Hours Off the Clock

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Abstract

To what extent do workers work more hours than they are paid for? The relationship between hours worked and hours paid, and the conditions under which employers can demand more hours "off the clock," is not well understood. The answer to this question impacts worker welfare, as well as wage and hour regulation. In addition, work off the clock has important implications for the measurement and cyclical movement of productivity and wages. In this paper, I construct a unique administrative dataset of hours paid by employers linked to a survey of workers on their reported hours worked to measure work off the clock. Using cross-sectional variation in local labor markets, I find only a small cyclical component to work off the clock. The results point to labor hoarding rather than efficiency wage theory, indicating work off the clock cannot explain the counter-cyclical movement of productivity. I find workers employed by small firms, and in industries with a high rate of wage and hour violations are associated with larger differences in hours worked than hours paid. These findings suggest the importance of tracking hours of work for enforcement of labor regulations.

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1 Introduction

How many hours do people work? Myriad government surveys of hours worked from households, and hours paid from establishments exist to answer this question, though each has drawbacks.[1] How much time employees spend at work, and whether this time is explicitly tracked and bargained for, is neither well measured nor understood. In addition to worker welfare, the difference between hours paid and hours worked has implications for the cyclical movement of productivity and wages. Specifically, off-the-clock work[2] is a possible explanation for the change in productivity from pro-cyclical to counter-cyclical during the last three business cycles.

The difficulty measuring work off the clock is not only a concern for economists and government statistical agencies, it is also essential for the understanding of firm profits and worker welfare. In the last few years, stories in the popular press recount hourly workers asked to show up to work and told to wait – without pay – until demand picked up.[3] Other times wage theft was more explicit, with employers doctoring reports of hours worked to show a higher hourly wage,[4] or workers asked to keep working after they had clocked out.[5] Salaried workers, too, were frequently asked to pick up some or all of the work for colleagues who were laid off.[6] The various stories are not uniform to all workers, but they all point to the various dynamics that influence bargaining over time in the workplace and how much work time happens off the clock. Empirical research that documents off-the-clock work specifically, and labor compliance more broadly, is growing, but little research using representative government datasets exists.[7]

In this study, I examine how shocks to labor demand and firm characteristics influence work off the clock. I construct a unique dataset of survey responses of hours worked from the U.S. Census Bureau's American Community Survey (ACS) with administrative data on hours paid from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program. I adjust the ACS survey weights to account for the shift in frame, so the analysis sample remains representative. To the best of my knowledge, this is the first study

[1] Establishment surveys of hours paid likely miss long hours for salaried workers and off-the-clock work. Household surveys rely on accurate recall of all jobs.

[2] I will refer to "off-the-clock" work synonymously with "the difference between hours worked and hours paid". I use this phrase only for its brevity.

[3] "More Workers Are Claiming 'Wage Theft'." *The New York Times*, Aug. 31, 2014.

[4] "Squeezed garment factories use check cashing services to mask true wages, workers say." *The Los Angeles Times*, Jul. 30, 2016.

[5] "Nearly 10,000 Chipotle Workers Join Class Action Wage Lawsuit." *The New York Daily News*, Aug. 30, 2016.

[6] "All Work and No Pay: The Great Speedup." *Mother Jones*, July/August, 2011.

[7] Bernhardt et al. (2013) and Milkman et al. (2012) are recent examples.

that links hours worked to hours paid at the *person*-level.

The dataset allows me to first answer an elementary, but essential question: how much do people work? The unconditional means of the analysis sample find that annual hours paid for full-year workers is 1,946 [500.3] compared to 2,079 [504.8] hours worked.[8] The difference of a little more than 130 hours per year works out to roughly an extra three weeks per year assuming the standard 40 hour work week. The unconditional mean log difference is 0.079 [0.237], which is close to the log difference of means. The unconditional means mask significant heterogeneity in differences between subgroups. In particular, workers who self-report working less than 40 hours or exactly 40 hours per week – the standard workweek in the U.S. – have a mean log difference between hours worked and hours paid of 0.031 [0.268] and 0.032 [0.179], respectively. For those who self-report working more than 40 hours per week, the mean log difference is 0.210 [0.238]. These are the first results to confirm that firms poorly track the hours of workers who work more than the standard workweek.

After quantifying the extent of off-the-clock work, I use variation in local labor market conditions to test whether and how shocks to labor demand effect off-the-clock work. I regress the log difference on the unemployment rate in the commuting zone of the ACS respondent at the time of her interview. The coefficient estimate for the effect of local labor market conditions is -0.00191 (0.00077), indicating that tighter labor markets increase off-the-clock work. A one percentage point decrease in the unemployment rate increases off-the-clock work by 0.19%, or an extra 4 hours annually. Further analysis reveals that the effect is driven by workers in production and non-supervisory occupations, low-skilled workers, as well as workers likely paid by the hour.

Due to concerns about about the endogeneity of hours reporting and other labor market programs that may effect labor force participation, I instrument the unemployment rate using a shift-share predicted employment index (Bartik, 1991). The instrumental variable coefficient estimates are slightly larger in magnitude, though still relatively small, with a coefficient estimate of -0.00274 (0.00154). A negative estimate indicates that off-the-clock work is not a viable explanation for the changing cyclicality of productivity.

Economic theory gives us insight as to why hours paid and hours worked should diverge. The negative coefficient estimate points to firms engaging in labor hoarding. In labor hoarding models, firms hold labor in excess of production requirements during a drop in demand. This is usually attributed to costs of adjusting employment, such as the difficulty of training new workers when demand picks up. In accordance with my results, labor hoarding models find relatively sluggish employment adjustment in response to a shock, with firms using the intensive margin to adjust labor inputs. One important implication is that productivity is

[8]All standard errors are in parentheses. All standard deviations are in brackets.

pro-cyclical.

In light of the result that off-the-clock work is probably pro-cyclical and driven by low-skill workers, I test for explanations centered on labor compliance. Although still an emerging literature, research finds that smaller firms are much less likely to comply with labor regulations. Consistent with this literature, I find that firms in the smallest firm size category, 0-19 employees, report higher incidence of work off the clock compared to firms with greater than 2,500 employees with a log difference of 0.0231 (0.0053). I find the effect is driven by production and non-supervisory workers who are likely paid on an hourly basis. I also show that off-the-clock work is concentrated in industries where wage and hour violations are prevalent.

The results on the cyclical nature of off-the-clock work challenge a recent literature testing for efficiency wage explanations for the counter-cyclical nature of productivity. Lazear et al. (2015) and Burda et al. (2016) use local labor market variation to test for greater effort in slack labor markets. Unlike this paper, they do not look for work off the clock, rather they model greater effort per unit of time at work. The empirical strategy in Lazear et al. (2015) employs data on a single firm with a wide geographic dispersion of establishments, that tracks piece-rate production. Burda et al. (2016) use an empirical strategy similar to Lazear et al. (2015), but they use the American Time Use Survey to measure time at work actually working, which is a proxy for greater effort. In contrast to my paper, both studies find evidence that greater local labor market slack is associated with greater effort provision.

My estimates quantifying off-the-clock work and its implications for productivity statistics confirm several previous papers. Aaronson and Figura (2010) also attempt to use off-the-clock work to explain the counter-cyclical turn in productivity. They construct time series of hours worked and hours paid from the Current Population Survey and the Current Establishment Statistics, respectively. Although they must rely on aggregate data, they too find little evidence for off-the-clock work biasing productivity estimates. Eldridge and Pabilonia (2010) use the American Time-Use Survey (ATUS) and the Work Schedules and Work at Home Supplement to the Current Population Survey to address whether the incidence of working from home biases productivity statistics. They find over the time span of their sample that unpaid work at home sometimes overstates, and other times understates the hours levels used in the BLS productivity series. The bias in all cases is exceedingly small, and unlikely to bias productivity statistics.

Recent research uses survey and administrative data to document non-compliance with minimum wage laws, overtime regulations, and work off the clock. Bernhardt et al. (2013) and Milkman et al. (2012) use the 2008 Unregulated Worker Survey, and they find that job and employer characteristics are responsible for much of the variation in noncompliance. Ji and Weil (2015) use a unique dataset of franchisor- and franchisee-owned establishments matched to Wage and Hour Administration investigations. They find that franchisee-owned establishments are more likely to commit wage and hour violations. My estimates of off-the-clock work are broadly consistent with this literature. Off-the-clock work is most concentrated in small firms, and within industries that disproportionately employ low-wage workers.

Since applied economics is moving towards the use of large administrative datasets, the results of my study also suggest caution when using administrative data to measure hours. Few studies have explicitly compared employer and employee reports of hours worked.[9] One exception is Mellow and Sider (1983) who use an employer validation supplement to the CPS to glean employer and worker responses to myriad questions. For hours, they find worker reports exceed employer reports by 3.9%, which is substantially less than the 7.9% in the preferred specification. The difference is likely due to the analysis sample in this study, which only considers full-time, full-year workers. Lastly, this study contributes to the growing body of research which uses administrative data to validate survey data.[10]

2 Hours Divergence: Theory and Implications

I construct a unique dataset of hours worked and hours paid in order to try to infer the causes, incidence, and implications of off-the-clock work. A natural question quickly arises: why should we expect the difference between hours paid and hours worked to reflect anything but errors in reporting? Although measurement error is no doubt present, this section lays out established economic theories of why hours paid may diverge from hours worked. The first two theories provide opposing predictions for the movement of off-the-clock work over the business cycle. Efficiency wage models predict workers will exert more effort – greater hours worked compared to hours paid – when labor markets are slack. In contrast, theories of labor hoarding predict the opposite relationship between off-the-clock work and macroeconomic conditions.

In addition to cyclical theories of why hours paid may diverge from hours worked, I view the difference through an older literature on labor regulation compliance. In these models the firm's profit motive leads them to skirt labor laws to realize greater profits. Firms must weigh the higher profit of non-compliance against the probability of getting caught and the penalties of non-compliance. The Great Recession and the ensuing debate

[9]See Duncan and Hill (1985), Bound and Krueger (1991), Bound et al. (1994), and Bound et al. (2001) for an overview.

[10]See Abraham et al. (2013) and Abowd and Stinson (2013).

about the declining wages and working conditions of low wage workers have brought this topic to greater prominence in the media. Better administrative data on employment, firms, and greater transparency and data around compliance investigations have invigorated this literature.

2.1 Efficiency Wages & Labor Hoarding

In efficiency wage theories of the labor market, workers would like to avoid being laid off, and firms would like workers to exert effort. At least since Kalecki (1943), who noted "under a regime of permanent full employment, the 'sack' would cease to play its role as a disciplinary measure," economists have studied the relationship between the labor market and worker effort. More recent discussions of efficiency wage models pick up with Shapiro and Stiglitz (1984). In their model, the firm's production depends on worker effort, which firms cannot perfectly monitor. Workers would prefer to shirk rather than exert effort. Firms offer wages in excess of the market clearing rate in order to induce effort. The theory provides a succinct explanation of involuntary unemployment.

The model relevant for the empirical tests in this paper does not provide a theory of unemployment. Although similar, the key is the cost to firms of replacing workers, or alternatively the cost to workers of finding a new job.[11] The driving variable is the tightness of the labor market. As the labor market becomes more slack, the cost of job loss increases due to worse prospects of finding a new job. Workers exert extra effort in the form of more hours worked in order to signal their worth to employers and avoid a lay off. In the case of hourly workers, this may be explicit off-the-clock work. For salaried workers, these extra hours are in excess of what is "normal" under more favorable labor market conditions.

In contrast, labor hoarding theories predict that labor productivity should be pro-cyclical Popular in the 1960s,[12] theories of labor hoarding hold that firms retain more workers in a downturn than production explicitly requires.[13] Firms may have incurred the costs of training workers to their specific production technology, or highly skilled workers may be scarce. In both cases firms would rather not risk laying off workers who may be difficult to rehire, or pay the upfront cost to train new hires. To meet reduced production targets, firms then adjust hours worked in order to meet production targets. If firms choose to keep a worker's labor earnings constant, hours paid may exceed hours worked. The implication for labor hoarding theory is that productivity will decline during downturns as hours paid

[11]Rebitzer (1987) is the most relevant paper capturing the former case. See Appendix A for the latter case.

[12]See Oi (1962) & Fair (1969).

[13]Biddle (2014) provides a nice history of the literature.

stays relatively constant and production declines.[14]

More modern theories of labor demand would interpret labor hoarding through the lens of adjustment costs. Firms face an explicit cost to adjusting their labor on the extensive margin. Depending on the size and functional form of the costs, firms will not always adjust employment to its optimal level in response to a shock. Firms will adjust employment less than in the absence of adjustment costs and use hours to adjust total labor input to its optimal level.[15]

Efficiency wage and labor hoarding models are not mutually exclusive. In fact, both are likely present in any given employment relationship. The empirical approach employed in this study will not be able to separately identify the two. The empirical analysis in this paper serves to answer the question of which is more salient for interpreting the cyclical changes in productivity and real wages. It should therefore help guide macroeconomists on how best to incorporate the costs of separations to workers and firms in their models.

2.2 Labor Regulation Compliance

In addition to the cyclical forces, explicit failure to comply with labor regulations is another reason why hours worked may exceed hours paid. The Fair Labor Standards Act (FLSA), enacted in 1938, established the federal minimum wage, and effectively enshrined the 40-hour work week by requiring overtime pay of time-and-a-half for all hours worked over 40 in a week. The literature on compliance with the FLSA centers on the firm. Firms weigh their profits from compliance against their expected profits from non-compliance (Ashenfelter and Smith, 1979). The model leads to the conclusion that firms need to take into account the costs of noncompliance, the odds of getting caught, the elasticity of labor demand, and the spread between the prevailing wage and the minimum wage in a given industry.[16]

Recent empirical research finds firm and job characteristics such as firm size, industry, and non-hourly pay arrangements drive non-compliance with labor regulations. Bernhardt et al. (2013) conduct a survey of low-wage workers in major American metropolitan areas. They survey non-compliance, but also collect detailed worker and firm characteristics. They have two important findings. First, larger firms (greater than 100 employees) are less likely to commit labor violations compared to firms less than 100 employees. Second, they find that non-hourly workers are more likely to incur wage and hour violations, and that off-the-clock work is more prevalent than straight minimum wage violations.

[14] Employer reports of hours paid are the main input to the BLS productivity series, while hours worked is the variable of economic interest. See Eldridge and Pabilonia (2010).

[15] See Cooper et al. (2007), Caballero et al. (1997), and Hamermesh (1989) for more recent examples. Appendix A describes the theory in more detail.

[16] See also Chang and Ehrlich (1985), and Basu et al. (2010).

There are a few reasons why smaller firms may be more likely to commit labor violations. First, small firms have fewer establishments and therefore stand less of a chance of getting caught for noncompliance if enforcement is equally probable for all establishments. Second, small firms are less likely to have in-house expertise (human resource departments) to negotiate regulations (Mendeloff et al., 2006), and are less likely to be unionized.[17] Small firms tend to have less capital and rely more heavily on labor inputs. Thus, if they are going to cut costs, it will likely be on labor.[18] Finally, the fact that small firms have less capital reduces the costs of non-compliance. Firms that owe back wages have the opportunity to declare bankruptcy and forsake owed back wages. The less capital a firm has, the smaller the costs to bankruptcy.[19]

The measurement of hours is often an important determinant for wage and hour violations. Recent changes in technology and the organization of firms make measuring hours a challenge in wage and hour compliance. Tracking hours is important for assessing off-the-clock work, overtime violations, and many minimum wage violations when workers are not paid by the hour. New technology makes assessing hours more difficult as more work takes place at home with computers outside of normal business hours. In addition, tracking hours for workers who may work at multiple work sites and who may be employed by third party entities pose new challenges to enforcement agencies (Weil, 2010). In short, the measurement of hours is invaluable for effective enforcement of wage and hour violations, and it constitutes a significant margin through which many violations take place.

