The Value of Working Conditions in the United States

and Implications for the Structure of Wages

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Abstract

We document variation in working conditions in the United States, present estimates of how workers value these conditions, and assess the impact of working conditions on estimates of wage inequality. We conduct a series of stated-preference experiments to estimate workers' willingness-to-pay for a broad set of working conditions, which we validate with actual job choices. We find that working conditions vary substantially, play a significant role in job choice, and are central components of the compensation received by workers. We find that accounting for differences in preferences for working conditions often exacerbates wage differentials and intensifies measures of wage inequality.

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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 trade higher wages for better job attributes when making job choices (e.g., Brown, 1980; Duncan and Holmlund, 1983; Rosen 1986; Kniesner et al., 2012).[1] These wage tradeoffs have the potential to obscure actual compensation differentials between workers, including differentials by gender, race, age, industry, or measures of general wage inequality. The most recent evidence 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), and two recent experimental studies confirm substantial and heterogeneous willingness-to-pay for schedule-related amenities (Mas and Pallais, 2017; Maestas et al., 2017a; Wiswall and Zafar, 2017).[2]

Despite the available evidence, it has been difficult to assess to what extent differences in the incidence and valuations of non-wage working conditions shape actual compensation differentials in the labor market. In the United States, there currently is no federal 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.[3] While the theoretical relationship between working conditions 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.

[1] Throughout the paper, we define compensation as the sum of wages and the monetary valuations of (desirable) working conditions, not including fringe benefits. We alternately refer to working conditions as job attributes, and desirable working conditions as job amenities.

[2] Other recent, related papers infer the overall value of job or firm characteristics using actual job acceptance decisions and job transitions (e.g., Hall and Mueller, 2018; Sorkin, 2018; Lehmann, 2022).

[3] 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 distributions 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.

To address these difficulties, we estimate the incidence of job attributes, willingness-to-pay for these attributes, and their impact on estimates of the wage structure using a new, nationally representative survey of working conditions and a stated-preference experimental approach. Our paper makes three primary contributions. First, to address the lack of comprehensive data about modern working conditions 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. 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, industry, and across the wage distribution. To obtain a comprehensive view of the incidence and importance of job amenities, we asked about a broad set of job attributes 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.

Second, we estimate the willingness-to-pay for each amenity in the same nationally representative sample of workers, using stated-preference experiments. The benefits of the stated-preference method are that we can manipulate offered job attributes 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 with heterogeneous preferences are willing to make between working conditions and wages. These tradeoffs yield transparent and robust 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, age, and industry, by adding the wage values of individuals' non-wage amenities to their wages, and test whether the inclusion of amenities significantly alters metrics of compensation 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 in preferences affects adjusted estimates of the wage structure beyond systematic differences in the incidence of amenities across demographic groups. For example, if women are willing to pay more than men for schedule flexibility, then jobs in which workers have more control over their hours are worth more to women and we adjust our compensation metric accordingly.

Our first main finding is that the incidence of 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 workers have uniformly better working conditions across nearly all categories we examined – some are more nuanced. For example, women and older workers hold jobs with a different mix of job attributes than men and younger workers, respectively. These patterns are consistent with there being important differences in access to amenities as well as differences in *preferences* for amenities that lead workers to sort into jobs with amenities they value.

Our second main finding is that workers have non-negligible willingness-to-pay for most dimensions of amenities included in our stated-preference experiments. The most highly valued amenities are paid time off, less demanding physical activity (as opposed to heavy physical activity), schedule flexibility and being evaluated based on one's own performance (as opposed team-based evaluation). Considering all amenities, we find that a switch from the worst job (having none of the preferred amenities included in our experiments) to the best job (having the best set) is equivalent to a 55% 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 demographic characteristics, and that, more generally, individuals with higher valuations for certain amenities are more likely to have those amenities in their current and future jobs.

Our third main finding is that accounting for both variation in amenities and variation in preferences affects measured wage differentials. We construct a measure of total compensation (excluding fringe benefits) by adding to each respondent's wage the valuations of the amenities associated with their current job. We perform this exercise twice: first, holding valuations constant at the estimated valuations for the full sample, and second, allowing valuations to differ based on the gender, race, education and age of respondents. When non-wage compensation is including, holding valuations fixed, we find that the gender wage gap narrows slightly, education and industry wage differentials widen, and overall wage inequality increases. When we let preferences vary, we find the gender wage gap narrows further, and education and industry wage differentials widen further; in addition, wage differentials associated with race and age widen when differences in preferences for working conditions are incorporated into non-wage compensation.

The advantages of the stated-preference approach come at potential costs, in particular the concern that actual job choices may differ from stated preferences for jobs (Diamond and Hausman, 1994; Manski, 1999; Hausman, 2012). Our data allow us to directly address this important concern in two ways. First, consistent with theory on compensating differentials, we show that those individuals who have a given amenity on their current job value the amenity more than those who do not. Second, the longitudinal nature of our data allows us to link stated preferences obtained from our experiments to actual job transitions. Further evidence in support of the stated-preference approach comes from Mas and Pallais (2017), who show that their findings based on experimental variation in actual wages 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 robust and theoretically consistent estimates of valuations across a broad set of working conditions for a representative sample from the United States labor force.

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), industries (e.g., Krueger and Summers, 1988), and regions (e.g., Moretti, 2013; Card, Rothstein and Yi 2022), 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 attributes in the labor market. Yet, the last publicly available, representative surveys of working conditions were fielded in the 1970s.[4] 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

[4] These were the Quality of Employment Surveys of 1973-1977. 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.

papers have estimated compensating differentials for job attributes such as injury and fatality risk, physical job demands, stress, hazard exposure, schedule flexibility, shift work, and many other working conditions.[5] 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. Yet, addressing such confounding factors has proven difficult.[6]

We sidestep these difficulties by generating randomized choice data using a stated-preference approach, thereby contributing to a more recent literature on job amenities that has used innovative approaches to address the identification challenges present in the prior compensating differentials 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

[5] 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).

[6] 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 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.

(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 attributes. This provides some of the first evidence on the importance of multiple job attributes jointly, such as paid time off, telecommuting option, 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 attributes 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 attributes. We present our main willingness-to-pay estimates in Section 5. Section 6 considers implications for the wage distribution, and Section 7 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 (ALP, 2015).[7] The second wave of the AWCS was administered from December 2015-February 2016 and consisted of the stated-preference experiments used in this paper (ALP, 2016). A subsequent wave in 2018 consisted of follow-up questions about changes in working conditions (ALP, 2018).

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 focus on workers in order to examine differences in both wages and working conditions across different segments of the population and to examine the effect of adjusting for valuations of working conditions on observed wage differentials. 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 1,738 individuals. All statistics are weighted using weights generated to match demographics in the Current Population Study (CPS). Maestas et al. (2017a) present summary statistics for the AWCS sample, unweighted and weighted, in comparison with the CPS, and find that the AWCS is similar to the CPS on most demographic and employment measures when weighted, with two exceptions. First, more AWCS respondents report that they are self-employed than do CPS respondents (11 vs. 7 percent, respectively), which may reflect that the CPS only counts unincorporated self-employment whereas the AWCS does not distinguish unincorporated from incorporated self-employment. Second, the percentage of employed respondents who report multiple jobs is higher in the AWCS compared to CPS (14 vs. 4 percent), though the difference is not statistically significant (see Table 2.3). Maestas et al. (2017a) detail specific differences in question wording and survey placement that could contribute to these differences and conclude that

[7] 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.

overall, when weighted, the AWCS is a nationally representative sample of the American working population.

Table 1 presents summary statistics for our analysis sample, overall and by gender, race, education, age, and for the bottom, middle and top wage quintiles.[8] On average, workers in our sample work 39.6 hours per week and there is little variation across demographic groups in mean weekly hours (with the exceptions of older and low-wage workers). The mean hourly wage in the sample is $30.30 (in 2015 $). Mean wages vary substantially by gender, race, education, and age, ranging from $24.11 for non-whites to $38.00 for those with a college degree or more. We find that women's wages are on average 17% lower than men's, non-whites' wages are 19% lower than those of whites, workers with a high school degree or less have 43% lower wages than those with a college degree, and workers with some college have 39% lower wages than those with a college degree.[9] Workers under age 35 have 13.3% lower wages than workers age 62 and older, and the difference narrows for age groups as they approach age 62. Overall, the log wage differential between 50th and 10th percentiles is 0.70, and the log wage differential between the 90th and 10th is 1.66. We explore how differences in working conditions and their valuations contribute to these wage gaps below.

2.B Main Dimensions of Working Conditions Used in Analysis

The recent experimental economics literature has considered a relatively targeted set of non-wage job attributes. Our goal was to investigate characteristics that broadly define non-wage job attributes currently available in the labor market and that are likely to be valued by workers. To identify these attributes, we performed a thorough review of the literature, across several fields. We

[8] Information about demographic variables available for all ALP respondents is available at https://www.rand.org/research/data/alp/panel/demographics.html. Gender is self-reported in response to the question "What is your gender?" with response options for "Male" and "Female" only. Race is self-reported in response to the question "Do you consider yourself primarily white or Caucasian, Black or African American, American Indian, or Asian?" with five mutually exclusive response options including "Other." Education is measured by responses to the question "What is the highest level of school you have completed or the highest degree received?" Age is calculated based on the difference between respondents' survey completion and self-reported birth dates.

[9] Table 1 reports the log-wage differential ϕ. The percent difference in observed wages is $100 \times [\exp(\phi) - 1]\%$.

looked for evidence or hypotheses that a given amenity was an intrinsic job characteristic and not a function of employee characteristics, with the potential to influence job choices and wages.[10] In addition, we analyzed the first wave of the 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 attributes does not capture all non-monetary aspects of a job, we believe that the nine dimensions of working conditions 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, even before the sweeping effects of the COVID-19 pandemic. Although the share of workers who have the option to work

[10] For example, we did not include commuting distance, which has recently been shown to differentially affect women's reservation wages for accepting a new job (Barbanchon, Rathelot and Roulet, 2021), since it is not an intrinsic feature of a given job but rather the result of a specific job-employee match (i.e., determined by the distance between the employee's residence and the location of the job). Similarly, we did not include job separation risk, which though important, is not an intrinsic feature of a job but depends in part on employee characteristics (e.g., job performance).

from home was rising (Oettinger, 2011; Mateyka et al., 2012), telecommuting was still relatively uncommon prior to the pandemic (Maestas et al., 2017a). Bloom et al. (2014) argue that working from home leads to productivity gains and prior research finds that workers place substantial value on having the flexibility to work at home (Mas and Pallais, 2017). Understanding how workers value telecommuting is even more important today, now that many American workers have experienced telecommuting firsthand. Using O*NET data, Dingel and Neiman (2020) estimate that 37% of jobs in the U.S. can be performed entirely at home.

Physical Job Demands. The role of physical job demands is a frequently studied question in the compensating differentials literature. Duncan and Holmlund (1983) estimate 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 reflect employers' cost of providing more or less worker independence. Job autonomy is significantly associated with 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 being evaluated on the basis of the team's performance versus one's own performance.

Job Training. There is a large literature on the wage effects of job training opportunities. 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 models of human capital investment (Leuven, 2005). Fewer papers assess differences in training across demographic groups and their impact on wage differentials, though systematic differences in the rates of training in the labor force have been documented.[11]

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).

[11] 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.

