				
Somewhat/Not Difficult	64%	67%	66%	65%
Very Difficult	36%	33%	34%	35%
<b>Household Economic Hardships</b>				
Mean	2.1	1.9	2	2
Median	2	2	2	2
<b>N</b>	2829	varies	2829	2829

Table 4: Health and Parenting Measures: Unweighted and Weighted Survey Data

	(1) Analysis Sample Unweighted	(2) Full Sample Unweighted	(3) Analysis Sample ACS Weights	(4) Analysis Sample CPS Weights
<b>Self Rated Health</b>				
Excellent/Very Good	33%	34%	36%	36%
Good/Fair/Poor	67%	66%	64%	64%
<b>Happiness</b>				
Very/Pretty Happy	67%	68%	67%	67%
Not too Happy	33%	32%	33%	33%
<b>Sleep Quality</b>				
Very Good/Good	24%	25%	26%	26%
Fair/Poor	76%	75%	74%	74%
<b>Serious Psychological Distress</b>				
Yes	43%	41%	42%	42%
<b>Psychological Distress Score</b>				
Mean	11.5	11.3	11.4	11.3
Median	12	11	11	11
<b>Parenting Stress Score</b>				
Mean	5.1	5	5	5
Median	5	5	5	5
<b>Parenting Time Score</b>				
Mean	11.9	12	11.8	11.8
Median	12	12	12	12
<b>N</b>	2829	varies	2829	2829

Table 5: Relationship between Work Scheduling Experiences and Worker Attitudes/Household Economic Security

	(1) Prefer More Hours	(2) Prefer More Regular Hours	(3) Income Volatile	(4) Difficulty Paying Bills	(5) # of Hardships
<b>Recent Weekly Hour Variation</b>	0.772**	0.361	1.950***	0.227	0.284
<b>Work Schedule Type</b>					
Regular Day Shift	(ref)	(ref)	(ref)	(ref)	(ref)
Variable Shift	0.267*	1.028***	0.532***	0.302*	0.525***
Regular Evening Shift	-0.122	-0.165	0.056	0.234	-0.001
Regular Night Shift	-0.051	-0.382*	-0.074	0.087	0.372
Rotating Schedule	0.398*	1.090***	0.359*	0.184	0.349*
Other Schedule	-0.221	0.227	-0.233	0.346	0.373
<b>Week of Advanced Notice</b>					
Less than 1 Week	(ref)	(ref)	(ref)	(ref)	(ref)
Between 1 and 2 Weeks	0.225	-0.013	-0.145	0.140	-0.153
Between 2 and 3 Weeks	0.254	-0.219	-0.448**	-0.006	-0.304*
3 Weeks or More	0.275	-0.388	-0.524*	-0.053	-0.164
<b>N</b>	2829	2829	2829	2829	1365

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$

All models include controls for race, age, gender, educational attainment, marital status, school enrollment, hourly wage, household income, average weekly work hours, employment tenure, and living with children as well as state and employer fixed-effects.

Table 6: Relationship between Work Scheduling Experiences and Worker Health and Wellbeing/Parenting

	(1) Self-Rated Health	(2) Happiness	(3) Sleep Quality	(4) Psychological Distress	(5) Serious Psych Distress	(6) Parenting Stress	(7) Parenting Time
<b>Recent Weekly Hour Variation</b>	-0.155	-0.133	-0.281	1.529**	0.502*	0.107	-0.872
<b>Work Schedule Type</b>							
Regular Day Shift	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)
Variable Shift	-0.176	-0.502***	-0.294*	0.826**	0.360**	0.502*	2.043***
Regular Evening Shift	0.102	0.253	0.053	-0.582	-0.171	1.205**	3.073***
Regular Night Shift	-0.514**	-0.206	-0.504**	0.482	0.201	0.421	0.678
Rotating Schedule	-0.116	-0.257	-0.281	0.444	0.210	-0.272	1.902**
Other Schedule	-0.347	-0.418	-0.168	-0.182	0.308	0.013	1.017
<b>Week of Advanced Notice</b>							
Less than 1 Week	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)
Between 1 and 2 Weeks	0.168	0.100	0.187	-0.622	-0.170	0.257	0.641
Between 2 and 3 Weeks	0.216	0.493**	0.344*	-1.536***	-0.535***	-0.0250	0.678
3 Weeks or More	0.267	0.441*	0.889***	-1.708**	-0.517*	0.184	-0.639
<b>N</b>	2829	2829	2829	2829	2829	883	883