3 Data

Making inferences about the differences between hours paid and hours worked requires data on both variables. Previous estimates of the divergence between hours paid and hours worked relied on aggregated time series data. An innovation of this paper is to link the two variables at the *person* level. To the best of my knowledge, this is the first paper to explicitly link workers' reports of hours worked to employers' reports of hours paid for a representative sample of workers. The result is a survey response of hours worked and the corresponding administrative reports of hours paid from the survey respondent's employers. To construct this difference measure, I use administrative data of hours paid from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program linked to survey responses to the American Community Survey from the U.S. Census Bureau.

[17] Weil (1991) shows labor unions correlate with OHSA investigations.

[18] See Ji and Weil (2015) for a similar discussion on franchisee vs. franchisor labor compliance.

[19] "Few California workers win back pay in wage-theft cases." *The Los Angeles Times*, April 6, 2015.

The LEHD is an administrative file system of linked employer-employee data derived from state unemployment insurance systems. The data result from a unique partnership between states and the U.S. Census Bureau, where the states provide the Census Bureau quarterly extracts of earnings records from their unemployment insurance systems. The core file is a job-based frame, named the Employment History File (EHF), with a unique record represented by a person-firm-year-quarter link with any positive earnings in a given quarter, which covers approximately 95% of all jobs in the United States.[20] The fact that the LEHD comprises a near-universe of jobs and employer-employee links is important as it lets me account for hours paid in all jobs of the survey respondent, as well as providing the link to survey data for hours worked.

In addition to quarterly earnings, four states provide quarterly reports of hours paid. The states are Washington, Minnesota, Rhode Island, and Oregon.[21] The quarterly hours data allow me to construct a measure of total hours paid across all jobs in the previous year for each person. The final LEHD sample consists of a person-level measure of all jobs paid in the previous year for each quarter from 2010 to 2013 for these states.[22]

Data on hours worked come from the U.S. Census Bureau's American Community Survey (ACS). The American Community Survey is a rolling monthly survey of 3.5 million households each year. The ACS replaced the Census long form after the 2000 census and as such, it asks questions on housing, demographic, and economic topics. I focus on the questions on weeks paid in the past year and the usual weekly hours worked. When combined, the two variables allow me to construct a measure of usual hours worked in the past year across all jobs from the perspective of the employee.

A point of clarification is needed regarding paid weeks worked for the annual hours worked measure. The ACS hours worked measure conflates both hours paid and hours worked due to the weeks worked variable including paid leave. I construct annual hours worked as the product of usual weekly hours and weeks worked. The ACS measure of annual hours worked includes some weeks for which the worker was paid, but for which no work was done. I do not adjust for this in what follows because both LEHD and ACS include paid leave. The difference in the annual hours measure therefore lets usual weekly hours drive the variation in the difference between the two measures. Alternatively, both measures could be adjusted to

[20] Self-employed workers are not currently incorporated into the LEHD. For a full description of the LEHD infrastructure files see Abowd et al. (2009).

[21] There does not appear to be an explicit administrative reason why some states collect hours paid in addition to quarterly earnings.

[22] The states vary considerably with respect to the time of reporting. Internal rules of the LEHD program dictate that at least three states must be used for any released results, which limits the analysis to begin in 2009 when Rhode Island first begins reporting hours until 2014 quarter one, which is the most recent hours data available for all states.

account for weeks worked rather than weeks paid. Because I am interested in the difference between the two measures, adjusting both down by the same amount will not influence the final measure of work off the clock. All statistics showing annual hours levels reflect the lack of adjustment.

3.1 Sample Construction

For the final merged ACS-LEHD analysis sample, I first separately prepare ACS respondents and create an analogous person-year-quarter frame for the LEHD. The ACS preparation begins by attaching a protected identification key (PIK) to each ACS respondent. A PIK is a person-level identifier that allows one to link ACS responses to other individual datasets within the U.S. Census Bureau.[23] Using an internal crosswalk, I link ACS responses from 2010 to 2013. For each year, an ACS respondent links to a PIK at rates between 91% and 94% per year. After deduplicating records within a year, I am left with 18.3 million ACS responses.

I merge the person-year-quarter LEHD frame and the ACS to create the final analysis dataset. The resulting sample contains 571,000 records. The small sample is a result of limiting the sample of ACS respondents to those who have positive hours paid in the previous year in the LEHD hours-reporting states from the time of their ACS interview. I further restrict the sample to ensure that the LEHD and the ACS frames accord as close as possible. For consistency with the LEHD, I restrict ACS respondents to those age sixteen and over, and I require that they have no jobs in other states over the previous year by consulting the standard LEHD EHF, which includes all available states.[24] Using the ACS-reported dominant job, I exclude federal government employees.[25] I use the ACS reported residence and exclude all respondents who neither live in an hours reporting state, nor in a border state. It is perfectly reasonable for an ACS respondent living in North Dakota, for example, to work in Minnesota. As a result of these restrictions, I reduce the sample to 438,000 observations.

The final sample contains additional restrictions to negate any anticipated frame differences, which could lead to biased measurement of work off the clock. I restrict the sample to records who report working a full year (50-52 weeks) in the ACS, and who report positive

[23]See Wagner and Layne (2014) for a description of the U.S. Census Bureau's PIK assignment process.

[24]I also exclude respondents for whom I find jobs with zero or missing hours data. This is evidence of unit non-response and would bias measures of work off the clock.

[25]The ACS-reported dominant job does not conform to the definition of a dominant job in the LEHD. For the ACS, the dominant job is the main job in the week prior to the ACS response. Given the stability of federal jobs in general, and the high tenure of my final sample, I use the two definitions interchangeably. Checks for consistency find a high degree of agreement.

hours in the LEHD for every quarter in the past year. This restriction is reasonable for a few reasons. First, the ACS sample restriction narrows weeks worked considerably. The weeks worked variable in ACS is binned, and the bins become coarser the fewer weeks one works.[26] The LEHD restriction to working in the reference quarter as well as the preceding four quarters simply ensures consistency with the ACS. Finally, I drop observations where usual weekly hours is imputed, and observations where workers receive more than 20 percent of their income from self-employment earnings as reported on the ACS. The final dataset contains 218,000 records.

In order for the final analysis sample to remain representative of the United States population, I adjust the ACS sample weights. When I merge the ACS to the LEHD universe of job records, the ACS weights are no longer representative of the U.S. population due to differences in frame. I first use inverse probability weighting to adjust the ACS sample weights for PIKs missing at random in the sense of Rubin (1987).[27] Second, I adjust the sample weights to match national demographic characteristics in the 2009-2013 ACS for full-year workers excluding federal employees. I adjust based on age, gender, race/ethnicity, and education. The resulting sampling weights allow for inferences about the population after linking the ACS to a different universe.

3.2 Variable Construction

I create the final total for hours paid from the LEHD over the previous year by summing hours over jobs and weighting the interview quarter and ending quarter by the ACS interview date. For person i employed at job j at any year-quarter t between 2010 and 2013, define $h_{j(i),t}$ as the gross quarterly hours for person i in job j in quarter t. I consider only LEHD jobs between the quarter of the ACS interview (t), and four quarters prior ($t-4$), inclusive. Total hours paid over the previous year therefore include five quarters of data, which is one too many. To calculate the final annual hours paid in the LEHD over the previous year from the survey interview date, I sum hours over all jobs, and take a weighted average of hours in the interview quarter and the last quarter,

$$H_{i,lehd} = (1-\rho)\left(\sum_{i\in J} h_{j(i),t-4}\right) + \left(\sum_{t=1}^{3}\sum_{i\in J} h_{j(i),t-k}\right) + \rho\left(\sum_{i\in J} h_{j(i),t}\right) . \tag{1}$$

[26]There is research pointing to quality problems in hours worked for the ACS for part-time workers (Baum-Snow and Neal, 2009). I include full-year part-time workers, though all results are robust to their exclusion with some loss of precision.

[27]This is also known as missing conditional on observable covariates. See appendix B for details on inverse probability weighting.

The first term on the right-hand side of equation 1 is the sum of all hours paid to respondent i across all jobs J in which the respondent worked in period $t-4$. This sum is multiplied by the weight $1-\rho$. The middle term is the sum of hours paid at all jobs in the three quarters immediately preceding the interview quarter. The last term is the sum of hours across all jobs in the interview quarter multiplied by weight ρ. The weights are based on the percentage of the interview quarter in scope for the total hours calculation.[28]

To construct annual hours worked in the ACS, I assume that usual weekly hours is equivalent to average weekly hours and then multiply usual weekly hours by 50, 51 and 52 weeks to get three measures of annual hours worked. Table 1 provides statistics for annual hours worked assuming a 52 week work year. This is my preferred hours measure for several reasons. First, the final sample contains workers with relatively high tenure (over six years), and I perform checks for continuous employment in the LEHD over the previous four quarters from the reference quarter. Second, the ACS asks for usual weeks worked including paid sick days, paid vacation, and military service. Given checks for continuous employment and because the ACS weeks worked question includes paid leave, 52 weeks seems the most reasonable measure of weeks paid that accords with the LEHD.

The final dependent variable of interest is the log difference between annual hours worked from the ACS, and total hours paid over the previous year from the LEHD. Recall that the sample is restricted to full-year workers, and that ACS weeks worked is binned for full-year workers. Denote the annual ACS hours measure $H^w_{i,acs}$ where $w \in \{50, 51, 52\}$ is the possible weeks worked. The annual LEHD hours measure is denoted $H_{i,lehd}$. The measure of difference between hours worked and hours paid is $y^w_i = \ln(H^w_{i,acs}) - \ln(H_{i,lehd})$. I construct the log difference for all three ACS measures of ACS annual hours. I then winsorize at the 5% and 95% level in order to mitigate bias induced by extreme outliers.[29]

Demographic, firm, and job characteristics come from a combination of the ACS and the LEHD. Many characteristics are available in both the LEHD and the ACS. I use the ACS for demographic characteristics, which are occasionally imputed in the LEHD. For the residence, I use the ACS reported residence. The LEHD residence is from a fixed time period each year, and will not necessarily correspond to the residence at the time of ACS interview. I use firm characteristics from the LEHD dominant job[30] as it comes from an administrative source and best hues towards my preferred definition of a dominant job. I make use of whether or

[28]For example, if an ACS respondent completed the survey on May 10th, the weight assigned to the interview quarter would be equal to the 40 days in the quarter divided by 91, which is total days in the second quarter. The weight on the end month is simply one minus the interview quarter weight.

[29]The following analysis has also been carried out with a dependent variable winsorized at the 1% and 99%. Results are qualitatively unchanged.

[30]I define the LEHD dominant job as the job with the most hours paid in the three quarters which lie completely within the preceding year from the date of the ACS interview.

Table 1: Summary Statistics for Analysis Sample

	mean	sd
ACS annual hours (52 Weeks)	2,079	500.3
LEHD annual hours	1,946	504.8
Annual hours error (50 weeks, ACS)	0.030	0.251
Annual hours error (51 weeks, ACS)	0.055	0.241
Annual hours error (52 weeks, ACS)	0.079	0.237
Firm/Job Characteristics		
Unemployment rate (%)	7.354	1.901
Private, for-profit firm	0.743	0.437
Supervisory, Non-production	0.275	0.447
Top Quartile, Liklihood Not Paid by Hour	0.277	0.448
Dominant job tenure (quarters)	26.96	21.0
Demographic Characteristics		
Age	42.30	12.87
Male	0.519	0.500
Non-white	0.239	0.426
Bachelor's degree or higher	0.325	0.468

Notes: $N = 218,000$, with 58 commuting zones. Annual hours error is the difference between log hours worked in the ACS and log hours paid from the LEHD. The ACS hours paid measure is defined by multiplying the usual weekly hours by the number of weeks paid. Supervisory workers adhere to the Bureau of Labor Statistics definition of supervisory or non-production workers. See text for details.

not a worker is paid by the hour. This is not available in either the ACS or LEHD.[31] I use the Current Population Survey to impute hourly/non-hourly pay using industry, occupation, and earnings according to the ACS. I then bin the resulting probability of non-hourly pay into quartiles for use in the empirical analysis.[32]

3.3 Summary Statistics

Summary statistics of the mean and standard errors for the final sample are found in Table 1. The first two lines give the summary statistics for estimates of annual hours worked from the ACS and annual hours paid from the LEHD. The bottom panel displays demographic characteristics used to match the analysis sample to the U.S. population. The restriction to full-year workers is perhaps the most salient for what follows. Note that the average tenure in LEHD dominant jobs is a little under 27 quarters, or slightly greater than 6.5 years.

Figure 1 shows the full distribution of the difference in log hours worked from log hours paid. I use my preferred ACS hours worked measure, which assumes 52 paid weeks. The distribution is centered slightly to the right of zero, but it is highly skewed with a long right tail implying many more people report working more than their employers say they do. Note that the distribution is winsorized at the 95% level, which slightly truncates the right tail of the distribution, but analysis relaxing the winsorization to the 99% level does not alter the results.

Partitioning the distribution by a few characteristics reveals large differences between hours worked and hours paid, particularly for those who report working more than 40 hours per week. Figure 2 shows the large disparity in work off the clock by workers who self-report working more than 40 hours per week. The figure partitions the distribution of the difference in log hours into those who self-report usually working less than 40 hours per week (top panel), those who usually work 40 hours per week (middle panel), and those who usually work more than 40 hours per week (bottom panel). The difference is stark. Those who work less than 40 hours per week show a small difference in hours worked compared to hours paid compared with those who usually work exactly 40 hours per week, with means of 0.031 [0.268] and 0.032 [0.179], respectively. Most of the mass is centered around zero in both distributions, with a slight right skew. In contrast, for those who report working more than 40 hours the distribution shifts to the right with the mass less sharply concentrated.

[31] Deciphering salaried workers in the LEHD is not as simple as looking at low variance in quarterly hours across quarters for a given job. Due to the abundance of weekly or bi-weekly pay periods, jobs with constant weekly hours paid will nonetheless display quarter to quarter variance in hours paid as the number of pay periods in a quarter fluctuates.

[32] See appendix C for details.

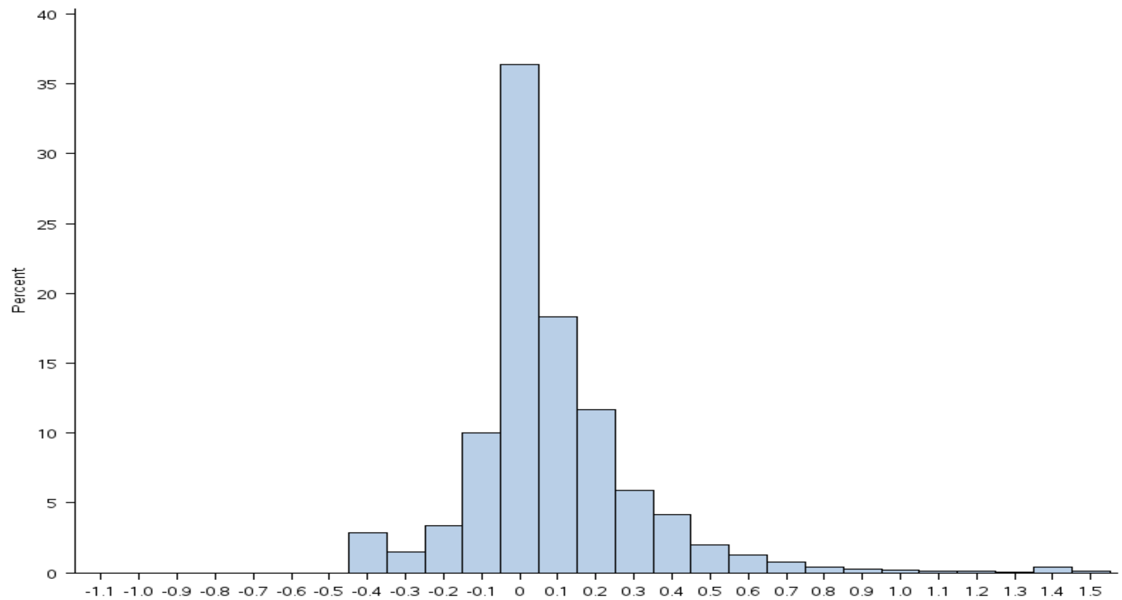

Figure 1: Distribution of the Difference of Log Hours Worked and Log Hours Paid

Notes: Variable is the difference in log ACS hours worked from log LEHD hours paid for the analysis sample, winsorized at the 5% and 95% level. $N = 218,000$. See Table 1 for summary statistics.