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 groups. We also examine differences in job attributes throughout the wage distribution. Table 1 presents summary statistics describing the incidence of job attributes in our sample of employed workers. (In Appendix Table 1, we jointly estimate differences in the incidence of job attributes by demographic group.)

Concentrating on differences by gender, race, age, and education, we find that working conditions differ substantially across groups, with some expected and unexpected differences. College-educated workers have uniformly better job amenities among almost all categories we considered. Non-whites tend to have somewhat worse job attributes than whites. 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 analyzing attribute preferences (as we do later). Throughout the present section, we highlight those differences in incidence of working conditions that are statistically significant after accounting for differences in other demographic characteristics (see Appendix Table 1).

Gender. Women are more likely to work in jobs that are less physically taxing and offer fewer training opportunities but also more frequent opportunities to make a positive community or social impact. For example, we find large differences in the physical demands of jobs: 24% of men report working in a job requiring heavy physical activity, compared to only 13% of women. In addition, 30% of men report having frequent opportunities to make a positive impact in their jobs, compared to 40% of women. At the same time, men are more likely than women to report opportunities on the job to learn new skills that would transfer to other jobs (74% versus 65%). 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 (rather than own) performance, perhaps related to different degrees of managerial duties and/or avoidance behaviors related to gender differences in recognition for group work (see, e.g., Sarsons et al., 2021).

Race. Due to the sample size, we restrict our analysis to comparisons between whites 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 in other characteristics are controlled for, only a few race-specific gaps remain (shown in Appendix Table 1). For example, non-whites have less control over their schedule, have fewer opportunities to work from home, and tend to be in physically demanding jobs, but 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. We find little evidence of differences in pace of work or autonomy by race, and small to moderate differences in terms of working in teams. In contrast, non-whites are more likely to report having at least some paid time off (though they are not more likely to have at least 15 days) and have more job training opportunities.

Education. We observe especially large and robust differences in working conditions by education. Overall, more education is associated with better working conditions across almost all dimensions we considered. For example, respondents with a college degree are more likely to report that they can adapt their hours (68%) than those with some college (56%) or those with a high school degree or less (42%). Workers with a college degree are substantially more likely to have opportunities to work from home (55%), compared to those with some or no college (27% and 20%, respectively). Those with a college degree are much less likely to engage in heavy physical activity (5%), compared to those with some or no college (21% and 34%, respectively). More education is also associated with a more relaxed environment, more autonomy, and more paid time off. Those with at least some college have more opportunities than those with a high school degree or less to learn new skills and make a positive impact on the community.

Age. Relative to older workers (age 62 and older), younger workers tend to have jobs that are more physically taxing, faster paced, and with fewer opportunities to telecommute (especially for those under age 35). In contrast, the percent reporting job training opportunities decreases from 79% in the youngest age group to 59% in the oldest age group, consistent with models of human capital investment and job choice over the life cycle. Interestingly, younger workers are more likely than older workers to report that they have at least some independence in how they choose to do their work (91% of those under 35 vs. 81% of those age 62 or older).

Wage Quintile. As an introduction to our analysis of how workers trading off wages for job amenities affects assessments of wage inequality, Table 1 shows the incidence of working conditions by quintile of the hourly wage distribution, ranging from $12.75 per hour or less (bottom 20% of working population), to $17.62-$25.00 (middle 20%), to $38.46 or more (top 20%). In general, working conditions improve with higher wages, but the patterns are not uniform and not always monotonic. Higher-wage workers tend to have jobs that are less physically taxing and have more control over their work schedule, more options to work from home, 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 at least 15 days of paid time off rises from 36% (bottom 20%) to 81% (top 20%). However, there is no clear gradient in autonomy or teamwork, and lower wage workers are slightly more likely to have slower paced jobs. 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.

4. Estimating Willingness-to-Pay for Job Amenities

To estimate measures of willingness-to-pay for the job amenities described in the previous sections, we administered ten stated-preference experiments to each respondent in the AWCS. In each experiment, survey respondents were asked to select between two jobs, each defined by a partially varying set of job attributes, hours, and monetary compensation as described in detail below. The nine job attributes and their potential values are listed in Appendix Table 2. The advantage of the stated-preference approach is that we can vary 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 attributes (Manski, 1999), we instructed respondents to assume that any job attributes not explicitly described were identical across jobs.

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, or 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 (see 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 1 and 2. We label respondents as "attentive" if they answered at least one of the questions correctly and examine whether attentive respondents trade off non-wage characteristics for wages differently from the full sample.

4.A. Creation of Hypothetical Job Profiles Based on Current Working Conditions

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 non-varying attributes in the 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, we varied two attributes at a time and 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 2. We show below that our willingness-to-pay estimates are invariant to the choice of baseline job and the presence of two-way interactions between attributes.

To define the baseline job, the stated-preference experiments were preceded by a short survey about current working conditions, where each survey item corresponded to one of the nine job attributes in the experiments. 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 3.

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 below $7 (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 or provide their hourly rate instead.

4.B. Random Variation in Hypothetical Job Profiles

Starting from the respondent's baseline job (either their current job or the common baseline job), we created hypothetical Job A and Job B by randomly selecting two non-wage attributes to vary across the two hypothetical jobs.[12,13] 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.

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_i, the hypothetical wages for Job A and Job B were $\theta_A w_i$, where $\theta_A \sim N(1,\ 0.1^2)$ and $\theta_B w_i$, where $\theta_B \sim N(1,\ 0.1^2)$, respectively. We truncated θ_A and θ_B to be between 0.75 and 1.25 so that the wage

[12] 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."
[13] Although randomization of non-wage attributes is not strictly necessary for identification, it facilitates full coverage of the attribute space without overburdening respondents. Note that there are 195 possible combinations of the nine job attributes varying two at a time.

difference between the two jobs could 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, monthly, or annually), by using the hours associated with the hypothetical job, and rounded it to the nearest $.50 if hourly, $10 if weekly, bi-weekly or monthly, or $100 if annually. When we converted the hourly wage to annual earnings, we assumed the job required 52 weeks of work (including any paid time off). When presenting an hourly wage offer for a given job, we also displayed in parentheses the implied weekly earnings including any overtime pay. We calculated overtime pay for weekly work hours exceeding 40 at 1.5 times the randomly assigned hourly wage.

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 values of the baseline job. The wage always varied, and similarly could equal 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, pairs where one job (potentially) dominated the other in all respects.[14]

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 3. 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.

[14] 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.

4.C. Estimation

The hypothetical choice experiments yielded choice data describing the preferred jobs of respondents given a set of job attributes and a wage. We begin by assuming that the underlying choice process can be approximated by a linear indirect utility function:

$$V_{ijt} = \alpha + A'_{ijt}\beta_i + \delta_i \ln w_{ijt} + \varepsilon_{ijt},$$

where V_{ijt} represents indirect utility for individual *i,* job alternative *j*=A,B, for choice pair *t*=1,…,10. A_{ijt} is a vector of non-wage characteristics of length R, and w_{ijt} is the wage offered to individual *i* for job alternative *j* in choice pair *t*.[15] The parameters β_i and δ_i allow for heterogeneity across individuals in the indirect utility derived from each characteristic and the wage. We use the log of the wage in our main specifications 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 i.i.d. Extreme Value Type I random variable, as is standard in the willingness-to-pay literature (see e.g., Breidert, Hahsler and Reutterer, 2006), we obtain the following closed form expression for the probability that an individual selects a job with characteristics A_{ijt} and wage w_{ijt} over a job with characteristics A_{ikt} and wage w_{ikt} with probability:

$$P(V_{ijt} > V_{ikt}) = \frac{\exp\,[(A'_{ijt} - A'_{ikt})\beta_i + \delta_i(\ln w_{ijt} - \ln w_{ikt})]}{1 + \exp\,[(A'_{ijt} - A'_{ikt})\beta_i + \delta_i(\ln w_{ijt} - \ln w_{ikt})]}.$$

We estimate the above equation using a mixed logit model, which explicitly allows for unobserved heterogeneity. If $\beta_i = \beta$ and $\delta_i = \delta$, overall or within a given subgroup, then a standard logit model recovers estimates of β and δ. In all models, we aggregate individual responses into a dichotomous variable indicating preference for Job A, and unless otherwise stated we use survey weights. In Section 5.A., we explore several robustness tests, including: 1) restricting the sample to

[15] Note that, because we dichotomize job attributes with more than two possible values into a series of binary variables, the length of R is greater than the number of non-wage attributes.

"attentive" respondents only (those who answered at least one of the trick questions correctly) to examine sensitivity of our estimates to inattention; 2) estimating a model with two-way interactions between non-wage characteristics to relax the assumption of additive separability; 3) estimating a probit model instead of a logit model to explore sensitivity to the distribution of the error term; 4) restricting the sample to choice pairs with the common baseline job to explore sensitivity to the values of background (i.e., non-varying) job attributes; 5) estimating an unweighted model to explore the importance of survey weights; and 6) using total earnings instead of hourly wage, and controlling flexibly for work hours, to relax the functional form restriction implicit in the log wage specification. We find that the willingness-to-pay estimates are robust across all of these variations.

Using the estimated parameters from the indirect utility function, we derive our willingness-to-pay measure for a particular (desirable) attribute *r* as follows. Consider an individual *i* who is indifferent between not having a particular attribute *r* at current wage w_i, and having the attribute with a corresponding wage decrease equal to WTP_i^r:

$$\delta_i \ln w_i = \beta_i^r + \delta_i \ln[w_i - WTP_i^r] \qquad (1)$$

where β_i^r is the individual's marginal utility of attribute *r*, and δ_i is the marginal utility of the log wage as before. Solving for willingness-to-pay, we obtain:

$$WTP_i^r = w_i \left[1 - e^{\left(\frac{-\beta_i^r}{\delta_i}\right)}\right]. \qquad (2)$$

In the following sections, we present our estimates in terms of $1 - e^{\left(\frac{-\beta_i^r}{\delta_i}\right)}$, such that gaining attribute *r* is equivalent to a $100\left(1 - e^{\left(\frac{-\beta_i^r}{\delta_i}\right)}\right)\%$ 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:

$$WTP_i^{FULL} = w_i \left[1 - e^{\left(-\frac{\Sigma r\, \beta_i^r}{\delta_i} \right)} \right], \tag{3}$$

where we add up the coefficients for the most preferred value of each attribute.[16] To focus on how non-monetary job attributes are valued in terms of the hourly wage, we do not include variations in offered hours in this calculation. Standard errors are calculated using the delta method (unless otherwise stated) and adjusted for clustering by respondent.

Identification of willingness-to-pay for job attributes depends on the construction of the stated-preference experiments. Specifically, the choice experiments allow us to observe wage tradeoffs between job offers that are fully characterized by non-wage attributes whose variation across job offers within a pair is unrelated to respondent characteristics (including current job attributes or demographic characteristics such as education). An implicit assumption is that respondents follow instructions to assume any non-specified attributes are the same across jobs within the choice pair. We also assume there are no systematic differences in respondents' ratings of subjective amenities such as heavy vs. moderate physical activity.[17]

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 Figure 1, we selected only those choice pairs where one job strictly dominated the other in terms of its non-wage attributes (but not necessarily its wage) and aggregated the data into bins of

[16] To avoid double counting for attributes with more than two potential values, 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 add the coefficient for sitting.

