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How reliable are administrative reports of paid work hours?

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ABSTRACT

This paper examines the quality of quarterly records on work hours collected from employers in the State of Washington to administer the unemployment insurance (UI) system, specifically to determine eligibility for UI. We subject the administrative records to four “trials,” all of which suggest the records reliably measure paid hours of work. First, distributions of hours in the administrative records and Current Population Survey outgoing rotation groups (CPS) both suggest that 52–54% of workers work approximately 40 hours per week. Second, in the administrative records, quarter-to-quarter changes in the log of earnings are highly correlated with quarter-to-quarter changes in the log of paid hours. Third, annual changes in Washington’s minimum wage rate (which is indexed) are clearly reflected in year-to-year changes in the distribution of paid hours in the administrative data. Fourth, Mincer-style wage rate and earnings regressions using the administrative data produce estimates similar to those found elsewhere in the literature.

JEL Classification Codes: C81, H83, J65

Key Words: unemployment insurance, administrative data, paid work hours, data quality

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1. Introduction

Reliance on self-reported work hours from survey data, which are prone to non-classical measurement error, has long been viewed as an impediment to studying the determinants of work hours (Heckman, 1993; Rodgers, Brown, and Duncan, 1993). In particular, the vast majority of research on labor supply has necessarily used survey data on self-reported work hours, although Bound et al. (1989) showed that the correlation between self-reported and payroll hours is only about 0.6.¹ Administrative data have led to important advances in the understanding of earnings determination and labor mobility, but they generally do not include information on work hours. The gap is limiting because the determination of work hours plays such a central role in labor economics and macroeconomics.

This paper examines the quality of administrative records on paid work hours reported by employers in the State of Washington. In order to manage and administer unemployment insurance (UI), all states require employers to report the earnings of each employee on a quarterly basis, but employers in Washington must in addition report quarterly paid work hours.² Reporting of hours is mandatory because eligibility for UI in

¹ Bound et al. (1989) and Rodgers, Brown, and Duncan (1993) analyzed the 1983 Panel Study of Income Dynamics (PSID) validation study, which matched self-reported records in the PSID to payroll records in a single company for approximately 500 workers, and quantified measurement error in the sample. Otherwise, little is known about the degree of measurement error in hours reporting in survey data, particularly in the CPS.

² Several papers have used Washington UI administrative records for research. Abowd, Finer, and Kramarz (1999) use a 10% sample of the data for years 1984–1993 to decompose log hourly wages of full-time workers into individual and firm components. They find that the individual and firm components each explain about 24% of the variation in the hourly wage. Johnson and Klepinger (1994) and Lachowska, Meral, and Woodbury (2015, 2016) use the data to analyze the effects of the work search requirement on unemployment duration and reemployment outcomes. Kurmann and McEntarfer (2017) and Jardim, Solon, and Vigdor (2019) use the data to examine the extent of downward nominal wage rigidity. They find less evidence of downward rigidity than has been previously documented, with a smaller spike at zero and more symmetry in the distribution of wage changes. Lachowska, Mas and Woodbury (2020a) use the data to decompose earnings after job displacement into hours and wages. Jardim et al. (2021) examine the hours

Washington is determined by the number of work hours a UI claimant has accumulated in roughly the year before a claim.³

Questions have long been raised about the suitability of UI administrative earnings records for research. Because they are central to financing and administering UI, most states randomly audit employer earnings reports (Blakemore et al., 1996; Burgess, Blakemore, and Low, 1998). Accordingly, it is not surprising that existing validation studies have concluded that UI earnings records, despite drawbacks, provide a good, and sometimes preferable, alternative to survey data for evaluation.⁴

We begin by examining the distribution of work hours in the Washington administrative data and comparing it with the hours distribution in the Current Population Survey outgoing rotation groups (CPS).⁵ We find that the Washington data and the CPS are consistent in suggesting that about half of employees work close to 40 hours per week. The main difference of substance between the Washington data and the CPS is that a larger proportion of workers report working more than 43 hours per week in the CPS. We interpret this as evidence that a substantial percentage of salaried workers are being

response to minimum wage increases in Seattle, and Cengiz et al. (2019) examine the large statewide increase in the minimum wage in 1999–2000, both using the Washington administrative data.

³ Washington is the only state that uses hours reports to determine UI eligibility, or to administer UI in any way. Minnesota has also collected data on hours for many years, but an analysis conducted by Kurmann and McEntarfer (2017) revealed a high nonresponse rate for hours in the Minnesota records. Recently, Rhode Island and Oregon have also started collecting employer reports on hours, but like Minnesota, neither uses these data to administer UI.

⁴ Kornfeld and Bloom (1999) compared UI earnings records with survey data in a 12-state sample of over 12,000 low-wage workers who participated in the National JTPA Study. They concluded that, except for young males with past arrests, UI earnings records are a valid alternative to surveys for evaluating employment and earnings outcomes of training programs. Wallace and Haveman's (2007) validation study focused on welfare recipients in Wisconsin and found that earnings records and survey data gave similar results on employment and earnings outcomes. Abraham et al. (2013) find discrepancies between CPS and administrative measures of employment status, but conclude that these discrepancies are mainly for marginal workers and nonstandard jobs.

⁵ We use data from the CPS outgoing rotation groups throughout the paper because they include data on usual hours worked per week, usual weekly earnings, and (for hourly paid workers) the hourly wage rate—see Flood et al. (2020), which is the source of the CPS data we use. When we refer to the CPS, we are referring to the outgoing rotation groups.

paid to work 40 hours per week (as reported in the administrative data) but have actual work hours greater than 40 per week.

Second, we assess the ratio of signal to noise in the Washington hours records by estimating slope coefficients in regressions of changes in log earnings on changes in log hours for workers who did not change employers. We find this slope coefficient is 0.80 for data analyzed at a quarterly frequency. Assuming that, for job-stayers, quarter-to-quarter earnings vary stochastically around a fixed per-hour wage, the estimates imply a high ratio of signal-to-noise in the Washington hours data.

Third, we construct a measure of hourly wages by dividing quarterly earnings by quarterly hours. We show that the distribution of this hourly wage rate exhibits a spike at the Washington minimum wage, and that the spike moves with year-to-year increases in Washington's minimum wage, which is indexed. Finally, we conduct a consistency check of the hours data by estimating Mincer-style regressions using log hourly wage rates and show that the age-wage profile, returns to education, and gender wage and earnings gaps are similar to analogous estimates based on survey data.

Our findings have implications for any analysis of paid work hours and for economic variables constructed using hours in the denominator, like hourly wage rates and output per hour (Ramey, 2012). They also have implications for the use of administrative data in analyzing employment-to-employment worker transitions, as we show in the concluding section 7. In the policy domain, the findings have implications for estimating the benefits and costs of income transfers, as well as for understanding the impacts of labor market regulations, notably minimum wage and overtime regulations under the Fair Labor Standard Act (FLSA)—see, for example, Quach (2021).

The rest of the paper is organized as follows. Section 2 describes the Washington administrative data, and section 3 compares the distributions of work hours in the Washington data and the CPS. Section 4 develops a regression-based test of signal-to-noise in the Washington hours data. Section 5 examines nominal hourly wage distributions generated by the Washington records (by year) and examines those distributions in relation to changes in the Washington minimum wage. Section 6 describes estimates of log wage and log earnings regressions estimated using the Washington data, and the final section offers some concluding observations.

2. Description of the Data

The data we examine come from the records maintained by the Employment Security Department (ESD) of Washington State to administer the state’s UI system: quarterly earnings records from all UI-covered employers in Washington from 2001:1 through 2014:4; and the UI claims records of all individuals who claimed UI in Washington at any time during the same period.⁶

The administrative earnings records of most states comprise a quarterly record for each worker-employer match that includes (a) an individual worker identifier, (b) a year-quarter identifier, (c) an employer identifier, (d) the NAICS industry code of the employer, and (e) the worker’s earnings from that employer in that quarter. In addition, employers covered by the Washington UI system are required to report each worker’s

⁶ The only employers not required to report quarterly earnings and hours are so-called reimbursable employers—government agencies, private non-profits, and federally recognized Indian tribes who elect to reimburse the UI agency for benefits paid to their laid off workers. Also, self-employed workers do not file quarterly earnings reports, and underground earnings are not reported. See Washington Administrative Code Title 192, Chapter 300, Section 060.

quarterly paid work hours. This requirement results from Washington’s practice, which is unique among the UI systems in the United States, of using work hours in (roughly) the year before claiming UI to determine eligibility for UI.⁷

The inclusion of work hours in the administrative earnings record is a distinct advantage of the Washington data, making it possible to construct an hourly wage rate in quarter t for most workers in Washington’s formal labor market.⁸

2.1 Washington reporting guidelines and compliance

Washington employers must follow specific guidelines for reporting hours of their UI-covered employees.⁹ Employers are specifically instructed to report the “number of hours worked in the quarter,” including regular hours, overtime hours, hours of vacation and paid leave. For salaried, commissioned, and piecework employees, employers are instructed to report actual hours unless those hours are not tracked, in which case they are instructed to report 40 hours per week. Failure to report hours, submitting an incomplete report, or filing in the wrong format results in a financial penalty after a first warning. Employers do not report whether a worker is salaried or paid hourly, and for this reason the hours measure in the Washington data is best thought of as hours paid, as opposed to hours worked.

In many cases, employers report that a worker had positive earnings and zero hours in the same quarter. In general, we take these reports to be accurate because the

⁷ As already mentioned, Minnesota, Oregon, and Rhode Island also include work hours in their earnings reports, but none uses work hours to determine eligibility or UI benefit amounts.

⁸ Exemptions from coverage are limited to the self-employed, including outside sales workers paid solely by commission and independent contractors meeting exemption tests specified in Washington’s UI law (Revised Code of Washington, Title 50). Nonprofit religious organizations are also exempt.

⁹ For details, see Washington Administrative Code, Title 192, Chapter 310, Section 010, as well as the materials posted by the Washington Employment Security Department explaining the requirements of the law: “Quarterly Reporting Requirements” <<https://www.esd.wa.gov/employer-taxes/reporting-requirements>> (last accessed November 9, 2021).

Washington ESD instructs employers to report back pay, bonuses, commissions, cafeteria and 401k plan payments, royalties and residuals, severance and separation pay, settlements, sick leave, and tips and gratuities as quarter t earnings if they were paid in quarter t , even if the worker no longer worked for the employer in that quarter.¹⁰ This has potentially important implications for tracking employment-to-employment transitions, as we show below in section 7.

Figure 1 shows the proportion of earnings records showing zero or missing hours, for all quarterly employer-worker records (panel A) and for records representing “full” quarters and primary employment (panel B).¹¹ Black and grey bars show the proportions of records with missing and zero hours, respectively.

Compared with all earnings records, those representing full quarters and primary employment have a smaller proportion reporting zero or missing hours. Compliance with the hours reporting requirements appears to be high and has improved during the period we observe: During 2001–2014 overall, less than 3% of earnings records showed zero or missing hours, and this proportion has steadily decreased over time to less than 1%. Also, starting in 2007, the proportion of zero hours for full quarters and primary employment stabilized at about one-sixth of 1%, and by 2014, missing hours had been virtually eliminated in such records.¹² Washington ESD personnel believe these improvements

¹⁰ See “Reporting Zero Hours” <https://esd.wa.gov/employer-taxes/zero-hour-reports> (last accessed November 9, 2021).

¹¹ As we describe more fully in the next section, the primary employer is the employer from whom the worker had the most earnings in a quarter, and a full quarter is a quarter that is book-ended by quarters with the same primary employer.

¹² The percentage of zero or missing hours in the Washington data compares favorably with the percentage of hours observations that are zero, allocated, top-coded, or reported by proxy in the CPS. In the CPS outgoing rotation groups for Washington during 2001–2014, there are 30,967 observations with weekly earnings that were positive, not top-coded, and not allocated. Of these, 14,235 (about 46%) had labor force information reported by proxy, and of the remaining 16,723, 988 (about 6%) had usual hours of 0, top-

have resulted from improvements in the software used by ESD that have made it simpler for employers to report earnings and hours and less likely that they will make errors and omissions.

