Labor Supply and the Value of Non-Work Time: Experimental Estimates from the Field *

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July 2017

Abstract

We use a field experiment to estimate the marginal value of non-work time (MVT). During a national application process for phone survey and data entry positions, we randomly offered applicants alternative wage-hour bundles. Jobseeker choices over these bundles yield estimates for the MVT as a function of hours worked. These quantities trace out a labor supply relationship. As predicted by the conventional model of the allocation of time, the substitution effect is positive. Individual labor supply is highly elastic at low hours and becomes more inelastic at higher hours. For unemployed job applicants, the opportunity cost of a full-time job due to lost leisure, household production, and other non-work activities is approximately 60% of their estimated market wage. A similar estimate is found when we reproduce elements of this experiment in a nationally-representative survey.

1 Introduction

The flow value of non-work time relative to a worker's marginal product is a crucial parameter in many macroeconomic models, including search models that seek to explain wage dispersion (Hornstein, Krusell and Violante, 2011) and the business cycle volatility of unemployment and vacancies (Shimer, 2005; Hagedorn and Manovskii, 2008). This parameter, which we denote as z, is typically calibrated, and for predictions of models to match the data it often requires extreme levels. For example, Hornstein, Krusell and Violante (2011) show that z has to be very low, even negative, in order for frictional wage dispersion to match observed wage dispersion. A very high value of z is required to match the business cycle volatility of unemployment and vacancies in the Mortensen-Pissarides (Mortensen and Pissarides, 1994) search and matching model (Hagedorn and Manovskii, 2008). As noted by Aguiar, Hurst and Karabarbounis (2013), understanding how individuals value marginal leisure time is necessary for computing the welfare costs of business cycles. Despite the relevance of this parameter to models of the wage structure and the business cycle, there is an active debate about its level, in large part because it is difficult to measure directly.[1]

We seek to fill this gap by estimating z using a natural field experiment. During two national application processes, one to staff a call center and the other to fill data entry positions, we asked workers to choose between two jobs with different hours per week and randomly-assigned wages. We use observed choices to estimate the marginal value of time (MVT) at different levels of weekly work hours. These estimates trace out a labor supply relationship from which we can back out parameters that are central to numerous applications, including the value of non-work time and labor supply elasticities.

In the experiment we posted ads on a major national job board for real phone survey and data entry positions. To isolate a substitution effect and eliminate the role of commuting times the positions were advertised as temporary and work from home.[2] Interested applicants, the majority who were female, were asked to choose between two positions that differed only in the number of weekly hours of work and the hourly wage. We use their choices and a simple discrete choice model to estimate the average wage workers are willing to accept to increase their working time by five hours per week. We use a similar procedure based on willingness to work overtime at varying overtime premia to estimate the wages workers are willing to accept to increase hours from 40 to 45 and 45 to 50 hours per week. To assess generality, we weight estimates to match the characteristics of hourly workers in the Current Population Survey based on age,

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[1]Borgschulte and Martorell (forthcoming) estimate a variant of z using reenlistment decisions of armed service personnel as a function of the unemployment rate, and their sensitivity to bonus payments. Chodorow-Reich and Karabarbounis (2016) argue that cyclical variation in average hours worked and consumption results in pro-cyclical variation in z, but in their calibration a large range of levels of z is possible.

[2]These characteristics accurately described the real jobs.

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gender, race, and education. We compare our estimates with data from a survey module we designed for the nationally-representative Understanding America Study (UAS).

For unemployed job applicants, we find that below 40 work hours MVT is increasing, but gradually. At 15 hours of work, the mean weighted MVT in our sample is 50% of the predicted market wage of jobseekers, and at 35 hours of work it is 86%. Above 40 hours the MVT increases substantially. At 40-45 hours it is 157% and at 45-50 hours it is 165% of workers' predicted market wage. Since the collection of MVT values trace out a labor supply function, we can use the MVT estimates to compute compensated labor supply elasticities. At low hours of work labor supply is highly elastic. Below 30 hours the elasticity of hours with respect to the wage is greater than 1. At or above 40 hours it is in the 0.4-0.6 range.

We use the MVT estimates of unemployed applicants along with their predicted market wage to estimate the flow value of non-work time relative to their market wage. For a full-time job, the estimates imply a value of non-work time relative to predicted pre-tax earnings of approximately $z = 0.6$. We get similar estimates when we weight the sample to match the age, gender, education and race distribution of hourly workers in the United States and when we use a hypothetical choice experiment in the nationally-representative Understanding America Study. Estimated z is moderately lower for unemployed jobseekers than for employed jobseekers but otherwise fairly stable when comparing across gender, local economic conditions, and unemployment insurance eligibility.

The overall body of evidence suggests that z is in the intermediate to higher range of values used in the search literature. Because both options presented to jobseekers required them to incur any fixed cost of employment, the experiment isolates the variable component of the opportunity cost that varies with time spent working. This includes substitution away from leisure, home production and child care.[3] It does not incorporate fixed costs like a potential reduction in unemployment insurance (UI) benefits or the cost of commuting. These fixed costs, if quantified, can be added on to our estimate. Note that with a replacement rate of 0.4, a worker with UI benefits in our sample could have a value of non-work time relative to their market wage of close to unity.[4]

Our estimates are also useful for value of time measurement that enters into benefit-cost analyses. Value of time is often explicitly incorporated into analyses of public policies that affect work hours, such as infrastructure projects. While the market wage is a good approximation to the opportunity cost of employed workers, for the unemployed the opportunity cost of work is difficult to measure since it reflects activities

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[3]It does not include any fixed cost of child care.

[4]However, as Chodorow-Reich and Karabarbounis (2016) note, on average the effective UI replacement rate of jobseekers is low due to low eligibility and take-up levels and cross-program effects with SNAP and Medicaid such as those found by Leung and O'Leary (2015).

that occur outside of the market, such as leisure, home production, and other non-work activities (Harberger, 1971, Bartik, 2012). This value is what we estimate.

Another noteworthy finding is that the shape of the implied labor supply function is only moderately increasing at low hours of work and becomes increasingly steeper at traditional full-time hours. The intensive margin labor supply elasticity therefore changes with hours worked. Labor supply estimated at particular hours levels may not generalize to other hour levels.

Our study is most closely related to survey measures of the reservation wage, such as Feldstein and Poterba (1984), Holzer (1986), and Krueger and Mueller (2016). The reservation wage is related to the flow value of non-market time, but it may differ if unemployed workers take into account the continuation value of unemployment (Mortensen, 1987) or if beliefs about attainable wages are biased (Krueger and Mueller, 2016). In addition, most reservation wage questions refer to a generic job without specifying the hours of work. Our approach allows us to measure the value of time at differing levels of hours of work. Since we find that the marginal value of non-work time is increasing in work hours, the lowest wage required for a worker to accept a 20 hour job will be lower than the lowest wage required for a worker to accept a 40 hour job. Importantly, our experimental measure is based on decisions of jobseekers in a natural environment. Our paper also adds to a small literature that uses field experiments to estimate labor supply relationships. Papers in the literature include Fehr and Goette (2007), Goldberg (2016), and Angrist et al. (2017). We also add to a larger quasi-experimental labor supply literature in situations where hours can vary freely, including Camerer et al. (1997), Oettinger (1999), Farber (2005), Farber (2008), Ashenfelter, Doran and Schaller (2010), Chen and Sheldon (2015), Farber (2015), Stafford (2015) and Chen et al. (2017).

The rest of the paper proceeds as follows. Section 2 lays out the experimental design, while Section 3 presents our conceptual framework and estimation strategy. Section 4 contains the main results on MVT and labor supply elasticity, while Section 5 explores heterogeneity in MVT. Finally, Section 6 concludes with a discussion of our results.

2 Experimental Design

The experimental design is similar to the one detailed in Mas and Pallais (forthcoming), with a number of elements that differ. Our experiment took place in 2017 during the hiring process to fill telephone interviewer and data entry positions. We posted advertisements for these real positions on a national U.S. job search platform in 80 large metro areas. The text of these ads is presented in Appendix Figure 1.[5] The ads provided

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[5]The desired skills specified were "good communication skills", "ability to work with others", and being "used to basic computer and/or mobile applications."

no information about the number of hours of work or the wage.

The ad had a link to our website where interested jobseekers could apply for a position. Once applicants followed the link, they could apply by creating an account and providing their year of birth, race/ethnicity and gender. The site prominently stated that providing race/ethnicity and gender was optional and that the questions could be skipped, though the vast majority of applicants responded.[6] After registering, applicants were shown two descriptions of job positions. To eliminate the possibility of income effects, both descriptions stated explicitly that the job was temporary and was expected to last one month, while to eliminate the role of commuting they stated that the job was work-from-home. All of these statements accurately described the real jobs.[7] The two positions differed only in the number of hours of work and the hourly wage, which were randomly assigned to applicants.[8] Individuals were asked to choose between a job that was [X] hours and a job that was [X+5] hours per week, where X varies from 5 to 35 in 5-hour increments.[9] The position descriptions were as follows:

"The position is a one-month work-from-home [type] position. ¶ The position is [X] hours per week. ¶ This position pays [Y] dollars per hour.

"The position is a one-month work-from-home [type] position. ¶ The position is [X+5] hours per week. ¶ This position pays [Z] dollars per hour.

In this comparison *[type]* denotes whether the position is for phone survey or data entry work and *[Y]* and *[Z]* are dollar amounts, described in detail below. All individuals were shown either two phone survey positions or two data entry positions.[10]

Each comparison can be summarized by the "effective" wage applicant *i* receives for working the 5 additional hours in the longer position:

$$e_{ih} = \frac{h_i \times w_{ih} - (h_i - 5) \times w_{ih-5}}{5}.$$

where h_i and w_{ih} are the number of hours and hourly wage in the longer job, respectively and w_{ih-5} is

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[6]By mistake, gender and race were not asked of some applicants. Of those who were asked, 94.7% percent of applicants provided their race and 95.3% provided their race. Overall, we have race information for 84.4% of the sample and gender for 85.0%. Results are similar if we restrict attention to the applicants for whom we collected gender or race.

[7]We have made 60 job offers.

[8]As noted in Mas and Pallais (forthcoming), we opted to show only two options to minimize cognitive load for the applicants.

[9]That is, the choices were 5 vs. 10, 10 vs. 15, 15 vs. 20, 20 vs. 25, 25 vs. 30, 30 vs. 35, and 35 vs. 40 hours per week.

[10]The ¶ indicates a line break.

the hourly wage in the shorter job. We randomly select $e_{ih} \in \{0, 4, 8, 12, 16, 18, 20, 24, 28\}$. For the three lowest hours choices (5 vs. 10, 10 vs. 15, and 15 vs. 20 hours), we let e_{ih} also take values of $\{2, 6, 10\}$. Piloting suggested that individuals' value of time would be lower at these hours levels and adding these lower effective wages would lead to less extrapolation.

The randomly-chosen effective wage determined the wages of the jobs. The higher hourly wage job always paid \$18. This was sometimes the shorter position and sometimes the longer position, depending on whether the effective wage was above or below \$18. The wage of the other job was adjusted so that e_{ih} took the selected value. For example, for $e_{ih} = 0$ in the 25 vs. 30 hour comparison, the 25 and 30 hour jobs pay the same weekly amount. Thus, the lower-hour (25 hour) job must pay \$18 per hour and the 30 hour job must pay \$15 per hour.[11] Without income effects, willingness to accept the higher hour position will depend on the effective wage e_{ih}, but not on the wage levels presented, w_{ih} and w_{ih-5}.[12] Appendix Table 1 shows the wages for each effective wage/hours combination. We rounded all wages to the nearest \$0.10, so the actual effective wage shown is not always a perfectly round dollar amount. In our estimation, we use the actual (non-rounded) effective wage.

