Varying Weekly Work Hours and Earnings Instability in the Great Recession

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ABSTRACT

Unstable work schedules are increasingly a prominent stratification outcome, particularly for low-wage workers. Nationally representative and longitudinal research on the topic is limited, however. This article examines varying numbers of weekly work hours among hourly workers, their increase during the Great Recession of the late 2000s, and their impact on growing earnings instability. Using from the Survey of Income and Program Participation (SIPP), the cumulative probability of ever reporting varying hours among hourly workers increased from 37 percent between 2004 and 2007 to 47 percent between 2008 and 2012. Changes in state-level economic conditions, particularly state-level unemployment rates and economic growth, largely explain the increase in varying hours, consistent with arguments that employers pass the costs of volatile demand onto workers. Finally, variance function regressions show the growth of varying hours accounts for the significant increase in earnings instability from 2004-7 to 2008-12.

INTRODUCTION

The growth of precarious employment has been a central feature of the contemporary U.S. labor market (Kalleberg 2011), particularly in the Great Recession of the late 2000s. Alongside the peak in unemployment rates, the number of underemployed workers reached the highest point in decades (Glauber 2013; Golden 2016; Mishel et al. 2012). Even with continuous employment in traditional employer-employee relations, varying numbers of work hours from week to week can be burdensome for workers. Though varying weekly hours may reflect desirable flexibility for employees, the majority of schedule variability is employer driven for hourly workers (Golden 2009; Henly, Shaefer, and Waxman 2006; Lambert, Fugiel, and Henly 2014). Many workers report wanting more or more stable hours, especially in services or retail (Schneider and Harknett 2016). Varying numbers of hours from week to week create earnings

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and income instability for hourly workers (Golden 2001a; Gottschalk and Moffitt 2009; Schneider and Harknett 2016; Western et al. 2012). Long-term budgeting or covering essential expenses is more difficult as a result (Morduch and Schneider 2017). In addition to the economic consequences of varying work hours, uncertainty over the supply and scheduling of work hours is also associated with lower mental and emotional well-being (Schneider and Harknett 2016).

Rising unemployment rates in the recession may have primarily been driven by economic conditions, but any growth in varying hours may also reflect more fundamental changes in employment relations. Employers often vary workers' numbers of hours to reduce labor costs (Lambert 2008). Particularly in industries like food service, retail sales, or hospitality, managers try to match staffing to demand as closely as possible (Appelbaum, Bernhardt, and Murnane 2003). To mitigate potential losses in the face of unpredictable demand, managers often change employees' hours and schedules at the last minute, requiring on-call shifts, cutting shifts short, or sending workers home before they even begin their shifts (Alexander and Haley-Lock 2015; Halpin 2015; Luce, Hammad, and Sipe 2014). The Great Recession of the late 2000s likely exacerbated these practices. Aside from laying off workers, employers could also respond to declining or fluctuating demand by varying workers' hours even more profoundly than before. Meanwhile, employees could be forced to accept such conditions due to the lack of viable alternative jobs. Unstable scheduling practices are just one facet of a broader shift of cost and risk from employers to workers (Hacker 2006; Lambert 2008), which may persist after the recession.

Literature on volatile work hours has grown in recent years (e.g., Alexander and Haley-Lock 2015; Golden 2001a; Henly and Lambert 2014; Lambert et al. 2014; Schneider and Harknett 2016), but nationally representative and particularly longitudinal research remains scarce. This paper contributes to existing literature by addressing three primary research questions with nationally representative panel data. To what extent did varying weekly hours become more common for hourly workers in the Great Recession? How much was any growth in varying hours driven by changes in local economic conditions? Finally, did any growth in varying weekly hours substantially contribute to growth in earnings instability?

The study analyzes the 2004-7 panel of the Survey of Income and Program Participation (SIPP) as the pre-recession period and the 2008-12 panel as the period during and after the recession. The analysis proceeds in multiple stages corresponding to each research question above, yielding three main findings. First, reports of variable work hours increased substantially during the Great Recession. The average probability of reporting varying hours among prime-age hourly workers increased from 7.2 to 10.4 percent between SIPP panels; the cumulative probability of ever reporting varying hours in a four-year period increased from 36 to 46 percent.

Second, changes in state-level economic conditions, notably state unemployment rates and economic growth, explain most of the increase in varying hours. The results are consistent with arguments that employers vary their workers' hours to reduce labor costs, motivated by fluctuating or declining demand and enabled by employers' increased power in weak labor markets (Kalleberg 2011; Lambert 2008). However, reports of varying hours remained elevated throughout the recovery, even as unemployment rates declined. The persistently high level of varying hours may reflect a longer-lasting shift of power from workers to employers than predicted by supply and demand (Hacker 2006) or the long-term adoption of variable scheduling practices (Alexander, Haley-Lock, and Ruan 2015; Lambert 2008).

Third, the paper assesses the contribution of varying hours to the upward trend in earnings instability (Gottschalk and Moffitt 2009; Stevens 2001) using variance function regression (Western and Bloome 2009). Earnings instability increased significantly even among continuously employed hourly workers during the recession, and the increase is largely accounted for by the growth of varying hours. The paper concludes by discussing potential long-term changes in work scheduling and related policies.

THEORETICAL BACKGROUND

Prior Research on Varying Work Hours

Varying weekly work hours represent one dimension of what Alexander and Haley-Lock (2015) call "work-hour insecurity." Alongside insufficient numbers of hours and unpredictability, varying weekly hours are common in studies of low-wage workers. Varying hours often overlap with insufficiency and unpredictability, particularly in service industries. There is relatively little research on the broader labor force however, partly because hours variability is less commonly measured than outcomes like job loss in traditional employment surveys (Lambert and Henly 2014; Schneider and Harknett 2016). Since 1994, the Current Population Survey (CPS) allows respondents to answer "hours vary" when asked the usual number of hours worked per week in their primary job. CPS estimates of varying hours among all workers are consistently around five to seven percent of workers (Alexander and Haley-Lock 2015; Lambert, Haley-Lock, and Henly 2012). Reports of varying hours in the CPS are more common for those in blue-collar occupations, and sales and service industries than others. Varying hours are also more common for workers who are not married than married, racial/ethnic minorities than whites, in the private sector than the public sector, non-unionized than union members, and part-time workers compared to full-time (Golden 2001a).

Survey results with alternative measures suggest the CPS underestimates true hours variability (Lambert and Henly 2014). In one survey of retail workers, 25 percent reported varying weekly hours when directly asked (Lambert et al. 2014). Another measure for hours variability is the range of weekly hours within a month. Recently the National Longitudinal Survey of Youth 1997 (NLSY97) asked a nationally representative sample of early career workers, ages 26-32, the most and fewest hours/week worked in the last month. Around half of workers reported a range of at least 10 hours between weeks (Lambert et al. 2014). Other surveys with the same measure similarly find that retail workers usually working 25 hours/week typically vary by ten hours week-to-week (Lambert and Henly 2014; Schneider and Harknett 2016).

These studies help demonstrate a high prevalence of varying hours for particular groups, but still do not represent the national labor force, hourly or otherwise. Moreover, they cannot speak to any increase in varying hours during the Great Recession. This paper complements this literature by estimating the rate of varying hours among all hourly workers between 2004 and 2012. Advantageously compared to other surveys, the SIPP is nationally representative of both the pre-recession period (2004-7 panel) and during/after the recession (2008-12 panel), is longitudinal within each period, and has closely spaced waves (i.e., every four months) for capturing fine-grained volatility.

Varying Work Hours and the Great Recession

The majority of workers' schedules are employer-driven in the United States, particularly among low-wage and non-professional workers (Golden 2001a; Henly et al. 2006; Lambert et al. 2014). Some portion of varying weekly hours could also reflect employee-driven flexibility. Many workers may exchange hours stability for flexible schedules (Golden 2001a), facilitating easier child care or other personal obligations and activities (Clawson and Gerstel 2014; Presser 2005). In one experiment with applicants to a national call center, applicants were generally unwilling to forgo earnings in favor of employee-driven scheduling. However, applicants would forgo 20 percent of earnings to have traditional weekday 9-5 schedules over employer-determined schedules with low predictability (Mas and Pallais 2016). Studies find beneficial effects of schedule control for work-life balance among both professional (Kelly, Moen, and Tranby 2011) and service workers (Henly and Lambert 2014; Henly et al. 2006). This study accounts for caregiving obligations that may drive varying hours, but as described below, I expect job and labor market factors to affect varying hours most strongly.