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ 

All models include controls for race, age, gender, educational attainment, marital status, school enrollment, hourly wage, household income, average weekly work hours, employment tenure, and living with children as well as state and employer fixed-effects.



Table 7: Relationship between Work Scheduling Experiences and Key Outcomes, Weighted to ACS

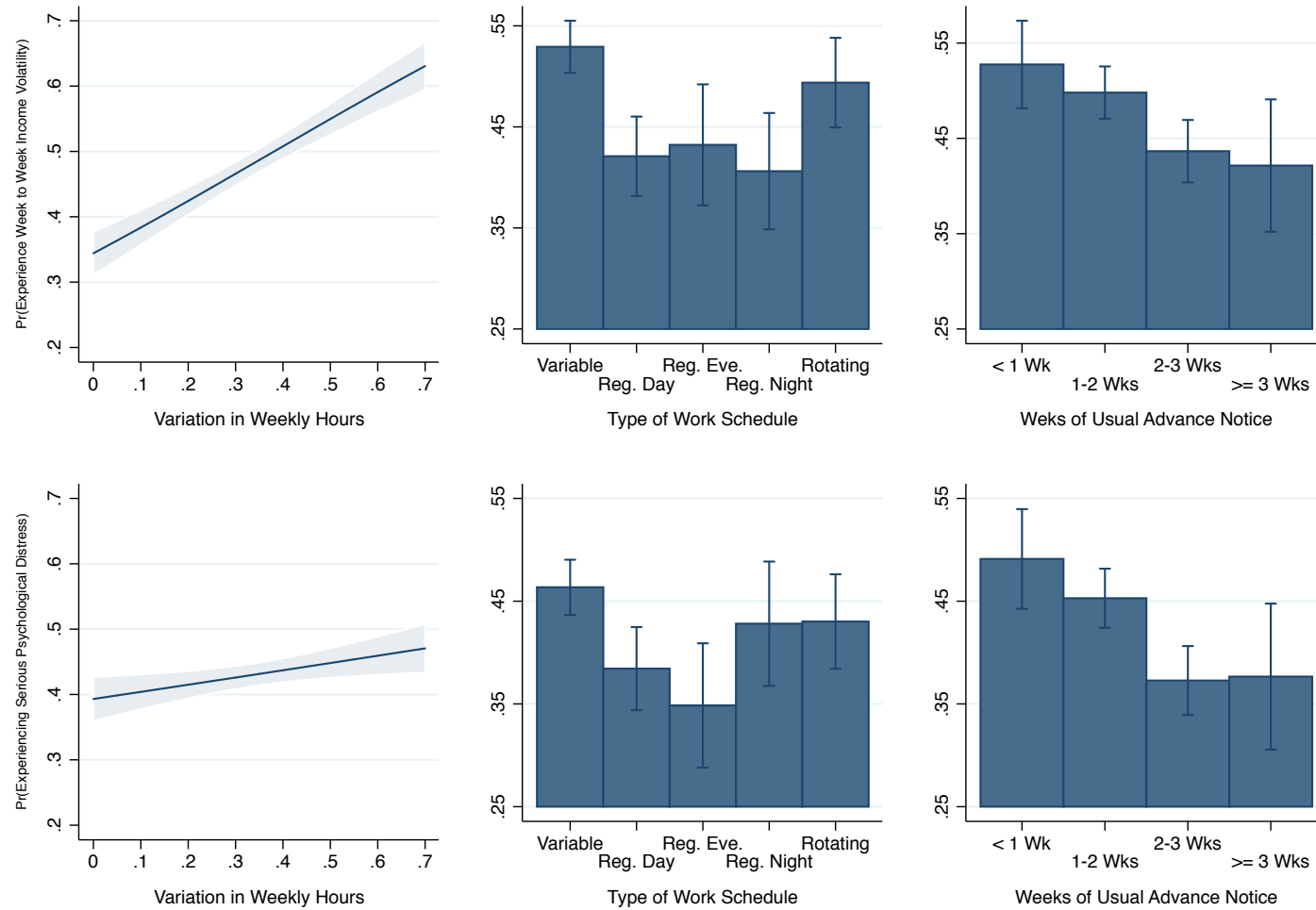
	(1) Prefer More Hours	(2) Prefer More Regular Hours	(3) Income Volatile	(4) Difficulty Paying Bills	(5) # of Hardships	(6) Self- Rated Health	(7) Happiness	(8) Sleep Quality	(9) Psych Distress	(10) Serious Psych Distress	(11) Parenting Stress	(12) Parenting Time
<b>Recent Wkly Hr Var</b>	0.908**	0.524	1.810***	0.349	0.134	-0.385	-0.557*	-0.425	2.442***	0.688**	1.031	-0.405
<b>Work Schedule Type</b>												
Regular Day Shift	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)
