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THE VALUE OF WORKING CONDITIONS IN THE UNITED STATES AND IMPLICATIONS FOR THE STRUCTURE OF WAGES

Nicole Maestas
Kathleen J. Mullen
David Powell
Till von Wachter
Jeffrey B. Wenger

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ABSTRACT

This paper documents variation in working conditions among workers in the United States, presents new estimates of how workers value these conditions, and assesses the impact of working conditions on estimates of the wage structure and inequality. We use evidence from a series of stated-preference experiments to estimate workers' willingness-to-pay for a broad set of job characteristics, which we validate with actual job choices. We find that working conditions vary substantially across workers, play a significant role in job choice decisions, and are central components of the compensation received by workers. Preferences vary by demographic groups and throughout the wage distribution. We find that accounting for differences in preferences for working conditions often exacerbates wage differentials by race, age, and education, and intensifies measures of wage inequality.

Nicole Maestas
Department of Health Care Policy
Harvard Medical School
180 Longwood Avenue
Boston, MA 02115
and NBER
maestas@hcp.med.harvard.edu

Kathleen J. Mullen
RAND Corporation
1776 Main Street
P.O. Box 2138
Santa Monica, CA 90407-2138
Kathleen_Mullen@rand.org

David Powell
RAND Corporation
1776 Main Street
P.O. Box 2138
Santa Monica, CA 90407
powelld@nber.org

Till von Wachter
Department of Economics
University of California, Los Angeles
8283 Bunche Hall
MC 147703
Los Angeles, CA 90095
and NBER
tvwachter@econ.ucla.edu

Jeffrey B. Wenger
RAND Corporation
1776 Main Street
P.O. Box 2138
Santa Monica, CA 90407-2138
jbwenger@rand.org

1. Introduction

It has long been recognized that wages do not reflect the full compensation that individuals receive from working, and that workers may be willing to sacrifice higher wages for better job characteristics when making job choices (e.g., Brown, 1980; Duncan and Holmlund, 1983; Rosen 1986; Kniesner et al., 2012). These wage tradeoffs have the potential to explain persistent differences in wages among observationally similar workers, such as by gender or race, or wage inequality more generally. The most recent evidence we have points to substantial variation in job attributes across demographic groups and across the wage distribution (e.g., Hamermesh, 1999; Pierce, 2001; Monaco and Pierce, 2015),[1] and two recent experimental studies confirm substantial and heterogeneous willingness-to-pay for schedule-related job amenities (e.g., Mas and Pallais, 2017; Wiswall and Zafar, 2017).

Despite the available evidence, it has been difficult to assess to what extent differences in the incidence and valuations of non-wage job characteristics shape persistent wage differentials in the labor market. In the United States, there currently is no survey of a representative sample of workers about a broad range of job attributes. Moreover, it has proven very difficult to estimate willingness-to-pay for job amenities based on observational data alone.[2] While the theoretical relationship between job characteristics and wages is clear (e.g., Rosen, 1986), the empirical literature documenting the existence and magnitude of such tradeoffs has faced substantial challenges given multiple sources of selection.

To address these difficulties, we study the incidence of job attributes, willingness-to-pay for these attributes, and their impact on estimates of the wage structure using a new, nationally

[1] Pierce (2001) and Monaco and Pierce (2015) primarily focus on fringe benefits and assign measures of costs, not values to workers, to each benefit.
[2] Clearly, working conditions are not randomly assigned and are potentially correlated with unobserved determinants of wages, generating non-causal correlations between wages and job amenities that do not reflect the tradeoffs individuals face. In particular, since the distribution of wages and job amenities are jointly determined by supply and demand, observed variation in wages reflects labor compensation received by workers, firms' costs of offering certain amenities and workers' preferences for them, and the resulting wage reductions associated with those amenities.

representative survey of working conditions and a stated-preference approach. Our paper makes three primary contributions. First, because of the surprising lack of comprehensive data about job characteristics in the United States, we fielded the American Working Conditions Survey (AWCS) in 2015 to a representative sample of workers enrolled in the American Life Panel. To obtain a comprehensive view of the incidence and importance of job amenities, we asked about a broad set of job characteristics including schedule flexibility, telecommuting opportunities, physical demands, pace of work, autonomy, paid time off, working with others, job training opportunities, and impact on society. We purposefully focused on amenities that would not be considered monetary job benefits, because fringe benefits, such as health insurance or pension plans, have been studied extensively elsewhere. These data enable us, for the first time since the 1970s, to provide a comprehensive assessment of whether there are systematic differences in these working conditions by gender, race, education, age, and across the wage distribution.

Second, we estimate the willingness-to-pay for each amenity in the same nationally representative sample of workers, using a stated-preference approach. The benefits of the stated-preference method are that we can randomize job characteristics and observe the tradeoffs individuals face, disentangling the presence of a job characteristic from the unobserved worker-, firm-, and market-specific attributes that affect estimates based on observational data. It also provides us with information about jobs *not* chosen as well as those chosen, information which is necessary to accurately measure tradeoffs underlying willingness-to-pay estimates. This method also permits us to test for the joint importance of multiple job attributes, providing respondents with choice sets that vary along a broad set of characteristics. We then fit a model of job choice to the choice data to estimate the tradeoffs that individuals are willing to make between working conditions and wages. These tradeoffs yield transparent willingness-to-pay metrics for each job amenity included in the choice experiments.

Third, we use the willingness-to-pay estimates from the stated-preference experiments to adjust typical estimates of wage differentials by gender, race, and age, and test whether the inclusion of amenities into the full measure of compensation significantly alters metrics of wage differentials. We also assess whether accounting for systematic differences in amenities changes the extent of wage inequality in the U.S. labor market more generally. An added advantage of our approach is that it also allows us to analyze whether willingness-to-pay for certain amenities differs by demographic groups, and whether this heterogeneity further affects the adjusted estimates of the wage structure. If women are willing to pay more for schedule flexibility, then jobs in which workers have more control over their hours are worth more to women and our compensation metrics can be adjusted accordingly.

Our first main finding is that a broad range of working conditions varies substantially across demographic groups and throughout the wage distribution. Our estimates paint a complex picture of working conditions in the U.S. labor market. While some patterns are expected – for example, college-educated and older workers have uniformly better job characteristics across nearly all categories we examined – some are more nuanced. Non-whites tend to have worse job characteristics than whites, but perhaps less so than expected. Women and older workers hold jobs with a different mix of job attributes than men and younger workers, respectively. These patterns imply potentially important effects of differential access to amenities and differential preferences for amenities on wage differentials and wage inequality.

Our second main finding is that workers have non-negligible willingness-to-pay for most dimensions of amenities included in our stated-preference experiments. Considering all amenities, we find that a switch from the worst job (having none of the amenities included in our experiments) to the best job (having the best set) is equivalent to a 56% wage increase, suggesting that non-wage characteristics play a central role in job choice and compensation. Moreover, we find evidence that these valuations differ, sometimes substantially, by demographics and across the wage distribution.

Our third main finding is that both variation in amenities and variation in preferences affect the wage structure. When differences in the incidence of working conditions alone are taken into account, we find that education-wage differentials are substantially increased. When we account for differences in preferences for working conditions across groups, we find that wage differentials by race, gender, and age are affected as well. Wage differentials by race and age widen, while the gender wage gap narrows. We also find that accounting for amenities exacerbates measured wage inequality.

We are of course aware that the advantages of the stated-preference approach come at potential costs, in particular concerns about external validity (Diamond and Hausman, 1994; Manski, 1999; Hausman, 2012). To address these concerns, we exploit the fact that we observe detailed information about the actual jobs held by our survey respondents. Most notably, we find that individuals who have a given amenity in their current job value that amenity more highly than workers who do not have that amenity. Further evidence in support of the stated-preference approach comes from Mas and Pallais (2017), who show that their findings based on actual wage variation are consistent with their findings from survey-based stated-preference experiments. Hence, while stated-preference estimates cannot substitute for revealed preference estimates, given the impossibility of generating fully comprehensive experimental evidence on the valuation of job amenities and the importance of the research question, we believe our approach provides important estimates of valuations across a broad set of working conditions for a representative sample from the United States labor market.

Our paper contributes to several strands of literature. One strand has investigated reasons for persistent wages differentials between workers and jobs. The majority of papers have focused on the importance of differences in worker skills and productivity (e.g., Mincer and Polachek, 1974; Neal and Johnson, 1996; Lang and Manove, 2006), wage differences between employers (e.g., Bayard et al., 2003; Price et al., 2018) and regions (e.g., Moretti, 2013), differences in labor supply (e.g., Neal, 2004), and discrimination in the labor market (e.g., Bertrand and Mullainaithan, 2004; Farber, Silverman, and von Wachter, 2016). Here, we contribute a comprehensive assessment of the importance of working conditions by documenting their incidence using a representative survey fielded for this purpose and providing new estimates of the willingness-to-pay for a broad set of working conditions.

Similarly, a long literature has analyzed the potential importance of job characteristics in the labor market. Yet, the last publicly-available, representative surveys of working conditions were fielded in the 1970s.[3] Typically, studies in this literature have implemented a hedonic pricing approach to assign monetary values to non-wage attributes, often referred to as compensating differentials. These papers have estimated compensating differentials for job characteristics such as injury and fatality risk, physical job demands, stress, hazard exposure, schedule flexibility, shift work, and many other working conditions.[4] The literature has recognized the difficulties of isolating compensating differentials in the presence of many unobservable variables such as skills, preferences, or search frictions, and missing information about the choice set. Addressing such confounding factors has proven difficult.[5]

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[3] These were the Quality of Employment Surveys of 1972-1973 and 1979. Information on monetary job benefits, such as health insurance or pension plans, but not other job amenities, is available in the Current Population Survey, the Survey of Income and Program Participation, and the National Compensation Survey.

[4] E.g., for fatality injury and fatality risk see Smith (1973), Thaler and Rosen (1976), Viscusi (1993), and Viscusi and Aldy (2003); for physical job demands see Lucas (1977), Bluestone (1974), Brown (1980), Duncan and Holmlund (1983); for stress see Brown (1980), for hazard exposure see Hamermesh (1977) and Duncan (1976); for schedule flexibility see Duncan (1976), Duncan and Stafford (1977), and Goldin and Katz (2011); for shift work see Kostiuk (1990).

[5] For example, workers with more skill in the labor market select into jobs with both higher wages and better amenities, creating a cross-sectional positive correlation between monetary and non-monetary compensation (e.g., Hwang et al. 1992). Alternatively, search frictions can cause sizeable bias when estimating willingness-to-pay measures (Dale-Olsen 2006 and Bonhomme and Jolivet 2009). Some researchers have conditioned on individual fixed effects to reduce concerns about skill heterogeneity (Brown, 1980; Duncan and Holmlund, 1983; Kniesner et al., 2012) but this assumes that skill is fixed over time such that selection into better jobs is orthogonal to human capital development. Other papers

We sidestep these difficulties by generating randomized choice data using a stated-preference approach. A recent literature on job amenities has used new approaches to circumvent the identification challenges present in the traditional compensating differential literature. For example, Mas and Pallais (2017) randomized schedule flexibility and the option for telecommuting across a sample of applicants for entry-level jobs at a national call center, requesting applicants to select across jobs varying on these dimensions. Wiswall and Zafar (2017) surveyed undergraduate students at New York University using hypothetical choices for jobs varying randomly based on job stability, whether part-time work is an option, and future earnings growth.

More generally, the stated-preference approach has provided valuable evidence for many economic topics including environmental policy (Carlsson and Martinsson, 2001; Carson, 2012), consumer preferences (Revelt and Train, 1998), labor supply (Kimball and Shapiro, 2008), retirement decisions (van Soest and Vonkova, 2014), and long-term care (Ameriks et al., 2015). We advance this line of research by allowing jobs to be multidimensional across a broader set of characteristics. This provides some of the first evidence on the importance of multiple job characteristics jointly, such as opportunities to contribute to the community, autonomy in terms of how one works on tasks, the opportunity to gain transferable skills, and other amenities that are potentially critical determinants of job choice and wages.

In Section 2, we introduce the data from the American Working Conditions Survey and describe how we selected job characteristics to investigate. In Section 3, we describe the incidence of working conditions in the U.S. workforce and explore differences based on demographics and throughout the wage distribution. In Section 4, we discuss our empirical approach for estimating valuations of different job characteristics. We present our main willingness-to-pay estimates in

have explicitly modelled the components of the job choice decision that may confound estimation of the true willingness-to-pay. Hamermesh and Wolfe (1990) model occupational choice while Gronberg and Reed (1994) model search frictions and use job duration to estimate the willingness-to-pay for job attributes. D'Haultfoeuille and Maurel (2013) adopt a Roy model approach to account for selection in different jobs.

Section 5 and consider the implications for the wage distribution in Section 6. Section 7 summarizes an extensive analysis of robustness, and Section 8 concludes.

2. Data on Working Conditions and Wages from American Working Conditions Survey

2.A The American Working Conditions Survey

The American Working Conditions Survey (AWCS) is a longitudinal survey designed to elicit detailed information about a broad range of working conditions in the American workplace. The AWCS was fielded on the RAND American Life Panel (ALP). The ALP is a nationally representative, probability-based panel designed for social science research. Panel members take regular surveys on their computer, tablet, or phone. Participants without access to technology are provided with internet service and/or a device. The initial wave of the AWCS, fielded during July-October 2015, is modeled on and harmonized with the sixth European Working Conditions Survey (EWCS), also fielded in 2015 to a representative sample of workers in 35 countries in Europe.[6] The second wave of the AWCS was administered from December 2015-February 2016 and consisted of the stated-preference experiments used in this paper. Subsequent waves have consisted of follow-up questions about changes in working conditions, and are ongoing.

There were 3,004 respondents to the stated-preference module, resulting in a response rate of 60.7%. For the purposes of this paper, we selected respondents who were currently working (N=1,947) and were between the ages of 25 and 71 (N=1,908). We excluded individuals reporting hourly wages over \$500 or below \$1 in our analysis. After further dropping individuals who did not complete the entire survey, our final analysis sample consists of 1,815 individuals. All statistics are weighted using weights generated to match demographics in the Current Population Study (CPS).

[6] See Maestas et al. (2017a; 2017b) for further information about the first wave of the AWCS, summary statistics by age, gender and education, and a data codebook. The first wave of data can be downloaded from: https://www.rand.org/pubs/tools/TL269.html.

Table 1 presents mean wages for our full sample, and by gender, race, education and age. The mean hourly wage in the sample is $29.92. Mean wages vary substantially by gender, race, education, and age, ranging from $23.69 for non-whites to $37.64 for those with a college degree or more. Estimating wage differentials jointly in a linear regression, we find that women's wages are on average 21.3% lower than men's, non-whites' wages are 13.2% lower than those of whites, and workers with less than a college degree have 54.8% lower wages than those with a college degree. We explore the potential of differences in working conditions and their valuations in explaining part of these wage gaps below. In Appendix Table 1, we compare the wage differentials in our data to those found in the CPS. The CPS topcodes weekly earnings so we present the ALP differentials with and without comparable topcoding. Overall, the estimated wage gaps are very similar across groups.[7]

2.B Main Dimensions of Working Conditions Used in Analysis

The economics literature has previously considered a rather limited set of non-wage job characteristics due to constraints in available data. Our goal was to investigate characteristics that broadly define non-wage job attributes currently available in the labor market that are likely to be valued by workers.

To identify these attributes, we performed a thorough review of the literature, across several fields. We looked for evidence or hypotheses that a certain amenity or amenities were key features of jobs, with the potential to influence job choices and wages. In addition, we analyzed the first wave of the American Working Conditions Survey (AWCS) to identify working conditions that respondents rated as important and that exhibited variation in the population (see Maestas et al., 2017a). While our final list of job characteristics does not necessarily capture all of the non-

[7] The exception is middle-aged workers, who have higher wages than older workers in the CPS, and lower wages than older workers in the ALP. While the ALP age-gradient in wages conforms to typical patterns, we do not put emphasis on our findings for this particular contrast.

monetary aspects of a job, we believe that the nine dimensions of job characteristics we selected, along with wages and hours, define a set of core job attributes for workers today. We directly verify that these attributes are salient by estimating workers' willingness-to-pay below. In the remainder of the section, we briefly summarize the attributes we selected and the prior literature that motivates their selection.

Schedule Flexibility. There is considerable interest in understanding work arrangements that facilitate greater flexibility in setting working hours (e.g., Katz and Krueger, 2016). Earlier work examined the association between flexible work schedules and wages (e.g., Gariety and Shaffer, 2007; Weeden, 2005), while more recent work has sought to determine employee preferences for schedule flexibility. Mas and Pallais (2017) found that, surprisingly, a majority of workers did not value schedule flexibility, although they noted considerable heterogeneity across workers and a long right tail in willingness-to-pay for flexibility. Wiswall and Zafar (2017) found that high-ability undergraduate women were willing to give up 7 percent of their pay to have a job that included the option of part-time hours, while men were willing to give up only 1 percent of pay.

Telecommuting. The ability to work from home or "telecommute" is another form of flexible work arrangement that has received attention in the literature. Although the share of workers who have the option to work from home has been rising (Oettinger, 2011; Mateyka et al., 2012), telecommuting is still relatively uncommon (Maestas et al., 2017a). Recent research argues that employer costs of allowing work from home have declined (Oettinger, 2011), and that work from home leads to productivity gains (Bloom et al., 2014). Recent research finds that workers place substantial value on having the flexibility to work at home (Mas and Pallais, 2017).

Physical Job Demands. The role of physical on-the-job demands has been studied often, including in many of the compensating differential papers mentioned earlier. Duncan and Holmlund (1983) study compensating differentials associated with hard physical work and find little evidence of wage adjustments. In addition, Hayward et al. (1989), Neumark and McLaughlin (2012), and Filer and Petri (1988) find that physically-demanding jobs predict earlier retirement.

Pace of Work. There is substantially less research on the importance of work pace and stress. Work pressure has been found to be associated with decreases in job satisfaction (Lopes et al., 2014) and work stress predicts retirement (Filer and Petri, 1988). Maestas et al. (2017a) find that two-thirds of American workers report frequently working at high speeds or under tight deadlines.

Autonomy at Work. Arai (1994) studies wage differentials associated with job autonomy, finding a positive relationship in the private sector and a negative relationship in the public sector. The study emphasizes that these differentials do not isolate worker preferences since wages also respond to the cost of providing more or less worker independence. Job autonomy is significantly related to job satisfaction and performance (Saragih, 2015).

Paid Time Off. An older literature has sought to determine whether workers in various sectors would be willing to trade income for reduced work time by asking workers to state their preferences for different tradeoffs. In one study, nearly half of public sector workers were willing to trade a portion of their income for additional paid vacation days (Best, 1978). In general, workers expressed a preference for added days of paid time off from work rather than a shortened work day (of equal cost to the firm) (Nealy and Goodale, 1967; Best, 1978).

Working in Teams. Teamwork has increased dramatically in recent decades as U.S. firms have recognized that teams of workers with complementary skills can be more productive than individuals working alone (e.g., Lazear and Shaw, 2007; Hamilton et al., 2003). That said, there is little evidence about workers' preferences for teamwork compared to working alone. We investigate preferences for teamwork as compared to working by oneself, as well as the importance of being evaluated on the basis of the team's performance versus one's own performance.

Job Training. There is a literature on the wage effects of job training opportunities (see e.g., Parent, 1999; Barron et al., 1999; Leuven, 2007). Parent (1999) finds substantial returns to on-the-job training in terms of higher hourly wages. Barron et al. (1999) finds that workers receiving on-the-job training receive slightly lower wages when they start a job, but experience greater subsequent wage growth, as predicted by some model of human capital investment. Fewer papers assess differences in training across demographic and their impact on wage differentials, though systematic differences in the rates of training in the labor market have been documented.[8]

Meaningful Work. Meaningful work is "underrepresented in current models and measures of work characteristics" (Fairlie, 2011) but has received attention among organizational psychologists and sociologists (e.g., Smyer and Pitt-Catsouphes, 2007; Matz-Costa et al., 2017; Steger and Dik, 2012; Steger et al., 2012). There is little evidence about compensating differentials associated with meaningful work, though there is research on wages and job satisfaction among workers at non-profit firms (e.g., Preston, 1989; Leete, 2001; Benz, 2005; Rosso et al., 2010).