Appendix Figure 2 provides an example of the page with the job descriptions. This page was designed to ensure that only the hour and wage information would affect workers' choice. To this end we referred to jobs only by number to minimize the extent to which job titles would affect workers' choices.[13] To maximize the fraction of applicants who read both job applications carefully, we forced applicants to physically click on each position to see the job descriptions. We also required applicants to manually type the number of the job they preferred to lessen the tendency to simply click through to the next page. We randomized which job was presented first.

We told applicants that the type of work in both jobs was the same and asked them which job they would choose if both were available. We told applicants that if they were hired they would be offered the position they chose, thereby making this a real decision. However, we also told applicants that they would be considered for all open positions. This was done to give us flexibility to also offer them more generous alternatives. We emphasized that their decision would not affect whether they were hired. All of these statements were truthful. Most workers (73%) who made a job choice completed the application. Our main analysis uses all choices made, but we show in an appendix table that the results are similar if we restrict

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[11]We do not include a \$28 effective wage for the 5 vs. 10 hour comparison as this would require the 5 hour job to pay \$8, below the minimum wage in many of the cities in our experiment.

[12]If there are income effects, higher values of w_{ih} and w_{ih-5} will result in a higher break-even effective wage for working five more hours.

[13]These numbers were randomly assigned to jobs. The numbers were also balanced within comparisons, so if some individuals were given a choice between Position #78 which was 30 hours per week and Position #81 which was 35 hours per week, other participants would be faced with a choice between Position #81 which was 35 hours and Position #78 which was 30 hours.

attention to workers who ultimately applied for the jobs.

We are also interested in how workers value their time above 40 hours per week. The difficulty is that by the Fair Labor Standards Act (FLSA) hourly workers have to get an overtime premium of at least 1.5 times their hourly pay for hours above 40. If we were to present the choice of 40 versus 45 hours or 45 versus 50 hours without mentioning overtime, it would be unclear how to interpret the choices since some applicants might assume there was overtime pay while others would not. Therefore, for randomly-selected applicants we implemented a second set of treatments where we offered the choice of either (1) a 40 versus 45 hour position or (2) a 45 or 50 hour position. Here, we randomly varied the overtime premium for hours over 40. The 40 hour choice read:

"The position is a one-month work-from-home [type] position. ¶ The position is 40 hours per week. ¶ This position pays 18.00 dollars per hour.

The 45 and 50 hour position descriptions read:

"The position is a one-month work-from-home [type] position. ¶ The position is [45/50] hours per week. ¶ This position pays 18.00 dollars per hour for the first 40 hours and [EW] dollars per hour for the remaining [5/10] hours.

Here, *EW* is the effective wage since both jobs pay the same wage up to 40 hours of work. We randomly select $EW \in \{27, 29, 31, 33, 35\}$. In the 45 versus 50 hour choice, the same *EW* is utilized in both positions. Due to the FLSA, $27 was the lowest overtime wage we could offer. A concern for comparing MVT estimates above and below 40 hours is that perhaps applicant responses differ depending on whether they are comparing average wages (below 40 hours) or marginal wages (above 40 hours). To assess this possibility we ran a separate validation study where we offered a 35 versus 40 hour choice with the same effective wages to different applicants, randomly phrasing the comparison as either (1) two differing wage rates or (2) the same wage rate up to 35 hours and a separate marginal rate for hours between 35 and 40. As we will show, both methodologies give similar results.[14]

Another issue is that for the 40 vs. 45 hour comparison there is significant extrapolation in calculating

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[14]An alternative to our approach would be to vary the marginal wage (as in the overtime comparisons) at all hours levels. We chose not to do this because of the minimum wage constraint. Varying the marginal wage only would not allows us to detect MVT values below the minimum wage which, depending on the state, are substantially higher than median MVT we estimate at low hours.

the MVT since mean MVT is below \$27 and at an effective wage of \$27 about three quarters of applicants choose the 45 hour job. Below we describe our approach to dealing with this extrapolation. Our estimates of the flow value of non-work time will not utilize MVT estimates above 40, so these issues are only relevant for evaluating the shape of the labor supply curve.

As found in Mas and Pallais (forthcoming), despite the fact that we forced applicants to physically click on the job descriptions and type the number of their preferred job, some applicants were inattentive. On the page after individuals made their choice, we asked them to report the number of hours they chose. They were presented with 11 choices (5 through 50 hours in 5 hour increments and "I don't remember"). Overall, 0.6% of people said they didn't remember and 9.0% chose incorrectly, indicating an 10.6% inattention rate.[15] We account for inattention in our estimation as described in Section 3. In practice, this inattention matters little when estimating the average value of time, but affects estimated dispersion.

Our focus in the paper will be on unemployed jobseekers because for this group there is a natural interpretation of MVT as the value of non-work time. For employed jobseekers, MVT likely includes not just leisure and household production but also possibly the wage in other jobs if they have to substitute hours between jobs. For completeness, we show estimates for the full sample as well.

3 Conceptual and Econometric Framework

Applicants are shown a shorter and a longer job, whose hours and wages are given by $\{h_i - 5, w_{ih-5}\}$ and $\{h_i, w_{ih}\}$, respectively. We use applicants' choices over a range of effective wages to determine the average mean value of time between $h - 5$ and h weekly hours of work ($\overline{MVT_h}$). We calculate z by combining $\overline{MVT_h}$ over different values of h up to 40 hours per week.

Applicant i chooses the higher hour package if $U((h_i w_{ih}, h_i) > U((h_i - 5) w_{ih-5}, h_i - 5)$. If the individual is fully attentive, she chooses the longer job if the effective wage (e_{ih}, defined in Equation 1) exceeds her average hourly opportunity cost of working 5 additional hours (MVT_{ih}), that is, if $MVT_{ih} < e_{ih}$. Assuming a logistic distribution for MVT_{ih} (an assumption that we can assess visually), we can estimate a logit with an indicator for choosing the longer position as the dependent variable and the effective wage e_{ih} as the explanatory variable. In this setup, our estimate of $\overline{MVT_h}$ is the estimated intercept divided by the slope coefficient.

To account for the fact applicants are inattentive, we estimate a mixture model of the form $Pr(h_i = $

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[15]To determine the inattention rate, we add the number of people reporting they did not remember and the fraction choosing incorrectly multiplied by 10/9. The 10/9 factor is to correct for the fact that 1/10 of the people who were inattentive but didn't report not remembering chose correctly by chance.

$1|e_{ih}) = P_e(1-\alpha) + (1-P_e)\alpha = F(be+c;\mu,\sigma)(1-2\alpha) + \alpha$ using maximum likelihood (ML), where $Pr(h_i = 1|e_{ih})$ is the probability of choosing the longer-hour job and P_e is the probability that an attentive individual truly prefers the longer-hour job. Here, 2α is the fraction of individuals who are inattentive (10.7% on average), calculated from whether individuals correctly recalled the number of hours they chose. Under the assumption that inattentive individuals make their choice at random, α will choose the longer job and α will choose the shorter job, regardless of the wages presented. (This inattention correction largely only affects estimated dispersion.) We assume a logistic cdf, though other cdfs provide similar estimates. In this model, our estimate of $\overline{MVT_h}$ is the intercept divided by the coefficient on the effective wage term.

We modify this procedure to estimate MVT for the overtime treatments. The FLSA necessitates we offer high effective wages in these treatments, so estimating the average MVT requires extrapolation in the 40-45 hour treatment. (Average MVT is higher between 45-50 hours so estimation in this hours choice requires almost no extrapolation, as will be seen in the data.) Estimating the above model, we constrain the intercept, $Pr(h_i = 1|e_{ih} = 0)$, based on the intercept in the non-overtime treatments, which allows the non-overtime treatments to inform the extrapolation, dramatically increasing precision in the 40 vs. 45 hour choice. Our preferred specification uses the estimated intercepts at lower hour treatments to predict the intercept as a function of h. We then constrain the intercepts in the two overtime treatments as the predicted intercepts at $h = 45$ and $h = 50$. We show estimates under different methods of picking the intercept constraint (e.g., using the average intercept or the estimated intercept in the 35 vs. 40 hour comparison) and results are very similar. Adding this constraint has almost no effect on estimates of mean MVT for the 45 vs. 50 hour treatment, where there was little extrapolation or imprecision without it.

MVT_{ih} is the wage that makes individual i indifferent between working $h_i - 5$ and h_i hours per week. Because theoretically work hours are set to equate the wage with the shadow value of time (Becker, 1965; Gronau, 1977; Heckman, 1974), MVT_{ih} is an approximation to $i's$ inverse labor supply function between $h_i - 5$ and h_i hours. Note that applicants cannot choose their exact desired number of hours; they can only choose $h_i - 5$ and h_i. If their labor supply function is strictly increasing, at MVT_{ih} dollars per hour, their inverse labor supply function $w_i(.)$ has $w_i(h_i - 5) < MVT_{ih} < w_i(h_i)$. That is, their value of time at h_i hours exceeds their average value of time between $h_i - 5$ and h_i hours (MVT_{ih}) which exceeds their value of time at $h_i - 5$ hours. At a wage of MVT_{ih}, they would choose to work strictly between $h_i - 5$ and h_i hours per week. Because all jobs were explicitly temporary (1 month long), we assume there are no income effects. Without income effects, the marginal rate of substitution between consumption and leisure at a given number of hours does not depend on the consumption level; in this case, MVT_{ih} does not depend on the wage paid up to $h_i - 5$ hours.

Note that $\overline{MVT_h}$ is an approximation to the average individual inverse labor supply curve. It gives the wage the average individual needs to work h (as opposed to $h-5$) hours. It is not an approximation to an aggregate labor supply curve. That is, it is not the wage at which, across the population, hours of work average h.[16]

To form our estimate of the average z, the flow value of non-work time for a full-time 40 hour job, we utilize the fact that $\overline{MVT_h}$ provides the average value of time between $h-5$ and h hours. Our experiment does not provide the average value of time between 0 and 5 hours since no applicants were given that choice. We estimate $\overline{MVT_5}$ using a linear prediction determined by $\overline{MVT_{10}}$ and $\overline{MVT_{15}}$. Other estimation methods give similar results. Then our estimate of the average z is simply

$$\hat{z} = \frac{1}{\hat{w}} \left[\frac{5(\overline{MVT_5} + \overline{MVT_{10}} + ... + \overline{MVT_{40}})}{40} \right].$$

Here, $\hat{w}$ is average predicted pre-tax hourly market wage. This term is calculated using applicant gender, race, education, and age and data from the 2016 Current Population Survey Monthly Outgoing Rotation Groups (CPS MORGs). Specifically, we predict an applicant's wages as the average wage of workers in the CPS with his or her gender, race, and education, and in his or her 5-year age bin.[17] For unemployed applicants we discount the resulting wage by 6%, which is the estimated wage penalty for employed hourly workers who left or lost their jobs in the last three years in the 2016 CPS Displaced Worker Supplement.[18] Then, $\hat{w}$ is the average predicted wage of all applicants.

After estimating the model on each treatment sample individually, we combine the parameter estimates and covariance matrices from all treatments (including overtime treatments) and calculate robust standard errors on MVT estimates and z's using the delta method.

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[16]To see this, imagine that at a wage of $\overline{MVT_h}$, individuals with $MVT_{ih} > \overline{MVT_h}$ may choose to work only a few hours less than h, whereas individuals with $MVT_{ih} < \overline{MVT_h}$, may choose to work many more hours In this case, average hours would exceed h.

[17]When applicants didn't report one or more of the characteristics used to assign wages, we assigned them the average wage of CPS respondents with the characteristics they did report weighted by the distribution of the missing characteristic(s) in the experiment data. For example, consider a 27 year-old white woman who didn't report her education. From the overall distribution of education levels in the data, her predicted wage is (0.02)*(average CPS wage of 25-30 y/o white women with less than HS) + (0.27)*(average CPS wage of 25-30 y/o white women with a high school degree) + (0.44)*(average CPS wage of 25-30 y/o white women with some college) + (0.24)*(average CPS wage of 25-30 y/o white women with a college degree) + (0.04)*(average CPS wage of 25-30 y/o white women with an advanced degree).