Variable Shift	0.108	0.727***	0.447**	0.283	0.425**	-0.205	-0.538***	-0.222	0.695	0.263	0.733**	1.849***
Regular Evening Shift	-0.210	-0.307	0.0468	0.190	-0.137	0.124	0.288	0.505*	-0.632	-0.282	1.338**	3.394***
Regular Night Shift	-0.293	-0.701**	-0.100	-0.130	0.455*	-0.655**	-0.194	-0.541*	0.537	0.133	0.590	1.110
Rotating Schedule	0.083	0.788**	0.380*	-0.005	0.306	-0.305	-0.247	-0.273	0.408	0.086	-0.004	1.457*
Other Schedule	-0.466	0.001	-0.535	0.313	0.291	-0.112	-0.395	0.0286	-0.990	0.047	-0.050	0.877
<b>Week of Advanced Notice</b>												
Less than 1 Week	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)	(ref)
Between 1 and 2 Weeks	0.331	-0.042	-0.113	0.034	-0.140	0.160	0.290	0.210	-1.070*	-0.235	-0.089	0.694
Between 2 and 3 Weeks	0.362	-0.257	-0.480*	-0.012	-0.306	0.162	0.638***	0.285	-1.582**	-0.568**	-0.134	0.815
3 Weeks or More	0.321	-0.435	-0.638*	0.114	-0.181	0.200	0.737**	0.838**	-2.596***	-0.745**	-0.122	-0.679
<b>N</b>	2829	2829	2829	2829	1365	2829	2829	2829	2829	2829	883	883

