# Overtime Premiums, Labor Supply, and the Social Value of Occupations*

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## Abstract

This paper proposes nonpecuniary reasons for salaried employees to work overtime. I observe that occupations in which the wage premium for long working hours is relatively small tend to be associated with high levels of job satisfaction. I find that the social value of an occupation, for example the degree to which jobs involve helping or providing service to others, is inversely related to overtime pay: workers in helping occupations are less likely to be directly compensated for weekly hours above 40. Furthermore, women are more strongly drawn to such occupations and willing to give up more in terms of overtime compensation without reducing their hours in exchange for higher occupational social value.

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# 1 Introduction

While standard labor supply models describe well the incentives and tradeoffs faced by hourly employees under the one and one-half overtime premium mandated by the Fair Labor Standards Act (FLSA), the choice of weekly hours for salaried workers involves a less explicit objective function and still constitutes a puzzle for labor economists. Unpaid overtime is driven by career concerns in the literature on rat race equilibria in the labor market (Landers, Rebitzer and Taylor 1996, Bell and Freeman 2001). Implicit wage-hour contracts, non-divisible tasks, or uncertainty about completion times may also account for salaried employees' longer working hours.

This paper aims to further our understanding of the labor supply choices of salaried employees by focusing on uncompensated overtime in jobs with pro-social characteristics. In the framework of this study, occupations differ in their social value, measured by the tendency of jobs to involve providing help or service to others. Examples of occupations that score high along this dimension include therapists, nurses and social workers. On the labor supply side, workers differ in the degree to which they value their job's helping orientation. I explore the possibility that gender differences in attitudes towards pro-social behavior can explain some of the observed gender differences in overtime compensation and sorting into occupations.

The assumption that the disutility of working hours is decreasing in the nonpecuniary value that an individual obtains from working in a particular job, assumed to be heterogeneous across workers, plays central role in the theory developed in Section 2. The theoretical model yields three testable predictions that are supported by the data. First, the average occupation overtime premium is decreasing in the occupation's nonmonetary social value. Second, workers self-select into jobs based on the occupation's pro-social characteristics and their individual valuation of such characteristics. Third, there exists an inverse relationship between job satisfaction and overtime premiums when the job's nonpecuniary attributes are ignored. Data from the 2000 Census and 2000–2012 American Community Surveys are used to calculate average occupation-level overtime premiums for men and women. Occupational pro-social characteristics are inferred from the Occupational Information Network (O*NET) database. The job satisfaction hypothesis is tested using the 1979 cohort of the National Longitudinal Survey of Youth.

There are few previous studies that focus on nonmonetary incentives – the consumption value of one's job – for salaried employees to donate labor. Gregg, Grout, Ratcliffe, Smith and Windmeijer (2011) use data from the British Household Panel Survey to show that workers in non-profit caring industries (health, education and social care) are more likely to report unpaid overtime. Carpenter and Myers (2010) show that their experimental measure of altruism is positively correlated with the labor supply of volunteer fire fighters. In Fehrler and Kosfeld's (2014) experimental study some, but not all participants, are motivated by pro-social behavior to exert a level of effort that exceeds what is optimal for a purely self-interested agent.

The self-selection mechanism in my paper is in line with Filer's (1986) early work, where he finds a link between occupational choice and preferences for job characteristics such as prestige or contribution of one's job to society. In their theoretical work, Besley and Ghatak (2005) present a model in which worker intrinsic motivation and incentive pay are substitutes in eliciting effort. Proposed applications are nonprofit organizations, education providers and public administration. In Brekke and Nyborg's (2010) model, workers differ in their preference for being important to others, and this desire can elicit effort in occupations, such as nursing, in which it is hard or impossible to reward effort monetarily. Heyes (2005) and Taylor (2007) develop models, relevant for markets in which effort is not contractible and applied to the labor market for nurses, in which lower pay can attract higher-quality workers, who are more dedicated to the job and regard is as a "vocation." The models suggest that such workers are underpaid from a social efficiency perspective in monopsony markets. The literature on intrinsic versus monetary motivation is further discussed in detail in Rebitzer and Taylor (2011).

My results are consistent with the hypothesis that women place more weight on their occupation's orientation towards providing help and service to others. Women tend to be better represented in occupations that score high on this social value measure, but at the same time, earn relatively lower overtime premiums compared to men in the same occupations. This result is in agreement with a strand of the literature, reviewed in Bertrand (2011), that finds women to be more socially-minded than men. Furthermore, women tend to act in a more socially-oriented manner in laboratory experiments (Eckel and Grossman 2008) and are more likely to favor public good and public health spending (Aidt and Dallal 2008, Miller 2008). There is little empirical evidence of gender differences in workers' preferences for pro-social job characteristics, but to the extent that it exists, it is also consistent with the theory and empirical findings presented in this paper. Grove, Hussey and Jetter (2011) show that among GMAT registrants, women are more likely to attribute very high importance to their job contributing to society (19 compared to 11 percent), and such preferences are associated with lower salary. Including the variable in a wage regression reduces the gender earnings gap. Fortin (2008) shows similar trends using the NLS72 and the NELS88 and a preference index based in part on the attributed importance in selecting a career of "Opportunities to be helpful to others or useful to society." In the survey of postsecondary graduates used by Chevalier (2007), men are slightly more likely to say that "status and respect" are very important job characteristics, while women attribute much more importance to the job being "socially useful."

In the next section I present a theoretical model that yields several testable predictions for the relationship between the size of the overtime premium, the occupation's social value (or another positive occupational characteristic), and labor supply. The rest of the paper describes the three data sets used in the empirical analysis and the estimation results.

## 2 Theory

It is assumed that worker utility in a given occupation is characterized by two idiosyncratic parameters: $b$, which measures the disutility of labor, and $\gamma$, which corresponds to the nonpecuniary value that an individual obtains from working in a particular job. While the disutility parameter $b$ is individual-specific and does not vary across jobs, $\gamma$ reflects both worker preferences and occupational characteristics. The labor disutility parameter $b$ is drawn from a known distribution $F(b)$.

Worker $i$'s utility in job $j$ is given by:

$$U(h_{ij}, w_j, \gamma_{ij}, b_i) = \begin{cases} w_j h_{ij} - \frac{b_i h_{ij}^2}{\gamma_{ij}} & \text{if} \quad h_{ij} \leq 40 \\ 40w_j + (h_{ij} - 40)w_j(1 + p_j) - \frac{b_i h_{ij}^2}{\gamma_{ij}} & \text{if} \quad h_{ij} > 40 \end{cases}$$

where $w_j$ is the hourly wage, assumed to be an exogenous job-specific parameter, $h_{ij}$ is hours worked, and $0 \leq p_j \leq 1$ is the occupation's overtime premium.[1] It is assumed that the premium is paid once weekly hours exceed 40, which is the conventional definition of overtime.[2]

When $\frac{w\gamma}{2b} \geq 40$, individuals choose to work overtime and supply

$$h_o^* = \frac{w(1+p)\gamma}{2b}$$

hours. When $\frac{w\gamma}{2b} < 40$, workers may still supply the overtime hours from above, as long as the utility of doing so is higher than the utility of 40 or fewer hours:

$$\frac{w^2(1+p)^2\gamma}{4b} - 40wp \geq \frac{w^2\gamma}{4b},$$

which implies that we will observe overtime when

$$\frac{w\gamma(2+p)}{4b} \geq 40. \tag{1}$$

If the worker chooses alternative employment (occupation), she receives reservation utility equal to $\overline{U}$. Workers will choose the outside employment option when

$$\max\left\{\frac{w^2\gamma}{4b}, \frac{w^2(1+p)^2\gamma}{4b} - 40wp\right\} < \overline{U}. \tag{2}$$

[1] Indices are dropped in the rest of the exposition.

