Income Volatility in the Service Sector: Contours, Causes, and Consequences

Daniel Schneider
UC Berkeley
Department of Sociology

Kristen Harknett
UC San Francisco
Department of Sociology

*Daniel Schneider (Corresponding author): UC Berkeley, Department of Sociology, 480 Barrows Hall, Berkeley, CA 94720; djschneider@berkeley.edu. We gratefully acknowledge grant support from the National Institutes of Child Health and Human Development (R21HD091578), the Robert Wood Johnson Foundation (Award No. 74528) the U.S. Department of Labor (Award No. EO-30277-17-60-5-6), the Washington Center for Equitable Growth (Award No. 39092), the Aspen Institute, the Hellman Family Fund, the Institute for Research on Labor and Employment, and the Berkeley Population Center. We received excellent research assistance from Carmen Brick, Paul Chung, Nick Garcia, Alison Gemmill, Tom Haseloff, Veronique Irwin, Sigrid Luhr, Robert Pickett, Adam Storer, Garrett Strain, and Ugur Yildirim. We are grateful to Liz Ben-Ishai, Annette Bernhardt, Michael Corey, Sarah Crow, Rachel Deutsch, Dennis Feehan, Carrie Gleason, Anna Haley-Lock, Heather Hill, David Harding, Julie Henly, Ken Jacobs, Susan Lambert, Adam Reich, Jennie Romich, Jesse Rothstein, Matt Salganik, Hana Shepherd, Stewart Tansley, Jane Waldfogel, and Joan Williams for very useful feedback. We also received helpful feedback from seminar participants at UC Berkeley Sociology, the Institute for Research on Labor and Employment, The Washington Center for Equitable Growth, the Institute for the Study of Societal Issues, UCSF, the Aspen Institute’s EPIC convening. This work was approved by the UC Berkeley Committee for the Protection of Human Subjects (2015-10-8014).
Abstract

This paper seeks to enhance our understanding of the connections between income swings and family outcomes for hourly retail workers. These workers are vulnerable to income shocks because they earn low wages, have changing, often unpredictable schedules, and are paid hourly. Many experience severe degrees of income volatility on a week-to-week basis, driven partly by unpredictable and unstable scheduling. We present results from a new, national survey of 19,000 service sector workers employed by 38 large retail or fast-food employers. The paper shows that income swings are common and sizable among hourly workers, with 40% of workers reporting that their income varies from week-to-week. We also show that unpredictable schedules are a significant driver of income and earnings volatility and that income and earnings volatility is connected to financial insecurity such as material hardship and trouble paying bills.
Introduction

The past fifty years have witnessed parallel trends in the labor market and the household towards growing insecurity. In the labor market, scholars have documented the growing precarity of employment in which workers are increasingly subject to low wages, few fringe benefits, non-standard contracts, and non-standard work hours (Kalleberg, 2009; Kalleberg, 2013; Fligstein and Shin, 2004). In the household, the last fifty years have witnessed increasing volatility in income and earnings (Dynan et al., 2012; Gottschalk and Moffitt, 2009). Most of this prior research has focused on year-to-year variation in income. This inter-year volatility is the product of positive shocks from bonuses and raises, though the volatility that is generally of concern arises from negative shocks stemming from unemployment or labor force exit. At first blush, increasing labor market precarity and rising volatility in income and earnings would seem obviously connected, and yet the literature on precarity does not find evidence of a sustained rise in unemployment that might account for increasing inter-year volatility in earnings or income.

However, new research in the literature on precarious employment which focuses on unstable and unpredictable schedule practices and new research in the literature on income volatility which focuses on intra-year volatility reveal a likely point of connection. Recent research has shown that there is significant volatility in incomes and earnings over shorter periods such as month-to-month and week-to-week (Farrell and Grieg 2016; Morduch and Schneider, 2014) and this intra-year volatility appears to be caused in large part by a set of precarious labor practices that lead to substantial volatility in the numbers of hours that employees work each week (Federal Reserve, 2016). This variability in work hours appears to be the product of a set of human resource management practices that are applied to hourly workers - particularly those in retail - whose hours vary in amount and timing week-to-week, have little advance notice of their schedules, are asked to work on-call, and often have shifts cancelled or added at the last minute (Lambert et al., 2014; Schneider and Harknett, 2017). Further, this intra-year volatility may also put workers and their families at risk of substantial financial insecurity in part because most major household expenses (such as rent and childcare) have a fixed monthly cost and in part because making ends meet on low wages makes it difficult to accrue savings and smooth income.