\*  $p < .05$ , \*\*  $p < .01$ , \*\*\*  $p < .001$ 

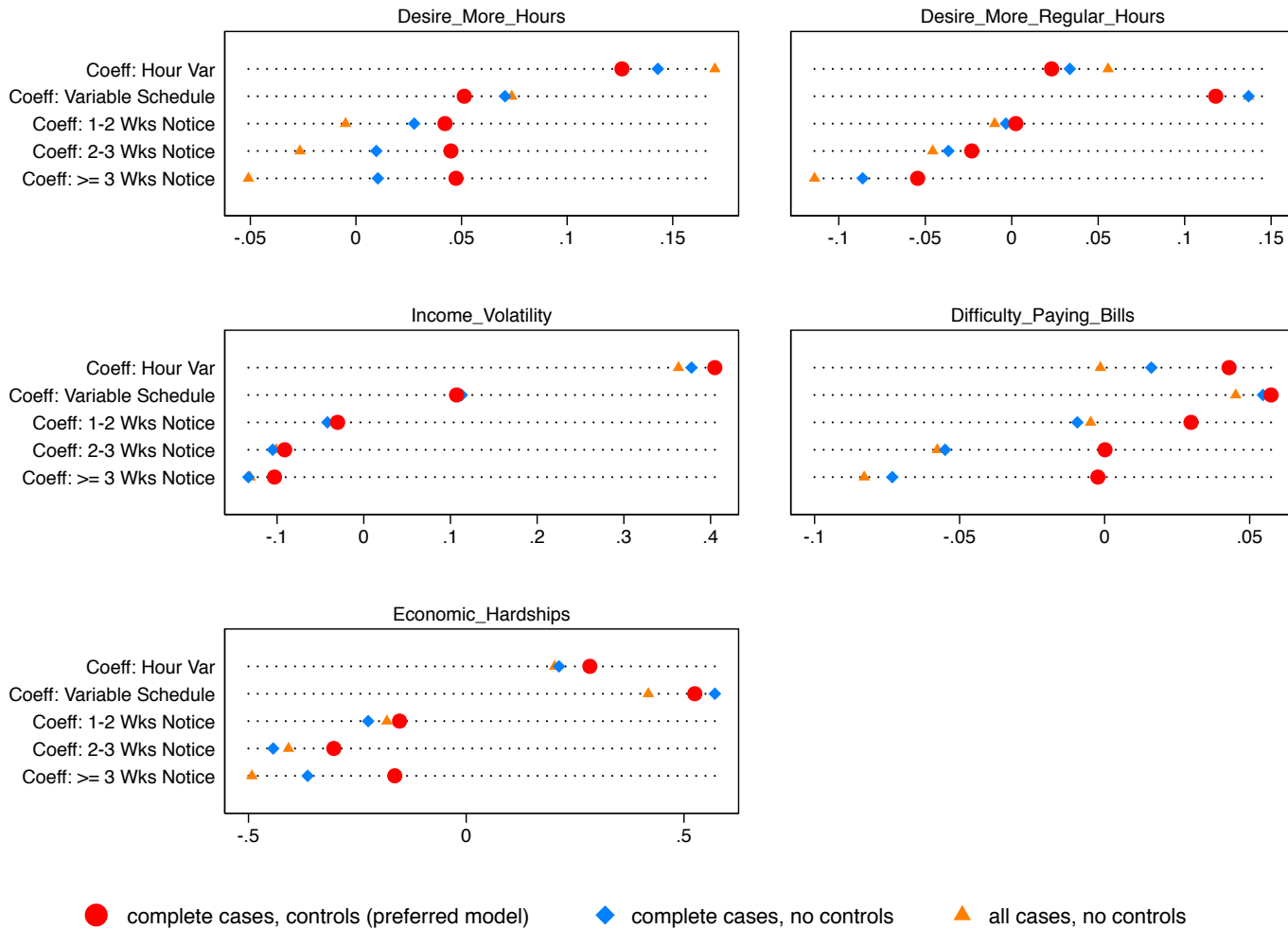
All models include controls for race, age, gender, educational attainment, marital status, school enrollment, hourly wage, household income, average weekly work hours, employment tenure, and living with children as well as state and employer fixed-effects.

## Figures

Figure 1: Predicted Probability of Household Income Volatility (top 3) and of Serious Psychological Distress (bottom 3) by Scheduling Experiences