[2] The exact number of standard hours likely differs slightly across occupations, similarly to how the number of hours that defines full-time employment is found to vary somewhat by gender and sector in Hotchkiss (1991).

Conditional on $\gamma = \gamma^*$, where $\gamma^*$ is some fixed value, employers set $p$ such that the fraction of workers with $\gamma = \gamma^*$ who put in overtime is equal to $m$, a target level that depends on the firm's production function.[3] In the empirical analysis, I implicitly assume that within a given occupation, $\gamma$ takes on one of two values, depending on the worker's gender. It follows from (1) that

$$m = F\left(\frac{w\gamma(2+p)}{160}\right). \tag{3}$$

Proposition 1: The observed overtime premium $p^*$ is decreasing in $\gamma$.

This follows from (3): keeping $m$ fixed,

$$\frac{w\gamma(2+p)}{160} = A,$$

where $A$ is a constant that depends on the specific functional form for $F(b)$. Then

$$p^* = \frac{160A}{w\gamma} - 2$$

and

$$\frac{\partial p^*}{\partial \gamma} = -\frac{160A}{w\gamma^2} < 0.$$

Proposition 2: The probability of selecting the alternative employment option associated with utility $\overline{U}$ is decreasing in $\gamma$.

[3] I also assume that the baseline wage $w$ does not vary with $\gamma$, which may not be realistic in the presence of compensating wage differentials. There is some evidence in the data that wages for workers whose weekly hours are between 35 and 40 vary inversely with the occupation's social value, but it is unclear whether this can be attributed to compensating differentials or other factors.

*Proof*: The left-hand side of (2) is increasing in $\gamma$ since when $h^* \leq 40$,

$$\frac{\partial U}{\partial \gamma} = \frac{w^2}{4b} > 0.$$

When $h^* > 40$,

$$\frac{\partial U}{\partial \gamma} + \frac{\partial U}{\partial p^*}\frac{\partial p^*}{\partial \gamma} = \frac{w^2(1+p)^2}{4b} + \left(\frac{2w^2(1+p)\gamma}{4b} - 40w\right)\left(-\frac{160A}{w\gamma^2}\right).$$

The expression above simplifies to

$$\frac{\partial U}{\partial \gamma} + \frac{\partial U}{\partial p^*}\frac{\partial p^*}{\partial \gamma} = \frac{w^2(1+p)}{4b}(1-p) + \frac{40wp}{\gamma} > 0.$$

This implies that when $\gamma$ takes on one of two values in the population, $\gamma_1 > \gamma_2$, there will be a higher concentration of workers with $\gamma = \gamma_1$ in the non-alternative occupation.

Proposition 3: Worker utility is decreasing in the overtime premium $p^*$ if the parameter $\gamma$ is not held constant.

All else equal, worker utility is increasing in the overtime premium. However, if $\gamma$ is not held constant, lower premiums correspond to higher values of $\gamma$ and thus higher utility. Overall, the net effect is negative correlation between utility (measured empirically by job satisfaction) and $p^*$.

Propositions 1–3 are tested empirically in Section 5, but first I describe the data in Section 3 and the methodology for calculating average occupational premiums in Section 4.

# 3 Data

## 3.1 Census and American Community Survey

Occupational overtime premiums are calculated using data from the 5 percent sample of the 2000 Census and the 2000–2012 American Community Surveys provided in the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. 2010). The main advantage of these data sets is the large sample size, which allows me to derive occupation-specific measures using reliable cell sizes. I restrict the time period to exclude pre-2000 Census data because of the possibility of differential time trends in occupational premiums; survey year indicators are included in the estimation to control for overall differences in average wages.

The estimation sample is comprised of all employed workers between the ages of 18 and 65 who report usual weekly hours higher than 35 and who worked at least 48 weeks during the year preceding the interview. Individuals in the armed forces and those who are self-employed are excluded from the data. Weekly and hourly earnings are inferred from reported labor income and the indicated pay period. Dollar amounts are converted to 2000 values using the Consumer Price Index. Workers are dropped from the sample if their inflation-adjusted hourly earnings are less than $2 or more than $120.

Other information used in the empirical work includes the respondent's age, marital status, race and Hispanic origin. I use the educational attainment variable to construct a set of indicators for highest level of completed schooling: grade 8, grade 12 but lacking a high school diploma, high school diploma (including GED), some college but no Bachelor's degree, completed Bachelor's degree, and any graduate degree.

The IPUMS data provide several constructed measures of occupational characteristics. I use the Nakao-Treas prestige score, which is based on data from the 1989 General Social Survey (GSS) and is linked to the 1990 Census occupational classification. These scores are derived from GSS respondents' ratings of the "social standing" of various occupations, with a higher score corresponding to higher social standing. Occupational prestige scores do not vary over time. The other occupation-level variable I use in the analysis is an education score that corresponds to the occupation-specific percentage of individuals among those in the labor force aged 16 and over and employed for at least part the previous year who had completed one or more years of college. The education score is also linked to the 1990 Census codes. The values for each occupation are year-specific. For more information about these measures, see Ruggles et al. (2010).

All occupation codes are converted, if necessary, to the 2010 SOC system for compatibility with the O*NET data, described below; see Appendix B for more details about the conversion procedure. Occupation-gender cells with fewer than 1000 observations are excluded from the analysis. The final sample consists of 6,839,543 male and 5,338,230 female workers in, respectively, 415 and 306 occupations.

## 3.2 O*NET Database

Occupational characteristics are inferred from the Department of Labor/Employment and Training Administration's O*NET database. I use the information provided on worker characteristics and worker, experience and occupational requirements. I combine measures provided in the data to generate three occupational characteristics. A natural way to combine several measures is to use principal component analysis, but the results from it (available upon request) suggest that each component should enter with approximately the same weight, so for the sake of simplicity, I average the scores for each factor.

The first occupational characteristic that I consider in the empirical analysis is the *Helping* score of an occupation. This measure combines the "Assisting and caring for others" work activity score, the "Social" occupational interest score, the occupation's "Service orientation" skill requirement, the "Concern for others" work style, and the "Relationships" work value[4]. The average score is calculated by rescaling each measure first since the "Social" and "Relationships"

[4] The Social interest definition includes "These occupations often involve helping or providing service to others." The Service Orientation requirement is defined as "Actively looking for ways to help people." The description of the Relationships value states, "Occupations that satisfy this work value allow employees to provide service to others and work with co-workers in a friendly non-competitive environment. Corresponding needs are Co-workers, Moral Values and Social Service." The other two measures are fairly self-explanatory.

scores are measured on a 7-point scale, while all others are measured on a 5-point scale.

The second composite occupational characteristic used in the analysis is the occupation's *Analytical* score. It is comprised of the following: "Deductive reasoning," "Inductive reasoning," and "Mathematical ability" among the available ability measures; "Mathematics" knowledge score; "Mathematics" and "Complex problem solving" skill scores; "Analytical thinking" work style score; and the score on the "Investigative" occupational interest. Where applicable, the importance rather than the level scale is used, but the difference between the two is not substantial. All but the "Investigative" score are measured on a 5-point scale, while the latter is measured on a 7-point scale. This difference is accounted for in the calculation of the average analytical value. I include this measure because a preliminary examination of occupational premiums reveals that premiums appear to be consistently lower in many areas that would rank high on the analytical scale. For this reason, I also separately use the indicators provided in the O*NET data for whether an occupation requires education in the STEM fields, with a particular focus on Engineering and Science.

Lastly, I incorporate as a comparison a measure of a likely undesirable occupational characteristic, namely how repetitive the job tends to be. This measure combines the "Degree of automation" and "Importance of repeating same tasks" work context scores, along with the "Conventional" interest score. All constructed occupational characteristics are standardized to have a mean of 0 and standard deviation of 1 among all occupations.