There are strong reasons to expect varying hours became significantly more common in the Great Recession. First, varying hours may have increased due to compositional changes in jobs. Job growth in the recovery after the Great Recession was relatively high in the low-wage service sector (Bernhardt, McKenna, and Evangelist 2012) where varying hours are common (Golden 2001a; Lambert et al. 2014; Schneider and Harknett 2016). Involuntary part-time employment also increased to historically high rates in the recession, remaining elevated years later partly due to the changed composition of jobs (Golden 2016; Valletta and van der List 2015). Varying hours are more common for part-time workers than full-time workers, so varying hours may have become more common as a result. If compositional changes in the labor market drive any increase in varying hours in the recession, the difference between SIPP panels should be explained by controls for individual characteristics like hourly wage rates, part-time employment, occupation, industry, and job tenure.

Second, management practices producing varying hours for workers may have become more common in the recession, even net of compositional changes in the labor force. Employers commonly use variable work schedules to minimize labor costs in excess of demand, especially in service industries (Appelbaum et al. 2003; Lambert 2008). Specific management practices include on-call shifts, split shifts (two shifts in the same day with a lengthy unpaid break between them), cutting shifts at the last minute, informal layoffs (reducing hours to zero), and mandatory overtime (Alexander and Haley-Lock 2015; Golden 2001b; Lambert 2008). Advantageously for employers, these strategies maximize flexibility without necessarily reducing the supply of available workers. These strategies also produce greater part-time employment. Many employers prefer having many part-time workers rather than fewer full-time workers to have greater scheduling flexibility along with lower labor costs (Halpin 2015).

This study assesses two primary aspects of local (i.e., state-level) economic and labor market conditions. First, economic growth rates are generally the basis for marking economic recessions. A common guideline for defining the start of a recession is two consecutive quarters of declining Gross Domestic Product, GSP (National Bureau of Economic Research n.d.). Negative economic growth at the state level measures the impact of a recession more locally. Declines in GSP partly indicate drops in business income. Firms may have increased pressure on frontline managers to minimize labor costs in response, thus exacerbating variable scheduling.

Second, the unemployment rate often indicates the severity of economic recessions for workers (Hout, Levanon, and Cumberworth 2011) and has been used to examine the impact of the recession within states (Hoynes, Miller, and Schaller 2012). High unemployment rates and low job availability would further disempower workers to resist management practices creating varying hours.

If economic conditions primarily drive any growth of varying hours, the difference between SIPP panels should be explained by factors like local (i.e., state-level) economic growth and unemployment rates. Any growth in varying hours beyond changes in economic conditions (i.e., residual differences between panels) could be driven by normative changes in expectations for stability in traditional employment (Kalleberg 2011). These recession-related changes may be heightened forms of long-run trends toward labor market polarization, suggesting varying hours may continue to increase even after the recession.

Varying Work Hours and Earnings Instability

Like nonstandard or unpredictable schedules (Enchautegui 2013; Golden 2015; Presser 2005), varying hours can disrupt family and social life. Varying numbers of hours from week-to-week also create significant earnings and income instability for hourly workers (Schneider and Harknett 2016). Even among ostensibly middle-class households, volatile earnings and income can lead to missed housing or utility payments, particularly in combination with irregular expenses (Morduch and Schneider 2017). Accordingly, many low-wage workers desire more and steadier weekly hours (Lambert et al. 2012; Schneider and Harknett 2016), sometimes even more so than higher hourly wages or benefits like health insurance (Edin and Shaefer 2015; Morduch and Schneider 2017).

Potential unpredictability due to earnings and income instability complicates individuals' and families' long-term budgeting (Halpern-Meekin et al. 2015; Morduch and Schneider 2017). Even when varying work hours are predictable, instability at the lower end of the earnings and income distributions generally reflects economic insecurity, with significant income losses triggering some form of hardship or deprivation (Gottschalk and Moffitt 2009; Hacker 2006; Western et al. 2012). Large income losses have contributed more to growing income instability among low-income families with children than have income gains (Western et al. 2016). Earnings and income instability also inhibit savings and asset accumulation for many middle-income households, deterring upward economic mobility (Morduch and Schneider 2017).

Earnings instability during and after the Great Recession was profound. About half of primary household earners experienced a month-to-month earnings decline of more than 50 percent between 2008 and 2013 (Stettner, Cassidy, and Wentworth 2016). Job loss substantially increases earnings instability (Stevens 2001), contributing to greater income instability during recession periods (Celik et al. 2009; Gottschalk and Moffitt 2009). However, annual earnings and income instability increased even during non-recession periods since the 1970s, especially among low-wage workers (Hacker 2006).[1] Earnings instability has also grown over time among the continuously employed (Stevens 2001), largely due to varying hourly wage rates or hours worked (Gottschalk and Moffitt 2009). Most relevant to this study, analysis of the 2008 SIPP panel show earnings instability is significantly higher among workers reporting varying weekly hours more often, even net of reported usual hours/week (Stettner et al. 2016).

This study examines how much earnings instability increased among employed hourly workers during the Great Recession and if any increase is accounted for by varying numbers of work hours. Beyond examining the extent and source of any growth in varying hours, this analysis assesses one of its major consequences. Lambert (2008) argues employers use unstable scheduling practices to reduce labor costs at workers' expense. Similarly, Hacker (2006) argues the steady growth of earnings instability represents a fundamental shifting of risk from businesses to individuals and families.

[1] The discussion section describes some contrasting evidence for the upward trend in earnings instability (e.g., Dahl, DeLeire, and Schwabish 2011).

DATA & METHODS

The Survey of Income and Program Participation (SIPP) is a nationally representative panel study of approximately 50,000 households, including more than 100,000 people.[2] The 2004 SIPP panel interviewed respondents every four months from January 2004 through December 2007, and the 2008 SIPP panel did so between August 2008 and December 2013. I use the 2004 panel as the pre-recession period, and the 2008 panel as the period during/after the recession. The analytic sample includes observations of employed, civilian, prime-age (25-55) hourly workers, excluding the self-employed. Though each four-month SIPP wave includes retrospective reports on many variables for each individual month, the question about usual hours per week refers to the entire four-month period. The sample includes only one record per wave. The 2004 SIPP included 12 waves, and the 2008 SIPP included 16. For symmetry, the main analytic sample includes only observations from the first 12 waves of the 2008 panel, through July 2012.

The analysis proceeds in two main stages. Analysis 1 addresses the paper's first two research questions: did varying hours become more common in the Great Recession, and do changes in state-level economic conditions account for any increase? Reports of varying weekly hours are the dependent variable in this portion of the analysis. Analysis 2 addresses the paper's third research question: did any growth in varying weekly hours substantially contribute to growth in earnings instability? Reports of varying weekly hours are the key independent variable in this portion of the analysis, and within-person variance in monthly earnings is the outcome.

Varying Weekly Hours

The SIPP uses a very similar question format as the CPS, allowing workers to volunteer that their 'hours vary' when asked the usual number worked per week in their primary job *in the last four months*, starting with the 2004 panel. As in the CPS, this measure likely underestimates the prevalence of workers with varying hours (Alexander and Haley-Lock 2015; Lambert and Henly 2014). Many workers report a usual number of hours despite large variation from week to week. As a result, the SIPP likely provides lower-bound estimates for the prevalence of varying weekly hours.

[2] The data were downloaded from the National Bureau of Economic Research (NBER): http://www.nber.org/data/survey-of-income-and-program-participation-sipp-data.html

This measure unfortunately cannot assess the degree of hours variability. Supplementary analyses in Appendix I compare binary reports that "hours vary" with alternative continuous measures of hours variability. First, SIPP respondents who report "hours vary" also have significantly greater variation in the reported usual number of hours per week between waves compared to those who never say their "hours vary" (Table A1). Second, I compare SIPP estimates of the prevalence of varying hours with a continuous measure of hours variability in the 2016 General Social Survey (GSS). In general, groups (i.e., industry, education, sex, race/ethnicity) that reported "hours vary" more commonly in the SIPP also have higher variability as a percentage of their usual hours per week (Table A2). Finally, most GSS respondents with high hours variability also had limited advanced notice of their upcoming work schedules (Figure A1).