2.2. Descriptive statistics and initial comparisons with the CPS

Table 1 displays summary statistics for the Washington data overall and for two subsamples. Column 1 shows summary statistics for all available quarterly worker-employer records. (These include multiple records per quarter for workers who have more than one employer in a quarter.¹³) Column 2 restricts the sample to quarterly records representing only “full” quarters and primary employment. (This is a subset of the sample in column 1. A primary employer is the employer from which the largest share of earnings was received in a quarter, and a “full” quarter is a quarter both preceded and succeeded by quarters of employment with the same primary employer.¹⁴) We do this to overcome the problem of workers switching primary employers mid-quarter, which would lead to understating usual quarterly earnings and quarterly hours.

The most notable difference between columns 1 and 2 pertains to industry composition: the proportion of observations in educational services and in health care and social assistance both drop markedly when only full quarters and primary employment are considered (column 2). This occurs because relatively many jobs in these sectors are secondary or short-term (Lachowska, Mas, Saggio, and Woodbury 2021), so they are not included in the full-quarter/primary job sample. The other difference is that the average

coded, or allocated. (An observation is allocated when a response is “don’t know,” “refused,” otherwise missing, or contradictory to other information.)

¹³ Also, as described in the notes to Table 1, we drop observations in the top and bottom 1% of the hours distribution (> 809 hours/quarter and < 34 hours/quarter).

¹⁴ For example, if employer A was a worker’s primary employer in quarter t , that quarterly observation remains in the sample only if employer A was also that worker’s primary employer in quarters $t-1$ and $t+1$.

wage rate for full quarters and primary employment (column 2) is *lower* than for all quarterly observations (column 1). This occurs because many partial quarters include quarters in which a separation occurred (column 1), and these quarters often include pay for accumulated leave, severance, and other payments that result in a very high nominal hourly wage (see section 2.1 above; see also Lachowska, Mas, and Woodbury 2020, Figure 5 and footnote 39).

For comparison with the Washington data, column 4 of Table 1 provides descriptive statistics from the CPS outgoing rotation groups for Washington during 2001–2014.¹⁵ The differences between columns 2 and 4 highlight some of the basic differences between administrative and survey data—the quarterly frequency of the Washington administrative data versus the monthly frequency (with a weekly reference) of the CPS; and the payroll-reporting nature of the administrative data versus the CPS questions about “usual” earnings and work hours.

The CPS asks respondents to report “actual” hours worked last week and “usual” weekly hours at their main job, so in the Washington data (column 2), we need to divide average quarterly hours by 13 to obtain a weekly measure. Doing this shows that average hours in the Washington data (column 2) are 36.4 hours per week, compared with 37.4 (for actual hours last week) and 38.4 (for usual hours) in the CPS (column 4).¹⁶ Reasons for these differences are discussed in section 3 below, but similar differences between hours measures based on administrative records and surveys have been found in many

¹⁵ See the notes to Table 1 for a full description of the restrictions we impose to obtain the CPS samples.

¹⁶ “Usual weekly hours” are consistently higher than “actual hours worked” in the CPS, as Frazis and Stewart (2014) have discussed. Their explanation is that CPS respondents tend to report modal hours when asked about usual hours, and if the distribution of weekly hours is right-skewed, the result is an overstatement of mean weekly hours.

countries (Fleck 2009).

Measured *average* hourly wages are substantially higher in the Washington data than in the CPS (\$28.34 compared with \$20.90). This difference reflects mainly top-coding in the CPS: whereas we have made no attempt to top-code the calculated wage rate in the Washington data, the wage rate for hourly workers in the CPS is top-coded at \$99.99 per hour, and the maximum calculated wage rate for salaried workers in the CPS is \$231 per hour. In contrast to *mean* hourly wage rates, *median* hourly wage rates in the Washington data and the CPS are much closer (\$19.74 in Washington, versus \$18.46 in the CPS—not shown in the table), which illustrates the sensitivity of the moments of wage distributions to top-coding.

The industry distributions in the Washington data (column 2) and the CPS (column 4) are broadly similar, although there are differences, most notably in educational services (10.4% in the CPS versus 3.0% in the Washington data) and public administration (7.1 percent in the CPS versus 3.1% in the Washington data). The three largest industries in both Washington data and the CPS are manufacturing, retail trade, and health care and social assistance, although in all three cases, the estimates from the Washington data and the CPS differ by 2.5 to 4.0 percentage points.

Three factors account for these differences in industry composition. First, many government and private non-profit employers do not file earnings records because they reimburse the UI agency for UI benefits paid to their laid-off workers (see footnote 6). The substantial under-representation of workers in educational services, public administration, and health care and social services in the Washington data compared with the CPS results from the concentration of “reimbursable” employers in those sectors.

Second, the industry codes shown for the CPS are NAICS “analogs” derived from a crosswalk from the 3-digit harmonized industry codes used in the IPUMS CPS (based on Census Industry Classification System codes) to NAICS 2-digit codes (used in the Washington administrative data), and the crosswalk is imperfect. For example, service activities that are distributed across industries in the NAICS are lumped into an “Other services” classification in the Census system.

Third, differences between administrative and survey data in the frequencies and methods of reporting lead to differences in the types of jobs that appear in the two types of data. For example, restricting the Washington administrative sample to full-quarter/primary jobs results in greater representation of industries that tend to offer more stable employment.¹⁷ The relatively high proportion of employment in manufacturing in column 2 (compared with column 1, which is not restricted to full-quarter/primary jobs) is one clear result.

A comparison of columns 4 and 5 of Table 1 suggests that the industry composition of employment in Washington is quite similar to the U.S. as a whole. The main exception is employment in information (NAICS sector 51), which is greater in Washington than in the U.S. by 1.5 percentage points. Washington’s economy is dominated by the Seattle metropolitan area, which Moretti (2012) has referred to as an innovation hub, so it makes sense that Washington has a relatively large information sector. This may in turn explain why the average wage in Washington is higher than in the U.S. as a whole by about \$2 per hour.

¹⁷ A similar finding has been noted by Schochet, Burghardt, and McConnell (2008).

2.3 Demographic characteristics in the Washington data

UI earnings records rarely include demographic characteristics. Rather, states typically record worker characteristics only when a worker claims UI benefits and registers for employment services through the public labor exchange. For that reason, we know worker characteristics—age, gender, race, education—only for the subset of about 30% of workers in the Washington data who claimed UI and registered with the public labor exchange at some point during 2001–2014. We focus on this subsample in Section 6, where we estimate Mincer wage and earnings regressions based on the Washington data for comparison with regressions based on CPS outgoing rotation group data.

Descriptive statistics for the subsample of workers for whom we observe demographics are displayed in column 3 of Table 1. Three points stand out about these workers: compared with the full-quarter/primary job sample (column 2), their average hourly wage rate is substantially lower (\$23.86, compared with \$28.84), their average quarterly work hours are higher (121, compared with 132), and their average quarterly earnings are lower (\$11,249, compared with \$13,203). Also, the demographic subsample tends to work for smaller employers, and it is more heavily concentrated in construction and manufacturing. All of these characteristics are consistent with what we would expect to observe in a sample of workers who have been UI claimants.

Overall, the strengths of the Washington data are substantial: they provide information on the employment, earnings, and work hours of the vast majority of workers employed in Washington over a period of 14 years. Nevertheless, three characteristics of the Washington data are potential shortcomings, as we have noted: first, although Washington’s industry composition is similar to the U.S. as a whole, it does have a

relatively large information sector and a substantially higher average wage rate than the U.S. overall, so it cannot be portrayed as representative of the U.S.; second, demographic information is available for only a subsample; and third, the data do not allow us to distinguish salaried employees from hourly-paid employees. We discuss this last issue further in Section 3.

3. Hours Distributions in the Washington data and the CPS

We face two challenges in “benchmarking” the Washington hours data against the CPS. First, as already mentioned, the CPS asks respondents to report “actual” hours worked last week and “usual” weekly hours at their main job, whereas the Washington data reports each worker’s quarterly hours for each employer. We have experimented with alternative methods of binning quarterly hours in the Washington data so as to conform with the weekly hours measures in the CPS. As will be seen, the different methods yield similar conclusions.

Second, the Washington records do not identify salaried workers. The concern is that, for some salaried workers whose hours are not tracked, hours worked will differ from paid hours, and hence be mismeasured—40 hours per week will be an understatement of actual hours worked for some, and possibly an overstatement for others. The result would be an unrealistic “pile-up” of measured hours worked per week at 40 in the Washington records. Interestingly, however, the distributions shown below suggest this is not happening.

Figure 2 (panel A) shows the distribution of quarterly work hours in the Washington data, including only primary employment and “full” quarters (the sample

summarized in column 2 of Table 1). The distribution is presented in one-hour-per-quarter bins—the natural unit of measurement. About 9% of employees worked exactly 520 hours per quarter for their primary employer—the modal quarterly hours worked. Assuming 13 weeks per quarter and five-day workweeks, 520 work hours per quarter represents 40 work hours per week. However, because the number of workdays per quarter is variable, a 40-hour workweek may sometimes translate into quarterly hours slightly greater or less than 520. This is evident in the distribution shown in Figure 2 (panel A), with mass just to the right and left of the 520-hour spike. Figure 2 (panel B) uses wider (10-hour-per-quarter bins) to subsume the mass near 520 hours per quarter, and produces a spike near 520 hours of 12.5%.

In both panels A and B, spikes in the hours distribution also appear at 480 and 560 hours per quarter. These spikes may result from many employers’ practice of using two-week pay periods, which result in either 12 paid weeks in a quarter (and 6 paychecks) or 14 paid weeks in a quarter (and 7 paychecks). If employers use payroll records to report workers’ hours, which seems likely, the result is that workers with 40 paid hours every two weeks will be reported as having either 480 or 560 hours in a quarter. These variations in quarterly hours affect both salaried and hourly workers.¹⁸

In Figure 3, we use the same sample as in Figure 2, but divide quarterly hours by 13 to obtain an approximate measure of weekly work hours. Effectively, this produces still wider bins (13 hours per quarter), and we see spikes at about 37, 40, and 43 hours per

¹⁸ We are grateful to Gary Solon for this point. Seth Murray (2020) has produced an exhaustive examination of alternative pay schedules by applying a machine-learning algorithm to LEHD data. One implication of employers using different pay schedules is that, when analyzing hours as an outcome in a regression model, it is important to control for employer by year by quarter fixed effects, so comparisons are not sensitive to employer pay schedules. See Lachowska, Mas, Saggio, and Woodbury (2021).

week, with the spikes at 37 and 43 hours per week corresponding to those at 480 and 560 hours per quarter in Figure 2. An upper-bound estimate of the percentage of workers whose hours are 40 per week can be obtained by summing the mass from 37 to 43 hours per week, which results in an estimate of about 52 percent. This is an upper-bound for at least two reasons. First, only “full” quarters are included in the sample underlying Figures 2 and 3, and jobs that span at least one full quarter are more likely to be stable, full-time jobs than those that do not. Second, it likely counts many workers who really worked more or less than 40 hours per week (notably those in the spikes at 37 and 43 hours per week) as working 40 hours per week.

3.1. Comparing hours distribution in the Washington data and CPS

The distribution of weekly hours in Figure 3 can be compared with two alternative hours distributions from the CPS. The CPS asks employed wage and salary workers about the “actual” number of hours they worked in the week before the survey (both on the main job and over all jobs). In addition, the CPS asks those who were either employed or “had a job but were not at work last week” about their “usual” weekly hours. Responses to these CPS questions give the closest available analogues to the measures of weekly hours worked in the Washington administrative records. Figure 4 displays the distribution of “actual” hours worked at the main job in the previous week, and Figure 5 shows the distribution of “usual” hours worked on the main job, both based on Washington wage and salary workers in the CPS from January 2001 through December 2014.¹⁹

The appearance of the distributions in Figures 4 and 5 (from the CPS) differs sharply from the distribution in Figure 3 (the Washington administrative data). In the

¹⁹ Distributions for the U.S. as a whole are strikingly similar to those for Washington alone.