3. Heterogeneity in Working Conditions in the United States

We next use survey data on the dimensions of job attributes outlined in Section 2 to examine the variation in working conditions across workers of different demographic and education groups. We also examine differences in job attributes throughout the wage distribution. Tables 2A and 2B present summary statistics that describe the incidence of actual job attributes in our sample of employed workers.

Concentrating on differences by gender, race, age, and education, we find that job characteristics differ substantially across groups, with some expected and unexpected differences. College-educated and older workers have uniformly better job amenities among almost all categories

[8] For example, Duncan and Hoffman (1979) and Barron et al. (1993) document that women receive less on-the-job training than men, and Duncan and Hoffman (1979) show blacks receive less training than whites.

we considered. Non-whites tend to have somewhat worse job attributes than whites, but perhaps less so than expected. Women and older workers hold different mixes of job attributes than do men and younger workers, respectively, but their relative values are less easily quantified without further analysis of differences in attribute preferences (as we do in Sections 4 and 5). Throughout the present section, we highlight those differences in incidence of job characteristics that are statistically significant after accounting for differences in other demographic characteristics (as noted in the table).

Gender Differences. Overall, women work in jobs that are less physically taxing, have more paid time off, and offer more frequent opportunities to make a positive community or social impact (39% versus 30%). For example, we find large differences in the physical demands of jobs: 25% of men report working in a job requiring intense physical activity, compared to only 13% of women. In addition, men are more likely than women to report opportunities on the job to learn new skills that would transfer to other jobs (73% versus 64%). These differences are likely to be related to the gender wage gap, something we return to in Section 6. A more nuanced result is that on average women are over 5 percentage points more likely to primarily work alone, while men are 9 percentage points more likely to work with others and be evaluated based on team performance, perhaps related to different degrees of managerial duties.

Differences by Race. Due to the sample size, we restrict our analysis to comparisons between whites (all ethnicities, including Latino) and non-whites ("Black/African-American", "American Indian or Alaskan Native", "Asian or Pacific Islander", "Other"). Overall, the incidence of job amenities reveals a mixed picture of white versus non-white differences in job quality. Once differences by other groups are controlled for, only a few race-specific gaps remain.[9] For example, non-whites have less control over their schedule, have fewer opportunities to work from home, and

[9] These results are shown in Appendix Table 2.

tend to be in physically demanding jobs. Only control over schedule appears to be directly related to race, while the other differences vanish once we control for education, gender, and age differences (see Appendix Table 2). We find little evidence of differences in pace of work by race, and small to moderate differences in terms of autonomy or working in teams. In contrast, non-whites report more generous paid time off and have more job training opportunities, with only the latter being robust to controlling for differences across groups.

Differences by Education Groups. We observe especially large and robust differences in job characteristics by education. Overall, a college degree is associated with better job characteristics across almost all dimensions we considered. For example, respondents with a college degree are more likely to report that they can adapt their hours (within limits) than those without a college degree (48% vs. 24%), they are substantially more likely to have opportunities to work from home (55% vs. 24%), and they are much more likely to sit throughout the day at work and less likely to engage in more intense physical activity (6% vs. 28%). College education is also associated with a more relaxed environment, more independence, more opportunities to learn new skills, and more opportunities to make a positive impact on the community. Interestingly, a college degree does not appear to confer an advantage in paid time off, suggesting rules governing paid time off are similar across firms and job hierarchies.

Differences by Age Groups. Relative to workers starting out in the labor market (ages 25-34), mature and older workers tend to have jobs that are less physically taxing, slower paced, with more opportunities to work from home, and more independence in work schedule and content. The availability of paid time off generally increases with age, while opportunities to have an impact on society tend to decrease with age. On average, the differences tend to be largest for workers 62 and above. In contrast, the percent reporting job training opportunities decreases from 77% in the youngest age group to 57% in the oldest age group, consistent with models of human capital investment and job choice over the life cycle. Interestingly, older workers are more likely to work alone than younger workers. If they are working in teams they are less likely to be evaluated on their own performance relative to the youngest age group, a pattern that could reflect occupational differences between age groups.

Working Conditions by Wage Quintile. As a segue to our analysis of how workers trade wages for job amenities, and how the presence of amenities affects assessments of wage inequality, Table 3 shows the incidence of job characteristics by quintiles of the hourly wage distribution, ranging from $12.50 per hour or less (bottom 20% of working population), to $17.05-$25.00 (middle 20%), to $38.18 or more (top 20%). In general, working conditions improve with higher wages, but the patterns are not uniform and not always monotonic. Clearly, higher-wage workers tend to have jobs that are less physically taxing, have more control over their work schedule, have more options to work from home, have more opportunities to learn new skills, and more opportunities to make a positive impact on society. Some of these differences are quite substantial. For example, the fraction of workers reporting job training opportunities rises from 61% (bottom 20%) to 77% (top 20%). However, there are smaller differences in the incidence of paid time off (with exception of a very low number of mean days but higher share reporting "as needed" for the bottom quintile). Similarly, the pace of work and the amount of autonomy in how to do a job shows no clear gradient, with the exception of more independence for the highest wage quintile.[10] In some cases, the bottom 20% appears to fare as well or even better than the top, for example in the fraction of workers setting their own schedule or the ability to take paid time off as needed. This variation is further indication that some workers may be willing to trade off wages for certain kinds of working conditions, something that we turn to in the next section.

[10] The relationship between wages and teamwork is less clear. For example, the highest wage group is least likely to work alone (27%), but the second highest wage group is the most likely (43%).

4. Estimating Willingness-to-Pay for Job Amenities

To obtain measures of willingness-to-pay for the job characteristics described in the previous sections, we administered ten stated-preference experiments to each employed respondent in the American Working Conditions Survey. In each of these experiments, survey respondents were asked to select between two jobs, each defined by a partially varying set of job characteristics, hours, and monetary compensation as described in detail below. The advantage of the stated-preference approach is that we can randomize offered job attributes in a manner that would be difficult to implement in the actual labor market. Moreover, we observe the full set of choices offered to each respondent. To minimize concerns that certain job attributes may signal other, unspecified, job characteristics (Manski, 1999), we instructed respondents to assume that any job attributes not explicitly described were identical across jobs. We address the robustness of our implementation approach as well as common concerns with stated-preference estimates in our sensitivity analysis below (Section 7).

4.A. Creation of Hypothetical Job Profiles Based on Current Job Characteristics

For each respondent, we first defined a "baseline" job around which job attributes would vary. The baseline job in 8 of the 10 stated-preference experiments was the respondent's current job. We chose to anchor the randomized job profiles around the current job in order to generate hypothetical profiles that would appear realistic to the respondent. This approach has the advantage of increasing salience by presenting respondents with job choices that partially reflect their personal work experiences. It has disadvantages if valuations are affected by familiarity or if interactions between attributes are important. To facilitate sensitivity analyses, in 2 of the 10 experiments we used a common baseline job for all respondents. The values of the common baseline job are shown in Appendix Table 3. We show below (Section 7.F) that our estimates are invariant to the choice of baseline job.

The stated-preference experiments were preceded by a short survey about current job characteristics, where each survey item corresponded to one of the nine job attributes in the experiments. This information was used to define the baseline job. To avoid negative characterizations of attributes in the job profiles and to reduce the dimensionality of the empirical analysis, we consolidated the number of possible values for some attributes. For example, in the initial short survey we asked respondents how often their job provides opportunities to make a positive impact on their community or society. The three values were "Frequently," "Occasionally," and "Never." In our hypothetical job profiles, there were only two possible values: "Frequently" and "Occasionally." To form the baseline job, we mapped people with jobs that never provide opportunities to make a positive impact to the "Occasionally" category. On the other hand, when we asked respondents about the pace of their job, they could choose between "Fast-Paced" and "Relaxed." Since the same two attribute values were used for the hypothetical jobs, the mapping between survey responses and the baseline job was one for one. The complete mapping is shown in Appendix Table 4.

Similarly, we used respondents' current wage to anchor the wage offers in the hypothetical job profiles. In the initial short survey, we allowed respondents to report their current earnings at the hourly, weekly, bi-weekly, twice monthly, monthly, or annual level, and we also asked about the number of hours worked per week and the number of weeks worked in a full year. We used this information to calculate an hourly wage for each employed person in the sample. If the implied hourly wage was very low (e.g., below the prevailing federal minimum wage), we asked the respondent to confirm their previous answers and provided them with an opportunity to change their original responses (see Appendix A).

4.B. Random Variation in Hypothetical Job Profiles

Starting from the respondents' baseline job, we created hypothetical Job A and Job B by randomly selecting two non-wage attributes to vary across the two hypothetical jobs. Within each of the two randomly selected attributes, attribute values were then chosen at random sequentially first for Job A and then for Job B *without replacement*. In this way, we guaranteed variation across the jobs for that characteristic. We included number of work hours in the set of non-wage attributes. Whenever hours were selected to vary, the number of hours was randomly chosen to be in one of five-hour intervals between 15 and 60 hours per week. When the number of hours was 35 or above, we labeled the job as "Full-Time." Otherwise, the job was labeled as "Part-Time."

While the non-wage attributes varied only when selected in the experiment, the offered wage always varied randomly across Job A and Job B. Given a respondent's actual hourly wage *w*, the hypothetical wages for Job A and Job B were $\theta_A w$, where $\theta_A \sim N(1, 0.01)$ and $\theta_B w$, where $\theta_B \sim N(1, 0.01)$, respectively. We truncated θ_A and θ_B to be between 0.75 and 1.25 so that the wage difference between the two jobs did not exceed 50% of the worker's current wage. In a final step, we converted the hypothetical wage values back to the units in which the respondent originally reported their earnings (hourly, weekly, bi-weekly, twice monthly, monthly, or annual rate), by using the hours associated with the hypothetical job, and rounded it. When we converted the hourly wage to annual earnings, we assumed the job required 52 weeks of work (including paid time off). When presenting an hourly wage offer for a given job, we also displayed the implied weekly earnings in parentheses. This enabled us to highlight overtime pay; we calculated overtime pay for weekly work hours exceeding 40 at 1.5 times the randomly assigned hourly wage and included these overtime earnings in implied weekly earnings.

Consequently, for any job pair, eight of the non-wage attributes were identical and had the same attribute values as the respondent's baseline job, while the values of two attributes varied between Job A and Job B and may or may not have been equal to the baseline job values. The wage always varied, and similarly could have been equal to the baseline wage by chance.

To increase statistical precision, we limited the number of job pairs in which one of the jobs dominated the other job on all varying dimensions. When one job was better on all dimensions (including the wage) than the other, we redrew the scaling parameters θ_A and θ_B, and recalculated the offered wage. This process limited, but did not eliminate, job pairs where one job (potentially) dominated the other in all respects.[11]

Once the hypothetical job pair was generated, we displayed the characteristics of Job A and Job B side by side as in the screenshot provided in Appendix Figure 1. The respondent was asked to select "Strongly Prefer Job A," "Prefer Job A," "Prefer Job B," or "Strongly Prefer Job B." We repeated the entire process 9 times for a total of 10 distinct experiments per respondent.

4.C. Estimation Strategy

The hypothetical choice experiments yield choice data describing the preferred jobs of respondents given a set of job attributes and a wage. For our main specification, we assume that the underlying choice process can be approximated by a linear indirect utility function:

$$V_{ijt} = \alpha + X'_{ijt}\beta + H'_{ijt}\theta + \delta \ln w_{ijt} + \varepsilon_{ijt},$$

where V_{ijt} represents indirect utility for individual *i,* alternative *j*, for choice pair *t*. X_{ijt} is the set of non-wage characteristics, H_{ijt} represents a flexible function of hours, and w_{ijt} is the wage. We use the log of the wage because we anchor each person's wage offer to their current wage and there are large cross-sectional wage differences in our data (see Table 1). Assuming that ε_{ijt} is an Extreme Value Type I random variable, we estimate the probability that an individual selects a job with

[11] If one job still dominated, we redrew the attribute values. At this point, we used the new draws regardless of their values. This approach required us to make to *a priori* judgments about which attribute values were likely preferred within a job characteristic. Any errors in this judgment will only reduce our statistical power.

characteristics X_{ijt}, hours H_{ijt}, and wages w_{ijt} over a job with characteristics X_{ikt}, hours H_{ikt}, and wages w_{ikt} with probability

$$P(V_{ijt} > V_{ikt}) = \frac{\exp\left[\left(X'_{ijt} - X'_{ikt}\right)\beta + \left(H'_{ijt} - H'_{ikt}\right)\theta + \delta(\ln w_{ijt} - \ln w_{ikt})\right]}{1 + \exp\left[\left(X'_{ijt} - X'_{ikt}\right)\beta + \left(H'_{ijt} - H'_{ikt}\right)\theta + \delta(\ln w_{ijt} - \ln w_{ikt})\right]}.$$

Using these parameters, we derive our willingness-to-pay measure for a particular attribute *r* as follows. Consider an individual who is indifferent between not having a particular attribute *r* at wage *w,* and having the attribute with a corresponding wage decrease equal to WTP^r:

$$\delta \ln w = \beta^r + \delta \ln[w - WTP^r] \qquad (1)$$

where δ and β^r are the marginal utilities for the log wage and attribute *r*, respectively.

Solving for willingness-to-pay, we obtain:

$$WTP^r = w\left[1 - e^{\left(\frac{-\beta^r}{\delta}\right)}\right] \qquad (2)$$

In the following sections, we present our estimates in terms of $1 - e^{\left(\frac{-\beta^r}{\delta}\right)}$, such that gaining attribute *r* is equivalent to a $100\left(1 - e^{\left(\frac{-\beta^r}{\delta}\right)}\right)\%$ wage increase. Similarly, we summarize the full valuation of amenities by defining the willingness-to-pay for the "best" job relative to the "worst" job:

$$WTP^{FULL} = w\left[1 - e^{\left(-\frac{\Sigma r\, \beta^r}{\delta}\right)}\right], \qquad (3)$$

where we add up the coefficients for the most preferred value of each attribute.[12] To focus on our main non-monetary job attributes, we do not include variations in offered hours in this calculation (even though we always control for offered hours in our main estimates). Instead, we discuss estimated preferences over hours separately below.

[12] To avoid double counting, we use only the coefficient for the attribute value with the largest willingness-to-pay estimate. For example, for physical demands, we only use the coefficient for moderate physical demands (the most preferred attribute value) and do not also add up the coefficients for sitting and heavy physical demands.

As described above, respondents had four different response options when making each job choice. In our main analysis, we aggregate responses into a dichotomous preference for either Job A or Job B, ignoring the strength of preferences. However, in Section 7.B, we present an ordered logit specification which uses the additional information. The results are similar.

Standard errors are calculated using the delta method and adjusted for clustering by respondent. We weight the regressions by the survey weights in the AWCS, though we show in Appendix Figure 2 that unweighted results are similar.

5. Main Estimates of Willingness-to-Pay for Job Amenities

Before presenting the willingness-to-pay estimates generated from our stated-preference experiments, we begin with a nonparametric illustration of the underlying choice patterns in the data. For each panel of Figure 1, we calculated the fraction of respondents selecting the job with the indicated characteristics over a job that did not have either of those characteristics. We created bins[13] based on the wage difference between the jobs and plotted the fraction of respondents who chose the job with the characteristics for each wage-difference bin. We held the x-axis constant across all panels in Figure 1 and labeled each bin by the average wage difference for that bin. Negative wage differences mean the job with the indicated characteristics offered a lower wage than the job without the characteristics, while positive wage differences mean the reverse. Note that because we have many job attributes in our experiments, any specific combination happens in only a small fraction of experiments.

Figure 1 shows that across the four panels, a large fraction of respondents are willing to take a job with better job characteristics even when the offered wage is substantially lower, indicating

[13] Bins were chosen so that they were approximately the same size. In general, bin sizes include about 30 responses. For Panel D of Figure 1, bin sizes include about 20 responses. The smaller bin sizes in Panel D occur because each category (physical demands and PTO) takes on 3 possible values, which means there are fewer instances of the combination that we focus on in Panel D.

substantial willingness-to-pay for non-wage job attributes. For example, Panel A shows that nearly 40% of respondents preferred a lower-wage job with a flexible work schedule and telecommuting over a higher-wage job without those attributes. Panel B shows that about 20% of respondents preferred a higher-wage job with a relaxed environment and no team-based work over a higher-wage job without those attributes. Not surprisingly, the rate of job acceptance rises as the relative wage for the job increases, as indicated by the tendency for the acceptance curve to slope upwards.[14]

5.A. Willingness-to-Pay Estimates for Full Sample

Figure 2 presents our estimated valuations for the full sample of respondents and thus contains the first main findings of our analysis. Overall, we find that differences in job amenities are clear predictors of stated job choices, and that individuals are willing to forego substantial earnings for better working conditions. We also find that, contrary to some of the earlier work based on hedonic regressions, our willingness-to-pay estimates are of expected signs and reasonable magnitude. They also compare well to other experimental estimates, where available.

The stated-preference estimates are all statistically significant from zero at the 1% level, suggesting that each of the job characteristics included in the experiments impacted job choices. Considering the various attributes separately, we estimate that setting one's own schedule is equivalent to a 9.0% wage increase. Telecommuting opportunities are estimated to be equivalent to a 4.1% wage increase. As further discussed below, these stated-preference estimates are similar to comparable revealed preference estimates (Mas and Pallais 2017), suggesting that stated-preference estimates are able to recover meaningful underlying valuations.

We also find that physical demands are very predictive of job choices. Relative to a job requiring "heavy physical activity," a job in which the person is mostly sitting is equivalent to a 12.0% wage increase while "moderate physical activity" is valued at 14.9% of the wage. We also

[14] As explained in Section 4, we always randomly varied two job attributes at a time in each job profile, and hence it is difficult to obtain nonparametric estimates of willingness-to-pay for a single job attribute.

estimate that a switch from a fast-paced job to a relaxed environment is equivalent to a 4.4% wage increase. Independence at work is worth 3.8% of the wage relative to a job with well-defined tasks.

Paid time off is also a strong predictor of job choice. We estimate that 10 days of paid time off is equivalent to a 16.4% wage increase. Twenty days of paid time off is equivalent, on average, to a 23.0% wage increase. If we assume that there are approximately 250 workdays in a year, then 10 days of paid time off represents a 4% reduction in labor supply. However, respondents are willing to sacrifice substantially more than 4% of their wages to work at a job with this amount of paid time off. Workers are only willing to forgo 6.6% of their monetary compensation for the subsequent ten days of paid time off, which suggests diminishing marginal returns to paid time off, though this magnitude is still larger than 4%. One explanation for the higher valuation is that paid time off represents more than just a reduction in labor effort. Paid time off also provides job protection, enabling a worker to take time off when desired and without threat of job loss, consistent with the higher valuation placed on the initial ten days. It is notable that willingness-to-pay is particularly high for low-educated workers (shown below) even though the average number of paid days off is similar by education group (Table 2B). It may be that these workers face scheduling constraints on other margins.

We also find that individuals prefer to work alone. We estimate that working by oneself is equivalent to an 8.4% wage increase relative to working on a team and being evaluated based on the performance of the team. However, we find that most of the value of working by oneself arises from a desire to be evaluated based on one's own performance, rather than the team's performance. Relative to evaluation as a team, evaluation based on one's own performance – but still working on a team – is equivalent to a 6.4% wage increase. As long as evaluation for teamwork is based on one's own performance, working alone is only valued at 2.0% of the wage.

Job training opportunities are equivalent to a 5.1% wage increase, suggesting that workers are willing to forgo some current earnings for human capital development opportunities and potentially higher future earnings.[15] Frequent opportunities to impact the community/society are worth an additional 3.9% relative to occasional opportunities.

Overall, it is clear that individuals systematically value non-monetary job characteristics, and exhibit substantial willingness-to-pay for these amenities. To quantify the maximum potential impact of job amenities implied by our findings we assessed the wage impact of an extreme job change, as measured by the attributes we examined. We estimate that a switch from the worst job, in terms of amenities, to the best job is equivalent to a 56.1% wage increase. Given the variance in actual job characteristics we found in the AWCS (Section 3), this is a first indication that willingness-to-pay for job amenities may play a substantial role in explaining observed variation in wages or meaningfully exacerbate observed differentials, something we return to in Section 6.