[17] For example, suppose women have a lower threshold than men for reporting the same objective level of physical activity as "heavy." Then if we observe women trade off more wages than men in order to obtain a job with (self-rated) moderate activity over one with heavy physical activity, we will *overestimate* the gender difference in willingness-to-pay for (objectively measured) moderate activity. At the same time, we will *underestimate* the gender difference in objective physical demands if we observe fewer women than men in jobs with self-reported heavy physical activity.

equal length based on the wage difference between the jobs.[18,19] We plot the fraction of respondents selecting the dominant job within each choice pair for each wage-difference bin, separately for the full sample (shown in solid circles) and the subsample of respondents who answered at least one trick question correctly (in open circles). The "attentive" subsample consists of 65% of the respondents in the full sample. Negative log wage differences mean the job with the dominant non-wage characteristics offered a lower wage than the job without the characteristics, while positive log wage differences mean the job with dominant non-wage characteristics also offered a higher wage.

Figure 1 shows that a large fraction of respondents are willing to take a job with better job attributes even when the offered wage is substantially lower than an alternative job without those attributes, indicating substantial willingness-to-pay for non-wage job attributes. Specifically, Figure 1 shows that 20% of respondents preferred a job with better amenities even if that job offered a 40% lower wage than a job without those amenities. The rate of job acceptance rises as the relative wage for the dominant job increases, as indicated by the tendency for the acceptance curve to slope upwards. For very large positive wage differences (i.e., the dominant job also pays a substantially greater wage) the acceptance rate approaches 100%. The patterns are similar for both the full sample and attentive subsample; attentive respondents are slightly less likely to accept the dominant job when it pays substantially less than the alternative job and all attentive respondents accepted the dominant job once it paid 40% more than the alternative job.

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

Table 2 presents our estimated valuations for the full sample of respondents and thus contains the first main findings of our analysis. As noted above, we present our estimates in terms of

[18] This leaves us with 11,433 (out of 17,380) choice pairs for the full sample. Since we limited the number of choice pairs in which one of the jobs dominated the other job on all dimensions (see Section 4.B.), we observe more pairs with negative wage differences than pairs with positive wage differences.

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

the *percentage* wage increase (decrease) needed to compensate for removing (adding) a given attribute. 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, and are robust across different model specifications.

To obtain a benchmark with respect to the earlier literature based on observed job choices, we first estimate a traditional compensating differential specification based on a hedonic regression model using each worker's current job attributes and wage. We regress the log of the wage on indicators for each job characteristic, controlling for age group, race, education, and citizenship indicators. To control for non-time-varying unobservable characteristics, we also estimate a first-difference model using panel data for the 977 respondents (56% of the full sample) who can be matched to the 2018 AWCS; note the AWCS does not contain exactly the same question wording as the survey of job attributes that preceded the stated preference experiments, so there is some noise in the mapping of job attributes across survey waves. The results for the cross-section and panel data are shown in columns 1 and 2 of Table 2, respectively. We report the implied willingness-to-pay, $-1 * (1 - e^{-\gamma})$, where γ represents the estimated coefficient on a job characteristic, since a valuable characteristic in principle *reduces* the wage in a hedonic pricing framework. In both models, the compensating differential estimates often do not have the expected sign, consistent with there being bias from unobserved factors that are correlated with both wages and job attributes (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.

The next two columns in Table 2 present estimates from a mixed logit model allowing for unobserved heterogeneity in individuals' marginal utilities for non-wage amenities.[20] Columns 3 and 4 present estimates of the mean and median willingness-to-pay, respectively, for each amenity. Column 5 presents estimates from a standard logit specification. [21] First, we find that the mean and median willingness-to-pay estimates from the mixed logit model are similar to one another,[22] but quite different in both sign and magnitude from the conventional cross-sectional and panel estimates in columns 1 and 2. Second, the mixed logit estimates are also similar to the standard logit estimates in column 5, indicating that unobserved preference heterogeneity is not introducing bias to the standard logit estimates (Train, 2003). As further evidence of this, Figure 2 overlays predicted choice probabilities using the estimates from column 5 against the observed choice probabilities as a function of the relative wage for the subsample of choice pairs in which one job dominates the other on non-wage characteristics (but not necessarily the wage).[23] We see that the standard logit model performs well in predicting actual choices. Across all specifications in columns 3-7, the stated-preference estimates are all statistically significant from zero at the 1% level, suggesting that each of the job attributes included in the experiments impacted respondents' choices. Because of the similarity between the mixed logit and standard logit estimates, we use the parsimonious logit model for the robustness checks and subgroup analyses in the remainder of the paper.[24]

Considering the various attributes separately, we estimate that setting one's own schedule is equivalent to a 8.9% wage increase. Telecommuting opportunities are estimated to be equivalent to a

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[20] Following standard practice, we assume β_i is normally distributed mean β and variance Σ_β and we fix $\delta_i = \delta$. We allow for non-zero covariances across attributes.
[21] For the standard logit model, we fix $\beta_i = \beta$ and $\delta_i = \delta$ in equation (2). We present willingness-to-pay estimates as percentages of the wage, which do not vary across individuals in the standard logit model.
[22] Since willingness-to-pay is a nonlinear function of β_i, mean and median willingness-to-pay may differ in the mixed logit model.
[23] Appendix Figure 4 shows the overlayed predictions for the attentive subsample.
[24] The fact that the willingness-to-pay estimates from the standard and mixed logit models are similar does not imply there is no unobserved heterogeneity in preferences, only that unobserved heterogeneity does not appear to bias estimates from the standard model.

4.2% wage increase. We also find that physical demands are very predictive of job choices. Relative to a job requiring "heavy physical activity," a job requiring "moderate physical activity" is equivalent to a 14.5% wage increase while a job in which the person is mostly sitting is valued at 11.6% of the wage. We also estimate that a switch from a fast-paced job to a relaxed environment is equivalent to a 4.3% wage increase. Autonomy at work is worth 4.0% 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.

We also find that individuals prefer to work alone. We estimate that working by oneself is equivalent to an 8.6% 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 6.5% wage increase. As long as evaluation for teamwork is based on one's own performance, working alone is only valued at 2.1% of the wage. Job training opportunities are equivalent to a 5.4% wage increase, suggesting that workers are willing to forgo some current earnings for human capital development opportunities and potentially higher future earnings.[25] Frequent opportunities to impact the community/society are worth an additional 3.6% relative to occasional opportunities.

Overall, it is clear that individuals systematically value non-monetary working conditions, 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 55.0% wage increase. Given the variance in actual working conditions (Section 3), this is a first indication that willingness-to-pay for job amenities may play a substantial role in affecting compensation 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 8.9% and 4.2% for these amenities, respectively. Our estimates are smaller in magnitude, which may reflect differences in the specific context studied in Mas and Pallais (2017).[26]

[25] 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.

[26] In addition, Mas and Pallais (2017) replicated their own findings using a stated-preference analysis.

Moreover, using matched employee-employer data, Sockin (2022) estimates that workers gain at least 50 percent of the average wage when moving from the worst- to the best-amenity firms, which is consistent with our finding that moving from the worst- to best-amenity job is equivalent to a 55% wage increase. Overall, despite obvious limitations of these direct comparisons, the available evidence suggests stated-preference estimates are able to recover meaningful underlying valuations. In Section 5.B., we present further evidence that our stated preference estimates correlate well with observed transitions between jobs with different amenities.

As mentioned above, a common concern with stated-preference experiments is that respondents may not pay sufficient attention when selecting jobs, which could add noise to the estimates.[27] We tested the importance of respondent inattention by asking each respondent two "trick questions" that appeared randomly throughout the survey. Column 6 presents willingness-to-pay estimates for the attentive subsample (comprising 65% of the full sample). The attentive subsample has slightly higher valuations for almost all amenities, but the estimates are also less precise. Overall, there is little evidence that our results are driven by systematic inattention.

Next, we estimated a logit model allowing for two-way interactions to test whether the presence of some amenities affected the willingness-to-pay for other amenities. Column 7 of Table 2 presents estimates of the average willingness-to-pay for each amenity conditional on each respondent's actual set of other amenities. To obtain standard errors for the average willingness-to-pay estimates, we bootstrap over 500 simulations, clustering by respondent. Though we do find that there are some meaningful interactions between amenities (not shown), accounting for interactions in the model specification does not change the average willingness-to-pay estimates.[28]

[27] Since we scale the coefficients on the amenities by the coefficient on the log wage, inattention will not necessarily *bias* the willingness-to-pay estimates.

[28] Appendix Table 4 presents the results of several other robustness checks. Column 1 reproduces the standard logit estimates (from column 5 of Table 2). Column 2 presents estimates from a probit model to test sensitivity to distributional assumptions. Column 3 presents estimates for the 20% of choice pairs using a common baseline job to test whether background characteristics are salient. Column 4 presents unweighted estimates. Column 5 presents estimates

Finally, although we varied weekly work hours in some of the stated-preference experiments, we do not treat hours as a non-wage attribute in our analyses because of their additional effect on earnings. Unlike other amenities, accepting a lower wage to obtain more work hours—and by construction, fewer leisure hours—does not necessarily reflect a preference for reduced leisure time since the effect on total earnings of an increase in work hours can offset the effect of a lower wage on total earnings. Therefore, to examine preferences for weekly work hours, we estimated a model using total earnings instead of hourly wages as the numeraire and including indicator variables for weekly work hours ranging from 15 to 60 hours per week, with 40 hours per week as the omitted group.[29] Figure 3 presents the estimated valuations of offered work hours as fractions of total earnings. The reference line shows the proportional change in total earnings resulting from a change in hours from a baseline of 40 hours.[30] From the figure we can see that the valuations are strictly decreasing in the number of weekly work hours (and increasing in leisure time), though there is an asymmetry in willingness-to-pay for reductions vs. increases in hours. For example, on average workers are only willing to give up 40.4% of earnings to obtain a 50% decrease in work hours (from 40 to 20 hours); at the same time, on average workers must be presented with a 57.7% increase in earnings to persuade them to take a job with a 50% increase in work hours (from 40 to 60 hours).[31]

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after adding hours controls (specifically, we amend the indirect utility function to include H_{ijt}, a vector of indicator variables for hours, ranging from 5 to 60 in multiples of 5). We find the willingness-to-pay estimates are robust across all of these specifications.

[29] We find that willingness-to-pay for non-wage attributes (shown in column 6 of Appendix Table 4) is similar whether scaled by the hourly wage or total earnings (controlling for hours); this suggests using log wage in our main specifications is not overly restrictive. Specifically, for column 6 indirect utility is specified as follows: $V_{ijt} = \alpha + A'_{ijt}\beta + \delta \ln e_{ijt} + H'_{ijt}\theta + u_{ijt}$, where e_{ijt} denotes total earnings and H_{ijt} is a vector of indicator variables for hours (ranging from 5 to 60 in multiples of 5).

[30] Appendix Figure 5 presents the corresponding valuations using hourly wages as the numeraire.

[31] Furthermore, we find that the presence of the non-wage attributes that we study does not appear to meaningfully affect workers' willingness to pay for leisure time (see Appendix Figure 6), which again suggests that specifying the model in terms of hourly wage rather than total earnings is not overly restrictive in this context. An interesting exception is teamwork, where we find that individuals who work in teams and are evaluated on their own performance have higher preferences for longer work hours than those who work on teams and are evaluated on team performance or those who work alone (Appendix Figure 6.G).