Individual-Level Variables

The analysis accounts for key individual characteristics associated with varying hours in past research (Golden 2001a; Lambert et al. 2014; Schneider and Harknett 2016). Key individual-level controls include: job tenure (years and months); logged hourly wage rates, adjusted for inflation with the Consumer Price Index (CPI); change in the primary job between waves (yes = 1); whether the individual worked fewer than 35 hours some weeks in the last month (yes = 1); 24 occupation categories; and 13 industry categories. The models also control for standard demographic and socioeconomic characteristics: age; sex (female = 1); race/ethnicity (White, Black, Latino/a, Asian, other race); marital status (married, separated, divorced, widowed, never married); household size; the presence of children under 6 years-old (yes = 1); metropolitan status (in a metro area, not in a metro area, not identified); education (less than high school, high school, some college, college, postgraduate); union membership (yes = 1); and public employment (yes = 1). Means for these variables are presented in Table A3 in Appendix II.

State-Level Variables

Most state-level data come from the National Welfare Database (University of Kentucky Center for Poverty Research 2015). Key economic indicators include the unemployment rate (percentage of the labor force currently employed and actively looking for work), logged total

Gross State Product per capita, ln(GSPpc), and economic growth (annual percentage change in GSPpc) in each state-year.[3] State-level control variables include logged total population, the unionization rate (from Hirsch and Macpherson 2003), and state minimum wage (or federal if higher). The GSPpc and minimum wage are adjusted for inflation with the CPI.

Analysis 1: Varying Work Hours and the Great Recession

I address the first research question, asking if varying hours became more common in the recession, by estimating annual trends in the prevalence of varying weekly hours in the SIPP. I focus on trends among hourly workers but include estimates for both hourly and salaried workers. I also estimate cumulative experiences with the total number of waves that individuals in each panel report varying hours.[4] As described above, the 2004-07 SIPP panel is the pre-recession period, and the 2008-12 SIPP panel is the period during and after the recession. I interpret the difference in the probability of varying hours between the panels as the change during the recession.

The second research question asks how much any increase in varying hours can be explained by changes in local economic conditions. Random-effects logistic regression models predict reports of varying hours and the difference between SIPP panels. If the introduction of variables for state-level economic conditions attenuates the coefficient for the difference between SIPP panels, I interpret this attenuation as the explanatory power of local economic conditions. The full model can be represented as,

$$ln\left(\frac{Pr(Hours\,Vary_{ijt})}{1-Pr(Hours\,Vary_{ijt})}\right) = \beta_1 2008\ Panel_t + X_{ijt}\beta_X + W_{jt}\beta_W + v_j + u_i,$$

where the outcome is the log-odds of *Hours Vary* for person *i* in state *j* and wave *t*. The variable $2008\ Panel_t$ is a binary variable equal to zero for the 2004 SIPP panel and one for the 2008 panel. I interpret its coefficient β_1 as the recession-related difference. The vector X_{ijt} represents

[3] Correlations between the state economic variables do not suggest collinearity. The unemployment rate and is correlated -0.42 with economic growth, and -0.17 with ln(GSPpc). Economic growth and ln(GSPpc) are correlated 0.14.

[4] Survey attrition limits cumulative estimates of varying hours. The average number of observations per person is 4.8 in the 2004 panel, and 5.1 in the 2008 panel. To adjust for this issue, I include the number of observations per person in a multinomial logistic regression to predict the categories 0 waves, 1 wave, 2 waves, and 3+ waves at the person level (2004 panel N = 29,357; 2008 panel N = 27,618). The model includes an indicator for the 2008 panel to estimate the increase during the recession. The predicted probabilities of each category estimate cumulative experiences of varying hours. The probabilities are predicted with the "margins" command in Stata, setting the number of observations per person to 12, the full length of each SIPP panel.

individual-level control variables, W_{jt} is the vector of state-level characteristics, and v_j represents state dummy variables. Finally, u_i represents person random effects—variance components which capture individual-specific qualities associated with varying hours that are assumed to be uncorrelated with X_{ijt}. An alternative strategy would model u_i as fixed effects, which would control for all between-person differences. Fixed-effects models are not suitable here because there is no within-person variation in the indicator for the 2008 panel.

The regression results are presented as differences in the predicted probability of varying hours for differences in the independent variables, or marginal effects. Marginal effects are more substantively interpretable than log-odds coefficients, and comparisons of log-odds coefficients between models may be misleading “[b]ecause coefficients depend both on effect sizes and the magnitude of unobserved heterogeneity” (Mood 2010: 79). The marginal effect for categorical variables is the difference in the predicted probabilities of varying hours between groups, also called a discrete change effect. The marginal effect for continuous variables is the average change in the predicted probability of vary hours for small differences in the independent variable, also called an average marginal effect (Long and Freese 2006). I estimate the marginal effects using the ‘margins’ command in Stata.

The first model includes only then indicator variable for the 2008 SIPP panel. The estimated ‘effect’ of the 2008 panel indicator is the predicted probability of varying hours in the 2008 panel minus the probability of varying hours in the 2004 panel. The second model includes individual-level controls. The difference between panels in this model estimates the recession effect net of compositional differences between time periods, like the decline of middle-wage professional jobs and the growth of low-wage service jobs. The third model adds state-level variables to the second model to determine whether changes in economic conditions fully explain any difference between time periods. This model also includes state dummy variables to control for all stable characteristics of states with stable effects on varying hours. With state fixed effects, the model estimates coefficients for the state-level variables using changes within states over time (i.e., changes in state unemployment rates between years).

Analysis 2: Varying Work Hours and Earnings Instability

The next stage of the analysis addresses the third research question by estimating the contribution of varying work hours to any increase in earnings instability. The dependent variable is logged total monthly earnings in the primary job, adjusted for inflation with the CPI. I first estimate any change in earnings instability between SIPP panels. Next, I introduce *Hours Vary* as the key independent variable. I assess its explanatory power as the extent to which the difference between SIPP panels is attenuated. Finally, I include individual- and state-level controls.

This analysis combines two regression approaches. First, variance function regression (VFR) predicts earnings instability within individuals over time, in addition to their average earnings. Second, 'hybrid' models for panel data decompose the predictor variables into between- and within-person variation. To the author's knowledge, these approaches have not previously been combined. This combination is needed because earnings instability is a within-person variable, but the comparison of the two SIPP panels is between individuals. Assessing the compositional effect of varying weekly hours on earnings instability also requires a between-person comparison.

Variance function regression predicts both mean earnings and the variance of earnings within individuals using Western and Bloome's (2009) maximum likelihood approach. VFR builds on earlier two-stage approaches that predict the mean of a dependent variable in the first model, then the variance of the residuals from that first model with a second model. VFR has been used to examine income and wage inequalities between and within groups defined by family structure (Western, Percheski, and Bloome 2008), union membership (Western and Rosenfeld 2011), and social class (Wodtke 2016). VFR can also be applied to panel data where individuals are the 'groups' and within-person variance represents instability over time. Western and Bloome (2009) use VFR to compare income volatility for those with and without previous incarceration by differencing income from each person's mean over time. This analysis similarly assesses earnings instability by predicting logged monthly earnings differenced from individuals' own mean earnings over the whole panel.

VFR predicts within-person instability in the dependent variable, and the second approach incorporates both between- and within-person differences in the independent variables. The 'hybrid' or fixed-effects vector decomposition model (Bell and Jones 2015; Firebaugh, Warner, and Massoglia 2013) decomposes time-varying independent variables into two components: individuals' mean values across all waves and individuals' deviations from their own means. The component with the mean values captures between-person variation in the independent variables. The component with individuals' deviations from their means captures changes over time, equivalent to fixed-effects models.