CPS, nearly 38% of wage and salary workers report “actual” work hours of 40 per week, and about 53.5% report “usual” work hours of 40 per week. This compares with just 17% of the Washington employer reports clustering at the 40-hour-per-week spike (Figure 3). In particular, the hours responses in the CPS appear to “heap” at round numbers: 20, 30, 40 (especially), 50, and 60 hours per week. Such heaping of self-reported work hours in the CPS has been noted previously by Farber (2005), among others. In contrast, the Washington hours distribution in Figure 3 shows a wider spread in hours, with no prominent gaps between the spikes at 37, 40, and 43 hours per week.

Nevertheless, the hours distributions from the Washington data and the CPS are similar in an important respect: The upper-bound estimate of the percentage of workers whose hours are 40 per week in Washington is about 52 percent, close to the 53.5 percent who report “usual” weekly hours of 40 per week in the CPS. This similarity between reported hours in the Washington administrative data and “usual” hours in the CPS makes sense because the Washington sample includes only “full” quarters (which tends to increase the percentage of full-time jobs observed), and because “usual” hours are likely to reflect a typical pay period, similar to the administrative reports.

3.2. Cumulative distribution functions

To better visualize the differences between the hours distribution in the Washington data (the density shown in Figure 3) and “actual” and “usual” hours distributions in the CPS (the densities in Figures 4 and 5), we plot the cumulative distribution functions (CDFs) of each. In this case, we maintain the quarterly units of the Washington hours, and we convert the actual and usual weekly hours reported in the CPS to quarterly units by multiplying by 13.

Figure 6 (panel A) plots the CDF of Washington quarterly work hours, along with the CDF of “actual” hours for Washington workers in the CPS. Figure 7 (panel A) repeats the CDF of the Washington quarterly hours, and superimposes the CDF of “usual” weekly hours from the CPS. In panel B of Figures 6 and 7, we show the differences in cumulative probabilities between the Washington hours and the CPS hours at each hour.

Figures 6 and 7 reveal two differences between the hours distributions in the Washington data and the CPS. First, compared with the Washington data, the CPS shows substantially reduced mass between approximately 450 and 520 hours per quarter. This is likely a result of the employers’ use of two-week pay periods (discussed above), although it could also partially result from workers over-reporting (or “rounding up”) their work hours. Second, again compared with the Washington data, the CPS shows reduced mass between about 550 and 800 hours per quarter. Only part of this can be explained by use of two-week pay periods, because the range of reduced mass exceeds 560 hours per quarter (the number of hours in a quarter with seven two-week pay periods). One possible explanation is that a significant proportion of salaried workers, who are paid for 40 hours per week, are working substantially more than 40 hours per week. An alternative explanation is that some workers over-report work hours (including overtime hours) in the CPS. In any event, paid hours in the Washington administrative data are less than work hours reported in the CPS.

To summarize, compared with the Washington data on hours, self-reported work hours in the CPS are more concentrated at 40 hours per week, and show substantial (though less dramatic) heaping at 20, 30, 50, and 60 hours per week. In the CPS, nearly 38% of workers report 40 “actual” work hours in the previous week, and 53.5% report 40

“usual” hours per week. The apparently smaller spike at 40 hours per week in the Washington data (only 17%) likely results from payroll practices, and once these practices are accounted for, it becomes clear that about 52% of workers are paid close to 40 hours per week. However, the reduced mass in the CPS hours distribution between about 550 and 800 hours per quarter (compared with the Washington hours distribution) suggests that a significant proportion of salaried workers—who are being paid to work 40 hours per week—are working more than 40 hours per week. These differences highlight the underlying payroll origins of the Washington administrative records, and suggest again that “hours” in these data should be interpreted as paid hours.

4. A Regression-Based Test of Signal-to-Noise in Hours Data

The earnings of an hourly worker who stays in a job can be expected to vary stochastically around a fixed hourly wage rate. This observation suggests that a simple regression of the change in log earnings between two quarters [$\Delta \ln(earn_{it})$] on the change in log hours [$\Delta \ln(hrs_{it})$] produces a test of the accuracy of hours measurement:

$$\Delta \log(earn_{it}) = \alpha + \beta \Delta \log(hrs_{it}) + \varepsilon_{it} \quad (1)$$

If hours are measured accurately, estimates of the coefficient on the change in log hours (β) should be close to one for hourly workers (or somewhat higher if overtime is taken into account); if hours are measured with substantial error, we would expect the slope coefficient in this simple regression to be attenuated.

Table 2 displays estimates of such regressions using observations of Washington workers observed with the same employer in successive quarters. The underlying sample is the same as that shown in column 2 of Table 1, but only “stayers”—workers observed

with the same primary employer in consecutive full quarters—are in the estimation sample. Four estimates of the slope coefficient β are shown: two from models without employer fixed effects [columns (1) and (2)] and two with employer fixed effects [columns (3) and (4)]. [Estimated standard errors in columns (2) and (4) are clustered; those in columns (1) and (3) are not.]

All four estimates of the slope coefficient equal 0.80, implying that the paid hours records contain considerable signal. Again, hourly workers should have a coefficient close to 1, or slightly higher than 1 when taking overtime into account.²⁰ For salaried workers with fixed quarterly earnings or hours, we would expect a slope coefficient equal to 0. But not all salaried workers' quarterly hours are fixed, both because the number of workdays per quarter varies and because payroll schedules result in proportional variation in hours and earnings from quarter-to-quarter (see the discussion in the previous section). It follows that we would expect the estimated slope for the full sample to be attenuated by *less* than the full proportion of salaried workers in the full sample.

The CPS sample underlying Table 1, column 4, suggests that about 37% of Washington workers were salaried during 2002–2014, so if hourly workers received no overtime, and if the quarterly earnings or hours of all salaried workers were fixed, we would expect a coefficient on the change of log hours of 0.63. But because many salaried workers have proportional changes in earnings and hours from quarter-to-quarter (for the reasons just discussed), we would expect a slope coefficient greater than 0.63, which is what we see. The magnitude of the estimates in Table 2 is consistent with what we expect

²⁰ We say “slightly” because in payroll data, only 0.1% of the median hourly worker’s annual gross earnings come from overtime pay—see Grigby, Hurst, and Yildirmaz (2021, Table 1).

from data with little error in hours measurement, given the mix of hourly and salaried workers.²¹

Although we do not observe whether a worker is hourly or salaried in the Washington data, we can use the CPS sample summarized in Table 1, column 4, to tabulate the proportion of hourly paid workers in each of the 20 NAICS 2-digit industries, then estimate equation (1) for each of the same 20 industries using the Washington data. We would expect the industry-specific estimates of β to be positively correlated with the proportion of hourly paid workers in the industry.

Figure 8 and Table 3 show the results of this exercise (the table shows the detail underlying the figure.) In Figure 8, the proportion of hourly paid workers in the industry is shown on the x -axis, and the estimated industry-specific β is shown on the y -axis. (The solid line is a 45-degree line.) The scatterplot shows a strong positive relationship between the proportion of hourly workers in an industry and β (the strength of the relationship between earnings changes and hours changes). The industry-employment weighed correlation coefficient is 0.74 (the unweighted correlation is 0.63), which is further evidence that paid hours records in the administrative records contain considerable signal.²²

²¹ The estimated coefficient is somewhat larger than would be suggested by Abowd and Card (1989) whose variance-covariance matrix of changes in earnings and hours in the PSID in the 1970s implies coefficients in the range of 0.5–0.7. The high correlation of hours and earnings implies either considerable signal in the hours variable, or a high measurement error in both hours and earnings, coupled with highly correlated measurement error between these two variables. As the data are administrative, the former explanation seems more likely.

²² Note that educational services (NAICS code 61) and public administration (NAICS code 92) appear to be outliers in the scatterplot. Recall that both are under-represented in the Washington data because many employers in these industries do not file wage records. It follows that the proportions of hourly workers in these industries observed in the CPS could differ greatly from the proportions in the Washington administrative data. Given the large positive residuals for both industries, we speculate that the proportions of hourly workers in educational services and public administration in the Washington data are substantially higher than 43% and 48% estimated in the CPS (see Table 3, column 3).

5. Minimum wage changes and nominal wage distributions in the Washington data

Since 2001, the minimum wage in Washington has been indexed to the Consumer Price Index for Urban Wage Earners and Clerical Workers (CPI-W) (Jardim et al., 2021; Washington State Department of Labor & Industries, 2018). It makes sense, then, to conduct a simple visual examination of whether the distribution of nominal hourly wages in the Washington data (quarterly earnings divided by quarterly hours) reflects annual changes in the Washington minimum wage.

Figure 9 plots the distribution of hourly wage rates with the primary employer for each year from 2001 through 2014, with a vertical bar indicating the Washington state minimum wage. The distributions are shown for wage rates less than \$15 per hour. The hourly wage distribution displays a spike at the minimum wage, which shifts each year with increases in the minimum wage. The patterns in Figure 9 would not be present if hours were measured with substantial error.²³

6. Earnings and Wage Rate Regressions

As a final assessment, we estimate Mincer-style models of log earnings and log hourly wages to examine whether estimates based on the Washington administrative data produce results similar to those based on the CPS. The analysis may be interesting in its

²³ Few reported hourly wage rates are below the minimum, but some reported wage rates less than the minimum are expected because coverage is incomplete. For example, businesses with annual dollar sales less than \$500,000 are not subject to the minimum wage, and certain groups of workers—student workers, learners, apprentices, and workers with disabilities—are exempt.

own right because Mincer estimates based on U.S. administrative data, particularly those that include employer identifiers, are not common.²⁴

In the Washington administrative data, we have information on demographic characteristics and education only for the one-third of workers who claimed UI at some time during the 2001–2014 period, so we are constrained to this subsample. Descriptive statistics for the subsample of all full-quarter/primary employment observations with demographic characteristics are displayed in column 3 of Table 1. (To be clear, this is a subset of the sample summarized in column 2.) Workers who claimed UI at some time during 2001–2014 appear to be negatively selected: compared with the sample in column 2, their average hourly wage rate was about 15% lower (\$23.86 versus \$28.34), and their average work hours were longer. Also, they tended to work for smaller employers and to be more heavily concentrated in relatively low-wage industries like retail trade, health care and social assistance, and accommodation and food service.

6.1 Estimates based on the Washington data

Table 4 displays estimated wage and earnings regressions based on the subsample of about 500,000 observations for which we have demographics in 2013:2 (a subset of the sample described in column 3 of Table 1). We use a single quarter to avoid using repeated observations of the same worker and to come as close as possible to estimating a garden-variety Mincer model using a cross-section. The dependent variable in columns 1 through 4 is the log of the hourly wage rate, and the dependent variable in columns 5 through 8 is the log of quarterly earnings. Columns 2 and 6 add NAICS 3-digit indicators

²⁴ Abowd, Finer, and Kramarz (1999), Abowd, Lengermann, and McKinney (2002), and Barth, Davis, and Freeman (2018) report estimates of Mincer models using LEHD data. A number of recent papers make use of estimates from Mincer regressions without reporting underlying estimates like those in Table 4—for example, Juhn, McCue, Monti, and Pierce (2018) and Hahn, Hyatt, and Janicki (2021).

to the basic specification, columns 3 and 7 add individual employer indicators, and columns 4 and 8 add employer-by-education indicators.

In the baseline log wage model (column 1), the age-wage profile peaks at age 48, but increases to age 52–53 in models that include employer effects, which suggest considerable heterogeneity in the age-wage profile across employers. A similar pattern can be seen with the addition of employer effects to the log earnings models (columns 5–8), although the age-earnings profile is less steep than the age-wage profile, peaking at ages 47 to 49), which implies that work hours tend to decrease with age.

Estimated returns to education are substantial in the baseline wage specification, with average wage rate penalties for high school dropouts of nearly 19 log points, and nearly 8 log points for workers with a GED diploma, after controlling for other observables. The return to post-secondary education is substantial: The hourly wage rate of workers with some college or an associate degree is 13–18 log points more than high school graduates, and the wage-rate premium of college graduates is 40 log points.

