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

Alexandre Mas Amanda Pallais *

Abstract

We estimate the marginal value of non-work time (MVT) using a field experiment. We offered job applicants randomized wage-hour bundles. Choices over these bundles yield estimates of the MVT as a function of hours, tracing out a labor supply relationship. The substitution effect is positive. Individual labor supply is highly elastic at low hours and more inelastic at higher hours. For unemployed applicants, our preferred estimate of the average opportunity cost of a full-time job due to lost leisure and household production is 60 percent of after-tax marginal product, and 72 percent when including fixed costs of employment and child care costs.

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

*Mas: Industrial Relations Section, Simpson International Building, Princeton University, Princeton, NJ 08544, and NBER, and IZA (email: amas@princeton.edu); Pallais: Department of Economics, Harvard University, Littauer Center, Cambridge, MA 02138, and NBER (email: apallais@fas.harvard.edu). We would like to thank Gabriel Chodorow-Reich, Jan Eckhout, Lawrence Katz, Kevin Lang, Bobby Pakzad-Hurson and seminar participants at Brown University, London School of Economics, Stanford University, University of Bonn, and Yale University for comments. We would also like to thank Jenna Anders, Stephanie Cheng, Kevin DeLuca, Jason Goldrosen, Disa Hynsjo, Carl Lieberman, and Amy Wickett for outstanding research assistance. Financial support from NSF CAREER Grant No. 1454476 is gratefully acknowledged. The project described in this paper relies on data from a survey administered by the Understanding America Study, which is maintained by the Center for Economic and Social Research (CESR) at the University of Southern California. The content of this paper is solely the responsibility of the authors and does not necessarily represent the official views of USC or UAS. This project received IRB approval from Princeton (#0000006906) and Harvard (#15-0673). This study can be found in the AEA RCT Registry (AEARCTR-0002404).

typically calibrated, and for predictions of models to match the data it often requires extreme levels. 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). Understanding how individuals value marginal leisure time is necessary for computing the welfare costs of business cycles (Aguiar, Hurst, and Karabarbounis, 2013). 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 fill this gap by estimating z using a field experiment. During national application processes to staff a call center and to fill data entry positions, we asked jobseekers to choose between two jobs with different weekly hours and randomly-assigned wages. Using workers' choices, we 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 back out parameters that are central to numerous applications, including the value of non-work time and labor supply elasticities.

We posted ads on a 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 (accurately) described as temporary and work from home. Applicants, who were primarily 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 focus on unemployed job seekers as, for this group, there is a natural interpretation of MVT as the value of non-work time.[2] On the other hand, for employed jobseekers, MVT may include not only the value of leisure and household production, but also the wage in another job if workers substitute hours between jobs.[3]

[1] Borgschulte and Martorell (forthcoming) estimate a variant of z using reenlistment decisions of armed service personnel. Chodorow-Reich and Karabarbounis (2016) note 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] For completeness, we also show estimates for the full sample.

[3] It is possible that unemployed job seekers' hours choice may include the value of job search if they continue to look for work and this job limits the amount of time they can search. It may also incorporate the value of an alternative job if unemployed workers have other options and this job limits the options they can take. We do not think these will influence the estimates much because the offered jobs only differ by 5 hours per week. Additionally, a large body

Estimated MVT is increasing in hours worked. Since the collection of MVT values trace out a labor supply function, we can use the MVT estimates to compute compensated labor supply elasticities. Below 30 work hours the elasticity of hours with respect to the wage is greater than 1. At or above 40 hours it is in the 0.5-0.6 range.

We combine our MVT estimates with workers' predicted market wages to estimate the flow value of non-work time relative to the market wage, which we denote by $\tilde{z}$. For a full-time job, the estimates imply a value of non-work time relative to predicted pre-tax earnings of $\tilde{z} = 0.58$ (s.e.=0.04). We get similar estimates when we weight the sample to match the characteristics of hourly workers in the United States and when we use a hypothetical choice experiment in the nationally-representative Understanding America Study (UAS). While generalizing from a sample of unemployed, primarily female jobseekers raises reasonable external validity concerns, these results are reassuring that our estimates do not depend on the demographics of this particular sample.

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, specifically leisure and home production. In Section 4 we discuss and quantify the contribution of fixed costs of commuting, foregone benefits, and child care.