However, data limitations have mostly precluded the examination of short-term income volatility broadly, of the connections to precarious scheduling practices in the private sector more specifically,
and of the consequences of this kind of intra-year volatility for household economic security.

We draw on new data from the Shift Project to advance our understanding of the contours, causes, and consequences of short-term income volatility for the large and growing number of workers employed in the service sector. We describe week-to-week volatility in earnings and in household income, show how unstable and unpredictable scheduling practices drive income volatility, and examine how income volatility matters for household economic security. The portrait that emerges shows that earnings and income instability upset the delicate balance of income and expenses for low-income households and are associated with a range of harmful consequences.

Background

Contours of Income Volatility

Recent research charts volatility in income and earnings between years and shows that income volatility from year to year is both prevalent and on the rise (Dynan et al. 2012; Gottschalk and Moffitt 2009). This important insight on annual income volatility has sparked further explorations into the extent of income fluctuations from month-to-month. In fact, month-to-month income volatility is also quite high: According to recent data from the Survey of Household Economics and Decision-making (SHED), one-third of all U.S. households report that their income varies from month-to-month (Federal Reserve 2016). High rates of month-to-month income volatility are also found in analyses of data from the financial diaries (Morduch and Schneider 2014; Hannagan and Morduch 2015) and in big data analyses of one million Chase banking customers (Farrell and Grieg 2016). These multiple data sources and studies reveal then that fluctuations in income from month-to-month are common and are sizable.

The more granular data on monthly income variation is valuable because many large household expenses, such as rent or utilities, are paid on a monthly basis. However, these broad portraits of monthly income fluctuations are limited in two respects. First, these descriptions combine high income households with the resources to smooth their incomes over time with low-income households that lack those resources. There is a need for closer examination of income dynamics for low-income families in particular. Second, these descriptions still elide even more granular income fluctuations from week-to-week. This more fine-grained analysis of week to week volatility is usually
not possible with existing data sources. Understanding week-to-week income volatility is important for low-income households because these week-to-week fluctuations can affect a household’s ability to afford basic daily necessities such as food as well as keep up with other regular household expenses.

**Causes of Income Volatility**

What causes volatility in income and earnings? Volatility is created both by dips and spikes. Workers who receive year-end bonuses, overtime pay, or raises will experience volatility in earnings between years and even between months. But, so will those who see their work hours reduced, who experience a period of unemployment, or take unpaid leave.

Recent research shows that volatility in labor market earnings is a large component of overall income volatility, and that a major driver of volatility in earnings is irregular work hours (Farrell and Grieg 2016; Federal Reserve 2016). Employment in the United States has become more “precarious” over the past fifty years. This precarity is manifest in low wages, few fringe benefits, and irregular and unpredictable work schedules. Particularly in the service sector, workers can no longer count on a regular day shift, or even a regular night or evening shift. Instead, work schedules are often set by employers on short-notice and the hours assigned to workers vary from day-to-day and the days worked vary from week-to-week (Lambert 2008). These practices, primarily affecting low-wage workers are likely to direct translate into earnings and income volatility - not just between years, or between months, but on a week-to-week basis. The income volatility that could stem from work hours that change from week-to-week is distinctive in being a source of routine and chronic income volatility that workers contend with week in and week out, rather than just once in a while. In short, workers with unstable schedules are likely to be subject to a kind of “routine unpredictability” in their income and earnings, similar to that described previously for those employed in the health care industry (Clawson and Gerstel 2015).