[18]Specifically, the sample is all employed hourly workers in the 2016 Displaced Worker Supplement. We regress log wages on a quadratic in age, education dummies, race/ethnicity dummies, gender dummies, and an indicator for whether the respondent left or lost his or her job in the previous three years.

4   Results

4.1   Descriptive Statistics and Randomization Assessment

The first column of Table 1 provides descriptive statistics for our sample. The majority (83%) of our sample is female. This is in large part because phone survey and data entry workers are primarily women. Applicants average 34 years old. The plurality of our sample has some college but no degree, while the rest of the sample is split between those with high school and college degrees. Our sample is also relatively racially diverse. Most of our sample (59%) is currently unemployed, the majority (63% of those) for under three months. Based on the length of their unemployment spell and their state of residence, we estimate that 72% of these individuals are eligible for UI.[19]

Table 2 assesses the randomization. For each of the nine different hours choices, we regress six applicant characteristics on indicators for each effective wage the applicant was randomly assigned among applicants who made a job choice. If the randomization was implemented correctly, the effective wage indicators should not be jointly significant. We consider only the variables that were collected before the jobs were presented: gender, race, and age. The table reports the p-value for each of the 54 regressions. The effective wage indicators are jointly significant for predicting the demographic characteristic in four regressions, a number we may reasonably expect to see by chance. Appendix Table 2 replicates this table, limiting the sample to workers who are unemployed. Observable characteristics look fairly balanced along this dimension as well, though with one additional demographic characteristic that is jointly significant. Appendix Table 3 shows that, consistent with random assignment, unemployed workers in each hours choice have similar demographic characteristics. Appendix Figures 3 and 4 show that neither the probability of making a choice nor the probability of continuing the application after the choice and entering the remaining demographic information is related to effective wages.

4.2   Main Treatments

We begin with visual nonparametric and parametric summaries of the data. We construct binned scatterplots of the inattention-corrected fraction of unemployed applicants who chose longer hours against the effective wage (e_{ih}) for each hours choice.[20] We overlay the scatterplot with the ML fit, which can be interpreted as

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[19]We consider individuals as UI eligible if they have been unemployed for less than the maximum duration of UI benefits in the state. We know only whether individuals have been unemployed for less than 3 months, 3 to 6 months, or more than 6 months. We consider individuals unemployed 3 to 6 months as eligible if the maximum benefit duration in their state is less than 4.5 months. Otherwise they are considered UI eligible. UI eligibility is still an approximation since people categorized as eligible may be ineligible for other reasons, like quitting their previous job or not having a sufficiently long employment history.

[20]At a given hours level h, the inattention-corrected fraction is $(Y_h - \hat{\alpha})/(1 - 2\hat{\alpha})$, where Y_h is the fraction of applicants who chose longer hours when given the choice of h or $h - 5$ hours. The presented fits are estimated off of the individual-level data, not

a cdf of the MVT distribution since it is monotonic and bounded between 0 and 1. These scatterplots are shown in Figure 1. Consistent with economic principles, there is a positive relationship between choosing the higher hours option and the effective wage in all cases. In all cases the logit assumption appears reasonable. Inattention-uncorrected figures (presented in Appendix Figure 5) look similar. Appendix Figure 6 presents data from the overtime validation study where we compare choices over 35 and 40 hours jobs when we show (1) different wage-hour bundles and (2) the same wage up to 35 hours per week and a higher marginal wage after 35 hours. As discussed earlier, this is done to check whether the different wage framing in the overtime study influences the responses. The estimates are quite close and we conclude that responses do not appear sensitive to framing.

Table 3 presents estimates of the mean and quantiles of MVT by hour of work for unemployed jobseekers.[21] For reference, using the 2016 CPS we predict that the market wage for the average unemployed job seeker in our sample is $13.93 pre-tax. (The predicted wages for different subgroups are in Appendix Table 7.) At this wage, on a pre-tax basis there is a large amount of worker surplus for the first few hours someone works. The estimated mean MVT is $4.63 between 5 and 10 hours of work and increases to $8.84 per hour between 20-25 hours of work. MVT increases relatively linearly through the first 40 hours, reaching about $15 between 30 and 40 hours of work. After 40 hours the slope MVT increases at a higher rate, reaching $22 between 40 and 45 hours of work.[22] Thus, on average, workers' MVT equals their average predicted market wage in the 30-40 hours of work per week range. This implies that the average job applicant in our sample would work full-time at their expected market wage. Overall, we calculate $z = 0.58$. Estimates that are weighted to match age, gender, race, and education of hourly workers in the CPS are shown in Table 4, again for the unemployed sample.[23] Weighting results in very similar values of non-work time.[24]

In the standard formulation of the static labor supply model, hours are set to equate wages with the MVT. The collection of MVT values as a function of hours therefore traces out a labor supply relationship. The labor supply function is plotted in Figure 2. The figure shows the estimated values connected by linear segments. We show the median as well as the 25th and 75th percentiles of the function.[25] The labor supply

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these points.

[21]Inattention-uncorrected estimates are in Appendix Table 4, while estimates for the full sample (not limited to unemployed applicants) are in Appendix Table 5 and estimates limited to unemployed workers who applied for the job are in Appendix Table 6.

[22]Appendix Table 8 shows the overtime estimates are robust to different intercept constraints.

[23]Specifically, we weight the full-sample to match the observable characteristics of hourly workers in the CPS and then limit the sample to unemployed workers.

[24]Appendix Table 9 shows descriptive statistics for the weighted samples, compared to the unweighted experiment and CPS samples.

[25]Note that to interpret these as labor supply functions for a given individual, we need to make the assumption that individuals have non-crossing inverse labor supply functions: for all individuals i, j and hours h, and h' if $MVT_{ih} \geq MVT_{jh}$, then $MVT_{ih'} \geq MVT_{jh'}$.

function is moderately upward sloping and becomes steeper around 40 hours of work.

Figure 3 plots the implied labor supply elasticity by hours worked. To compute the elasticity we first estimate a smoothed labor supply relationship by fitting a quartic polynomial to the MVT points shown in Figure 2. Elasticities are then read off of the smoothed relationship. Labor supply is highly elastic at low hours levels, exceeding 1 until 25-30 hours of work. At that point they drop, reaching 0.5-0.6 after 40 hours per week. Table 5 shows the elasticities implied by the quartic model and several other smoothing models, while Figure 4 shows the individual MVT points with the quartic fit. Depending on the model, elasticities after 40 hours are in the 0.4-0.6 range. Appendix Figure 7 shows that the labor supply function looks similar when not limited to unemployed applicants, while Appendix Table 10 shows that elasticities look similar as well.

5   Heterogeneity in Valuations

Figure 1 and Table 3 show that there is substantial heterogeneity in MVT. The 25th percentile of MVT is below \$2 per hour until about 30 hours per week. On the other hand, at the lowest hours choices the 75th percentile MVT is close to double the median, and it increases to \$33 per hour by 40-45 hours per week.

We have explored whether any of this heterogeneity is explained by individual characteristics. Table 6 shows estimates of z by gender, employment status, and potential UI eligibility. For each subgroup, we estimate the MVT separately. To calculate z, we also calculate separate predicted wages by subgroup, estimating each individual's predicted wage as described above and averaging them within the subgroup.

Our estimate of z is slightly, but insignificantly larger for women (z=0.64) than for men ($z = 0.59$).[26] Estimated z is somewhat larger for employed ($z = 0.66$) than unemployed ($z = 0.58$) jobseekers, though this difference is not statistically significant at conventional levels (p=0.14). It is unsurprising that employed jobseekers have a higher estimated value of time, since their alternative to working in the job we advertise is possibly more hours in another job. As we have discussed, a cleaner estimate of the flow value of non-work time is from the unemployed sample since for this group the alternative is truly not working. Among the unemployed, estimated z is similar among those who are potentially eligible for UI benefits and those who are not.

In Table 7 we examine how MVT varies with the predicted market wage of jobseekers, and how z varies with labor market conditions. Here, again we limit the sample to unemployed applicants. To gain power, we stack the data for all the (non-overtime) hours choices and estimate a model where the dependent variable

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[26]For comparisons by gender we combine employed and unemployed jobseekers to maximize statistical power. Separate estimates by gender of the mean and quantiles of MVT for each hours choice are in Appendix Table 11.

is choosing the longer hours job. The independent variables are an indicator for every hours choice and the interaction of the effective wage with each hours choice dummy. We also interact an individual's predicted wage with each of the hours choice indicators and the effective-wage-by-hours-choice variables. We constrain all of the predicted wage × hours choice variables to take the same value and all of the predicted wage × effective wage × hours choice variables to have the same value. This allows an individual's predicted wage to affect both the intercept and the slope of the ML fit, but to affect of the different hours choices in the same way.

In the first panel of Table 7 we report the MVT for a jobseeker with a mean predicted market wage among unemployed applicants ($13.93 per hour) and the MVT for a predicted wage that is one standard deviation ($3.82) higher than the mean, and one standard deviation lower. MVT significantly increases with the predicted wage, but not one-for-one. A two standard deviation increase in predicted wage ($7.64) increases the average MVT by $2.10 per hour (p=0.06).

The second two panels show how z varies with the MSA unemployment rate and the deviation of this rate from its historical mean. We use the BLS's Local Area Unemployment Statistics program to calculate the unemployment rate of the MSA in the month of the job posting (April, May, or June 2017) and the difference between this rate and its 10-year average. Then, separately, we estimate how MVT varies with these two variables as we did for predicted wages. In presenting z's for areas with higher and lower unemployment rates, we allow predicted wages to vary with the unemployment rate, though in practice, this does not matter much.[27] We find that z does not vary significantly with either measure of local economic conditions.

We can use variation in MVT to assess the likely variation in z. Estimating the quantiles of z presents challenges relative to estimating the quantiles of MVT because we don't have external information on the market wage of jobseekers by MVT quantile. Table 3 shows the quantiles of z assuming the market wage for the quantiles is the same as the mean. However, given the finding that MVT is increasing in the market wage, the spread of the z-quantiles is likely exaggerated. Since low MVT people have a lower market wage, their value of z is going to be higher than when using the mean wage.

We utilize the Understanding America Survey (UAS) to explore the external validity of our results. The UAS is a nationally-representative survey in which a panel of randomly-selected individuals responds to web-based surveys. We asked hourly workers:

Imagine that you are applying for a new job in the same line of work as your [main, last] job and you have been offered two positions. Both positions are the same as your [main, last] job and to each other in

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[27]We regress predicted wages on the unemployment rate (or unemployment rate relative to trend) and predict wages for areas with rates one standard deviation above and below the mean.

all ways including benefits, other than the work schedule and how much they pay. Assume you can take no other jobs. ¶ Please read the descriptions of the positions below. ¶ Position 1) This position is X+10 hours per week and has a fixed Monday-Friday daytime schedule. The position pays $Y per hour. ¶ Position 2) This position is X hours per week and has a fixed Monday-Friday daytime schedule. The position pays $Z per hour. ¶ Which position would you choose?

Here, "X" is 10, 20, or 30 hours per week and "Y" – the hourly wage in the longer job – is a worker's current hourly wage. The hourly wage in the shorter job, "Z", is a random multiple of the worker's current hourly wage: [65%, 80%, 90%, 95%, 98%, 100%, 102%, 105%, 110%, 120%, 135%]. We use these wages to calculate effective wages by inverting Equation (1). [Main, last] is "main" for employed workers and "last" for unemployed workers.[28] Each employed or unemployed participant answered all four hypotheticals. The order of the questions was randomized as was which job was Position 1.[29]

Table 6 shows that the UAS estimate is $z = 0.61$ (s.e.=0.03). This value is very similar to the full sample z that combines employed and unemployed applicants ($z = 0.63$).