The data for most occupations include a job zone number based on how much education, experience and training are necessary to work in the occupation. The scores range from 1 (little or no preparation needed) to 5 (extensive preparation needed). All occupations in job zones 1 and 2 are excluded from the analysis because workers in these occupations are more likely to be paid an hourly rate and be subject to the legally mandated overtime premium. The job zone score is missing for 13 occupations in the data, which are also dropped. For male workers, there are 237 occupations in the final data with job scores of 3, 4 or 5; the corresponding number of occupations for female workers is 198. I show descriptive statistics by average overtime premium in Section 4.1, after I describe the procedure for constructing the premiums.

Table 1 shows the correlation coefficients among the occupational characteristics I consider, including the prestige and education scores from the Census/ACS data. Three correlation coefficients exceed 0.5 in absolute value: between the analytical and prestige scores (0.571) and analytical and education scores (0.574), as well as the prestige and education scores (0.752). The analytical score also has a relatively high correlation with the indicators for engineering and science knowledge. The helping score is moderately negatively correlated with the analytical and repetitive scores and the indicators for required engineering and science knowledge. Finally, Table 2 shows the ten occupations in the data with the highest helping scores. Five of these occupations are in the health care sector (SOC codes between 29-1000 and 29-2090). The other five include guidance and vocation counselors, clergy, psychologists, social workers, and special education teachers.

### 3.3 NLSY79

To explore the relationship between occupation overtime premiums and job satisfaction I use data from the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79). The NLSY79 sample size is much smaller than the Census/ACS data, so most occupation cells are not populated enough to conduct a systematic analysis of occupation premiums, but the NLSY79 has several advantages that can be exploited once occupation-level variables are derived from other data sets. In particular, each installment of the survey asks about employed respondents' levels of job satisfaction. In addition, individual heterogeneity can be differenced out due to the panel nature of the data.

Information on average overtime premiums for males and females, the standard deviation of wages within an occupation, prestige and education scores, and the O*NET characteristics described in Section 3.2 is merged to the NLSY79 data after the NLSY79 occupation codes are converted to the 2010 SOC system (see Appendix B). Observations for which the individual is in an occupation in job zones 1 or 2 are dropped, as are those observations for which the gender-occupation cell has fewer than 1000 observations in the Census/ACS data. Only observations for which the respondent is older than 19 and reports being employed in the government, private or non-profit sectors and working more than 30 hours per week are used in the estimation. I drop 176 respondents who have fewer than eight years of education.

Each installment of the survey asks respondents to rate their job satisfaction on a four-point scale. The job satisfaction measure used in the empirical analysis is a binary variable equal to 1 if the highest satisfaction category was selected, and 0 otherwise. Other variables that I use include gender, education, race, actual experience and tenure. The final sample consists of 25,557 observations for 3,986 men and 28,908 observations for 4,266 women.

# 4 Overtime Premiums and Occupational Characteristics

## 4.1 Calculation of Overtime Premiums and Descriptive Evidence

Without overtime pay, observed weekly earnings are given by $y = h_s w$, where $w$ is the hourly wage, and $h_s$ denotes standard hours. In this paper $h_s$ is assumed to equal 40. If the overtime premium is $p$ and an individual works $h_o$ overtime hours beyond the standard 40, observed weekly earnings are $y = h_s w + h_o(1 + p)w$. To estimate $p$ empirically from observed weekly earnings $y$ and hours $h$, I first use the sample of workers in the 2000 Census and 2000–2012 ACS whose hours are between 35 and 40 to estimate separately by gender:

$$\log w_{ijt} = w_{0j} + X'_{it}\beta + \nu_t + e_{ijt},$$

where $i$ denotes worker, $j$ stands for occupation, and $t$ is year (2000–2012). The variables in $X$ are age, age squared, a marriage indicator, indicators for nonwhite and Hispanic, the binary variables measuring educational attainment, and indicators for whether the worker is in the private for-profit sector and whether she is currently attending school. Observations are weighted using the personal weights in the IPUMS data.

Next, for workers who report usual hours higher than 40, I construct the predicted wage

$$\hat{w}_{ijt} = \exp\{\hat{w}_{0j} + X_{it}'\hat{\beta} + \hat{\nu}_t\}\exp\{\hat{\sigma}^2/2\}$$

using the sample standard deviation of the regression residuals $\hat{\sigma}$. Then the estimated premium for worker $i$ is

$$1 + \hat{p}_{ijt} = \frac{y_{ijt} - 40\hat{w}_{ijt}}{(h_{ijt} - 40)\hat{w}_{ijt}}.$$

Premiums are then averaged for each occupation separately for men and women:

$$\bar{p}_j = \frac{1}{n_j^o}\sum_i \hat{p}_{ijt} \tag{4}$$

given $n_j^o$ workers in occupation $j$ who work more than 40 hours per week. It is assumed that occupation premiums did not change during the sample period, so the individual estimates of $p_{ijt}$ are averaged across all years. This approach conditions on observable characteristics when estimating the baseline wage $\hat{w}$, but it assumes that overtime and non-overtime workers have the same earning potential and choose to work overtime for exogenous reasons. An alternative would be to model selection into the standard hours or overtime group as a first-stage function that depends on observables.

I rank occupations separately by gender in terms of the estimated average premium. Table 3 shows the resulting percentile that a few selected groups of occupations fall in. Along with that, the table also displays the average weekly hours reported by male and female workers. While only a small fraction of the data are shown in the table, these occupations are chosen as examples of the types of jobs that tend to be associated with low overtime premiums. It is also evident from the table that average hours in these occupations are not strikingly high or low.

Engineers comprise the first group of occupations in Table 3. The table shows four engineering occupations, all of whose premiums are below the ninth percentile for men and the 21st percentile for women, but all engineering occupations (SOC codes in the 17-2000 group) have premiums below the median for men, and all but one's premiums are lower than the median for women. To account for the concentration of engineering occupations among those with low premiums, the empirical specifications will include indicators for the occupation requiring education in two of the STEM fields: Engineering and Science, as well as the constructed analytical score.[5]

The next three occupations that are grouped together in Table 3 are fire fighters, police patrol officers and airline pilots. These occupations also pay relatively low premiums for overtime, but average hours are fairly high, particularly for fire fighters and pilots. These occupations are generally regarded as providing a social service, but also considered to be risky.[6] Further, Table 3 shows that workers in other social service occupations, such as psychologists, social workers, guidance counselors, and clergy, also earn low overtime premiums. Average hours for the first three of these occupations are slightly lower than the sample average, while for the latter occupation they tend to be fairly high (50 for males and 48 for females).

Elementary, middle and secondary school, including special education, teachers earn particularly low premiums (all below the third percentile) but put in hours close to the sample average. Education administrators' premiums are slightly higher (31st percentile for men and 49th percentile for women) but still below the median, and average hours in this occupation are fairly high. Low premiums ($25^{\text{th}}$ percentile or lower) are also observed among all therapist occupations in the sample (SOC group 29-1120), and this is a group for which average hours are slightly lower than the sample average. Nursing occupations and veterinarians also earn low premiums, with veterinarians' weekly hours being fairly high (50 for men and 47 for women). Interestingly, the premium for registered nurses, the majority of whom are female, ranks much lower for female workers (seventh percentile) than for male workers (30th percentile).

Consistent with Proposition 1 in Section 2, all of the top ten occupations in terms of their

[5] With a few exceptions, occupations in the life and physical sciences also tend to pay low premiums.