To obtain a benchmark for our stated-preference estimates, we can contrast these results to revealed-preference estimates for a subset of these amenities by Mas and Pallais (2017). For example, Mas and Pallais (2017) found that their sample of workers applying to call-center jobs was, on average, willing to accept 20% lower wages to avoid jobs in which the employer had discretion over scheduling. Similarly, Mas and Pallais (2017) estimated that job applicants were willing, on average, to accept 8% lower wages for the opportunity to work from home. Our estimates implied willingness-to-pay of 9% and 4.1% for these amenities, respectively. Given differences in the study populations and approach, our stated-preference estimate is reasonably similar. In addition, Mas and Pallais' (2017) replicated their own findings using a stated-preference analysis. Overall, despite

[15] It is difficult to gauge the magnitude of this valuation. Based on the National Longitudinal Study of Youth, Parent (1999) reports that one year of on the job training yields an increase in hourly wages of approximately 10%, and that on average individuals receive 14 weeks of training. For a 14-week on-the-job training course, that would imply a wage increase of 2.8% (=0.1*14/50). Given the return to training accrues over many years, the estimated valuation appears low. But given we do not know what the typical duration of training workers have in mind, and who pays the cost of training, it is hard to evaluate this magnitude.

obvious limitations of these direct comparisons, the available evidence suggests stated-preference estimates are able to recover meaningful underlying valuations.

To obtain a benchmark with respect to the earlier literature based on observed job choices, we also estimate a traditional compensating differential specification based on a hedonic regression model using each worker's current job characteristics and wage. We regress the log of the wage on indicators for each job characteristic, controlling for age group, race, education, and citizenship indicators. We report $e^{-\gamma} - 1$, where γ represents the estimate on a job characteristic, since a valuable characteristic – in principle – *reduces* the wage in a hedonic pricing framework. The results are shown in Figure 2 alongside our main willingness-to-pay estimates. The compensating differential and stated-preference estimates are often opposite signs. While the stated-preference estimates take the expected signs, the compensating differential estimates often do not, consistent with there being bias from unobserved factors that are correlated with both wages and job characteristics (Hwang et al., 1992). While the literature has sought to improve on the basic hedonic estimates in various ways, we did not pursue this further. Overall, these results offer further confirmation that the stated-preference approach can yield findings that are both novel and meaningful.

5.B. Heterogeneity in Willingness-to-Pay

In the remainder of this section, we use our data to assess systematic differences in the willingness-to-pay for job amenities in the population. We purposefully focus on the key differentials that have been the focus of much of the literature on the wage structure – differences in valuations by gender, race, education, age, and by position in the wage distribution itself. We find precisely estimated differences in how workers value amenities across groups, with women, older and more educated workers placing on average a higher value on job amenities, and non-whites placing a somewhat lower value on amenities. These differences turn out to be numerically important when we assess the impact of job amenities on wages differentials in Section 6. We present results in this section graphically, but point estimates and standard errors can also be seen in Appendix Table 5.

Gender Differences. We estimate the valuations separately by gender and present the results graphically in Figure 3. Overall, women are more willing to trade off monetary compensation for on-the-job amenities than men. A switch from the worst job to the best job is equivalent to a 53.3% wage increase for men and a 59.5% wage increase for women. Most notably, we find large differences in preferences to avoid heavy physical activity by gender – women value primarily sitting at work at 15.3% of the wage and moderate physical activity at 19.0%. We estimate smaller valuations for men at 9.2% and 11.6%, respectively. Paid time off also plays a more important role in job choice for women. Women value a switch from no paid time off to 10 days paid time off as equivalent to an 18.2% wage increase, while men only value it at 14.8%. An additional 10 days receives similar valuations for both men (5.7%) and women (7.7%). While there are small differences for other amenities, the valuations are generally similar across all other characteristics.

Race Differences. Figure 4 presents estimates of valuations separately for whites and non-whites. In general, whites place more value on job amenities than non-whites. A switch from the worst job to the best job is equivalent to a 50.5% wage increase for non-whites and a 57.6% wage increase for whites. We find some interesting differences by race in terms of valuations of hours flexibility, work autonomy, working alone, and being evaluated in teams. We find that whites place more value on schedule flexibility. For whites, setting their own schedule is equivalent to a 10.2% wage increase, compared to only 4.0% for non-whites. We also observe large differences in work autonomy, valued at 4.8% for whites but a small, statistically insignificant *negative* valuation for non-whites. It also appears that while non-whites value working alone as equivalent to a (statistically significant) 6% wage increase, they do not value being evaluated based on their own performance.

Whites, on the other hand, value evaluation based on their own performance at 7.5% of their wage, while they place little additional value on working alone.

Education Differences. We divide our sample into three education categories: high school degree or less, some college, and at least a college degree. We estimate substantial education gradients for many of our job characteristics. Overall, we find that the value of job amenities increases monotonically with education. Respondents with a high school degree or less consider a switch from the worst job to the best job as worth a 52.0% wage increase. By comparison, those with a college degree consider such a switch equivalent to a 60.1% wage increase. Individuals without any college experience are estimated to place no value on telecommuting opportunities while those with some college and those with a college degree are willing to pay 4% and 7%, respectively, of their wage for this option. We also estimate monotonic relationships for physical demands. The lowest education group values the job amenity "mostly sitting" ("moderate physical activity") at 9.4% (12%) of the wage, but the highest education group values it at 13.6% (17.1%). We observe a similar monotonic relationship for the value of work autonomy.[16]

Differences by Age. We examined preferences for job characteristics based on age groups (Figure 6). Overall, we find that job amenities matter much more to workers at older ages. A move from the worst job to the best job is equivalent to a 47.8% wage increase for ages 25-34, 56.2% for ages 35-49, 58.9% for ages 50-61, and 74.3% for ages 62+. As expected, we estimate especially large differences based on the physical demands of the job. The valuations for both sitting and moderate physical activity increase monotonically by age. Workers ages 62 and above value moderate physical activity as equivalent to a 30.1% wage increase and sitting as equivalent to a 24.0% wage increase.

[16] In fact, we cannot reject the hypothesis that the lowest education group places no value on work autonomy (point estimate is 0.1%) while the highest education group considers it equivalent to a 5.8% wage increase.

Schedule flexibility and work autonomy are also disproportionately important at older ages.[17] Older workers also have stronger preferences for paid time off. Interestingly, while younger workers appear to be indifferent towards team-based evaluation, willingness-to-pay for this job attribute increases to 6.8% for ages 35-49, 9.2% for ages 50-61, and 13.7% for ages 62+. We estimate similar patterns for working alone, increasing from 3.3% for the youngest age group to 17.8% for the oldest. There is less evidence of age heterogeneity for training opportunities and opportunities to impact the community.

Differences throughout Wage Distribution. We create five groups based on wage quintiles (the same groups as in Table 3).[18] In general, as shown in Figure 7, the highest wage group appears to value job amenities more than respondents with lower wages. For the lowest-wage workers, we estimate a total value of 47.9% of the wage while the corresponding estimate for the highest wage group is 61.4%. This pattern is consistent with on-the-job amenities being normal goods, as high-wage workers are willing to sacrifice some of their additional compensation for better working conditions.[19] This suggests that estimates of the wage distribution that do not take into account amenity differences may understate the true extent of inequality in underlying productivity. For example, willingness-to-pay increases with the wage for schedule flexibility, telecommuting, work autonomy, and lower physical activity on the job. Exceptions to these patterns are the valuations for paid time off, which follow an inverse U-shape pattern, increasing at lower wages and peaking at the third quintile. Training opportunities appear valued similarly across the wage distribution.

5.C. Preferences for Hours Worked

[17] For ages 25-34, we estimate the schedule flexibility is worth about 7.0% of the wage, but this valuation increases to 14.6% for ages 62+. For the younger three age groups, we estimate autonomy as worth 2-5% of the wage. For the oldest age group, this estimate jumps to 11.2%.

[18] The lowest wage group makes $12.50 per hour or less; the second group makes between $12.50 and $17.05 per hour; the third group's wages are between $17.05 and $25.00; the fourth quintile has wages between $25.00 and $38.18; the highest wage group consists of respondents with wages above $38.18.

[19] The observed wage distribution is, of course, "treated" by the existing distribution of amenities and the compensating differentials attached to these amenities, suggesting that the differences across the untreated wage distribution (i.e., wages holding amenities constant) would be even starker.

In this section, we report estimates of preferences for hours worked generated from the same model underlying our main results in Figure 2. In the classic model of labor supply, individuals work until the marginal disutility of work equals the wage. However, for infra-marginal choices individuals may place more or less value on an additional hour of work than their prevailing (marginal) wage. Moreover, factors such as fixed costs of working may lead to deviations between workers' valuation of an additional hour worked from the marginal wage. The choice of hours worked may also itself be a job amenity, for example representing an element of flexibility.

We normalize the coefficient for "60 hours" to zero and evaluate hours preferences relative to this excluded category.[20] The estimates and 95% confidence intervals are presented graphically in Figure 8. Willingness-to-pay for work hours follows an inverse U-shape that peaks at 45 hours per week.[21] The estimates imply that respondents are willing to pay 10% of their wage to move from a 60-hours-per-week job to a 45-hours-per-week job, and to pay 17% to move from a 20-hours-per-week job to an equivalent 40-hours-per-week.[22] In Appendix Figure 3, we show these patterns separately by gender. As might be expected, men have a higher willingness-to-pay for moving from part- to full-time work. The general patterns of the estimates are similar for men and women – increasing until 45-hours-per-week and then decreasing -- though we can statistically reject that the estimates are identical across the two groups.

6. Implications of Incidence and Valuation of Job Amenities for the Wage Distribution

[20] In forthcoming work, Mas and Pallais (forthcoming) estimate willingness-to-pay measures for an additional five hours of work given a job involving 5 to 35 hours per week.

[21] Note that in our experiments, jobs with 35+ hours per week were labeled "Full-Time" while jobs with fewer than 35 hours per week were labeled "Part-Time." We do not observe an especially large jump in valuation at 35 hours per week in Figure 8 when compared to the increasing trend at lower levels of hours, suggesting that respondents did not disproportionately value the switch to full-time work beyond the explicit increase in hours.

[22] As a point of comparison, from their sample of call center applicants Mas and Pallais (2017) estimate valuations of about 20% to 40% of wages for moving from a 20-hours-per-week to a 40-hours-per-week job, depending on baseline earnings. The wider range could be due to the fact that their study population was primarily comprised of lower-wage workers in need of additional hours.

In this section, we assess how wage differentials grow or shrink when differences in amenities are accounted for.[23] We perform this assessment of wage differentials in two different ways. First, we use the attribute valuations estimated for the full sample (see Figure 2) to calculate each respondent's total compensation based on the attributes of their current job, as they reported them in the short initial survey preceding the stated-preference experiments. Second, we perform the same exercise, but allow the attribute valuations to differ based on the individual characteristics of the respondent (e.g., gender, race, education and age). Both approaches provide important information. The first approach quantifies the contribution to wage differences arising only from differences in the incidence of amenities across groups (as discussed in Section 3), using a common metric for determining which attributes are considered positives and which are considered negatives, and a simple way to aggregate them together. The second approach adjusts for the fact that holding preferences constant may misrepresent the true value of the bundle of job characteristics for some demographic groups. For example, if women value schedule flexibility more than men, then providing this amenity to women generates a larger increase in compensation than providing equivalent schedule flexibility to men. Using these approaches, we investigate differentials based on gender, race, education, and age as well as measures of wage inequality.

For both of these cases, we show two metrics capturing the effect of job amenities on total compensation. Let A_r be an indicator equal to one if the respondent's current job has attribute *r*. Given our estimated valuation for attribute *r*, we can adjust the respondent's wage for the value of this attribute based on whether they have that attribute. We report several metrics. Based on our random utility model introduced in Section 4, the log of the total value of on-the-job characteristics is equal to

[23] As before, we do not consider "number of hours" as an amenity for these calculations.

$$\ln\left(w\left[1-e^{\left(-\frac{\sum_r A_r\beta^r}{\delta}\right)}\right]\right),$$

where β^r is the marginal utility of a given attribute *r*, and δ is the marginal utility of the log wage *w*. We refer to this term as the *"amenity value"* and to log of the term in square brackets as the *"amenity multiplier*." We will also provide differentials with respect to the log of "*total compensation,*" defined as the log of the wage plus the total value of the respondent's current attributes:

$$\ln\left(w+w\left[1-e^{\left(-\frac{\sum_r A_r\beta^r}{\delta}\right)}\right]\right).$$

Because the preference parameters are estimated, to obtain standard errors we bootstrap the entire process – estimation of equation (2) followed by estimation of a wage differential specification – using a block (by respondent) bootstrap.[24]

We present our estimates of these compensation differentials in Table 4. We find that accounting for differences in the incidence and valuation of job amenities has different effects on different groups in the labor market. It substantially reduces the gender wage gap (by 30% relative to the wage gap unadjusted for amenities); it substantially raises the gap between whites and nonwhites (by 25%) and the gap between older and younger workers (by close to 100%); and it increases the cross-sectional returns to education (by 16%). Overall wage inequality also increases once we account for amenities, particularly at the bottom of the wage distribution.[25]

Gender Wage Gap. Accounting for the presence of job amenities reduces the gender wage gap by about a third. In our data, we estimate a log-wage gender differential equal to -0.187,

[24] We use this approach even when the dependent variable is the log of the wage, which does not use any estimated valuations, for uniformity across all outcomes.

[25] We also analyzed how total compensation differs across groups, holding constant differences in amenities *and* preferences based on other individual covariates by jointly estimating preferences across all groups. The results are shown in Appendix Table 7. The approach is complex and explained in Appendix B, since amenities and preferences enter total compensation in a nonlinear fashion. While we find the results interesting and reassuring in their similarity to the estimates in Table 4, we do not include these in the main text given the added complexity.

implying that women have 17% lower wages than men.[26] The amenity multiplier is positive and statistically different from zero (Panel A), implying that conditional on their wage, women have better amenities. However, the effect is moderate – when amenities are factored in, the compensation gap is reduced to -0.172 (-15.8%), representing an 8% reduction in the size of the differential. In contrast, when we also allow valuations to vary by gender (Panel B), the log compensation gap shrinks to -0.131 (-12%), representing a substantial 30% reduction in the size of the differential. The further reduction in the gap arises primarily because women place more value on paid time off and avoiding heavy physical activity.[27]

Race Wage Gap. Accounting for amenities increases the race wage gap. The unadjusted white-nonwhite log wage differential is -0.214, implying 19% lower wages for non-whites in our data. Holding amenity valuations constant, we estimate only small and statistically insignificant amenity multiplier differentials by race, consistent with our finding in Section 3 that there are few racial differences in the incidence of amenities after controlling for differences in education and other characteristics. However, we found in Section 5 that whites value amenities much more highly than non-whites. When we permit valuations to differ by race, we estimate that the amenity multiplier is statistically different between whites and non-whites and reinforces the wage gap. As a result, the total compensation differential is estimated to *increase* in magnitude to -0.268, representing a 25% increase relative to the wage differential unadjusted for amenities.

Returns to Education. Accounting for amenities substantially increases the cross-sectional returns to education. In our data, workers with a college degree have 70% higher wages than those without a college degree (a differential of 0.532 log points). Since we found large differences in the

[26] We report $100 \times [\exp(\hat{\beta}) - 1]\%$ throughout this section where $\hat{\beta}$ represents the coefficient on the demographic indicator of interest.

[27] To provide information about which specific amenities are affecting wage differentials the most, we have also sequentially added each amenity into the above expression. The order matters in terms of how large of a difference adding another amenity can make relative to the baseline. While the patterns differ by demographic group, paid time off and physical demands tend to have the largest impacts on wage differentials. The results are shown in Appendix Tables 6A (constant values) and 6B (heterogeneous valuations).

incidence of amenities by education in Section 3, at constant valuations the education gap in total compensation increases to 0.577 log points (80%), representing an 8% increase. We also found in Section 5 that college graduates value job amenities more highly, and when we permit amenity valuations to differ based on education, the total log compensation differential increases even further to 0.619 (85%). This corresponds to an increase of 16% relative to the unadjusted cross-sectional returns to education.

Wage-Age Gradient. As with the race gap, differences in the valuation of job amenities play a key role when adjusting the age-wage gradient. We estimate small and statistically insignificant amenity multiplier differentials across all age groups (relative to ages 62-71) when we hold valuations constant. However, when we permit valuations to vary, we find that the wage differential between older workers and workers ages 25-34 and 35-49 more than doubles, since older workers have strong preferences for non-wage amenities.

Overall Wage Inequality. Finally, as a summary of the overall net effect of adjusting for amenities on the wage structure, we report how our adjustments affect differences between the 90th, 50th, and 10th percentiles of the hourly wage distribution in Table 5. Overall, adjusting for the presence of job amenities increases wage inequality, particularly so in the bottom half of the wage distribution. The effect is present and precisely estimated when we hold valuations constant (Panel A), but roughly doubles in magnitude when we allow valuations to vary (Panel B). For example, converting the numbers in Table 5 to percentages, the unadjusted 90th-50th log difference is 168% (0.986 in column 1), increases to 179% (1.027 in column 2, Panel A) when we introduce amenities at common values, and increases to 184% (1.043 in column 2, Panel B) when we allow valuations to vary. The corresponding numbers for the 50th-10th log difference are 100% (0.692, unadjusted), 106% (0.723, common valuations), and 120% (0.787, differing valuations), respectively. These results underscore that wage inequality is exacerbated by the incidence of amenities and systematic differences in the valuations of those amenities throughout the wage distribution.

7. Robustness Analysis

Our analysis has relied on several assumptions that we test in this section, including the statistical methods used to estimate our willingness-to-pay metrics, the attentiveness of survey participants to the stated-preference questions, and the effectiveness of our stated-preference estimates in capturing the true preferences of the respondents. We explored these issues in great detail, but only summarize the main findings here. In general, we find that our results are robust to our estimation technique and to respondent attentiveness. We also find that our willingness-to-pay estimates are correlated to actual job choices. Since we also show that anchoring the randomization around current jobs does not drive our estimates, the correlation between actual job attributes and stated preferences provides some direct validation of the stated-preference approach in our context.

7.A. Accounting for Valuations of Amenity Combinations (Interaction Terms)

If workers care about particular combinations of job amenities, interactions between job characteristics would matter in explaining job choices, something not captured by our approach based on a linear additive indirect utility function. Even though these interactions are likely to be orthogonal to our main effects since we randomize job characteristics in our experiments, we tested this assumption explicitly. We permitted utility and choices to also respond to all two-way interactions of job characteristics and estimated the valuations of the main effects and these two-way effects (not shown). When interactions are included, we estimate that moving from the worst to the best job is equivalent to a 53% wage increase, compared to 56% to our main findings. While it is still possible that more flexible interactions may matter to some workers, the similarity of these estimates suggests that the additive specification is not driving our main results.

7.B. Accounting for Preference Ordering (Ordered Logit)

We further test the importance of our functional form and distributional assumptions in Appendix Figure 4. In our experiments, we provided respondents with four options: Strongly Prefer Job A, Prefer Job A, Prefer Job B, and Strongly Prefer B. Our analysis above dichotomizes these options into whether the respondent preferred Job A over Job B. However, we can exploit the additional information provided by the full range of options and estimate valuations using an ordered logit model. We find little difference in the estimated valuations across all job characteristics and our estimates are relatively unaffected by focusing on the dichotomous choice between the two jobs.

7.C. Accounting for Unobserved Heterogeneity in Preferences (Mixed Logit)

For simplicity, we have modeled preferences as static across individuals and provided evidence that they vary based on observable characteristics. It is possible that preferences vary based on unobservable characteristics as well, in which case logit estimates may be biased (Train, 2003). To test for the importance of modeling preferences as homogenous, we estimate a mixed logit model, permitting the coefficients on job characteristics (including hours) to be normally distributed. We further allow for correlations in preferences across all job characteristics. We report the mean valuation estimates in Appendix Figure 4 as well. The results are similar to our main results, indicating that unobserved preference heterogeneity is not introducing bias to our estimates.

7.D. Robustness to Assumption of Extreme Value Distribution (Special Regressor Method)

To assess the robustness of our findings to assuming a specific distribution for the error term, we use the so-called special regressor estimator which does not require distributional assumptions on the error term and estimates mean valuations even in the presence of random coefficients (Dong and Lewbel, 2015; Lewbel, 2014). This approach has been used previously in estimating willingness-to-pay parameters (e.g., Kalisa et al., 2016; Bontemps and Nauges, 2015;

Agarwal and Somaini, 2014).[28] The resulting willingness-to-pay estimates are similar to the main estimates (Appendix Figure 4).