The hourly pay and fluctuating hours in low-wage employment help explain why prior research has shown that income volatility is most pronounced among the households in the bottom income quintile. In the bottom quintile, 74 percent of households experienced income fluctuations of 30 percent or more from month-to-month (Farrell and Grieg 2016). Further, recent research from the SHED suggests that unpredictable and unstable work scheduling practices may play an important
role in household income volatility dynamics. Of the one-third of respondents who reported that their household income varies from month-to-month, the single most common reason cited for this volatility was an “irregular work schedule.”

However, the SHED does not contain other detailed measures of work scheduling practices that would allow us to further examine this potentially important relationship and map these scheduling practices onto finer-grained measures of volatility. The new data we present extends and fleshes out this useful research by delving more deeply into work schedules, income volatility, and household financial security in the service sector.

**Consequences of Income Volatility**

We saw that income volatility is particularly common for low-income households. The consequences of income volatility are also most pronounced for low-income households, which often have few economic resources to buffer income shocks (Hannagan and Morduch, 2015). Income fluctuations also pose the largest challenge when they are unpredictable and outside of an individual’s control. All of these conditions - few resources, unpredictable work schedules, and low autonomy - typify work in the service sector.

While a substantial amount of research describes levels and trends in volatility and begins to identify the causes of volatility, there is much less known about the consequences of income volatility for household wellbeing (Aspen Institute, 2016). Previous research finds that income volatility has consequences for household economic security, food insecurity, and economic hardship (Bania and Leete, 2007; Federal Reserve, 2016). Research also suggests that income volatility is linked to adverse schooling outcomes for children and worse emotional health among adults (Gennetian et al, 2015; Yeung et al, 2002; Hardy, 2014; Prause et al, 2009). However, in general the literature on the effects of income volatility remains quite thin.

**Data and Methods**

**Data**

We use data from The Shift Project, which uses an innovative method of collecting web-based surveys from a population of low-wage service-sector workers. We use audience-targeted adver-
tisements 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 (Greenwood et al., 2016). 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., 2015), 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. In an approach more akin to ours, Zhang et al (2017) compare respondents drawn from Facebook and the ACS in terms of veteran status, homeownership, and nativity and find a high degree of similarity.

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). Facebook offers several options for advertisement placement within the site. We place our advertisement in the Desktop Newsfeed, Mobile Newsfeed, and on Instagram, but not in audience networks or in the desktop right column. Each advertisement is made up of four main elements. The top banner of the advertisement displays the text “UC Berkeley Work and Family Study.” This text is hyperlinked to our official Facebook study page. Below the banner, we include the text of our advertisement. Third, the center of the advertisement is dedicated to a picture. Finally, below the picture, we include a “headline” that reads “Chance to win an iPad!” A sample advertisement is shown as Figure 1.

Each advertisement is targeted to users age 18-50, in the United States, who speak English. Each advertisement is also targeted to the employees of one of 38 large service-sector companies. We selected these companies by drawing from the top 100 retailers by sales in the United States (National Retail Federation, 2015), after excluding Amazon.com (#8) and Apple Stores/iTunes (#13) from the list because their rank is the product exclusively or partially of internet sales rather than traditional brick-and-mortar retail operations.

Users who click on the link in our ad 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. We then conduct a drawing to award prizes to eligible respondents.

We fielded recruitment advertisements to Facebook users employed at 38 large retail firms, drawn from among the 100 largest retail firms by revenue in 2015 (National Retail Federation, 2015). We fielded these advertisements between September of 2016 and June of 2017. In total, our advertisements were shown to 3,821,451 Facebook users, including some who were shown one of our advertisements on more than one occasion. These advertisements generated 204,053 link clicks through to the introductory page of our survey at a total advertising and prize cost of $85,000. Then, 42,249 respondents contributed at least some survey data. In all, 5.3% of those who saw one of our advertisements clicked through to begin the survey and 21% of those individuals contributed
Of the 42,249 respondents who contribute some survey data, we eliminate 8,498 respondents who report that they were not paid hourly. In addition, the survey included a data quality check that instructed respondents to select a specific option on a question. 93% of respondents who were presented with this item complied. However, this item was not asked of respondents who attrited early in the survey. The result is a sample of 32,433 respondents.