We also discuss how $\tilde{z}$ (which compares workers' MVT to their pre-tax market wage) and z (which compares workers' MVT to their post-tax marginal product) relate. Drawing from estimates of the gap between wages and marginal product from the literature on imperfect competition in the labor market (Manning, 2011), our preferred estimate (including fixed costs) is $z = 0.72$, which is in the intermediate to higher range of values used in the search literature. It is important to note, however, that there is not consensus in the gap between wages and marginal product. For example, calibrations of the Diamond-Mortensen-Pissarides (DMP) model (e.g., Hall and Milgrom, 2008) imply only a small divergence. Under this model, our estimate of z is 0.87.

Our estimates are also useful for the value of time measurement that enters cost-benefit analyses. The 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

of research (e.g., Krueger and Mueller, 2010; Aguiar et al., 2013) shows that jobseekers spend relatively little time actively searching for work.

employed workers' opportunity cost of work, unemployed workers' opportunity cost is difficult to measure since it reflects activities that occur outside the market (Harberger, 1971; Bartik, 2012). This value is what we estimate.

Finally, while the implied labor supply function is only moderately increasing at low hours of work, it becomes increasingly steeper near full-time work. This implies that labor supply elasticities estimated at particular hours levels may not generalize to other hours levels. A high labor supply elasticity at low hours may also rationalize why there are relatively few part-time workers: there is a limited wage range where individuals would find it optimal to work part-time.

Our study is most closely related to survey measures of the reservation wage, such as Feldstein and Poterba (1984), Holzer (1986), Krueger and Mueller (2016), and Le Barbanchon, Rathelot, and Roulet (forthcoming). The reservation wage is related to the flow value of non-market time, but differs if jobseekers account for the continuation value of unemployment (Mortensen, 1987) or beliefs about attainable wages are biased. Our approach also allows us to measure the value of time at differing hours of work. Importantly, our experimental measure is based on jobseekers' decisions in a natural environment.

Our paper also adds to a small literature that uses field experiments to estimate labor supply relationships. Papers in this literature include Burtless and Hausman (1978), Moffitt (1979), Ashenfelter (1983), Fehr and Goette (2007), Goldberg (2016), and Angrist, Caldwell, and Hall (2017). We also add to a larger quasi-experimental labor supply literature on situations where hours can vary freely, including Kahn and Lang (1991), 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).

1 Experimental Design

Our experiment took place in 2017 during the hiring process to fill telephone interviewer and data entry positions. The design is similar to that in Mas and Pallais (2017). We posted advertisements for these positions (shown in Appendix Figure 1) on a national U.S. job search platform in 80 large metro areas. The ads provided no information about the number of work hours or the wage, and did not specify that the job was work-from-home.

The ads linked to our website where interested jobseekers could apply for a position. Applicants began by creating an account and providing demographic information.[4] They were then shown two descriptions of job positions which differed only in the number of hours of work and the hourly wage. Individuals were asked to choose between a job that was [X] hours and a job that was [X+5] hours per week, where X varied from 5 to 35 in 5-hour increments. To minimize income effects, and abstract away from investment rationales for taking a longer hours job in terms of skill accumulation, both descriptions explicitly stated that the job was temporary and expected to last one month.[5] To eliminate the role of commuting the descriptions stated that the job was work-from-home. All of these statements accurately described the real jobs.[6] The position descriptions were as follows:

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

"This 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.[7]

We randomly varied the additional earnings an applicant would receive from working the longer job instead of the shorter job. Specifically, we define e_{ih} as the additional earnings for each of the five extra hours in the longer job:

$$e_{ih} = \frac{h_i \times w_{ih} - (h_i - 5) \times w_{ih-5}}{5}. \tag{1}$$

[4] The site prominently stated that providing race/ethnicity and gender was optional and that the questions could be skipped. Of those who were asked, 94.7 (95.3) percent of applicants provided their race (gender). By mistake, gender and race were not asked of some applicants. Overall, we have race (gender) information for 84.4 (85.0) percent of the sample. Results are similar if we restrict attention to applicants for whom we collected gender and race.

[5] While income differences between temporary jobs that differ by 5 hours per week are certainly small in a lifetime sense, it is possible that there are liquidity constraints in this population.

[6] We made 65 job offers.

[7] The ¶ indicates a line break.

We refer to e_{ih} as the "effective" hourly wage for these final five hours. Here, h_i and w_{ih} are the number of hours and hourly wage in the longer job, respectively and w_{ih-5} is the shorter job's hourly wage. 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 workers' values of time were lower at these hours levels and adding these lower effective wages would lead to less extrapolation.