6   Discussion and Conclusion

It is known that a significant component of time in unemployment is spent on leisure and home production (Aguiar et al. 2013). Our estimates suggest that this use of time is valued. Our estimate of z=0.58 is in the intermediate to upper end of the literature which, largely comes from calibrations. Chodorow-Reich and Karabarbounis (2016) report a range of assumed estimates of 0.45-0.5 prior to the Hagedorn and Manovskii (2008) study and 0.73-0.92 after.[30] In their calibration, they report z in the range of 0.47-0.75, but their values are based on post-tax marginal product. In our case, an effective tax rate of 0.2 results in a value of non-work time relative to after tax wages of $z = 0.73$. Another difference between our estimate and some of the literature is that it is based on the market wage rather than the marginal product. Estimates of z based on marginal product will be the same or smaller than those based on the wage since marginal product is likely to be greater than or equal to the wage. Estimates of the elasticity of labor supply to the firm provide guidance on the degree of this divergence since in the dynamic monopsony framework the percentage difference between marginal product and the wage ("the rate of exploitation") is equal to the inverse of the elasticity

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[28]To measure inattention, we gave individuals a choice between two 40 hour-per-week jobs, one of which paid more than the other. Our inattention rate is double the fraction of people who chose the lower-paying job. Half of inattentive individuals who are choosing at random will choose the lower-paying job by chance.

[29]See Appendix A for additional details on sample selection for the UAS analysis.

[30]Among the papers that calibrate or assume z values are Mortensen and Nagypal (2007), Costain and Reiter (2008), Bils et al. (2012), Hagedorn and Manovskii (2008), Hall and Mueller (forthcoming), Hall and Milgrom (2008), Hornstein et al. (2011), and Shimer (2005).

of labor supply to the firm (Robinson, 1969). If we assume an elasticity of around 4, which in the range of estimates reported in Manning (2011), the marginal product will be 25% higher than the wage, implying significant market power. This degree of market power implies an after-tax value of z roughly equal to the one we estimate, or about 0.46 before tax.

Estimates of the opportunity cost will be higher if one were to add in possible reduction in UI benefits and commuting costs. Estimates of the valuation of travel time are reviewed in Small (2012). A reasonable approximation is that commute time is valued at half the gross wage. The average worker spends approximately one hour a day commuting. With these estimates we would add 0.06 to the estimated value of z. A conservative estimate of the UI replacement rate is 0.3, but only a small fraction of jobseekers are on UI at any point in time. A fixed cost that is more difficult to quantify is any fixed component to child care, such as time spent searching for child care providers.

The fact that labor supply is highly elastic at low hours of work is not incompatible with the labor literature that estimates relatively inelastic labor supply at the intensive margin. Our sample is comprised primarily of women, who tend to have higher labor supply elasticities. Additionally, the less elastic part of the labor supply relationship corresponds to the range of hours where most people work. Since most workers are working close to full-time, any local variation in the wage will show only moderate variation in hours since workers tend to be located in the more inelastic region of the labor supply function.

The shape of the labor supply function we estimate can potentially rationalize the distribution of hours in the economy. In the U.S. labor market there are many full-time workers, many individuals who are out of the labor force entirely, and fewer who choose part-time work. This distribution can be explained by the labor supply relationship we estimate, the key feature being that it goes from more elastic to more inelastic. There are relatively few part-time workers because part-time work lies on the elastic part of the labor supply curve, implying a limited wage range where a worker would find it optimal to work intermediate hours. Small positive deviations in the wage push workers to full-time work, and small negative deviations in the wage push them out of the labor force.

The estimated value of z can also be applied to benefit-cost analyses that involve valuation of time for unemployed workers. To do this, an analyst could compute the predicted market wage of individuals in the study, given their characteristics, and the relevant opportunity cost of a full-time job would be 60% of that value.

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Appendix A. UAS Survey Details

The Understanding American Study (UAS) Survey 79 was distributed by the University of Southern California Center for Economic and Social Research (CESR) to 5,812 people in their nationally-representative panel of respondents who speak English and had completed a background survey. The survey was in the field from December 15, 2016 until February 7, 2017, and 74% of the invited panel participants completed the survey. Respondents were compensated $3 for the survey, which averaged 4 minutes.

Respondents were asked for their labor force status and were then routed to corresponding sections of the survey. All respondents were asked the easiest way to report their earnings (hourly, weekly, etc.) at their main or last job, and how much they typically earn(ed) at their main or last job in that pay period.

Employed and unemployed respondents then saw a series of vignettes that paired two hypothetical jobs which differed only in the number of hours per week and their wages. (See the text for details.) Before proceeding to the next vignette, respondents chose the job that they would prefer. The (randomized) wages in these vignettes were percentage multiples of their current or previous wage, entered earlier in the survey.

Respondents were also asked to choose between two jobs which required the same number of hours per week but offered different wages. The inattention rate used in the regressions for UAS respondents is double the fraction of individuals choosing the lower-paying option.

The remainder of the survey asked about respondents' marital status, parental status, and any partner's/spouse's labor supply behavior.

The estimate for z presented in the text is based on a sample of respondents who are in the labor force and reported their pay hourly. This includes 2,354 choices made by 785 people. The average wage presented uses this sample excluding wages above $99.99/hour. The exclusion affects 78 people (another 3 did not report wages).

Figure 1. Marginal Value of Time
Unemployed Applicants
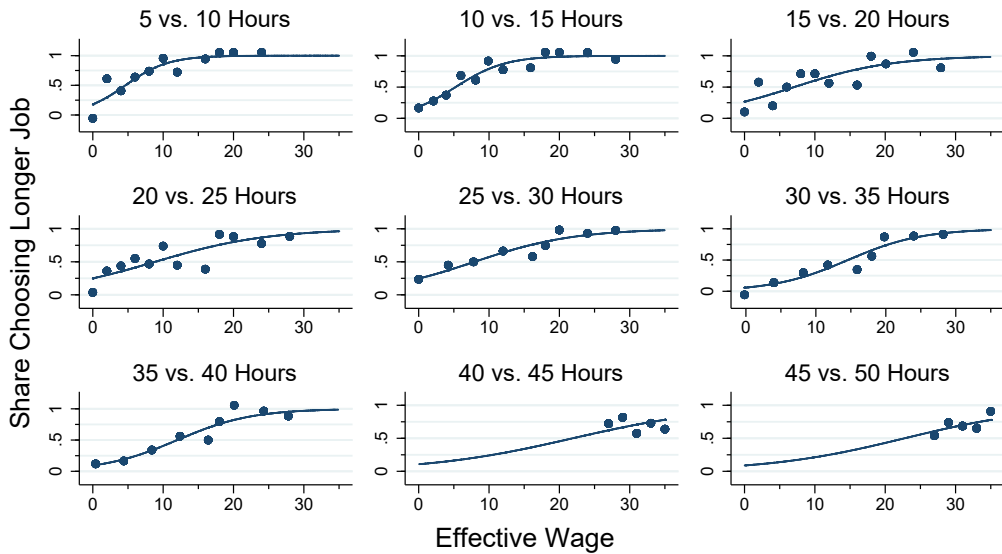
Notes: Applicants chose between two jobs with different hours per week and hourly wages. Each panel shows results from a different choice. The points show the inattention-corrected fraction of applicants who chose the longer job at each effective wage (calculated as described in the text). Due to the inattention correction, these 'shares' can be below zero or above one. The maximum likelihood fit is estimated off the individual-level data, correcting for applicant inattention as described in the text.

Figure 2. Labor Supply Function
Unemployed Applicants
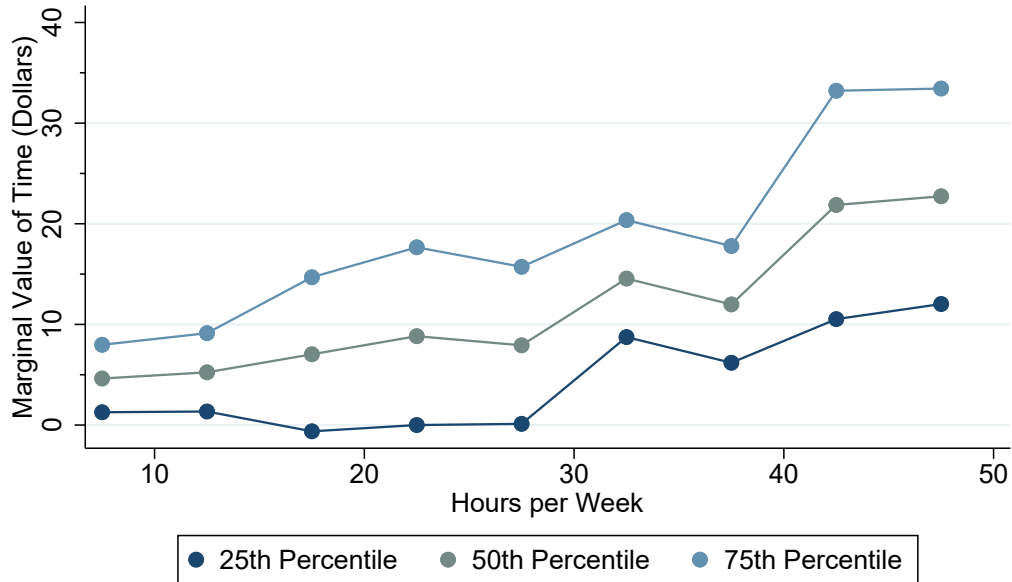
Notes: The figure shows the 25th, 50th, and 75th percentile marginal value of time estimates from each hours choice in the experiment. Estimates are connected with linear segments. Only unemployed applicants are included.

Figure 3. Labor Supply Elasticity
Unemployed Applicants; MVT Predicted from a Quartic Fit
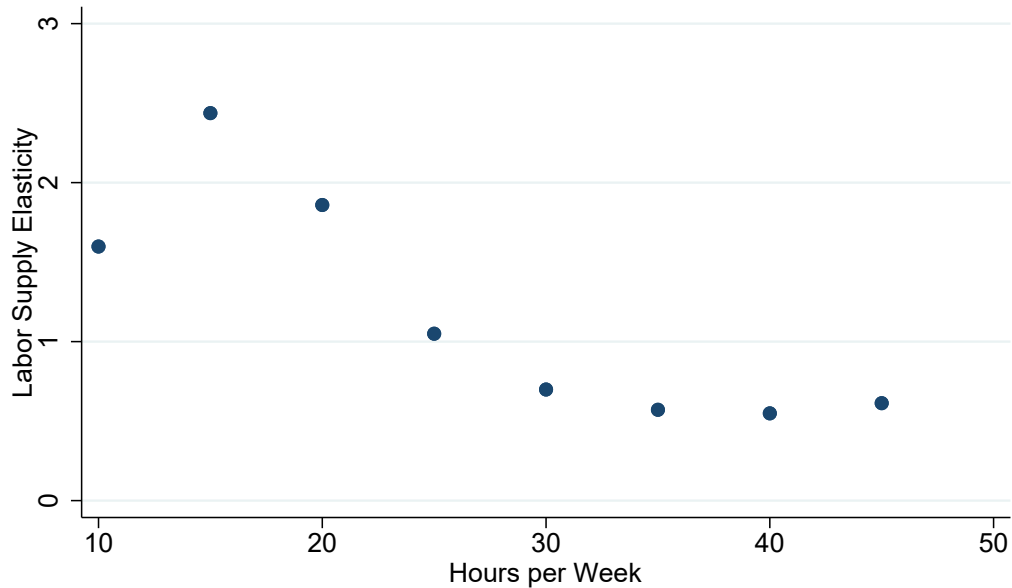
Notes: A quartic function was fit to the labor supply curve in Figure 2. The figure shows the labor supply elasticity calculated from the mean value of time as predicted from this function.