The combined regression approach includes two models, which can be presented as,

$$\Delta ln(Earnings_{ijt}) = \beta_1 2008\ Panel_t + \beta_2 \overline{Varying\ Hours}_{ij} + \beta_3 \Delta Varying\ Hours_{ijt} + \bar{X}_{ij}\beta_{\bar{X}} + \Delta X_{ijt}\beta_{\Delta} + W_{jt}\beta_W + e_{ijt},$$

and

$$log(\sigma_i^2) = \lambda_1 2008\ Panel_t + \lambda_2 \overline{Varying\ Hours}_{ij} + \lambda_3 \Delta Varying\ Hours_{ijt} + \bar{X}_{ij}\lambda_{\bar{X}} + \Delta X_{ijt}\lambda_{\Delta X} + W_{jt}\lambda_W.$$

In both models, X_{ijt} and W_{jt} are the vectors of individual- and state-level variables, respectively. The vector $\bar{X}_{ij}$ represents the person-level means of the individual-level variables, and ΔX_{ijt} represents individuals' deviations from their own means over time. For example, a person reporting varying hours for four of their twelve interviews has $\overline{Varying\ Hours} = 0.33$. In waves reporting steady hours, $\Delta Varying\ Hours = 0 - 0.33 = -0.33$; in waves with varying hours, $\Delta Varying\ Hours = 1 - 0.33 = 0.67$.

The first model is a weighted least squares regression. The coefficient β_1 is the predicted average difference between SIPP panels, which should be approximately zero because $\Delta ln(Earnings_{ijt})$ has mean zero in both panels. The coefficient β_3 is the average change in logged monthly earnings when a person switches from steady to varying hours.

The second model is a gamma regression predicting the logged residual variance of earnings within individuals, $log(\sigma_i^2)$, which measures earnings volatility. In this model, σ_i^2 is the variance of the error term from the first model, e_{ijt}. This error term is net of the predictor variables from the OLS regression, so the second model predicts residual earnings instability. The coefficient λ_1 is the predicted difference in earnings volatility between SIPP panels. The coefficient λ_2 is the association between earnings volatility and average experiences of varying hours (i.e., earnings instability for those with repeatedly variable hours compared to those with repeatedly steady hours). The change in earnings volatility with transitions into varying hours is λ_3.

Sample Attrition

Those with varying hours may have greater probabilities of attrition from the SIPP than those with steady hours, underestimating rates of varying hours in later waves of the panel.

Varying hours may be further underestimated if they are a precursor to job loss, which would remove the respondent from the analytic sample. To assess potential bias, a logistic regression model predicted the probability of attrition from the sample in wave *t+1* with *Hours Vary* in wave *t* and its interaction with the 2008 panel indicator. Observations with varying hours have a significantly greater probability of attrition by 4.0 percent in the 2004 panel and 3.5 percent in the 2008 panel. Varying hours would be underestimated in later waves if these observations would have been more likely to continue reporting varying hours. However, the association between *Hours Vary* and attrition was not statistically significantly different between SIPP panels. The impact of selective attrition for the differences between panels is likely relatively minor as a result.

RESULTS

Varying Work Hours and the Great Recession

Estimated trends in the percentage of workers reporting varying weekly hours are presented in Figure 1. The prevalence among hourly workers, represented by the dark solid markers, increased from just over seven percent in 2004-6 to more than 11 percent in 2009-10. Varying hours remained elevated throughout the rest of the 2008 panel. The increase is also visible within each panel. The trend in varying hours began to increase by 2007, at the end of the 2004 panel. It continued to increase in the beginning of the 2008 panel. Varying hours were less common among salaried workers, represented by the hollow markers, but the trend is similar.

The average state-level unemployment rate for workers in the SIPP sample is presented for comparison. Trends in rates of varying hours and local unemployment are similar, but the growth of varying hours was earlier than the growth of unemployment. Rates of varying hours also remained high even after unemployment rates declined. The trend in varying hours is similar to the trend in involuntary part-time employment, which also remained persistently elevated years after the recession (Golden 2016; Valletta and van der List 2015).

Table A2 in Appendix I presents estimated rates of varying hours among hourly workers by sex, race/ethnicity, education, and for selected industries. The growth of varying hours was slightly larger for female workers than males, and for Latinos/as and Asians than other groups. Varying hours were most common for those with less than education, likely reflecting employer-driven instability, and those with postgraduate degrees, likely reflecting employee-driven flexibility (Lambert et al. 2014). Finally, varying hours were particularly common in services and construction relative to other industries, and the increase between SIPP panels was particularly pronounced.

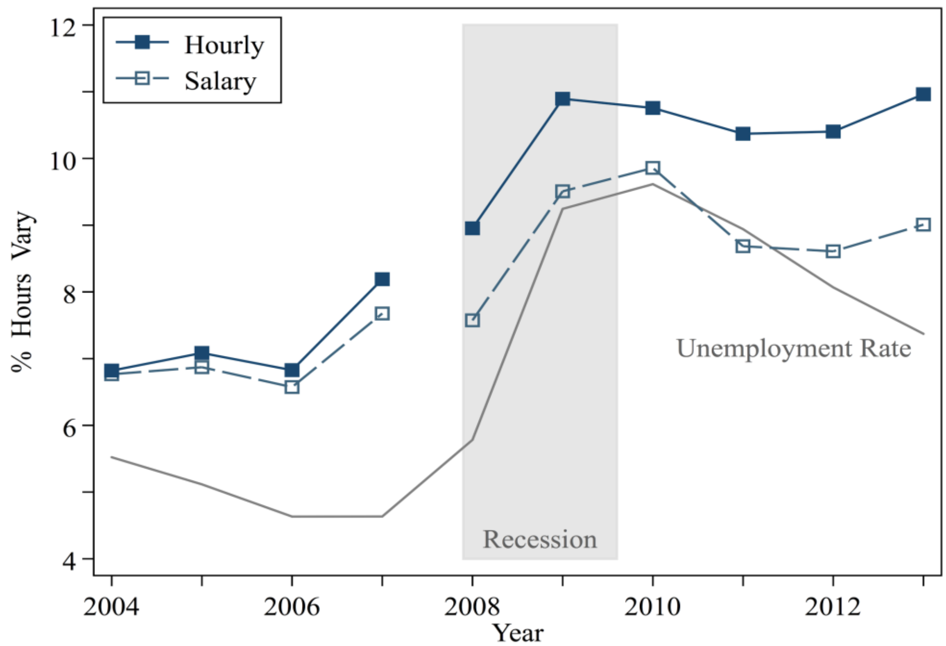

Figure 1. Estimated trends in the percentage of workers reporting varying weekly hours. Average state unemployment rate presented for comparison.
Note: Trends are among prime-age (25-55) workers who report a primary job, positive earnings, and are not self-employed.

Table 1. Percentage of observations and cumulative reports of varying weekly hours among hourly workers by SIPP panel.

	2004 Panel	2008 Panel
% Observations Varying Hours	7.23	10.43
N	135,101	136,008
Cumulative Varying Hours		
0 Waves	64.38	53.91
1 Wave	15.40	16.94
2 Waves	8.34	10.55
3+ Waves	11.88	18.60
N	28,904	27,165

Note: Cumulative experiences are predicted from multinomial logistic regression to adjust for attrition. All differences between panels are statistically significant with p<0.001.

Cumulative reports of varying hours within each SIPP panel are presented in Table 1. The percentage of all person-waves reporting varying hours increased from 7.2 percent in the 2004 panel to 10.4 percent in the 2008 panel. Cumulative reports of varying hours in each panel are much higher. The predicted probability of reporting varying hours at least once is 36 percent between 2004 and 2007, and 46 percent between 2008 and 2012. The probability of reporting varying hours in at least three four-month waves, totaling at least one year, also increased significantly from 11.9 to 18.6 percent.[5]

Table 2. Results from random-effects logistic regressions predicting varying weekly hours, presented as marginal effects and (z-statistics).

	Bivariate Model	+ Individual Variables	+ State Variables
2008 Panel	0.035***	0.031***	0.007
	(19.22)	(17.92)	(1.55)
State Unemployment			0.003***
			(3.92)
Econ. Growth			-0.001**
			(-3.29)
ln(GSPpc)			-0.003
			(-0.09)
State Unionization			-0.001
			(-1.12)
Minimum Wage			0.005**
			(3.19)
ln(Population)			0.068
			(1.74)
Persons	50,565	50,565	50,565
Person-Waves	235,452	235,452	235,452

Note: Log-odds coefficients for control variables are presented in Table A4. The model with state-level variables includes state fixed effects.