[6] According to the 2013 Census of Fatal Occupational Injuries, the hours-adjusted fatal injury rate for fire fighters was 8.2 per 100,000 full-time equivalent workers, the one for police officers was 10.6, and for aircraft pilots and flight engineers: 50.6 (the specific data for airline pilots are not reported). The aggregate fatal injury rate for all civilian wage and salary workers was 2.7 in 2013. (http://stats.bls.gov/iif/oshwc/cfoi/cfoi_rates_2013hb.pdf accessed October 17, 2014)

O*NET helping score, as shown in Table 2, pay relatively low overtime premiums, as shown in Table 3. Table 4, which is reprinted from Smith (2007), shows the ten occupations with the highest job satisfaction scores in the 1972–2006 waves of the GSS. There is considerable overlap between Tables 4 and 3. In line with Proposition 3 of the theoretical model, along with having relatively low overtime premiums, four occupations (clergy, physical therapists, psychologists and special education teachers) rank very highly in both helping score and job satisfaction. Tables 2, 3 and 4 provide preliminary descriptive evidence that overtime premiums, the social value of occupations, and job satisfaction are closely related, which is in line with the main theoretical assumption that utility increases in the social value parameter $\gamma$. The next section offers a more systematic investigation of these relationships.

# 5 Empirical Results

## 5.1 Occupational Characteristics and Overtime Premiums

Descriptive characteristics for several occupation-level variables of interest are shown in Table 5. The aggregated occupation-level sample is split by gender, and within gender, it is also divided based on whether the estimated overtime premium is above or below the 25th percentile. The table shows that for males, average weekly hours, the fraction of workers who put in between 35 and 40 hours, and the fraction of workers who report hours equal to or greater than 55 do not differ by premium category. For both groups average hours are about 45, and close to 60 percent of employees work regular hours while eleven to fourteen percent report hours greater than 54. Among women, average hours are slightly higher in occupations that rank among the top 75 percent on overtime premium: 43 compared to 42.3 hours. The difference stems from fewer females reporting between 35 and 40 hours and more women working 55 hours or more in these occupations. Furthermore, Table 5 shows that the prestige and education scores from the IPUMS data are both significantly higher in low-premium occupations. Comparing the unconditional standard deviation in wages, it appears that higher-premium occupations may be more competitive, since wages in these jobs are more dispersed. Median wages for workers who put in between 35 and 40 hours are \$2 to \$3 higher in low-premium occupations, which may reflect compensating wage differentials, a tradeoff between regular and overtime wages similar to the one for employees covered by the FLSA as demonstrated in Trejo (1991), measurement error, or a combination of factors.

The last five rows in Table 5 compare occupational characteristics from O*NET for the high- and low-premium occupations in the data. The difference in the helping score for men is about 0.1 standard deviation and is not statistically significant, but in the sample of women the helping score is about two thirds of a standard deviation higher in low-premium occupations. Low-premium jobs also tend to be characterized by higher analytical scores, particularly for men, and lower scores on the undesirable characteristic, repetitiveness. As observed to some degree in Table 3, low-premium occupations, especially among male workers, are concentrated in fields requiring engineering education.

The unconditional relationships observed in the descriptive statistics from Table 5 are investigated in more detail by estimating a regression of average premiums on the group of occupational characteristics.[7] The coefficients are presented in Table 6.[8] The model in column 1 includes only the O*NET characteristics. The model in column 2 also controls for the occupation's prestige score, and the education score is further included in column 3. Consistent with the descriptive statistics shown in the previous section, premiums tend to be lower in "helping" jobs with the relationship being stronger for women. For men the estimated coefficient is significant at the 10 percent level in columns 1 and 3 but not in column 2, while for women the difference in premiums between helping and non-helping occupations is always different from zero and greater than it is for men. In some specifications the gender difference is only significant at the ten percent level,

[7]Some other occupational characteristics based on O*NET data are considered in Appendix A. Because of high multicollinearity in a regression model, I show simple correlation coefficients between average premiums and the characteristics.

[8]The models also include job zone dummies, which are assumed to not differ by gender.

but for women the difference from zero is always highly significant.

For men, premiums are lower in more analytical occupations and in occupations deemed to be more prestigious. Men are more likely to be compensated for less desirable working conditions such as repetitiveness of the job. Occupations that require engineering education pay lower premiums particularly for men. The fraction of workers in an occupation who have completed some college is positively correlated with the overtime premium for men, but the coefficient for women is essentially zero.

Finally, the model presented in column 4 excludes occupations in the health care sector with SOC codes between 29-1000 and 29-2090. This restriction is made as a robustness check because Table 3 suggests that many health-related occupations pay low overtime premiums – the bottom nine rows of Table 3 fall in this group – while five of the ten occupations in Table 2 with very high helping score are also in the health care sector. Since the negative relationship between helping scores and overtime premiums appears to be very strong for this group, it is important to check whether all or most of the results are driven by the health care sector. Column 4 in Table 6 suggests that this is not the case. While the relationship between the occupation's social service component and its overtime premium is attenuated somewhat for both genders, it remains negative and statistically significant for women. Other coefficients do not change much in this specification. It could be inferred that while the negative relationship between overtime pay and the job's social value is particularly strong in the health services sector, it affects women in other fields as well. The results in Table 6 justify the theoretical assumptions made in Section 2 that a job's pro-social value is utility-increasing for women but less so for men.

As a robustness check, Table 7 shows that the gender difference in the correlation between helping scores and overtime premiums does not differ by job zone. The table shows that the coefficients are similarly negative in all three job zones considered in the analysis for women, while for men the variation is more pronounced, with the strongest negative relationship recorded in job zone 4 and least negative relationship in job zone 5.

## 5.2 Labor Supply Results

I next examine the relationship between occupation characteristics, premiums, and labor supply. The results in Table 8 are from regressions of occupation-level labor supply on the O*NET characteristics, as well as the education and prestige scores. The regressions also include job zone dummies and control for the standard deviation of hourly wages for employees in the occupation who report hours greater than 40. The latter is intended to capture the incentive to compete with other workers by supplying more labor in occupations in which wages are more dispersed and thus the reward for career advancement is greater.[9] The dependent variable in column 1 of Table 8 is the average hours in an occupation; in column 2 it is the fraction of workers whose reported hours are between 35 and 40; the dependent variable in column 3 is the fraction of workers whose weekly hours exceed 54.

The results suggest that conditional on occupational characteristics, hours are higher in lower-premium occupations, especially for males. This relationship could in part be due to reporting errors in hours worked. Keeping overtime premiums constant, workers in more "helping" occupations tend to work longer hours. At the same time, workers in occupations that score high on the repetitiveness measure put in fewer hours, keeping premiums constant. Hours in science, engineering and analytical occupations do not differ from the sample average. Hours in more prestigious occupations tend to be higher, but the opposite is true in fields with more college-educated employees. Similarly to the finings in Bell and Freeman (2001), hours are higher in occupations with more dispersed wages.

## 5.3 Within-Occupation Gender Differences

The results presented so far have shown some evidence that occupations with large concentration of female workers, such as registered nurses or psychologists, often pay higher overtime premiums to men (see for example Table 3), and these occupations also score high on the helping measure.

[9]Bell and Freeman (2001) offer an in-depth analysis of the relationship between occupation wage dispersion and labor supply.

At the same time, occupations with lower helping scores and higher concentrations of male workers, such as some engineering jobs, tend to rank higher in terms of overtime premiums for the underrepresented gender, women in this case. This is consistent with the idea that women extract more utility from supplying labor in jobs with higher social value, and are thus more likely to choose these occupations (Proposition 2 in Section 2), but require less in compensation for working longer hours (Proposition 1).

Figure 1a plots the ratio of estimated premiums for female and male workers against the share of females in an occupation, based on the Census and ACS data. The sample consists of 167 occupations that have at least 1000 observations for both males and females and excludes 9 occupations for which the ratio of the female-to-male premium is over 3 or less than 0 because these are very influential outliers given the small sample size. A negative fairly linear relationship can be inferred from Figure 1a: the larger the share of female workers in an occupation, the lower the relative premiums tend to be for female workers. Furthermore, Figure 1b shows a positive relationship between an occupation's helping score and the share of female workers in that occupation.