The returns to education shrink substantially when NAICS 3-digit industry indicators (columns 2 and 6) and individual employer indicators (columns 3 and 7) are included in the model.²⁵ For example, the return to some college relative to high school is nearly 50% smaller when employer effects are controlled for (about 7 log points versus about 13 log points). This attenuation suggests that a substantial portion of the return to education results from how workers sort to employers. Similarly, the return to a bachelor's degree relative to a high school diploma only about half as large within

²⁵ The estimates reflect well-known patterns of industry earnings differentials (often interpreted as industry rents—for example, Krueger and Summers 1988) and employer earnings differentials (often interpreted as premiums paid by certain firms or employers—for example, Abowd, Kramarz, and Margolis 1999; Card Heining, and Kline 2013).

employer as in the baseline wage model (about 21 log points versus about 40 log points), again suggesting that the return to education occurs in large part through sorting to a higher wage employers.

Comparing columns 1 and 5 suggests the returns to education are driven mainly by hourly wages rather than work hours. In contrast, the male-female earnings gap (37 log points) substantially exceeds the male-female wage rate gap (about 26 log points), implying that women both earn a lower wage rates and work fewer hours. The gender gap shrinks substantially when NAICS 3-digit industry indicators and individual employer indicators are included in the model, as did the returns to education. Within employer, women's hourly wages are about 10 log points lower than men's, and their earnings are lower by 15 log points. These gaps are less than half the size of the gaps without employer controls (nearly 26 log points for wages and 37 log points for earnings), suggesting that a large part of the gender wage gap manifests itself via sorting to employers. Goldin et al. (2017) reach the same conclusion using LEHD data.

Although sorting to employers is also an important part of the black-white wage gap, most of the black-white gap is a within-employer phenomenon. When we control for employer fixed effects (in column 3 of Table 4) the estimated black-white wage is 10.1 log points, compared with 17.5 log points in the baseline model. This finding is similar to Carrington and Troske (1998), who conclude that (in manufacturing) most of the black-white wage gap occurs within-employer.

In the richest models in Table 4 (columns 4 and 8), we interact employer with education categories, so we estimate the average difference in log wages for workers with the same education level at the same employer. In these models, the black-white wage

gap is 9.2 log points (compared with 17.5 overall), and the female-male wage gap is 9.7 log points (compared with 25.6 overall), reinforcing the importance of within-employer wage gaps.

6.2 Comparisons with the CPS

Table 5 reports log hourly wage regressions (in columns 1 and 2) and log weekly earnings regressions (in columns 3 and 4), based on CPS outgoing rotation group data for the United States during 2013 (a subset of the sample described in column 5 of Table 1.²⁶) We examine a U.S. sample, rather than a sample restricted to Washington, in order to obtain a sample large enough to give us reasonably precise estimates.²⁷

The estimated hourly wage and weekly earnings regressions based on this CPS sample are broadly similar to those in Table 4. The age-wage profile peaks about age 50–51, and the age-earnings profile peaks about age 46–47, so again the age-earnings profile is steeper than the age-wage rate profile. Focusing on hourly wage rates, the returns to education are generally larger in the CPS data than in the Washington administrative data: the return to high school graduation is 22 log points in the CPS (19 in the Washington data), the return to an associate degree is substantially larger in the CPS (24 log points, versus 12 log points in the Washington data), and the return to a bachelor’s degree is somewhat larger (44 log points in the CPS, versus 40 log points). In the CPS, as in the Washington data, the returns to education shrink when industry indicators are included in the model.

²⁶ In addition to the restrictions imposed to obtain the sample in column 5 of Table 1 (see the notes to Table 1), we restrict the sample to individuals aged 25 and older.

²⁷ Restricting the sample to just Washington workers yields only 644 observations.

The male-female wage rate gap is substantially smaller in the CPS than in the Washington data (19.4 log points, versus 25.6 log points), although again a large part of the gender earnings gap can be attributed to women working fewer hours (in the CPS, the earnings gap is nearly 33 log points, compared with the wage rate gap of 19.4 log points). Within industry, women's wage rates are lower by nearly 14 log points, and their earnings are lower nearly 24 log points, similar to the pattern is observed in the Washington data (columns 2 and 6 of Table 4).

The difference in the black-white wage gaps estimated from the CPS and the Washington data is striking (10 log points in the CPS, versus 17.5 log points in the Washington data), although with industry included in the model, the estimated black-white wage gaps are quite similar in the CPS (9 log points) and the Washington data (11 log points in the Washington data).

To summarize, given the substantial differences between the populations from which the CPS and the subsample of Washington data with demographics are drawn—the at-large U.S. labor force versus workers who have claimed UI in Washington at some time—the differences between the estimated Mincer equations in Tables 4 and 5 are fewer than might be expected. The most conspicuous difference between the regressions based on the CPS and Washington data is the attenuated returns to education in the Washington sample relative to the CPS. However, we have seen that the Washington sample with demographics is negatively selected. If negative selection increases with education, which would not be surprising, we would then observe attenuated returns to education.

7. Discussion

Our examination of employers' reporting of hours in the Washington data and individual reporting of hours in the CPS suggests that the reliability of paid hours reporting in the Washington administrative data is high. The analysis in section 4 checked the longitudinal properties of hours and earnings, examining what the data imply about known economic relationships. That analysis found a high correlation of quarter-to-quarter changes in log earnings and log hours. In section 5, we found that annual distributions of hourly wages constructed using administrative earnings and hours variables show spikes that track the annual movement in the Washington minimum wage, which is indexed. This is what would be expected from data with limited error. Section 6 described Mincer-style regressions using log earnings and log hourly wages. These show age-wage profiles, returns to education, and wage differentials by race and gender similar both to those found elsewhere in the literature and to our estimates using CPS data. For example, the gender gap is larger for the hourly wage rate than for quarterly earnings, but the returns to education are similar when estimated using hourly wages and quarterly earnings. These findings are consistent with what is known about differences in work hours by gender and education.

The main contrast between the Washington data and the CPS is in the distribution of work hours: when compared with the Washington data, the CPS distribution of hours suggests substantially more employment with hours in excess of 43 per week. We attribute this difference mainly to the payroll basis of the administrative data, as opposed to the survey basis of the CPS. That is, the Washington administrative hours reports are best interpreted as quarterly paid hours, whereas the CPS survey hours self-reports are

best interpreted as hours spent working, with the survey data subject to the usual caveats about response error.²⁸

Our conclusion that the Washington hours data are reliable squares with the literature that has used validation studies to estimate measurement error in labor force surveys. Using the PSID validation study, Bound et al. (1989) found a rate of error to total variance in hours worked in the range of 0.28 to 0.37. It has also been noted that aggregate hours in the Current Employment Statistics (CES), which are obtained from employer reports, tend to be lower and trend differently than hours measured from the CPS (Abraham, Spletzer and Stewart, 1998).²⁹

As we mentioned in the introduction, using data on hours to track labor mobility—transitions from job to job and employment to nonemployment—is likely to be more accurate than using earnings data. The reason is that earnings records frequently report that a worker received earnings in a quarter following a worker’s separation from an employer (see the discussion in section 2.1 above). It follows that using earnings to infer whether a worker experiences a quarter of nonemployment between employment spells with different employers may be misleading.

We illustrate this issue in Figure 10, which shows quarterly job-to-job transition rates inferred from quarterly earnings (the dark dashed line) and from hours records (the lighter dotted line). Because workers frequently receive payment for accumulated leave, severance, and other payments from an employer in a quarter after they have separated,

²⁸ To the extent response error exists in the CPS, the implication is that any variable constructed with hours in the denominator, like the hourly wage or hourly output, will be understated when using CPS data. This could help reconcile differences in estimated labor supply elasticities at the intensive and extensive margins, given the latter is better measured and the error is non-classical.

²⁹ See also Frazis and Stewart (2009, 2010), who examine differences among hours data in the CPS, the Current Employment Statistics data (based on payrolls), and the American Time Use Survey,

the immediate job-to-job transition rate based on earnings is higher than the rate based on hours. In 2002–2004, the earnings-based transition rate exceeded the hours-based rate by about 0.5 percentage point (or about 6 percent on a base of 8 percent). This gap fell after 2004, and following the Great Recession it was less than 0.2 percentage points (about 3 percent on a base of 7 percent)—less substantial but not insignificant. Much of the reduction in the gap between transition rates estimated from earnings and from hours appears to result from the drop in missing and zero hours shown in Figure 1, but the gap remaining after 2010 would appear to be accurate, and its implications could be usefully explored in future research.

A limitation of this study is that we can only examine administrative hours data from one state. We speculate that the hours data collected by Washington are of good quality because they are used to determine eligibility for UI benefits, which in turn has led the Washington ESD to implement software that prompts employers to make accurate reports. As a counterexample, Minnesota does not use hours reports to administer UI, and when Kurmann and McEntarfer (2017) examined Minnesota’s administrative hours reports, they found a high nonresponse rate. Officials at the U.S. statistical agencies have discussed encouraging states to add hours reports to their wage records data and ultimately making administrative hours records part of the national system of data collection (Bostic, Jarmin, and Moyer, 2016; Jarmin, 2019). If high quality hours data collected through state UI systems are to become a workhorse dataset for the study of the labor market in the United States, then understanding the measures needed to ensure the quality of such data will be important.

References

- Abowd, John M, and David Card, 1989. On the covariance structure of earnings and hours changes. *Econometrica*, 57(2): 411–445.
- Abowd, John M., Hampton Finer, and Francis Kramarz. 1999. Individual and firm heterogeneity in compensation: An analysis of matched longitudinal employer-employee data for the State of Washington. In: J. Haltiwanger, J. Lane, J. Spletzer, J. Theeuwes, and K. Troske (Eds.), *The Creation and Analysis of Employer-Employee Matched Data*. Amsterdam: North Holland, pp. 3–24.
- Abowd, John M., Francis Kramarz, and David N. Margolis. 1999. High wage workers and high wage firms. *Econometrica* 67(2): 251–333.
- Abowd, John M., Paul A. Lengermann, and Kevin L. McKinney. 2002. “The measurement of human capital in the U.S. economy.” Technical paper No. TP-2002-09, U.S. Census Bureau, LEHD Program.
- Abraham, Katharine G., John Haltiwanger, Kristin Sandusky, and James R. Spletzer. 2013. Exploring differences in employment between household and establishment data. *Journal of Labor Economics* 31 (April, part 2): S129–S172.
- Abraham, Katharine G., James R. Spletzer, and Jay C. Stewart. 1998. Divergent trends in alternative wage series. In: J. Haltiwanger, M. Manser, and R. Topel (Eds.), *Labor Statistics Measurement Issues*. Chicago: University of Chicago Press, pp. 292–324.
- Barth, Erling, James C. Davis, and Richard B. Freeman. 2018. Augmenting the human capital earnings equation with measures of where people work. *Journal of Labor Economics* 36(S1): S71–S97.
- Blakemore, Arthur E., Paul L. Burgess, Stuart A. Low, and Robert St. Louis. 1996. Employer tax evasion in the unemployment insurance system. *Journal of Labor Economics* 14(2): 210–230.
- Bostic, William G. Jr., Ron S. Jarmin, and Brian Moyer. 2016. Modernizing federal economic statistics. *American Economic Review Papers & Proceedings* 106(5): 161–164.
- Burgess, Paul L., Arthur E. Blakemore, and Stuart A. Low. 1998. Using statistical profiles to improve unemployment insurance tax compliance. In: L. J. Bassi and S. A. Woodbury (Eds.), *Reform of the Unemployment Insurance System*. Stamford, CT: JAI Press, pp. 243–271.
- Bound, John, Charles Brown, Greg J. Duncan, and Willard L. Rodgers. 1989. “Measurement error in cross-sectional and longitudinal labor market surveys: Results from two validation studies.” NBER Working Paper No. 2884.