However, there was substantial attrition. Of the 32,433 respondents who began, 17,880 fully completed the survey. We perform multiple imputation to account for this missing data. First, we impute data only for those respondents who completed the survey (excluding providing phone and email address), but had item non-response. Second, we impute data for all respondents who completed the first survey module, including those who finished the survey with some item non-response and those respondents who attrited from the survey at various points. Our final analysis sample for a single implicate using the first approach is 17,849 responses and for the second imputation approach is 32,060 responses, both distributed across 38 companies.

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.

Statisticians have developed a set of calibration and post-stratification methods that are often deployed in the analysis of non-probability sample 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 data collected by the American Community Survey (ACS).

Before weighting, our sample is disproportionately female and White, non-Hispanic as compared to the ACS sample. However, the age distribution of our unweighted data is not notably different.
from that of the ACS sample. 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, the share with some college is somewhat higher than in those data. However, the share enrolled in school is consistently about 25%. We construct weights that when applied allow our sample to more closely mirror the population of service-sector workers we are aiming to represent.

We first divide our survey data into groups by employer and our ACS data into 8 groups based on corresponding industry (1990 codes): hardware (581), department stores (591), general merchandise (600), grocery stores (601), eating and drinking establishments (641), apparel stores (623), radio, TV, and computer stores (633), and drug stores (642). Within each group, we then post-stratify our data into a set of 24 cells defined by the characteristics of age, gender, and race/ethnicity.\(^1\) For each industry group, we construct weights by comparing distributions across these 24 cells in our data to distributions in the ACS data, for respondents age 18-55 working in non-managerial occupations. We construct the 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 for a given industry. The ACS data is not a perfect analog to the Shift data - the ACS includes a much wider range of employers, including many that are substantially smaller than the 38 large firms in our data. While we cannot solve this problem (indeed, that is in part the rationale for our study), we replicated our weights in the CPS where we can limit the sample to those employed at large firms. We find substantively identical results when using the CPS weights.

Next, our sample is composed of respondents employed at 38 large service-sector companies. However, the representation of each employer in our survey data is not proportional to each employer’s contribution to the total workforce of the 38 companies. We assembled data on the number of U.S. employees of each company. To do so, we use the Reference USA U.S. Business Database to calculate total U.S. employment at each firm by aggregating up from establishment-level employment counts. Using this data, we adjust our weights so that each company contributes in proportion to their share of the 38 company total employment. Finally, we adjust the weights so that they sum to the original sample size in our survey sample so as not to affect standard errors.

\(^1\) Gender is coded as a male/female dichotomy, and is aligned to the same sex categories in the ACS. 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 18-29, 30-39, and 40-55. Together, these 3 variables create 24 groups (2x4x3).
Key Variables

Volatility
We use data on the number of hours respondents reported working in the week with the fewest hours and the number of hours worked in the week with the most hours in the prior month. We then multiply each weekly hours estimate by the respondent’s hourly wage, and then calculate the percent difference. We bottom code hourly wage at the federal minimum and top-code hourly wage at the 99th percentile in the data.

We also examine a second, broader measure of household income volatility, which captures fluctuations in income from all sources. To measure household income volatility, we asked workers to report whether “week-to-week your household income is” either “basically the same” or “goes up and down.” Because earned income is a major component of overall household income volatility, these two measures of volatility are closely related, and workers with highly volatile earnings are at high risk of a having a volatile household income as well.

Work Scheduling
First, we code schedule type. We asked our survey respondents to characterize their work schedules as either being regular day, regular night, regular evening or being a variable schedule or a rotating schedule.

Second, respondents report on the amount of advance notice that they have of their work schedules - that is how far in advance they generally know when and how much they will work (categorized as less than a week, 1-2 weeks, 2-3 weeks, or 3 weeks or more).

Third, respondents report the frequency with which they were required to be “on-call” for work shifts in the prior month. “On Call” shifts mean that employees must be available for a work shift if called, but may also not be called-in.

Fourth, we asked respondents to report on whether one of their work shifts had ever been scheduled but cancelled in the prior month.

Fifth, we gauge workers’ control over their schedules. Respondents report if their work schedules is entirely determined by their employer, if it is determined by the employer with some employee input, or if it is largely or solely determined by the worker.