The randomly-chosen effective wage determined both jobs' hourly wages. 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 determined by Equation (1). 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 25 hour job must pay \$18 per hour and the 30 hour job must pay \$15 per hour.[8] 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}. Appendix Table 1 shows the wages for each effective wage/hours combination. We rounded all jobs' hourly wages to the nearest \$0.10, so the actual effective wage was not always a round dollar amount. In our estimation, we use the actual (non-rounded) effective wage.

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 said that if they were hired they would be offered the position they chose, thereby making this a real decision.[9] We emphasized that their decision would not affect whether they were hired, only which position they received.

Appendix Figure 2 provides an example of the page with the job descriptions. This page was designed to ensure that only the jobs' wages and weekly hours of work would affect workers' choices. We referred to jobs by number to minimize the extent to which job titles would affect workers' choices.[10] To maximize the fraction of applicants who read both job applications carefully, we forced applicants to click on each position to see the job descriptions and to type the number of the job they preferred. We randomized which position was presented first.

We are also interested in workers' values of time above 40 hours per week. The Fair Labor

[8] 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.

[9] We also told them they would be considered for all open positions to give us flexibility to also offer them more generous alternatives.

[10] These numbers were randomly assigned to jobs and balanced within comparisons.

Standards Act (FLSA) requires paying hourly workers an overtime premium of at least 1.5 times their hourly pay for hours above 40. 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 versus 50 hour position and randomly varied the overtime premium. The 40 hour choice read:

"This 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:

"This 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 hourly wage until the final 5 hours. In the 45 versus 50 hour choice, the overtime wage is the same in both positions. We randomly select $EW \in \{27, 29, 31, 33, 35\}$. (Due to the FLSA, $27 was the lowest overtime wage we could offer.)

It may be easier for workers to make choices when only marginal wages differ (as in the overtime treatments) than when average wages differ and they have to determine effective wages (as in the non-overtime treatments).[11] In a validation study we assessed whether applicants make similar decisions when the choices are over marginal versus average wages. Specifically, we offered a 35 versus 40 hour choice with the same effective wages to different applicants, randomly phrasing the comparison as either (1) two separate hourly wage rates or (2) the same wage rate up to 35 hours and a separate marginal rate for the final 5 hours of the 40 hour job. As discussed in Section 3, both methods give similar results.

[11] In the main (non-overtime) treatments, we chose to vary average wages instead of marginal wages because varying only marginal wages would not allows us to detect MVT values below the minimum wage, which is sometimes substantially higher than our median MVT estimate.

2 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. Each individual i has a mean hourly value of time between $h-5$ and h weekly hours of work, which we denote by MVT_{ih}. We first use applicants' choices over the h and $h-5$ hour jobs to estimate $\overline{MVT_h} = E[MVT_{ih}]$, the average marginal value of time in our sample. Then we combine our estimates of $\overline{MVT_h}$ for different hours levels up to 40 hours per week to form our $\widetilde{z}$ estimate.

An individual chooses the longer job if the money she earns from working the additional five hours ($5e_{ih}$) exceeds the cost of working these additional hours ($5MVT_{ih}$). That is, if $MVT_{ih} < e_{ih}$. We assume a logistic distribution for MVT_{ih} (an assumption that we assess visually). Then, we estimate the probability of choosing the longer job $Pr(1[h_i] = 1|e_{ih}) = Pr(MVT_{ih} < e_{ih}|e_{ih})$ using a logit with an indicator for choosing the longer position ($1[h_i]$) as the dependent variable and the effective wage (e_{ih}) as the explanatory variable. Our estimate of $\overline{MVT_h}$ is -1 times the estimated intercept divided by the slope coefficient.[12][13]

We modify this procedure to estimate $\overline{MVT_h}$ for the overtime treatments. The FLSA necessitates we offer high effective wages in these treatments, so estimating $\overline{MVT_h}$ requires extrapolation.[14] We estimate the model constraining the intercept, $Pr(1[h_i] = 1|e_{ih} = 0)$, based on the intercept in the non-overtime treatments. This allows the non-overtime treatments to inform the extrapolation, dramatically increasing precision in the 40 vs. 45 hour choice. (It has little effect on the estimates for the 45 vs. 50 hour choice where there is less extrapolation.) Our preferred specification uses the estimated intercepts at lower hour treatments to predict the intercept as a function of h. In the appendix, we show different methods of picking the intercept constraint give similar estimates. These adjustments do not affect estimates of $\widetilde{z}$, which measure the value of time through 40 hours of work.