To investigate the relationship in more detail, I estimate a regression model in which the ratio of an occupation's female to male premium is modeled as a function of occupational characteristics. Only the O*NET variables are used in the specification in column 1,[10] and the helping score has a negative and highly significant relationship with the gender ratio of premiums. This result suggests that women earn lower overtime premiums relative to men in occupations with higher social value. Of the other O*NET variables, only the measure of repetitiveness is statistically significant at the 10 percent level, suggesting that men are compensated more for overtime in more repetitive jobs.

The negative coefficient on the helping score is robust to controlling for the prestige and education scores, although it decreases slightly in absolute value. Education scores are positively correlated with relative female premiums. The results in column 3 suggest that the ratio of

[10]In addition, all models include job zone indicators.

average hours worked by females in a given occupation to the average hours reported by male workers in that occupation is uncorrelated with the premium ratio or with occupational characteristics. The coefficient on the hours ratio is not statistically different from zero, and including this variable does not affect any of the other coefficients.

Finally, the model in column 4 of Table 9 includes the share of females in an occupation. As Figure 1 suggests, this variable is positively correlated with the occupation's social value and negatively correlated with the premium ratio. Consistent with the plot in Figure 1a, the coefficient on the share of females is negative and highly significant: men earn higher overtime premiums in occupations in which women are overrepresented. Controlling for the gender ratio also drives down the absolute values of the estimated coefficients on the helping score and education index. The results support Propositions 1 and 2 when the parameter $\gamma$ measures the job's tendency to provide help or service to others and when women have higher values of $\gamma$.

### 5.4 Job Satisfaction

Finally, NLSY79 data allow me to explore the relationship between occupation premiums and job satisfaction. Proposition 3 from the model in Section 2 states that without conditioning on the job's nonpecuniary value $\gamma$, we should observe a negative relationship between overtime premiums and job satisfaction. Tables 3 and 4 are consistent with this hypothesis, but here I offer a more systematic analysis. The model also implies that when $\gamma$ is fully accounted for, we should expect to see job satisfaction increasing with the premium. While empirically it is not feasible to fully control for the utility-shifting job characteristics represented by $\gamma$, I present results with and without the occupational characteristics discussed earlier in this section, in particular the occupation's social value as measured by the helping score. The results would be consistent with the model when the relationship between job satisfaction and the overtime premium becomes less negative with the inclusion of the additional characteristics, particularly for women since it was shown that the helping score is a better predictor of women's rather than men's nonpecuniary job benefits.

Table 10 shows results from a linear probability model in which the dependent variable is an indicator for the highest level of job satisfaction. The top panel in the table presents results for males in the NLSY79 sample, while the results in the bottom panel are for women. All models control for the occupation premium estimated from the Census/ACS data, as well as education, actual experience and experience squared, tenure and tenure squared, race, job zone and survey year indicators, and the standard deviation of wages for workers in the occupation who report overtime hours. The latter is intended to measure the occupation's competitiveness, since some workers may derive positive or negative utility from jobs with a steeper wage profile. The job zone and wage dispersion variables are based on the Census/ACS data. The specifications in columns 2 and 4 of Table 10 also include the O*NET occupational characteristics and the prestige and education scores, since some of these factors were found to be correlated with overtime premiums, and the helping score is designed to be a measure of the parameter $\gamma$ from Section 2. Furthermore, the models in columns 3 and 4 include worker-level fixed effects.

The results for men suggest that there is indeed a strong negative relationship between overtime premiums and job satisfaction. The estimated relationship is attenuated when individual fixed effects are included but remains negative and statistically significant. Including the helping score and other occupational characteristics decreases the absolute value of the coefficient on the overtime premium only slightly, especially in the fixed effects model. The helping score coefficient is positive and significant in column 2, but once the fixed effects are included in column 4, the coefficient is statistically indistinguishable from zero. Interestingly, job satisfaction conditional on the overtime premium is lower in engineering occupations.[11] It appears that engineering and science occupations tend to be associated with low overtime premiums and lower than average job satisfaction, so it is likely that some other characteristics that is not included in the analysis here may be driving the relationship. Conditional on an individual's level of education, men tend to experience higher job satisfaction in occupations in which other workers are more highly

[11]The relationship is slightly weaker but still present when the premium is not included in the model; these results are available on request.

educated. Overall, the regression $R$-squared suggests that job satisfaction is idiosyncratic and very little of it is explained by the independent variables other than the fixed effects.

The results for women are consistent with the model in Section 2 when the helping score acts as an imperfect measure of $\gamma$. The coefficient on the overtime premium is negative and highly significant in column 1, but drops by about two thirds in absolute value when the additional occupational characteristics are included in column 2. The coefficient on the helping score is positive and highly significant. The only other characteristics that are correlated with job satisfaction in this model are the occupation's repetitiveness score and the indicator for science-related education required for the job; both are negatively correlated with job satisfaction. Once fixed effects are included, the relationship between overtime premiums and job satisfaction is attenuated, similarly to the case for men. The inclusion of occupational characteristics has a more pronounced attenuation effect and causes the coefficient on overtime premiums to drop in absolute value and lose statistical significance. The coefficient on the helping score remains positive and significant at the 1 percent level, although smaller in absolute value compared to column 2. All of the other characteristics have coefficients close to zero in the fixed effects specification.

# 6 Conclusion

When wages in the labor market are competitive but occupations differ in nonpecuniary utility-enhancing characteristics such as the job's social value, it is possible that employers can incentivize workers to supply the optimal amount of labor by setting higher overtime wage premiums in jobs with low social value. A composite measure of the occupation's tendency to provide service and help to others, derived from the O*NET database, is used in this paper as a measure of pro-social characteristics. Occupation-specific overtime premiums are calculated empirically from the large samples of workers available in the 2000 Census and 2000–2012 American Community Surveys.

The results suggest that women derive higher utility than men from their job's social value, as measured by the propensity to help others, as women are disproportionately found in heling occupations and earn lower overtime premiums in these jobs. Men tend to earn lower overtime premiums in jobs deemed more prestigious, so it is possible that how prestigious a job is seen to be by outsiders also enters the utility function. Conditioning on occupational characteristics, workers tend to supply fewer hours in occupations with higher overtime premiums, but more hours in jobs that have higher social value or are more prestigious. Using NLSY79 data, a negative relationship is found for both genders between the occupation's overtime premium and job satisfaction.

The findings are consistent with the idea that the social value of jobs can affect labor supply. The results contribute to our understanding of the labor supply choices of salaried workers. Few previous studies, (e.g. Gregg et al. 2011) have explored the idea that workers in certain occupations may be more likely to donate labor, and there has not been much discussion of the economic significance of such tendencies. The question of how employers make decisions based on the occupation's social value remains to be examined in future work.