The mean for this distribution is 0.21 [0.238].[33]

Figure 3 displays the distribution of log hours worked less log hours paid by LEHD hours paid. I divide the annual hours paid measure from the LEHD by 52 weeks to obtain average weekly hours paid. Figure 3 partitions the log difference distribution into those who on average were paid less than 40 hours per week (top panel), 40 hours per week (middle panel), and more than 40 hours per week (bottom panel). The top two panels show a significant right skew in the distribution – what would be predicted from Figure 2. However, firms who report paying for over 40 hours per week on average have a more symmetric distribution with a mean of -0.020 [1.18]. In general, Figure 3 reinforces the finding that hours worked and hours paid accord quite closely, but that hours worked over 40 hours per week are not well recorded by employers.

The distributions of log hours worked less log hours paid suggest that hours worked is accurately reported except for workers who report working more than 40 hours per week. Recent studies support this finding by comparing survey responses from the Current Population Survey (CPS) to the American Time Use Survey (ATUS). The ATUS is a time use survey, and it is generally thought to more accurately reflect hours worked due to its short

[33]For comparison, Figure A.1 in appendix D shows the earnings error for the same two groups. Here, the distributions show a significant left skew, but in general they are quite similar.

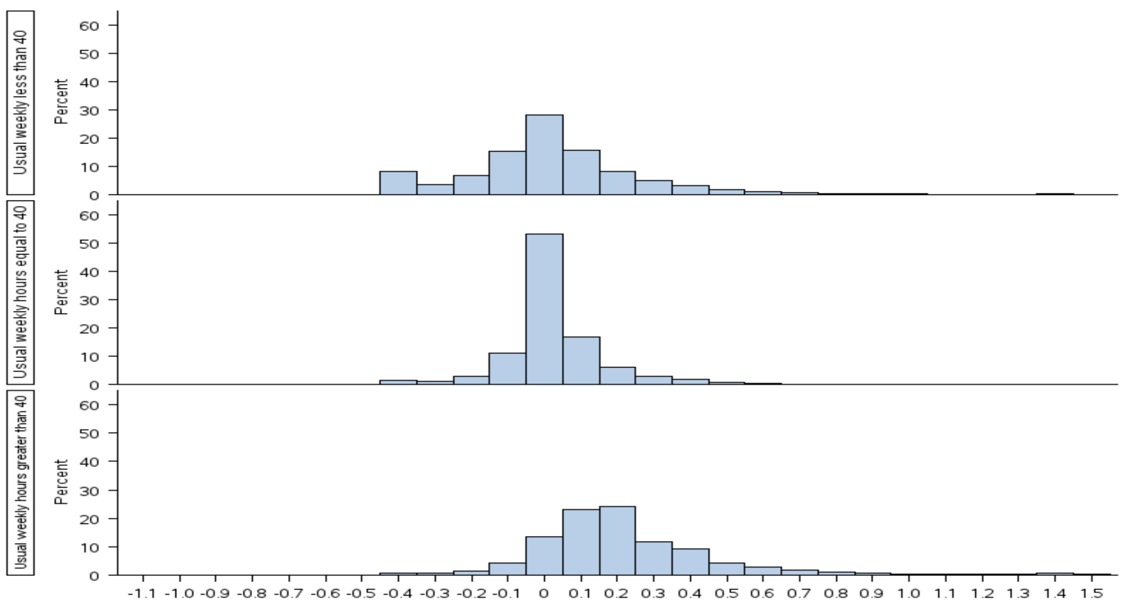

Figure 2: Distribution of the Difference of Log Hours Worked and Log Hours Paid by ACS usual weekly hours

Notes: Variable is the difference in log ACS hours worked from log LEHD hours paid for the full sample, winsorized at the 5% and 95% level. The variable is partitioned by whether an ACS respondent answers that she usually works either 1) less than 40 hours per week (top panel) or 2) exactly 40 hours per week (middle panel) or 3) more than 40 hours per week (bottom panel). Top panel $N = 49,000$, middle panel $N = 108,000$, bottom panel $N = 61,000$. Mean of top panel 0.031 [0.268], middle panel 0.032 [0.179] and bottom panel 0.21 [0.238].

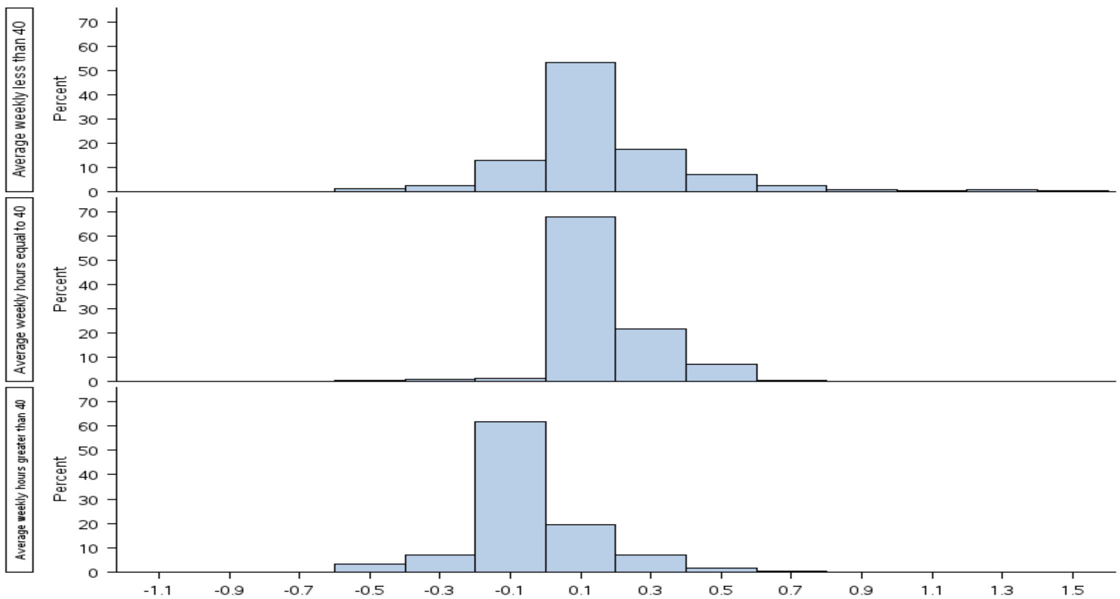

Figure 3: Distribution of the Difference of Log Hours Worked and Log Hours Paid by LEHD Hours Paid

Notes: Variable is the difference in log ACS hours worked from log LEHD hours paid for the full sample, winsorized at the 5% and 95% level. The variable is partitioned by average weekly hours paid (annual LEHD hours divided by 52). Top panel: less than 40 hours per week. Middle panel: exactly 40 hours a week. Bottom panel: more than 40 hours per week. Top panel $N = 116,000$, middle panel $N = 24,000$, bottom panel $N = 79,000$. Mean of bottom panel 0.158 [1.91], middle panel 0.108 [1.09] and bottom panel -0.020 [1.18].

recall period. Frazis and Stewart (2009) compare hours worked per job in the two surveys at the person level. They find that survey responses from the CPS of hours worked are remarkably close to the ATUS, with any overstatement confined to multiple jobholders.[34] The conclusion of these validation studies is that respondents report work hours accurately in surveys.

4 Hours & the Business Cycle

4.1 Empirical Strategy

Differentiating between the hypothesis of extra effort from employees in the form of off the clock work when labor markets are slack versus the competing labor hoarding hypothesis is the key empirical question. The ideal design for such an analysis would randomly assign different unemployment rates, or other measures of labor market slack, to many identical self-contained economies and then observe the co-movement of hours paid and hours worked. Such a fantasy experiment is not feasible. This paper uses variation in local labor market slack to infer the relationship between the business cycle and the difference between hours paid and hours worked. Specifically, I use the variation in the change in unemployment rates in commuting zones to identify hours off the clock. This approach takes advantage of the large geographic dispersion of the United States, which effectively partitions the country into many self-contained regional economies.[35]

I use the ACS respondent's place of residence for the local labor market defined as a commuting zone. Given the relatively small geographic area of four states and their adjoining neighbors, I use commuting zones as the primary local labor market unit as it classifies all counties into a commuting zone. The metropolitan statistical area (MSA) is also an appealing geographic delineation for a local labor market as it is defined as a collection of counties around a major (or minor) city usually including its suburbs. However, the MSA excludes some mostly-rural counties from any MSA, which leads to further reductions in sample size.[36]

I use the unemployment rate to measure the local labor market from the Local Area Unemployment Statistics (LAUS) from the Bureau of Labor Statistics (BLS). LAUS provides local area unemployment rates derived from BLS surveys and unemployment insurance data. The data are available monthly for small areas including MSAs and counties. I use county unemployment rates to construct monthly commuting zone unemployment rates by averaging

[34] See Frazis and Stewart (2010) and Frazis and Stewart (2004) for similar results.
[35] Schaller (2016) is a recent example who employs a similar approach.
[36] Headline results are robust to to local labor markets defined by MSA.

county unemployment rates for each county in a commuting zone weighting the average by the labor force of each county. I then average monthly commuting zone unemployment rates into a quarterly commuting zone unemployment rate. I use the quarterly commuting zone unemployment rate corresponding to the quarter of the ACS survey response as an indicator of labor market conditions. The LAUS unemployment rates are known to be noisy. By averaging over the months in the reference quarter, I allow the data to accord to the underlying analysis sample, and eliminate some of the noise.

Figure 4 shows the time series of quarterly unemployment rates for the two largest commuting zones by population in the analysis sample. One commuting zone contains Minneapolis, Minnesota and the other contains Seattle, Washington. The unemployment rates for both commuting zones rise quickly at the onset of the Great Recession before gradually declining. Seattle's commuting zone increases to almost 10% at its peak before declining to below 7% at the end of the analysis sample. Minneapolis's unemployment rate peaks at over 7% before 2010, and then declines to slightly below 5% at the end of 2013. For comparison, the national unemployment rate declined from 9.8% in January 2010 to 6.6% in January 2014. All results that follow should be interpreted with these general macroeconomic conditions in mind. Although this is just two commuting zones, Figure 4 shows that there is ample variation both within and across commuting zones in the unemployment rate.[37]

The specification for the ordinary least squares (OLS) estimate is given by,

$$y^{52}_{i,t} = \beta U_{cz,t} + \delta \mathbf{X}_i + \psi \mathbf{J}_{j(i)} + \alpha_s + \omega_t + \phi_{cz} + \epsilon_{i,t,cz} \quad . \tag{2}$$

where $y^{52}_{i,t}$ is the difference between the logarithm of ACS annual hours worked and the logarithm of annual LEHD hours paid. I use my preferred 52-week measure for ACS hours worked in the dependent variable. For this linear specification, the choice of dependent variable corresponding to different weeks worked will not matter for the final estimates. Differences in the dependent variable due to varying weeks worked only shift the intercept of the regression line and have no effect on the slope, and therefore the coefficient of interest.

The variable $U_{cz,t}$ is the unemployment rate in the commuting zone of the residence of person i in interview quarter t. The vector $\mathbf{X}_i$ captures demographic characteristics of person i, while $\mathbf{J}_{j(i)}$ captures job and firm characteristics of person i employed at dominant job j. Job characteristics include tenure, industry fixed effects and an indicator variable for whether a worker is employed in a supervisory or non-production occupation.[38]

[37] Figure A.3 shows the full distribution of unemployment rate changes across all commuting zones in the analysis sample.

[38] I use the BLS definition for production and non-supervisory workers, which is defined by industry and occupation. See U.S. Bureau of Labor Statistics (2004) for a detailed description.

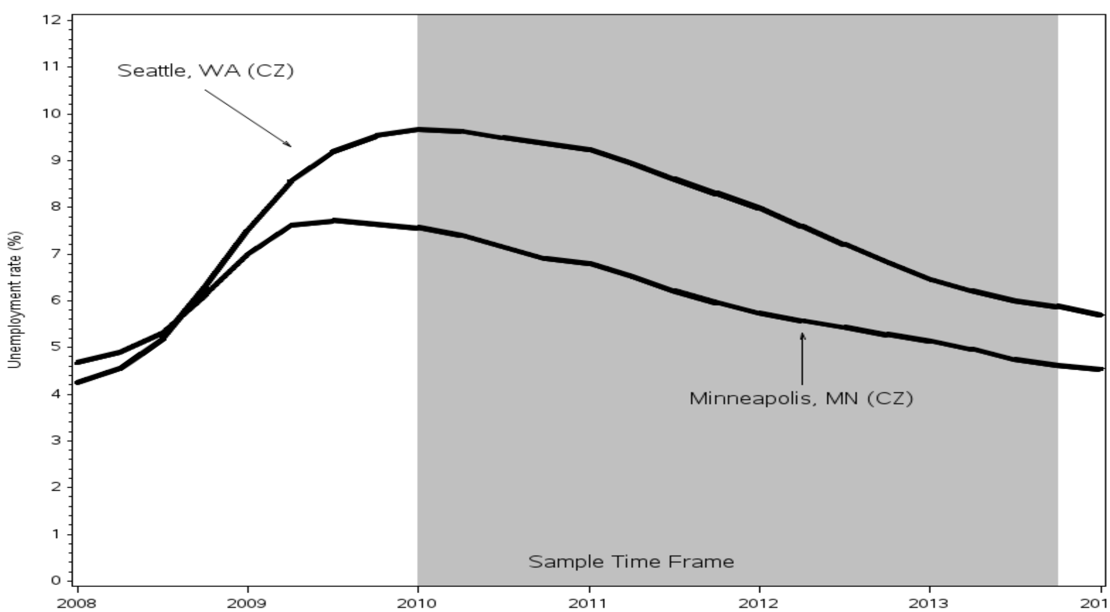

Figure 4: Quarterly unemployment rates, Seattle, WA and Minneapolis, MN Commuting Zones

Notes: Seattle, WA (CZ) refers to the entire commuting zone which contains the city of Seattle, Washington. Minneapolis, MN refers to the entire commuting zone which contains the city of Minneapolis, Minnesota. The shaded region marks the time frame of the analysis sample.

I also include fixed commuting zone effects. Denoted ϕ_{cz}, the inclusion of fixed commuting zone effects identifies the effect of the unemployment rate on the difference of log hours using time-series variation within commuting zones. The inclusion of commuting zone time trends in some specifications identifies the effect using de-trended time series variation within commuting zones. I include additional controls for fixed year-quarter and state fixed effects in the specification denoted ω_t and α_s, respectively. Finally, $\epsilon_{i,t,cz}$ is the error term.

Although commonly used in the literature, the use of local unemployment rates presents some problems for measures of labor market slack. The unemployment rate confounds both supply and demand induced responses of labor force participation. Changes in the unemployment rate may be endogenous to other variables forcing changes in work off the clock. In this setting, where the dependent variable is the difference in log hours worked from log hours paid, such endogenous changes are harder to envision, but it is not implausible that changes in state or local labor programs to encourage labor force participation may also change an employer's unemployment insurance hours reporting requirements.[39]

In order to buttress the results using the local unemployment rate, I also construct an employment shift-share measure of plausibly exogenous labor demand. This shift-share index commonly credited to Bartik (1991), but used extensively in local labor market analyses,[40] uses a local labor market's industrial composition in a base year to predict employment growth in the local labor market in subsequent years. The intuition behind the instrument is to fix local industrial composition, and allow national employment growth to predict local employment growth. If drivers of national growth are applied uniformly, local labor markets with greater concentrations of the growth industries should see greater predicted employment growth simply due to their industrial composition. I follow Autor and Duggan (2003) and construct predicted employment growth in labor market cz at time t from base year t_0 as

$$\hat{G}_{t,cz} = \sum_k \delta_{t_0,cz,k} G_{t,k} \quad .$$

The first term, $\delta_{t_0,cz,k}$, gives the share of employment in NAICS sector k in local labor market cz at time t_0, and the second term, $G_{t,k}$, is the change in log national employment in NAICS sector k between the base year and time t. I exclude the local labor market cz for the computation of national growth rates for each local labor market.[41]

[39]It appears Rhode Island began requiring employers to report hours paid at the same time it began a new labor market policy. Whether the former is in response to the latter has proven difficult to pin down.