[12] Assume MVT_{ih} has mean μ and variance ${s^2\pi}/{3}$, where s is the scale parameter. $Pr(1[h_i] = 1) = Pr(MVT_{ih} < e_{ih}) = Pr(\frac{MVT_{ih}-\mu}{s} < \frac{1}{s}e_{ih} - \frac{\mu}{s}) = \Lambda\left(\frac{1}{s}e_{ih} - \frac{\mu}{s}\right) = \Lambda(\beta_1 e + \beta_0) = \frac{1}{1+e^{-(\beta_1 e+\beta_0)}}$, where $\Lambda()$ is the standard logistic function. The logit slope coefficient is $\beta_1 = 1/s$ and the intercept is $\beta_0 = \mu/s$. The logit cdf is 0.5 when $e = -\,{\beta_0}/{\beta_1}$. We show in the appendix that estimates are robust to assuming normality.

[13] As shown in Mas and Pallais (2017), some applicants are inattentive. Because inattention doesn't affect estimates of the mean (see Mas and Pallais, 2017) we do not explicitly model it. We show in an appendix table that modeling inattention using a mixture model gives similar results.

[14] In the 40 vs. 45 hour comparison, about three quarters of applicants choose the 45 hour job at the lowest effective wage offered.

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. If an individual's inverse labor supply function, $w_i(.)$, is strictly increasing, $w_i(h_i - 5) < MVT_{ih} < w_i(h_i)$. That is, her value of time at h_i hours exceeds her average value of time between $h_i - 5$ and h_i hours which exceeds her value of time at $h_i - 5$ hours. At a wage of MVT_{ih}, she would choose to work strictly between $h_i - 5$ and h_i hours per week.[15]

To calculate $\widetilde{z}$, the average flow value of non-work time for a 40 hour job, we combine our estimates of $\overline{MVT_h}$, the average value of time between $h-5$ and h hours, for different values of h. Since no applicants were given a 0 versus 5 hour 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. Our estimate of $\widetilde{z}$ is

$$\widetilde{z} = \frac{1}{\hat{w}} \left[\frac{5(\overline{MVT_5} + \overline{MVT_{10}} + ... + \overline{MVT_{40}})}{40} \right]. \tag{2}$$

Here, $\hat{w}$ is average predicted pre-tax hourly market wage, calculated using applicant gender, race, education, and age and data from the 2016 Current Population Survey Merged Outgoing Rotation Groups (CPS MORGs). Specifically, we predict an applicant's wages as the average wage of hourly workers in the CPS living in cities with his or her gender, race, and education, and in his or her 5-year age bin. For unemployed applicants we discount the resulting wage by 6 percent, the estimated wage penalty for employed hourly workers who separated from their last job in the last three years in the 2016 CPS Displaced Worker Supplement.[16] We average these individual predictions to form $\hat{w}$.

After estimating the model for each hours choice individually, we combine the parameter estimates and covariance matrices from all hours choices and calculate robust standard errors on MVT and $\widetilde{z}$ estimates using the delta method.

[15]Note that $\overline{MVT_h}$ is an approximation to the average individual inverse labor supply curve, not an aggregate labor supply curve.

[16]Using 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.

3 Results

3.1 Descriptive Statistics

The majority (83 percent) of our sample is female (Appendix Table 2). This is in large part because phone survey and data entry workers are primarily women. Applicants average 34 years of age. 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. Most of our sample is currently unemployed, most commonly for under three months.

Appendix Table 3 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, limiting the sample to applicants who made a job choice. Out of these 54 regressions, the effective wage indicators are jointly significant in four regressions, a number we may reasonably expect to see by chance. Appendix Table 4 shows that 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.

3.2 Main Treatments

We begin with visual nonparametric and parametric summaries of the data. We construct binned scatterplots of the fraction of unemployed applicants who chose longer hours against the effective wage (e_{ih}) for each hours choice. We overlay the scatterplot with the logit ML fit, which can be interpreted as 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.[17] In all cases the logit assumption appears reasonable.

Panel A of Table 1 presents estimates of the mean MVT by hours of work for unemployed jobseekers.[18] For reference, using the 2016 CPS we predict that the pre-tax market wage for the

[17]Inattention-corrected figures (Appendix Figure 5) look similar.