7.E. Attentiveness to Survey Questions

One common concern with stated-preference experiments and surveys more generally is that respondents may not read the questions closely. This tends to introduce noise, if individuals choose randomly, but could impart a status-quo bias if inattentive individuals gravitate toward characteristics similar to their current job. We tested the importance of respondent inattention by asking each respondent two "trick questions" that appeared randomly (and non-consecutively) between the third and the last experiment (e.g., Berinsky et al., 2014). The introductory text of the question specified that the respondent should answer in a specific manner, regardless of their true answer to a question presented immediately below. The questions were ostensibly about job search and job preferences and are shown in Appendix Figures 5 and 6. We label respondents as paying attention if they answered at least one of the questions correctly. This sample consists of 65% of the respondents in our full sample.

In Appendix Figure 7, we display our valuations separately for the group that correctly answered both trick questions. The valuations are quite similar. The "attentive" sample has slightly higher valuations for almost all amenities with the exception of sitting, frequent opportunities to serve the community, and schedule flexibility.[29] Overall, however, there is little evidence that our results are driven by systematic respondent inattention.

7.F. Anchoring to Baseline Job

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[28] The log of the wage in our specification meets the three assumptions necessary for a special regressor. It enters the specification additively and is independent of $(\varepsilon_{i1t} - \varepsilon_{i2t})$ given the randomization in our stated-preference experiments. Finally, it has large support as we permitted differences in wages as large as 50% of the individual's current wage. To the extent that this range is too small to capture the full distribution of valuations for the job characteristic, Magnac and Maurin (2007) shows that there is no bias if the tails of the distribution are symmetric where the "tails" of the distribution are the parts that are not captured by the support of the special regressor. For more details on this method, see Appendix C.

[29] Since we scale the coefficients on the amenities by the coefficient on the log wage, inattention will not necessarily bias the estimates.

As discussed in Section 4, we based our hypothetical job profiles on each respondent's current job for all but two experiments. In two randomly selected experiments, the baseline job was the same for all respondents (as defined in Appendix Table 3). By using a uniform baseline job, we reduce concerns that omitted interaction terms are confounding our linear utility estimates since the interaction terms will not systematically vary across respondents in the experiments (see also Section 7.A above). Appendix Figure 8 shows that using a common baseline barely affects our results, although confidence intervals increase given the reduced sample size. This suggests our results are not driven by our decision to anchor the job characteristics to respondents' most recent jobs.

7.G. Stated vs. Actual Preferences

Using a stated-preference approach permits us to randomize job attributes across respondents, minimizing concerns that the available or chosen job characteristics are confounded by unobserved individual, job, or market factors. However, there are concerns that respondents may not answer in a manner that is consistent with how they would actually respond in the labor market, given the same options. Our data allow us to investigate the consistency between respondent selections and their revealed preferences by testing whether individuals who have selected into jobs with specific amenities value those amenities more. To do so, we add to our main specification interactions of each of amenity with the respondent's actual characteristics in their current job. In Appendix Figure 9 we show the estimated valuation for respondents without a particular job amenity as well as the estimated valuations for respondents with that job amenity. We only report interactions in which the respondent's current job characteristic is the same as the characteristic in the experiment.[30]

[30] For attributes such as physical demands in which there are more than two possible options, we include the interaction of "sitting" with an indicator for whether the respondent's current job involves moderate physical activity in the model, but we suppress these interactions in Appendix Figure 9. All estimates displayed in Appendix Figure 9 are estimated jointly.

We find substantial evidence that individuals who have selected into jobs with specific amenities disproportionately value those characteristics. For example, those with flexibility in setting their schedule consider this job characteristic equivalent to a 10.6% wage increase, four percentage point higher than the valuation of those without schedule flexibility. For workers in intense physical activity jobs, we estimate a small, statistically insignificant negative valuation for sitting. However, people with jobs that require mostly sitting place high valuations on this amenity, equivalent to a 16.0% wage increase. Such differences are true for most other amenities we consider, including a relaxed environment and autonomy at work, working by oneself and evaluation by oneself, and frequent opportunities to serve the community among those selecting into such jobs.

Overall, we find strong evidence that workers selected hypothetical jobs in the stated-preference experiments based on characteristics that they have also selected in real jobs. This suggests that stated preferences indeed reflect actual preferences. It could be, of course, that the relationship arises because workers are more familiar with their actual jobs and less familiar with alternative options, and hence 'default' into these choices. However, our finding in Section 7.F that switching the baseline profile from the current job to a fixed, common job profile did not affect our willingness-to-pay estimates speaks against such an interpretation. We are well aware that these added findings cannot conclusively link stated to actual preferences. However, they give added confidence in our main findings.

8. Conclusion

A large group of studies has examined sources of persistent wage differentials by gender, race, age, and education, and wage inequality more generally, typically studying the traits of workers or firms. In this paper, we assess to what extent differences in job characteristics can help explain some of these persistent wage differences. To do so, we first provide comprehensive evidence about how working conditions differ across demographic groups and throughout the wage distribution based on the American Working Conditions Survey, a nationally representative survey we fielded for this purpose. We also estimate how much workers are willing to pay for those job characteristics based on carefully designed stated-preference experiments. To capture a broad range of working conditions, we focus on nine specific dimensions of job characteristics. We then use the incidence of job characteristics and our estimated willingness-to-pay measures to adjust typical wage differentials and measures of wage inequality in order to illustrate the effect of job amenities on total compensation.

Overall, we find that job characteristics differ systematically across the U.S. labor market. We also document substantial willingness-to-pay for all of the amenities we study, and show that valuations can differ substantially across workers. This preference heterogeneity is a critical component when studying differences in compensation. Accounting for both differences in the incidence of working conditions and preference heterogeneity attenuates the gender wage gap but exacerbates the race wage gap when comparing whites to non-whites. It also increases the cross-sectional returns to college education. We further find that working conditions become increasingly important throughout the lifecycle. Finally, both job amenities and preferences for job amenities rise throughout the wage distribution. Consequently, metrics of wage inequality increase further as we account for systematic differences in job characteristics.

Overall, our analysis confirms recent experimental and stated-preference estimates that suggest that workers have substantial willingness-to-pay for certain job amenities. A key advantage of our stated-preference approach is that it allows us to study a broad range of job amenities that are difficult to analyze in a truly randomized setting. Another advantage is that our data allow us to extend the existing evidence for specific amenities and populations to a broad range of working conditions and a nationally representative sample while linking it to that population's existing job amenities. This allows us to quantify the total potential effect of working conditions on the wage structure.

It is also worth highlighting a few caveats of our analysis. As we discussed, we are aware of the potential limitations of the stated-preference approach, and we sought to address this directly in the analysis. Future waves of the American Working Conditions Survey will further allow us compare stated and revealed preferences in a longitudinal setting. As a partial-equilibrium analysis of willingness-to-pay, it also bears noting that the experimental analysis we have conducted here to monetize how individuals value job amenities is distinct from a counterfactual analysis in which firms would randomly add or remove amenities from jobs. Our analysis recovers *average* valuations across individuals for particular amenities. Although we have demonstrated that there is substantial heterogeneity in valuations across individuals, it is not possible to know which of these individuals are on the margin of a given labor market equilibrium without further information about labor demand by firms when amenities may be costly to provide. In a counterfactual analysis, for example, marginal valuations may be more informative than average valuations, and there may be additional wage adjustments by firms that would depend on the costs of providing particular amenities.

However, our results suggest that amenities play a critical role in job choices. While we limit our attention to only a subset of workplace amenities, we nevertheless estimate that these characteristics compose an important component of compensation, suggesting a first-order role for non-wage amenities for understanding the level and structure of wages in the U.S. labor market.

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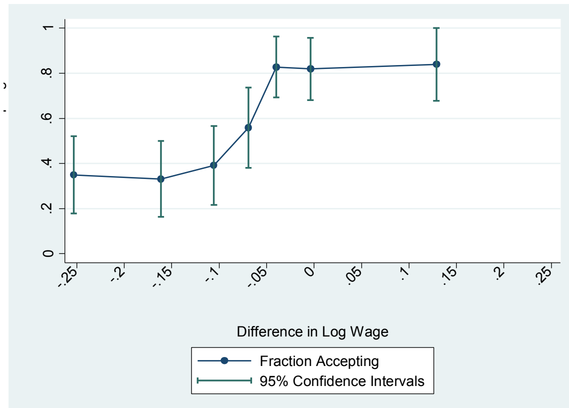
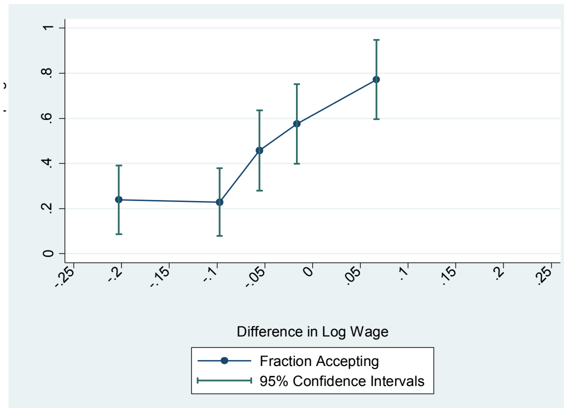
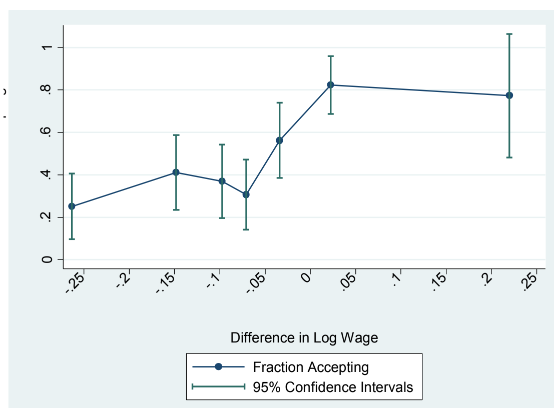
Figure 1: Fraction Preferring Job with Indicated Attributes (over Job without Indicated Attributes) by Relative Wage, Based on Stated-Preference Experiments



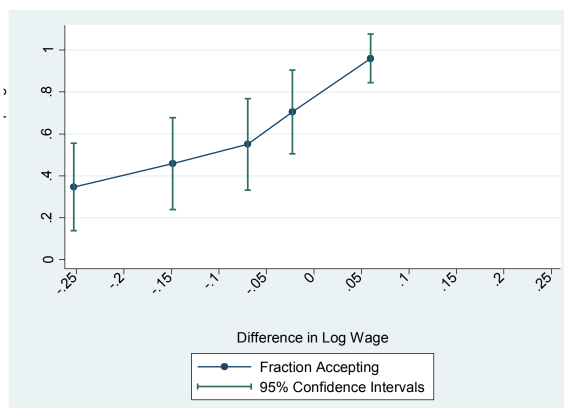
A: Flexible Work Schedule and Telecommuting



B. Relaxed Environment and Work by Self



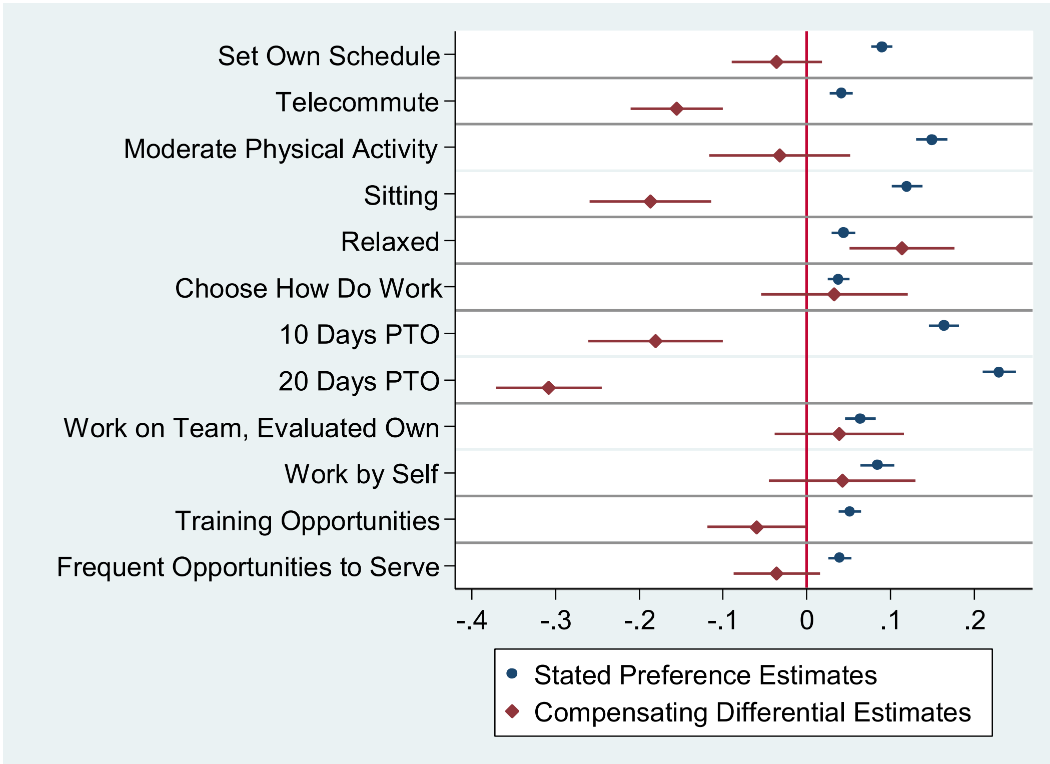
C: Independence and Training



D: Sitting and 20 Days PTO

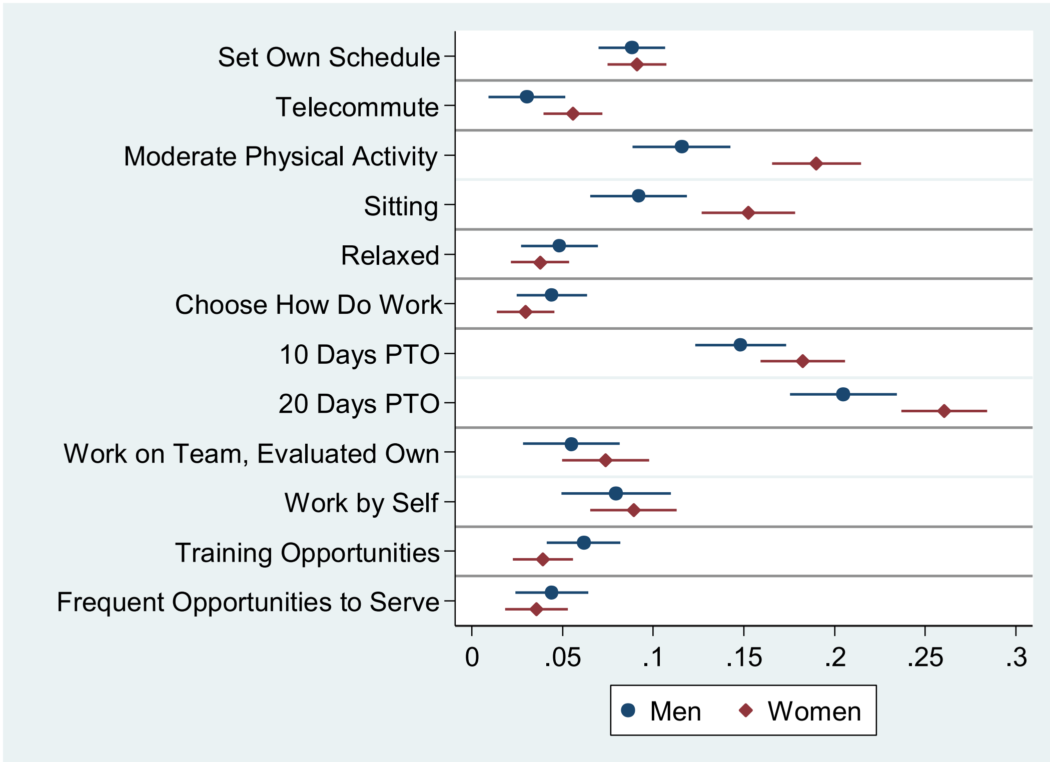
Notes: This figure shows that higher relative wages for a given set of job characteristics is associated with a higher share of respondents selecting that job. To show this we created "bins" of approximately 30 observations (20 for Panel D) for job choice experiments in which one job offer provided the two listed amenities while the other job choice did not. The bins are defined by the difference in the wage offers; the lowest 30 wage offers for the job with the listed amenities relative to the alternative job option are placed in the first bin. The next lowest 30 are placed in the next bin, etc. We plot each point on the x-axis based on the *average* log wage difference for that bin. The y-axis represents the share of respondents in that bin accepting the job with the two indicated amenities.

Figure 2: Estimates of Willingness-to-Pay from Stated-Preference Experiments and Compensating Differential Estimates from Hedonic Regressions



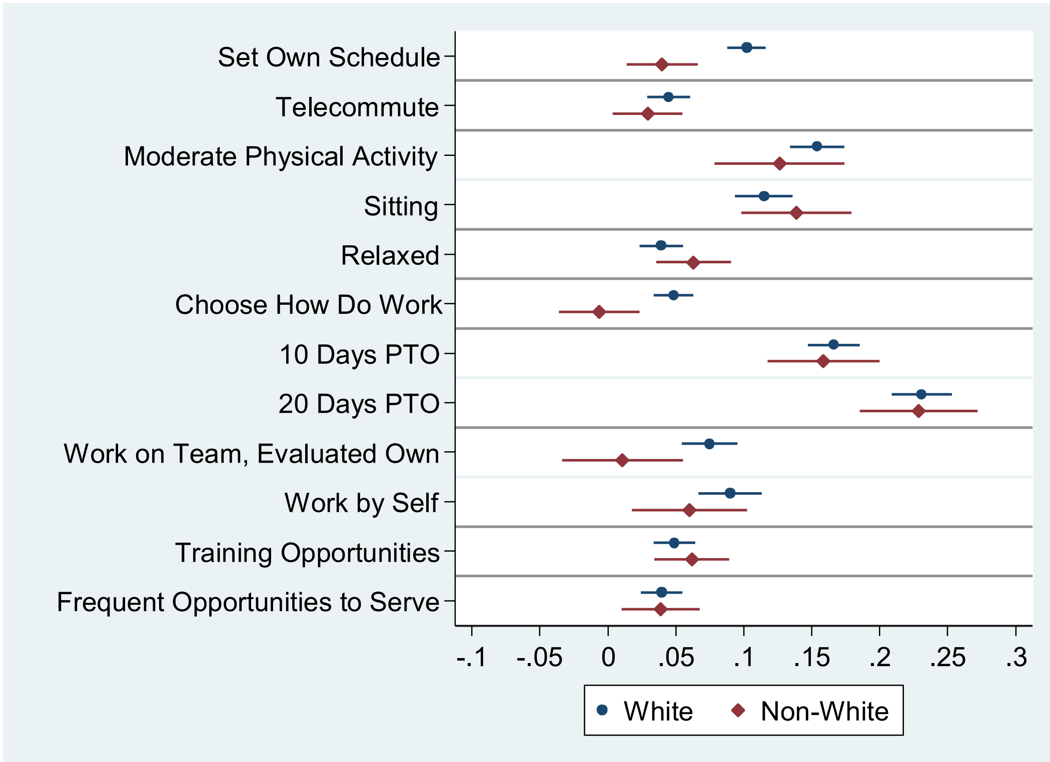
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. Willingness-to-pay estimates from stated-preference experiments are expressed as a percent of respondents' wage. Compensating differential estimates are the implied value from a traditional hedonic pricing model. Controls variables for the compensating differential model include age group, gender, education, race, and citizenship indicators. All results are weighted using population weights; unweighted counts are N=18,150 for stated-preference estimates and 1,815 for compensating differential estimates.