Sixth, the conditions of low-wage work in the service sector vary such that some workers ex-
experience stability in their schedules, others experience a great deal of instability, and many fall in between the extremes. We count up the number of types of schedule instability that a worker experiences to create an additive scale. A score of 0 on the instability means that the worker has a regular day, night, or evening schedule type; at least two weeks advance notice of his/her work schedule; does not work on-call shifts; and has not experienced cancelled shifts. A score of 4 on the instability scale means that a worker has a variable or rotating schedule type; less than two weeks advance notice of his/her schedule; works on-call shifts; and experienced shift cancellations. On this scale, 1 out of 10 service sector workers enjoy a regular and predictable schedule with 0 types of instability and an additional 30% experience just 1 source of instability. But, 50% of workers experience 2 or 3 sources of instability and a highly exposed minority - about 10% - experience 4 or 5 types of schedule instability.

**Household Economic Insecurity**

We construct a measure of household exposure to material hardship that is coded as “1” if the respondent reports experiencing any of 7 situations and “0” if none were experienced: (1) going hungry, (2) using a food pantry, (3) having utilities shut off for non-payment, (4) needing informal financial assistance from family or friends, (5) moving in with family or friends because could not afford housing, (6) living in a shelter because could not afford housing, or (7) deferring needed medical care because of the cost.

We also 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 a measure of the use of alternative financial service credit products that is coded as “1” if respondents took out a payday loan or used a pawnshop in the prior 12 months and “0” otherwise.

Finally, we include a measure of respondent’s perceived financial insecurity. Following Lusardi, Schneider, and Tufano (2011), we ask respondents to rate their confidence in their ability to cope with a hypothetical expense, in this case of $400. We code respondents as financially fragile if they reported that they certainly could not or probably could not come up with that amount of funds.
Controls

We also measure a set of job characteristics - usual work hours, if the respondent is a manager, and job tenure - as well as demographic characteristics - age, gender, race/ethnicity, educational attainment, marital status, the presence of children in the household, and estimated annual household income.

Analysis

First, we descriptively characterize income and earnings volatility in our sample and show how exposure to these two measures of volatility varies by gender, educational attainment, and race-ethnicity.

Second, we examine the extent to which our six measures of exposure to unstable and unpredictable work scheduling practices are associated with week-to-week volatility in earnings and in household income. To do so, we estimate two regression models: a logistic regression model with household income volatility as the outcome and an OLS regression model with earnings volatility as the outcome. The models include controls for work and demographic characteristics. Each model is weighted to the industry composition by age, education, and gender derived from the American Community Survey and adjusted for the size of the employer in terms of number of US Employees. We estimate a separate model for each of our six measures of schedule instability. In each instance, we calculated the predicted values of the outcome across observed values of the key predictors.

Third, we examine the association between income and earnings volatility and several measures of household economic insecurity. To do so, we estimate a set of logistic regression models to predict household economic hardship, difficulty paying bills, confidence in ability to cope with an expense shock, and use of AFS loan products as a function first of reported household month-to-month income volatility and then, in a second set of models, substitute earnings volatility as the key predictor. As in the previous models, we include a set of demographic and work control variables, weight the data to the ACS estimate of industry composition and employer size, and present predicted values.
Results

Week-to-Week Earnings and Income Volatility in the Service Sector

Earnings in the service sector are highly volatile. The median service sector worker in our sample experiences a 28% fluctuation in weekly earnings between the lowest and highest earning week in the month prior to completing our survey. More concretely, the median worker earned as little as $280 and as much as $405 per week over the past month - a substantial amount of week-to-week volatility. These fluctuations can create severe hardships. Few service sector workers are making more than the bare minimum they need to make ends meet, even in the week they work the most hours.

Compared with the median service sector worker, some service sector workers have more stable earnings and some have even more volatile earnings. The workers who were in the top quartile in terms of earnings stability experienced less than a 13% swing in their earnings from week-to-week. In contrast, the workers who were in the quartile with the least earnings stability experienced at least a 50% swing in earnings from week-to-week. Across the board, though, earnings volatility is nearly universal in the service sector. 12% of workers reported less than a 5% change in earnings from week-to-week. We also find a striking degree of volatility in respondents’ reports of change in their household income: 41% of all respondents report that week-to-week, their household income goes up and down.