5.B. Preference Heterogeneity and Sorting

A central hypothesis of the compensating differentials literature is that workers with higher valuations of certain working conditions will tend to sort into jobs with those conditions (see e.g., Rosen 1986). Our panel data allow us to investigate the consistency between respondent selections in the stated-preference experiments and their revealed preferences in the labor market.[32]

First, we test whether individuals who have selected into jobs with specific amenities value those amenities more. Columns 1-2 of Table 3 shows the estimated valuation for respondents with a particular job amenity as well as the estimated valuations for respondents without that job amenity, respectively.[33] Column 3 displays the differences between the willingness-to-pay estimates in columns 1 and 2, and the last row of column 3 reports the average difference across all amenities. 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 10.4% wage increase, 3.6 percentage points 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 15.3% wage increase. Such differences are true for most other amenities we consider, including telecommuting, a relaxed environment and autonomy at work, working by oneself and evaluation by

[32] Below we examine preference heterogeneity and sorting into jobs with different attributes, but we can also examine how preferences for non-wage attributes relate to individuals' employment status. Appendix Table 5 shows that workers who reported searching for a new job in July 2015 tend to have slightly higher valuations than workers overall (column 2 vs. column 1). Also, individuals who are not currently working (whether unemployed or not in the labor force) tend to have higher valuations than those who are currently working (column 3 vs. column 1).

[33] For attributes such as physical demands in which there are more than two possible options, we include the interaction of the middle-valued option (e.g., sitting) in the estimation but we suppress these interactions in Table 3. In these cases, column 2 shows the estimated valuations conditional on the respondent having the omitted category (e.g., heavy activity). All estimates displayed in columns 1-2 of Table 3 are estimated jointly.

oneself. Overall, those who select into jobs with amenities value the amenities 6.1 percentage points more than those who select into jobs without these amenities.

Next, to study the relationship between stated preferences and actual job transitions, we link our 2015 data to follow-up data recording job transitions that occurred up to three years later, in 2018. We relate stated preferences to job transitions rather than the respondents' current job to avoid concerns that any correlation between stated preferences and current job attributes might be due to an "endowment effect," where respondents disproportionately value amenities they are accustomed to. We hypothesize that, among those who have a desired attribute initially (in 2015), those who remain in a job with that attribute have a higher willingness-to-pay for the attribute than those who transition to a job without the attribute. Similarly, among those who lack a desired attribute initially, those who remain in a job without that attribute have a lower willingness-to-pay than those who transition to a job with the attribute. Note that a respondent need not change jobs *per se* to report a change in working conditions between waves. We test these hypotheses for each attribute separately as well as for all attributes combined. We observe 977 respondents (56% of the full sample) who can be matched to the 2018 AWCS.[34]

Columns 4-5 and 7-8 of Table 3 presents estimates of willingness-to-pay for each attribute conditional on whether the individual has or lacks that attribute in period 1 (2015) or period 2 (2018), respectively, interacted with their amenity status in 2018. Columns 6 and 9 display the differences in willingness-to-pay by amenity status, for individual attributes and overall. On average, for those individuals that have a desired job attribute in 2015, we find that those who remain in jobs with that attribute value it 4.1 percentage points more than those who transition to jobs without the attribute ($p<0.01$). For those who lack the desired attribute in 2015, we find that those who

[34] Recall the AWCS does not contain exactly the same question wording as the survey that preceded the stated preference experiments, so there will be some noise in mapping job attributes across survey waves.

transition to jobs with the desired attribute value it 1.7 percentage points more on average, though the average difference is not statistically significant. This suggests that on average individuals' actual job choices align with the choices in the stated preference experiments. We also find some significant differences for single attributes, but because of the small sample sizes in each transition group we generally lack statistical power for this analysis.

Overall, we find evidence that workers select hypothetical jobs that are consistent with characteristics they select in real jobs. This suggests that stated preferences indeed reflect actual preferences and provides supporting evidence of sorting based on preference heterogeneity.

5.C. Heterogeneity in Willingness-to-Pay

In 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 subject of much of the literature on the wage structure – differences in valuations by gender, race, education, and age. We obtain precisely estimated differences in how workers value amenities across groups, with women, whites, older and more educated workers placing a higher value on job amenities, on average. These differences turn out to be numerically important when we assess the impact of job amenities on wages differentials in Section 6. The subgroup models in this section are estimated using standard logit models and Appendix Table 6 presents comparable estimates of median willingness-to-pay by subgroup using mixed logit. Below we present estimated valuations by demographic subgroup without accounting for differences in other demographic variables; however, we provide estimates using samples that are reweighted to be balanced across other demographic characteristics in Appendix Tables 7-10. We highlight differences in willingness-to-pay across subgroups that are statistically significant in both the unweighted and reweighted samples.

Gender. We estimate amenity valuations separately by gender and present the results in Table 4. Overall, women are more willing to trade off monetary compensation for job amenities than men. A switch from the worst job to the best job is equivalent to a 58.8% wage increase for women and a 51.7% wage increase for men. Most notably, we find large gender differences in preferences to avoid physically demanding work – in comparison to heavy physical activity, women value moderate physical activity at 18.4% of the wage and sedentary work at 14.7%. We estimate smaller valuations for men at 11.4% and 9.1%, 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 18.7% wage increase, while men only value it at 14.6%. An additional 10 days is worth 7.8% of the wage for women and 5.6% for men. These differences are statistically significant at the 5% level even after reweighting to control for differences in other demographic characteristics (see Appendix Table 7). The valuations are generally similar by gender across all other amenities.

Race. Table 5 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 45.5% wage increase for non-whites and a 57.0% wage increase for whites. Most notable are differences by race in valuations of schedule flexibility and work autonomy. Whites place more value on schedule flexibility—setting their own schedule is equivalent to a 10.1% wage increase, compared to only 3.8% for non-whites. We also observe large differences in work autonomy, valued at 5.1% for whites but a small, statistically insignificant *negative* valuation for non-whites. Although it appears that non-whites do not value being evaluated based on their own performance, compared to whites, who value evaluation based on their own performance at 7.5% of their wage, this difference is not statistically significant when controlling for other demographic variables (see Appendix Table 8).

Education. 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 in willingness-to-pay for many job amenities. Overall, we find that the value of job amenities increases monotonically with education (Table 6). Respondents with a high school degree or less consider a switch from the worst job to the best job as worth a 48.0% wage increase. By comparison, those with some college consider such a switch equivalent to a 54.3% wage increase and those with a college degree consider such a switch equivalent to a 60.0% 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 4.6% and 6.9%, respectively, of their wage for this option. We find a similar monotonic relationship for physical demands, though we do not detect statistically significant differences between those with some college and college degrees on this dimension. The lowest education group values the job amenity "moderate activity" ("mostly sitting") at 11.1% (8.2%) of the wage, but the highest education group values it at 16.8% (13.7%). We also cannot reject that individuals without any college experience place no value on work autonomy (estimated at 1% of the wage), though once we control for other demographic characteristics we cannot reject that they value autonomy at the same level as college graduates (see Appendix Table 9).

Age. We examined preferences for job amenities based on age groups (Table 7). 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 47.5% wage increase for ages 25-34, 53.5% for ages 35-49, 58.9% for ages 50-61, and 74.5% for ages 62+. We estimate especially large differences based on the physical demands of the job. The valuations for both moderate physical activity and sitting increase monotonically by age. Workers ages 62 and above value moderate physical activity as equivalent to a 30.5% wage increase and sitting as equivalent to a 24.1% wage increase. Schedule flexibility and work autonomy are also disproportionately important at older ages. Interestingly, while younger workers appear to be indifferent towards evaluation based on one's own work in a team, willingness-to-pay for this job attribute increases to 6.8% for ages 35-49, 9.5% for ages 50-61, and 14.0% for ages 62+. We estimate similar patterns for working alone, increasing from 3.8% for the youngest age group to 17.9% for the oldest. These patterns are statistically significant even after controlling for other demographic variables (see Appendix Table 10). There is little evidence of age heterogeneity for training opportunities and opportunities to impact the community.

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

In this section, we assess how compensation differentials grow or shrink when differences in amenities are accounted for.[35] To do this, we add to each respondent's wage the valuations of each attribute associated with their current job, as they reported them in the short initial survey preceding the stated preference experiments, to calculate each respondent's total compensation. We perform this exercise twice: first, holding valuations constant at the estimated values for the full sample (shown in column 5 of Table 2), and second, allowing valuations to differ based on the individual characteristics of the respondent (specifically, gender, race, education and age). For the latter exercise, we estimate valuations jointly, letting demographic characteristics affect willingness-to-pay for each attribute additively. The first exercise allows us to examine how differences in the incidence of generally desirable job amenities affect compensation differentials. The second exercise allows us to examine the combined effects of differences in incidence and amenity valuations on compensation differentials.

In a long run competitive equilibrium, workers sort into jobs that equate, at the margin, their willingness-to-pay for an amenity with the wage-amenity tradeoff required by the firm to maintain zero profits, effectively producing a market clearing "price" of that amenity (Rosen, 1986).[36] Thus, in

[35] As before, we do not consider number of hours as an amenity for these calculations.
[36] Herzog and Schlottmann (1990) point out that the equivalence of workers' willingness-to-pay and the market "price" of amenities may not hold under certain conditions existing within imperfect labor markets, such as imperfect information, ineffective bargaining and transaction costs.

the first exercise we add back to individuals' wages the estimated market price of each amenity they have, under the assumption that individuals' wages have been reduced by that amount to compensate for the provision of the amenities. In the second exercise, where we allow valuations to vary by demographic group, we include in our measure of compensation the effective "rents" that accrue to individuals who hold jobs with amenities for whom their willingness-to-pay exceeds (or falls short of) the market prices of those amenities. For example, if women value paid time off more than men, then providing this amenity to women generates a larger increase in compensation than providing equivalent paid time off to men.

Let A_{ir} 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. Based on the random utility model introduced in Section 4, the log of "*total compensation,*" defined as the log of the wage plus the total value of the respondent's current attributes, is equal to:

$$\ln\left(w_i + w_i\left[1 - e^{\left(-\frac{\sum r A_{ir}\beta_i^r}{\delta_i}\right)}\right]\right),$$

where β_i^r is the marginal utility of a given attribute *r* and δ_i the marginal utility of the log wage w_i.[37]

For each measure of compensation—the unadjusted wage, total compensation holding valuations constant, and total compensation allowing valuations to vary by demographic characteristics—we estimate *separate* regressions of log compensation on indicator variables for age, gender, race and education, and industry (aggregated into "supersectors"),[38] and calculate the

[37] Although we tried to select a broad set of core job attributes to examine in this paper, it is not possible to include all potential attributes. The extent to which these unobserved attributes affect actual vs. measured compensation differentials depends on the net effect of differences in incidence of and preferences for the unobserved attributes.
[38] See https://www.bls.gov/sae/additional-resources/naics-supersectors-for-ces-program.htm for more details about the aggregation of industries. For the industry analyses, we regress de-meaned log compensation on all industry supersectors with no constant. We obtain worker industry from the 2015 AWCS, so the analysis of inter-industry wage differentials is limited to the 59% of the full sample who are also observed in the 2015 AWCS. In addition, there may be some measurement error from the different timing of the survey waves (July vs. December 2015).

differences between the 90th, 50th, and 10th percentiles. 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. We present our estimates of the wage and compensation differentials by demographic characteristics (Panel A) and industry (Panel B), and percentile of the wage distribution (Panel C), in Table 8. [39]

Gender. In our data, we estimate a log-wage gender differential equal to -0.192, implying that women have 17% lower wages than men.[40] The log compensation gap shrinks to -0.177 (-16%) when accounting for differences in the incidence of amenities and -0.142 (-13%) when accounting for differences in both the incidence of and preferences for amenities. This represents a substantial 24% reduction in the size of the differential, with most of the reduction coming from women placing more value than men on amenities such as paid time off and avoiding heavy physical activity. Our analysis suggests that, by focusing solely on wages, one *over*-estimates the size of the gender gap in compensation, since women differentially place greater value on the nonwage characteristics of their jobs. At the same time, preferences for amenities such as schedule flexibility and paid time off may be influenced by cultural factors, such as availability of and expectations regarding childcare, that affect men and women differently (see e.g., Duchini and Van Effenterre, Forthcoming).