Figure 3: Estimates of Willingness-to-Pay for Job Amenities by Gender from Stated-Preference Experiments



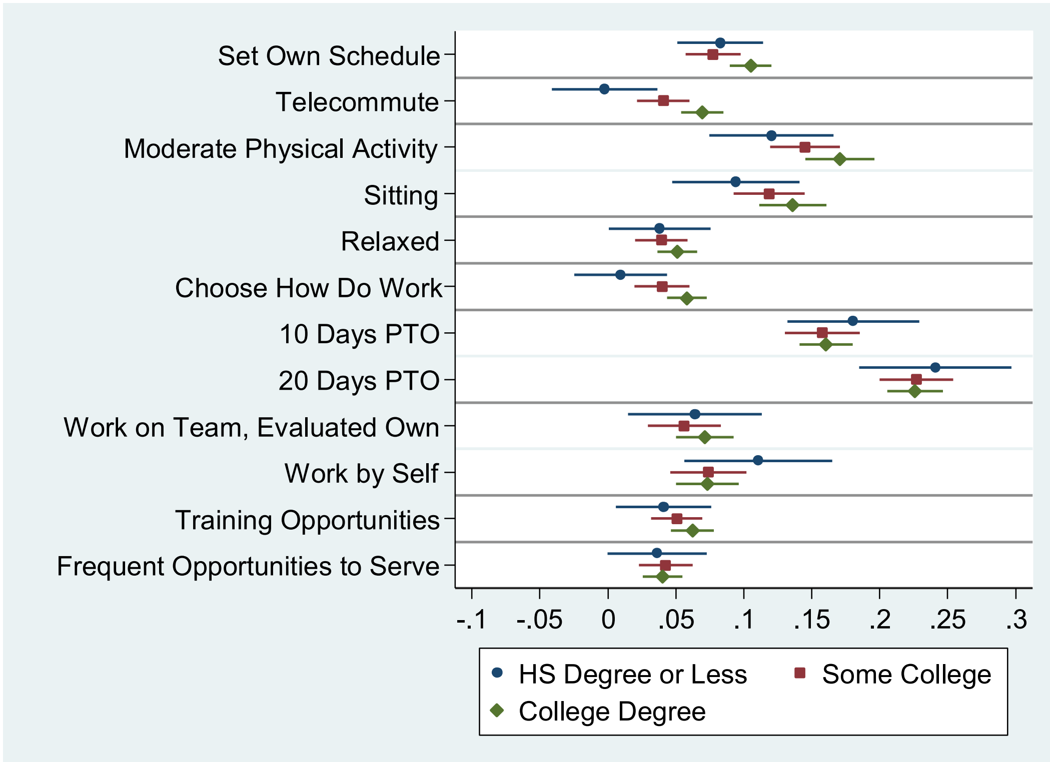
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. All results are weighted using population weights; unweighted counts are N=8,040 for men; 10,110 for women.

Figure 4: Estimates of Willingness-to-Pay for Job Amenities by Race from Stated-Preference Experiments



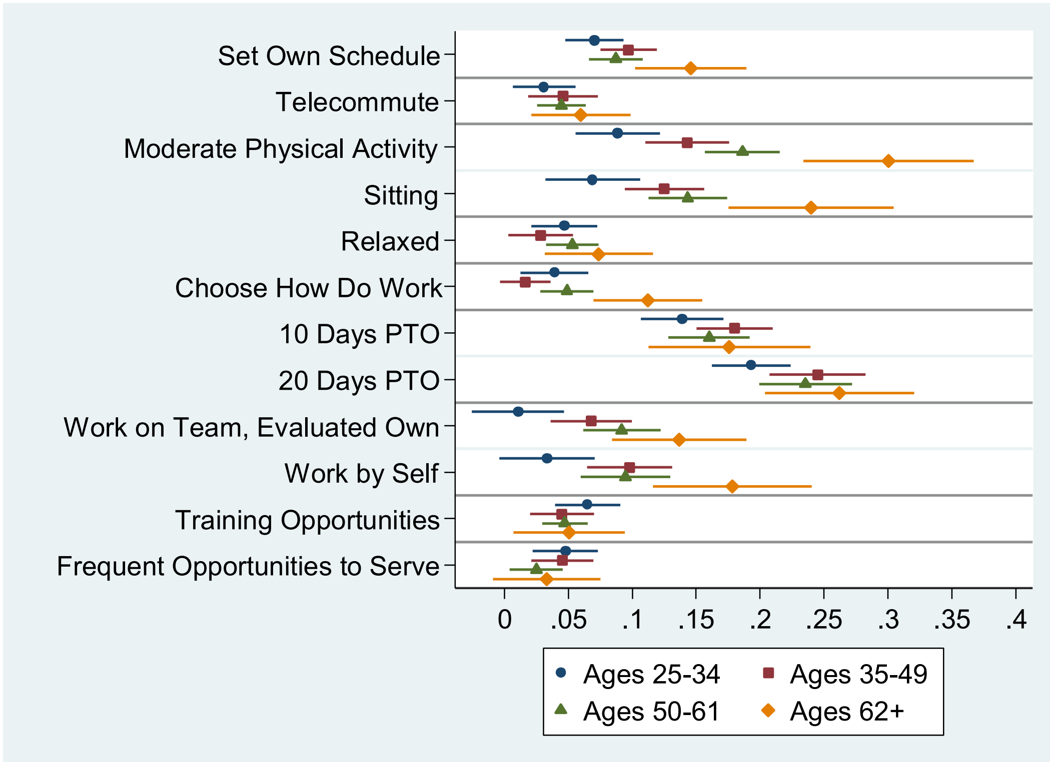
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. All results are weighted using population weights; unweighted counts are N=14,160 for whites; 3,990 for non-whites.

Figure 5: Estimates of Willingness-to-Pay for Job Amenities by Education from Stated-Preference Experiments



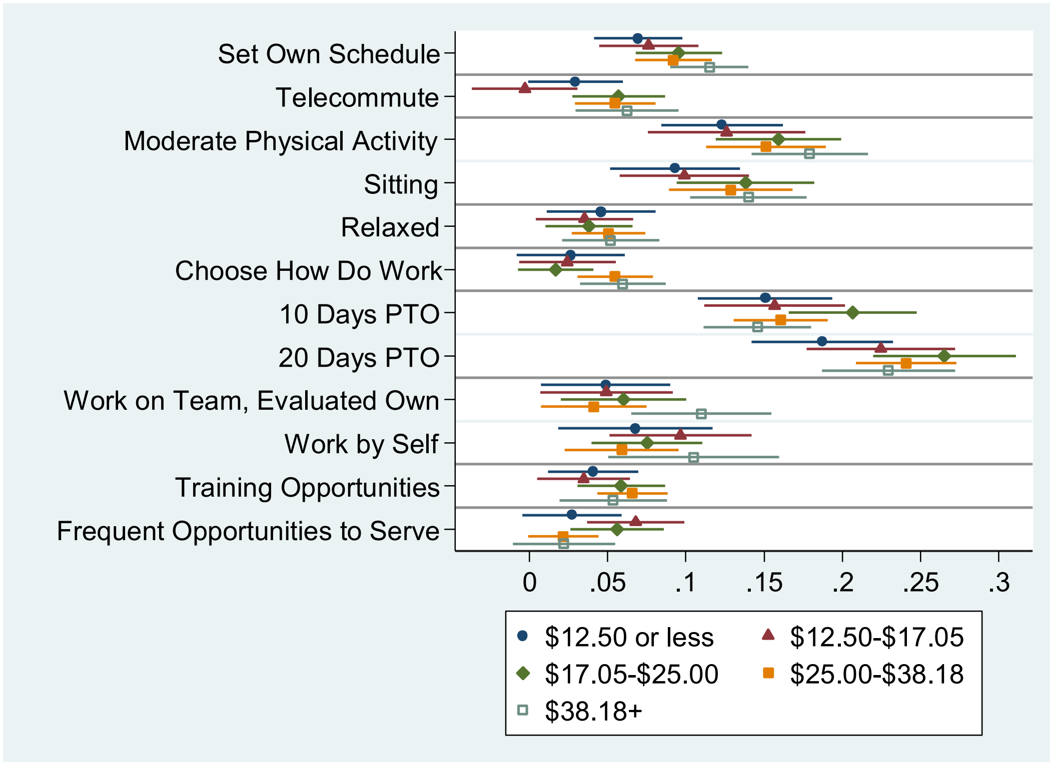
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. All results are weighted using population weights; unweighted counts are N=2,360 for high school degree or less; 6,370 for some college; 9,420 for college degree.

Figure 6: Estimates of Willingness-to-Pay for Job Amenities by Age from Stated-Preference Experiments



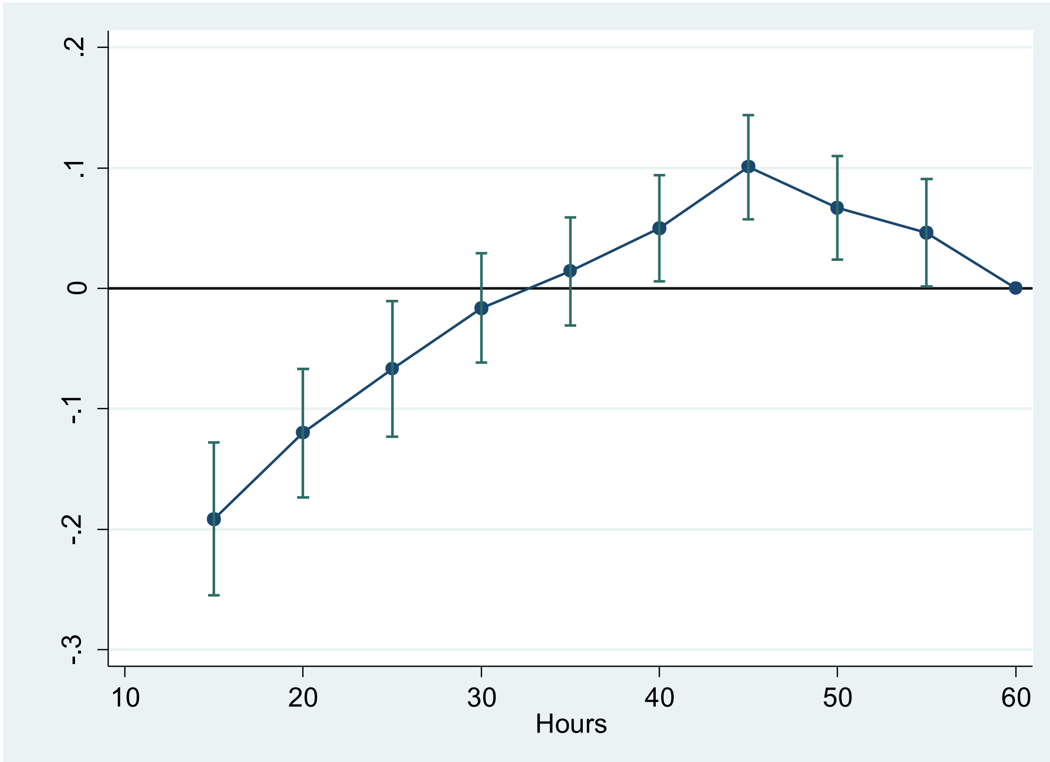
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. All results are weighted using population weights; unweighted counts are N=3,000 for ages 25-34; 5,420 for ages 35-49; 7,000 for ages 50-61; 2,730 for ages 62+.

Figure 7: Estimates of Willingness-to-Pay for Job Amenities by Wage Quintile from Stated-Preference Experiments



Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. All results are weighted using population weights. Unweighted counts are N=4,050; 3,120; 3,900; 3,470; and 3,610 for the wage quintile categories, respectively. Wage quintiles were determined by the weighted sample such that the unweighted size of each quintile is not uniform.

Figure 8: Estimates of Willingness-to-Pay for Weekly Work Hours Based on Stated-Preference Experiments



Notes: 95% confidence intervals are presented and adjusted for clustering by respondent. Estimates are jointly estimated along with other amenities in Figure 2. All results are weighted using population weights; unweighted count is N=18,150.

Table 1: Differences in Hourly Wages by Gender, Race, Education, and Age from American Working Conditions Survey 2015

	Observations	Mean Hourly Wage	Raw Log Wage Differential	Log Wage Differential from Joint Regression
Full Sample	1,815	29.92	--	--
		Gender		
Female	1,011	25.86	-0.187***	-0.213***
Male	804	33.54	(0.047)	(0.042)
		Race Groups		
Non-White	399	23.69	-0.214***	-0.132***
White	1,416	31.47	(0.057)	(0.050)
		Education Groups		
Less than College	873	24.67	-0.532***	-0.548***
College or More	942	37.64	(0.044)	(0.045)
		Age Groups		
Ages 25-34	300	29.93	-0.155*	-0.177**
			(0.088)	(0.079)
Ages 35-49	542	28.62	-0.093	-0.033
			(0.066)	(0.059)
Ages 50-61	700	30.21	-0.042	-0.001
			(0.063)	(0.056)
Ages 62-71	273	34.31		

Notes: Tabulations based on American Working Conditions Survey as explained in text. Column 3 shows the unadjusted difference in log wages, whereas column 4 shows the differences from a joint regression when dummies for all the groups are included jointly. Standard errors in parentheses. Corresponding wage differentials in the Current Population Survey are shown in Appendix Table 1.

Table 2A: Working Conditions in the United States by Gender and Race from the American Working Conditions Survey 2015

		Gender		Race	
	Full Sample	Female	Male	Non-White	White
How much **control** do you have **over your working schedule?**					
My schedule is set by my company/organization with no possibility for changes.	**43.33%**	**41.06%**	**45.36%**	**49.78%**	**41.73%**
I can choose between several fixed working schedules set by my company/organization.	**8.04%**	**8.35%**	**7.76%**	**12.98%**	**6.81%[(a)]**
I can adapt my hours within limits.	**33.41%**	**35.05%**	**31.94%**	**26.88%**	**35.02%**
I can determine my schedule.	**15.23%**	**15.54%**	**14.95%**	**10.36%**	**16.43%[(a)]**
Is it possible for you to **work from home** or another location of your choosing at least some of the time?					
Yes	**36.45%**	**37.25%**	**35.73%**	**31.10%**	**37.77%**
How would you describe the **physical demands of this job?**					
I primarily sit throughout the day.	**42.77%**	**49.51%**	**36.76%[(a)]**	**37.31%**	**44.13%**
My job requires moderate physical activity, such as standing for periods of time or regular walking.	**38.19%**	**37.85%**	**38.49%**	**40.96%**	**37.50%**
My job requires more intense physical activity, such as heavy lifting, stooping, or prolonged walking.	**19.04%**	**12.63%**	**24.75%[(a)]**	**21.74%**	**18.37%**
How would you describe **the pace of this job?**					
Fast-Paced	**69.47%**	**66.79%**	**71.85%**	**69.42%**	**69.48%**
Relaxed	**30.53%**	**33.21%**	**28.15%**	**30.58%**	**30.52%**
How much **independence** do you have in determining what you work on and how you do your work?					
A lot of independence	**43.36%**	**45.37%**	**41.56%**	**40.55%**	**44.06%**
Some independence	**43.31%**	**41.64%**	**44.81%**	**42.96%**	**43.40%**
Very little independence	**13.33%**	**12.99%**	**13.63%**	**16.49%**	**12.54%**
How much **paid time off** (sick days plus vacation days, but not counting paid holidays) do you get per year?					
As needed	**18.61%**	**19.95%**	**17.42%**	**22.99%**	**17.53%**
Mean Number of Days (if not "As needed")	**19.09**	**22.22**	**16.39[(a)]**	**20.16**	**18.84**
Which statement best describes **how much you work with others** at your place of work?					
I primarily work by myself.	**32.88%**	**35.79%**	**30.29%[(a)]**	**29.74%**	**33.66%**
I primarily work with others and I am evaluated mostly based on the team's performance.	**18.52%**	**13.84%**	**22.69%[(a)]**	**23.11%**	**17.38%**
I primarily work with others but I am evaluated mostly based on my own performance.	**48.60%**	**50.38%**	**47.02%**	**47.15%**	**48.96%**
Does your job provide you with **opportunities to learn new skills** that would transfer to other jobs?					
Yes	**69.09%**	**64.49%**	**73.19%[(a)]**	**74.70%**	**67.70%[(a)]**
How often does your job provide opportunities to make a **positive impact on your community or society?**					
Frequently	**34.59%**	**39.43%**	**30.29%[(a)]**	**30.65%**	**35.57%**
Occasionally	**47.01%**	**42.82%**	**50.75%[(a)]**	**50.61%**	**46.12%**
Never	**18.39%**	**17.75%**	**18.97%**	**18.75%**	**18.31%**

Notes: Tabulations from American Working Conditions Survey. Sample sizes for each column are in Table 1.
(a) These cells are found to be statistically significantly different from the reference group in a regression of a dummy for the given amenity category (row) on indicators for all groups (omitting indicators for females, non-whites, non-college and ages 25-34). Point estimates and standard errors are shown in Appendix Table 2.

Table 2B: Working Conditions by Education and Age from the American Working Conditions Survey 2015

		Education		Age			
	Full Sample	Less than College	College	Ages 25-34	Ages 35-49	Ages 50-61	Ages 62+
How much control you have over your working schedule?							
My schedule is set by my company/organization with no possibility for changes.	**43.33%**	**50.67%**	**32.53%[a]**	**42.59%**	**45.94%**	**43.16%**	**35.35%**
I can choose between several fixed working schedules set by my company/organization.	**8.04%**	**10.14%**	**4.94%[a]**	**8.31%**	**8.19%**	**8.60%**	**4.88%**
I can adapt my hours within limits.	**33.41%**	**23.64%**	**47.77%[a]**	**36.93%**	**32.07%**	**31.84%**	**33.92%**
I can determine my schedule.	**15.23%**	**15.54%**	**14.77%**	**12.17%**	**13.79%**	**16.40%**	**25.86%[a]**
Is it possible for you to work from home or another location of your choosing at least some of the time?							
Yes	**36.45%**	**24.00%**	**54.76%[a]**	**34.09%**	**37.13%[a]**	**35.31%**	**43.77%[a]**
How would you describe the physical demands of this job?							
I primarily sit throughout the day.	**42.77%**	**32.80%**	**57.44%[a]**	**39.05%**	**45.25%[a]**	**43.05%**	**42.24%**
My job requires moderate physical activity, such as standing for periods of time or regular walking.	**38.19%**	**39.13%**	**36.79%**	**43.11%**	**32.68%[a]**	**38.61%**	**45.48%**
My job requires more intense physical activity, such as heavy lifting, stooping, or prolonged walking.	**19.04%**	**28.07%**	**5.76%[a]**	**17.83%**	**22.07%**	**18.35%**	**12.29%**
How would you describe the pace of this job?							
Fast-Paced	**69.47%**	**73.21%**	**63.97%[a]**	**75.32%**	**71.01%**	**66.46%[a]**	**56.37%[a]**
Relaxed	**30.53%**	**26.79%**	**36.03%[a]**	**24.68%**	**28.99%**	**33.54%[a]**	**43.63%[a]**
How much independence do you have in determining what you work on and how you do your work?							
A lot of independence	**43.36%**	**40.64%**	**47.36%[a]**	**43.57%**	**41.93%**	**43.79%**	**47.22%**
Some independence	**43.31%**	**42.47%**	**44.56%**	**47.69%**	**43.18%**	**42.31%**	**34.85%[a]**
Very little independence	**13.33%**	**16.89%**	**8.09%[a]**	**8.74%**	**14.90%**	**13.90%**	**17.92%[a]**
How much paid time off (sick days plus vacation days, but not counting paid holidays) do you get per year?							
As needed	**18.61%**	**19.38%**	**17.49%**	**18.44%**	**18.19%**	**17.27%**	**24.98%**
Mean Number of Days (if not "As needed")	**19.09**	**19.09**	**19.08**	**15.44**	**21.02[a]**	**21.49[a]**	**13.29**
Which statement best describes how much you work with others at your place of work?							
I primarily work by myself.	**32.88%**	**32.09%**	**34.04%**	**27.22%**	**32.40%**	**36.85%[a]**	**38.17%[a]**
I primarily work with others and I am evaluated mostly based on the team's performance.	**18.52%**	**21.39%**	**14.30%[a]**	**15.58%**	**21.86%**	**18.23%**	**14.07%**
I primarily work with others but I am evaluated mostly based on my own performance.	**48.60%**	**46.52%**	**51.65%**	**57.20%**	**45.74%[a]**	**44.92%[a]**	**47.76%[a]**
Does your job provide you with opportunities to learn new skills that would transfer to other jobs?							
Yes	**69.09%**	**66.14%**	**73.42%[a]**	**77.42%**	**69.41%**	**65.27%[a]**	**56.60%[a]**
How often does your job provide opportunities to make a positive impact on your community or society?							
Frequently	**34.59%**	**31.44%**	**39.23%**	**30.24%**	**37.87%[a]**	**35.20%**	**31.57%**
Occasionally	**47.01%**	**45.43%**	**49.33%**	**56.55%**	**42.33%[a]**	**45.71%[a]**	**43.50%[a]**
Never	**18.39%**	**23.12%**	**11.44%[a]**	**13.21%**	**19.80%**	**19.09%**	**24.92%[a]**

Notes: Tabulations from American Working Conditions Survey. Sample sizes for each column are in Table 1.
(a) These cells are found to be statistically significantly different from the reference group in a regression of a dummy for the given amenity category (row) on indicators for all groups (omitting indicators for females, non-whites, non-college and ages 25-34). Point estimates and standard errors are shown in Appendix Table 2.