* p<0.05, ** p<0.01, *** p<0.001

Results for the main variables of interest from the random-effects logistic regressions predicting varying hours are presented as marginal effects in Table 2. Table A4 Appendix III presents the log-odds coefficients for the individual-level controls. The bivariate model shows

[5] Multiple waves reporting varying hours are not necessarily contiguous and may reflect several short but separate experiences of variability.

the probability of varying weekly hours significantly increased by 3.5 percentage points between the 2004-7 and 2008-12 SIPP panels.

The second model in Table 2 adds all individual-level controls. Even net of controls, the probability of varying hours increased by 3.1 percentage points between SIPP panels. Varying hours are significantly more common for workers with lower wages (Table A4). Similar to past research (Golden 2001a), varying hours are more common for those working part-time some weeks, those with less than high school education, workers with short job tenure, and private-sector workers. Varying hours are also significantly more common for Black workers than Whites, and males compared to female workers.

The third model in Table 2 adds all state-level variables, including state fixed effects. The state-level variables explain about 80 percent of the predicted difference in varying hours between SIPP panels. The remaining predicted increase is less than one percentage point, and not statistically significant. A model with the unemployment rate as the only additional variable reduces the panel coefficient by more than 40 percent.

The marginal effects should be interpreted as the difference in the probability of varying hours for a change in the state-level variables over time. As expected, the probability of varying hours is significantly greater as the state unemployment rate increases and significantly lower with economic growth. Varying hours are more strongly associated with unemployment rates than economic growth, however. The average probability of varying hours is 8.3 percent at the 10th percentile of unemployment rates and 10.5 percent at the 90th percentile. For comparison, the probability of varying hours is 8.9 percent at the 90th percentile of economic growth and 9.5 percent at the 10th percentile.[6]

Varying hours are less probable with greater GSPpc, but the association is not statistically significant. Neither population growth nor declining state unionization have significant associations. Finally, varying hours are more probable with increases in the state minimum wage. One potential explanation is that minimum wage hikes increase labor costs, thus increasing employers' incentives to reduce costs through variable scheduling. Milkman, Gonzáles, and Ikeler (2012) found higher rates of wage violations in Los Angeles than New York or Chicago in 2008, which was partly attributable to the higher minimum wage in California at the time.

[6] The 10th percentile of unemployment rates is 4.3 percent, and the 90th percentile is 10.4 percent. The 90th percentile of economic growth is 5.4 percent and the 10th percentile is -2.2 percent.

The positive association with the minimum wage in Table 2 could also be spurious, however. The federal minimum wage increased in 2009, occurring alongside growth in varying hours and unemployment rates. As a robustness check, I fit the third model in Table 2 with year fixed effects rather than a single dummy for the 2008 panel. Year fixed effects control for temporal factors common to all workers, like changes in the federal minimum wage. The marginal effect of changes in the minimum wage is close to zero and not statistically significant when including year fixed effects. The marginal effect of unemployment rates is significantly positive and stronger than in Table 2. The marginal effect of economic growth is close to zero and not significant. State unionization is significantly negative, though weaker than the effect of unemployment.

Table 3. Results from variance function regressions predicting changes in mean earnings, presented as linear coefficients and (robust t-statistics).

	Bivariate Model	+ Varying Hours	+ Individual Variables	+ State Variables
2008 Panel	0.000*	0.000	0.001	0.002
	(2.53)	(1.17)	(1.60)	(0.58)
Varying Hours		-0.000	0.004**	0.004**
(mean)		(-0.28)	(3.09)	(3.13)
Varying Hours		-0.137***	-0.076***	-0.076***
(change)		(-22.24)	(-15.95)	(-16.10)
State Unemployment				-0.001
				(-0.91)
Econ. Growth				-0.000
				(-1.27)
ln(GSPpc)				-0.004
				(-0.18)
State Unionization				0.000
				(0.02)
Minimum Wage				0.000
				(0.27)
ln(Population)				0.000
				(0.00)
Persons	50,565	50,565	50,565	50,565
Person-Waves	235,452	235,452	235,452	235,452

Note: Coefficients for control variables are presented in Table A5. The model with state-level variables includes state fixed effects.

* p<0.05, ** p<0.01, *** p<0.001

Varying Work Hours and Earnings Instability

Table 3 presents selected coefficients from the variance function regressions predicting within-person changes in logged monthly earnings. Coefficients for control variables are presented in Table A5 in Appendix III. The coefficients in Table 3 are from the linear model predicting mean earnings, and positive coefficients indicate greater earnings with higher values of the independent variable.

As expected, mean earnings when centered within persons are almost the same between panels, despite statistical significance. Similarly, the time-invariant (mean) component of varying hours has a coefficient close to zero. With transitions into varying hours from steady hours (change), earnings decline significantly by 12.8 percent $(-0.128 = \mathrm{e}^{-0.137} - 1)$ in the second model. Even controlling for all individual-level variables in the third model, earnings significantly decline by 7.3 percent when hours vary. These controls include logged hourly wage rates, so the drop in earnings must be due to a drop in hours. None of the state-level variables significantly predict changes in mean earnings, net of individual-level variables. As shown in Table A5, mean earnings are also greater with increases in hourly wage rates, attaining higher education, longer job tenure, transitioning to full-time hours, and becoming a union member.

Table 4 presents coefficients from the gamma regressions predicting the residual variance in logged earnings, based on estimates from models in Tables 3. Positive coefficients indicate greater earnings volatility, and coefficients from the control variables are presented in Table A5. In the baseline model, earnings volatility is significantly greater by 14.1 percent $(0.141 = e^{0.132} - 1)$ in the 2008 panel than the 2004 panel.

The growth of earnings volatility between panels is largely explained by varying hours, added in the second model. Those who commonly experience varying hours have significantly higher earnings volatility than those who do not, reflected by the coefficient for the mean component. For example, someone who reports varying hours in three of the twelve SIPP waves has 51.6 percent $(0.516 = e^{1.663 \times 0.25} - 1)$ greater earnings volatility than someone who never reports varying hours. Earnings volatility also increases by 56.2 percent when workers change from steady to varying hours (change component). These positive associations with earnings volatility are attenuated when including individual- and state-level controls in the third and fourth models but are still large and statistically significant.

Table 4. Results from variance function regressions predicting earnings volatility (logged variance of residual logged earnings), presented as log coefficients and (robust t-statistics).

	Bivariate Model	+ Varying Hours	+ Individual Variables	+ State Variables
2008 Panel	0.132***	0.057	0.040	-0.009
	(4.17)	(1.82)	(1.20)	(-0.11)
Varying Hours		1.663***	1.257***	1.250***
(mean)		(20.88)	(14.00)	(14.59)
Varying Hours		0.446***	0.375***	0.374***
(change)		(12.11)	(9.38)	(9.76)
State Unemployment				-0.031
				(-1.81)
Econ. Growth				0.011
				(1.84)
ln(GSPpc)				-0.819
				(-1.56)
State Unionization				0.001
				(0.08)
Minimum Wage				0.048
				(1.31)
ln(Population)				2.491**
				(2.78)
Persons	50,565	50,565	50,565	50,565
Person-Waves	235,452	235,452	235,452	235,452

Note: Coefficients for control variables are presented in Table A5. The model with state-level variables includes state fixed effects.

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Of the state-level variables, only population growth is significantly associated with greater earnings volatility. Of the individual-level variables, earnings volatility is lower with higher hourly wage rates, working full-time, those not changing jobs between waves, and working in the public sector. Volatility becomes greater with attaining a high school degree due to earnings increases. Only part-time work, education, and job changes have stronger coefficients than varying hours when predicting earnings volatility.