[18]Inattention-corrected estimates are in Appendix Table 5, estimates for all applicants regardless of employment status are in Panel A of Appendix Table 6, and estimates limited to unemployed workers who applied for the job are in Panel B of Appendix Table 6. Appendix Table 7 shows results using probit and lowess specifications.

average unemployed job seeker in our sample is \$13.93. 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 \$4.80 between 5 and 10 hours of work and increases to \$8.95 per hour between 20 and 25 hours of work. MVT increases relatively linearly through the first 40 hours, reaching about \$15 between 30 and 40 working hours. After 40 hours MVT increases more quickly, reaching almost \$22 between 40 and 45 working hours.[19] On average, workers' MVT equals their average predicted market wage in the 30 to 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 $\widetilde{z} = 0.58$ $(s.e. = 0.04)$.

Appendix Figure 6 compares workers' choices over a 35 hour and 40 hour job when (1) the jobs have two separate hourly wages (and workers have to calculate effective wages) and (2) the 40 hour job has the same hourly wage as the 35 hour job for the first 35 hours and a separate hourly wage for the final 5 hours. The estimates are close and we conclude that the framing of the choice is not affecting the estimated MVT.

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. Figure 2 plots this labor supply function, both the estimated values and a quartic fit. The function is moderately upward sloping and becomes steeper around 30 to 40 hours of work.

Table 2 presents labor supply elasticities by hours worked, calculated both of off the raw points and the quartic fit. Labor supply is highly elastic at low hours levels, exceeding 1 until 30 hours of work. At that point the elasticity drops, reaching 0.5 to 0.6 after 40 hours per week.

We do two analyses to assess whether our estimates are relevant for a broader population of workers outside of our experiments. First, we weight our estimates to match the age, gender, and race of hourly workers in the CPS. The weighted value of time estimates by hours choice are shown in Panel B of Table 1.[20] Weighting results in very similar values of non-work time: 0.57 (s.e.=0.07).

Second, we replicate our results using the UAS, a nationally-representative survey in which a panel of individuals responds to web-based surveys. We asked hourly workers to make choices

[19] Appendix Table 8 shows the overtime estimates are robust to different intercept constraints.
[20] Appendix Table 9 shows descriptive statistics for the weighted and unweighted samples.

over 10 vs. 20, 20 vs. 30, and 30 vs. 40 hour per week jobs, with randomized wages. Respondents were told to assume that aside from the wages and hours of work, the positions were the same as their current main job (if they were employed) or their last job (if they were unemployed). Appendix A includes the exact wording of the question and estimation details. The UAS estimate of $\widetilde{z}$ is 0.61 (s.e.=0.03) (Table 3). This value is very similar to the estimated $\widetilde{z}$ in the field study.

4 Discussion

A significant component of time in unemployment is spent on leisure and home production (Aguiar, Hurst, and Karabarbounis, 2013). Our estimates suggest that, clearly, this use of time is highly valued. To compare our estimates to assumed or calibrated opportunity cost parameters in the search literature, we need to account for possible wedges between wages and marginal products, taxes, fixed costs of employment, and child care costs. We discuss these issues below.

Wages versus Marginal Products

Since workers' marginal products likely weakly exceed their wages, estimates of z based on marginal product are likely weakly smaller than those based on wages. Estimates of the elasticity of labor supply to the firm provide guidance on the degree of this divergence. In the monopsony framework the percent difference between marginal product and the wage equals the inverse of the elasticity of labor supply to the firm. Assuming an elasticity of around 4, in the range of estimates reported in Manning (2011), marginal product will be 25 percent higher than the wage, implying that z will be 20 percent lower than $\widetilde{z}$. Calibrations of DMP models yield a substantially smaller divergence between wages and marginal products. Hall and Milgrom (2008) calculate a ratio of the wage to marginal product of 0.985 (see also Hall and Mueller, forthcoming), implying a value of z based on marginal product that is close to the one we estimate.

Taxes

Estimates of z are often based on the after-tax marginal product (Chodorow-Reich and Karabarbounis, 2016). Applying an effective tax rate of 0.2 increases our estimate of z by 25 percent.

Fixed Costs

Estimates of the opportunity cost of work will be higher if we account for commuting costs and forgone benefits associated with working. A reasonable approximation is that commute time is valued at half the gross wage (Small, 2012). Since the average worker spends approximately one hour a day commuting, this would add 0.06 to the estimated value of z.