Some earnings and income volatility is experienced by nearly all service sector workers but this volatility is not evenly distributed across workers. We plot this variation in our two measures by gender, education, and race/ethnicity in Figure 2.

For household income volatility, there is a stark gender divide - 43% of women versus 35% of men report that week-to-week household income volatility. The degree of volatility also varies by level of educational attainment, with higher levels of educational attainment having a stabilizing influence. Among our sample of service sector workers, 45% of workers with a high-school degree or less report week-to-week variation in household income compared with 33% of those with a college degree. We also observe large racial disparities in the experience of income volatility: 51% of African American (non-Hispanic) respondents report week-to-week household income volatility compared with 44% of Hispanic respondents, and 39% of white, non-Hispanic workers.
We see similar patterns in earnings volatility. Women see week-to-week variation in earnings of 29% at the median vs. 24% for men. There is a similar gap between those with less than a high school education (30% at the median), some college (27%), and a BA or more (22%). Stratifying by race, we see that the median volatility for white, non-Hispanic respondents is 26%, but is much higher - at 33% - for Black, non-Hispanic, Hispanic, and for workers of other race/ethnicities.

**Work Schedules and Volatility**

In Figure 3, we plot predicted probabilities from our regression models of reporting that household income varies from week to week. We estimate 48% of workers who have a variable schedule report that their household income changes from week-to-week, compared with just 33% of workers who have a regular day schedule. Those who work a regular night shift or evening shift also report lower levels of income volatility than those who work a variable schedule. Notably, while workers with a rotating shift experience variation in hours, in theory that variation is predictable and these workers experience less volatility than those with variable shifts. Workers who receive more advance notice of their work schedules also report lower levels of income volatility - 45% of those with less than one weeks’ notice versus 37% of those with at least two weeks’ notice. Workers exposed to on-call work and to cancelled shifts are also significantly more likely to report household income volatility - 55% of those who had cancelled shifts and 49% of those who worked on call (vs. 39% and 38%). There though weaker associations between schedule control and household income volatility. Finally, we observe an essentially monotonically positive relationship between the number of courses of schedule instability and household income volatility. The regression coefficients from these models are shown in Column 1 of Table 1.

Unstable and unpredictable work schedules also have consequences for week-to-week variability in earnings. Workers who have a variable schedule experience larger week-to-week swings in income than those with a regular day shift - but also larger swings than those with regular non-standard shifts. Workers who have more advanced notice of their schedules also have smaller swings in earnings - 35% variation for those with less than 1 week of notice versus 30% for those with at least two weeks. The experience of cancelled shifts and of on-call shifts is also associated with more earnings variability - for both practices, those who are exposed have about 37% variability versus 31% for those who are not. Notably, we see no associations between earnings variability
and schedule control. But, as with household income volatility, there is a roughly linear positive relationship between exposure to more sources of schedule instability and earnings volatility. The regression coefficients from these models are shown in Column 2 of Table 1.

It is important to note that, while these scheduling practices are significantly related to volatility in our data, we also see high levels of income and earnings volatility among service sector workers who have stable and predictable schedules. This volatility could come about because other earners contributing to household income experience volatility, because of volatility in income from second jobs or odd jobs, or because of ups and downs in the receipt of child support, public benefits, or informal support. Although work schedules are an important input influencing income volatility, there are clearly other factors at work.

Consequences of Volatility

Week-to-week volatility of income and earnings is widespread among hourly service sector workers and is significantly shaped by work scheduling practices. What are the consequences of this income volatility for household economic security?

Figures 5 and 6 present the results of models that examine the association between our two measures of income volatility and four indicators of household economic insecurity - experience of material hardship, difficulty paying bills, low confidence in ability to cope with an expense shock, and use of alternative financial service loan products (payday loans and/or pawn brokerage). We present predicted values from models that control for a large set of demographic and work characteristics. The regression estimates are presented in Table 2.