[40]See Blanchard and Katz (1991) Bound and Holzer (2000) Autor and Duggan (2003) for other examples.

[41]National employment growth rates are from the Bureau of Labor Statistics CEW, and I construct local labor market shares from the U.S. Census Bureau's QWI, which is benchmarked to the CEW. I use 2007 for the base year because it is the peak of previous business cycle, though results are robust to using year 2000.

4.2 Results

The results of the specification employed in equation 2 are presented in Table 2. All standard errors in parentheses are cluster-robust, clustered by commuting zone (Cameron and Miller, 2015). Columns (1) to (4) add time trends, firm/job characteristics, and demographic characteristics to the regressions, respectively. Column (4) shows my preferred specification including commuting zone specific time trends, as well as time varying firm, job and demographic controls. The preferred specification has a coefficient (β) of -0.00191 (0.000767), which is small but precisely measured.

Table 2: The Effect of the Unemployment Rate on Work Off the Clock

	(1)	(2)	(3)	(4)
Unemployment rate (β)	-0.00143*	-0.00198**	-0.00182**	-0.00191**
	(0.00075)	(0.00081)	(0.00075)	(0.00077)
State FE	X	X	X	X
Commuting Zone Time Trends		X	X	X
Firm & Job controls			X	X
Demographic controls				X
R^2	0.006	0.007	0.093	0.104

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. All regressions estimated using ordinary least squares. Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

The estimated sign of the coefficient suggests labor hoarding best explains the data. As labor markets become tighter (the unemployment rate decreases), hours worked expand faster than hours paid (the wedge between hours worked and hours paid increases). To provide a valid explanation for the counter-cyclical change in productivity, the sign on the coefficient would be positive. The magnitude of the coefficient indicates a small cyclical component to off the clock work. In my preferred specification, a one point decline in the unemployment rate results in an increase in off the clock work of 0.1%. The OLS results find a relationship that lacks a strong cyclical component, and therefore cannot explain the cyclical change in productivity.

The instrumental variables estimates confirm the OLS results. These results are presented in Table 3 with my preferred specification contained in panel A, column (3). Panel B shows the first stage results. The Bartik shift-share instrument is highly correlated with

Table 3: The Effect of the Unemployment Rate on Work Off the Clock, Two Stage Least Squares Results

	(1)	(2)	(3)
	Panel A: 2SLS Results		
Unemployment rate (β)	-0.00286	-0.00254	-0.00274*
	(0.00177)	(0.00159)	(0.00154)
	Panel B: First Stage Results		
Bartik Shift-Share	-29.07***	-27.78***	-27.80***
	(3.790)	(3.987)	(3.994)
First stage F-Statistic	58.84	48.57	48.43
State FE	X	X	X
Commuting Zone Time Trends		X	X
Firm & Job controls			X
Demographic controls			X
R^2	0.005	0.006	0.104

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Panel A shows two stage least squares estimates. Panel B shows the corresponding first stage regressions. Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

the unemployment rate across all specifications. The coefficient on predicted employment growth is −27.8 (3.99), with the sign in the correct direction (higher predicted employment growth leads to a lower unemployment rate), and a first stage F-statistic of 48.43. The two stage least squares coefficient on the unemployment rate in column (3) is still negative and larger in absolute value than in the OLS specification in column (2). The coefficient on unemployment is now −0.00274 (0.00154). The instrumental variables estimates come with the cost of a loss in precision with the coefficient only significant at the 10% level. The instrumental variables results provide evidence for supply-induced responses possibly attenuating the OLS results.

The headline results of a limited cyclical component mask heterogeneity in off the clock work and the business cycle. Table 4 fits the same model given in equation 2, but interacts the unemployment rate with subgroups most likely to work off the clock.[42] Column (1) shows the slopes of the regression lines associated with production and non-supervisory workers and their complement, supervisory workers. Supervisory workers are most likely to be paid a fixed salary and seem likely candidates to be driving off the clock work.[43] Somewhat surprisingly, column (1) shows that it is production and non-supervisory workers driving the results. The coefficient estimate is −0.00219 (0.00075). In contrast, the estimate for the coefficient for supervisory workers is imprecise and slightly positive, 0.00111 (0.00080).

Similar results obtain when interacting the unemployment rate by method of pay and by skill level. Column (3) in Table 4 interacts the results by whether the ACS respondent is likely paid by the hour. Workers most unlikely to be paid hourly have a coefficient on the slope of the regression line of 0.00049 (0.00091). In contrast, workers most likely be paid by the hour have an estimated coefficient of −0.00214 (0.000852). Column (2) shows the results for workers with and without a bachelor's degree. Although there is no *a priori* reason why workers with a bachelor's degree would be more or less likely to work off the clock, in practice a bachelor's degree is highly correlated with supervisory work and non-hourly pay arrangements. The point estimate for workers without a bachelors degree is qualitatively similar to the coefficient on non-supervisory workers, and precise, obtaining an estimate of −0.00220 (0.00079). The results confirm that it is lower skilled workers likely paid by the hour who are driving the results.

The preceding results show support for labor hoarding driving the cyclical component of off the clock work, though the effect is small. Another further confirmation of the labor hoarding hypothesis is the tenure of workers. Firms holding onto excess labor in a downturn

[42]Table A.5 shows qualitatively similar results by running the regression separately for each group.

[43]This is due to the duties test for exemption from overtime in the FLSA. A key component of the test is whether an employee works in a supervisory capacity.

Table 4: The Effect of the Unemployment Rate on Work Off the Clock, Heterogeneous Effects

	(1)	(2)	(3)
$U_{cz,t}$ * Non-supervisory	-0.00219***		
	(0.00075)		
$U_{cz,t}$ * Supervisory	-0.00108		
	(0.00108)		
$U_{cz,t}$ * Less than Bachelor's Degree		-0.00214***	
		(0.00085)	
$U_{cz,t}$ * Bachelor's Degree or higher		-0.00164*	
		(0.00095)	
$U_{cz,t}$ * Least likely non-hourly pay			-0.00228**
			(0.00079)
$U_{cz,t}$ * Most likely non-hourly pay			-0.00091
			(0.00099)
p-value (from F-test coefficients are equal)	0.17	0.59	0.09
R^2	0.104	0.105	0.103

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Non-supervisory is an indicator for observations who meet the definition of a production or non-supervisory worker according to the occupation and industry of her dominant job. Supervisory refers to the compliment of non-supervisory. The definition of non-supervisory or production worker comes from the Bureau of Labor Statistics. "Least likely non-hourly pay" refers to observations who are below the median in likelihood they are not paid by the hour. "Most likely non-hourly pay" refers to observations above the median likelihood not paid by the hour. All regressions run using OLS with the same specification as Table 2 column (4). Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

will be eager to deploy it once demand picks up. In contrast, in an efficiency wage setting it seems plausible that workers with strong attachment to particular jobs who also happen to retain their dominant job after the Great Recession are particularly good matches with their employers, and their high tenure precludes them from feeling threatened with layoffs.[44]

Table 5 shows the results interacting various firm and job characteristics with the local unemployment rate. Column (1) gives the results for tenure, where the estimating equation augments equation 2 with indicator variables for length of tenure one year or less, 1-3 years, 3-5 years, and greater than 5 years. The estimated slopes show that it is longer tenured workers driving the results with point estimates of -0.00230 (0.00786), -0.00223 (0.00803), and -0.00170 (0.00754), for workers with 1-3 years, 3-5 years, and greater than 5 years of tenure, respectively. These coefficient estimates are all significant, and much larger in magnitude than for workers who have less than one year of tenure. Table 5 also shows that off the clock work is concentrated in large, old firms. The results suggest a labor hoarding model where firms work the excess labor they have kept during a downturn harder during the ensuing recovery.[45] The results further suggest that although likely paid a salary, higher skill workers likely have better outside options and are better able to resist pressures to vary hours according to cyclical labor market pressure.

4.3 Robustness Checks

The first robustness check tests for sensitivity of the results to the specification of the dependent variable. The first two columns of Table 6 run regression 2 using alternate specifications of work off the clock. Column (1) shows the results using the disparity between hours worked and hours paid according to Tornqvist et al. (1985).[46] This measure is defined if either hours measure is equal to zero, and is roughly equivalent to the log measure of the percent difference. I also do not winsorize this variable. Column (2) uses a binary indicator variable for the dependent variable, which equals unity if hours worked in the ACS exceeds hours paid from the LEHD. This makes equation 2 a linear probability model. The point estimates on the unemployment rate for columns (1) and (2) are -0.00183 (0.00080) and -0.00505 (0.00204), respectively. The estimates are precise, and indicate that the results are not sensitive to the specification of the dependent variable.

[44] This is one result of the model of Rebitzer (1987).

[45] Table A.6 shows the correlation between off the clock work and firm employment growth. There is little correlation. This is not inconsistent with a model of firms with large fixed adjustment costs who work their existing workforce as long and hard as possible before eventually adjusting.

[46] Formally, this is $y_i^{alt} = \frac{H_{i,acs} - H_{i,lehd}}{\frac{1}{2}(H_{i,acs} + H_{i,lehd})}$. Within the economics literature, this measure is usually credited to Haltiwanger et al. (1996).

Table 5: Regression Results for Unemployment Rate and Work Off the Clock, Heterogeneous Effects, Additional Results

	(1)	(2)	(3)
$U_{cz,t}$ * Tenure: 1 year or less	-0.00058		
	(0.00096)		
$U_{cz,t}$ * Tenure: 1-3	-0.00230***		
	(0.00078)		
$U_{cz,t}$ * Tenure: 3-5	-0.00223***		
	(0.00080)		
$U_{cz,t}$ * Tenure: +5	-0.00170**		
	(0.00075)		
$U_{cz,t}$ * Firm size: 0-19		0.00052	
		(0.00083)	
$U_{cz,t}$ * Firm size: 20-49		-0.00203**	
		(0.00090)	
$U_{cz,t}$ * Firm size: 50-249		-0.00241***	
		(0.00083)	
$U_{cz,t}$ * Firm size: 250-999		-0.00310***	
		(0.00086)	
$U_{cz,t}$ * Firm size: 1,000-2,499		-0.00147*	
		(0.00077)	
$U_{cz,t}$ * Firm size: + 2,500		-0.00238***	
		(0.00079)	
$U_{cz,t}$ * Firm age: 0-1			0.00105
			(0.00124)
$U_{cz,t}$ * Firm age: 2-3			0.00000
			(0.00119)
$U_{cz,t}$ * Firm age: 4-5			0.00000
			(0.00105)
$U_{cz,t}$ * Firm age: 6-10			-0.00060
			(0.00103)
$U_{cz,t}$ * Firm age: +11			-0.00211***
			(0.00075)
R^2	0.104	0.105	0.104

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Tenure is measured in years on the dominant job. All regressions run using OLS with the same specification as Table 2 column (4). Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 6: The Effect of the Unemployment Rate and Work Off the Clock, Robustness Checks

	(1) DHS	(2) Binary	(3) Interview Quarter	(4) Log Diff.	(5) Log Diff.	(6) Log Diff.
Unemployment rate (β)	-0.00183**	-0.00505**	0.0182***			
	(0.00080)	(0.00204)	(0.0023)			
Year/Year job growth				0.0024***		
				(0.0004)		
$U_{cz,t}$ * Full-time					-0.00148*	
					(0.00084)	
$U_{cz,t}$ * Part-time					-0.00192	
					(0.00125)	
$U_{cz,t}$ * More than one job						-0.00152
						(0.00155)
$U_{cz,t}$ * One job						-0.00172**
						(0.00070)
p-value (from F-test coefficients are equal)					0.71	0.88
R^2	0.085	0.057	0.110	0.074	0.104	0.117

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable in column (1) is Haltiwanger et al. (1996) measure, column (2) is an indicator for whether ACS annual hours exceeds LEHD annual hours, and column (3) is the difference in log ACS hours measured in the ACS interview quarter, and log LEHD hours in the ACS interview quarter. For columns (4)-(6) dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Year/Year Job Growth is defined for the commuting zone using the Haltiwanger et al. (1996) measure calculated from the Quarterly Workforce Indicators. Full-time is defined as usual weekly hours greater than or equal to 35 in the ACS. Part-time is less than 35 usual weekly hours in the ACS. More than one job is defined as holding more than one job over the previous year from the ACS interview in the LEHD. All regressions run using OLS with the same specification as Table 2 column (4). Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

The next threat to identification comes from recall bias. The ACS asks the respondent for usual weekly hours over the previous year. My measure of work off the clock assumes "usual" weekly hours is equivalent to average weekly hours, to respondents.[47] Hours are growing in the analysis sample as the unemployment rate trends down between 2010 and 2013. It is possible that workers simply report their usual hours right around the time of interview, and not over the previous year. If this is the case, then my results will show a positive relationship between work off the clock and tightening of the local labor market – exactly what I find. To test for this, in column (3) of Table 6 I use the difference between log hours worked and log hours paid in the interview quarter.[48] If ACS respondents understand usual hours to mean hours over the previous year, this new measure should yield a positive coefficient – the average over the previous year will be smaller than the interview quarter. If respondents are giving usual hours in the interview quarter, the point estimate on the unemployment rate should be close to zero and/or imprecisely measured. The positive estimate in column (3) of 0.0182 (0.0023), suggests that respondents interpret usual weekly hours as asking for average hours in the analysis time frame.

Table 6, column (4) tests whether the results are sensitive to the measure of labor market slack. The Local Area Unemployment Statistics from the BLS are model based, and known to be noisy. In column (3) I use the year-over-year job growth rate for the commuting zone calculated using the approximate log change credited to Haltiwanger et al. (1996). The year over year growth rate is measured from one year prior to the interview quarter. The data come from the Quarterly Workforce Indicators (QWI) from the U.S. Census Bureau. The QWI are the public-use version of the LEHD, and are therefore derived from administrative unemployment insurance data. The coefficient estimate using the year over year job growth rate is 0.0024 (0.0041). The estimate is precise and the sign of the coefficient is in the correct direction. That is, a positive coefficient for local employment growth is consistent with a negative coefficient for the local unemployment rate.[49]

Another potential problem with my specification is that some jobs may not be reported to the unemployment insurance system at all. If the ACS respondent includes the hours from these jobs in usual weekly hours, this could bias the results to look like labor hoarding.[50] The

[47]The exact question is (capitalization as in original), "During the PAST 12 MONTHS, in the WEEKS WORKED, how many hours did this person usually work each WEEK?"

[48]I use the log of gross hours in the interview quarter for hours paid and the log of usual weekly hours scaled by the number of weeks in the quarter for hours worked.

[49]Results are robust to sensitivity of included commuting zones, and the later inclusion of Oregon in 2012, though with a loss of precision in the latter case. Due to disclosure risks, these results are not able to be released at this time.

[50]From the perspective of a statistical agency calculating productivity, this distinction between "off the books" and "off the clock" is likely irrelevant.

construction of the analysis sample makes this scenario unlikely, but I test for off the books work by interacting the unemployment rate by full time status and multiple job holding.[51] The assumption is that workers who hold multiple jobs and/or work part-time are more likely to pick up short, informal jobs that are not reported to the unemployment insurance system. The results are given in columns (5) and (6) of Table 6. The coefficients for the slope of part-time workers and multiple job holders are 0.00044 (0.001199) and −0.00155 (0.00154), respectively. Neither estimate is precise, though the coefficient on multiple job holders suggests that it is not implausible off the books work may be influencing the results.