Figure 4. Smoothed Labor Supply Curve
Unemployed Applicants; Quartic Fit
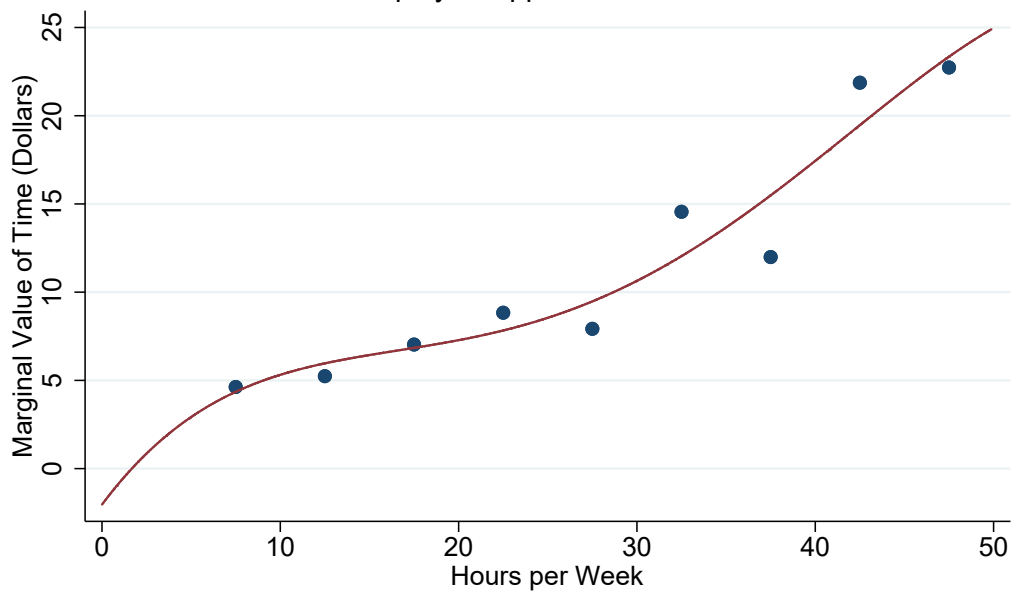
Notes: The figure plots the mean MVT for unemployed applicants in each hours choice. These points are overlaid by a quartic polynomial estimated off of those points.

Table 1. Descriptive Statistics

	Experiment		CPS	
	All	Unemployed Applicants	All	Phone Survey and Data Entry Workers
Female	83%	83%	51%	67%
Currently Employed	41%	0%	95%	100%
Full-time	14%	0%	79%	81%
Part-time	28%	0%	16%	19%
Unemployed	59%	100%	5%	0%
Unemployed for < 3 Months	37%	64%		
Unemployed for 3-6 Months	7%	13%		
Unemployed for > 6 Months	14%	23%		
Age				
Average Age	33.6	32.7	39.8	37.0
< 30 years old	46%	49%	30%	37%
30-40 years old	30%	30%	22%	24%
> 40 years old	24%	21%	48%	39%
Education				
Less than High School	2%	2%	14%	6%
High School	27%	30%	27%	30%
Some College	44%	44%	19%	29%
College Degree	24%	21%	29%	31%
Advanced Degree	4%	2%	10%	4%
Race				
White	45%	44%	61%	57%
Black	34%	34%	13%	16%
Hispanic	11%	12%	18%	19%
Other	9%	10%	9%	8%
Observations	2,658	1,152	248,596	3,542

Notes: The first column of data presents descriptive statistics of the entire experiment sample, while the second column focuses on unemployed applicants. The third column presents statistics on respondents ages 16 to 64 in the 2016 CPS Monthly Outgoing Rotation Groups (MORGs), while the final column includes only CPS respondents in phone survey occupations (telemarketers, bill and account collectors, customer service representatives, and interviewers, except eligibility and loan) and data entry keyers, where observations on workers in phone survey and data entry occupations are weighted by the prevalence of each position in the experiment.

Table 2. Randomization Assessment
p-Values from Regressions of Covariates on Effective Wage Dummies

	5 vs. 10	10 vs. 15	15 vs. 20	20 vs. 25	25 vs. 30	30 vs. 35	35 vs. 40	40 vs. 45	45 vs. 50
Age	0.79	0.83	0.95	0.51	0.72	0.78	0.19	0.69	0.47
Female	0.94	0.11	0.14	0.85	0.50	0.21	0.58	0.70	0.43
White	0.51	0.61	0.98	0.83	0.95	0.53	0.84	0.02	0.95
Black	0.75	0.77	0.62	0.91	0.37	0.01	0.42	0.28	0.47
Hispanic	0.30	0.89	0.72	0.83	0.03	0.77	0.14	0.38	0.18
Other Race	0.15	0.44	0.79	0.40	0.78	0.21	0.54	0.01	0.84
Applicants in Treatment	304	305	323	292	305	319	272	272	266

Notes: Each cell reports the p-value of an F-statistic from a separate regression of the demographic characteristic indicated by the row on effective wage dummies. This table includes all applicants who chose one of the jobs presented to them.

Table 3. Marginal Value of Time
Unemployed Applicants

	Mean	Standard Deviation	Quantiles			N
			25th	50th	75th	
5 vs. 10 Hours	$4.63	$5.54	$1.27	$4.63	$7.99	117
	(0.95)	(1.33)	(1.24)	(0.95)	(1.25)	
10 vs. 15 Hours	$5.24	$6.43	$1.34	$5.24	$9.14	124
	(1.05)	(1.58)	(1.50)	(1.05)	(1.35)	
15 vs. 20 Hours	$7.03	$12.65	-$0.63	$7.03	$14.70	128
	(1.77)	(3.53)	(3.24)	(1.77)	(2.21)	
20 vs. 25 Hours	$8.84	$14.59	-$0.01	$8.84	$17.68	153
	(1.72)	(3.36)	(2.88)	(1.72)	(2.43)	
25 vs. 30 Hours	$7.92	$12.89	$0.11	$7.92	$15.74	135
	(1.85)	(2.81)	(2.97)	(1.85)	(1.95)	
30 vs. 35 Hours	$14.56	$9.60	$8.74	$14.56	$20.38	133
	(1.40)	(1.82)	(1.71)	(1.40)	(1.85)	
35 vs. 40 Hours	$11.99	$9.59	$6.18	$11.99	$17.80	112
	(1.53)	(2.29)	(2.23)	(1.53)	(1.88)	
40 vs. 45 Hours	$21.87	$18.75	$10.51	$21.87	$33.23	121
	(1.75)	(1.50)	(0.84)	(1.75)	(2.66)	
45 vs. 50 Hours	$22.73	$17.69	$12.01	$22.73	$33.45	129
	(1.57)	(1.22)	(0.83)	(1.57)	(2.31)	
Implied z	0.58		0.16	0.58	0.99	902
	(0.04)		(0.06)	(0.04)	(0.05)	

Notes: The table provides statistics on workers' mean value of time in each hours range. Estimates are limited to applicants who are unemployed and are derived from an inattention-corrected maximum likelihood model described in the text. Robust standard errors calculated using the delta method are in parentheses. The implied z estimate is based on hours up to 40.

| | A. Weights using Pre-Experiment Characteristics | | | | | | B. Weights using All Characteristics | | | | | |
| | | | Quantiles | | | | | | Quantiles | | | |
	Mean	Standard Deviation	25th	50th	75th	N	Mean	Standard Deviation	25th	50th	75th	N
5 vs 10 Hours	$6.00	$4.09	$3.52	$6.00	$8.47	94	$5.21	$3.84	$2.88	$5.21	$7.54	94
	(1.29)	(1.11)	(1.52)	(1.29)	(1.38)		(1.09)	(0.88)	(1.31)	(1.09)	(1.10)	
10 vs 15 Hours	$6.65	$3.50	$4.53	$6.65	$8.77	99	$7.33	$3.46	$5.23	$7.33	$9.43	99
	(1.15)	(1.24)	(1.20)	(1.15)	(1.53)		(1.01)	(0.81)	(1.13)	(1.01)	(1.12)	
15 vs 20 Hours	$5.29	$26.09	-$10.53	$5.29	$21.10	108	$6.06	$20.75	-$6.51	$6.06	$18.63	108
	(6.07)	(23.10)	(18.46)	(6.07)	(11.16)		(4.42)	(17.47)	(13.50)	(4.42)	(8.99)	
20 vs 25 Hours	$8.25	$17.47	-$2.34	$8.25	$18.84	125	$10.33	$24.04	-$4.23	$10.33	$24.90	125
	(3.40)	(7.42)	(6.46)	(3.40)	(4.68)		(4.41)	(13.01)	(9.67)	(4.41)	(8.35)	
25 vs 30 Hours	$8.84	$10.27	$2.61	$8.84	$15.06	110	$10.68	$9.37	$5.00	$10.68	$16.35	110
	(2.15)	(3.22)	(3.33)	(2.15)	(2.40)		(1.87)	(2.81)	(2.88)	(1.87)	(2.11)	
30 vs 35 Hours	$16.71	$6.15	$12.98	$16.71	$20.44	102	$16.99	$6.99	$12.76	$16.99	$21.23	102
	(1.86)	(2.02)	(1.92)	(1.86)	(2.49)		(2.44)	(2.36)	(1.94)	(2.44)	(3.50)	
35 vs 40 Hours	$14.20	$5.46	$10.89	$14.20	$17.50	88	$14.53	$5.94	$10.93	$14.53	$18.12	88
	(1.67)	(1.24)	(1.75)	(1.67)	(1.90)		(1.93)	(1.37)	(2.09)	(1.93)	(2.12)	
40 vs 45 Hours	$20.01	$14.63	$11.15	$20.01	$28.88	97	$21.61	$14.54	$12.79	$21.61	$30.42	97
	(1.96)	(1.43)	(1.09)	(1.96)	(2.82)		(2.17)	(1.46)	(1.28)	(2.17)	(3.05)	
45 vs 50 Hours	$22.11	$14.67	$13.22	$22.11	$30.99	99	$23.35	$13.99	$14.87	$23.35	$31.83	99
	(2.06)	(1.36)	(1.23)	(2.06)	(2.88)		(2.21)	(1.32)	(1.41)	(2.21)	(3.01)	
Implied z	0.57		0.19	0.57	0.95	726	0.62		0.22	0.62	1.01	726
	(0.07)		(0.17)	(0.07)	(0.11)		(0.07)		(0.15)	(0.07)	(0.11)	

Notes: Weights are calculated using the DiNardo, Fortin and Lemieux (1996) method, matching the covariate distribution of hourly workers ages 16-64 in the March 2017 CPS. We weight the whole experimental sample to match the March 2017 CPS and then limit observations to unemployed workers. Panel A uses only characteristics collected before the job options were presented to create weights. Specifically, it uses race dummies, a female dummy, age, and age*race, age*female, and female*race interaction terms. Panel B adds educational attainment categories, which were collected after individuals made a choice. Sample weights are capped at a maximum of 10 standard deviations above the sample mean weight. This restriction affects 1 observation in Panel A and 5 observations in Panel B. Estimates are based on an inattention-corrected maximum likelihood logit model described in the text. Robust standard errors calculated using the delta method are in parentheses.

Table 5. Labor Supply Elasticities
Unemployed Applicants

	Raw Points	Quadratic	Quartic	Spline
10 Hours	4.02	6.08	1.60	1.24
15 Hours	1.14	2.03	2.44	1.16
20 Hours	1.10	1.18	1.86	1.12
25 Hours	-1.84	0.87	1.05	1.10
30 Hours	0.28	0.72	0.70	1.08
35 Hours	-0.74	0.64	0.57	1.07
40 Hours	0.21	0.60	0.55	0.53
45 Hours	2.88	0.57	0.61	0.40
RMSE		2.24	2.68	2.38

Notes: The columns show estimates of labor supply elasticities at different hours per week. Points in the first column are calculated from the mean MVT at each hours choice from the experiment (e.g., the 25 hours estimate is created from the MVTs at 20-25 hours and 25-30 hours). The remaining columns fit a curve to the MVT points and use this curve to calculate labor supply elasticities. The fitted curves use a quadratic, quartic, and spline with a knot at 40 hours per week, respectively. The final row shows the root mean squared error for each of the fits. Only unemployed applicants are included.