- Card, David, Joerg Heining, and Patrick Kline. 2013. Workplace heterogeneity and the rise of West German wage inequality. *Quarterly Journal of Economics* 128(3): 967–1015.
- Carrington, William J. and Kenneth R. Troske. 1998. Interfirm segregation and the black/white wage gap. *Journal of Labor Economics* 16(2): 231–260.
- Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. The effect of minimum wages on low-wage jobs. *Quarterly Journal of Economics* 134(3): 1405–1454.
- Farber, Henry S. 2005. Is tomorrow another day? The labor supply of New York City cabdrivers. *Journal of Political Economy* 113(1): 46–82.
- Fleck, Susan E. 2009. International comparisons of hours worked: An assessment of the statistics. *Monthly Labor Review* (May): 3–31.
- Flood, Sarah, Miriam King, Steven Ruggles, and J. Robert Warren. 2020. Integrated public use microdata series, Current Population Survey: Version 5.0 [dataset]. Minneapolis, MN: University of Minnesota.
- Frazis, Harley, and Jay Stewart. 2009. Comparing hours worked per job in the Current Population Survey and the American Time Use Survey. *Social Indicators Research* 93(1): 191–195.
- Frazis, Harley, and Jay Stewart. 2010. Why do BLS hours series tell different stories about trends in hours worked? In: K. Abraham, J. R. Spletzer, and M. Harper (Eds.), *Labor in the New Economy*. Chicago: University of Chicago Press, pp. 343–374.
- Goldin Claudia, Sari Pekkala Kerr, Claudia Olivetti, and Erling Barth. 2017 The expanding gender earnings gap: Evidence from the LEHD-2000 Census. *American Economic Review Papers and Proceedings* 107(5): 110–114.
- Grigsby, John, Erik Hurst, and Ahu Yildirmaz. 2021. Aggregate nominal wage adjustments: New evidence from administrative payroll data. *American Economic Review* 111(2): 428–471.
- Heckman, James J. 1993. What has been learned about labor supply in the past twenty years? *American Economic Review Papers and Proceedings* 83(2): 116–121.
- Jardim, Ekaterina, Long, Mark C., Plotnick, Robert, van Inwegen, Emma, Vigdor, Jacob, and Wething, Hilary. 2021. Minimum wage increases and low-wage employment: Evidence from Seattle. *American Economic Journal: Economic Policy*, forthcoming.
- Jardim, Ekaterina, Gary Solon, and Jacob Vigdor. 2019. How prevalent is downward rigidity in nominal wages? Evidence from payroll records in Washington State. NBER Working Paper No. 25470.

Jarmin, Ron S. 2019. Evolving measurement for an evolving economy: Thoughts on 21st century U.S. economic statistics. *Journal of Economic Perspectives* 33(1): 165–184.

Johnson, Terry R., and Daniel R. Klepinger. 1994. Experimental evidence on unemployment insurance work search policies. *Journal of Human Resources* 29(3): 695–717.

Juhn, Chinhui, McCue, Kristin, Monti, Holly, Pierce, Brooks. 2018. Firm performance and the volatility of worker earnings. *Journal of Labor Economics* 36(S1): S99–S133.

Hahn, Joyce K., Hyatt, Henry R., and Janicki, Hubert P. 2021. Job ladders and growth in earnings, hours, and wages. *European Economic Review* 133 (April).

Kornfeld, Robert and Howard S. Bloom. 1999. Measuring program impacts on earnings and employment: Do unemployment insurance wage reports from employers agree with surveys of individuals? *Journal of Labor Economics* 17(1): 168–197.

Krueger, Alan B., and Lawrence H. Summers. 1988. Efficiency wages and the inter-industry wage structure. *Econometrica* 56(2): 259–293.

Kurmann, Andre and Erika McEntarfer. 2017. “Downward wage rigidity in the U.S.: New evidence from administrative data.” Unpublished manuscript.

Lachowska, Marta, Alexandre Mas, and Stephen A. Woodbury. 2020a. Sources of displaced workers’ long-term earnings losses. *American Economic Review* 110(10): 3231–3266.

Lachowska, Marta, Alexandre Mas, and Stephen A. Woodbury. 2020b. Online appendix: Sources of displaced workers’ long-term earnings losses. <<https://assets.aeaweb.org/asset-server/files/13097.pdf>>.

Lachowska, Marta, Alexandre Mas, Raffaele Saggio, and Stephen A. Woodbury. 2021. Wage posting or wage bargaining? A test using dual jobholders. *Journal of Labor Economics*, forthcoming.

Lachowska, Marta, Merve Meral, and Stephen A. Woodbury. 2015. The effects of eliminating the work search requirement on job match quality and other long-term employment outcomes. Washington, D.C.: U.S. Department of Labor.

Lachowska, Marta, Merve Meral, and Stephen A. Woodbury. 2016. Effects of the unemployment insurance work test on long-term employment outcomes. *Labour Economics* 41: 246–265.

Moffitt, Robert, Abowd, John, Bollinger, Christopher, Carr, Michael, Hokayem, Charles, McKinney, Kevin, Wiemers, Emily, Ziliak, James, Zhang, Sisi. 2021. Reconciling trends

in U.S. male earnings volatility: Results from survey and administrative data. *Journal of Business and Economic Statistics*, forthcoming.

Moretti, Enrico. 2012. *The New Geography of Jobs*. Boston: Houghton Mifflin Harcourt.

Murray, Seth. 2020. “Measurement of nominal wages in administrative earnings data and evidence on models of wage adjustment.” Working Paper, July
<https://www.sethmurrayecon.com/research>.

Quach, Simon. 2021. “The labor market effects of expanding overtime coverage.” Working Paper, University of Southern California (October).

Ramey, Valerie A. 2012. “The impact of hours measures on the trend and cycle behavior of U.S. labor productivity.” Working Paper, University of California San Diego.

Rodgers, Willard L., Charles Brown, and Greg J. Duncan, 1993. Errors in survey reports of earnings, work hours, and hourly wages. *Journal of the American Statistical Association* 88(424): 1208–1218.

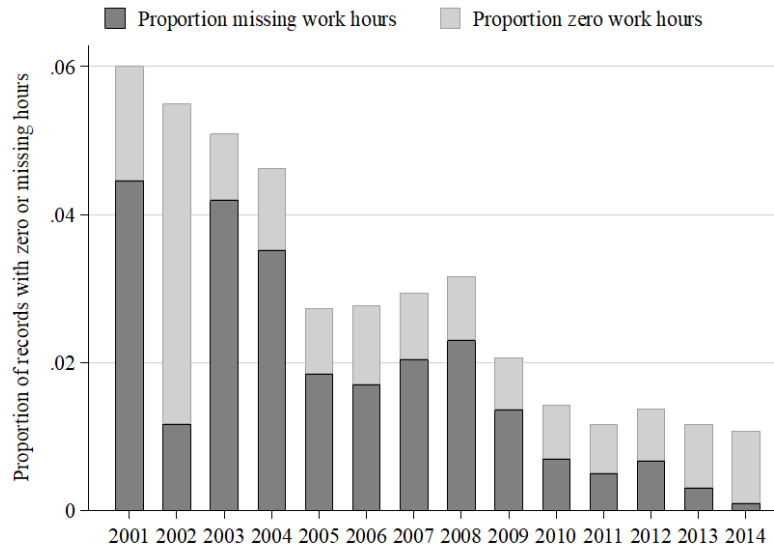
Schochet, Peter Z., John Burghardt, and Sheena McConnell. 2008. Does Job Corps work? Impact findings from the National Job Corps Study. *American Economic Review* 98(5): 1864–86.

Wallace, Geoffrey L. and Robert Haveman. 2007. The implications of differences between employer and worker employment/earnings reports for policy evaluation. *Journal of Policy Analysis and Management* 26: 737–753.

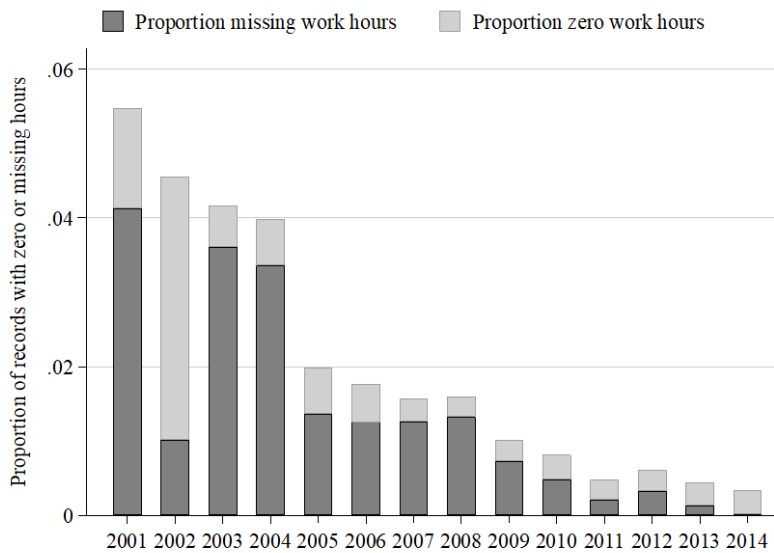
Washington State Department of Labor & Industries. 2018. History of Washington minimum wage.
<<http://www.lni.wa.gov/workplacerrights/wages/minimum/history/default.asp>>.

Figure 1
 Proportion of observations with zero or missing work hours, Washington administrative wage records, 2001–2014

Panel A: All quarters, all worker-employer observations



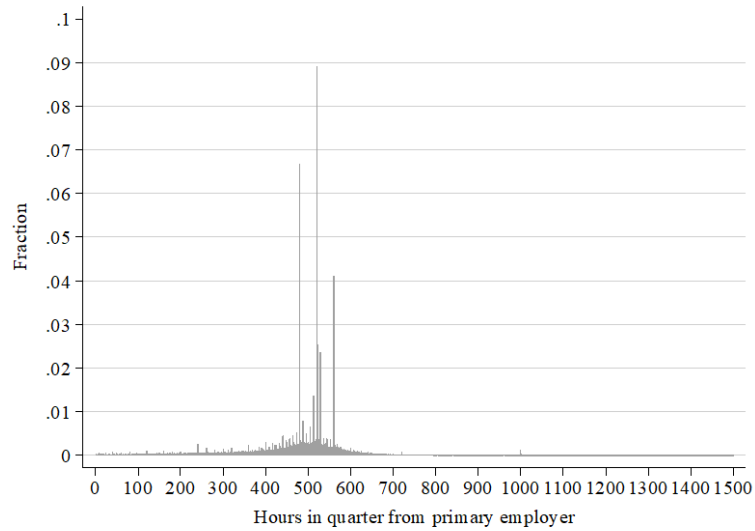
Panel B: Full quarters, primary employment only



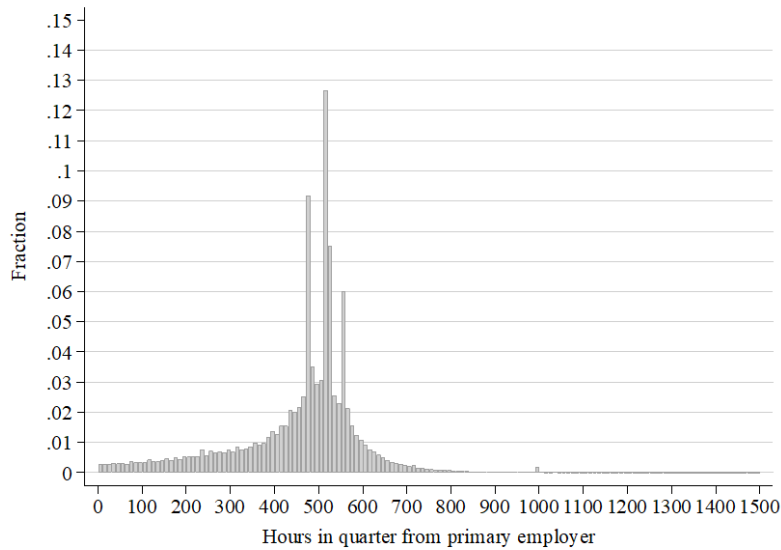
Notes: Samples come from Washington administrative records, 2001:1–2014:4. Panel A is constructed from all worker-quarter observations—the sample summarize in Table 1, column 1. Panel B is restricted to “full” quarters and primary employment—the sample summarized in Table 2, column 2. (The primary employer is the employer from whom the worker had the most earnings in a quarter. A full quarter is a quarter that is book-ended by quarters with the same primary employer.)