Table 3: Working Conditions by Quintile of the Distribution of Hourly Wages from the American Working Conditions Survey 2015

	Full Sample	$12.50 or less	$12.50-$17.05	$17.05-$25.00	$25.00-$38.18	$38.18+
How much control you have over your working schedule?						
My schedule is set by my company/organization with no possibility for changes.	**43.33%**	**44.63%**	**61.76%**	**51.58%**	**36.48%**	**21.81%**
I can choose between several fixed working schedules set by my company/organization.	**8.04%**	**11.20%**	**7.33%**	**6.76%**	**6.68%**	**8.07%**
I can adapt my hours within limits.	**33.41%**	**22.42%**	**22.17%**	**31.77%**	**40.65%**	**50.64%**
I can determine my schedule.	**15.23%**	**21.76%**	**8.75%**	**9.88%**	**16.20%**	**19.47%**
Is it possible for you to work from home or another location of your choosing at least some of the time?						
No	**63.55%**	**76.92%**	**79.91%**	**69.57%**	**54.89%**	**35.59%**
How would you describe the physical demands of this job?						
I primarily sit throughout the day.	**42.77%**	**23.77%**	**35.09%**	**41.09%**	**53.03%**	**62.08%**
My job requires moderate physical activity, such as standing for periods of time or regular walking.	**38.19%**	**50.64%**	**37.16%**	**39.43%**	**32.79%**	**30.04%**
My job requires more intense physical activity, such as heavy lifting, stooping, or prolonged walking.	**19.04%**	**25.59%**	**27.75%**	**19.48%**	**14.18%**	**7.88%**
How would you describe the pace of this job?						
Fast-Paced	**69.47%**	**73.94%**	**63.21%**	**71.53%**	**68.93%**	**69.24%**
Relaxed	**30.53%**	**26.06%**	**36.79%**	**28.47%**	**31.07%**	**30.76%**
How much independence do you have in determining what you work on and how you do your work?						
A lot of independence	**43.36%**	**36.56%**	**40.29%**	**40.73%**	**43.27%**	**56.25%**
Some independence	**43.31%**	**48.54%**	**44.51%**	**47.97%**	**43.12%**	**32.00%**
Very little independence	**13.33%**	**14.90%**	**15.20%**	**11.30%**	**13.60%**	**11.76%**
How much paid time off (sick days plus vacation days, but not counting paid holidays) do you get per year?						
As needed	**18.61%**	**26.92%**	**16.54%**	**14.69%**	**12.23%**	**22.17%**
Mean Number of Days (if not "As needed")	**19.09**	**8.02**	**19.00**	**21.99**	**23.24**	**22.21**
Which statement best describes how much you work with others at your place of work?						
I primarily work by myself.	**32.88%**	**31.28%**	**34.67%**	**29.32%**	**42.86%**	**27.17%**
I primarily work with others and I am evaluated mostly based on the team's performance.	**18.52%**	**16.14%**	**22.16%**	**21.45%**	**14.15%**	**18.46%**
I primarily work with others but I am evaluated mostly based on my own performance.	**48.60%**	**52.58%**	**43.16%**	**49.23%**	**42.99%**	**54.36%**
Does your job provide you with opportunities to learn new skills that would transfer to other jobs?						
Yes	**69.09%**	**61.01%**	**66.21%**	**71.09%**	**70.09%**	**77.22%**
How often does your job provide opportunities to make a positive impact on your community or society?						
Frequently	**34.59%**	**28.67%**	**34.75%**	**35.83%**	**33.24%**	**40.56%**
Occasionally	**47.01%**	**47.32%**	**42.48%**	**42.63%**	**52.13%**	**50.91%**
Never	**18.39%**	**24.02%**	**22.77%**	**21.54%**	**14.63%**	**8.54%**

Notes: Tabulations from American Working Conditions Survey. Sample sizes for each column are in Table 1.

Table 4: Effect of Adjusting for the Incidence and Valuation of Job Amenities on Wage Differentials by Gender, Race, Age, and Education

Panel A: Log Differentials, Holding Valuations Constant

	Unadjusted Wage Differential	Difference in Amenity Multiplier	Difference in Total Value of Amenities	Adjusted Wage Differential (Gap in Total Compensation)
Female	-0.187***	0.070***	-0.113*	-0.172***
	(0.047)	(0.026)	(0.059)	(0.049)
Non-White	-0.214***	-0.003	-0.214***	-0.217***
	(0.057)	(0.025)	(0.070)	(0.059)
College	0.532***	0.177***	0.713***	0.577***
	(0.044)	(0.023)	(0.053)	(0.045)
Ages 25-34	-0.155*	-0.004	-0.160	-0.155*
(relative to 62-71)	(0.088)	(0.032)	(0.100)	(0.090)
Ages 35-49	-0.093	-0.033	-0.132	-0.100
(relative to 62-71)	(0.066)	(0.039)	(0.087)	(0.070)
Ages 50-61	-0.042	0.004	-0.037	-0.041
(relative to 62-71)	(0.063)	(0.027)	(0.077)	(0.066)

Panel B: Log Differentials, Allowing Valuations to Vary Across Groups

	Unadjusted Wage Differential	Difference in Amenity Multiplier	Difference in Total Value of Amenities	Adjusted Wage Differential (Gap in Total Compensation)
Female	-0.187***	0.206***	0.023	-0.131**
	(0.047)	(0.072)	(0.093)	(0.054)
Non-White	-0.214***	-0.202**	-0.412***	-0.268***
	(0.057)	(0.094)	(0.118)	(0.065)
College	0.532***	0.322***	0.858***	0.619***
	(0.044)	(0.074)	(0.092)	(0.050)
Ages 25-34	-0.155*	-0.564***	-0.720***	-0.320***
(relative to 62-71)	(0.088)	(0.094)	(0.135)	(0.094)
Ages 35-49	-0.093	-0.373***	-0.473***	-0.205***
(relative to 62-71)	(0.066)	(0.089)	(0.119)	(0.074)
Ages 50-61	-0.042	-0.258***	-0.300***	-0.127
(relative to 62-71)	(0.063)	(0.077)	(0.110)	(0.072)

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses generated from block bootstrap in which new willingness-to-pay measures are estimated for each bootstrap sample. The “Wage” and “Amenity Multiplier” columns mechanically add to the “Amenity Value” column.

Table 5: Effect of Adjusting for the Incidence and Valuation of Job Amenities on the Distribution of Hourly Wages

Percentile Difference	Difference in ln(Wage) (1)	Difference in ln(Compensation) (2)	Change Accounting for Amenities (2)-(1)	p-value for H_0: (1)=(2)
Panel A: Holding Valuations Constant				
90th-50th	0.986	1.027	0.041	0.054
	(0.047)	(0.047)		
50th-10th	0.692	0.723	0.031	0.032
	(0.036)	(0.038)		
90th-10th	1.678	1.751	0.073	0.002
	(0.054)	(0.054)		
Panel B: Allowing Valuations to Vary Across Groups				
Percentile Difference	**Difference in ln(Wage) (1)**	**Difference in ln(Compensation) (2)**	**Change Accounting for Amenities (2)-(1)**	**p-value for H_0: (1)=(2)**
90th-50th	0.986	1.043	0.057	0.138
	(0.047)	(0.056)		
50th-10th	0.692	0.787	0.095	0.000
	(0.036)	(0.045)		
90th-10th	1.678	1.830	0.152	0.000
	(0.054)	(0.061)		

Notes: Standard errors in parentheses results from block bootstrap in which new willingness-to-pay measures are estimated for each bootstrap sample. Compensation refers to the wage adjusted for amenity valuations.

Web Appendix

For

"The Value of Working Conditions in the United States and Implications for the Structure of Wages"

Nicole Maestas
Harvard University and NBER

Kathleen J. Mullen
RAND

David Powell*
RAND

Till von Wachter
University of California Los Angeles and NBER

Jeffrey Wenger
RAND

* Corresponding author: dpowell@rand.org

Appendix A: Surveying Respondents about Their Wage

We asked all respondents for information concerning monetary payments at the frequency that they wanted to report this information (hourly rate, weekly, bi-weekly, twice monthly, monthly, or annually). We also asked for information on weeks worked and hours worked per week. Using this information, we calculated their hourly wage. If this wage was less than $7, we asked the respondent to confirm their previous information on compensation, hours, and weeks. If the respondent had not directly provided their hourly wage, their implied rate was still less than $7, and they had previously answered that they were paid hourly, then we asked them to provide their hourly rate instead.

Appendix B: Fully-Interacted Model to Account for Effect of Amenities on Wage Differentials 'Holding Constant' Differences in Amenity and Wages from Other Groups

For Appendix Table 7, we replicate Table 4 but estimate all parameters jointly. We implement this approach by interacting all job amenities (including hours) and log wages in our main specification with indicators for female, non-white, and college-educated as well as age group dummies. This approach permits job choice decisions to vary based on these covariates additively. We use this approach instead of a fully-interacted model because of the small number of individuals in some of the cells and because we will analyze the generated outcomes in a linear, additive model. This part of the method helps isolate the preferences that men have for job characteristics relative to women, conditional on other individual covariates, accounting for observable differences between groups.

Given these estimates, we can calculate each person's amenity value using the estimated preferences relative to the log wage (which vary based on individual covariates) and the amenities that they currently have at their job. We then create the same metrics as analyzed in Table 4. In Table 4, we studied differences in these outcome for women relative to men. Here, we regress the outcome on all individual covariates to jointly estimate the relationship between the covariates and measures of compensation. The motivation of this exercise is to determine whether women receive different compensation *conditional on other covariates*.

Appendix C: Details on the Special Regressor Method

The special regressor method first requires estimation of

$$T_{it} \equiv \frac{D_{it} - 1(\ln w_{i1t} \geq \ln w_{i2t})}{f_{v|x}(\ln w_{i1t} - \ln w_{i2t}| X_{i1t} - X_{i2t})}$$

where the denominator is the conditional probability density function of the difference in the log of the wages between the two jobs conditional on the job characteristics and D_{it} represents a binary outcome. This variable is the outcome for the OLS regression. Lewbel (2014) shows that this expected value of T_{it} is equal to the expected value of the mean willingness-to-pay. The only difficulty in estimating T_{it} is often that it requires estimating a conditional density function for the denominator and it is often necessary to winsorize this variable. However, we generated the wages for both jobs, making it straightforward for us to accurately simulate this distribution. For a given set of characteristics for individual *i*, we simulate the distribution of $\ln w_{i1t} - \ln w_{i2t}$ by re-drawing the wages in the same manner as the experiment. For each (i, t), we replicate this process 1000 times and then estimate a kernel density function, evaluated at the difference in the log of the wages used in that job choice experiment. Given this estimate, we calculate $\hat{T}_{it}$. This variable is used as the outcome of an OLS regression on the difference in the job characteristics (including the log of hours). The coefficient estimates are the estimated mean willingness-to-pay measures.

Appendix Figure 1: Screenshot of Hypothetical Job Pair Evaluated by a Respondent

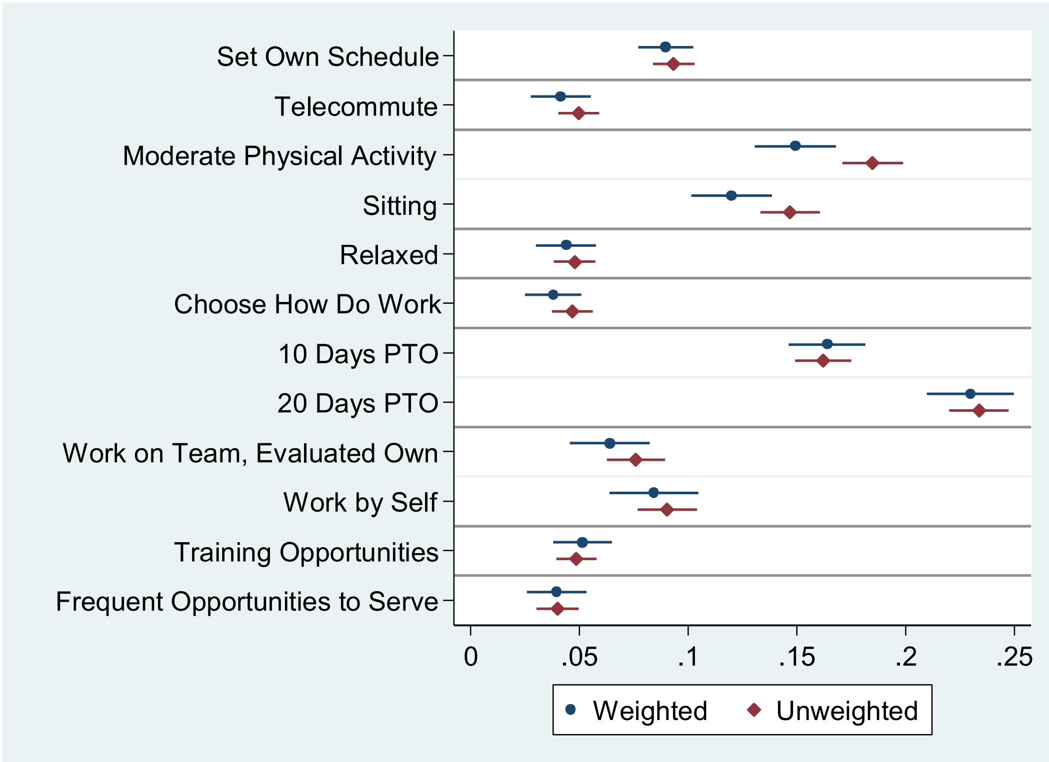
First question of the survey for respondent '5121056:1' Imagine you are offered the two jobs shown below. Except for the characteristics highlighted below, please assume the jobs are the same in all other ways, including on characteristics not listed in the table. You may scroll over the characteristics to see their definitions. Please review the jobs and indicate below whether you prefer Job A or Job B.

	Job A	Job B
Hours	Part-Time - 20 hours per week	Part-Time - 20 hours per week
Control Over Hours	Set your own schedule	Set your own schedule
Option to Telecommute	No	No
Physical Demands	Moderate physical activity	Heavy physical activity
Pace	Relaxed	Relaxed
Independence	You can choose how you do your own work	Your tasks and procedures are well-defined
Paid Time Off (Vacation and Sick Leave)	None	None
Working with Others	Mainly work by yourself	Mainly work by yourself
Training	You have the skills for this job and there are opportunities to gain valuable new skills	You have the skills for this job and there are opportunities to gain valuable new skills
Impact on Society	Occasional opportunities to make a positive impact on your community or society	Occasional opportunities to make a positive impact on your community or society
Pay	$18.50 per hour ($370 per week)	$19.50 per hour ($390 per week)

	Strongly Prefer Job A	Prefer Job A	Prefer Job B	Strongly Prefer Job B
Which job do you prefer?	○	◉	○	○

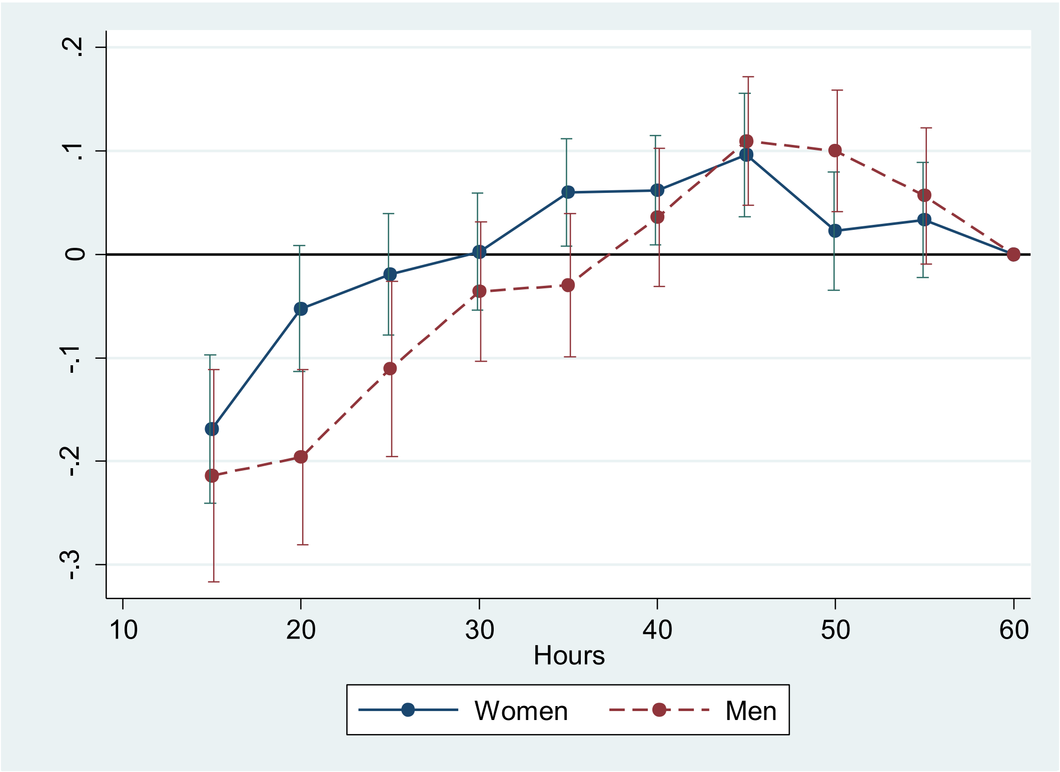
Back Next

Appendix Figure 2: Weighted vs Unweighted Willingness-to-Pay Estimates



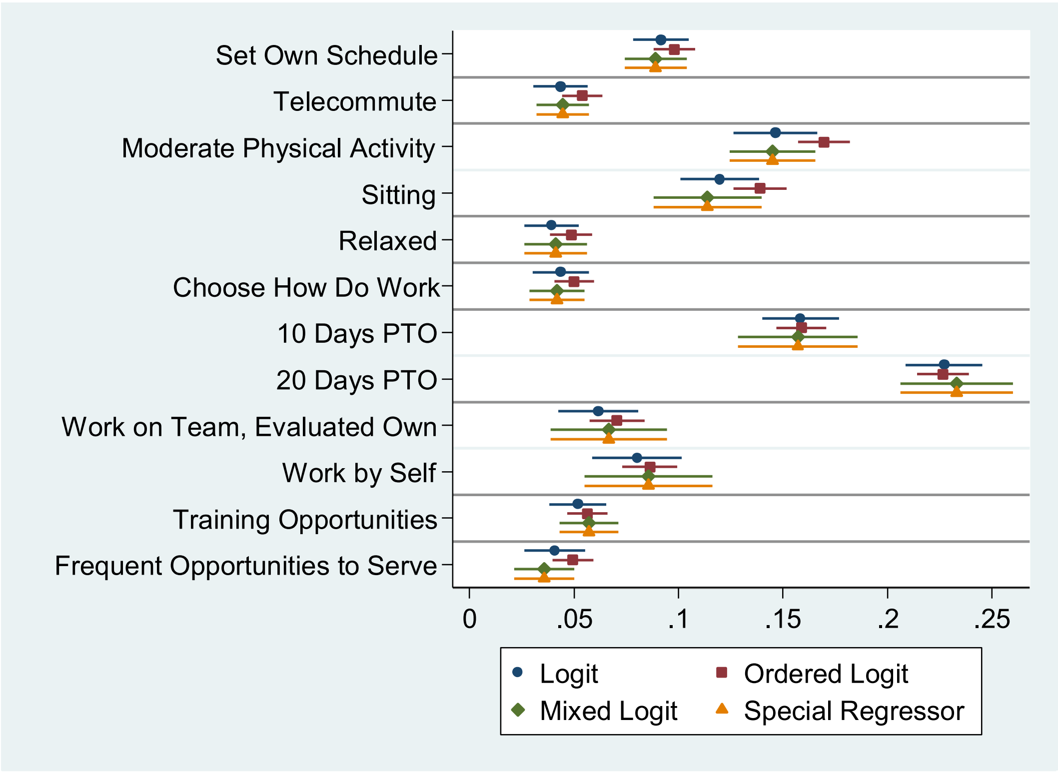
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments.