Income volatility increases the experience of material hardship over the past year. Such experience of material hardship is widespread in this sample of the working poor. But, the experience differs significantly by volatility. Respondents who report that their household income varies from week-to-week experienced a two standard-deviation increase in the number of material hardships (0.6 hardships) than those whose income was steady. The chance of experiencing material hardship also rises in tandem with increases in weekly earnings volatility, with those who experience the least earnings volatility experiencing about 2/3 less of a standard deviation in hardship than those experiencing the highest levels of earnings volatility.

Respondents dealing with income and earnings volatility are also substantially more likely to
report difficulty paying bills and making ends meet. 30% of workers who report week-to-week variation in household income had trouble versus 22% of those with more stable incomes. Earnings volatility was also a significant predictor of difficulty paying bills.

Volatility seems to also shape a more general financial vulnerability. Workers who report volatile household incomes also reported being less confident of their capacity to cope with a hypothetical $400 expense shock: 57% of those who experienced volatility reported being uncertain about their ability to cope against 44% of those who had stable household income. We did not though find significant variation in confidence in ability to cope with an expense shock by the degree of earnings volatility.

In the face of regular expenses, income and earnings volatility present households with the need to somehow smooth consumption. One way households may do so is through the use of alternative financial services (AFS) loan products such as payday loans or pawnshops. We find that 21% of respondents who report week-to-week volatility in income report using a payday loan or pawnshop in the past 12 months against 16% of those with stable incomes week-to-week. We also find a marginally significant gradient in AFS loan product use by earnings volatility with 17% of those with the most stable earnings reporting use a payday loan or pawnshop against 20% of those whose earnings were most variable.

Discussion

We find widespread income and earnings volatility among service sector workers. This volatility plays out on a weekly basis and we find that exposure to unstable and unpredictable scheduling is a significant determinant of this volatility. Moreover, workers who experience week-to-week volatility in their incomes and earnings are more financially insecure. They are more likely to have experienced serious material hardships over the prior year, more likely to have difficulty paying bills, and less likely to feel confident in their ability to cope with a moderate expense shock. These workers are more likely to turn to alternative financial services like payday loans and pawnning.

This research is subject to some important limitations. First, our data are not drawn from a traditional probability sample and so we must acknowledge some uncertainty about the representativeness of our data even as recent work suggests that with statistical adjustment, such samples as
ours can approximate “gold standard” approaches. Second, we cannot establish any causal evidence on the effects of unstable and unpredictable schedules on volatility or of volatility on household economic security. It is certainly possible that unobserved individual or community characteristics drive this complex web of associations. While it seems unlikely that earnings volatility cause unstable schedules, it is possible that household economic insecurity might interfere with work in ways that cause work hour variability and so earnings volatility.

Our work suggests that recent policy and corporate action to reduce the use of unstable and unpredictable work scheduling practices could meaningfully reduce income and earnings volatility. Policy action on scheduling has been led by several west-coast cities, with San Francisco passing the first legislation to regulate unpredictable scheduling in 2014 and then with Emeryville, CA and Seattle, WA following suit in late 2016. All of these ordinances aim to reduce the unpredictability, and so perhaps also the variability, of work schedules by requiring large companies in the service sector to provide two weeks of advanced notice and to provide “predictability pay” when schedules change within two weeks of the shift. Because of the strong evidence linking schedule instability to income volatility, recent local ordinances that improve schedule instability can be expected to reduce income volatility at the same time. Alongside these legislative changes, some companies are also beginning to change their scheduling practices, with Walmart announcing that it will offer all Associates the opportunity to work a regular fixed schedule. These changes seem likely to be important, if partial, solutions to the problem of income and earnings volatility.

Our results also show that workers who experience income and earnings volatility are more likely to turn to alternative financial service providers like payday lenders and pawn brokers, presumably to smooth consumption in the face of volatile incomes. Solutions that could provide lower cost ways to satisfy this financial function could also be valuable. In this domain, FinTech innovations such as Even, Digit, and Active Hours that help workers smooth erratic incomes, may mitigate some of the harms of volatility.