Table 6. Estimates of z

| | All Applicants | Employment Status | | Gender | | UI Eligibility | | UAS |
		Employed	Unemployed	Women	Men	Eligible for Benefits	Ineligible for Benefits	Hourly Workers
Estimate of z	0.63	0.66	0.58	0.64	0.59	0.56	0.60	0.61
	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.10)	(0.03)
Observations	2,120	660	902	1,494	315	644	251	2,354
Difference		0.09		0.05		-0.04		
		(0.06)		(0.07)		(0.12)		

Notes: Each cell reports the z calculated for the subgroup indicated by the column. The "UI Eligibility" columns are limited to unemployed applicants. In all columns except that with Understanding America Study (UAS) results, sample sizes show total numbers of applicants in the subgroup who are included in the z calculation. In the UAS, survey respondents were each asked to make multiple hypothetical choices; the sample size shows the total number of choices used to estimate z, made by 785 survey respondents. Robust standard errors calculated using the delta method are in parentheses. In the UAS results, standard errors are clustered by person.

	Mean	Mean + 1 SD	Mean - 1 SD	Difference Between Value at (Mean + 1 SD) and (Mean - 1 SD)
	A. Predicted Wage			
	Mean ($13.93), Standard Deviation ($3.82)			
Mean Value of Time	$7.99	$9.06	$6.95	$2.10*
	(0.60)	(0.80)	(0.82)	(1.12)
	B. Local Unemployment Rate			
	Mean (4.22%), Standard Deviation (0.78%)			
Implied z	0.58	0.58	0.57	0.01
	(0.04)	(0.05)	(0.06)	(0.08)
	C. Local Unemployment Relative to 10-Year Historical Mean			
	Mean (-2.56%), Standard Deviation (1.14%)			
Implied z	0.57	0.58	0.56	0.02
	(0.04)	(0.04)	(0.07)	(0.08)

Notes: The table shows results obtained by fitting a stacked maximum likelihood model with additional covariates as described in the text. Each panel presents the mean value of time or implied *z* associated with the mean value, mean value plus one standard deviation, and mean value minus one standard deviation of the covariate (predicted wage, local unemployment rate, or local unemployment rate relative to the 10-year historical mean). Local unemployment rates from the BLS's Local Area Unemployment Statistics program are at the MSA-level and are unadjusted in Panel B and seasonally adjusted in Panel C. Panel C uses monthly unemployment rates from April 2007 to March 2017. Robust standard errors calculated using the delta method are in parentheses. Standard errors in Panels B and C are clustered by MSA.

<center>Appendix Figure 1. Job Advertisement</center>

[center] [Phone Survey Associate / Data Entry Associate ([city, state])

[center] is currently recruiting [phone survey interviewers / data entry associates].

This is not a sales or telemarketing position.

Please follow the link [link] to apply to this opportunity. We do not accept applications through email.

Essential Functions
[Make phone calls in order to implement phone surveys / Accurately and quickly perform data tasks]

Desired Skills
Good communication skills
Ability to work with others
Used to basic computer and/or mobile applications

- Principals only. Recruiters, please don't contact this job poster.
- do NOT contact us with unsolicited services or offers

compensation: Hourly
employment type: employee's choice

Notes: The name of the center is redacted.

Appendix Figure 2. Job Description

Job Description

Tell us which of the following two positions you prefer. The type of work is the same in both jobs. Please click on each job title in order to review the work descriptions.

It is important that you read the position descriptions carefully so you can indicate your preference below.

Positions

Phone Survey Associate Position #104 (click for description)

This is a one-month work-from-home phone survey position.

The position is 25 hours per week.

This position pays 15.60 dollars per hour.

Phone Survey Associate Position #126 (click for description)

This is a one-month work-from-home phone survey position.

The position is 20 hours per week.

This position pays 18.00 dollars per hour.

If you were selected for both positions, which one would you prefer? Write your preferred position in the box below. If you are hired, we will offer you your choice. Your choice will not affect whether you receive a job offer. It will only be reviewed after hiring decisions have been made. If there are other open positions at   you will also be considered for those. If you are not interested in applying, simply click on "No thanks, this isn't for me".

Notes: Here, the name of the center is redacted.

Appendix Figure 3. Probability of Choosing
a Job Option by Effective Wage
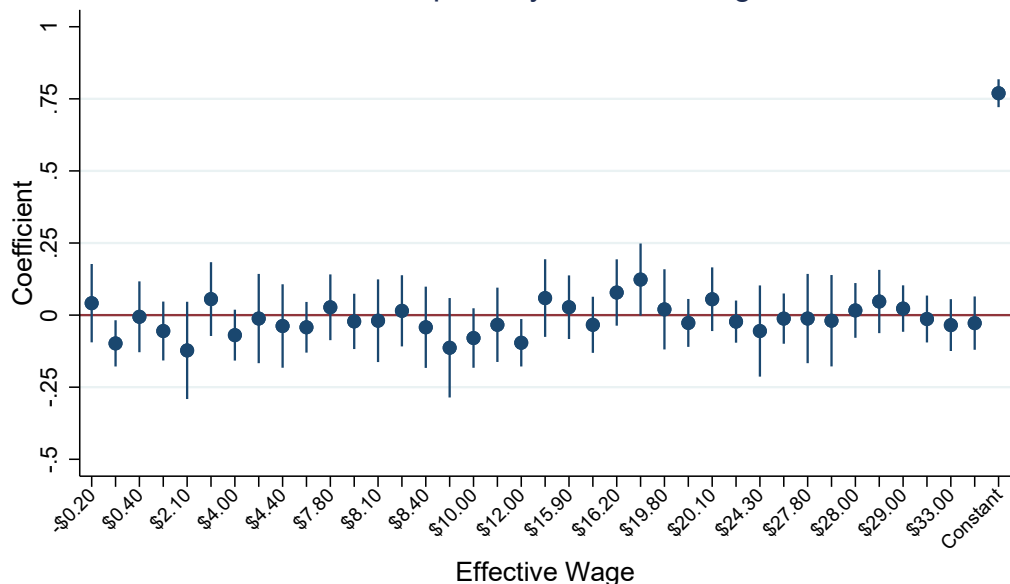
Notes: The figure plots the coefficients from a regression of an indicator for choosing one of the two job options on (non-rounded) effective wage dummies. Applicants are included if they were presented with the job options. The omitted category is an $18 effective wage. Vertical bars show the 95% confidence interval.

Appendix Figure 4. Probability of Submitting Subsequent
Demographic Information by Effective Wage
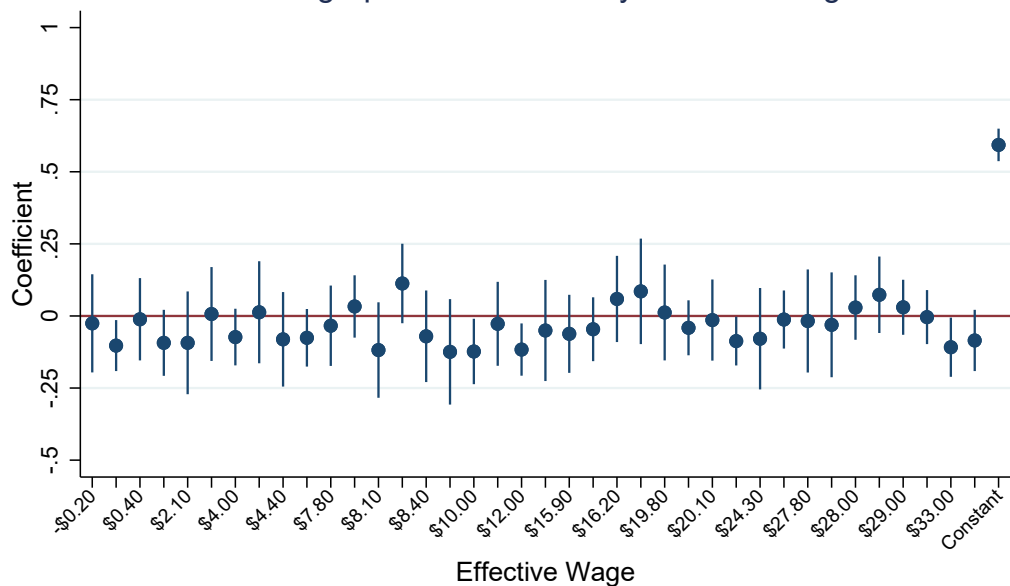
Notes: The figure plots the coefficients from a regression of an indicator for submitting the demographic information after the job choice on (non-rounded) effective wage dummies. The omitted category is an $18 effective wage. Vertical bars show the 95% confidence interval.

Appendix Figure 5. Marginal Value of Time
Uncorrected for Inattention
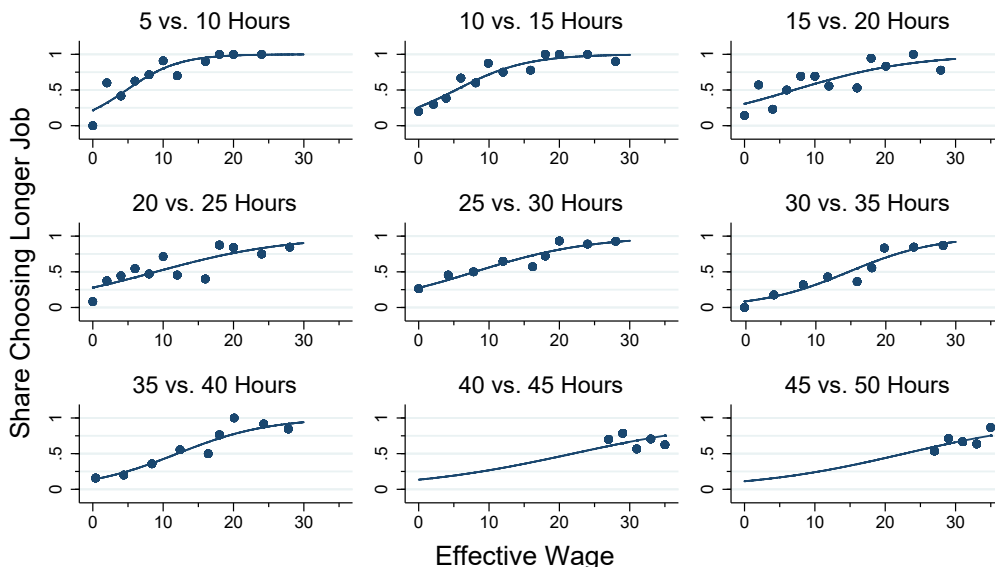
Notes: Applicants chose between two jobs with different hours per week and hourly wages. Each panel shows results from a different choice. The points show the raw fraction of applicants who chose the longer job at each effective wage. The maximum likelihood fit is estimated off the individual-level data as described in the text.