5 Hours & Labor Compliance

5.1 Empirical Strategy

Somewhat surprisingly, this paper finds that off the clock work has a small pro-cyclical component, which is driven by low-skill workers likely paid by the hour. Non-compliance with labor market regulations offers a possible explanation for these results. Non-compliance can either be explicit, by paying workers under the table, or refusing to pay over-time for hours worked over 40 hours per week. There are also subtle ways this can arise. For example firms may mis-classify employees who should be non-exempt as exempt, and shift more hours to these workers. To test this theory, we need to use the characteristics of firms. In particular, theory and survey evidence suggest that small firms are more likely to engage in non-compliance behavior due to lower costs of bankruptcy, diminished reputation, and lower productivity firms.[52]

The relevant facts presented in Section 2 indicate that off-the-clock work, and wage and hour violations often times operate through the (mis)management of hours of work. Even in the case of minimum wage violations, non-hourly pay frequency and its associated ambiguity of work hours is correlated with FLSA violations. In this section I test for whether hours-based evidence for work off the clock is present in my representative microdata. I use ordinary least squares regression and follow the specification of Bernhardt et al. (2013) using survey data, as well as Ji and Weil (2015) who use administrative data.

Before analyzing firm characteristics in greater depth, I study the following specification in order to ensure that key variables behave roughly as expected. The model is,

$$y^{52}_{i,t} = \delta \mathbf{X}_i + \psi \mathbf{J}_{j(i)} + \alpha_s + \omega_t + \epsilon_{i,t,cz} \quad , \tag{3}$$

[51] I calculate multiple job holding summing the number of jobs in the LEHD over the previous year.

[52] Milkman et al. (2012) and Mendeloff et al. (2006) provide recent examples.

where the vector $\mathbf{X}_i$ captures demographic characteristics of person i, while $\mathbf{J}_{j(i)}$ captures job and firm characteristics of person i employed at dominant job j. The specification is close to equation 2, except for the omission of commuting zone effects. The empirical strategy used to identify off the clock work for labor compliance does not rely on variation in local labor market conditions. I therefore drop the commuting zone effects as well as commuting zone time trends.

In addition to the standard firm and individual controls, I augment the model with indicators for firm size. Both Bernhardt et al. (2013) and Ji and Weil (2015) emphasize the role played by firm size in labor violations. I therefore augment equation 3 vector $\mathbf{J}_{j(i)}$ with bins for firm size given by,

$$\sum_{b=1}^{B} \psi_b \mathbf{1}\{k_b \leq firmsize_{j(i)} < k_{b+1}\} \quad ,$$

where b indexes the bins with B total bins, and k is the set of bounds defining the bins with $B+1$ bounds. The indicator function takes a value of one if $firmsize_{j(i)}$ – the firm size of the LEHD dominant job – falls within the specified firm size category. The firm-person match which constitutes a job in the LEHD uses a definition of a firm as a state-level tax reporting entity. It is not uncommon for a larger national entity to be the real owner of a firm, with the state distinction a product of the state-based nature of unemployment insurance records. The LEHD remedies this by bringing in firm size from the U.S. Census Bureau's Longitudinal Business Database (LBD). All firm size categories use the LBD's definition of a firm taking into account inter-state ownership.

5.2 Results: Firm Size

The estimation results for equation 3 are given in Table 7. My preferred specification given in column (1) lines up well with prior research. Workers with a bachelors degree, men, and workers whose main job is with a private, for profit firm are more likely to report more hours worked than hours paid. Two curious results are that the model indicates that people of color report fewer hours worked than hours paid, and U.S. citizens slightly more hours worked than hours paid. The higher incidence of work off the clock for U.S. citizens is likely due to the fact that previous survey evidence included workers who are not able to legally work in the U.S. The analysis sample includes only workers who are found in the administrative data. Inclusion in the UI data generally necessitates a social security number suggesting that non-citizens in the sample are likely different than non-citizens in purely survey data. For workers of color, the difference in sign has no easy explanation, other than previous results found only a tenuous relationship between race and labor compliance.

The coefficients of greatest interest are on the indicator variables for supervisory workers and on the quartiles of likelihood a worker is not paid by the hour. It is generally assumed that employers pay little attention to the hours for supervisory workers because they are exempt from overtime and usually not paid by the hour. In such cases one should expect hours worked to exceed hours paid. The coefficient on the indicator for supervisory workers in the main specification in column (1) is 0.00909 (0.0050) indicating that supervisory workers, all else equal, work 0.9% more hours than those for which they are paid over the course of the year. At first glance this seems low, but it is important to realize that this indicator, based on BLS definitions of supervisory workers, is highly correlated with my imputation of non-hourly pay probability.

I measure non-hourly pay probability and its association with work off the clock by indicators for quartiles of probability of non-hourly pay. In Table 7 column (1) the indicators for quartile of non-hourly pay are measured relative to the lowest quartile, where workers most are likely to be paid by the hour. The results indicate that workers most likely to be in non-hourly pay arrangements are the most likely to report more hours worked than hours paid. The coefficient in this case is 0.0136 (0.0059). Column (2) in the same table fits equation 3 using OLS but subsets the data to only include those in the top quartile of likelihood of non-hourly pay. Results are in general qualitatively unchanged, though the coefficient on the indicator for supervisory flips sign – it is now negative – indicating the limited explanatory power of this distinction in comparison to the pay type, although these two effects are difficult to distinguish.

Table 7: Characteristics of Work Off the Clock: OLS Results

	(1)	(2)
Private, for-profit firm	0.0125***	0.0135***
	(0.00281)	(0.00497)
Not White	-0.0270***	-0.0483***
	(0.00563)	(0.00306)
Hispanic	-0.00869*	-0.00969
	(0.00522)	(0.00624)
Male	0.00445**	0.00830***
	(0.00180)	(0.00142)
U.S. Citizen	0.0319***	0.0203***
	(0.00584)	(0.00269)
Bachelors degree of higher	0.0486***	0.0572***
	(0.00175)	(0.00316)
Supervisory Worker	0.00909*	-0.00970*
	(0.00502)	(0.00566)
Second Quartile	-0.0463***	
	(0.00346)	
Third Quartile	-0.0355***	
	(0.00538)	
Top Quartile	0.0136**	
	(0.00591)	
Firm Controls	X	X
Year-Quarter FE	X	X
State FE	X	X
Demographic Controls	X	X
Observations	218,000	67,000
R^2	0.073	0.096

Notes: Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Quartile is the quartile of likelihood paid non-hourly. Supervisory worker is defined by observation's industry and occupation according to BLS definition of production and non-supervisory workers. Column (2) subsets the regression to only observations in the top quartile of likely non-hourly pay. Cluster-robust standard errors clustered by state-firm. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Summary Statistics for Analysis Samples by Firm Size

Firm Employment Size	**0-19**		**20-49**		**50-249**		**250-999**		**1,000-2,499**		**+2,500**	
	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd	mean	sd
ACS annual hours (52 Weeks)	1,973	584.4	2,054	536.6	2,090	486.6	2,096	462.4	2,117	452.6	2,104	483.5
LEHD annual hours	1,800	572.3	1,912	533.2	1,965	494.5	1,990	493.6	1,963	480.8	1,977	475.2
Annual hours error (50 weeks, ACS)	0.055	0.284	0.035	0.256	0.025	0.246	0.017	0.240	0.043	0.253	0.024	0.243
Annual hours error (51 weeks, ACS)	0.084	0.271	0.062	0.244	0.050	0.238	0.042	0.232	0.068	0.241	0.049	0.231
Annual hours error (52 weeks, ACS)	0.109	0.270	0.086	0.242	0.074	0.237	0.066	0.229	0.091	0.238	0.073	0.225
Firm/Job Characteristics												
Unemployment rate (CZ)	0.074	2.008	7.292	1.955	7.331	1.955	7.326	1.928	7.423	1.854	7.327	1.817
Private, for-profit firm	0.856	0.352	0.812	0.391	0.745	0.436	0.613	0.487	0.668	0.471	0.754	0.431
Likely Exempt occupation (Management)	0.283	0.450	0.287	0.452	0.273	0.446	0.265	0.441	0.248	0.432	0.280	0.449
Top Quartile, Liklihood Not Paid by Hour	0.176	0.381	0.258	0.438	0.260	0.439	0.265	0.441	0.320	0.466	0.322	0.467
Dominant Job tenure (quarters)	23.84	19.43	26.14	20.76	26.44	20.43	28.09	20.95	28.13	21.21	27.81	21.81
Demographic Characteristics												
Age	41.79	13.73	41.43	13.48	42.26	12.99	43.11	12.59	43.15	12.62	42.20	12.46
Male	0.528	0.499	0.563	0.496	0.532	0.499	0.507	0.500	0.494	0.500	0.509	0.500
Non-white	0.163	0.369	0.181	0.385	0.213	0.409	0.250	0.433	0.270	0.444	0.280	0.449
Bachelors degree or higher	0.226	0.418	0.266	0.442	0.279	0.449	0.318	0.466	0.352	0.478	0.393	0.488
Observations	24,000		18,000		35,000		31,000		17,000		75,000	

Notes: $N = 218,000$. Annual hours error is the difference between log hours worked in the ACS and log hours paid from the LEHD. The ACS hours paid measure is defined by multiplying the usual weekly hours by the number of weeks paid in each row. Firm size employment groups are based on employment firm size on the 12th of the month of the year of ACS interview.

Table 8 presents the summary statistics for the analysis sample by firm size. First, ACS and LEHD average annual hours generally increase as firm size increases, though the mean difference between log hours worked and log hours paid decline slightly as firm size increases. Characteristics of firms and workers employed show more variation by firm size. Slightly more than 85% of firms in the smallest firm size category (0-19) work at private, for profit firms compared to slightly more than 75% in the largest firm size category (firms with more than 2,500 employees). In addition, workers in the smallest firms are much more likely to be paid by the hour. Firms with 0-19 employees employ 17.6% of workers in the analysis sample in top quartile of non-hourly pay probability compared to 32.0% and 32.2% in the largest two firm size categories, respectively. Finally, 22.6% of workers in the smallest firms have at least a bachelors degree compared to 39.3% in the largest firm size category.

Table 9: Off the Clock Work by Firm Size, Coarse Firm Size Bins

	(1)	(2)
0-19	0.0358***	0.0231***
	(0.0057)	(0.0053)
20-49	0.0132**	-0.0002
	(0.0063)	(0.0097)
50-249	0.00117	0.0009
	(0.0057)	(0.0046)
250-999	-0.0070	-0.0075
	(0.0063)	(0.0050)
1,000-2,499	0.0180**	0.0032
	(0.0083)	(0.0066)
Firm controls		X
Year-Quarter FE		X
State FE		X
Demographic controls		X
R^2	0.003	0.116

Notes: $N = 218,000$. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. All coefficients reported in reference to largest firm size group; firms with employment greater than or equal to 2,500. Cluster-robust standard errors clustered by state-firm. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

The results of including firm size in equation 3 are given in Table 9. The coefficients correspond to the indicator variables of their respective firm sizes. All coefficients should be interpreted as the increased (decreased) difference in hours worked compared to hours paid in firms with $2,499$ employees or more. The results in column (2) show that workers whose primary job is in small firms appear to work more hours than they are paid. The coefficient on the 0-19 employment category is positive at 0.0231 (0.0053) and precise. The same results are displayed graphically in Figure 5.

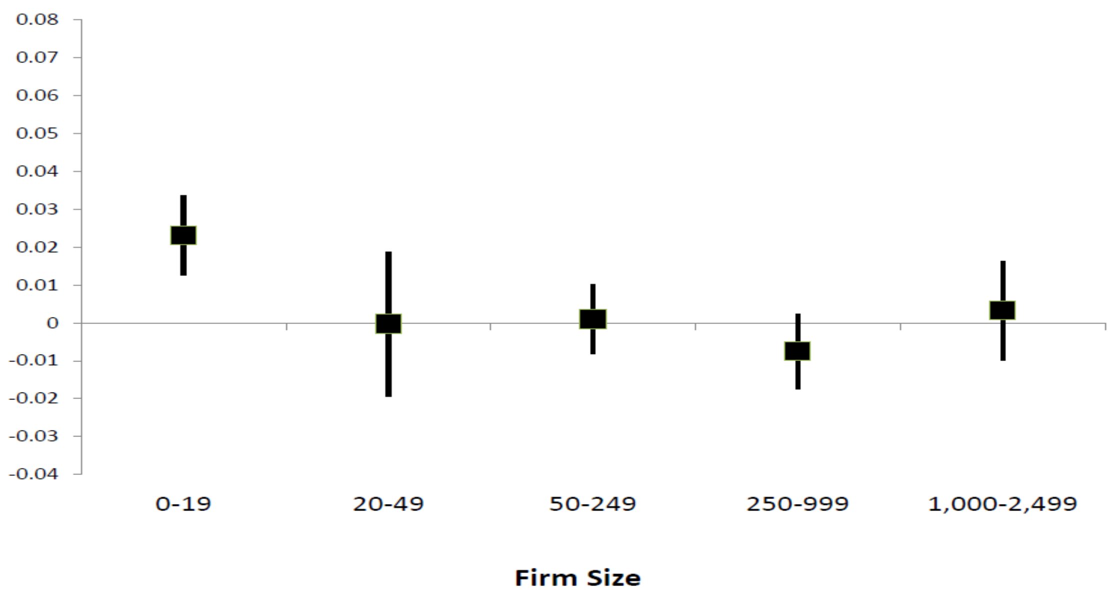

Figure 5: Regression Coefficients for LEHD Firm Size Categories

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +2,500 employment. See Table 9 column (3).

One potential issue with this specification is the worry that firm size bins are arbitrarily chosen. In addition, I have continued to use the winsorized difference in logs as the measure of off the clock work. I check for the robustness of both of these concerns in additional specifications. The first two columns of Table 10 use finer firm size bins and reach largely similar conclusions. The results from column (2) are also presented graphically in Figure 6. The coefficients on all three firm size bins with employment less than 20 employees are significant and positive, and of similar magnitude to the coefficients in Table 9. The exception is the coefficient on the smallest firm size bin, 1-4, is a little less than twice the next two firm size bins. Coefficients in this specification should be interpreted again in reference to the largest firm size, which is now firms with employment greater than 10,000. In addition to the finer firm size categories, columns (3) and (4) in Table 10 show results for the same specification but using Haltiwanger et al. (1996) measure of differences in hours worked compared to hours paid. Even though this measure is not winsorized, it shows quantitatively similar results to previous specifications.

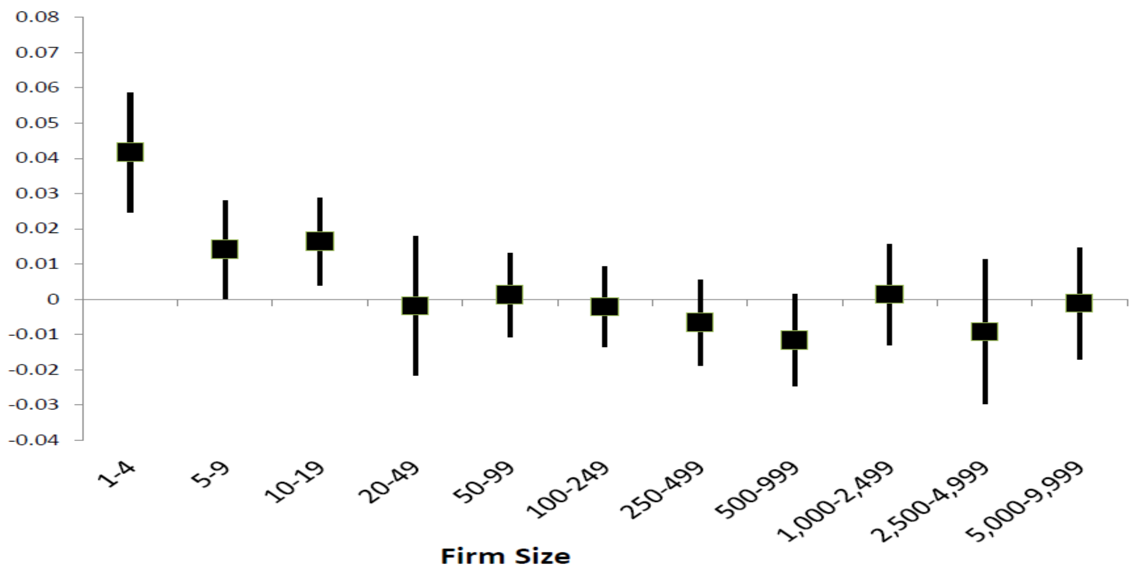

Figure 6: Regression Coefficients for BDS Firm Size Categories

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +10,000 employment. See Table 10 column (2).