Race. Accounting for amenities increases the race-wage gap. The unadjusted white-nonwhite log wage differential is -0.208, implying 19% lower wages for nonwhites in our data.

[39] Appendix Table 11 presents alternative estimates of compensation differentials. Column 1 reproduces the estimates from column 2 of Table 8, where compensation is calculated using parameter estimates from column 5 of Table 2. Column 2 presents estimates of compensation differentials where compensation is calculated by adding to wages the valuations estimated conditional on having the amenity (from column 1 of Table 3). The estimates are similar to the estimates in column 1, suggesting that accounting explicitly for sorting into jobs based on preference heterogeneity does not substantially affect our findings. Column 3 of Appendix Table 11 presents estimates of compensation differentials where compensation is calculated by adding to wages the valuations estimated using the mixed logit model allowing for unobservable preference heterogeneity that is orthogonal to observed characteristics. Again, the estimates are similar to those in column 1.

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

Holding amenity valuations constant, we estimate only a small and statistically insignificant difference in wage vs. compensation 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 other characteristics. Consistent with our finding in Section 5 that whites value amenities more highly than non-whites, after allowing valuations to differ by demographic characteristics, the total compensation differential is estimated to increase in magnitude to -0.274, representing a 27% increase relative to the wage differential unadjusted for amenities. As with gender, cultural factors (e.g., systemic racism) likely play a role in racial differences in preferences over working conditions.

Education. Accounting for amenities substantially increases the cross-sectional returns to education. In our data, workers with a high school degree or less have 43% lower wages than those with a college degree (a differential of -0.559 log points). Similarly, workers with some college but without a college degree have 39% lower wages than those with a college degree (-0.502 log points). Recall that we found large differences in both the incidence (Section 3) and valuation (Section 5) of amenities by education. Adjusting wages for both of these differences, the total log compensation differentials increase in magnitude to -0.667 (-49%) and -0.564 (-43%), respectively. This corresponds to an increase of 9-14% relative to the unadjusted cross-sectional returns to education.

Age. As with the race gap, differences in the valuation of job amenities play a key role when adjusting the age-wage gradient. We find that the wage differential between older workers and workers ages 25-34 and 35-49 more than doubles after adjusting for differences in job attributes, since older workers have strong preferences for non-wage amenities.

Inter-Industry Wage Differentials. A long-standing literature has tried to understand why inter-industry wage differentials persist even after controlling for occupation, union penetration and other characteristics. A seminal study by Krueger and Summers (1988) tested whether compensating differentials could explain the presence of inter-industry wage differentials by estimating inter-industry wage differentials with and without controls for ten working conditions using data from the 1977 Quality of Employment Survey.[41] They found that including controls for working conditions did not substantially alter the weighted standard deviation of wage differentials (0.113 vs. 0.118, without and with controls for working conditions, see Table VI) and concluded that compensating differentials were not playing an important role in determining industry wage differentials.

As established in Section 5, our experimental data enable us to obtain better measures of workers' valuations of non-wage amenities than traditional hedonic regression methods. Therefore we can use our valuations to revisit the role of compensating differentials in inter-industry wage differentials, for a broad range of working conditions. Specifically, if compensating differentials for unpleasant working conditions increase wages in certain industries, then adding the value of desirable job attributes to the wages of those who hold jobs with desirable attributes should *narrow* inter-industry compensation differentials. Instead, we find the opposite. Panel B of Table 8 presents a standard summary measure of inter-industry compensation differentials, the weighted (by employment shares) standard deviation. We find that adjusting for the value of non-wage working conditions increases the weighted standard deviation of inter-industry wage differentials, from 0.130 to 0.155.[42]

Overall Wage Inequality. Finally, we investigate how accounting for the incidence of and preferences for working conditions affects overall compensation inequality. Figure 4 explores the relationship between amenities and wages by plotting the mean amenity value of workers' jobs against their position in the wage distribution, aggregating into 20 groups each representing 5% of

[41] The conditions they examined included indicators for hazardous conditions, shift work, commuting time, control over overtime, pleasant physical conditions, and weekly work hours. Because hours are potentially endogenous, they estimated versions both with and without hours and found similar results.

[42] Appendix Table 12 shows the unadjusted and adjusted inter-industry wage differentials and employment shares for the eleven industry supersectors; adjusting for the value of working conditions intensifies the differentials for all industries except for natural resources, which shrinks from -0.050 (relative to the global mean) to -0.029.

the sample, using valuations from the logit specification estimated on the full sample (column 5 of Table 2). We see that amenity values are positively correlated with wages (ρ=0.32) and that the mean amenity value increases from 35% of the wage at the bottom of the wage distribution to 45% at the top of the distribution. Interestingly, we find that even individuals at the bottom of the wage distribution have non-wage amenities that are worth a substantial fraction of their compensation.

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 Panel C of Table 8. Overall, adjusting for the presence of job amenities increases wage inequality, particularly in the bottom half of the wage distribution. Adjusting for the valuation of job attributes increases the log 90/50 wage ratio by approximately 4.7 log points (from 0.963 to 1.011). To put this number in context, Autor et al. (2008) found that between 1980 and 2005 the 90/50 male wage gap increased steadily at the rate of approximately 1 log point per year. Thus, adjusting the 90/50 wage ratio for the value of working conditions is equivalent to nearly 5 years' worth of observed earnings growth at the top end of the distribution. Even more strikingly, we find that adjusting for the valuation of job attributes increases the log 50/10 wage ratio by 5.7 log points; Autor et al. (2008) show that the 50/10 wage ratio remained relatively flat between the late 1980s and 2005. We also compare our findings with those of Pierce (2001), who performed a similar exercise using data on employer costs of fringe benefits between 1981 and 1997.[43] Pierce (2001) found that accounting for paid leave, pensions and health insurance each added about 5-6 log points to the 90/10 log wage differential, while accounting for legally required benefits (e.g., Social Security, Medicare, workers' compensation, unemployment insurance) narrowed the differential by 5 log points. On net, accounting for fringe benefits increased the 90/10 wage gap by about 10 log

[43] Pierce (2001) used employer costs to approximate employees' valuations of benefits, which could be over- or understated depending on the net effect of factors such as preferential tax treatment and adverse selection.

points—similar in magnitude to our finding that accounting for the value of non-wage amenities (excluding fringe benefits) increases the 90/10 wage gap by 10.5 percentage points.

7. Conclusion

A large body of literature has examined sources of persistent wage differentials by gender, race, age, education, industry, and wage inequality more generally, typically studying the traits of workers or firms. In this paper, we assess to what extent differences in working conditions 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 attributes based on carefully designed stated-preference experiments. To capture a broad range of working conditions, we focus on nine specific job attributes. We then use the incidence of job attributes 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 working conditions differ systematically across the U.S. labor force. We also document substantial willingness-to-pay for all of the amenities we study, and show that valuations can differ substantially across different types of workers. This observed preference heterogeneity is a critical component when studying differences in compensation. Accounting for both differences in the incidence of working conditions and preference heterogeneity based on demographic characteristics 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 as the lifecycle progresses. 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 attributes.

Overall, our analysis confirms recent experimental and stated-preference estimates that suggest 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 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. 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.

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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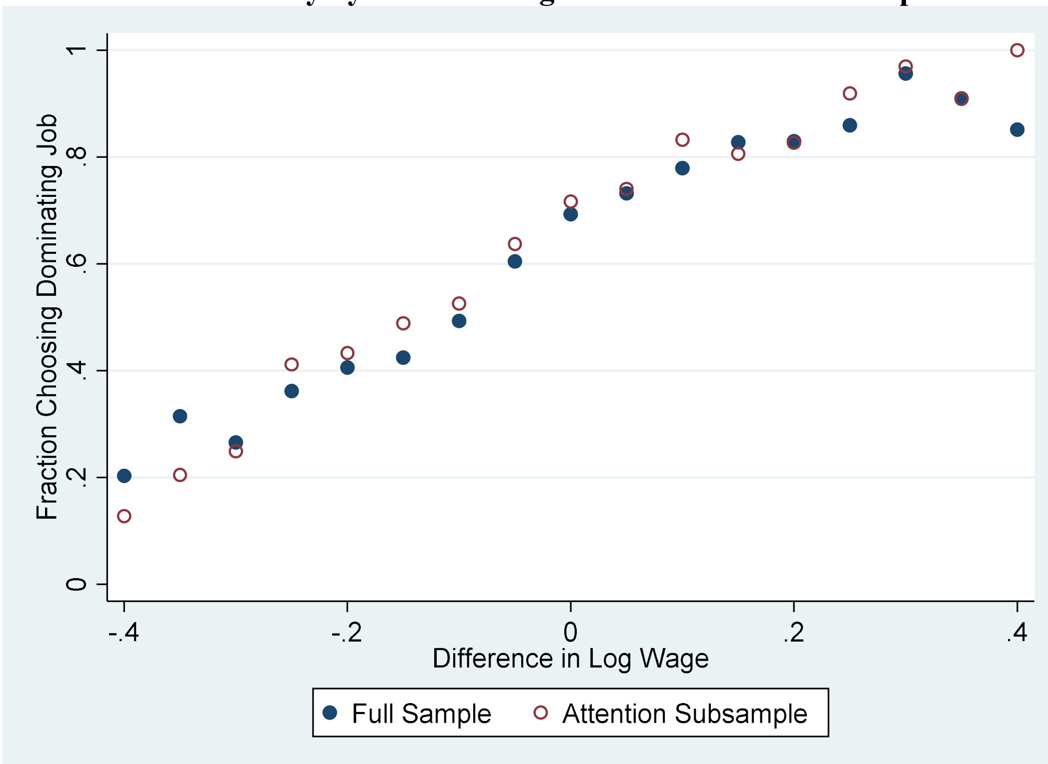
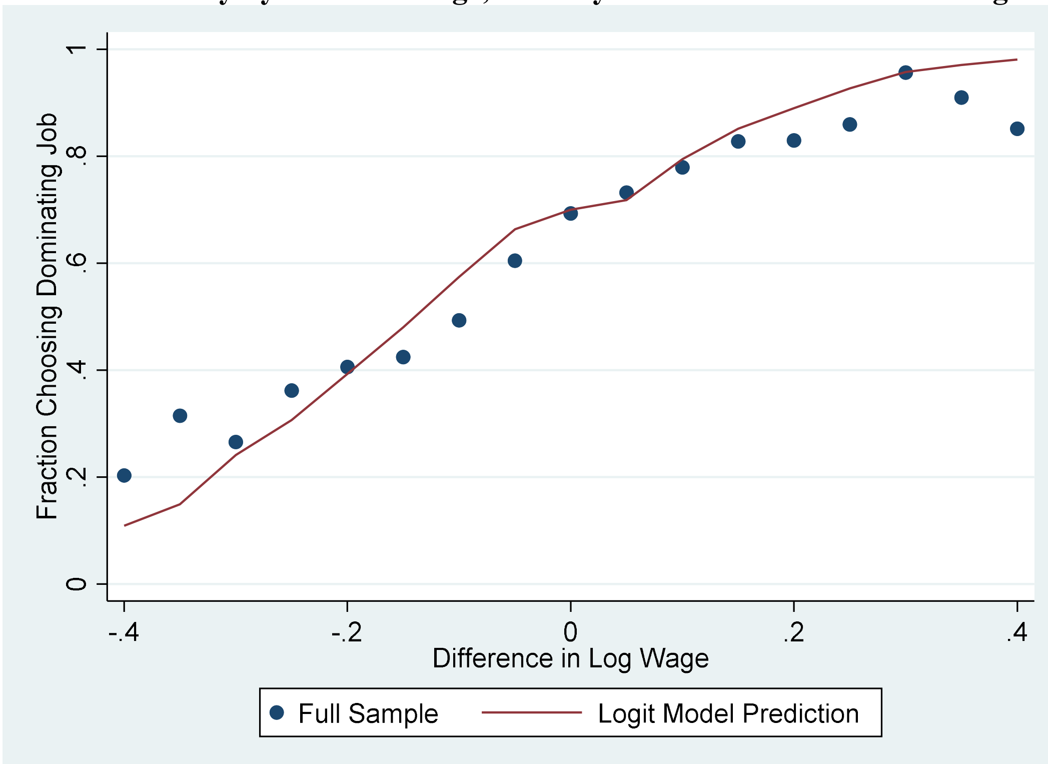
Figure 1: Fraction Preferring Job with Both Randomized Amenities Over Job with Neither Randomized Amenity by Relative Wage in Stated Preference Experiments