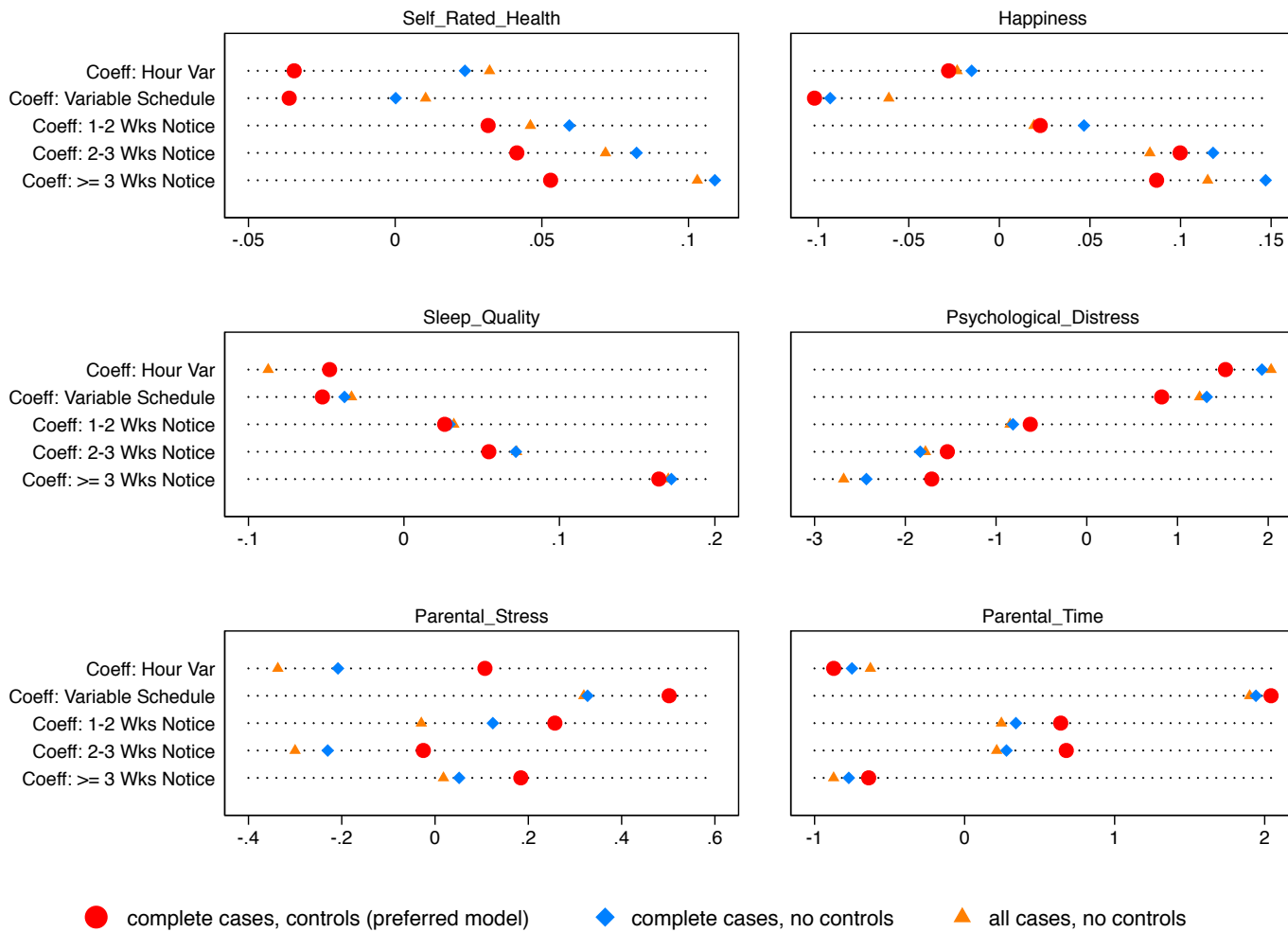


**Figure 2a: Variation in Association between Scheduling and Attitudinal and Household Economic Security Outcomes by Treatment of Missing Data and Inclusion of Controls**



Note: All models estimated using OLS Regression.

**Figure 2b: Variation in Association between Scheduling and Health, Wellbeing, and Parenting Outcomes by Treatment of Missing Data and Inclusion of Controls**



Note: All models estimated using OLS Regression.