Figure 2
Distribution of quarterly work hours in full quarters and primary employment, Washington administrative wage records, 2001–2014

Panel A: One-hour-per-quarter bins

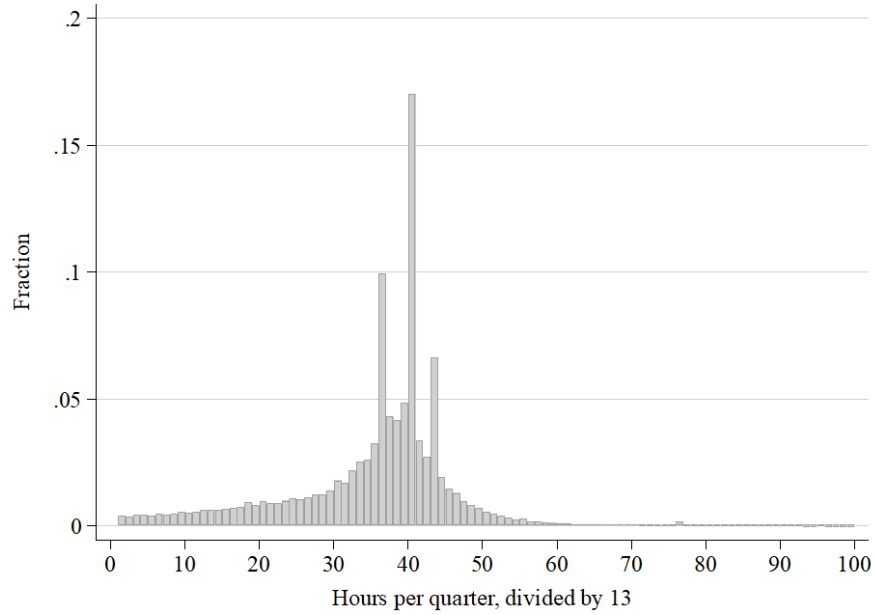


Panel B: 10-hour-per-quarter bins



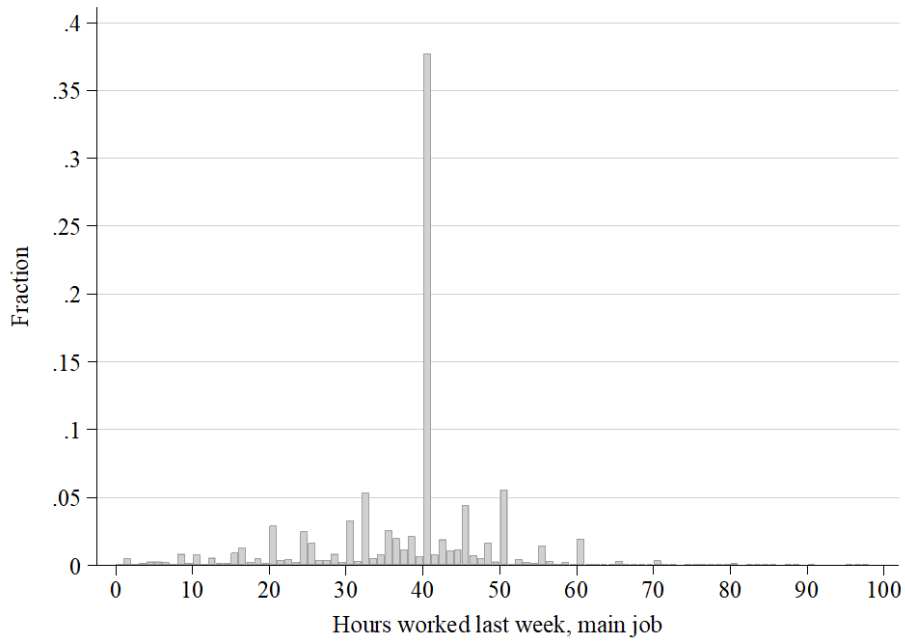
Notes: Work hour distributions are based on the sample summarized in Table 1, column 2. The sample is restricted to worker-quarter observations representing full quarters and primary employment (see the notes to Table 1). Observations with more than 1,500 hours per quarter have been dropped.

Figure 3
Distribution of weekly work hours (quarterly hours divided by 13) in full quarters and primary employment, Washington administrative records, 2001:1–2014:4



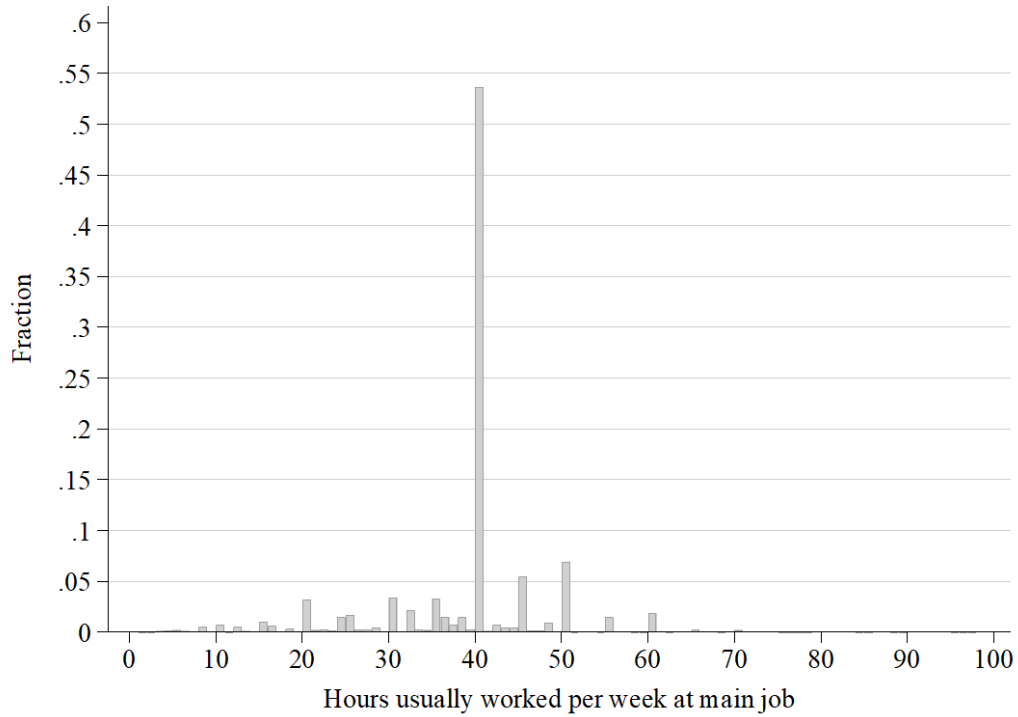
Notes: Weekly work hours are constructed as the number of hours worked for the primary employer in a quarter divided by 13, using the sample summarized in Table 1, column 2. The sample is restricted to worker-quarter observations representing full quarters and primary employment (see the notes to Table 1). Observations with more than 100 hours per week have been dropped.

Figure 4
“Actual” hours worked in the previous week on the main job, Washington observations in the Current Population Survey Outgoing Rotation Groups, January 2001–December 2014



Notes: The distribution is based on the sample summarized in Table 1, column 4—see the notes to Table 1 for details.

Figure 5
Usual weekly hours worked on the main job, Washington observations in the Current Population Survey Outgoing Rotation Groups, January 2001–December 2014

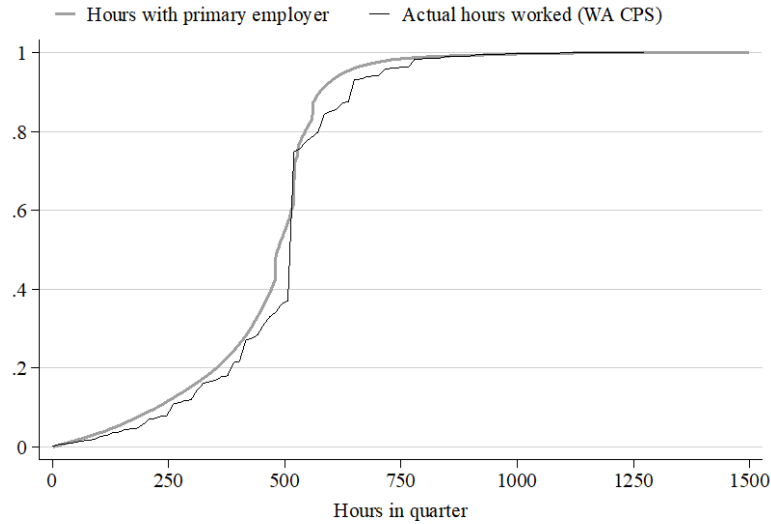


Notes: The distribution is based on the sample summarized in Table 1, column 4—see the notes to Table 1 for details.

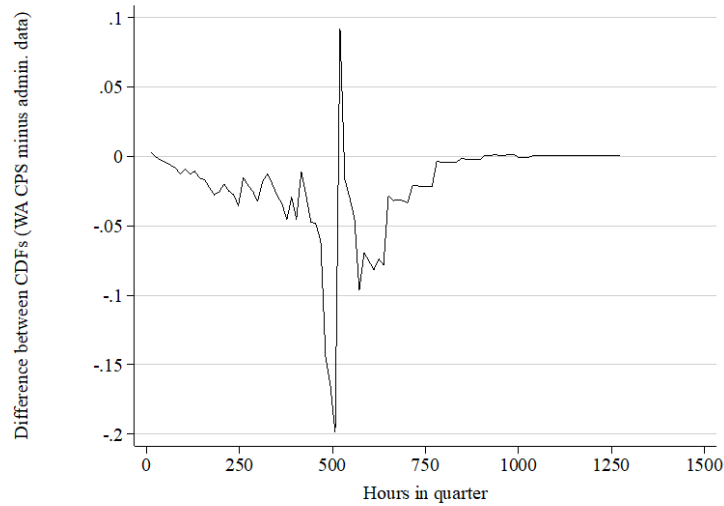
Figure 6

Empirical cumulative distribution functions (CDFs) of quarterly work hours, Washington administrative records (2001:1–2014:4) and actual hours worked, Washington observations in the Current Population Survey Outgoing Rotation Groups (January 2001–December 2014)

Panel A: CDFs



Panel B: Difference between CDFs

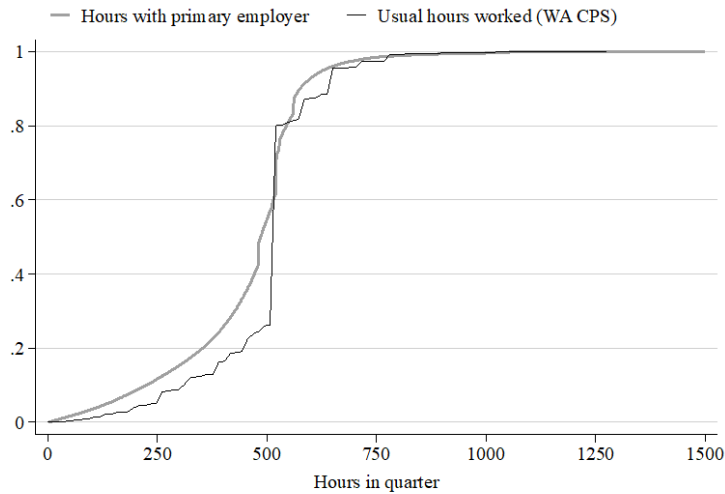


Notes: See the notes to Figures 2 and 4. For the CPS, “actual” hours last week have been converted to quarterly by multiplying the weekly values by 13. The data for the plots are obtained by collapsing the data to the mean CDF of each hour, then graphing these averages against hours per quarter. The vertical line denotes 520 hours per quarter (40 hours per week).