The finding that smaller firms are associated with higher self-reported hours worked compared to hours paid is consistent with the current literature on non-compliance, but masks some of the story. Recall that the previous results center around low-skill workers, who are more likely to be paid an hourly wage. To test whether the firm size results are being driven by supervisory (likely exempt) or non-supervisory workers, I run the same specification with the firm size indicators, but now I interact the firm size indicator variables with an indicator for supervisory employees.

I plot the results graphically in Figures 7 and 8. The results are also available in Table A.2 column (1). All results are shown relative to non-supervisory workers in the largest firm size category. What the two Figures make clear is that the greater off the clock work in the smallest firm size category appears to be driven by workers in non-supervisory jobs. Figure 7 plots the estimated coefficients and their associated 95% confidence intervals for all firm sizes interacted with supervisory workers. The key point from this Figure is the uniformity and statistical significance of almost all coefficients. The estimated coefficients range from 0.0198 to 0.599. Given the near uniformity across firm size categories, it seems unlikely that

Table 10: Off the Clock Work by Firm Size, Fine Firm Size Bins

	(1)	(2)	(3)	(4)
1-4	0.0586***	0.0418***	0.0505***	0.0425***
	(0.0096)	(0.0086)	(0.0106)	(0.0095)
5-9	0.0302***	0.0142**	0.0295***	0.0205**
	(0.0080)	(0.0070)	(0.0093)	(0.0081)
10-19	0.0241***	0.0164***	0.0250***	0.0228***
	(0.0078)	(0.0063)	(0.0092)	(0.0074)
20-49	0.0119	-0.0018	0.0125	0.00247
	(0.0081)	(0.0101)	(0.0095)	(0.0110)
50-99	0.00165	0.0012	0.0052	0.0071
	(0.0079)	(0.0060)	(0.0091)	(0.0070)
100-249	-0.0013	-0.0021	0.0000	0.0012
	(0.0078)	(0.0057)	(0.0091)	(0.0067)
250-499	-0.0057	-0.0065	-0.0029	-0.00278
	(0.0082)	(0.0061)	(0.0096)	(0.0071)
500-999	-0.0104	-0.0116*	-0.0081	-0.0088
	(0.0089)	(0.0066)	(0.0101)	(0.0075)
1,000-2,499	0.0167*	0.0013	0.0182*	0.0033
	(0.0097)	(0.0072)	(0.0109)	(0.0080)
2,500-4,999	-0.0036	-0.0091	0.0000	-0.0052
	(0.0118)	(0.0105)	(0.0136)	(0.0117)
5,000-9,999	-0.0042	-0.00117	-0.0006	0.0013
	(0.0103)	(0.0081)	(0.0113)	(0.0086)
Firm controls		X		X
Year-Quarter FE		X		X
State FE		X		X
Demographic controls		X		X
R^2	0.004	0.116	0.002	0.099

Notes: $N = 218,000$. Dependent variable for columns (1) and (2) is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. For columns (3) and (4) dependent variable is Haltiwanger et al. (1996) change. All coefficients reported in reference to largest firm size group; firms with employment greater than 10,000. Cluster-robust standard errors clustered by state-firm. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1

supervisory workers are driving the results by firm size.

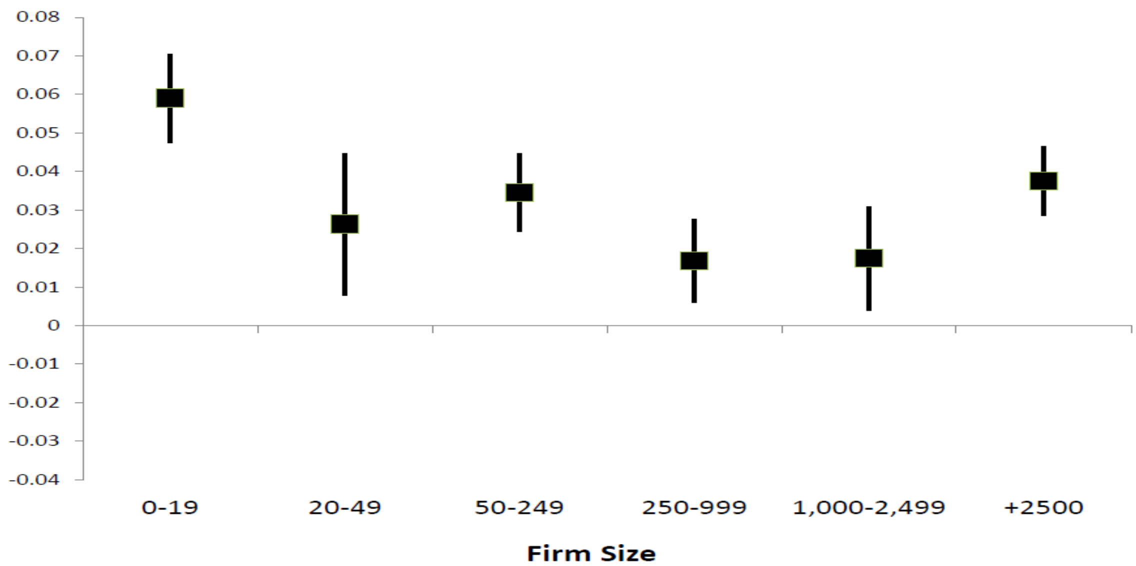

Figure 7: Regression Coefficients for Firm Size: Supervisory Workers

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +2,500 employment, for production and non-supervisory workers. See Table A.2 column (1), bottom panel.

In contrast, the estimated coefficients on non-supervisory workers depict a different pattern. Figure 8 plots these coefficients, which are also available in Table A.2 column (1), top panel. The estimated coefficients are uniformly small, and an estimate of zero cannot be rejected at the 5% confidence level. The estimate for the smallest firm size category is the only positive point estimate, 0.0294 (0.0294). The pattern on the coefficients for the firm size indicators follows the same pattern as firm size overall. The results provide support for the predictions of fewer hours reporting in smaller firms, and wage and hour compliance. The effect is not driven by supervisory or non-production workers, rather by production or non-supervisory workers.

Figures 9 and 10 provide further evidence for non-supervisory workers explaining the firm size effect. Figure 9 shows the results of firm size interacted with an indicator for the bottom half of hourly pay distribution. The coefficients are similar in magnitude to the coefficients interacting firm size with and indicator for non-supervisory workers. Turning to Figure 10, the case of the top half of the probability of hourly pay distribution, the results are again similar to non-supervisory workers in Figure 8. This is somewhat curious as we would expect non-hourly workers to be driving the variation. Due to the imputation of pay

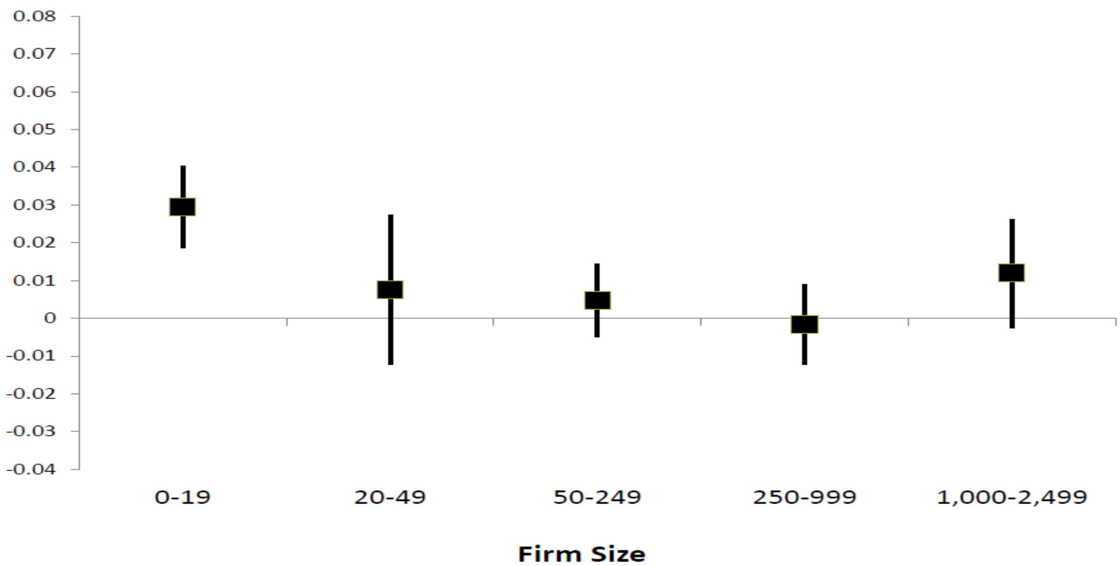

Figure 8: Regression Coefficients for Firm Size: Non-supervisory and Production Workers

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +2,500 employment, for production and non-supervisory workers. See Table A.2 column (1), top panel.

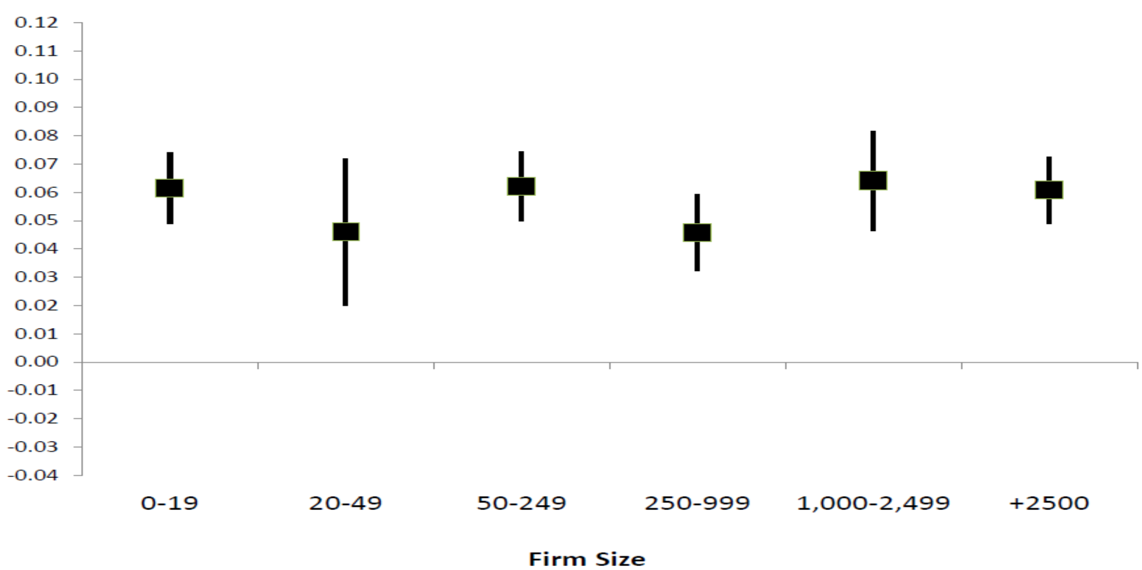

Figure 9: Regression Coefficients for Firm Size: Worker's Likely Paid a Salary, Top 50%

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +2,500 employment, for production and non-supervisory workers. See Table A.2 column (2), bottom panel.

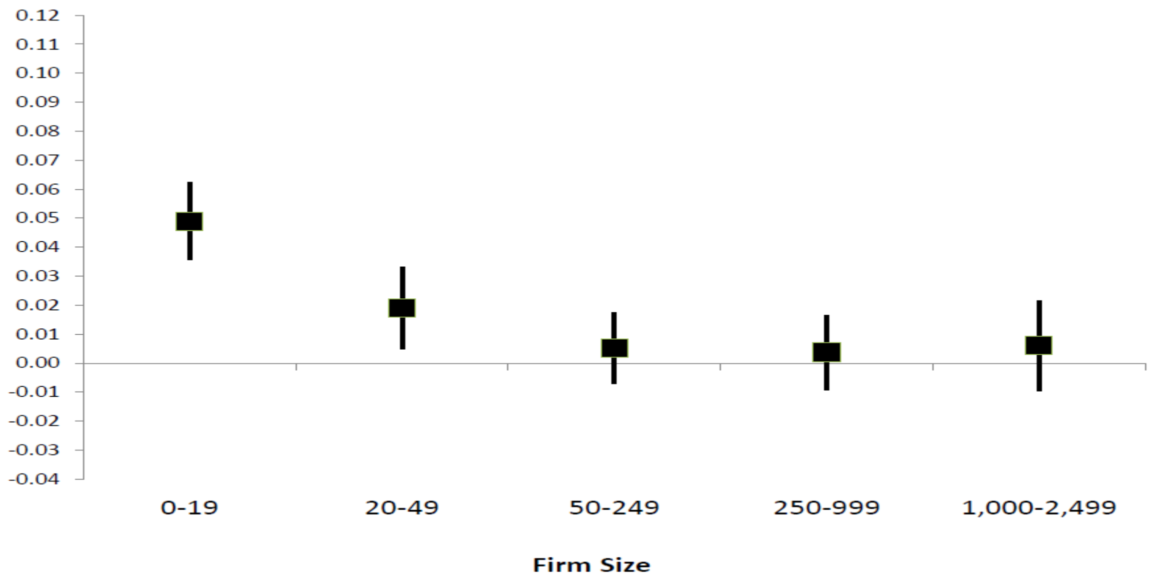

Figure 10: Regression Coefficients for Firm Size: Worker's Likely Paid a Salary, Bottom 50%

Notes: Boxes are regression coefficient point estimates and lines are 95% confidence intervals. All results are relative to the largest firm size category, +2,500 employment, for production and non-supervisory workers. See Table A.2 column (2), top panel.

status, this cannot be explicitly ruled out. It is possible that those who are unlikely to be paid hourly are driving the variation. What is clear is that the results indicate that small firms overwhelming report more hours worked than hours paid, and that the results are driven by low-skill production and non-supervisory workers.

5.3 Results: Industry

In addition to firm size, industry is often a strong predictor of hours off the clock. More generally, one implication of true failure to record and track employee hours should be wage and hour violations. Table 11 displays the top ten NAICS three-digit industries ranked by their share of all Department of Labor investigative actions where a violation was found to have occurred between 2010 and 2013. The top ten industries account for 62.6% of all violations, and comprise 36.1% of private employment, on average, between 2010 and 2013. Violations are further concentrated in the top three industries: Food Services & Drinking Places, Specialty Trade Contractors (roofers, for example), and Administrative & Support Services (temporary employment services, janitors, and security guards). In general, low-wage service industries account for the majority of wage and hour violations.

If the difference between hours worked and hours paid is indicative of employers working

Table 11: Industries with Largest Share of Wage and Hour Violations, 2010-2013

Industry (NAICS, 3-digit)	Share of Wage and Hour Violations (%) Actions	Employees	Overall share (%), QCEW Establishments	Employment
Food Services & Drinking Places (722)	22.8	22.6	6.5	8.9
Specialty Trade Contractors (238)	6.0	5.8	5.5	3.2
Administrative & Support Services (561)	5.9	10.2	5.1	6.8
Social Assistance (624)	5.2	3.6	3.6	2.4
Accommodation (721)	5.0	3.7	0.7	1.6
Nursing & Residential Care Facilities (623)	4.8	5.0	0.8	2.9
Ambulatory Health Care Services (621)	3.9	3.2	6.3	5.7
Gasoline Stations (447)	3.3	1.4	1.2	0.8
Food and Beverage Stores (445)	3.2	2.0	1.6	2.6
Construction of Buildings (236)	2.6	1.9	2.6	1.1
Total				
Cumulative share of total (%)	62.6	59.4	33.9	36.1
Cumulative count	34,100	398,000		
Mean count (2010-2013)			2,980,000	39,400,000

Notes: Wage and Hour violations from U.S. Department of Labor, Wage & Hour division. Sample is all compliance actions with findings beginning and ending between 2010 and 2013, and where at least one wage and hour violation occurred. Employees is share of all affected employees in actions with findings of at least one violation. Shares of establishments and employment are the average shares between 2010-2013. Data are from the Bureau of Labor Statistics, Quarterly Census of Employment and Wages of all private establishments.

low-wage workers more than they report, this should be concentrated in the industries displayed in Table 11. To test this hypothesis, I create three indicator variables that evaluate to unity if an ACS respondent's LEHD dominant job is in one of the top ten, top five, or top three NAICS 3-digit industries by share of enforcement actions, respectively. I fit equation 3 separately for each of the three indicator variables including demographic, job, firm, and local labor market controls. The hypothesis is that the progression to industries with higher concentrations of wage and hour violations should yield increased incidence of off the clock work.