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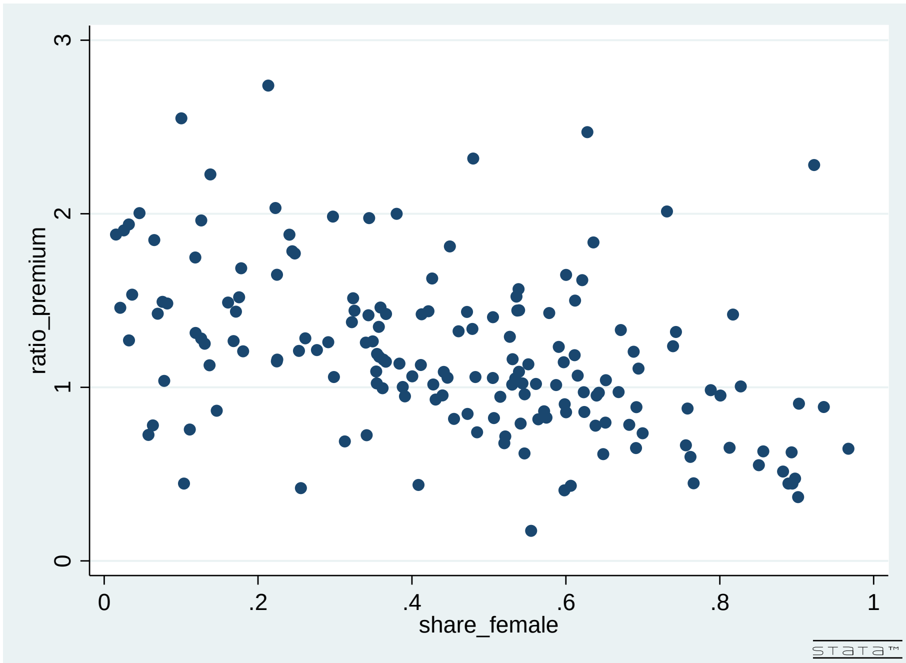
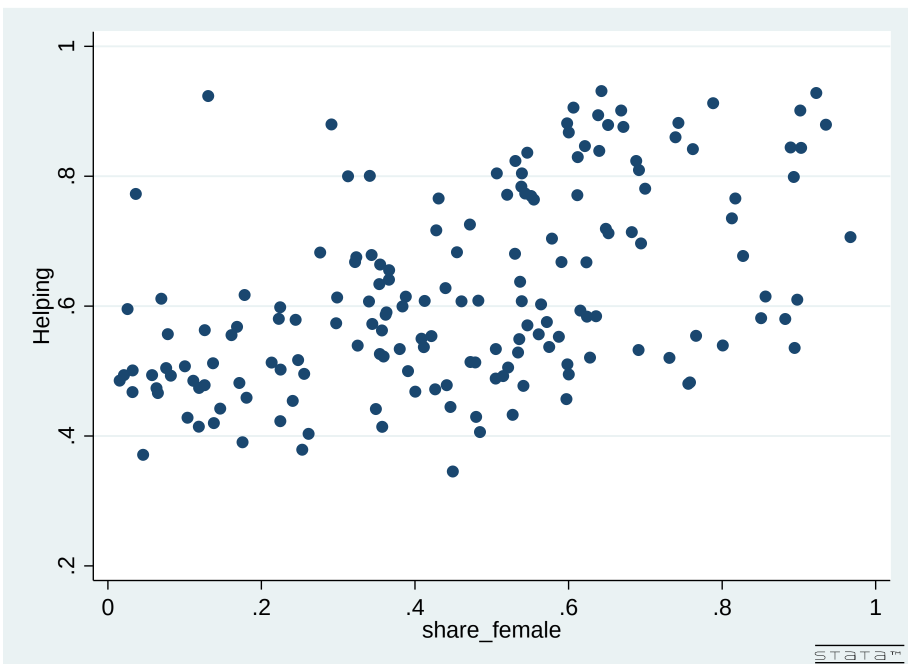
(a) Relative Overtime Premium




(b) Helping Score




The figures are based on a sample of 167 occupations. The $Y$ axis in panel (a) plots the ratio of the average overtime premium for females and the average overtime premium for males in a given occupation. The $Y$ axis in panel (b) shows the occupation's helping score. The $X$ axis in both diagrams plots the fraction of female workers in an occupation.

Figure 1: Correlates of Occupational Gender Ratios

Table 1: Occupational Characteristics Correlation Matrix

| | Helping | Analytical | Repetitive | Eng | Sci | Prestige | Educ |
|---|---|---|---|---|---|---|---|
| Mean | .191 | .524 | .023 | .106 | .110 | 51.6 | 70.4 |
| Helping | 1 | | | | | | |
| Analytical | -.241 | 1 | | | | | |
| Repetitive | -.227 | -.0277 | 1 | | | | |
| STEM Engineering | -.28 | .382 | -.112 | 1 | | | |
| STEM Science | -.135 | .368 | -.122 | .124 | 1 | | |
| Prestige score | .0923 | .571 | -.129 | .175 | .126 | 1 | |
| Education score | .215 | .574 | -.0715 | .139 | .151 | .752 | 1 |

Data for 255 occupations.

Table 2: Occupations with Highest Helping Score

| | |
|---|---|
| 1 | Recreational Therapists |
| 2 | Physical Therapists |
| 3 | Educational, Guidance, School, and Vocational Counselors |
| 4 | Licensed Practical and Vocational Nurses |
| 5 | Clergy |
| 6 | Child, Family, and School Social Workers |
| 7 | Clinical, Counseling, and School Psychologists |
| 8 | Registered Nurses |
| 9 | Occupational Therapists |
| 10 | Special Education Teachers, Secondary School |

Table 3: Selected Low-Premium Occupations

| Occupation | Male Workers Pctile | Male Workers Avg Hours | Female Workers Pctile | Female Workers Avg Hours |
|---|---|---|---|---|
| Aerospace Engineers | 5.8 | 44 | 8.5 | 43 |
| Mechanical Engineers | 8.5 | 45 | 4.9 | 44 |
| Marine Engineers | 2.4 | 47 | - | - |
| Industrial Engineers, Including Health and Safety | 4.4 | 45 | 20 | 44 |
| | | | | |
| Firefighters | 26 | 54 | 36 | 52 |
| Police Patrol Officers | 4.1 | 44 | 9.8 | 43 |
| Airline Pilots, Copilots, and Flight Engineers | 25 | 49 | - | - |
| | | | | |
| Clinical, Counseling, and School Psychologists | 24 | 44 | 6.2 | 43 |
| Child, Family, and School Social Workers | 5.1 | 42 | 3.3 | 41 |
| Educational, Guidance, School, and Vocational Counselors | 21 | 43 | 20 | 42 |
| Clergy | 16 | 50 | 19 | 48 |
| | | | | |
| Education Administrators | 31 | 48 | 49 | 45 |
| Elementary and Middle School Teachers | .49 | 45 | .98 | 43 |
| Secondary School Teachers | .73 | 46 | .66 | 44 |
| Special Education Teachers, Secondary School | 2.6 | 43 | 8.1 | 42 |
| | | | | |
| Occupational Therapists | - | - | 3 | 41 |
| Physical Therapists | 21 | 44 | 16 | 42 |
| Recreational Therapists | - | - | 4.6 | 41 |
| Respiratory Therapists | 3.4 | 42 | 2.3 | 40 |
| Speech-Language Pathologists | - | - | .33 | 41 |
| Therapists, All Other | 2.2 | 43 | 4.3 | 42 |
| | | | | |
| Registered Nurses | 30 | 43 | 6.6 | 42 |
| Licensed Practical and Vocational Nurses | 5.6 | 43 | 7.2 | 42 |
| Veterinarians | 1.2 | 50 | 1.6 | 47 |

Only occupations with at least 1000 observations over the sample period are shown; empty cells indicate that there were fewer than 1000 observations for that gender. Occupation rankings are gender-specific.

Table 4: Top Occupations in Job Satisfaction (General Social Survey 1972-2006)

| | |
|---|---|
| 1 | Clergy |
| 2 | Physical Therapists |
| 3 | Firefighters |
| 4 | Education Administrators |
| 5 | Painter, Sculptors, Related |
| 6 | Teachers |
| 7 | Authors |
| 8 | Psychologists |
| 9 | Special Education Teachers |
| 10 | Operating Engineers |

Source: Smith (2007).