Among the unemployed, estimated $\tilde{z}$ is similar among those who are potentially eligible for UI benefits and those who are not (Table 3).[21] This may indicate that many applicants who are potentially UI-eligible are not receiving benefits. If individuals in our sample are not collecting UI benefits, the estimates do not fully capture the value of the reduced benefits that accompany working. However, as noted by Chodorow-Reich and Karabarbounis (2016), the average value of unemployment benefits across all unemployed workers is small because only 40 percent of the unemployed receive UI benefits. Chodorow-Reich and Karabarbounis (2016) estimate that the average opportunity cost of employment due to benefit loss, which includes UI, SNAP, TANF and Medicaid, is 6 percent of the after-tax marginal product. While this is relatively low, a jobseeker who is receiving UI will have a value of z close to unity at typical replacement rates.

Child Care

Applicants who are more likely to have children under 15 (those aged 26-39) do not have a significantly higher value of $\tilde{z}$ than those who are less likely to have children under 15 (age$\leq$ 25 or age$>$ 40) (Table 3). This comparison is suggestive that jobseekers do not intend to pay for additional child care for this job.[22] Average child care expenses in the labor force are low because only 30 percent of workers have children under 15 and, conditional on having a child under 15, only a small share pay anything for child care. Among women who have children under 15 and full-time jobs, only 35 percent have any childcare expenditures. The average childcare expense nationally is \$148 per week conditional on being non-zero, and \$51.8 overall, approximately 2.3 percent of an individual's weekly income.[23] While the average child care expenditure is low, any worker who requires unsubsidized center-based care or a babysitter will have a value of z close to or greater than unity. However, these workers are the exception rather than the rule.

In sum, if we assume the monopsony case, a z based on after-tax marginal product will be close to our estimate of $\tilde{z}$=0.58, based on pre-tax wages. (The decrease in z from normalizing by the marginal product instead of the wage is directly offset by accounting for taxes.) Adding

[21] We classify individuals as potentially eligible for UI if they have been unemployed for less than their state's maximum UI duration. These workers may not actually be UI-eligible, for example, if their work history is too short.

[22] This makes sense since the position is work-from-home and temporary.

[23] Statistics are derived from the 2008 SIPP, available at https://www2.census.gov/library/publications/2013/demo/p70-135.pdf. Average weekly earnings for women are from the 2008 CPS.

average commuting costs, foregone benefits, and child care costs would increase z to approximately $z = 0.72$. This estimate is in the intermediate to upper end of the search literature. Chodorow-Reich and Karabarbounis (2016) report a range of estimates of 0.45-0.5 prior to the Hagedorn and Manovskii (2008) study and 0.73-0.92 after.[24] In their calibration, they report z in the range of 0.47-0.75 based on after-tax marginal product. This estimate of $z = 0.72$ is in this range, providing support for their utility function calibration approach that is the basis for estimating the cyclicality of the value of time. If instead of the monopsony case, we use the smaller Diamond-Mortensen-Pissarides wedge between wage and marginal product, our estimate is larger, at $z = 0.87$.

A high value of z could be due to perceptions that the occupations in our study are poorly perceived. The consistency of the field estimates with the UAS survey, which has a representative distribution of occupations, suggests that working conditions are not playing a large role in our estimates. Moreover, the telephone interviewer occupation (representing 86 percent of our sample) is in the 71st percentile of the occupational distribution of job satisfaction.[25] Since most of our sample is from an occupation with high job satisfaction, it seems unlikely that perceptions of poor working conditions are driving up the opportunity cost of work.[26]

Workers may also obtain psychological benefits from having a job. To the extent that having a 5 hour job gives utility relative to no job, we will not capture this benefit in our estimate. Including this psychic benefit would result in a lower value of z. However, if utility from employment accrues with higher weekly hours, our estimates will capture this.

Our study sheds light on the labor supply relationship. Highly elastic labor supply at low hours of work is not incompatible with the literature that estimates relatively inelastic labor supply at the intensive margin. The less elastic part of the labor supply relationship corresponds to the range of hours where most people work. Since most workers are full-time, any local variation in the wage will show only moderate variation in hours.