The results of this exercise are displayed in Table 12. The first column shows the results of the indicator variable, denoted "High Incidence of Violation", for the top ten industries. The coefficient estimate is 0.0016 (0.0037), indicating workers report working 0.16% more hours in these industries, although with little precision. Moving to column (2) and concentrating on the top 5 industries, the estimate is now precise and 1.54% (0.0037) higher than in other industries. Finally, column (3) focuses on the top 3 industries, which account for over a third of enforcement actions. Again, the coefficient estimate is precise and increases, as expected, with workers in these industries reporting working 3.04% (0.0035) more than they are paid.

Table 12: Off the Clock Work by Industry

	(1) Top 10	(2) Top 5	(3) Top 3
High Incidence of Violation	0.0016	0.0154***	0.0304***
	(0.0037)	(0.0037)	(0.0035)
R^2	0.137	0.137	0.138

Notes: $N = 218,000$. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. "High Incidence of Violation" is an indicator variable, which evaluates to unity if the LEHD dominant job is in the top 10, 5, or 3 NAICS 3-digit industries ranked by incidence of wage and hour violations. See Table 11 for ranking and details. All regressions estimated using OLS, and include firm, job, demographic, and local labor market controls. Cluster-robust standard errors clustered by state-firm. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

This study uses a unique dataset of person-level survey responses of hours worked linked to the person's employer reports of hours paid. To the best of my knowledge, this is the first study in United States linking hours worked to administrative reports of hours paid at the person-level. I interpret this as a measure of work off the clock. I use the measure to test various theories of employer-employee bargaining.

I differentiate efficiency wage and labor hoarding theories of hours bargaining by testing the association of off the clock work with cross-section variation in local labor market slack. The hypothesis that greater work time off the clock may have a significant impact on measured productivity is not supported by the empirical findings of this study. The results find support for labor hoarding, though the effect is small. I find further evidence that the cyclical component of work off the clock is driven by low-skill workers likely paid by the hour.

The results also contribute to the emerging literature on labor compliance, and specifically on more explicit determinants of work off the clock. In line with previous studies, I find evidence that smaller firms are more likely to have employees report higher hours worked compared to hours paid. The results indicate that for the smallest firms, work off the clock is driven by production and non-supervisory employees.

At a broader level this study argues that hours of work should become a more prominent topic in labor economic research. The measurement of hours is important for the study of wages and productivity, and the often times casual tracking of hours by firms and workers leads to failures of labor market compliance. Finally, this paper also advises caution when using data on hours. The greater emphasis the economics profession is placing on administrative data combined with casual hours reporting by firms may produce misleading results when using administrative data on hours. More stringently tracking hours worked for both hourly and non-hourly workers would be an appropriate policy response. This will help both administrative data collection and analysis, and may also have the beneficial effect of greater wage and hour compliance.

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Appendices

A Models of Efficiency Wages and Labor Hoarding

A.1 Model of Increased Worker Effort

The model is intentionally simple, and as such does not present a formal theory of unemployment determination, or any equilibrium outcomes. What it does is clarify the continuous implicit bargain between workers and firms, and give intuition for the difference between hours worked and hours paid. The model is similar to the one presented in Lazear et al. (2015), but here effort takes the form of hours worked above what is explicitly recorded by employers. Workers are assumed to be paid a fixed salary implying that their wage is really a gross earnings measure quoted over a fixed period that does not vary with hours worked. Employer-recorded weekly hours are therefore an estimate usually determined by prevailing laws and/or employer knowledge. In the United States, it is typical for a salaried employee to be quoted a salary on a yearly basis (usually paid every two weeks or twice per month), with 40 hours per week that is loosely monitored by the employer. Workers therefore have some latitude to choose the hours they actually work in a given week, trading off their distaste for work against employers' expectations of output.

In the model, time is discrete and workers are already matched with firms for a negotiated period earnings measure, which I assume is fixed. Workers are exempt from overtime and employers assume workers put in at least the statutory overtime limit of $\bar{h}$ hours. Employers would like to terminate employees deemed to be shirking. Employers monitor worker effort and they use observed hours as a proxy, whether perfectly observed, or a noisy measure. For example, a worker who chooses not to show up to work stands a high risk of being fired. Conversely, a worker who chooses to put in more hours likely produces more, and sends a (possibly) valuable signal to employers about her ability to produce, which reduces her probability of being fired. I define the function $P(h) : \mathbb{R}_+ \to [0,1] \subset \mathbb{R}$, which maps hours worked to the probability a worker retains her job in a given period. The probability of retention is an increasing and concave function of hours worked with $P(0) = 0$ and $P'(h) > 0, P''(h) < 0$.

Putting forth effort is costly for workers, both because work is generally unpleasant, and because workers are paid a lump sum regardless of how many hours they actually work. Therefore, workers would prefer to work as little hours as possible. I capture the cost to workers of putting forth greater effort by the function $c(h) : \mathbb{R}_+ \to \mathbb{R}_+$. The costs to greater working hours are increasing and convex with $c(0) = 0$ and $c'(h) > 0, c''(h) > 0$. In addition to the direct costs of more hours, workers must also weigh the costs of unemployment. More specifically, the costs of losing one's job in times of greater labor market slack are much greater than when labor markets are tight, and the probability of contacting and finding a suitable job is much higher. Define the unemployment rate by u, which both employers and workers take as given. Further, define the option value of search from unemployment by R. Although this sounds like the beginnings of a rudimentary search model, no formal theory of of the aggregate determination of vacancies, unemployment and search will be presented here.

Workers choose the optimal hours to work conditional on the explicit costs of working and the indirect costs of aggregate labor market conditions. The problem of the worker is

$$\max_{h} \quad V(h) = P(h)\left[W - c(h)\right] + (1 - P(h))(1 - u)R \; , \tag{A.1}$$

where W is the gross earnings in the period, and $V(h)$ is the asset value to the worker of holding the job. The worker chooses the optimal hours of work to maximize A.1. Using the first order condition and the implicit function theorem yields the following equation,

$$\frac{\partial h}{\partial u} = -\frac{P'(h)R}{\frac{\partial^2 V(h)}{\partial h}} > 0 \quad . \tag{A.2}$$

The inequality follows from the fact that $W - c(h) > (1 - u)R$ in order for the employment relationship to continue. Higher unemployment leads to greater hours worked.

Intuitively, hours increase in order to the decrease the probability of being fired, due to the decrease in the payoff from unemployment. The second term in equation A.1 gives the value of outside employment, R. As the probability of ascending to employment decreases – as u increases – workers put forth more hours to avoid unemployment. With the employer's report of hours paid fixed at $\bar{h}$, higher unemployment rates lead to a greater spread between hours worked and hours paid.

A.2 Model of Labor Hoarding

The labor hoarding model is best conceptualized using a model of labor demand with adjustment costs to employment. I describe the problem and the result loosely through the "gap approach" (Caballero and Engel, 1993; Caballero et al., 1997). Consider a firm whose production technology in a period uses only total labor inputs $f(m_t)$, with $f_m(\cdot) > 0$, and $m_t = e_t h_t$, where e_t is total employment and h_t is average hours worked. I assume there is an upper bound on the average hours worked per worker in a period so that firms seek to employ more than one worker. Further, define $\bar{h}$ as the long-run average hours per employee in the firm. For the purposes of this discussion, we can assume $\bar{h} = 40$ and that these are recorded by the firm as hours paid regardless of actual hours worked. Production faces aggregate shocks A_t drawn from a probability distribution $F(A)$. I assume only that the probability distribution and production function are such that $f_A(\cdot) > 0$, which implies that negative aggregate shocks should lead to decreased production in the absence of adjustment costs.

Consider a firm faced with negative aggregate demand shock in the next period. Suppose the current period's employment as e_{t-1} and without a loss of generality that $h_{t-1} = \bar{h}$. Following the gap approach, define e_t^* as the *frictionless* optimal employment target for next period given the realization of the negative aggregate demand shock. This is the optimal employment for the firm if for the current period, and the current period only, the firm did not have to pay any costs to adjust employment. Given the nature of the production function, it holds that $e_t^* \leq e_{t-1}$, and $e_t \in [e_t^*, e_{t-1}]$. In other words, the optimal employment level given the shock will be bounded above by the current employment level, and bounded below by the optimal frictionless level. The firm would like to get as close to its optimal production level as possible, but in most cases the optimal employment level will lie above the frictionless level. Thus, firms will adjust average hours down in order to further decrease production beyond what was possible by only adjusting labor yielding $h_t \leq h_{t-1}$. The same logic, but in the opposite direction holds for a positive aggregate demand shock.

Putting this altogether, we see that a negative aggregate demand shock leads to less hours worked. Note that in this model employment and hours move in the same direction in response to a negative aggregate demand shock. The empirical results posit a relationship between labor market slack and the difference between hours paid and hours worked. Given the model, we need to assume the unemployment rate is negatively correlated with aggregate demand shocks. That is, a positive demand shock produces non-positive movement in the unemployment rate. This assumption seems straightforward.

To wrap up, a negative aggregate demand shock raises unemployment and forces firms to cut production as well as raising the unemployment rate. Employment cannot fall to its frictionless level so firms reduce hours worked to get closer to the optimal level of output. As long as hours paid stay near constant, this produces the desired empirical test of greater labor market slack and a non-positive gap between hours worked and hours paid.

B Details on Inverse Probability Weighting

The ACS links to the LEHD via a protected identification key (PIK). A PIK is a random number mapped to a social security number, which serves as an internal Census Bureau person-level identifier. PIK assignment is usually assumed to be correct, however survey responses who fail to receive a PIK are known to be missing at random in the sense of Rubin (1987).

Following (Meyer and Goerge, 2011) who point out that PIKs appear to be missing at random, I use inverse probability weights to correct the ACS weights for PIKs missing at random. I fit a probit model with a rich set of characteristics to predict the probability of receiving a PIK. Using the fit model, I estimate the predicted probability for each cell, and then multiply the ACS weights by the inverse of the probability of receiving a PIK for each cell. Results obtained using weights adjusted in this manner differ very little from when they are omitted. At no point do the qualitative findings change.

The terms of my data use for this project preclude the disclosure of ACS estimates without commingled LEHD data. As such, I am not able to disclose the probit estimates for the inverse probability weighting. The variables are summarized in Table A.4. However, I am able to describe the key parameters qualitatively. In general, the included covariates and results adhere closely to those used in Meyer and Goerge (2011).

The probability of receiving a PIK increases with age, likely due to greater work experience. The same holds true with education. The probability of receiving a PIK increases with the highest level of educational attainment. People of color and Hispanics are slightly less likely to receive a PIK than white non-Hispanics. Women and American citizens are more likely to receive a PIK, while respondents who report speaking English “Well” or “Very Well” are more likely to receive a PIK than respondents who report speaking English “Not Well” or “Not at All”. Finally, respondents who did not move residences in the last year have a higher probability of receiving a PIK than those who did.

C Details on Hourly/Nonhourly Imputation

Neither the ACS nor the LEHD datasets provide information on frequency or method of pay for their earnings variables. This section describes the imputation of the probability that an ACS respondent was not paid by the hour. This can include earnings or salaries paid at annual, monthly, weekly or biweekly rate. This would also include workers who are paid a piece rate. I use the Current Population Survey Outgoing Rotation Group (CPS ORG) files, which asks respondents if they were paid by the hour or by some other arrangement on their main job last week. I model the probability that a job is not paid by the hour using a logit model, with covariates describing firm and job characteristics common to both the CPS ORG and ACS. After fitting the model, I generate a predicted probability for each cell of covariates. The final estimates are then attached to the ACS using the common covariates.

A more detailed explanation is offered below.

The CPS is a monthly survey of 60,000 households, which ask about labor market activities during the previous week. Respondents are surveyed for four consecutive months, they are then not interviewed for 8 months, and then they are reinterviewed for another four months. The interviews conducted on the 4th and 8th months contain additional questions on earnings and hours for jobs worked the previous week. I use data from all months from 2010-2013, which corresponds to the ACS years in my sample. I include only records who worked in the private sector, state government, or local government. This discards federal government workers, and the self-employed, neither of whom are included in the ACS-LEHD matched sample. Finally, I keep only records for which the dependent variable, "Hourly/Non-hourly status" is neither edited nor allocated.

To impute hourly/non-hourly pay, I fit a fully interacted least squares model with a LASSO penalty. The LASSO provides a parsimonious model for both covariate shrinkage and subset selection for an OLS model (Tibshirani, 1996). I use the LASSO in this setting primarily as a tool for subset selection, using both five fold cross validation and the Akaike information criterion (AIC) for selecting the LASSO parameter, which effectively chooses the non-zero covariates in the model. Both methods return similar results, with the best model including an indicator for whether a respondent has a Bachelor's degree or more, and an indicator for whether weekly earnings on the main job is in the top tercile of earnings, as well as their interaction.

For the final imputation model I run a logit model interacting occupation, industry, and tercile of weekly earnings. Although the LASSO indicated that a variable for Bachelor's degree or higher should be included, I omit it from the final imputation model for two reasons. First, although highly correlated with non-hourly pay, there is no *a priori* reason for its inclusion. Unlike weekly earnings, education is not part of the duties test for exemption from overtime. Second, although correlated, I would like to evaluate education separately in the statistical analysis. Including it in the non-hourly imputation would make the results hard to identify and interpret. Finally, I include NAICS industry sectors and major occupation groups in the final model. Job duties is one of the major tests for exemption from overtime, which correlates highly with non-hourly status. Various industries carve out exemptions for overtime and determine pay norms, which argues for its inclusion.

After fitting the model on the CPS, I attach the predicted probabilities for each cell to the final analysis sample. Attaching major occupation groups and industry is straight forward. I do not observe weekly earning for either the ACS or the LEHD. I calculate annual earnings terciles based on the LEHD, and use that as the tercile to which I map weekly earnings. This assumes the same weekly earnings is earned each week, which scales weekly earnings to an annual earnings measure.[53] I then bin each observation in the final analysis sample by quartile of their likelihood of non-hourly pay.

Summary statistics for the analysis sample by quartile of non-hourly pay are available in Table A.3. Based on prior knowledge and casual observation, the results are largely what one would expect. Observations in the highest quartile of probability they are not paid by the hour have much higher reported hours worked compared to hours paid averaging 14.3% assuming 52 weeks worked. In contrast, quartiles one through three are relatively uniform with hours worked exceeding hours paid by 6.8%, 4.0%, and 6.3% for quartiles one through three, respectively. The remaining stratifying variables change by quartile as expected. Workers in the top quartile are much more likely to be white, male, and have a Bachelor's degree.

D Additional Tables and Figures

[53]Recall the final analysis sample is only for full-year workers.