Figure 3a: Variation in Association between Scheduling and Health, Wellbeing, and Parenting Outcomes by Survey Recruitment Message (“Not Getting Enough Hours” vs. “Overworked”) (90% CI)

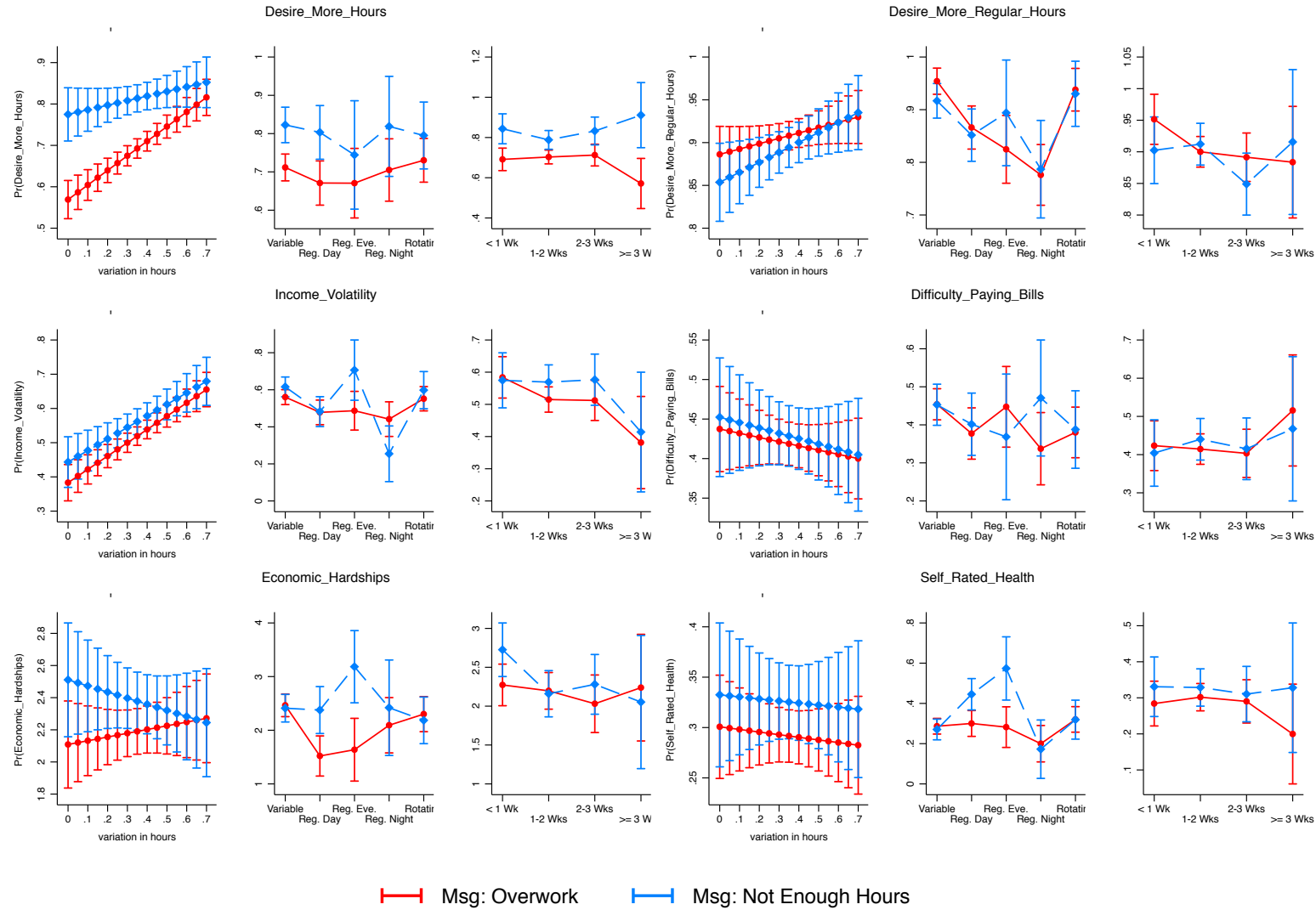
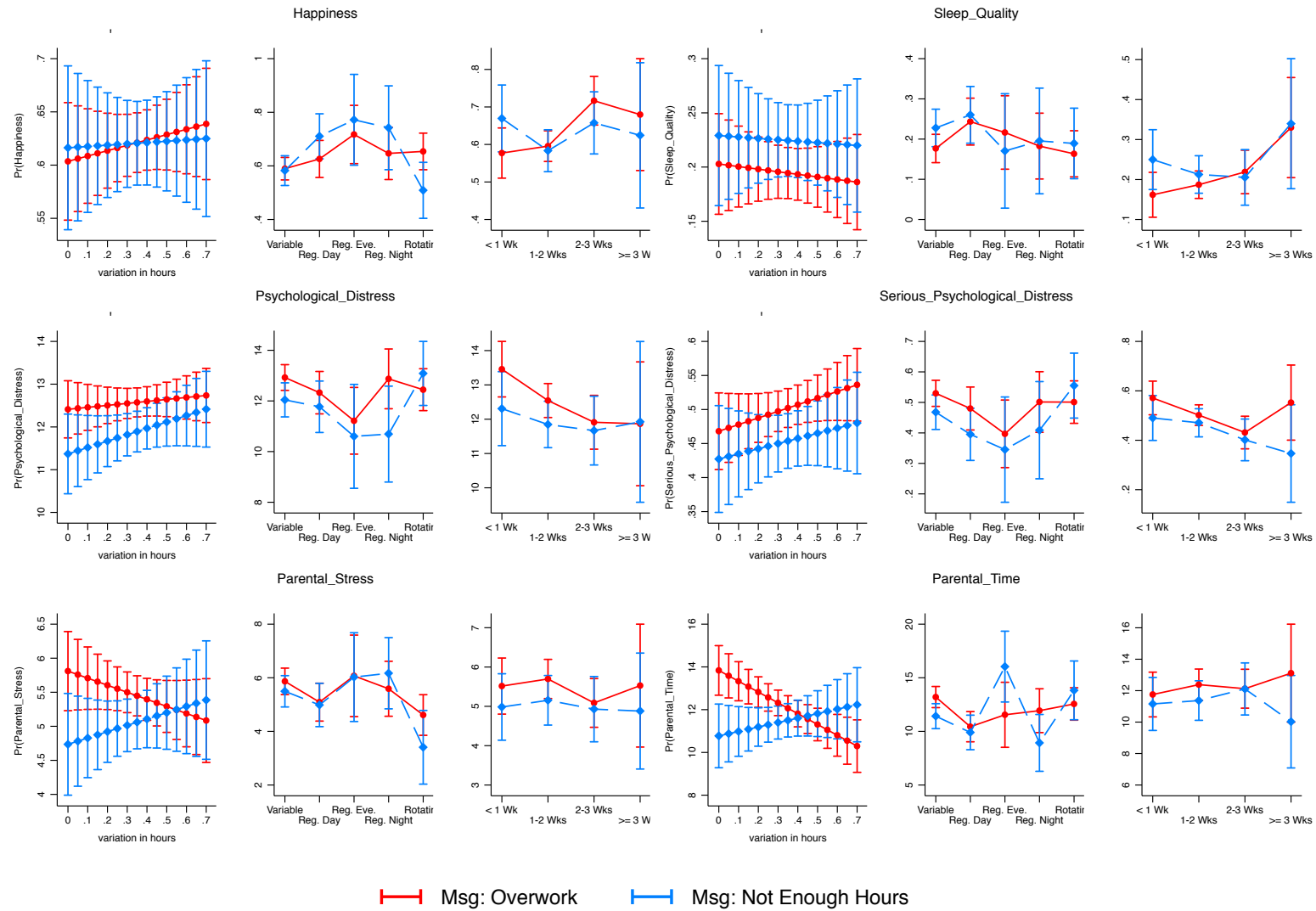