Appendix Figure 6. Validation of Overtime Framing
35 vs. 40 Hours
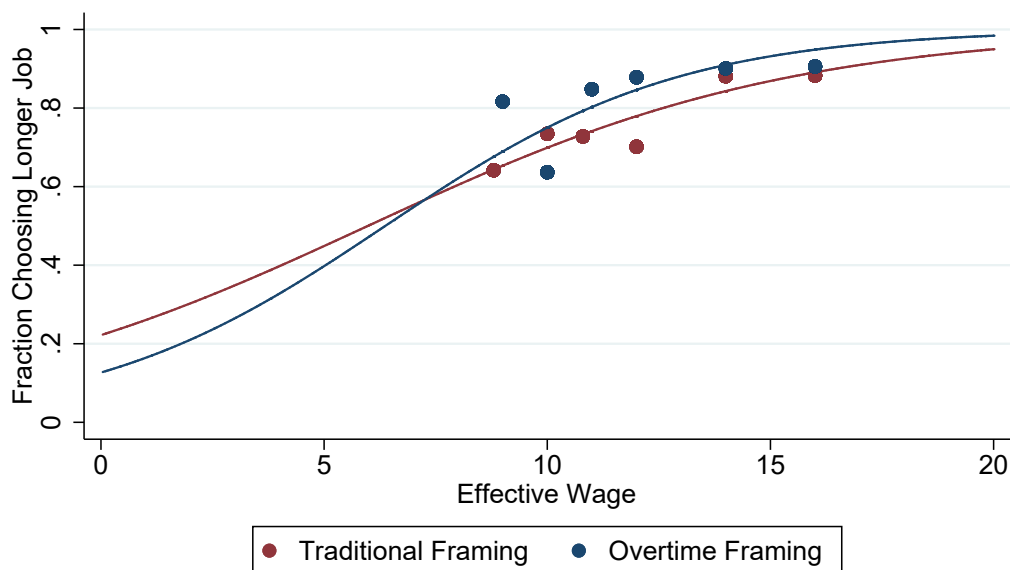
Notes: The figure shows the results from the overtime validation treatment described in the text. In the "traditional framing," the 35 and 40 hour jobs had two separate wage rates. In the "overtime framing," the 35 and 40 hour jobs both paid the same wage up to 35 hours per week. The 40 hour job paid a separate wage for the last five hours (hours over 35 hours per week).

Appendix Figure 7. Labor Supply Function
All Experiment Applicants
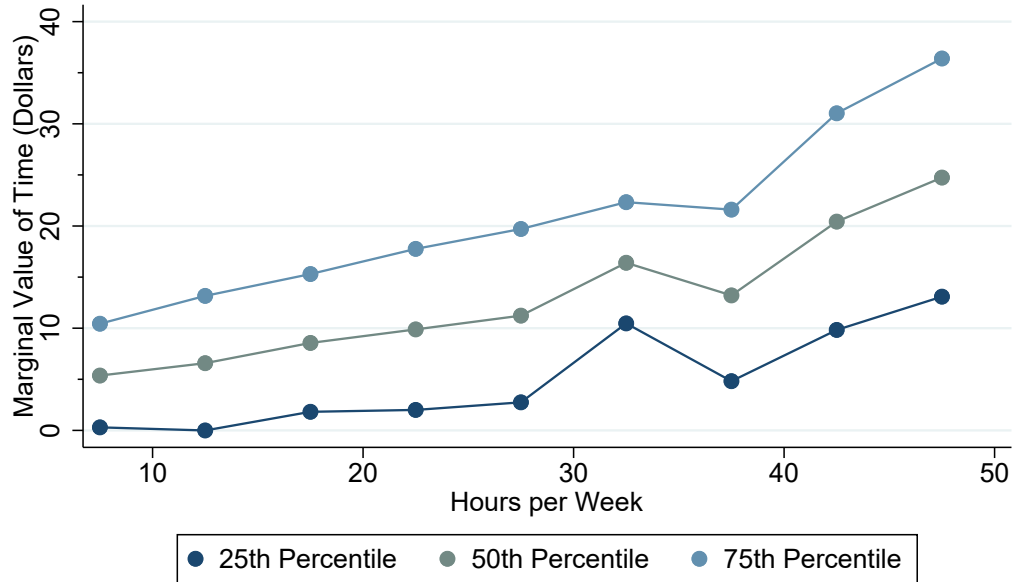
Notes: The figure shows the 25th, 50th, and 75th percentile marginal value of time estimates from each hours choice in the experiment. Estimates are connected with linear segments. Experimental applicants are included regardless of employment status.

Appendix Table 1. Hourly Wages by Effective Wage

Effective Wage	5 vs. 10 Hours		10 vs. 15 Hours		15 vs. 20 Hours		20 vs. 25 Hours		25 vs. 30 Hours		30 vs. 35 Hours		35 vs. 40 Hours	
	5 Hours	10 Hours	10 Hours	15 Hours	15 Hours	20 Hours	20 Hours	25 Hours	25 Hours	30 Hours	30 Hours	35 Hours	35 Hours	40 Hours
$0.00	18.00	9.00	18.00	12.00	18.00	13.50	18.00	14.40	18.00	15.00	18.00	15.40	18.00	15.80
$2.00	18.00	10.00	18.00	12.70	18.00	14.00	18.00	14.80						
$4.00	18.00	11.00	18.00	13.30	18.00	14.50	18.00	15.20	18.00	15.70	18.00	16.00	18.00	16.30
$6.00	18.00	12.00	18.00	14.00	18.00	15.00	18.00	15.60						
$8.00	18.00	13.00	18.00	14.70	18.00	15.50	18.00	16.00	18.00	16.30	18.00	16.60	18.00	16.80
$10.00	18.00	14.00	18.00	15.30	18.00	16.00	18.00	16.40						
$12.00	18.00	15.00	18.00	16.00	18.00	16.50	18.00	16.80	18.00	17.00	18.00	17.10	18.00	17.30
$16.00	18.00	17.00	18.00	17.30	18.00	17.50	18.00	17.60	18.00	17.70	18.00	17.70	18.00	17.80
$18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00	18.00
$20.00	16.00	18.00	17.00	18.00	17.30	18.00	17.50	18.00	17.60	18.00	17.70	18.00	17.70	18.00
$24.00	12.00	18.00	15.00	18.00	16.00	18.00	16.50	18.00	16.80	18.00	17.00	18.00	17.10	18.00
$28.00			13.00	18.00	14.70	18.00	15.50	18.00	16.00	18.00	16.30	18.00	16.60	18.00

Notes: For each applicant, we randomly selected an hours choice and an effective wage. Each row displays the hourly wages associated with a given effective wage.

	5 vs. 10	10 vs. 15	15 vs. 20	20 vs. 25	25 vs. 30	30 vs. 35	35 vs. 40	40 vs. 45	45 vs. 50
Age	0.96	0.65	0.24	0.94	0.85	0.98	0.01	0.60	0.79
Female	0.69	0.11	0.78	0.65	0.38	0.01	0.58	0.81	0.47
White	0.35	0.19	0.72	0.67	0.91	0.26	0.43	0.09	0.75
Black	0.85	0.39	0.51	0.90	0.23	0.00	0.20	0.75	0.17
Hispanic	0.45	0.82	0.62	0.47	0.25	0.41	0.59	0.85	0.04
Other Race	0.15	0.69	0.08	0.75	0.58	0.49	0.78	0.02	0.88
Applicants in Treatment	117	124	128	153	135	133	112	122	129

Notes: Each cell reports the p-value of an F-statistic from a separate regression of the demographic characteristic indicated by the row on effective wage dummies. This table includes only unemployed applicants.

	5 vs. 10	10 vs. 15	15 vs. 20	20 vs. 25	25 vs. 30	30 vs. 35	35 vs. 40	40 vs. 45	45 vs. 50	p-value of difference
Age	31.9	31.8	32.2	33.2	31.9	32.7	31.0	33.9	35.3	0.097
Number Reporting Age	116	121	126	150	134	131	108	120	128	1,134
Female	86.7%	80.8%	84.8%	76.9%	85.3%	81.8%	84.8%	83.8%	84.1%	0.658
Number Reporting Gender	98	104	112	130	116	110	92	99	107	968
Race/Ethnicity										
White	42.9%	53.8%	47.8%	43.1%	37.4%	41.7%	45.4%	49.0%	38.6%	0.311
Black	33.7%	28.8%	28.7%	36.2%	36.5%	38.0%	34.0%	31.4%	42.6%	0.483
Hispanic	12.2%	9.6%	14.8%	11.5%	16.5%	13.0%	12.4%	6.9%	6.9%	0.353
Other Race/Don't Want to Respond	11.2%	7.7%	8.7%	9.2%	9.6%	7.4%	8.2%	12.7%	11.9%	0.905
Number Reporting Race/Ethnicity	98	104	115	130	115	108	97	102	101	970
Education										
Less than High School	4.3%	2.4%	3.1%	2.6%	3.0%	0.8%	1.8%	2.5%	0.8%	0.700
High School	29.1%	39.5%	28.9%	27.5%	32.6%	30.1%	33.0%	32.2%	21.7%	0.190
Some College	42.7%	33.9%	45.3%	45.1%	53.3%	46.6%	38.4%	45.5%	45.7%	0.143
College Degree	23.1%	23.4%	21.1%	23.5%	8.9%	18.0%	23.2%	18.2%	26.4%	0.027
Advanced Degree	0.9%	0.8%	1.6%	1.3%	2.2%	4.5%	3.6%	1.7%	5.4%	0.148
Number Reporting Education	117	124	128	153	135	133	112	121	129	970
Total Applicants in Regression Sample	117	124	128	153	135	133	112	122	129	1,153

Notes: The first nine columns of data show the mean of the demographic characteristic indicated by the row for applicants in the hours choice indicated by the column. The final column shows the p-value from a test that the means across hours choices are equal. The table also provides the number of applicants who reported each piece of demographic information.

Appendix Table 4. Marginal Value of Time
Unemployed Applicants; Uncorrected for Inattention

	Mean	Standard Deviation	Quantiles			N
			25th	50th	75th	
5 vs 10 Hours	$4.80	$6.76	$0.70	$4.80	$8.89	117
	(0.96)	(1.29)	(1.35)	(0.96)	(1.11)	
10 vs 15 Hours	$5.27	$9.15	-$0.28	$5.27	$10.81	124
	(1.22)	(2.18)	(2.08)	(1.22)	(1.46)	
15 vs 20 Hours	$7.00	$15.53	-$2.41	$7.00	$16.41	128
	(1.91)	(4.03)	(3.74)	(1.91)	(2.30)	
20 vs 25 Hours	$8.95	$17.07	-$1.39	$8.95	$19.29	153
	(1.74)	(3.67)	(3.15)	(1.74)	(2.46)	
25 vs 30 Hours	$7.97	$14.92	-$1.08	$7.97	$17.01	135
	(1.84)	(3.08)	(3.15)	(1.84)	(1.96)	
30 vs 35 Hours	$14.68	$11.33	$7.82	$14.68	$21.55	133
	(1.34)	(1.90)	(1.70)	(1.34)	(1.82)	
35 vs 40 Hours	$12.00	$11.82	$4.84	$12.00	$19.16	112
	(1.50)	(2.38)	(2.22)	(1.50)	(1.93)	
40 vs 45 Hours	$21.89	$21.36	$8.94	$21.89	$34.83	121
	(1.70)	(1.66)	(0.69)	(1.70)	(2.71)	
45 vs 50 Hours	$22.69	$19.97	$10.59	$22.69	$34.80	129
	(1.54)	(1.35)	(0.72)	(1.54)	(2.36)	
Implied z	0.58		0.09	0.58	1.08	902
	(0.04)		(0.07)	(0.04)	(0.05)	

Notes: This table replicates Table 3, where the data are not corrected for inattention.

Appendix Table 5. Marginal Value of Time
All Experiment Applicants

	Mean	Standard Deviation	Quantiles			N
			25th	50th	75th	
5 vs. 10 Hours	$5.37	$8.37	$0.30	$5.37	$10.44	304
	(0.78)	(1.53)	(1.23)	(0.78)	(1.20)	
10 vs. 15 Hours	$6.58	$10.87	-$0.01	$6.58	$13.16	305
	(1.03)	(1.64)	(1.64)	(1.03)	(1.19)	
15 vs. 20 Hours	$8.56	$11.12	$1.82	$8.56	$15.30	323
	(0.97)	(1.79)	(1.59)	(0.97)	(1.30)	
20 vs. 25 Hours	$9.88	$13.00	$2.01	$9.88	$17.76	292
	(1.15)	(2.01)	(1.81)	(1.15)	(1.51)	
25 vs. 30 Hours	$11.23	$14.00	$2.75	$11.23	$19.71	305
	(1.21)	(2.12)	(2.01)	(1.21)	(1.48)	
30 vs. 35 Hours	$16.40	$9.79	$10.47	$16.40	$22.33	319
	(0.89)	(1.51)	(1.36)	(0.89)	(1.18)	
35 vs. 40 Hours	$13.21	$13.85	$4.82	$13.21	$21.60	272
	(1.22)	(2.41)	(1.97)	(1.22)	(1.84)	
40 vs. 45 Hours	$21.19	$16.15	$11.41	$21.19	$30.98	272
	(1.03)	(0.78)	(0.55)	(1.03)	(1.51)	
45 vs. 50 Hours	$25.50	$16.85	$15.29	$25.50	$35.71	266
	(1.13)	(0.74)	(0.67)	(1.13)	(1.58)	
Implied z	0.63		0.19	0.63	1.07	2,120
	(0.03)		(0.05)	(0.03)	(0.04)	

Notes: This table replicates Table 3, where all experiment applicants are included regardless of employment status.