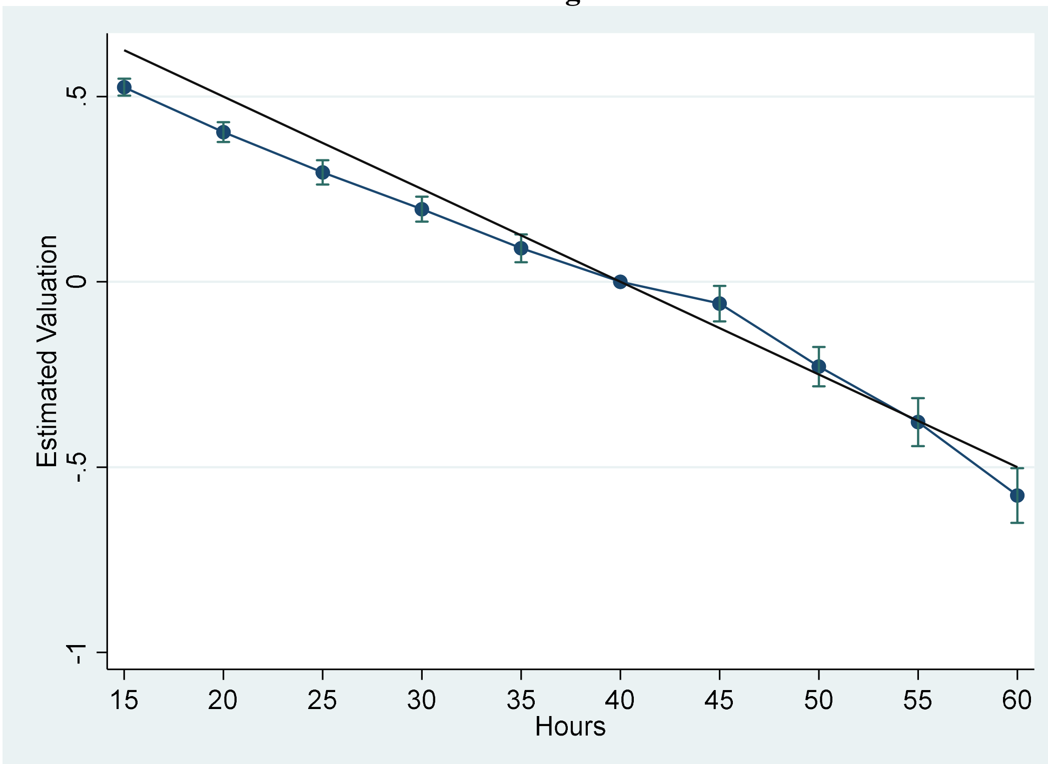
Notes: This figure shows that higher relative wages for a job with dominating job attributes is associated with a higher share of respondents selecting that job. To show this, we aggregated the experimental data into bins of equal length based on the difference in log wage offers within each choice pair for the subsample of N=11,433 choice pairs where the randomized amenities in one job strictly dominated the other job. We present data for the full sample as well as for the attentive subsample (defined by answering at least one of two trick questions correctly).

Figure 2: Fraction Preferring Job with Both Randomized Amenities Over Job with Neither Randomized Amenity by Relative Wage, Overlayed with Predictions from Logit Model



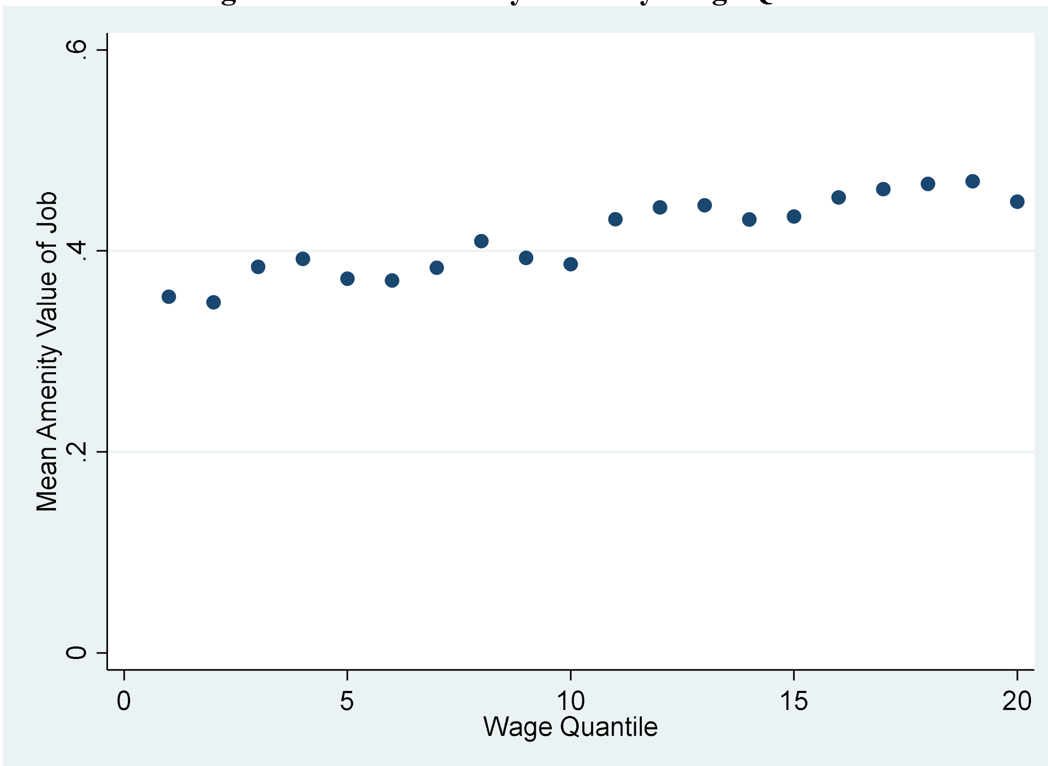
Notes: This figure reproduces Figure 1 (the share of respondents selecting a job with dominating attributes not present in the alternative job, by the difference in the log wage), overlayed with the predicted share of respondents calculated using parameter estimates from the logit model (column 5 of Table 2).

Figure 3. Estimates of Willingness-to-Pay for Weekly Work Hours as Fraction of Total Earnings



Notes: To examine preferences for weekly work hours, we estimated a model using total earnings instead of hourly wages as the numeraire and including indicator variables for weekly work hours ranging from 15 to 60 hours per week, with 40 hours per week as the omitted group. The figure presents the estimated valuations of offered work hours as fractions of total earnings. 95% confidence intervals are presented and adjusted for clustering by respondent. The reference line shows the proportional change in total earnings resulting from a change in hours from a baseline of 40 hours.

Figure 4. Mean Amenity Value by Wage Quantile



Notes: The figure plots the mean amenity value of workers' jobs against their position in the wage distribution, aggregating into 20 groups each representing 5% of the sample, using valuations from the logit specification estimated on the full sample (column 5 of Table 2).

Table 1. Working Conditions in the United States in 2015, Overall and by Demographic Group

	Overall (1)	Women (2)	Men (3)	Nonwhite (4)	White (5)	High Sch. or Less (6)	Some College (7)	College (8)
Mean Hours per Week	39.62	37.32	41.64	38.99	39.77	39.71	38.58	40.23
	(9.89)	(9.58)	(9.73)	(8.28)	(10.24)	(10.01)	(9.25)	(10.17)
Mean Wage (in 2015 $)	30.30	25.99	34.09	24.11	31.81	24.51	25.48	38.00
	(36.55)	(27.96)	(42.38)	(20.83)	(39.32)	(38.77)	(40.59)	(30.10)
Log Wage Differential		-0.192		-0.208		-0.559	-0.502	
		(0.048)		(0.055)		(0.063)	(0.042)	
<u>% with Each Working Condition</u>								
Set Own Schedule	56.5	58.8	54.4	49.6	58.2	42.1	56.8	67.5
Telecommute	36.4	37.0	35.9	30.5	37.9	20.4	27.4	54.9
Heavy Physical Activity	18.7	12.6	24.2	21.3	18.1	33.8	21.1	5.4
Moderate Physical Activity	38.4	38.1	38.7	40.4	37.9	36.9	42.8	36.7
Mostly Sitting	42.9	49.4	37.2	38.2	44.0	29.4	36.1	57.9
Relaxed Pace	29.8	32.6	27.3	28.8	30.0	22.3	30.0	35.5
Choose How Do Work	86.4	86.4	86.4	83.9	87.0	79.6	86.3	91.8
No Paid Time Off (PTO)	14.3	13.6	14.9	10.2	15.3	18.9	15.3	10.1
1-14 PTO Days	26.0	25.1	26.7	31.3	24.7	30.3	27.9	21.3
15+ PTO Days	59.7	61.2	58.4	58.4	60.0	50.8	56.8	68.7
Team-Based, Evaluated as Team	18.6	13.7	22.9	22.9	17.5	22.4	20.4	14.4
Team-Based, Evaluated on Own	49.1	51.3	47.1	47.7	49.4	45.0	49.2	52.1
Work by Self	32.4	35.1	30.0	29.4	33.1	32.6	30.4	33.5
Training Opportunities	70.0	65.4	74.1	76.1	68.5	64.6	70.3	74.0
Frequent Opp. Positive Impact	34.5	39.5	30.1	30.4	35.5	28.6	34.8	39.0
No. Observations	1,738	968	770	380	1,358	223	607	908

Notes: Tabulations from American Working Conditions Survey, Stated Preference Experimental Wave. Sample statistics are weighted using survey weights. Standard deviations are shown in parentheses.