Figure 3b: Variation in Association between Scheduling and Health, Wellbeing, and Parenting Outcomes by Survey Recruitment Message (“Not Getting Enough Hours” vs. “Overworked”) (90% CI)



## Appendix: Weighting Methodology

In order to generalize the findings from our Facebook survey to a wider population, we construct weights that align the observable characteristics of our sample to those characteristics in larger population surveys. The population surveys we draw on are the American Community Survey (ACS) 2015 5-year sample, and the latest 5 years of Current Population Survey (CPS) data (2010-2014), both downloaded from IPUMS (Ruggles et al. 2015 and Flood et al. 2015). We do not expect that the results from weights based on the CPS will differ in any systematic way from those based on the ACS. We use both simply to show the robustness of our results to the choice of population survey.

Because our Facebook survey is limited to 18-50 year olds, working in one of 8 companies (Target, Costco, Walmart, Krogers, Walgreens, CVS, Home Depot, and McDonalds), we restrict the ACS and CPS samples to those aged 18-50, and working in the industries of: “general merchandise store,” “grocery,” “retail food stores,” “drug stores,” or “hardware store.” These industries correspond to the 1990 Industry codes 600, 642, 601, 581, and 611.

Because our sample excludes managers, we also exclude ACS and CPS respondents who report managerial occupations, such as supervisors and managerial and professional specialty occupations (Occupation codes 243, 678, and 96). We respondents in all remaining occupations where the most common occupations are Cashier (276), stock and inventory (365), retail sales clerks (275), Butchers and meat cutters (686), cooks (436), kitchen workers (439), customer service representatives (376), miscellaneous food preparation (444), and laborers outside of construction (889).

Because there are effectively two samples in our data (data that is complete on all demographic characteristics, and data that is complete on both all demographic characteristics and all covariates of interest) we conduct this weighting methodology twice, once for each group.

Once the ACS and CPS samples have been constructed, we align our Facebook survey to these samples along categories of gender, race/ethnicity, and age group. Gender is coded as a male/female dichotomy, and is aligned to the same sex categories in the ACS and CPS. Race and ethnicity are grouped into categories of Non-Hispanic White, Non-Hispanic Black, Non-Hispanic Other / Two or More, and Hispanic of any race. Age is grouped into categories of 18-19, 20-29, 30-39, 40-49, and 50-55. Together, these 3 variables create 40 groups (2x4x5).

Once the Facebook survey, ACS, and CPS samples have been split into these 40 groups, weights are constructed such that within a group the sum of weights within the Facebook survey equals the total number of observations in that group in the ACS or CPS. Because we want our Facebook survey to be proportionally aligned to the ACS and CPS, but not to have an artificially inflated sample size for our regressions, we then multiply all the weights by the Facebook survey sample size divided by the sum of all weights. Thus, given groups of age,  $a$ , race-ethnicity,  $r$ , and gender/sex,  $s$ , the Facebook survey,  $FS$ , with sample size  $N_{FS}$ , is aligned to the ACS and CPS samples, with sample sizes  $N_{ACS}$  and  $N_{CPS}$  respectively, such that an equation for the survey weights,  $W_i^{ACS}$  and  $W_i^{CPS}$  can be written:

$$\begin{aligned}\sum \mathbb{1}(i)_{a,r,s}^{ACS} * \frac{N_{FS}}{N_{ACS}} &= \sum W_i^{ACS} * \mathbb{1}(i)_{a,r,s}^{FS} \\ \sum \mathbb{1}(i)_{a,r,s}^{CPS} * \frac{N_{FS}}{N_{CPS}} &= \sum W_i^{CPS} * \mathbb{1}(i)_{a,r,s}^{FS}\end{aligned}$$

and thus,

$$\begin{aligned}W_i^{ACS} &= \frac{\sum \mathbb{1}(i)_{a,r,s}^{ACS}}{\sum \mathbb{1}(i)_{a,r,s}^{FS}} * \frac{N_{FS}}{N_{ACS}} \\ W_i^{CPS} &= \frac{\sum \mathbb{1}(i)_{a,r,s}^{CPS}}{\sum \mathbb{1}(i)_{a,r,s}^{FS}} * \frac{N_{FS}}{N_{CPS}}\end{aligned}$$

A summary of weighted descriptive statistics can be found in Table 1.