DISCUSSION

Unemployment and underemployment increased profoundly in the Great Recession of the late 2000s (Golden 2016; Hout et al. 2011), but less research has examined any increase in volatile numbers of hours from week to week. Varying work hours directly lead to earnings instability for hourly workers and are associated with a number of other negative consequences for workers and families (Henly and Lambert 2014; Schneider and Harknett 2016). This study examined the growth of varying hours in the Great Recession and its impact on earnings instability using individual-level data from the 2004-7 and 2008-12 SIPP panels merged with state-level data on economic conditions. The article shows that reports of varying weekly hours among hourly workers increased substantially during the Great Recession. The probability of reporting varying hours at least once over four years increased from 36 percent in 2004-7 to 46 percent in 2008-12 (Table 1).

Changes in state unemployment rates and other economic conditions explain 80 percent of the growth in varying hours (Table 2). The results are consistent with arguments that employers vary their workers hours to reduce costs due to fluctuating demand (Appelbaum et al. 2003; Halpin 2015; Kalleberg 2011; Lambert 2008). About one-fifth of the increase between periods remains unexplained by worker and state characteristics, although that residual increase was not statistically significant (Table 2). The residual difference is primarily due to the persistently high levels of varying hours in 2011 and onward while unemployment rates declined (Figure 1).

A possible interpretation for the persistently high rate of varying hours is that the Great Recession ushered in institutional or otherwise structural changes to the labor market (Redbird and Grusky 2016). Employers increasingly relied on variable scheduling to cope with reduced and volatile demand in the recession, but the changing climate of the labor market also helped increase employers' power to dictate acceptable work conditions (Kalleberg 2011; Lambert 2008). Similarly, any recession-driven adoption of labor-cost-reducing strategies and technologies may have becoming normalized as standard practice (Alexander et al. 2015). For example, declining revenue in the recession may have accelerated the already growing adoption of computerized scheduling software (Lambert 2008). Computerized scheduling systems in service and retail establishments predict customer demand down to fifteen-minute intervals or less, often resulting in irregular employee schedules to match. Once in place, firms' investments in these systems likely create permanent changes in scheduling practices.

The conversion of full-time positions to multiple part-time positions would also sustain elevated levels of hours instability (Alexander et al. 2015). Involuntary part-time employment—

working fewer than 35 hours per week due to slack work or inability to find full-time work—similarly remained elevated after the recession despite declines in unemployment (Golden 2016; Valletta and van der List 2015). Unstable and unpredictable hours represent two dimensions of 'work-hour insecurity' (Alexander and Haley-Lock 2015), and involuntary part-time work represents the third.[7] Future research with more recent data would be necessary to assess any long-term increase in varying hours. The recently released 2014 SIPP panel does not allow respondents to answer "hours vary" when asked their usual number of hours per week, making it incompatible with the earlier 2004 and 2008 panels for this study.

Any permanent increase in rates of varying weekly hours would contribute substantially to long-term increases in earnings instability (Gottschalk and Moffitt 2009; Hacker 2006; Moffitt and Gottschalk 2012). The final portion of this article's analysis combined variance function regression (Western and Bloome 2009) with 'hybrid' panel models (Firebaugh et al. 2013) to examine monthly earnings instability. Even among continuously employed hourly workers, earnings instability significantly increased by 14 percent during the recession. Most of the increase is explained by the growth of varying hours; workers reporting varying hours have lower average earnings and substantially more instability. The explanatory power of varying hours is robust to controls for hourly wage rates and other worker characteristics, as well as using a fixed-effects estimator (Table 4).

This study's strengths and limitations hopefully complement existing research on unstable work scheduling. Sector- and establishment-specific studies of work scheduling (Henly and Lambert 2014; Schneider and Harknett 2016) and newly developed measures in the NLSY97 (Lambert et al. 2014) and GSS provide more detailed and robust measures of hours variability. This study complements this growing literature by proving a nationally representative comparison both before and after the recession. For example, workers in leisure and hospitality industries have high rates of varying hours, but not exceptionally so. Varying hours are also common in construction, agriculture, and various other service industries. Research on the dynamics of work variability among retail workers may also inform our understanding of experiences in those sectors as well.

[7] Involuntary part-time employment and varying hours often overlap in the SIPP. Involuntary part-time employment increased from 6.4 to 12.1 percent of observations between the 2004 and 2008 panel. Among involuntary part-time observations, 17.5 percent reported varying hours in the 2004 panel and 20.8 percent did in the 2008 panel.

As described above, the SIPP's self-reported measure for varying weekly hours likely underestimates hours variability. If so, the patterns found here may understate the true growth of varying hours in the recession and the impact on earnings volatility. The SIPP measure is also unable to assess the degree of hours variability, although the self-reports do correlate with variation in reported numbers of usual hours/week (Table A3).

The study also contributes to research on the growth of earnings instability but inherits similar methodological challenges. It extends existing literature by explicitly assessing the contribution of varying weekly hours to earnings instability among the employed. However, Dahl, DeLeire, and Swabish (2011) find survey-based research may overstate both the extent of earnings instability and its long-term upward trend. Their study examined SIPP survey data matched with administrative earnings reports but did not include the 2008 SIPP panel. Survey measures of work hours correlate strongly with employer data (Lambert and Henly 2014), so analyses of the most recent linked data could help further assess this study's robustness.

Finally, this paper's findings speak to policies targeting unstable work schedules, many of which would increase schedule predictability as well. The Federal Labor Standards Act (FSLA) provides little protection from unstable scheduling (Alexander et al. 2015). Labor union negotiations have traditionally included minimum hours guarantees and other hours protections, but the steady erosion of union strength in the United States limits their reach (Rosenfeld 2014). Many state and local governments have also instituted various scheduling regulations. For example, "call-in pay" requires employers compensate workers for remaining available or for last-minute additional work. Similarly, "send-home" or "reporting pay" laws require employers to pay workers for at least some portion of their scheduled shift in the event of last minute cuts or schedule changes (Alexander and Haley-Lock 2015; Alexander et al. 2015). The city of San Francisco passed multiple ordinances in 2014 through 2016 comprising what labor activists called the "Retail Workers Bill of Rights." Similar policies are taking effect in Seattle, New York, and several other cities. These ordinances require retail employers to provide their workers with estimates of their work amount when hired, schedules at least two weeks in advance, expanded "reporting pay" protections, and pay for "on-call" shifts. Increased access to sufficient numbers of work hours could also come through employer practices first giving part-time workers more hours when demand increases, rather than hiring additional part-time workers.

This study's findings suggest policies limiting volatility in work hours would also significantly limit earnings instability and its related hardships for workers and families.

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APPENDIX

I. The Degree and Predictability of Work Hour Variability

One limitation of binary self-reported varying weekly hours is the inability to assess the degree of variability. This appendix presents results from two additional analyses of continuous measures of variability for comparison. First, Table A1 presents the average within-person standard deviation in usual hours/week for those reporting varying hours 0, 1, 2, or 3+ times in each panel. Within-person variability in the usual hours/week is greater among those that report their "hours vary" more often, supporting the validity of the binary measure. The average standard deviation is one-third to almost one-half larger for those who report varying hours even once compared to those who never do. The standard deviation of reported usual hours likely underestimates hours variability because survey waves reporting "hours vary" are excluded from the calculation.

Table A1. Standard deviation in usual hours/week by cumulative reports of varying weekly hours among hourly workers by SIPP panel.

	2004 Panel	2008 Panel
All Workers	3.50	3.70
By Times Reporting Varying Hours		
0 Waves	3.21	3.34
1 Wave	4.65	4.57
2 Waves	4.71	4.75
3+ Waves	5.09	5.40
N	29,356	27,618

Note: Cumulative experiences are predicted from multinomial logistic regression to adjust for attrition. All differences between panels are statistically significant with p<0.001.

Table A2 presents the percentage of observations reporting varying hours in each SIPP panel by industry, education, sex, and race/ethnicity. For comparison, it also summarizes a continuous measure of hours variability from the 2016 General Social Survey (GSS). The most recent wave of the GSS included three questions on work hours, asking: the usual number of hours worked per week, the greatest number of hours per week in the last month, and the least number of hours per week in the last month. The degree of hours variability can then be measured with the $Hours\ Instability\ Ratio = \frac{Most - Least}{Usual\ Hours}$ (see Lambert, Henly, and Fugiel 2014). The 2016 GSS unfortunately does not record whether workers are paid hourly or salaried; the comparisons below may be off to the degree that groups differ in hourly/salaried status (e.g., highly educated workers are most commonly salaried).