Appendix Figure 3: Estimates of Willingness-to-Pay for Weekly Work Hours by Gender



Notes: Joint test of equality of all estimates rejects equality (p<.01)

Appendix Figure 4: Estimates of Willingness-to-Pay Using Different Estimation Techniques



Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments.

Appendix Figure 5: First "Trick" Question to Test Whether Respondents Were Paying Attention

We want to know which methods people think are most effective when searching for a new job. We also want to know whether people read questions like this carefully. To show you've read this much, please ignore the question and select both asking friends and job fairs, no matter what method you think is most effective. Yes, ignore the question and select both of these options. Thank you very much.

Which of the following methods do you think is MOST effective when searching for a new job?

- ☐ Newspaper/Trade publication (either electronic or print)
- ☐ Internet-based job search site such as Monster.com™
- ☐ Ask friends, relatives and colleagues about jobs
- ☐ In-person/Walk-in
- ☐ Social media site such as Facebook/Linkedin
- ☐ Other social media such as Twitter
- ☐ Job Fairs/Hiring Halls
- ☐ One stop centers/Help from government job services
- ☐ Headhunter or private career coach

‹ Back   Next ›

RAND American Life Panel

Appendix Figure 6: Second "Trick" Question to Test Whether Respondents Were Paying Attention

As you have seen in this survey, we are interested in the reasons people choose to accept one job versus another. We are also interested in whether people read questions like this carefully. To show you've read this much, please ignore the question below, select other and write "none" as your answer. Thank you very much.

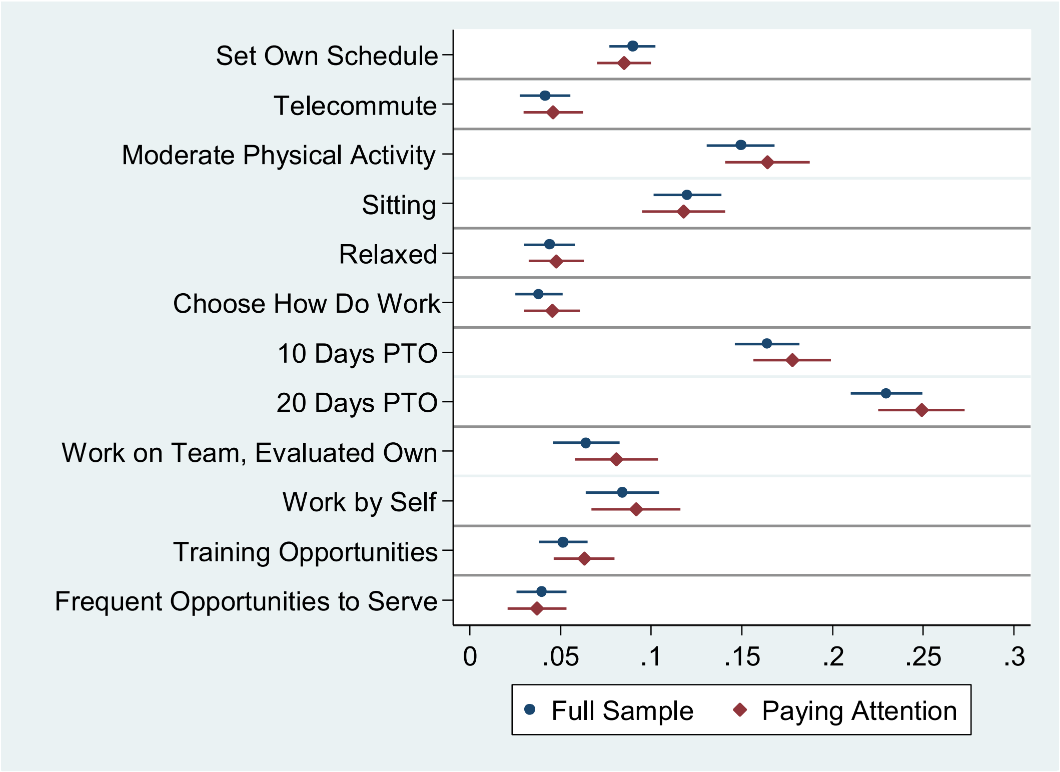
In thinking about possible work in the future, what is the MOST important reason you would choose a new job?

- ○ The job allows you to provide for yourself and your family financially.
- ○ The job is not physically demanding.
- ○ The job provides you with control over your schedule.
- ○ The job has the right number of hours.
- ○ The job gives you control over how you do your work.
- ○ The job allows you to work at your own pace.
- ○ The job is not stressful.
- ○ The job gives you opportunities to work with others.
- ○ The job gives you opportunities to learn new things.
- ○ The job will lead to opportunities for career advancement.
- ○ The job is morally, socially, personally, or spiritually significant.
- ○ Other, please specify. ____________

Back　　Next

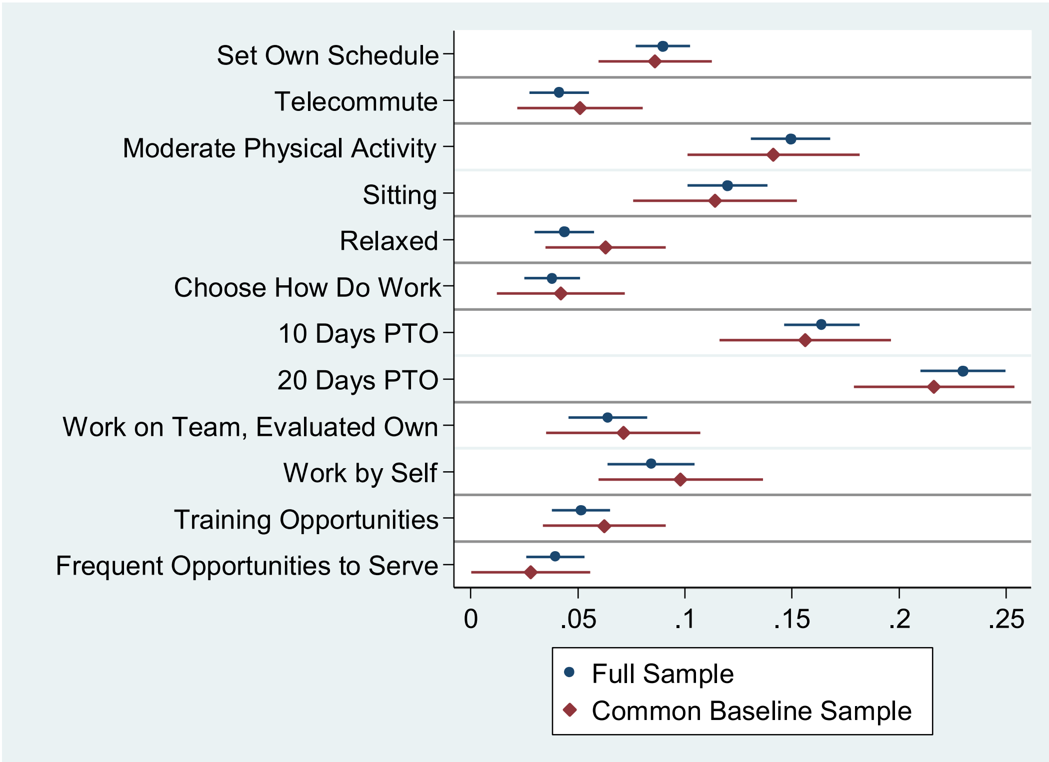
RAND American Life Panel

Appendix Figure 7: Estimates of Willingness-to-Pay Using Sample that Correctly Answered Trick Questions



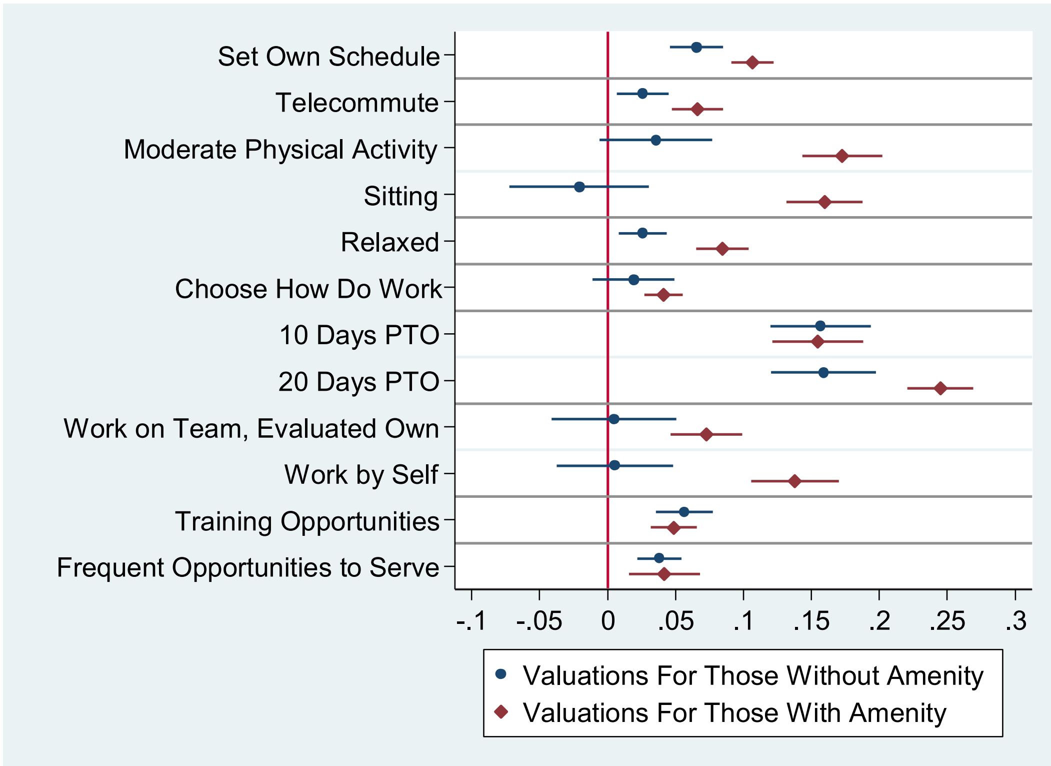
Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. N=11,760 for the "Paying Attention" sample.

Appendix Figure 8: Estimates of Willingness-to-Pay Using Common Baseline Job



Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments. The "common baseline sample" consists of responses to 2 of these 10 experiments, in which attribute randomization was performed around the same baseline job for all respondents, rather than the respondent's current job.

Appendix Figure 9: Estimates of Willingness-to-Pay by Selection into Job Characteristics



Notes: 95% confidence intervals adjusted for clustering by respondent. Each respondent provided responses to 10 stated-preference experiments.

Appendix Table 1: Comparison of Wage Differentials in American Life Panel (ALP) to Current Population Survey (CPS)

	CPS		ALP	
	Raw Log Wage Differential	Log Wage Differential from Joint Regression	Topcoded as in CPS	Not Topcoded (As in Table 1)
Female	-0.185	-0.227	-0.155	-0.187
Non-White	-0.185	-0.115	-0.184	-0.214
Less than College	-0.423	-0.436	-0.535	-0.532
Ages 25-34	-0.120	-0.136	-0.165	-0.155
Ages 35-49	0.067	0.065	-0.095	-0.094
Ages 50-61	0.076	0.084	-0.035	-0.042
90th-50th	0.877	--	0.897	0.986
50th-10th	0.663	--	0.692	0.692
90th-10th	1.540	--	1.590	1.678

Notes: We use the 2015 December CPS, selecting on employed individuals ages 25-71 (N=13,300). Weights are generated based on race*education, education*gender, age group*gender, and income categories*marital status.

Appendix Table 2: Differences in Log Wages and Incidence of Amenities by Demographic Groups, Holding Differences Across Other Groups Constant (Additional Job Characteristics in Separate Table)

	Log Hourly Wage	Control over Schedule				Tele-commuting	Physical Demands			Pace	
		None	*A little*	*Some*	*Lots*	*No*	*Sit*	*Moderate*	*Intense*	*Fast*	*Relaxes*
Male	8.182***	0.036	-0.007	-0.022	-0.008	-0.001	-0.116***	0.006	0.110***	0.043	-0.043
	(2.622)	(0.032)	(0.020)	(0.029)	(0.022)	(0.028)	(0.031)	(0.032)	(0.027)	(0.027)	(0.027)
White	5.695**	-0.061	-0.055**	0.058	0.058**	-0.029	0.046	-0.032	-0.014	0.017	-0.017
	(2.542)	(0.042)	(0.028)	(0.037)	(0.024)	(0.035)	(0.038)	(0.042)	(0.037)	(0.034)	(0.034)
College	13.009***	-0.173***	-0.048***	0.234***	-0.012	-0.312***	0.247***	-0.032	-0.215***	-0.096***	0.096***
	(3.014)	(0.031)	(0.018)	(0.030)	(0.021)	(0.028)	(0.030)	(0.031)	(0.024)	(0.027)	(0.027)
Ages 35-49	0.618	0.009	-0.007	-0.015	0.013	-0.077*	0.097**	-0.108**	0.012	-0.057	0.057
	(5.426)	(0.048)	(0.028)	(0.044)	(0.031)	(0.040)	(0.043)	(0.047)	(0.040)	(0.037)	(0.037)
Ages 50-61	1.698	-0.011	0	-0.027	0.037	-0.048	0.064	-0.047	-0.017	-0.100***	0.100***
	(5.372)	(0.046)	(0.024)	(0.043)	(0.030)	(0.038)	(0.040)	(0.047)	(0.036)	(0.037)	(0.037)
Ages 62-71	4.793	-0.075	-0.033	-0.024	0.132***	-0.109**	0.037	0.025	-0.062	-0.194***	0.194***
	(5.627)	(0.053)	(0.022)	(0.051)	(0.039)	(0.047)	(0.047)	(0.054)	(0.040)	(0.048)	(0.048)
N	1,815	1,815	1,815	1,815	1,815	1,815	1,815	1,815	1,815	1,815	1,815

Notes: Each column corresponds to a separate worker-level linear regression, with the dependent variable being either the wage or a dummy indicating presence the value of the particular amenity. Standard errors in parentheses. * 10%, ** 5%, ***1% Significance levels

Appendix Table 2 (continued): Differences in Log Wages and Incidence of Amenities by Demographic Groups, Holding Differnces Across Other Groups Constant

	Independence			Paid Time Off (PTO)		Working with Others			Job Training	Meaningful Work		
	A lot	*Some*	*Very little*	*Can take as needed*	*PTO Days*	*Self*	*Team / Team*	*Team / Self*	*Yes*	*Frequent*	*Occ-asional*	*Never*
Male	-0.036	0.031	0.004	-0.024	-5.686**	-0.054*	0.088***	-0.034	0.092***	-0.088***	0.081**	0.007
	(0.032)	(0.033)	(0.024)	(0.025)	(2.764)	(0.030)	(0.026)	(0.033)	(0.029)	(0.031)	(0.032)	(0.025)
White	0.029	0.005	-0.034	-0.052	-1.42	0.034	-0.056	0.021	-0.076**	0.045	-0.048	0.004
	(0.042)	(0.043)	(0.032)	(0.034)	(3.717)	(0.038)	(0.035)	(0.042)	(0.035)	(0.037)	(0.042)	(0.032)
College	0.062*	0.019	-0.081***	-0.018	0.525	0.02	-0.056**	0.036	0.078***	0.079***	0.034	-0.113***
	(0.032)	(0.032)	(0.021)	(0.024)	(2.120)	(0.029)	(0.024)	(0.032)	(0.028)	(0.030)	(0.031)	(0.022)
Ages 35-49	-0.008	-0.042	0.05	-0.004	5.630*	0.053	0.057	-0.110**	-0.066	0.086*	-0.135***	0.049
	(0.048)	(0.048)	(0.031)	(0.036)	(2.889)	(0.042)	(0.036)	(0.048)	(0.041)	(0.046)	(0.047)	(0.034)
Ages 50-61	0.007	-0.051	0.044	-0.011	6.035***	0.096**	0.025	-0.120***	-0.106***	0.055	-0.100**	0.045
	(0.046)	(0.046)	(0.027)	(0.034)	(2.216)	(0.041)	(0.034)	(0.045)	(0.040)	(0.043)	(0.045)	(0.030)
Ages 62-71	0.036	-0.127**	0.091**	0.068	-2.126	0.107**	-0.012	-0.095*	-0.197***	0.012	-0.123**	0.112***
	(0.053)	(0.053)	(0.037)	(0.043)	(1.624)	(0.048)	(0.039)	(0.053)	(0.049)	(0.048)	(0.053)	(0.042)
N	1,815	1,815	1,815	1,815	1,462	1,815	1,815	1,815	1,815	1,815	1,815	1,815

Notes: Each column corresponds to a separate worker-level linear regression, with the dependent variable being either the wage or a dummy indicating presence the value of the particular amenity. Standard errors in parentheses. * 10%, ** 5%, ***1% Significance levels

Appendix Table 3: Common Baseline Job Used for All Respondents in 2 of 10 Experiments

Job Characteristic	Assigned Baseline Value
Hours	30 Hours (Part-Time)
Control Over Hours	Set your own schedule
Option to Telecommute	Yes
Physical Demands	Mostly Sitting
Work Environment	Relaxed
Independence	You can choose how you do your work
Paid Time Off (Vacation and Sick Leave)	20 paid days per year
Working with Others	Team-based but you are evaluated on your own performance
Training	You have the skills for this job and there are opportunities to gain valuable new skills
Impact on Society	Frequent opportunities to make a positive impact on your community or society

Appendix Table 4: Mapping from Current Working Conditions to Baseline Jobs for Experiments

Question asked to respondent…	Attribute assigned based on response
How much control you have over your working schedule?	**Control Over Hours**
My schedule is set by my company/organization with no possibility for changes.	Schedule set by manager
I can choose between several fixed working schedules set by my company/organization.	Set your own schedule
I can adapt my hours within limits.	Set your own schedule
I can determine my schedule.	Set your own schedule
Is it possible for you to work from home or another location of your choosing at least some of the time?	**Option to Telecommute**
Yes	Yes
No	No
How would you describe the physical demands of this job?	**Physical Demands**
I primarily sit throughout the day.	Mostly sitting
My job requires moderate physical activity, such as standing for periods of time or regular walking.	Moderate physical activity
My job requires more intense physical activity, such as heavy lifting, stooping, or prolonged walking.	Heavy physical activity
How would you describe the pace of this job?	**Pace**
Fast-Paced	Fast-Paced
Relaxed	Relaxed
How much independence do you have in determining what you work on and how you do your work?	**Independence**
A lot of independence	You can choose how you do your work
Some independence	You can choose how you do your work
Very little independence	Your tasks and procedures are well-defined
How much paid time off (sick days plus vacation days, but not counting paid holidays) do you get per year?	**Paid Time Off (Vacation and Sick Leave)**
As needed	20 paid days per year
(Integer)	If 0, assign to 0. If greater than 0 and less than 15, assign to 10. Otherwise, assign to 20.
Which statement best describes how much you work with others at your place of work?	**Working with Others**
I primarily work by myself.	Mainly work by yourself
I primarily work with others and I am evaluated mostly based on the team's performance.	Team-based and evaluated on performance of team
I primarily work with others but I am evaluated mostly based on my own performance.	Team-based but you are evaluated on your own performance
Does your job provide you with opportunities to learn new skills that would transfer to other jobs?	**Trainings**
Yes	You have the skills for this job and there are opportunities to gain valuable new skills
No	You already have the skills for this job
How often does your job provide opportunities to make a positive impact on your community or society?	**Impact on Society**
Frequently	Frequent opportunities to make a positive impact on your community or society
Occasionally	Occasional opportunities to make a positive impact on your community or society
Never	Occasional opportunities to make a positive impact on your community or society
How are you paid?	
Hourly wage	Hourly
Annual salary	Salaried
Other	Hourly
Enter the number of hours that you usually work per week:	**Hours**
Integer	Same integer

Appendix Table 5A: Estimates of Willingness-to-Pay from Stated-Preference Experiments and Compensating Differential Estimates from Hedonic Regressions (Point Estimates and Standard Errors Corresponding to Figure 2)

	Full Sample	Compensating Differentials	Excluded Category
Set Own Schedule	0.090***	-0.036	Schedule set by manager
	(0.006)	(0.027)	
Telecommute? Yes	0.041***	-0.155***	No
	(0.007)	(0.028)	
Moderate Physical Activity	0.149***	-0.032	Heavy Physical Activity
	(0.010)	(0.043)	
Sitting	0.120***	-0.187***	
	(0.010)	(0.037)	
Relaxed	0.044***	0.114***	Fast-Paced
	(0.007)	(0.032)	
Choose How do Work	0.038***	0.033	Tasks well-defined
	(0.007)	(0.045)	
10 days PTO	0.164***	-0.181***	0 Days
	(0.009)	(0.041)	
20 days PTO	0.230***	-0.308***	
	(0.010)	(0.032)	
Team-Based, Evaluate Own	0.064***	0.039	Team-Based, Evaluate Team
	(0.009)	(0.039)	
Work by Self	0.084***	0.043	
	(0.010)	(0.045)	
Training Opportunities	0.051***	-0.059**	Already have skills
	(0.007)	(0.030)	
Frequent Opportunities to serve community	0.039***	-0.036	Occasional Opportunities to serve community
	(0.007)	(0.026)	
Best Job	0.561***		Worst Job
	(0.016)		
N	18,150	1,851	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. "Best Job" metric compares the best possible job (as measured by estimates) to "Worst Job." Compensating differential estimates refer to estimates from a regression of log(wage) on covariates and the job characteristics listed above. We report the implied valuation of these estimates.