The shape of the labor supply function we estimate can potentially rationalize the distribution of hours in the economy. In the U.S. many people work full-time or are out of the labor force. There

[24]Papers include Mortensen and Nagypal (2007), Costain and Reiter (2008), Bils, Chang, and Kim (2012), Hagedorn and Manovskii (2008), Hall and Mueller (forthcoming), Hall and Milgrom (2008), Hornstein, Krusell, and Violante (2011), and Shimer (2005).

[25]This is calculated from 2004-2016 General Social Survey data.

[26]The data entry occupation is in the 10th percentile of job satisfaction. Excluding the data entry position leads to a similar z estimate.

are fewer part-time workers. 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 intermediate hours are on the elastic part of the labor supply curve, implying a limited wage range where a worker would find it optimal to work part-time.[27]

The estimated value of z can also be applied to cost-benefit analyses that involve the 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 percent of that value, before fixed costs and child care expenditures.

[27] There are other explanations for the relative scarcity of low hour jobs, such as fixed costs of employing workers and productivity that is convex in hours.

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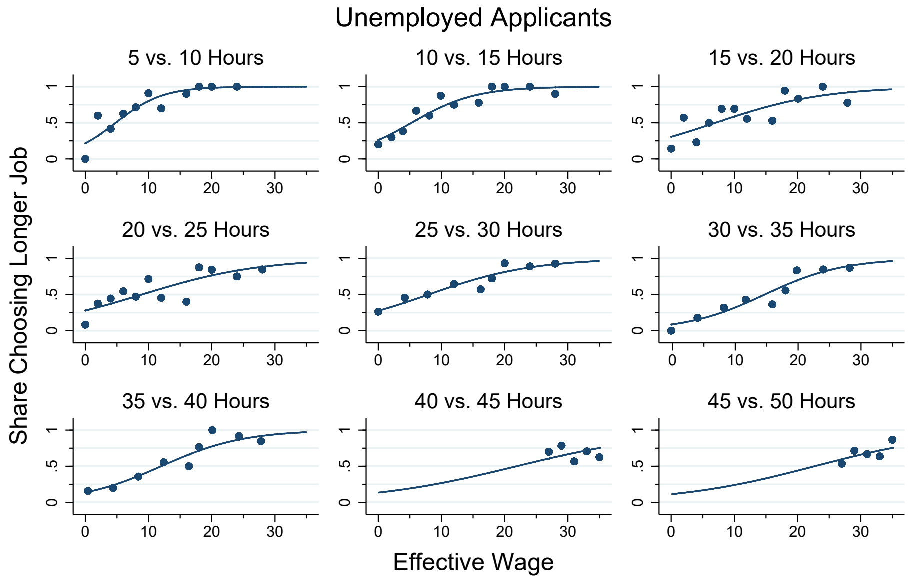
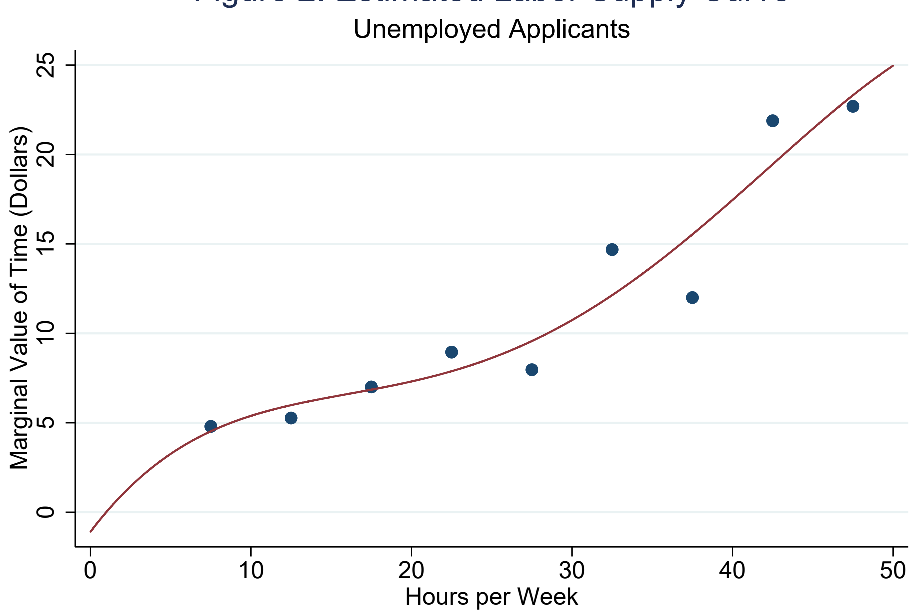
Figure 1. Marginal Value of Time



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 fraction of applicants who chose the longer job at each effective wage. The logit fit is estimated off the individual-level data. In the '40 vs. 45 Hours' and '45 vs. 50 Hours' panels, we constrain the intercepts, $Pr(1[h_i] = 1|e_{ih} = 0)$, to values predicted using the estimated intercepts at lower hour treatments, as described in the text.