Table 5: Summary Statistics

| | Male | | | Female | | |
|---|---|---|---|---|---|---|
| Variable | High prem | Low prem | t-stat | High prem | Low prem | t-stat |
| Avg hours | 45.1 | 44.5 | 1.66 | 43 | 42.3 | 2.29* |
| Pct hours 35-40 | .569 | .602 | -1.62 | .69 | .736 | -2.23* |
| Pct hours 55+ | .135 | .113 | 1.82 | .077 | .059 | 1.87 |
| Prestige score | 50.2 | 56.3 | -3.54*** | 51.3 | 56.9 | -2.98** |
| Education score | 67.8 | 76 | -2.56* | 71.1 | 82.6 | -3.77*** |
| Med wage (35-40 hours) | 20.1 | 23 | -2.97** | 16.6 | 18.6 | -2.24* |
| Med wage (40+ hours) | 19.9 | 20 | -0.17 | 16.7 | 16.7 | -0.00 |
| SD of wage (35-40 hours) | 11.6 | 10.1 | 2.86** | 9.28 | 7.91 | 2.96** |
| SD of wage (40+ hours) | 13.8 | 10.2 | 4.65*** | 10.9 | 7.76 | 5.00*** |
| | | | | | | |
| Helping | .075 | .191 | -0.77 | .24 | .893 | -3.76*** |
| Analytical | .438 | .916 | -3.82*** | .466 | .676 | -1.49 |
| Repetitive | .098 | -.199 | 2.17* | .209 | -.216 | 2.57* |
| STEM Engineering | .064 | .25 | -4.12*** | .062 | .157 | -2.10* |
| STEM Science | .087 | .172 | -1.85 | .096 | .118 | -0.44 |
| N | 172 | 64 | | 146 | 51 | |

* p<0.10, ** p<0.05, *** p<0.01. The helping, analytical and repetitive scores, as well and the engineering and science variables are from the O*NET database. All other statistics are based on the Census and ACS data. Only occupations-gender cells with 1000 or more workers are used in the estimation. High-premium occupations are those that rank among the highest 75 percent in terms of average overtime premium. Low-premium occupations are in the $25^{\text{th}}$ percentile or lower. The ranking is gender-specific.

Table 6: Occupation Premiums

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Helping | -0.060* | -0.049 | -0.079** | -0.042 |
| | (0.034) | (0.035) | (0.036) | (0.038) |
| Analytical | -0.097** | -0.057 | -0.098* | -0.073 |
| | (0.049) | (0.056) | (0.058) | (0.052) |
| Repetitive | 0.099*** | 0.097*** | 0.086** | 0.106*** |
| | (0.036) | (0.036) | (0.036) | (0.038) |
| STEM Engineering | -0.374*** | -0.372*** | -0.368*** | -0.387*** |
| | (0.115) | (0.115) | (0.114) | (0.116) |
| STEM Science | -0.153 | -0.171 | -0.178 | -0.172 |
| | (0.112) | (0.111) | (0.111) | (0.113) |
| Female | 0.101 | 0.148 | 0.235 | 0.112* |
| | (0.064) | (0.252) | (0.257) | (0.065) |
| Helping × Female | -0.117** | -0.117** | -0.088* | -0.097* |
| | (0.051) | (0.052) | (0.053) | (0.058) |
| Analytical × Female | 0.041 | 0.049 | 0.103 | 0.050 |
| | (0.064) | (0.079) | (0.082) | (0.070) |
| Repetitive × Female | -0.087* | -0.088* | -0.082 | -0.108** |
| | (0.052) | (0.052) | (0.052) | (0.055) |
| STEM Engineering × Female | -0.189 | -0.174 | -0.182 | -0.202 |
| | (0.184) | (0.184) | (0.183) | (0.187) |
| STEM Science × Female | 0.051 | 0.042 | 0.041 | 0.017 |
| | (0.170) | (0.170) | (0.169) | (0.175) |
| Prestige score | | -0.006* | -0.013*** | |
| | | (0.004) | (0.004) | |
| Prestige score × Female | | -0.001 | 0.006 | |
| | | (0.005) | (0.006) | |
| Education score | | | 0.007** | |
| | | | (0.003) | |
| Education score × Female | | | -0.007* | |
| | | | (0.004) | |
| R-squared | 0.131 | 0.139 | 0.149 | 0.127 |
| N | 433 | 433 | 433 | 395 |

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. The dependent variable is the gender-specific occupation overtime premium. The results in column 4 exclude occupations in the health care sector with SOC codes between 29-1000 and 29-2090. The specifications include job zone indicators.

Table 7: Occupation Premiums by Job Zone

| | | |
|---|---|---|
| Helping × | Male × Job zone 3 | -0.066 |
| | | (0.050) |
| | Male × Job zone 4 | -0.123** |
| | | (0.061) |
| | Male × Job zone 5 | -0.056 |
| | | (0.070) |
| | Female × Job zone 3 | -0.164*** |
| | | (0.054) |
| | Female × Job zone 4 | -0.174*** |
| | | (0.062) |
| | Female × Job zone 5 | -0.171** |
| | | (0.068) |
| | N | 433 |

* p<0.10, ** p<0.05, *** p<0.01. The dependent variable is the gender-specific occupation overtime premium. The specifications include the full set of controls from Table 6.

Table 8: Occupation Premiums and Labor Supply

| | (1) $\overline{H}$ | (2) % $35-40$ | (3) % 55+ |
|---|---|---|---|
| Female | -2.559** | 0.170*** | -0.059* |
| | (1.015) | (0.057) | (0.032) |
| Premium | -0.870** | 0.036* | -0.030** |
| | (0.374) | (0.021) | (0.012) |
| Helping | 0.542*** | -0.016** | 0.024*** |
| | (0.134) | (0.008) | (0.004) |
| Analytical | 0.391* | -0.020 | 0.009 |
| | (0.217) | (0.012) | (0.007) |
| Repetitive | -0.686*** | 0.038*** | -0.022*** |
| | (0.135) | (0.008) | (0.004) |
| STEM Engineering | 0.005 | -0.017 | -0.005 |
| | (0.423) | (0.024) | (0.013) |
| STEM Science | 0.071 | 0.003 | 0.006 |
| | (0.405) | (0.023) | (0.013) |
| Prestige score | 0.038** | -0.002* | 0.001** |
| | (0.016) | (0.001) | (0.001) |
| Education score | -0.068*** | 0.003*** | -0.002*** |
| | (0.010) | (0.001) | (0.000) |
| SD of wage (40+ hours) | 0.359*** | -0.019*** | 0.012*** |
| | (0.041) | (0.002) | (0.001) |
| Premium × Female | 0.416 | -0.035 | 0.011 |
| | (0.541) | (0.030) | (0.017) |
| Helping × Female | -0.199 | -0.001 | -0.010* |
| | (0.200) | (0.011) | (0.006) |
| Analytical × Female | -0.217 | 0.009 | -0.008 |
| | (0.309) | (0.017) | (0.010) |
| Repetitive × Female | 0.135 | -0.003 | 0.006 |
| | (0.191) | (0.011) | (0.006) |
| STEM Engineering × Female | -0.007 | -0.014 | -0.005 |
| | (0.685) | (0.038) | (0.021) |
| STEM Science × Female | 0.107 | -0.015 | -0.001 |
| | (0.616) | (0.034) | (0.019) |
| Prestige score × Female | 0.017 | -0.001 | 0.000 |
| | (0.024) | (0.001) | (0.001) |
| Education score × Female | 0.009 | -0.000 | 0.001 |
| | (0.015) | (0.001) | (0.000) |
| SD of wage (40+ hours) × Female | -0.000 | -0.000 | -0.001 |
| | (0.069) | (0.004) | (0.002) |
| R-squared | 0.499 | 0.542 | 0.491 |
| N | 433 | 433 | 433 |

* p<0.10, ** p<0.05, *** p<0.01. The specifications include job zone indicators.