Industries with large percentages of workers reporting their usual "hours vary" also have relatively high instability ratios. For example, 14.7 percent of construction workers reported varying hours in the 2008 SIPP panel; the median instability ratio for construction workers was 0.50, indicating hours per week varied in the last month by 50 percent of the usual number. Similarly, manufacturing workers reported varying hours the least in the SIPP and had the lowest median instability ratio in the

GSS. The rank ordering is not identical between surveys, however. Caution is warranted with the GSS results due to small sample sizes in some cells.

Table A2. Varying hours by worker characteristics and year/survey.

	SIPP 2004-7 % Hours Vary	SIPP 2008-13 % Hours Vary	GSS 2016 Median Instability Ratio
Industry			
Retail Stores	7.8	10.7	0.28
Food Service	10.3	13.7	0.31
Other Services	7.3	11.8	0.40
Manufacturing	5.1	8.0	0.13
Construction	9.2	14.7	0.50
All Other	7.0	9.7	0.25
Education			
Less than HS	8.5	12.5	0.28
HS/GED	7.0	10.7	0.23
Some College	6.9	9.7	0.20
College	7.3	10.0	0.30
Postgrad	8.5	10.9	0.31
Sex			
Male	7.4	10.7	0.29
Female	7.1	10.2	0.24
Race/Ethnicity			
White	7.4	9.8	0.30
Black	7.9	10.6	0.23
Latino/a	6.5	11.6	0.25
Asian	5.8	13.6	(with other race)
Other	7.5	10.2	0.40
Persons	28,906	27,165	563
Person-Waves	135,103	136,008	--

The majority of hours instability in the GSS is also unpredictable. The 2016 GSS includes a measure of advanced schedule notice, coded as the number of weeks in advance workers receive their schedule. To adjust for some small cell sizes, I combine the seven recorded categories into three: one week or less, two to four weeks, and four or more weeks (including the category “my schedule never changes”). Figure A1 presents advanced schedule notice by the degree of hours variability, measured here as the quintiles of the hours instability ratio. Among workers in the top 20 percent of hours instability, about 60 percent of workers know their schedules one week or less in advance. Even among workers in the top three quintiles of hours instability, fewer than half know their schedules more than a week in advance and more than two-thirds know their schedules less than four weeks in advance.

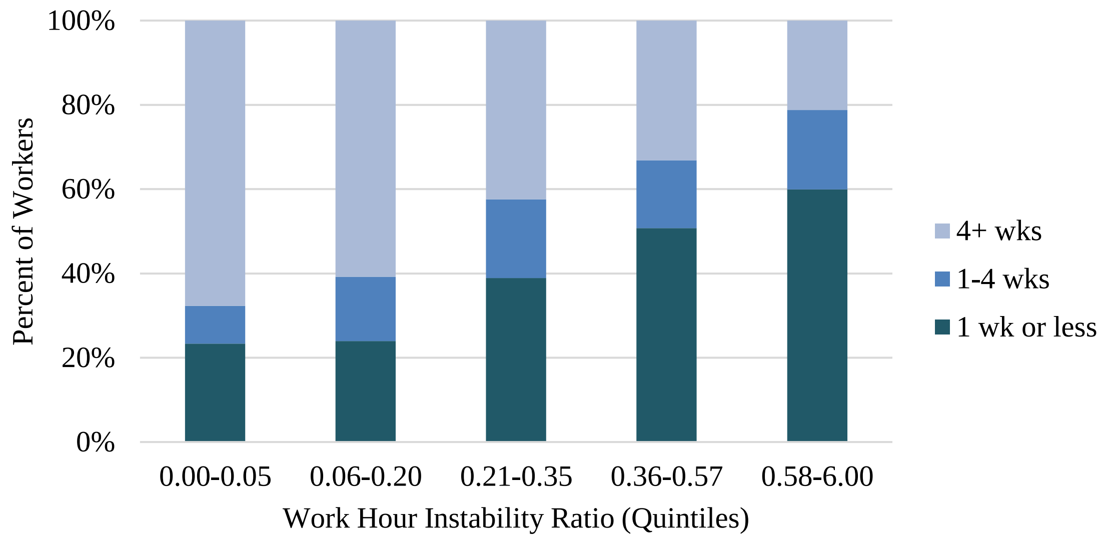

Figure A1. Weeks of advanced schedule notice by work-hour instability in the GSS (N = 562).

II. Summary Statistics

Table A3. Variable means by SIPP panel.

Variable	2004 Panel	2008 Panel
ln(Earnings)	7.721	7.643
Variance of ln(Earnings)	0.138	0.150
Usual hours/week	37.987	36.838
Unemployment Rate	4.956	9.033
Econ. Growth	1.693	-0.197
ln(GSPpc)	3.963	3.929
State Unionization	12.180	11.745
Minimum Wage	7.097	8.023
ln(Population)	15.990	16.038
Age	39.194	39.419
Female	0.498	0.504
White	0.618	0.603
Black	0.130	0.130
Latino/a	0.192	0.205
Asian/PI	0.029	0.034
Other Race	0.030	0.028
U.S. Born	0.803	0.797
For. Born Citizen	0.121	0.119

For. Born Noncitizen	0.076	0.083
Married	0.589	0.558
Separated	0.031	0.030
Divorced	0.129	0.122
Widowed	0.010	0.011
Never Married	0.241	0.278
HH Size	3.346	3.330
Children under 6 y.o.	0.290	0.308
Less than HS	0.134	0.117
HS/GED	0.319	0.309
Some College	0.408	0.410
Bachelor's Degree	0.114	0.132
Post-Grad. Degree	0.025	0.032
Hourly Wage	16.436	16.232
Job Tenure	6.275	6.511
Changed Jobs	0.172	0.174
Part-Time Some Weeks	0.280	0.320
Union Member	0.134	0.123
Public Sector	0.076	0.083
Northeast	0.163	0.159
South	0.255	0.253
Midwest	0.337	0.349
West	0.245	0.239
Urban Area	0.762	0.781
Rural Area	0.196	0.176
Urban not Identified	0.042	0.043
Persons	26,037	24,528
Person-Waves	116,570	118,882

Note: Means are from the regression sample in Table 2 and are calculated with SIPP sample weights.

III. Coefficient Estimates for Control Variables

Table A4. Results from control variables in random-effects logistic regressions predicting varying weekly hours (Table 2), presented as log-odds coefficients and (z-statistics).

	+ Individual Variables	+ State Variables
Age	0.009***	0.009***
	(4.63)	(4.53)
Female (ref = Male)	-0.105**	-0.115**
	(-2.78)	(-3.06)
Black (ref = White)	0.093	0.008
	(1.90)	(0.16)
Latino/a (ref = White)	-0.042	-0.105
	(-0.77)	(-1.87)
Asian/PI (ref = White)	0.137	0.096
	(1.45)	(1.02)
Other Race (ref = White)	0.049	0.073
	(0.58)	(0.86)
For. Born Citizen (ref = US Born)	-0.084	-0.098
	(-1.40)	(-1.65)
For. Born Noncitizen (ref = US Born)	0.085	0.073
	(1.33)	(1.15)
Separated (ref = Married)	0.061	0.066
	(0.85)	(0.91)
Divorced (ref = Married)	0.029	0.040
	(0.66)	(0.90)
Widowed (ref = Married)	0.099	0.117
	(0.78)	(0.93)
Never Married (ref = Married)	0.169***	0.162***
	(4.32)	(4.15)
HH Size	0.011	0.007
	(1.07)	(0.74)
Children under 6 y.o. (yes = 1)	-0.073	-0.064
	(-1.95)	(-1.74)
HS/GED (ref = <HS)	-0.135**	-0.121*
	(-2.63)	(-2.39)
Some College (ref = <HS)	-0.192***	-0.174***
	(-3.65)	(-3.32)
Bachelor's Degree (ref = <HS)	-0.149*	-0.137*
	(-2.24)	(-2.08)
Post-Grad Degree (ref = <HS)	-0.096	-0.070
	(-0.95)	(-0.70)
ln(Hourly Wage)	-0.305***	-0.319***
	(-8.17)	(-8.54)
Job Tenure	-0.013***	-0.014***
	(-5.56)	(-5.82)
Part-Time Some Weeks (yes = 1)	0.959***	0.972***
	(40.37)	(40.90)
Changed Jobs	0.018	0.020

	(0.69)	(0.77)
Union Member	-0.068	-0.069
	(-1.41)	(-1.44)
Public Sector (ref = Private)	-0.175**	-0.183**
	(-3.02)	(-3.17)
Rural (ref = Urban)	0.388***	0.442***
	(10.29)	(11.41)
Urban not Identified (ref = Urban)	-0.165*	1.817
	(-2.03)	(1.12)
Constant	-3.087***	-21.696*
	(-14.03)	(-2.08)
Persons	50,565	50,565
Person-Waves	235,452	235,452

Notes: Both models include occupation and industry controls. The model with individual-level controls includes geographic region. The model with state-level variables includes state fixed effects.
* p<0.05, ** p<0.01, *** p<0.001

Table A5. Results for control variables from variance function regressions predicting mean earnings (Table 3) and earnings instability (Table 4), presented as coefficients and (robust t-statistics).