Table 1, Continued. Working Conditions in the United States in 2015, Overall and by Demographic Group

	Age Group				Wage Quintile		
	25-34	**35-49**	**50-61**	**62+**	**Bottom**	**Middle**	**Top**
	(9)	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**
Mean Hours per Week	39.40	40.42	39.73	36.49	34.39	42.13	41.23
	(9.17)	(10.17)	(9.22)	(12.02)	(10.92)	(8.45)	(9.70)
Mean Wage (in 2015 $)	30.68	29.17	30.50	33.28	10.30	21.35	73.56
	(44.68)	(33.30)	(33.59)	(33.16)	(1.82)	(2.33)	(63.94)
Log Wage Differential	-0.143	-0.081	-0.038			0.701	1.664
	(0.086)	(0.065)	(0.060)			(0.040)	(0.054)
<u>% with Each Working Condition</u>							
Set Own Schedule	57.0	54.2	56.5	64.6	54.3	47.8	78.0
Telecommute	33.2	37.2	35.7	44.6	21.1	29.3	64.2
Heavy Physical Activity	16.4	22.0	18.4	13.1	24.7	19.3	7.8
Moderate Physical Activity	43.8	32.7	38.6	46.2	53.0	39.1	30.1
Mostly Sitting	39.9	45.3	43.0	40.7	22.3	41.6	62.1
Relaxed Pace	23.5	29.0	32.4	42.3	25.2	25.6	30.0
Choose How Do Work	90.9	85.2	85.7	80.7	84.3	89.2	87.9
No Paid Time Off (PTO)	14.0	13.0	13.9	22.4	34.2	9.1	5.9
1-14 PTO Days	29.8	26.8	22.9	21.5	29.7	27.9	13.4
15+ PTO Days	56.2	60.2	63.2	56.1	36.2	63.0	80.7
Team-Based, Evaluated as Team	16.1	21.4	18.3	14.9	14.6	19.9	19.0
Team-Based, Evaluated on Own	57.3	45.9	45.7	49.3	54.9	50.1	55.5
Work by Self	26.6	32.7	35.9	35.7	30.5	30.0	25.5
Training Opportunities	78.5	70.2	65.6	59.4	62.1	70.5	78.1
Frequent Opp. Positive Impact	30.6	37.4	34.8	33.0	28.9	34.8	40.9
No. Observations	285	525	676	252	375	356	336

Notes: Tabulations from American Working Conditions Survey, Stated Preference Experimental Wave. Sample statistics are weighted using survey weights. Standard deviations are shown in parentheses.

Table 2. Willingness-to-Pay Estimates for Job Amenities

	Observational Data		Experimental Data				
			Mixed Logit		Standard Logit		
	X-Sect.	Panel	Mean	Median	Full	Attent.	Interact.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Set Own Schedule	-0.071	0.007	0.088	0.092	0.089	0.087	0.088
[Schedule Set by Manager]	(0.041)	(0.055)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Telecommute	-0.163	0.008	0.041	0.045	0.042	0.054	0.037
[No Telecommuting]	(0.037)	(0.059)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Moderate Physical Activity	0.081	-0.048	0.145	0.154	0.145	0.167	0.137
[Heavy Physical Activity]	(0.082)	(0.083)	(0.010)	(0.010)	(0.010)	(0.015)	(0.010)
Sitting	-0.094	-0.084	0.112	0.129	0.116	0.123	0.110
[Heavy Physical Activity]	(0.069)	(0.096)	(0.012)	(0.011)	(0.010)	(0.014)	(0.010)
Relaxed	0.094	-0.018	0.040	0.044	0.043	0.046	0.040
[Fast Pace]	(0.042)	(0.036)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Choose How Do Work	0.038	0.050	0.037	0.041	0.040	0.062	0.035
[Tasks Well-Defined]	(0.071)	(0.063)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
10 Days PTO	-0.217	-0.157	0.173	0.178	0.164	0.174	0.163
[No Days PTO]	(0.063)	(0.085)	(0.010)	(0.011)	(0.009)	(0.013)	(0.010)
20 Days PTO	-0.339	-0.015	0.237	0.249	0.230	0.256	0.229
[No Days PTO]	(0.040)	(0.113)	(0.011)	(0.014)	(0.010)	(0.014)	(0.011)
Team-Based, Evaluate Own	0.019	-0.060	0.063	0.070	0.065	0.084	0.063
[Team-Based, Evaluate Team]	(0.044)	(0.052)	(0.010)	(0.011)	(0.010)	(0.014)	(0.011)
Work by Self	0.010	-0.040	0.086	0.094	0.086	0.088	0.083
[Team-Based, Evaluate Team]	(0.062)	(0.063)	(0.010)	(0.011)	(0.010)	(0.014)	(0.011)
Training Opportunities	0.005	-0.037	0.050	0.054	0.054	0.068	0.052
[Already Have Skills]	(0.055)	(0.035)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)
Frequent Opp. to Serve	-0.008	0.046	0.028	0.030	0.036	0.029	0.041
[Occasional Opp. to Serve]	(0.035)	(0.061)	(0.007)	(0.007)	(0.007)	(0.011)	(0.008)
Best Job			0.507	0.569	0.550	0.603	0.499
[Worst Job]			(0.019)	(0.017)	(0.016)	(0.018)	(0.025)
No. Observations	1,737	977	17,380	17,380	17,380	8,020	17,380

Notes: Columns (1) and (2) present estimates from traditional hedonic pricing regressions using observational data. Column (1) includes controls for gender, age group, citizenship, ethnicity and education. Columns (3)-(7) are estimated using data from stated-preference experiments. Columns (3) and (4) present estimates of mean and median willingness-to-pay (WTP) from mixed logit model assuming normal distribution for marginal values of amenities. Columns (5) and (6) present estimates from standard logit model estimated on full sample and attentive subsample, respectively. Column (7) presents average WTP estimates from standard logit model with two-way interactions between amenities. All models are estimated using survey weights. Standard errors are estimated using the delta method for columns (1)-(6) and by bootstrap with 500 iterations for column (7), and are adjusted for clustering by respondent.

Table 3. Preference Heterogeneity and Sorting: Estimates of Willingness-to-Pay Interacted with Amenity Status in 2015 & 2018

	Has in 2015 (1)	Lacks in 2015 (2)	Diff. (1)-(2) (3)
Set Own Schedule	0.104	0.068	0.036
[Schedule Set by Manager]	(0.009)	(0.010)	(0.013)
Telecommute	0.066	0.027	0.039
[No Telecommuting]	(0.010)	(0.010)	(0.014)
Moderate Physical Activity	0.169	0.033	0.136
[Heavy Physical Activity]	(0.015)	(0.023)	(0.027)
Sitting	0.153	-0.025	0.178
[Heavy Physical Activity]	(0.014)	(0.028)	(0.031)
Relaxed	0.083	0.026	0.057
[Fast Pace]	(0.010)	(0.009)	(0.014)
Choose How Do Work	0.044	0.015	0.029
[Tasks Well-Defined]	(0.007)	(0.016)	(0.018)
10 Days PTO	0.151	0.162	-0.011
[No Days PTO]	(0.017)	(0.021)	(0.026)
20 Days PTO	0.247	0.159	0.088
[No Days PTO]	(0.012)	(0.020)	(0.023)
Team-Based, Evaluate Own	0.079	0.011	0.068
[Team-Based, Evaluate Team]	(0.014)	(0.024)	(0.028)
Work by Self	0.133	0.017	0.116
[Team-Based, Evaluate Team]	(0.017)	(0.021)	(0.027)
Training Opportunities	0.050	0.061	-0.011
[Already Have Skills]	(0.009)	(0.011)	(0.014)
Frequent Opp. to Serve	0.037	0.036	0.001
[Occasional Opp. to Serve]	(0.014)	(0.008)	(0.016)
Average Difference			**0.061**
			(0.008)

Notes: Estimates in columns (1)-(2) estimated jointly on full sample (N=17,380). Average difference in column (3) estimated using delta method. Standard errors in parentheses are adjusted for clustering by respondent.

Table 3, Continued. Preference Heterogeneity and Sorting: Estimates of Willingness-to-Pay Interacted with Amenity Status in 2015 & 2018

	Has in 2015			Lacks in 2015		
	Has in 2018 (4)	**Lacks in 2018 (5)**	**Diff. (5)-(6) (6)**	**Has in 2018 (7)**	**Lacks in 2018 (8)**	**Diff. (7)-(8) (9)**
Set Own Schedule	0.099	0.050	0.048	0.070	0.047	0.024
[Schedule Set by Manager]	(0.012)	(0.029)	(0.031)	(0.020)	(0.014)	(0.025)
Telecommute	0.099	0.069	0.031	0.014	0.025	-0.010
[No Telecommuting]	(0.016)	(0.018)	(0.023)	(0.031)	(0.014)	(0.034)
Moderate Physical Activity	0.176	0.136	0.040	-0.019	0.016	-0.035
[Heavy Physical Activity]	(0.029)	(0.040)	(0.050)	(0.045)	(0.034)	(0.053)
Sitting	0.157	0.142	0.015	0.042	-0.050	0.092
[Heavy Physical Activity]	(0.019)	(0.056)	(0.059)	(0.072)	(0.049)	(0.066)
Relaxed	0.113	0.078	0.035	0.057	0.022	0.036
[Fast Pace]	(0.024)	(0.015)	(0.028)	(0.024)	(0.012)	(0.027)
Choose How Do Work	0.036	0.066	-0.030	0.010	0.025	-0.015
[Tasks Well-Defined]	(0.009)	(0.026)	(0.028)	(0.023)	(0.025)	(0.034)
10 Days PTO	0.211	0.152	0.059	0.207	0.221	-0.014
[No Days PTO]	(0.029)	(0.050)	(0.057)	(0.051)	(0.044)	(0.044)
20 Days PTO	0.283	0.160	0.123	0.206	0.243	-0.038
[No Days PTO]	(0.017)	(0.037)	(0.040)	(0.049)	(0.035)	(0.048)
Team-Based, Evaluate Own	0.086	0.054	0.032	0.050	-0.006	0.056
[Team-Based, Evaluate Team]	(0.019)	(0.047)	(0.051)	(0.023)	(0.052)	(0.050)
Work by Self	0.117	0.065	0.052	0.085	-0.030	0.115
[Team-Based, Evaluate Team]	(0.034)	(0.047)	(0.059)	(0.045)	(0.047)	(0.045)
Training Opportunities	0.057	0.033	0.024	0.075	0.069	0.007
[Already Have Skills]	(0.014)	(0.014)	(0.020)	(0.019)	(0.018)	(0.026)
Frequent Opp. to Serve	0.047	-0.015	0.062	0.027	0.047	-0.020
[Occasional Opp. to Serve]	(0.015)	(0.046)	(0.049)	(0.014)	(0.014)	(0.020)
Average Difference			**0.041**			**0.017**
			(0.014)			(0.011)

Notes: Estimates in columns (4)-(5) and (7)-(8) estimated jointly on subsample merged to 2018 AWCS (N=9,770). Average differences in columns (6) and (9) estimated using delta method. Standard errors in parentheses are adjusted for clustering by respondent.