Figure 2. Estimated Labor Supply Curve



Notes: The figure shows the mean MVT for unemployed applicants in each 5 hour range, plotted at the midpoint of the range (e.g., the mean MVT calculated from the 5 vs. 10 hours choice is plotted at 7.5 hours per week). The points are overlaid by a quartic polynomial estimated off of these points.

Table 1. Marginal Value of Time
Unemployed Applicants

	A. Unweighted		B. Weighted	
	Mean	N	Mean	N
5 vs. 10 Hours	\$4.80	117	\$5.88	94
	(0.96)		(1.15)	
10 vs. 15 Hours	\$5.27	124	\$7.00	99
	(1.22)		(1.14)	
15 vs. 20 Hours	\$7.00	128	\$5.09	108
	(1.91)		(6.56)	
20 vs. 25 Hours	\$8.95	153	\$8.30	125
	(1.74)		(3.44)	
25 vs. 30 Hours	\$7.97	135	\$8.85	110
	(1.84)		(2.17)	
30 vs. 35 Hours	\$14.68	133	\$16.80	102
	(1.34)		(1.81)	
35 vs. 40 Hours	\$12.00	112	\$13.89	88
	(1.50)		(1.51)	
40 vs. 45 Hours	\$21.89	121	\$20.35	97
	(1.70)		(1.79)	
45 vs. 50 Hours	\$22.69	129	\$22.19	99
	(1.54)		(1.97)	
Implied $\tilde{z}$	0.58	902	0.57	726
	(0.04)		(0.07)	

Notes: The table provides statistics on workers' marginal value of time in each hours range. Estimates are limited to applicants who are unemployed and are derived from a logit model, as described in the text. Robust standard errors calculated using the delta method are in parentheses. The implied $\tilde{z}$ estimate is based on hours up to 40. Weights are calculated using the DiNardo, Fortin and Lemieux (1996) method, matching the covariate distribution of hourly workers ages 16-64 in the 2016 CPS Merged Outgoing Rotation Groups (CPS MORGs). We weight the whole experimental sample to match the 2016 CPS MORGs and then limit observations to unemployed workers. Sample weights are created using race dummies, a female dummy, age, and age*race, age*female, and female*race interaction terms. Weights are capped at a maximum of 10 standard deviations above the sample mean weight, affecting 1 observation in Panel B.

Table 2. Labor Supply Elasticities
Unemployed Applicants

	Raw Points	Quartic Fit
10 Hours	5.36	1.80
15 Hours	1.18	2.47
20 Hours	1.02	1.79
25 Hours	-1.72	1.03
30 Hours	0.28	0.71
35 Hours	-0.71	0.58
40 Hours	0.21	0.56
45 Hours	3.07	0.62

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 second column fits a quartic function to the MVT points and uses this curve to calculate labor supply elasticities. Only unemployed applicants are included.

Table 3. Estimates of $\tilde{z}$

	UI Eligibility		Childcare Responsibility			UAS
	Eligible for Benefits	Ineligible for Benefits	Age 25 or Younger (13.5%)	Age 26-39 (51.9%)	Age 40 or Older (21.7%)	Hourly Workers
Estimate of $\tilde{z}$	0.57	0.61	0.74	0.53	0.53	0.61
	(0.05)	(0.10)	(0.13)	(0.06)	(0.10)	(0.03)
Observations	644	251	279	419	188	2,354

Notes: Each cell reports the $\tilde{z}$ calculated for the subgroup indicated by the column. Data from the experiment include only unemployed applicants. We consider applicants "Eligible for Benefits" if they have been unemployed for less than 3 months or if they have been unemployed for 3-6 months and live in a state where the maximum duration of UI benefits is at least 4.5 months. In the "Childcare Responsibility" columns, the percents in parentheses show the percent of people in each age group with children under 15 (calculated from the 2008 CPS, conditional on being in the labor force). 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 $\tilde{z}$ 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 $\tilde{z}$, 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.