When assessing the financial well-being of America’s working families, this paper adds to a growing chorus calling for attention not just to the level of annual income but also to the stability and volatility in income streams. The Shift Project shows that volatility is prevalent and consequential for working families in the service sector, and that work schedules play an important role in driving this income volatility, and therefore represent an important avenue for crafting solutions.
References


### Tables

#### Table 1. Association between Work Scheduling and Income and Earnings Volatility, Regression Coefficients

<table>
<thead>
<tr>
<th>Schedule Type</th>
<th>HH Income Volatility</th>
<th>Earnings Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
<td>0.71***</td>
<td>0.03***</td>
</tr>
<tr>
<td>Regular Day</td>
<td>ref</td>
<td>ref</td>
</tr>
<tr>
<td>Regular Evening</td>
<td>-0.11</td>
<td>-0.01</td>
</tr>
<tr>
<td>Regular Night</td>
<td>0.31*</td>
<td>-0.01</td>
</tr>
<tr>
<td>Rotating</td>
<td>0.38***</td>
<td>0.01</td>
</tr>
<tr>
<td>Other</td>
<td>0.33*</td>
<td>-0.00</td>
</tr>
</tbody>
</table>

| **Advanced Notice**    | 0.36***              | 0.05***             |
| Less than 1 Week       | ref                  | ref                 |
| 1-2 Weeks              | 0.23**               | 0.03***             |
| More than 2 Weeks      | ref                  | ref                 |

| **Shift Cancelled in Last Month** | 0.71*** | 0.06*** |
| No                               | ref      | ref      |
| Yes                              | 0.47***  | 0.06***  |

| **Work on Call in Last Month**  | 0.22*    | -0.01    |
| No                               | ref      | ref*     |
| Yes                              | 0.00     | -0.01    |

| **Schedule Control**           | 0.22*    | -0.01    |
| Employer Alone                 | ref      | ref*     |
| Employer with Employee Input   | 0.00     | -0.01    |
| Employee with Input or Employee Alone | ref | ref* |

| **Instability Scale**          | 0.23     | 0.01     |
| 1                                | 0.67***  | 0.05***  |
| 2                                | 0.95***  | 0.06***  |
| 3                                | 1.26***  | 0.11***  |
| 4                                | 1.51***  | 0.13***  |

| **Demographic Controls**       | Y        | Y        |
| **Work Controls**              | Y        | Y        |
| **Observations**               | 17849    | 17849    |

Note: All models include controls for race, age, gender, educational attainment, marital status, school enrollment, household income, average weekly work hours, employment tenure, managerial status, and living with children.
Table 2. Income and Earnings Volatility and Household Financial Insecurity

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Hardships</td>
<td>Difficulty</td>
<td>Low Confidence in Coping</td>
<td>Pawn/Payday</td>
</tr>
<tr>
<td>Household Income Goes Up and Down</td>
<td>0.59***</td>
<td>0.47***</td>
<td>0.59***</td>
<td>0.37***</td>
</tr>
<tr>
<td>Earnings Volatility</td>
<td>0.29*</td>
<td>0.36*</td>
<td>0.12</td>
<td>0.35</td>
</tr>
<tr>
<td>Demographic Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Work Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>17849</td>
<td>17849</td>
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<td>17849</td>
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</tbody>
</table>

Note: All models include controls for race, age, gender, educational attainment, marital status, school enrollment, household income, average weekly work hours, employment tenure, managerial status, and living with children.
Figures

Figure 1: Example Survey Recruitment Advertisements
Figure 2: Household Income Volatility and Earnings Volatility by Gender, Education, and Race/Ethnicity
Figure 3: Associations between Precarious Work Schedules and Household Income Volatility
Figure 4: Associations between Precarious Work Schedules and Earnings Volatility
Figure 5: Associations between Household Income Volatility and Household Financial Insecurity

- **# of Material Hardships**
  - Stable: 1
  - Variable: 2

- **Difficulty Paying Bills**
  - Stable: 0.4
  - Variable: 0.5

- **Use of Payday or Pawn**
  - Stable: 0.2
  - Variable: 0.3
Figure 6: Associations between Earnings Volatility and Household Financial Insecurity