Table 4. Estimates of Willingness-to-Pay, by Gender

	Women (1)	Men (2)
Set Own Schedule	0.093	0.085
[Schedule Set by Manager]	(0.008)	(0.010)
	0.513	
Telecommute	0.055	0.032
[No Telecommuting]	(0.009)	(0.011)
	0.093	
Moderate Physical Activity	0.184	0.114
[Heavy Physical Activity]	(0.013)	(0.014)
	<0.001	
Sitting	0.147	0.091
[Heavy Physical Activity]	(0.013)	(0.014)
	0.003	
Relaxed	0.035	0.049
[Fast Pace]	(0.008)	(0.011)
	0.275	
Choose How Do Work	0.032	0.045
[Tasks Well-Defined]	(0.008)	(0.010)
	0.336	
10 Days PTO	0.187	0.146
[No Days PTO]	(0.012)	(0.013)
	0.020	
20 Days PTO	0.265	0.202
[No Days PTO]	(0.012)	(0.015)
	0.001	
Team-Based, Evaluate Own	0.074	0.057
[Team-Based, Evaluate Team]	(0.013)	(0.014)
	0.372	
Work by Self	0.087	0.085
[Team-Based, Evaluate Team]	(0.012)	(0.015)
	0.928	
Training Opportunities	0.041	0.063
[Already Have Skills]	(0.009)	(0.010)
	0.105	
Frequent Opp. to Serve	0.033	0.039
[Occasional Opp. to Serve]	(0.009)	(0.010)
	0.682	
Best Job	0.588	0.517
[Worst Job]	(0.018)	(0.024)
	0.017	
No. Observations	19,360	15,400

Notes: For each amenity, first row shows WTP estimated jointly using standard logit model, second row shows standard error in parens., and third row shows p-value for test of signif. diff. from last column.

Table 5. Estimates of Willingness-to-Pay, by Race

	Nonwhite (1)	White (2)
Set Own Schedule	0.038	0.101
[Schedule Set by Manager]	(0.014)	(0.008)
	<0.001	
Telecommute	0.027	0.046
[No Telecommuting]	(0.013)	(0.008)
	0.244	
Moderate Physical Activity	0.116	0.151
[Heavy Physical Activity]	(0.023)	(0.010)
	0.165	
Sitting	0.128	0.113
[Heavy Physical Activity]	(0.020)	(0.011)
	0.508	
Relaxed	0.056	0.039
[Fast Pace]	(0.014)	(0.008)
	0.312	
Choose How Do Work	-0.008	0.051
[Tasks Well-Defined]	(0.015)	(0.008)
	<0.001	
10 Days PTO	0.154	0.167
[No Days PTO]	(0.021)	(0.010)
	0.569	
20 Days PTO	0.219	0.234
[No Days PTO]	(0.022)	(0.011)
	0.544	
Team-Based, Evaluate Own	0.021	0.075
[Team-Based, Evaluate Team]	(0.022)	(0.011)
	0.031	
Work by Self	0.066	0.091
[Team-Based, Evaluate Team]	(0.020)	(0.012)
	0.291	
Training Opportunities	0.065	0.051
[Already Have Skills]	(0.014)	(0.008)
	0.368	
Frequent Opp. to Serve	0.032	0.038
[Occasional Opp. to Serve]	(0.014)	(0.008)
	0.709	
Best Job	0.455	0.570
[Worst Job]	(0.034)	(0.017)
	0.002	
No. Observations	7,600	27,160

Notes: For each amenity, first row shows WTP estimated jointly using standard logit model, second row shows standard error in parens., and third row shows p-value for test of signif. diff. from last column.

Table 6. Estimates of Willingness-to-Pay, by Education

	High School (1)	Some College (2)	College Degree (3)
Set Own Schedule	0.080	0.076	0.104
[Schedule Set by Manager]	(0.017)	(0.011)	(0.008)
	0.219	0.033	
Telecommute	-0.005	0.046	0.069
[No Telecommuting]	(0.020)	(0.010)	(0.008)
	0.001	0.071	
Moderate Physical Activity	0.111	0.144	0.168
[Heavy Physical Activity]	(0.023)	(0.014)	(0.013)
	0.029	0.199	
Sitting	0.082	0.117	0.137
[Heavy Physical Activity]	(0.023)	(0.014)	(0.013)
	0.040	0.285	
Relaxed	0.034	0.039	0.052
[Fast Pace]	(0.019)	(0.010)	(0.007)
	0.361	0.278	
Choose How Do Work	0.010	0.045	0.059
[Tasks Well-Defined]	(0.017)	(0.011)	(0.007)
	0.010	0.289	
10 Days PTO	0.183	0.157	0.158
[No Days PTO]	(0.024)	(0.015)	(0.010)
	0.346	0.937	
20 Days PTO	0.241	0.230	0.226
[No Days PTO]	(0.028)	(0.014)	(0.011)
	0.616	0.807	
Team-Based, Evaluate Own	0.062	0.057	0.074
[Team-Based, Evaluate Team]	(0.025)	(0.015)	(0.011)
	0.677	0.354	
Work by Self	0.114	0.076	0.073
[Team-Based, Evaluate Team]	(0.027)	(0.014)	(0.012)
	0.160	0.872	
Training Opportunities	0.040	0.056	0.064
[Already Have Skills]	(0.018)	(0.010)	(0.008)
	0.231	0.573	
Frequent Opp. to Serve	0.031	0.039	0.039
[Occasional Opp. to Serve]	(0.018)	(0.011)	(0.008)
	0.716	0.979	
Best Job	0.480	0.543	0.600
[Worst Job]	(0.044)	(0.023)	(0.016)
	0.010	0.039	
No. Observations	4,460	12,140	18,160

Notes: For each amenity, first row shows WTP estimated jointly using standard logit model, second row shows standard error in parens., and third row shows p-value for test of signif. diff. from last column.

Table 7. Estimates of Willingness-to-Pay, by Age Group

	Age Group			
	25-34	**35-49**	**50-61**	**62+**
	(1)	**(2)**	**(3)**	**(4)**
Set Own Schedule	0.071	0.092	0.088	0.147
[Schedule Set by Manager]	(0.012)	(0.012)	(0.011)	(0.024)
	0.005	0.044	0.027	
Telecommute	0.034	0.045	0.043	0.062
[No Telecommuting]	(0.013)	(0.014)	(0.010)	(0.022)
	0.272	0.495	0.422	
Moderate Physical Activity	0.088	0.134	0.183	0.305
[Heavy Physical Activity]	(0.018)	(0.017)	(0.015)	(0.038)
	<0.001	<0.001	0.003	
Sitting	0.071	0.115	0.141	0.241
[Heavy Physical Activity]	(0.020)	(0.016)	(0.016)	(0.037)
	<0.001	0.002	0.013	
Relaxed	0.047	0.030	0.051	0.079
[Fast Pace]	(0.014)	(0.013)	(0.011)	(0.024)
	0.234	0.069	0.276	
Choose How Do Work	0.042	0.017	0.051	0.120
[Tasks Well-Defined]	(0.015)	(0.010)	(0.011)	(0.025)
	0.007	<0.001	0.011	
10 Days PTO	0.140	0.176	0.163	0.190
[No Days PTO]	(0.017)	(0.015)	(0.016)	(0.036)
	0.216	0.727	0.496	
20 Days PTO	0.196	0.239	0.239	0.277
[No Days PTO]	(0.017)	(0.018)	(0.019)	(0.032)
	0.026	0.302	0.310	
Team-Based, Evaluate Own	0.014	0.068	0.095	0.140
[Team-Based, Evaluate Team]	(0.020)	(0.017)	(0.016)	(0.030)
	<0.001	0.036	0.186	
Work by Self	0.038	0.101	0.095	0.179
[Team-Based, Evaluate Team]	(0.019)	(0.016)	(0.018)	(0.034)
	<0.001	0.040	0.029	
Training Opportunities	0.074	0.044	0.047	0.056
[Already Have Skills]	(0.013)	(0.013)	(0.009)	(0.026)
	0.547	0.682	0.753	
Frequent Opp. to Serve	0.043	0.041	0.024	0.038
[Occasional Opp. to Serve]	(0.013)	(0.013)	(0.011)	(0.025)
	0.845	0.913	0.612	
Best Job	0.475	0.535	0.589	0.745
[Worst Job]	(0.031)	(0.027)	(0.026)	(0.038)
	<0.001	<0.001	0.001	
No. Observations	5,700	10,500	13,520	5,040

Notes: For each amenity, first row shows WTP estimated jointly using standard logit model, second row shows standard error in parens., and third row shows p-value for test of signif. diff. from last column.

Table 8. Effect of Adjusting for the Incidence and Valuation of Job Amenities on Wage Differentials

		Log Compensation			
	Log Wage	Holding Valuations Fixed	Letting Valuations Vary	Difference in Columns (2) - (1)	Difference in Columns (3) - (2)
	(1)	(2)	(3)	(4)	(5)
A. Demographic Wage Differentials					
Women	-0.192	-0.177	-0.142	0.016	0.034
[Men]	(0.048)	(0.050)	(0.053)	[0.007,0.025]	[0.006,0.060]
Nonwhite	-0.208	-0.211	-0.274	-0.003	-0.063
[White]	(0.055)	(0.058)	(0.064)	[-0.012,0.007]	[-0.097,-0.027]
High school or less	-0.559	-0.618	-0.667	-0.058	-0.049
[College]	(0.063)	(0.065)	(0.074)	[-0.071,-0.046]	[-0.088,-0.005]
Some college	-0.502	-0.532	-0.564	-0.031	-0.032
[College]	(0.042)	(0.043)	(0.047)	[-0.038,-0.024]	[-0.059,-0.004]
Under 35	-0.143	-0.142	-0.314	0.001	-0.172
[Age 62+]	(0.086)	(0.089)	(0.095)	[-0.011,0.014]	[-0.221,-0.124]
Age 35-49	-0.081	-0.085	-0.217	-0.004	-0.133
[Age 62+]	(0.065)	(0.068)	(0.075)	[-0.017,0.010]	[-0.182,-0.088]
Age 50-61	-0.038	-0.037	-0.140	0.001	-0.103
[Age 62+]	(0.060)	(0.063)	(0.070)	[-0.010,0.013]	[-0.152,-0.056]
B. Inter-Industry Wage Differentials					
Weighted Std. Dev.	0.130	0.147	0.155	0.017	0.008
of Differentials	(0.019)	(0.021)	(0.022)	[0.011,0.021]	[0.002,0.013]
C. Log Wage Differentials					
90th - 50th percentile	0.963	1.001	1.011	0.038	0.009
	(0.047)	(0.047)	(0.050)	[0.001,0.054]	[-0.027,0.064]
50th - 10th percentile	0.701	0.740	0.759	0.039	0.019
	(0.040)	(0.040)	(0.040)	[0.013,0.075]	[-0.021,0.045]
90th - 10th percentile	1.664	1.741	1.769	0.077	0.028
	(0.054)	(0.053)	(0.054)	[0.041,0.103]	[-0.017,0.084]

Notes: Compensation in column (2) is calculated using parameter estimates from column 5 of Table 2. Compensation in column (3) is calculated using parameter estimates from a model jointly estimating valuations additively by gender, race, education and age. For each measure of compensation, including the wage, we estimate separate regressions of log compensation on indicator variables for age, gender, race and education, and industry (aggregated into "supersectors"), and calculate the differences between the 90th, 50th, and 10th percentiles. Standard errors in parentheses, and 95% confidence intervals in brackets, obtained by block bootstrap (500 iterations). N=1,738 for panels A and C; N=1,528 for panel B. See text for details.