Appendix Table 6. Marginal Value of Time
Unemployed Applicants who Completed the Application

	Mean	Standard Deviation	Quantiles 25th	Quantiles 50th	Quantiles 75th	N
5 vs. 10 Hours	$4.53	$5.73	$1.06	$4.53	$8.00	113
	(0.99)	(1.39)	(1.29)	(0.99)	(1.31)	
10 vs. 15 Hours	$5.25	$6.49	$1.32	$5.25	$9.18	123
	(1.06)	(1.61)	(1.51)	(1.06)	(1.37)	
15 vs. 20 Hours	$7.03	$12.65	-$0.63	$7.03	$14.70	128
	(1.77)	(3.53)	(3.24)	(1.77)	(2.21)	
20 vs. 25 Hours	$8.72	$14.64	-$0.15	$8.72	$17.60	150
	(1.75)	(3.44)	(2.97)	(1.75)	(2.45)	
25 vs. 30 Hours	$7.98	$13.20	-$0.02	$7.98	$15.98	131
	(1.92)	(2.95)	(3.11)	(1.92)	(2.02)	
30 vs. 35 Hours	$14.64	$9.78	$8.72	$14.64	$20.57	131
	(1.43)	(1.89)	(1.73)	(1.43)	(1.92)	
35 vs. 40 Hours	$11.99	$9.59	$6.18	$11.99	$17.80	112
	(1.53)	(2.29)	(2.23)	(1.53)	(1.88)	
40 vs. 45 Hours	$21.25	$18.10	$10.28	$21.25	$32.21	118
	(1.71)	(1.46)	(0.83)	(1.71)	(2.60)	
45 vs. 50 Hours	$22.60	$17.36	$12.08	$22.60	$33.12	128
	(1.55)	(1.19)	(0.83)	(1.55)	(2.27)	
Implied z	0.57		0.16	0.57	0.99	888
	(0.04)		(0.06)	(0.04)	(0.06)	

Notes: This table replicates Table 3, where only unemployed applicants who finished the application are included.

Appendix Table 7. Predicted Wages by Subgroup

		Employment Status		Gender		Weighting Scheme		UI Eligibility	
	Unemployed	All	Employed	Women	Men	Pre-Experiment Characteristics	All Characteristics	Eligible for Benefits	Ineligible for Benefits
Predicted Wage	$13.93	$15.00	$16.14	$14.56	$16.86	$15.55	$15.01	$13.68	$14.53
Observations	902	2,120	660	1,494	315	726	726	644	251

Notes: Predicted wages are created as described in the text. The "Weighting Scheme" and "UI Eligibility" columns are limited to unemployed applicants.

Appendix Table 8. Overtime Marginal Value of Time: Robustness to Constraints
Unemployed Applicants

| | A. 40 vs. 45 Hours | | | | | B. 45 vs. 50 Hours | | | | |
| | | | Quantiles | | | | | Quantiles | | |
	Mean	Standard Deviation	25th	50th	75th	Mean	Standard Deviation	25th	50th	75th
Intercept Constrained Using										
Linear Extrapolation From	$21.87	$18.75	$10.51	$21.87	$33.23	$22.73	$17.69	$12.01	$22.73	$33.45
Non-Overtime Hours Choices	(1.76)	(1.51)	(0.84)	(1.76)	(2.67)	(1.57)	(1.22)	(0.83)	(1.57)	(2.32)
Quadratic Extrapolation From	$27.31	$5.38	$24.05	$27.31	$30.57	$27.77	$5.47	$24.45	$27.77	$31.08
Non-Overtime Hours Choices	(0.88)	(0.17)	(0.78)	(0.88)	(0.99)	(0.73)	(0.14)	(0.64)	(0.73)	(0.82)
Linear Extrapolation From	$22.15	$18.11	$11.18	$22.15	$33.13	$22.44	$18.35	$11.32	$22.44	$33.56
Non-Overtime Hours Choices:	(1.73)	(1.41)	(0.87)	(1.73)	(2.58)	(1.61)	(1.32)	(0.81)	(1.61)	(2.41)
Both Choices Use Same Intercept										
Average Intercept from	$19.62	$23.83	$5.18	$19.62	$34.06	$19.89	$24.17	$5.25	$19.89	$34.54
Non-Overtime Hours Choice	(1.97)	(2.40)	(0.52)	(1.97)	(3.43)	(1.86)	(2.27)	(0.49)	(1.86)	(3.24)
Intercept from 35 vs. 40 Choice	$22.28	$17.82	$11.48	$22.28	$33.08	$22.57	$18.05	$11.64	$22.57	$33.51
	(1.71)	(1.37)	(0.88)	(1.71)	(2.54)	(1.59)	(1.27)	(0.82)	(1.59)	(2.36)
No Intercept Constraint	$42.87	-$26.97	$59.21	$42.87	$26.53	$24.76	$12.99	$16.89	$24.76	$32.63
	(15.61)	(33.40)	(35.64)	(15.61)	(6.02)	(3.60)	(7.88)	(8.16)	(3.60)	(2.19)

Notes: The table shows the estimated mean and quantiles of MVT for the overtime treatments using different constraints on the "intercept": the fraction choosing the longer job at a $0 effective wage. In the first five methods, the constraints are calculated using the estimated intercepts from non-overtime treatments. The first is the preferred method used in the text, where estimated intercepts from the non-overtime hours choices are regressed on the average hours in the choice and this function is used to predict the intercept in the 40 vs. 45 and 45 vs. 50 hours treatments. The second uses the same method, where the function used to predict the intercepts is a quadratic function of hours. The third uses the same linear extrapolation as the first but constrains the intercepts in both overtime choices to the predicted intercept at 45 hours per week (instead of 42.5 and 47.5 hours). The fourth uses the average intercept from non-overtime hours choices. The fifth uses the estimated intercept in the 35 vs. 40 hours choice. The last row of data shows results without intercept constraints. Estimates are limited to applicants who are unemployed and are derived from an inattention-corrected maximum likelihood model. Robust standard errors calculated using the delta method are in parentheses. There are 121 observations in Panel A and 129 observations in Panel B.

Unemployed Applicants

	CPS	Experiment		
	Hourly Workers	Unweighted	Weighted Using Pre-Experiment Demographics	Weighted Using All Demographics
Female	50%	83%	50%	53%
Age	38.0	32.7	36.2	34.9
Race				
White	58%	44%	60%	64%
Black	14%	34%	15%	14%
Hispanic	21%	12%	18%	16%
Other Race	8%	10%	7%	7%
Education				
Less than High School	12%	2%	2%	13%
High School	34%	28%	31%	34%
Some College	23%	46%	44%	25%
College Degree	27%	22%	20%	26%
More than College	4%	2%	3%	3%
Observations	92,378	1,152	922	922

Notes: The first column of data shows descriptive statistics for hourly workers in the 2016 CPS Monthly Outgoing Rotation Groups. The second, third, and fourth columns of data show descriptive characteristics for unemployed applicants, with different weights. Pre-experiment demographics are collected before the job options are presented. These weights are constructed using race categories, a female dummy, age, and age*race, age*female, and female*race interaction terms. The weights in the final column are generated using these characteristics and educational attainment categories. Sample weights are capped at a maximum of 10 standard deviations above the sample mean weight. This restriction affects 1 observation in the third column of data and 5 in the fourth.

Appendix Table 10. Labor Supply Elasticities
All Experiment Applicants

	Raw Points	Quadratic	Quartic	Spline
10 Hours	2.46	4.34	2.57	1.67
15 Hours	1.27	2.03	1.39	1.45
20 Hours	1.74	1.31	1.23	1.34
25 Hours	1.57	1.00	1.25	1.27
30 Hours	0.45	0.83	1.19	1.22
35 Hours	-0.66	0.74	0.93	1.19
40 Hours	0.27	0.68	0.62	0.54
45 Hours	0.60	0.64	0.42	0.40
RMSE		1.96	2.13	1.63

Notes: This table replicates Table 5, where the sample is not limited to unemployed applicants.

	A. Women			Quantiles			B. Men			Quantiles		
	Mean	Standard Deviation	25th	50th	75th	N	Mean	Standard Deviation	25th	50th	75th	N
5 vs 10 Hours	$5.03 (1.11)	$9.91 (1.80)	-$0.97 (1.76)	$5.03 (1.11)	$11.03 (1.33)	226	$5.43 (1.20)	$3.19 (1.22)	$3.50 (1.38)	$5.43 (1.20)	$7.36 (1.43)	38
10 vs 15 Hours	$6.25 (1.36)	$11.45 (2.13)	-$0.69 (2.23)	$6.25 (1.36)	$13.18 (1.45)	208	$8.48 (1.85)	$6.53 (2.41)	$4.52 (2.34)	$8.48 (1.85)	$12.44 (2.37)	43
15 vs 20 Hours	$7.78 (1.21)	$11.29 (2.13)	$0.94 (2.07)	$7.78 (1.21)	$14.63 (1.42)	241	$9.63 (3.04)	$14.90 (8.14)	$0.59 (5.42)	$9.63 (3.04)	$18.66 (6.14)	46
20 vs 25 Hours	$9.81 (1.25)	$11.08 (1.88)	$3.09 (1.78)	$9.81 (1.25)	$16.53 (1.60)	194	$13.29 (3.76)	$21.11 (10.06)	$0.50 (6.98)	$13.29 (3.76)	$26.08 (7.34)	56
25 vs 30 Hours	$11.83 (1.32)	$12.48 (2.06)	$4.27 (2.06)	$11.83 (1.32)	$19.40 (1.54)	211	$13.72 (3.16)	$14.68 (6.23)	$4.83 (4.40)	$13.72 (3.16)	$22.62 (5.40)	45
30 vs 35 Hours	$16.37 (1.13)	$10.32 (1.90)	$10.12 (1.76)	$16.37 (1.13)	$22.63 (1.45)	222	$15.75 (1.19)	$3.88 (1.72)	$13.40 (1.71)	$15.75 (1.19)	$18.10 (1.43)	51
35 vs 40 Hours	$13.11 (1.57)	$15.27 (3.20)	$3.86 (2.59)	$13.11 (1.57)	$22.36 (2.41)	192	$10.68 (3.07)	$11.29 (4.84)	$3.84 (5.04)	$10.68 (3.07)	$17.52 (3.26)	36
40 vs 45 Hours	$21.99 (1.17)	$15.37 (0.82)	$12.67 (0.68)	$21.99 (1.17)	$31.31 (1.67)	203	$14.65 (2.91)	$14.73 (2.93)	$5.72 (1.14)	$14.65 (2.91)	$23.57 (4.68)	31
45 vs 50 Hours	$26.76 (1.31)	$15.22 (0.74)	$17.54 (0.86)	$26.76 (1.31)	$35.98 (1.76)	177	$20.00 (3.02)	$20.35 (3.08)	$7.67 (1.16)	$20.00 (3.02)	$32.33 (4.89)	38
Implied z	0.64 (0.04)		0.17 (0.06)	0.64 (0.04)	1.10 (0.05)	1,494	0.59 (0.06)		0.25 (0.09)	0.59 (0.06)	0.93 (0.09)	315

Notes: This table replicates Table 3, where results are shown by gender.