	+ Individual Variables		*+ State Variables*	
	Beta coefficients	Lambda coefficients	Beta coefficients	Lambda coefficients
Age (mean)	0.000	0.004	0.000	0.004
	(0.04)	(1.85)	(0.33)	(1.67)
Age (change)	0.003*	-0.039***	0.003*	-0.059***
	(2.28)	(-3.60)	(2.28)	(-4.16)
Female	0.001*	-0.023	-0.000	-0.019
	(2.14)	(-0.55)	(-0.85)	(-0.47)
Black	-0.001	-0.005	-0.000	-0.034
	(-1.25)	(-0.08)	(-0.85)	(-0.65)
Latino	-0.001*	-0.155**	-0.002**	-0.151*
	(-2.57)	(-2.64)	(-2.74)	(-2.56)
Asian	-0.002	-0.176*	-0.001	-0.155
	(-1.68)	(-2.00)	(-1.33)	(-1.76)
Other Race	0.000	0.183	-0.000	0.164
	(0.15)	(1.67)	(-0.17)	(1.42)
For. Born Citizen (mean)	-0.000	-0.092	-0.000	-0.089
	(-0.42)	(-1.28)	(-0.55)	(-1.23)
For. Born Non-Citizen (mean)	-0.001	0.090	-0.001	0.079
	(-1.29)	(1.26)	(-1.32)	(1.14)
For. Born Citizen (change)	-0.004	0.060	-0.003	0.090
	(-0.31)	(0.44)	(-0.27)	(0.63)
For. Born Non-Citizen (change)	-	-	-	-
	-	-	-	-
Separated (mean)	-0.001	0.022	-0.001	0.021

	(-0.63)	(0.21)	(-0.54)	(0.20)
Divorced (mean)	-0.001*	-0.065	-0.001*	-0.057
	(-2.46)	(-1.26)	(-2.18)	(-1.13)
Widowed (mean)	-0.000	-0.026	-0.000	-0.027
	(-0.12)	(-0.15)	(-0.01)	(-0.16)
Never Married (mean)	-0.000	0.025	-0.000	0.004
	(-0.87)	(0.51)	(-0.92)	(0.08)
Separated (change)	-0.018	0.357**	-0.017	0.343**
	(-1.61)	(2.74)	(-1.53)	(2.88)
Divorced (change)	-0.005	0.103	-0.007	0.129
	(-0.57)	(1.14)	(-0.74)	(1.49)
Widowed (change)	-0.030	0.045	-0.026	0.076
	(-1.65)	(0.20)	(-1.44)	(0.36)
Never Married (change)	-0.021*	0.126	-0.020*	0.114
	(-2.14)	(1.59)	(-2.11)	(1.47)
HH Size (mean)	0.000	0.015	-0.000	0.011
	(0.09)	(1.19)	(-0.01)	(0.85)
HH Size (change)	-0.002	0.011	-0.002	0.011
	(-1.03)	(0.54)	(-1.12)	(0.57)
Children under 6 y.o. (mean)	0.000	0.049	0.000	0.042
	(0.51)	(1.08)	(0.25)	(0.99)
Children under 6 y.o. (change)	0.005	-0.029	0.005	-0.036
	(0.53)	(-0.29)	(0.50)	(-0.37)
HS/GED (mean)	-0.001	-0.013	-0.001	-0.004
	(-1.72)	(-0.22)	(-1.85)	(-0.07)
Some College (mean)	-0.000	0.052	-0.000	0.066
	(-0.46)	(0.85)	(-0.70)	(1.13)
Bachelor's Degree (mean)	0.000	0.064	0.000	0.084
	(0.33)	(0.87)	(0.05)	(1.17)
Post-Grad Degree (mean)	0.001	0.131	0.001	0.141
	(0.64)	(1.32)	(0.51)	(1.45)
HS/GED (change)	0.027	0.369**	0.025	0.350**
	(1.74)	(3.01)	(1.65)	(2.97)
Some College (change)	0.012	0.219	0.011	0.260
	(0.55)	(1.00)	(0.52)	(1.24)
Bachelor's Degree (change)	0.058*	0.313	0.051*	0.352
	(2.38)	(1.41)	(2.13)	(1.66)
Post-Grad Degree (change)	0.089*	0.263	0.084*	0.302
	(2.34)	(1.07)	(2.19)	(1.25)
ln(Hourly Wage) (mean)	0.001	-0.193**	0.001	-0.188**
	(1.09)	(-3.11)	(0.83)	(-3.19)
ln(Hourly Wage) (change)	0.556***	-0.151***	0.561***	-0.160***
	(37.09)	(-3.51)	(37.66)	(-3.84)
Job Tenure (mean)	-0.000***	-0.001	-0.000***	-0.001
	(-6.87)	(-0.38)	(-7.08)	(-0.48)
Job Tenure (change)	0.002**	0.004	0.002**	0.003
	(2.58)	(1.01)	(2.69)	(0.91)
Part-Time Some Weeks (mean)	0.003***	0.950***	0.003***	0.965***
	(6.12)	(18.81)	(5.76)	(19.57)

Part-Time Some Weeks (change)	-0.138***	0.406***	-0.137***	0.407***
	(-43.06)	(13.70)	(-43.18)	(14.36)
Changed Jobs (mean)	0.012***	1.466***	0.012***	1.451***
	(13.53)	(21.09)	(13.43)	(21.69)
Changed Jobs (change)	-0.013***	0.445***	-0.013***	0.449***
	(-4.23)	(16.28)	(-4.23)	(17.13)
Union Member (mean)	-0.000	0.055	0.000	0.051
	(-0.03)	(0.89)	(0.11)	(0.88)
Union Member (change)	0.045**	-0.052	0.044**	-0.047
	(3.20)	(-0.60)	(3.17)	(-0.57)
Public Sector (mean)	-0.000	-0.133	-0.000	-0.159*
	(-0.03)	(-1.72)	(-0.21)	(-2.35)
Public Sector (change)	-0.039*	0.134	-0.037	0.138
	(-1.99)	(1.31)	(-1.89)	(1.43)
Rural (mean)	-0.001	0.002	-0.001	0.015
	(-1.73)	(0.04)	(-1.68)	(0.33)
Urban not Identified (mean)	-0.001	-0.095	0.006	5.182**
	(-0.92)	(-1.10)	(0.11)	(2.60)
Rural (change)	-0.005	0.068	-0.006	0.040
	(-0.44)	(0.71)	(-0.49)	(0.40)
Urban not Identified (change)	0.086*	0.372	0.107	5.552**
	(2.21)	(1.50)	(1.66)	(2.77)
Constant	-0.004	-2.858***	0.012	-38.297**
	(-1.34)	(-9.04)	(0.03)	(-2.79)
N	235,452		235,452	

Notes: Both models include occupation and industry controls. The model with individual-level controls includes geographic region. The model with state-level variables includes state fixed effects. Very few observations changed citizenship status during the SIPP panels, making the change component of *For. Born Non-Citizen* collinear with other variables.

* p<0.05, ** p<0.01, *** p<0.001