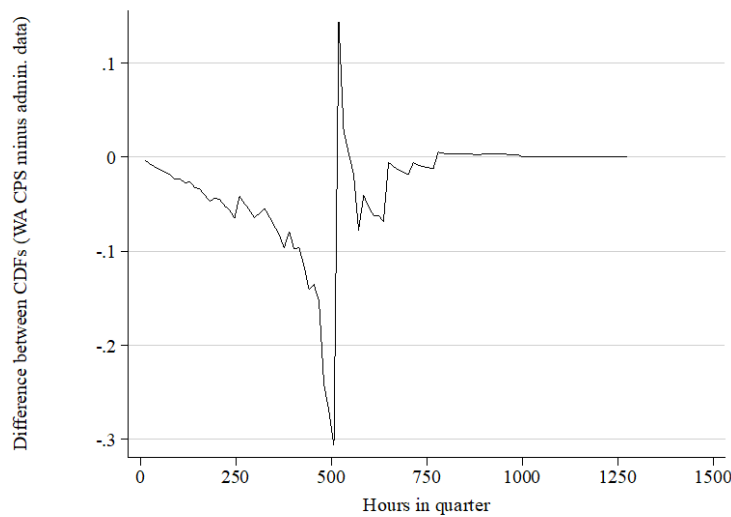
Figure 7

Empirical cumulative distribution functions (CDFs) of quarterly work hours, Washington administrative records (2001:1–2014:4) and usual hours worked, Washington observations in the Current Population Survey Outgoing Rotation Groups (January 2001–December 2014)

Panel A: CDFs

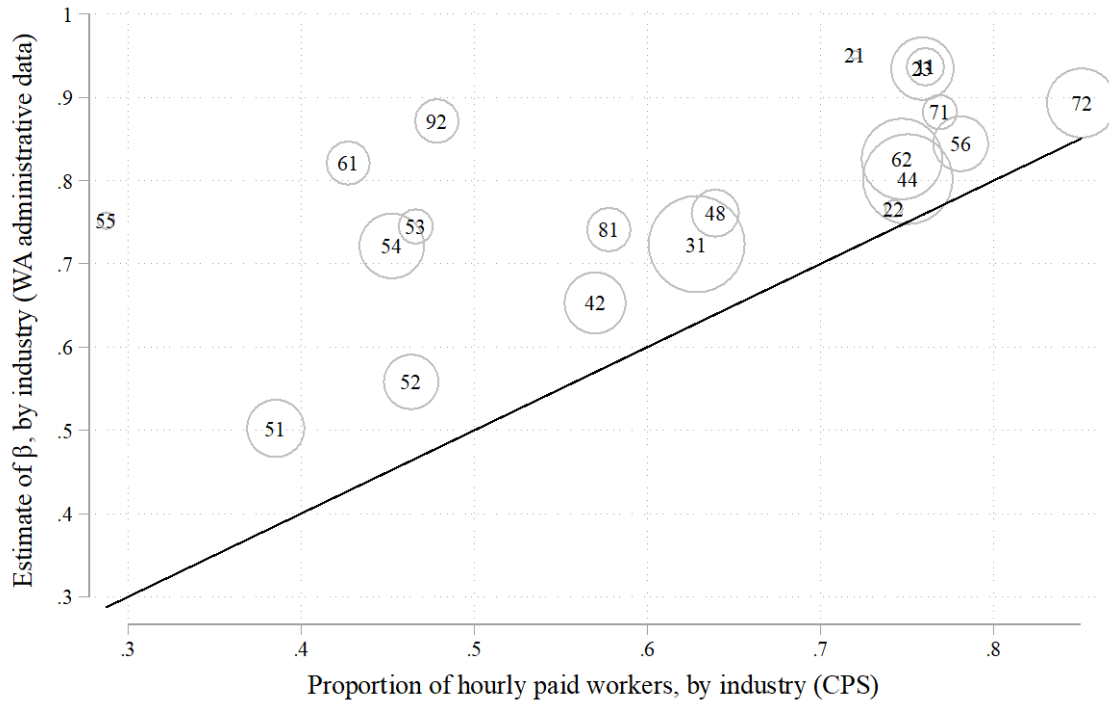


Panel B: Difference between CDFs



Notes: See the notes to Figures 2 and 5. Usual weekly hours worked in the CPS have been converted to quarterly hours by multiplying the weekly values by 13. The data for the plots are obtained by collapsing the data to the mean CDF of each hour, then graphing these averages against the hours per quarter. The vertical line denotes 520 hours per quarter (40 hours per week).

Figure 8
 Bin-scatterplot of estimated β (coefficient on $\Delta \log$ hours in equation (1)), by industry (Washington administrative data) against the proportion of hourly-paid workers (CPS)



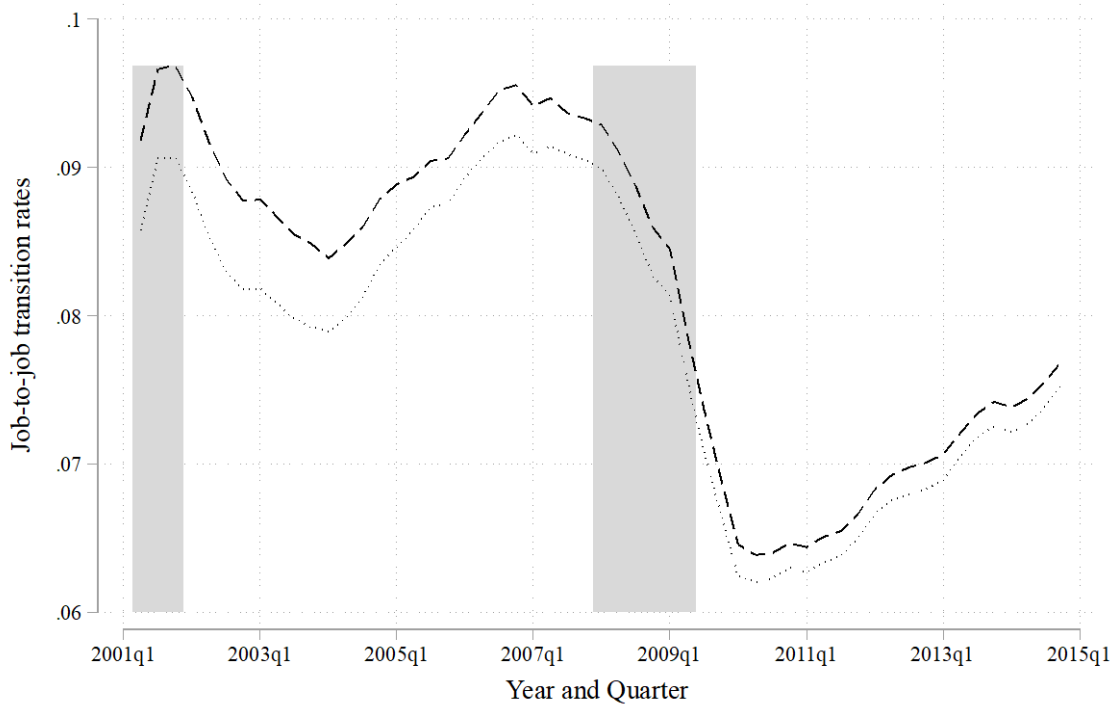
Notes: Estimated β s (coefficients on $\Delta \log$ hours in equation (1)) for each industry come from Table 3, column 1. The proportion of Washington workers in each industry paid on an hourly basis come from Table 3, column 3. (See the notes to Table 3 for details.) The solid line is a 45-degree line. The unweighted correlation between the values on the vertical and horizontal axes is 0.63, and the industry-size weighted correlation is 0.74. The weighted regression of β on the proportion of hourly-paid workers has an intercept of 0.397 and a slope coefficient of 0.582 ($R^2 = 0.55$). Table 1 includes definitions of the NAICS 2-digit industry codes.

Figure 9
 Hourly wage rate distributions and the Washington minimum wage, 2001–2014



Notes: Distributions shown are for non-missing wage rates less than \$15 per hour, using \$1 bins, constructed from the sample summarized in Table 1, column 2 (the sample of worker-quarter observations representing full quarters and primary employment). Each dark vertical line denotes the nominal Washington minimum wage in a given year. The distributions are presented by calendar year.

Figure 10
 Job-to-job transition rates in Washington 2001–2014



Notes: The dashed line shows the 4-quarter moving average job-to-job transition rate based on earnings. The numerator is the number of transitions defined as observations where a worker has a different primary employer in quarter $t+1$ than in t and has positive earnings in both t and $t+1$. The denominator is the total number of observations with positive earnings in t . The dotted line shows a 4-quarter moving average job-to-job transition rate based on reported hours. The numerator is the number of transitions defined as observations where a worker has a different primary employer in quarter $t+1$ than in t and has positive work hours in both t and $t+1$. The denominator is the total number of observations with positive work hours in t . The sample includes all worker-quarter observations of primary employment in the Washington administrative wage records, 2001:1–2014:4. Shaded bars denote recession quarters as defined by the National Bureau for Economic Research, imported from the Federal Reserve Bank of St. Louis (<https://fred.stlouisfed.org/series/USRECQ>, last accessed on August 24, 2021).

Table 1

Summary statistics for alternative samples in the Washington administrative wage records (2001:1–2014:4) and comparison samples from the Current Population Survey Outgoing Rotation Groups (Washington and United States, January 2001–December 2014)

	(1)	(2)	(3)	(4)	(5)
	Washington administrative wage records ¹			Current Population Survey, Outgoing Rotation Groups ²	
	All quarters, all worker-employer observations	Full quarters, primary worker-employer observations only	Full quarters, primary worker-employer observations with demographics	Washington	United States
Number of worker-quarter observations	177,386,793	80,170,975	25,842,865	n/a	n/a
Number of worker-month observations	n/a	n/a	n/a	14,968	775,729
Number of unique workers	7,620,144	4,628,295	1,349,864	11,798	617,805
Number of employers	482,645	332,609	220,217	n/a	n/a
Quarterly work hours, mean (std. err.)	363.2 (0.016)	459.5 (0.015)	473.8 (0.024)	n/a	n/a
"Actual" hours last week, mean (std. err.)	n/a	n/a	n/a	37.38 (0.10)	37.72 (0.01)
"Usual" weekly hours, mean (std. dev.)	n/a	n/a	n/a	38.43 (0.08)	38.59 (0.01)
Quarterly earnings (\$), mean (std. err.)	9,658 (0.725)	13,203 (4.53)	11,249 (3.20)	n/a	n/a
Weekly earnings (\$), mean (std. err.)	n/a	n/a	n/a	837.56 (4.33)	753.85 (0.57)
Wage rate (\$/hour), mean (std. err.)	32.23 (0.225)	28.34 (0.013)	23.86 (0.008)	n/a	n/a
Hourly wage rate (\$/hr) (std. dev.)	n/a	n/a	n/a	20.90 (0.10)	18.86 (0.02)
NAICS (two-digit industry)					
Agriculture, forestry, fishing, hunting (11)	0.049	0.023	0.023	0.012	0.007
Mining, quarrying, oil/gas extraction (21)	0.001	0.001	0.002	0.001	0.005
Utilities (22)	0.005	0.005	0.003	0.008	0.009
Construction (23)	0.060	0.063	0.112	0.051	0.047
Manufacturing (31)	0.096	0.149	0.177	0.124	0.117
Wholesale trade (42)	0.041	0.060	0.063	0.036	0.029
Retail trade (44)	0.117	0.130	0.111	0.104	0.106
Transportation and warehousing (48)	0.033	0.036	0.040	0.041	0.040
Information (51)	0.035	0.053	0.041	0.051	0.036
Finance and insurance (52)	0.033	0.048	0.044	0.029	0.036
Real estate, rental, leasing (53)	0.017	0.019	0.021	0.035	0.037
Professional, scientific, technical (54)	0.050	0.067	0.064	0.046	0.048
Mgt. of companies and enterprises (55)	0.003	0.004	0.005	0.006	0.007
Admin. and support and waste mgt. (56)	0.063	0.049	0.062	0.029	0.029
Educational services (61)	0.084	0.030	0.015	0.104	0.115
Health care, social assistance (62)	0.123	0.105	0.088	0.147	0.154
Arts, entertainment, recreation (71)	0.024	0.019	0.020	0.020	0.019
Accommodation and food services (72)	0.085	0.077	0.058	0.051	0.058
Other services (except public admn.) (81)	0.030	0.031	0.030	0.033	0.036
Public administration (92)	0.051	0.031	0.020	0.071	0.067
Missing or unknown (999)	0.000	0.000	0.000	n/a	n/a
Employer size (std. err.)	3,777 (0.903)	5,615 (1.81)	3,302 (2.48)	n/a	n/a
Employer size categories					
1-49 employees	0.297	0.311	0.339	n/a	n/a
50-249 employees	0.220	0.232	0.267	n/a	n/a
250-999 employees	0.186	0.170	0.184	n/a	n/a
1,000+ employees	0.298	0.287	0.210	n/a	n/a

1. All samples come from Washington quarterly administrative wage records, 2001:1–2014:4. Column 1 includes all worker-employer-quarter observations. (In column 1, a worker with two or more employers in a quarter contributes two or more worker-employer-quarter observations.) Column 2 includes only worker-quarter observations representing “full” quarters and primary employment. (A worker's primary employer is the employer from which the largest share of earnings was received in a quarter. In a “full” quarter, a worker with a given primary employer in quarter t had the same primary employer in quarters $t-1$ and $t+1$.) Column 3 is further restricted to workers for whom we observe demographic information (i.e., those who claimed UI at some time during 2001:1–2014:4). In columns 2 and 3, observations in the top and bottom 1% of the hours distribution have been dropped (> 809 hours/quarter and < 34 hours/quarter).