Table A.1: The Effect of the Unemployment Rate on Hours Worked and Hours Paid

	(1)	(2)	(3)	(4)
	Panel A. Dependent Variable: Log Annual ACS Hours			
Unemployment rate (β)	-0.00126	-0.000917	-0.00206**	-0.00213**
	(0.00110)	(0.00129)	(0.000820)	(0.000851)
	Panel B. Dependent Variable: Log Annual ACS Hours, Winsorized 5%			
Unemployment rate (β)	-0.000763	-0.000275	-0.00138*	-0.00146*
	(0.001000)	(0.00116)	(0.000742)	(0.000767)
	Panel C. Dependent Variable: Log Annual LEHD Hours			
Unemployment rate (β)	0.000121	0.000829	-0.000451	-0.000414
	(0.00123)	(0.00129)	(0.000766)	(0.000747)
	Panel D. Dependent Variable: Log Annual LEHD Hours, Winsorized 5%			
Unemployment rate (β)	0.000387	0.00123	1.10e-05	2.92e-05
	(0.00109)	(0.00113)	(0.000610)	(0.000604)
State FE	X	X	X	X
Commuting Zone Time Trends		X	X	X
Firm & Job controls			X	X
Demographic controls				X

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable indicated by panel title. All regressions estimated using ordinary least squares using the specification outlined in equation 2. Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.2: Firm Size by Likely Exempt Status

	(1)	(2)	(3)
	Non-Supervisory Occ.	*Bottom Half Quartiles*	*Bottom Three Quartiles*
0-19	0.0294***	0.0489***	0.0412***
	(0.0069)	(0.0068)	(0.0054)
20-49	0.00846	0.0190***	0.0138**
	(0.0114)	(0.0072)	(0.0067)
50-249	0.00647	0.00521	0.0009
	(0.0059)	(0.0062)	(0.0050)
250-999	0.0000	0.00371	-0.0046
	(0.0064)	(0.0065)	(0.0053)
1,000-2,499	0.0126	0.00596	0.00232
	(0.0081)	(0.0079)	(0.0069)
	Supervisory Occupations	*Top Half Quartiles*	*Top Quartile*
0-19	0.0599***	0.0615***	0.0591***
	(0.0065)	(0.0064)	(0.00659)
20-49	0.0280***	0.0460***	0.0534***
	(0.0099)	(0.0133)	(0.0163)
50-249	0.0384***	0.0620***	0.0870***
	(0.0058)	(0.0062)	(0.00611)
250-999	0.0198***	0.0457***	0.0690***
	(0.0060)	(0.0068)	(0.00756)
1,000-2,499	0.0202***	0.0641***	0.0902***
	(0.0073)	(0.0089)	(0.0103)
+2,500	0.0391***	0.0607***	0.0823***
	(0.0049)	(0.0060)	(0.00710)
Firm controls	X	X	X
Year-Quarter FE	X	X	X
State FE	X	X	X
Demographic controls	X	X	X
R^2	0.098	0.119	0.124

Notes: $N = 218,000$. Dependent variable in all columns is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Each column is its own regression specification. All coefficients reported in reference to largest firm size group (+2,500) interacted with top panel in each of the three regressions. For column (1) that is non-supervisory occupations, column (2) is the bottom two quartiles of probability non-hourly pay, and column (3) is the bottom three quarters of probability non-hourly pay. Cluster-robust standard errors clustered by state employer of dominant job. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1

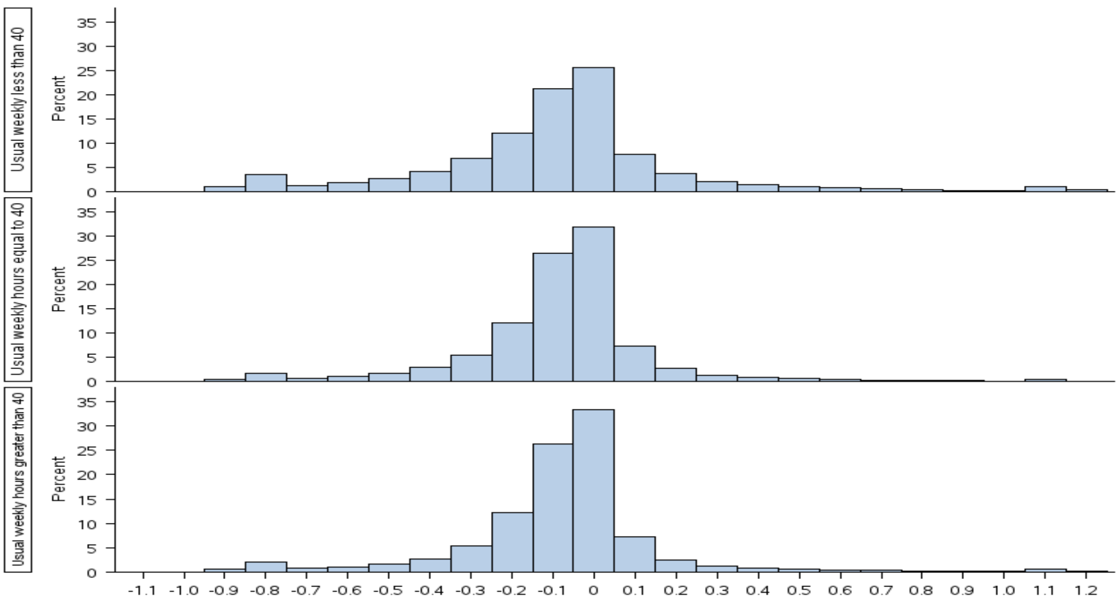

Figure A.1: Distribution of the Difference of Log Labor Earnings (ACS) and Log Labor Earnings (LEHD) by Usual Weekly Hours

Notes: Variable is the difference in log ACS earnings from log LEHD earnings for the full sample, winsorized at the 5% and 95% level. The variable is partitioned by whether an ACS respondent answers that she usually works either 1) less than 40 hours per work (top panel) or 2) exactly 40 hours a week (middle panel) or 3) more than 40 hours per week (bottom panel). Top panel $N = 49,000$, middle panel $N = 108,000$, bottom panel $N = 61,000$. Mean of bottom panel -0.094 [0.318], middle panel -0.077 [0.247] and bottom panel -0.078 [0.248].

Table A.3: Summary Statistics by Quartile of Probability of Non-hourly Pay

Quartile Liklihood Not Paid by Hour	**(1)**		**(2)**		**(3)**		**(4)**	
	mean	sd	mean	sd	mean	sd	mean	sd
ACS annual hours (52 Weeks)	1,755	575.9	2,040	446.8	2,116	457.9	2,303	401.6
LEHD annual hours	1,690	627.7	1,993	502.5	2,014	481.0	2,006	361.6
Annual hours error (50 weeks, ACS)	0.011	0.301	-0.010	0.238	0.014	0.237	0.099	0.225
Annual hours error (51 weeks, ACS)	0.041	0.284	0.016	0.223	0.039	0.230	0.121	0.222
Annual hours error (52 weeks, ACS)	0.068	0.278	0.040	0.218	0.063	0.228	0.143	0.222
Firm/Job Characteristics								
Unemployment rate (CZ)	7.277	1.956	7.386	1.935	7.377	1.924	7.332	1.802
Private, for-profit firm	0.880	0.325	0.827	0.378	0.586	0.493	0.702	0.457
Likely Exempt occupation (Management)	0.092	0.289	0.199	0.399	0.203	0.402	0.541	0.498
Dominant Job tenure (quarters)	20.07	17.35	25.67	20.12	29.25	21.78	30.89	22.26
Demographic Characteristics								
Age	39.08	15.12	41.69	13.05	43.37	12.11	44.13	11.09
Male	0.455	0.498	0.564	0.496	0.450	0.497	0.575	0.494
Non-white	0.307	0.461	0.248	0.432	0.222	0.416	0.197	0.398
Hispanic	0.090	0.286	0.079	0.269	0.053	0.224	0.033	0.179
Bachelors degree or higher	0.068	0.252	0.122	0.327	0.365	0.482	0.674	0.469
Observations	33,000		60,000		57,000		67,000	

Notes: $N = 218,000$. Annual hours error is the difference between log hours worked in the ACS and log hours paid from the LEHD. The ACS hours paid measure is defined by multiplying the usual weekly hours by the number of weeks paid in each row. The hourly/non-hourly imputation and the description of the construction of the quartiles provided in appendix C.

Table A.4: Covariates in Inverse Probability Weighting Probit

Variable	Description
Gender	Indicator for whether male.
Age	16-19, 20-34, 35-49, 50-65, 65+
Education	Less than high school, High School, Some College, BA+
White	Indicator for whether race is white
Hispanic	Indicator for hispanic ethnicity
Citizen	Indicator for whether U.S. citizen
Married	Indicator for whether married
Kids	Indicator for presence of own children
Moved	Indicator for whether moved in last year
Disability	Indicator for whether has a disability
English	Indicator for whether speaks English "Very well" or "Well"
Labor Force	Indicator for whether in labor force

Notes: Variables used for reweighting sample weights to account for PIKs missing at random. All variables are indicator variables unless otherwise noted. Construction and use of the weights is described in appendix B.

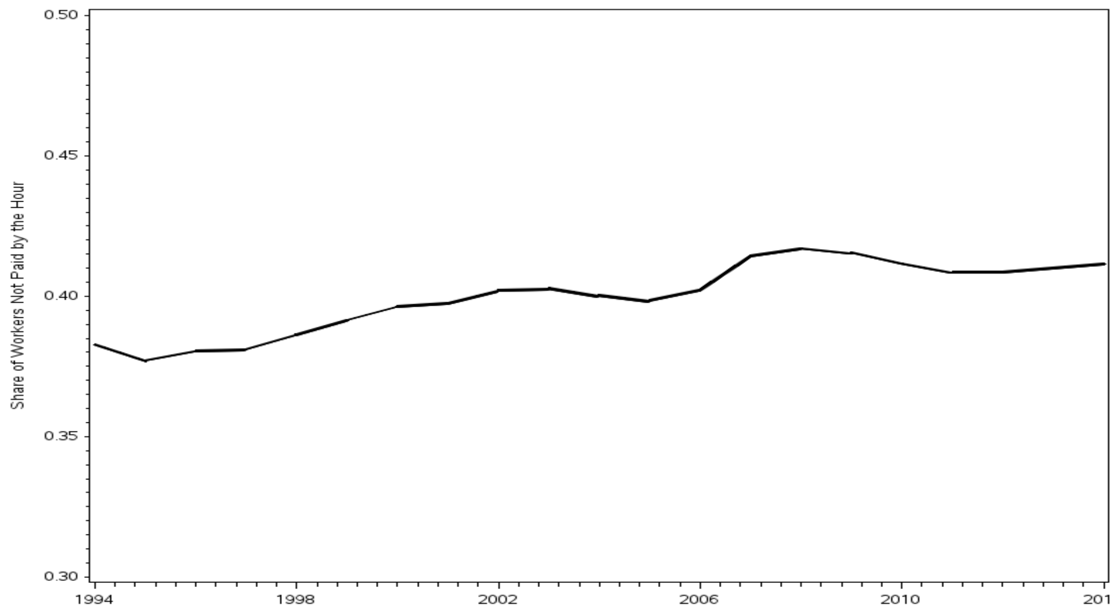

Figure A.2: Share of Wage and Salary Workers not Paid by the Hour, 1994-2015

Notes: Author's Analysis of Current Population Survey, Outgoing Rotation Group data. Sample excludes self-employed and those who worked without pay.

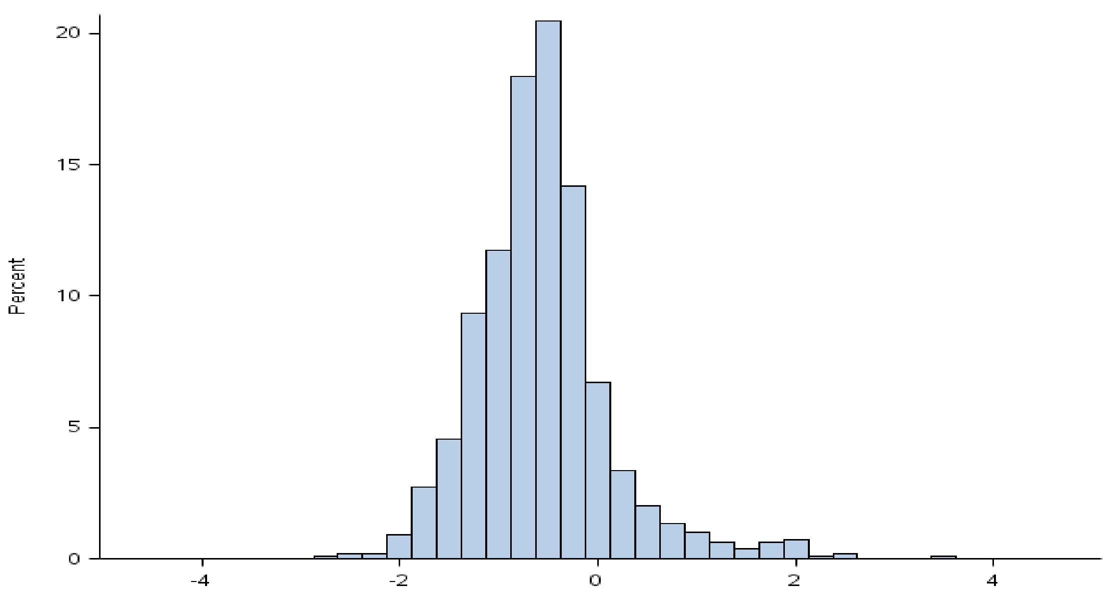

Figure A.3: Distribution of Year-over-year Change in Quarterly Unemployment rates by Commuting Zone

Notes: N=218,000. Mean -0.568 [0.689].

Table A.5: Regression Results for Unemployment Rate and Work Off the Clock, Heterogeneous Effects Subsets

	(1) Supervisory	(2) Non-Supervisory	(3) Top half likely paid non-hourly	(4) Bottom half likely paid non-hourly	(5) At least B.A. degree	(6) Less than B.A. degree
Unemployment rate (β)	-0.00097	-0.00213*	-0.00107	-0.00287*	0.00000	-0.00231**
	(0.00138)	(0.00112)	(0.00120)	(0.00151)	(0.00126)	(0.00099)
Observations	74,000	145,000	131,000	87,000	75,000	143,000
R^2	0.133	0.070	0.129	0.096	0.125	0.075

Notes: $N = 218,000$, with 58 commuting zones. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Supervisory, Column (1), refers to the compliment of non-supervisory. The definition of non-supervisory or production worker comes from the Bureau of Labor Statistics. Column (2), Non-supervisory, is an indicator for observations who meet the definition of a production or non-supervisory worker according to the occupation and industry of her dominant job. "Bottom half likely paid non-hourly", Column (3), refers to observations who are below the median in likelihood they are not paid by the hour. "Top half likely paid non-hourly", Column (4), refers to observations above the median likelihood not paid by the hour. B.A refers to Bachelor's degree. All regressions run using OLS with the same specification as Table 2 column (4), subset to cell listed at the top of each column. Cluster-robust standard errors clustered by commuting zone. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Regression Results for Firm Growth and Work Off the Clock

					Single Establishment Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
Year/Year Firm Growth	0.00511				0.00585	
	(0.00465)				(0.00531)	
Year/Year Firm Growth Bins						
Low		0.00523				0.00127
		(0.00359)				(0.00314)
Mid-low		-0.00170				-0.00593*
		(0.00327)				(0.00310)
Mid-high		-0.00612*				-0.00930***
		(0.00354)				(0.00298)
High		0.00362				-0.000451
		(0.00374)				(0.00317)
Year/Year Establishment Growth			-0.00510			
			(0.00331)			
Year/Year Establishment Growth Bins						
Low				0.00369		
				(0.00342)		
Mid-low				-0.00461		
				(0.00337)		
Mid-high				-0.00565*		
				(0.00317)		
High				-0.000300		
				(0.00353)		
Observations	218,000	218,000	218,000	218,000	126,000	126,000
R^2	0.102	0.102	0.102	0.102	0.114	0.115

Notes: $N = 218,000$. Dependent variable is the difference between log annual ACS hours calculated at 52 weeks and log annual LEHD hours. Cluster-robust standard errors clustered by state-firm. All year/year growth measures calculated using Haltiwanger et al. (1996). Firm growth calculated using state-firm employment counts in ACS interview quarter and one year prior. Establishment growth rates use the modal establishment from the LEHD unit-to-worker imputation. Firm and establishment growth bins calculated as evenly spaced quintiles of the analysis sample according to firm and establishment growth rates, respectively. Firm/Establishment growth rate bins interpreted in relation to middle quintile, which has mean approximately zero. Columns (5) and (6) subset the sample to only single establishment firms negating use of unit-to-worker imputation. All results estimated with OLS and include firm, job, demographic, and local labor market controls. Stars on standard errors accord to p-values as follows: *** p<0.01, ** p<0.05, * p<0.1.