Table 9: Relative Overtime Premiums for Male and Female Workers

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Helping | -0.121*** | -0.092** | -0.091** | -0.033 |
| | (0.041) | (0.042) | (0.042) | (0.046) |
| Analytical | 0.012 | 0.042 | 0.043 | 0.009 |
| | (0.064) | (0.070) | (0.071) | (0.070) |
| Repetitive | -0.084* | -0.075* | -0.075* | -0.017 |
| | (0.044) | (0.043) | (0.044) | (0.048) |
| STEM Engineering | -0.132 | -0.141 | -0.143 | -0.225 |
| | (0.157) | (0.154) | (0.156) | (0.155) |
| STEM Science | 0.162 | 0.173 | 0.173 | 0.164 |
| | (0.137) | (0.135) | (0.136) | (0.133) |
| Prestige score | | 0.008 | 0.008 | 0.003 |
| | | (0.005) | (0.005) | (0.006) |
| Education score | | -0.010*** | -0.010*** | -0.006 |
| | | (0.004) | (0.004) | (0.004) |
| Female/male avg hours | | | 0.167 | 0.912 |
| | | | (2.126) | (2.099) |
| Share Female | | | | -0.604*** |
| | | | | (0.218) |
| R-squared | 0.053 | 0.087 | 0.081 | 0.118 |
| N | 167 | 167 | 167 | 167 |

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. The dependent variable equals the average overtime premium for females divided by the average overtime premium for males in a give occupation. The specifications include job zone indicators.

Table 10: Overtime Premiums and Job Satisfaction: NLSY79 Results

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | Males | | |
| Premium | -0.080*** | -0.057*** | -0.048*** | -0.044*** |
| | (0.011) | (0.014) | (0.014) | (0.017) |
| Helping | | 0.167*** | | 0.041 |
| | | (0.035) | | (0.046) |
| Analytical | | -0.178** | | -0.014 |
| | | (0.078) | | (0.097) |
| Repetitive | | -0.291*** | | -0.035 |
| | | (0.040) | | (0.048) |
| STEM Engineering | | -0.023** | | -0.024** |
| | | (0.010) | | (0.011) |
| STEM Science | | -0.024* | | -0.030* |
| | | (0.014) | | (0.017) |
| Prestige score | | -0.001 | | -0.000 |
| | | (0.001) | | (0.001) |
| Education score | | 0.002*** | | 0.001*** |
| | | (0.000) | | (0.000) |
| Fixed effects | No | No | Yes | Yes |
| Adj. R-squared | 0.013 | 0.021 | 0.298 | 0.298 |
| N | 25,557 | 25,557 | 25,557 | 25,557 |
| | | Females | | |
| Premium | -0.052*** | -0.017** | -0.024*** | -0.014 |
| | (0.006) | (0.008) | (0.008) | (0.009) |
| Helping | | 0.212*** | | 0.141*** |
| | | (0.031) | | (0.040) |
| Analytical | | -0.075 | | -0.010 |
| | | (0.070) | | (0.086) |
| Repetitive | | -0.135*** | | -0.060 |
| | | (0.028) | | (0.037) |
| STEM Engineering | | -0.005 | | 0.000 |
| | | (0.022) | | (0.025) |
| STEM Science | | -0.061*** | | -0.003 |
| | | (0.019) | | (0.021) |
| Prestige score | | 0.001 | | -0.000 |
| | | (0.001) | | (0.001) |
| Education score | | -0.000 | | 0.001 |
| | | (0.001) | | (0.001) |
| Fixed effects | No | No | Yes | Yes |
| Adj. R-squared | 0.006 | 0.011 | 0.256 | 0.257 |
| N | 28,908 | 28,908 | 28,908 | 28,908 |

* p<0.10, ** p<0.05, *** p<0.01. The dependent variable equals 1 if very satisfied with job and 0 otherwise. Additional controls include actual experience and experience squared, tenure and tenure squared, job zone and survey year indicators, and the standard deviation of wages for workers in the occupation who report overtime hours (from the Census and ACS data). The models in columns 1 and 2 also control for education and race.

# A Other Occupational Characteristics

Table A.1: Coefficients of Correlation between Overtime Premium and Occupational Characteristics

| | (1)<br>Male | (2)<br>Female |
|---|---|---|
| Helping | -0.037 | -0.260* |
| Analytical | -0.176* | -0.062 |
| Repetitive | 0.219* | 0.172* |
| Achievement | -0.017 | 0.084 |
| Leadership | -0.048 | 0.046 |
| Teamwork | 0.012 | -0.123 |
| Creative | 0.011 | 0.022 |
| Competitive | 0.248* | 0.421* |
| Structured work | 0.282* | 0.236* |
| Time Pressure | 0.160* | 0.194* |
| Enterprising | 0.286* | 0.429* |
| STEM Engineering | -0.260* | -0.201* |
| STEM CompSci | -0.013 | 0.041 |
| STEM Math | 0.094 | 0.080 |
| STEM Science | -0.157* | -0.035 |
| Prestige score | -0.181* | -0.174* |
| Education score | -0.035 | -0.137 |

* $p<0.05$

*Achievement* – Achievement and Recognition work values and Acievement/Effort work style.
*Leadership* – "Developing Objectives and Strategies," "Coordinating the Work and Activities of Others," "Developing and Building Teams," "Guiding, Directing, and Motivating Subordinates" and "Coaching and Developing Others" activities; "Coordinate or Lead Others" work context; Monitoring, Social Perceptiveness, Coordination, Negotiation, Persuasion and Management of Personnel Resources skills; Leadership work style.
*Teamwork* – "Establishing and Maintaining Interpersonal Relationships" activity; "Contact with Others," "Work With Work Group or Team" work context; Coordination and Social Perceptiveness skills; Cooperation, Social Orientation and Adaptability/Flexibility work styles; Relationships work value.
*Creative* – Fluency of Ideas and Originality abilities; Thinking Creatively work activity; Innovation work style; Artistic interest.
*Competitive* – "Level of Competition" work context; *Structured work* – "Structured versus Unstructured Work" context; *Time pressure* – Time pressure work context; *Enterprising* - Enterprising work interest.

# B Occupational Crosswalks

I convert all occupation codes to the 2010 Standard Occupational Classification (SOC) system, which the O*NET data are based on. For some occupations the O*NET database assigns a more detailed code. For example, SOC code 11-3031 (Financial Managers) is divided into two subcategories, 11-3031.01 (Treasurers and Controllers) and 11-3031.02 (Financial Managers, Branch or Department). In these cases, I average the data values across all subcategories.

Occupations in the 2000 Census and 2000–2009 ACS are coded using the 1998 SOC system, while the 2010–2012 ACS data use the 2010 SOC system. Some occupation codes are combined in the public use data for confidentiality reasons. The conversion of 1998 SOC codes to the 2010 system is based on Ruggles et al. (2010). When multiple O*NET occupation codes match to one Census/ACS code, I assign the O*NET occupation with the highest employment level based on estimates from the May 2013 Occupational Employment Statistics program (Bureau of Labor Statistics, U.S. Department of Labor 2013).

Occupations in the 2002–2010 waves of the NLSY79 are coded using the 2000 Census codes, which are based in the 2000 SOC. I convert them to the SOC system used in the Census/ACS data according to the crosswalk provided by Ruggles et al. (2010) and then map these codes to the O*NET classification system using the method described above. Respondents' current or most recent job is coded using the 1980 Census system for the 1982–2000 waves of the survey. The 1980 codes are first converted to 1990 Census codes using the methodology in Autor, Levy and Murnane (2003), which involves only a small number of changes. The Census occupational classification system underwent a more major revision in the year 2000. The 1990 Census codes are converted to 2000 codes using the crosswalk in Scopp (2003). In the cases when a 1990 code corresponds to multiple 2000 codes, I match it to the 2000 code with the highest employment level. The 2000 Census codes are then mapped to the O*NET classification system using the approach outlined previously.