2. CPS samples are drawn from the outgoing rotation groups (CPS interviews 4 and 8) for each month from January 2001 through December 2014 (Flood et al., 2020) and include salaried and hourly paid workers

who were eligible for the so-called earner study. The sample excludes workers in the Annual Social and Economic Supplement (ASEC), workers whose labor force information was reported by proxy, and workers whose “actual” work hours last week were top-coded or allocated. All workers in the sample reported positive usual weekly earnings and work hours that were not top-coded or allocated.

Table 2
 Regression estimates of the change in log quarterly earnings on the change log of quarterly hours (equation (1)), Washington administrative wage records

	(1)	(2)	(3)	(4)
Change in log quarterly hours	0.800 (0.000)	0.800 (0.000)	0.800 (0.000)	0.800 (0.000)
Constant	0.013 (0.000)	0.013 (0.000)	0.013 (0.000)	0.013 (0.000)
Employer fixed effects	No	No	Yes	Yes
Standard errors	Standard	Clustered by worker	Standard	Clustered by worker
Number of quarter-to-quarter changes	70,188,078	70,188,078	70,188,078	70,188,078
Adjusted <i>R</i> -squared	0.499	0.499	0.499	0.499

Notes: The sample is the same as that described in column 2 of Table 1, but only “stayers”—workers observed with the same primary employer in consecutive full quarters—are in the estimation sample. Standard errors are in parentheses.

Table 3

Estimated β s (coefficient on $\Delta \log$ hours in equation (1)), by industry (Washington administrative data) and proportion of hourly paid workers (CPS)

NAICS 2-digit industry	(1)	(2)	(3)
	Washington administrative data		CPS
	Estimated β for the industry	Industry sample size	Proportion of Washington workers paid hourly
Agriculture, forestry, fishing, hunting (11)	0.94	1,437,269	0.76
Mining, quarrying, oil/gas extraction (21)	0.95	88,052	0.72
Utilities (22)	0.77	354,100	0.74
Construction (23)	0.94	4,257,898	0.76
Manufacturing (31)	0.72	10,919,465	0.63
Wholesale trade (42)	0.65	4,341,687	0.57
Retail trade (44)	0.80	9,008,397	0.75
Transportation and warehousing (48)	0.76	2,585,126	0.64
Information (51)	0.50	3,879,013	0.39
Finance and insurance (52)	0.56	3,474,484	0.46
Real estate, rental, leasing (53)	0.75	1,329,025	0.47
Professional, scientific, technical (54)	0.72	4,765,274	0.45
Management of companies and enterprises (55)	0.75	308,300	0.29
Administrative and support and waste mgt. (56)	0.84	3,140,164	0.78
Educational services (61)	0.82	2,151,240	0.43
Health care, social assistance (62)	0.83	7,407,072	0.75
Arts, entertainment, recreation (71)	0.88	1,297,991	0.77
Accommodation and food services (72)	0.89	5,033,149	0.85
Other services (except public administration) (81)	0.74	2,125,007	0.58
Public administration (92)	0.87	2,284,627	0.48
Missing or unknown (999)	0.74	738	—
All observations	0.80		0.63

Notes: Samples used to estimate β for each industry (column 1) are subsets of the sample described in column 2 of Table 1, but only “stayers”—workers observed with the same primary employer in consecutive full quarters—are in the estimation sample. (The estimates come from the version of equation (1) that does not control for employer fixed effects.) Column 2 (“Industry sample size”) shows the number of quarter-to-quarter changes in earnings and hours used to estimate β for each industry. The proportion of Washington workers in each industry paid on an hourly basis (column 3) is based on the CPS sample described in Table 1, column 4.

Table 4
Hourly wage rate and earnings regressions, Washington administrative wage records, 2013:2

Control variables	Mean (std. dev.)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Dependent variable: log wage rate				Dependent variable: log earnings			
NAICS 3-digit industry indicators	—	No	Yes	No	No	No	Yes	No	No
Employer fixed effects	—	No	No	Yes	Yes	No	No	Yes	Yes
Education × employer interaction terms	—	No	No	No	Yes	No	No	No	Yes
Age	43.57 (11.57)	0.058*** (0.000)	0.046*** (0.000)	0.035*** (0.000)	0.034*** (0.000)	0.083*** (0.001)	0.066*** (0.001)	0.052*** (0.000)	0.050*** (0.000)
Age squared/100	—	-0.060*** (0.000)	-0.046*** (0.000)	-0.033*** (0.000)	-0.033*** (0.000)	-0.089*** (0.001)	-0.070*** (0.001)	-0.053*** (0.000)	-0.052*** (0.001)
Educational attainment									
Less than high school	0.093	-0.186*** (0.003)	-0.121*** (0.002)	-0.065*** (0.002)	n/a	-0.216*** (0.003)	-0.138*** (0.003)	-0.070*** (0.003)	n/a
GED diploma	0.040	-0.076*** (0.003)	-0.048*** (0.003)	-0.021*** (0.003)	n/a	-0.088*** (0.005)	-0.053*** (0.004)	-0.026*** (0.004)	n/a
High school graduate	0.357	reference	reference	reference	n/a	reference	reference	reference	n/a
Some college, no degree	0.178	0.134*** (0.002)	0.117*** (0.002)	0.072*** (0.001)	n/a	0.149*** (0.003)	0.130*** (0.002)	0.076*** (0.002)	n/a
Associate's degree	0.130	0.116*** (0.002)	0.095*** (0.002)	0.049*** (0.002)	n/a	0.103*** (0.003)	0.086*** (0.003)	0.037*** (0.002)	n/a
Bachelor's degree	0.159	0.404*** (0.002)	0.345*** (0.002)	0.212*** (0.002)	n/a	0.425*** (0.003)	0.357*** (0.002)	0.204*** (0.002)	n/a
Master's, professional, or doctorate	0.043	0.668*** (0.003)	0.583*** (0.003)	0.402*** (0.003)	n/a	0.690*** (0.004)	0.597*** (0.004)	0.387*** (0.004)	n/a
Gender									
Female	0.404	-0.256*** (0.001)	-0.148*** (0.001)	-0.103*** (0.001)	-0.097*** (0.001)	-0.369*** (0.002)	-0.219*** (0.002)	-0.156*** (0.002)	-0.149*** (0.002)
Race/ethnicity									
White non-Hispanic	0.731	reference	reference	reference	reference	reference	reference	reference	reference
Black non-Hispanic	0.042	-0.175*** (0.003)	-0.109*** (0.003)	-0.101*** (0.003)	-0.092*** (0.003)	-0.193*** (0.004)	-0.113*** (0.004)	-0.120*** (0.003)	-0.109*** (0.004)
Hispanic	0.086	-0.145*** (0.003)	-0.083*** (0.002)	-0.066*** (0.002)	-0.054*** (0.002)	-0.117*** (0.003)	-0.062*** (0.003)	-0.063*** (0.003)	-0.049*** (0.003)
Asian/Pacific Islander	0.081	-0.058*** (0.002)	-0.045*** (0.002)	-0.072*** (0.002)	-0.065*** (0.002)	-0.022*** (0.003)	-0.019*** (0.003)	-0.053*** (0.003)	-0.044*** (0.003)
American Indian or Alaskan Native	0.017	-0.101*** (0.005)	-0.073*** (0.005)	-0.041*** (0.004)	-0.037*** (0.004)	-0.118*** (0.007)	-0.090*** (0.006)	-0.066*** (0.006)	-0.057*** (0.006)
Missing, unknown or not available	0.043	-0.008** (0.003)	-0.002 (0.003)	-0.018*** (0.002)	-0.016*** (0.003)	-0.027*** (0.004)	-0.018*** (0.004)	-0.033*** (0.003)	-0.027*** (0.004)
Constant	—	1.778*** (0.009)	1.987*** (0.008)	2.222*** (0.007)	n/a	7.423*** (0.012)	7.741*** (0.011)	8.022*** (0.010)	n/a
Dependent variable mean (std. dev.)			3.058 (0.539)				9.172 (0.694)		
Adjusted R-squared		0.243	0.401	0.632	0.647	0.203	0.365	0.597	0.613

Notes: Estimates are based on the sample of 505,745 primary-employer/full-quarter observations for whom we observe demographic characteristics in the Washington administrative records in 2013:2. This is a subset of the sample described in Table 1, column 3. (We observe demographics only for workers who claimed UI at some time during 2001:1–2014:4.) In addition to the sample restrictions described in the notes to Table 1, we restrict the sample to include only workers aged 25 or older. Standard errors are in parentheses (** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 5
Hourly wage rate and weekly earnings regressions, Current Population Survey Outgoing Rotation Groups,
United States, 2013

Control variables	Mean (std. dev.)	Dependent variable			
		Log hourly wage rate		Log weekly earnings	
		(1) No	(2) Yes	(3) No	(4) Yes
NAICS 3-digit industry indicators	–				
Age	44.8 (12.2)	0.049*** (0.001)	0.040*** (0.001)	0.082*** (0.002)	0.069*** (0.002)
Age squared/100	–	-0.049*** (0.001)	-0.039*** (0.001)	-0.088*** (0.002)	-0.075*** (0.002)
Educational attainment					
Less than high school	0.058	-0.217*** (0.011)	-0.144*** (0.011)	-0.262*** (0.014)	-0.184*** (0.014)
High school graduate	0.244	reference	reference	reference	reference
Some college, no degree	0.182	0.123*** (0.007)	0.096*** (0.007)	0.142*** (0.009)	0.118*** (0.009)
Associate's degree	0.125	0.238*** (0.008)	0.180*** (0.008)	0.254*** (0.011)	0.202*** (0.010)
Bachelor's degree	0.251	0.444*** (0.007)	0.373*** (0.007)	0.489*** (0.009)	0.427*** (0.009)
Master's, professional, or doctorate	0.140	0.631*** (0.008)	0.574*** (0.008)	0.693*** (0.010)	0.665*** (0.010)
Gender					
Female	0.543	-0.194*** (0.005)	-0.138*** (0.005)	-0.329*** (0.006)	-0.236*** (0.006)
Race/ethnicity					
White non-Hispanic	0.718	reference	reference	reference	reference
Black non-Hispanic	0.101	-0.102*** (0.008)	-0.093*** (0.008)	-0.091*** (0.010)	-0.076*** (0.010)
Hispanic	0.111	-0.096*** (0.008)	-0.071*** (0.008)	-0.099*** (0.010)	-0.069*** (0.010)
Asian/Pacific Islander	0.054	0.017 (0.011)	0.014 (0.010)	-0.001 (0.014)	-0.005 (0.013)
American Indian or Alaskan Native	0.016	-0.114*** (0.019)	-0.093*** (0.018)	-0.101*** (0.024)	-0.071*** (0.023)
Other race/ethnicity	0.001	0.160 (0.099)	0.178* (0.091)	0.182 (0.125)	0.180 (0.116)
Constant	–	1.651*** (0.031)	1.853*** (0.029)	4.730*** (0.039)	4.967*** (0.037)
Dependent variable mean (std. dev.)		2.923 (0.594)		6.555 (0.751)	
Adjusted R-squared	–	0.231	0.342	0.222	0.329

Notes: Estimates are based on a sample of 40,040 observations drawn from the Current Population Survey Outgoing Rotation Groups from January–December 2013 (Flood et al., 2020). This is a subset of the sample described in Table 1, column 5. In addition to the sample restrictions described in the note to Table 1, workers younger than age 25 have been dropped. For salaried workers, we calculate an hourly wage by dividing usual weekly earnings by usual weekly hours. For hourly workers, we use the hourly wage reported in the outgoing rotation group interview. Standard errors are in parentheses (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).