Appendix Table 5B: Estimates of Willingness-to-Pay from Stated-Preference Experiments by Gender (Point Estimates and Standard Errors Corresponding to Figure 3)

	Women	Men	Excluded Category
Set Own Schedule	0.091***	0.088***	Schedule set by manager
	(0.008)	(0.009)	
Telecommute? Yes	0.056***	0.030***	No
	(0.008)	(0.011)	
Moderate Physical Activity	0.190***	0.116***	Heavy Physical Activity
	(0.012)	(0.014)	
Sitting	0.153***	0.092***	
	(0.013)	(0.014)	
Relaxed	0.038***	0.048***	Fast-Paced
	(0.008)	(0.011)	
Choose How do Work	0.029***	0.044***	Tasks well-defined
	(0.008)	(0.010)	
10 days PTO	0.183***	0.148***	0 Days
	(0.012)	(0.013)	
20 days PTO	0.260***	0.205***	
	(0.012)	(0.015)	
Team-Based, Evaluate Own	0.074***	0.055***	Team-Based, Evaluate Team
	(0.012)	(0.014)	
Work by Self	0.089***	0.079***	
	(0.012)	(0.015)	
Training Opportunities	0.039***	0.062***	Already have skills
	(0.008)	(0.010)	
Frequent Opportunities to serve community	0.036***	0.044***	Occasional Opportunities to serve community
	(0.009)	(0.010)	
Best Job	0.595***	0.533***	Worst Job
	(0.017)	(0.025)	
N	10,110	8,040	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. "Best Job" metric compares the best possible job (as measured by estimates) to "Worst Job."

Appendix Table 5C: Estimates of Willingness-to-Pay from Stated-Preference Experiments by Race (Point Estimates and Standard Errors Corresponding to Figure 4)

	White	Non-White	Excluded Category
Set Own Schedule	0.102***	0.040***	Schedule set by manager
	(0.007)	(0.013)	
Telecommute? Yes	0.045***	0.029**	No
	(0.008)	(0.013)	
Moderate Physical Activity	0.154***	0.126***	Heavy Physical Activity
	(0.010)	(0.024)	
Sitting	0.115***	0.139***	
	(0.011)	(0.021)	
Relaxed	0.039***	0.063***	Fast-Paced
	(0.008)	(0.014)	
Choose How do Work	0.048***	-0.006	Tasks well-defined
	(0.007)	(0.015)	
10 days PTO	0.166***	0.159***	0 Days
	(0.010)	(0.021)	
20 days PTO	0.231***	0.229***	
	(0.011)	(0.022)	
Team-Based, Evaluate Own	0.075***	0.011	Team-Based, Evaluate Team
	(0.010)	(0.023)	
Work by Self	0.090***	0.060***	
	(0.012)	(0.022)	
Training Opportunities	0.049***	0.062***	Already have skills
	(0.008)	(0.014)	
Frequent Opportunities to serve community	0.039***	0.039***	Occasional Opportunities to serve community
	(0.008)	(0.015)	
Best Job	0.576***	0.505***	Worst Job
	(0.018)	(0.031)	
N	14,160	3,990	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. “Best Job” metric compares the best possible job (as measured by estimates) to “Worst Job.”

Appendix Table 5D: Estimates of Willingness-to-Pay from Stated-Preference Experiments by Race (Point Estimates and Standard Errors Corresponding to Figure 5)

	HS Degree of Less	Some College	College Degree	Excluded Category
Set Own Schedule	0.083***	0.077***	0.105***	Schedule set by manager
	(0.016)	(0.010)	(0.008)	
Telecommute? Yes	-0.003	0.041***	0.070***	No
	(0.020)	(0.010)	(0.008)	
Moderate Physical Activity	0.120***	0.145***	0.171***	Heavy Physical Activity
	(0.023)	(0.013)	(0.013)	
Sitting	0.094***	0.119***	0.136***	
	(0.024)	(0.013)	(0.013)	
Relaxed	0.038**	0.039***	0.051***	Fast-Paced
	(0.019)	(0.010)	(0.007)	
Choose How do Work	0.009	0.040***	0.058***	Tasks well-defined
	(0.018)	(0.010)	(0.007)	
10 days PTO	0.180***	0.158***	0.161***	0 Days
	(0.025)	(0.014)	(0.010)	
20 days PTO	0.241***	0.227***	0.226***	
	(0.029)	(0.014)	(0.010)	
Team-Based, Evaluate Own	0.064**	0.056***	0.071***	Team-Based, Evaluate Team
	(0.025)	(0.014)	(0.011)	
Work by Self	0.110***	0.074***	0.073***	
	(0.028)	(0.014)	(0.012)	
Training Opportunities	0.041**	0.051***	0.062***	Already have skills
	(0.018)	(0.010)	(0.008)	
Frequent Opportunities to serve community	0.036*	0.043***	0.040***	Occasional Opportunities to serve community
	(0.019)	(0.010)	(0.008)	
Best Job	0.520***	0.546***	0.601***	Worst Job
	(0.046)	(0.022)	(0.016)	
N	2,360	6,370	9,420	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. "Best Job" metric compares the best possible job (as measured by estimates) to "Worst Job."

Appendix Table 5E: Estimates of Willingness-to-Pay from Stated-Preference Experiments by Race (Point Estimates and Standard Errors Corresponding to Figure 6)

	Ages 25-34	Ages 35-49	Ages 50-61	Ages 62+	Excluded Category
Set Own Schedule	0.070***	0.097***	0.087***	0.146***	Schedule set by manager
	(0.012)	(0.011)	(0.011)	(0.022)	
Telecommute? Yes	0.031**	0.046***	0.044***	0.060***	No
	(0.012)	(0.014)	(0.010)	(0.020)	
Moderate Physical Activity	0.089***	0.143***	0.186***	0.301***	Heavy Physical Activity
	(0.017)	(0.017)	(0.015)	(0.034)	
Sitting	0.069***	0.125***	0.144***	0.240***	
	(0.019)	(0.016)	(0.016)	(0.033)	
Relaxed	0.047***	0.028**	0.053***	0.074***	Fast-Paced
	(0.013)	(0.013)	(0.010)	(0.022)	
Choose How do Work	0.039***	0.016	0.049***	0.112***	Tasks well-defined
	(0.014)	(0.010)	(0.011)	(0.022)	
10 days PTO	0.139***	0.180***	0.160***	0.176***	0 Days
	(0.016)	(0.015)	(0.016)	(0.032)	
20 days PTO	0.193***	0.245***	0.236***	0.262***	
	(0.016)	(0.019)	(0.018)	(0.030)	
Team-Based, Evaluate Own	0.011	0.068***	0.092***	0.137***	Team-Based, Evaluate Team
	(0.018)	(0.016)	(0.015)	(0.027)	
Work by Self	0.033*	0.098***	0.095***	0.178***	
	(0.019)	(0.017)	(0.018)	(0.032)	
Training Opportunities	0.065***	0.045***	0.047***	0.051**	Already have skills
	(0.013)	(0.013)	(0.009)	(0.022)	
Frequent Opportunities to serve community	0.048***	0.045***	0.025**	0.033	Occasional Opportunities to serve community
	(0.013)	(0.012)	(0.011)	(0.021)	
Best Job	0.478***	0.562***	0.589***	0.743***	Worst Job
	(0.033)	(0.027)	(0.026)	(0.033)	
N	3,000	5,420	7,000	2,730	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. “Best Job” metric compares the best possible job (as measured by estimates) to “Worst Job.”

Appendix Table 5F: Estimates of Willingness-to-Pay from Stated-Preference Experiments by Race (Point Estimates and Standard Errors Corresponding to Figure 7)

	$0-12.50	$12.50-$17.05	$17.05-$25.00	$25.00-$38.18	$38.18+	Excluded Category
Set Own Schedule	0.069***	0.076***	0.095***	0.092***	0.115***	Schedule set by manager
	(0.014)	(0.016)	(0.014)	(0.012)	(0.013)	
Telecommute? Yes	0.029*	-0.003	0.057***	0.055***	0.062***	No
	(0.015)	(0.017)	(0.015)	(0.013)	(0.017)	
Moderate Physical Activity	0.123***	0.126***	0.159***	0.151***	0.179***	Heavy Physical Activity
	(0.020)	(0.026)	(0.020)	(0.020)	(0.019)	
Sitting	0.093***	0.099***	0.138***	0.129***	0.140***	
	(0.021)	(0.021)	(0.022)	(0.020)	(0.019)	
Relaxed	0.046**	0.035**	0.038***	0.050***	0.052***	Fast-Paced
	(0.018)	(0.016)	(0.014)	(0.012)	(0.016)	
Choose How do Work	0.026	0.024	0.017	0.055***	0.060***	Tasks well-defined
	(0.018)	(0.016)	(0.012)	(0.012)	(0.014)	
10 days PTO	0.151***	0.157***	0.207***	0.161***	0.146***	0 Days
	(0.022)	(0.023)	(0.021)	(0.015)	(0.018)	
20 days PTO	0.187***	0.225***	0.265***	0.241***	0.230***	
	(0.023)	(0.024)	(0.023)	(0.016)	(0.022)	
Team-Based, Evaluate Own	0.049**	0.049**	0.060***	0.041**	0.110***	Team-Based, Evaluate Team
	(0.021)	(0.022)	(0.020)	(0.017)	(0.023)	
Work by Self	0.068***	0.096***	0.075***	0.059***	0.105***	
	(0.025)	(0.023)	(0.018)	(0.019)	(0.028)	
Training Opportunities	0.041***	0.034**	0.059***	0.066***	0.053***	Already have skills
	(0.015)	(0.015)	(0.014)	(0.012)	(0.018)	
Frequent Opportunities to serve community	0.027*	0.068***	0.056***	0.022*	0.022	Occasional Opportunities to serve community
	(0.016)	(0.016)	(0.015)	(0.012)	(0.017)	
Best Job	0.479***	0.521***	0.590***	0.573***	0.614***	Worst Job
	(0.044)	(0.040)	(0.029)	(0.025)	(0.032)	
N	4,050	3,120	3,900	3,470	3,610	

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses are adjusted for clustering by respondent. Each respondent is surveyed 10 times. “Best Job” metric compares the best possible job (as measured by estimates) to “Worst Job.”

Appendix Table 6A: Change in Wage Differential When the Value of Each Amenity is Taken Into Account Separately (Homogeneous Valuations)

	Unadjusted Wage Differential (Table 4)	Adjusted Wage Differential (Gap in Total Compensation, see Table 4A)	Change in Unadjusted Wage Differential When Only the Value of Given Amenity is Taken Into Account											
			Schedule Flexibility	Tele-commute	Moderate Physical Activity	Sitting	Relaxed	Autonomy	10 Days PTO	20 Days PTO	Work on Team, Evaluated Own	Work by Self	Training	Impact
Female	-0.187***	-0.172***	-0.183***	-0.183***	-0.184***	-0.171***	-0.169***	-0.170***	-0.174***	-0.172***	-0.171***	-0.170***	-0.173***	-0.172***
	(0.047)	(0.049)	(0.048)	(0.048)	(0.047)	(0.048)	(0.048)	(0.048)	(0.047)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
Non-White	-0.214***	-0.217***	-0.220***	-0.223***	-0.219***	-0.224***	-0.224***	-0.225***	-0.218***	-0.216***	-0.216***	-0.218***	-0.216***	-0.217***
	(0.057)	(0.059)	(0.058)	(0.059)	(0.058)	(0.059)	(0.059)	(0.059)	(0.058)	(0.060)	(0.060)	(0.060)	(0.059)	(0.059)
College	0.532***	0.577***	0.548***	0.558***	0.554***	0.576***	0.578***	0.578***	0.567***	0.578***	0.578***	0.577***	0.576***	0.577***
	(0.044)	(0.045)	(0.044)	(0.045)	(0.044)	(0.045)	(0.044)	(0.044)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Ages 25-34	-0.155*	-0.155*	-0.162*	-0.165*	-0.167*	-0.170*	-0.175**	-0.172*	-0.163*	-0.160*	-0.157*	-0.161*	-0.155*	-0.155*
(relative to 62-71)	(0.088)	(0.090)	(0.088)	(0.089)	(0.088)	(0.089)	(0.089)	(0.089)	(0.089)	(0.090)	(0.090)	(0.090)	(0.090)	(0.090)
Ages 35-49	-0.094	-0.100	-0.103	-0.105	-0.119*	-0.116*	-0.120*	-0.118*	-0.111*	-0.102	-0.103	-0.105	-0.101	-0.1
(relative to 62-71)	(0.066)	(0.070)	(0.068)	(0.068)	(0.067)	(0.068)	(0.068)	(0.068)	(0.067)	(0.069)	(0.069)	(0.069)	(0.070)	(0.070)
Ages 50-61	-0.042	-0.041	-0.049	-0.051	-0.059	-0.058	-0.06	-0.058	-0.057	-0.043	-0.044	-0.044	-0.042	-0.041
(relative to 62-71)	(0.063)	(0.066)	(0.064)	(0.065)	(0.064)	(0.065)	(0.065)	(0.065)	(0.064)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)

Notes: Adjustment of wage differential as discussed in text, where each column from 3 to 14 adjusts for only the particular amenity. Column 2 shows adjustments for all amenities. Standard errors in parentheses. * 10%, ** 5%, ***1% Significance levels

Appendix Table 6B: Change in Wage Differential When the Value of Each Amenity is Taken Into Account Separately (Valuations Allowed to Differ by Group)

	Unadjusted Wage Differential (Table 4)	Adjusted Wage Differential (Gap in Total Compensation, see Table 4B)	Change in Unadjusted Wage Differential When Only the Value of Given Amenity is Taken Into Account											
			Schedule Flexibility	Tele-commute	Moderate Physical Activity	Sitting	Relaxed	Autonomy	10 Days PTO	20 Days PTO	Work on Team, Evaluated Own	Work by Self	Training	Impact
Female	-0.187***	-0.131**	-0.182***	-0.174***	-0.154***	-0.121**	-0.123**	-0.134**	-0.135***	-0.122**	-0.119**	-0.118**	-0.130**	-0.131**
	(0.047)	(0.054)	(0.048)	(0.049)	(0.049)	(0.051)	(0.051)	(0.053)	(0.052)	(0.053)	(0.053)	(0.054)	(0.054)	(0.054)
Non-White	-0.214***	-0.268***	-0.251***	-0.256***	-0.258***	-0.253***	-0.247***	-0.279***	-0.269***	-0.259***	-0.273***	-0.278***	-0.268***	-0.268***
	(0.057)	(0.065)	(0.058)	(0.059)	(0.059)	(0.061)	(0.061)	(0.065)	(0.063)	(0.065)	(0.066)	(0.066)	(0.065)	(0.065)
College	0.532***	0.619***	0.562***	0.589***	0.594***	0.622***	0.626***	0.643***	0.626***	0.622***	0.622***	0.617***	0.619***	0.619***
	(0.044)	(0.050)	(0.045)	(0.045)	(0.045)	(0.047)	(0.047)	(0.048)	(0.047)	(0.049)	(0.050)	(0.051)	(0.051)	(0.050)
Ages 25-34	-0.155*	-0.320***	-0.195**	-0.204**	-0.269***	-0.320***	-0.330***	-0.346***	-0.333***	-0.312***	-0.329***	-0.343***	-0.324***	-0.320***
(relative to 62-71)	(0.088)	(0.094)	(0.090)	(0.091)	(0.090)	(0.094)	(0.093)	(0.096)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
Ages 35-49	-0.094	-0.205***	-0.122*	-0.126*	-0.185***	-0.214***	-0.227***	-0.262***	-0.244***	-0.206***	-0.211***	-0.215***	-0.209***	-0.205***
(relative to 62-71)	(0.066)	(0.074)	(0.069)	(0.070)	(0.069)	(0.072)	(0.072)	(0.072)	(0.070)	(0.072)	(0.073)	(0.074)	(0.074)	(0.074)
Ages 50-61	-0.042	-0.127	-0.073	-0.078	-0.117*	-0.141**	-0.148**	-0.165**	-0.158**	-0.126*	-0.128*	-0.131*	-0.127*	-0.127*
(relative to 62-71)	(0.063)	(0.072)	(0.067)	(0.068)	(0.068)	(0.071)	(0.071)	(0.071)	(0.070)	(0.071)	(0.072)	(0.072)	(0.072)	(0.072)

Notes: Adjustment of wage differential as discussed in text, where each column from 3 to 14 adjusts for only the particular amenity. Column 2 shows adjustments for all amenities. Standard errors in parentheses. * 10%, ** 5%, ***1% Significance levels

Appendix Table 7: Effect of Adjusting for the Incidence and Valuation of Job Amenities on Wage Differentials by Gender, Race, Age, and Education - Holding Differences for Other Groups Constant by Estimating the Effects of Amenities Jointly

Panel A: Log Differentials, Holding Valuations Constant

	Unadjusted Wage Differential	Difference in Amenity Multiplier	Difference in Total Value of Amenities	Adjusted Wage Differential (Gap in Total Compensation)
Female	-0.213***	0.060**	-0.149***	-0.200***
	(0.041)	(0.024)	(0.051)	(0.043)
Non-White	-0.132***	0.015	-0.113*	-0.130**
	(0.050)	(0.024)	(0.061)	(0.052)
College	0.548***	0.175***	0.727***	0.593***
	(0.045)	(0.022)	(0.052)	(0.046)
Ages 25-34	-0.177**	-0.012	-0.190**	-0.179**
(relative to 62-71)	(0.081)	(0.031)	(0.088)	(0.082)
Ages 35-49	-0.033	-0.015	-0.054	-0.035
(relative to 62-71)	(0.058)	(0.036)	(0.076)	(0.060)
Ages 50-61	-0.001	0.017	0.016	0.003
(relative to 62-71)	(0.054)	(0.026)	(0.066)	(0.057)

Panel B: Log Differentials, Allowing Valuations To Vary Across Groups

	Unadjusted Wage Differential	Difference in Amenity Multiplier	Difference in Total Value of Amenities	Adjusted Wage Differential (Gap in Total Compensation)
Female	-0.213***	0.173**	-0.036	-0.168***
	(0.041)	(0.071)	(0.086)	(0.046)
Non-White	-0.132***	-0.188*	-0.315***	-0.181***
	(0.050)	(0.097)	(0.114)	(0.057)
College	0.548***	0.318***	0.870***	0.630***
	(0.045)	(0.072)	(0.089)	(0.050)
Ages 25-34	-0.177**	-0.588***	-0.765***	-0.349***
(relative to 62-71)	(0.081)	(0.103)	(0.135)	(0.087)
Ages 35-49	-0.033	-0.366***	-0.406***	-0.145**
(relative to 62-71)	(0.058)	(0.093)	(0.115)	(0.066)
Ages 50-61	-0.001	-0.265***	-0.265**	-0.09
(relative to 62-71)	(0.054)	(0.085)	(0.109)	(0.065)

Notes: * 10%, ** 5%, ***1% Significance levels. Standard errors in parentheses generated from block bootstrap in which new willingness-to-pay measures are estimated for each bootstrap sample. The "Wage" and "Amenity Multiplier" columns mechanically add to the "Amenity Value" column. All estimates in the same column are estimated jointly. Valuations are also estimated jointly for Panel B.