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Abstract

Economists and sociologists have proposed arguments for why there can exist wage penalties for work involving helping and caring for others, penalties borne disproportionately by women. Evidence on wage penalties is neither abundant nor compelling. We examine wage differentials associated with caring jobs using multiple years of Current Population Survey (CPS) earnings files matched to O*NET job descriptors that provide continuous measures of 'assisting and caring' and 'concern' for others across all occupations. This approach differs from prior studies that assume occupations either do or do not require a high level of caring. Cross-section and longitudinal analyses are used to examine wage differences associated with the level of caring, conditioned on worker, location, and job attributes. Wage level estimates suggest substantive caring penalties, particularly among men. Longitudinal estimates based on wage changes among job switchers indicate smaller wage penalties, our preferred estimate being a 2 percent wage penalty resulting from a one standard deviation increase in our caring index. We find little difference in caring wage gaps across the earnings distribution. Measuring mean levels of caring across the U.S. labor market over nearly thirty years, we find a steady upward trend, but overall changes are small and there is no evidence of convergence between women and men.

1. Introduction

Caring labor has been described as jobs in which workers "provide a face-to-face service that develops the human capabilities of the recipient" (England et al., 2002, p. 455).[1] Health, child, and elder care services, along with education, account for a substantial share of paid employment and personal consumption expenditures in the U.S. (Folbre 2008). It is widely believed that there exist wage penalties for caring work. Research in economics and sociology provides theoretical rationales for why caring penalties can exist.[2] Yet there are surprisingly few empirical analyses examining whether such wage penalties exist and, if so, the sources of these penalties.

The approach taken by economists and other social scientists – and in our study – is to examine whether wages for caring jobs are high or low relative to similarly skilled workers in otherwise similar jobs and locations. The term "caring penalty" is used to mean that among workers with similar skills in similar locations working in similar jobs (apart from caring), lower wages are found in jobs requiring higher levels of caring. In previous work, England et al. (2002) find overall wage penalties for caring labor in the U.S. They find that the type of care work matters, with nurses enjoying a significant wage premium and workers in most other caring occupations suffering penalties. Their study, as well as others in the literature, assumes a dichotomy in care work with occupations classified as either involving or not involving a high degree of care.

The question of whether there exist significant wage penalties for caring work is important for several reasons. Depending on the source, wage penalties for care work might be viewed as an equity problem if the incidence of such penalties disproportionately affects women (or other groups). And penalties might be viewed as a social and economic problem if low wages in the care sector create higher than optimal turnover and low quality care in socially valuable jobs (England et al., 2002). Moreover, a finding of sizable wage gaps among truly similar workers in similar jobs (apart from the degree of caring) can raise the question of whether labor market outcomes deviate substantially from what is predicted by standard theory, depending on the source of these differentials.

Our paper provides evidence intended to enhance knowledge about wage differences associated with caring. In what follows, we first discuss how standard theory might account for wage

[1] England et al. refer to "human capabilities" as "health, skills, or proclivities that are useful to oneself or others." "Caring labor" refers to jobs (occupations) that require caring tasks. The literature attempts to estimate wage differences among jobs that involve high and low levels of caring tasks. This is not necessarily the same thing as wage differences between workers who do and do not have caring attitudes and behaviors. Labor market sorting no doubt results in caring persons working disproportionately in jobs with caring tasks.
[2] Works include England and Folbre (1999), Folbre and Nelson (2000), England (2005) and Folbre (2006, 2008, 2012).

penalties for caring work. We then provide detailed empirical analysis on how wages differ across workers and jobs with respect to caring attributes. To do so, we match employee data from Current Population Survey (CPS) earnings files with detailed occupational job descriptors, including multiple measures of caring, from the 2007 Occupational Information Network (O*NET). Cross section analysis is conducted using large CPS data files for 2006-2008. Longitudinal analysis is conducted using large CPS panels for worker-year-pairs from 2003/4 to 2008/9, with each pair consisting of two-observations per worker, one year apart. The panel analysis identifies differentials for caring work based on wage changes among job switchers who increase or decrease the required levels of caring in their jobs. As compared to prior literature, our analysis provides more recent evidence, uses large cross-sectional and panel samples of workers, provides multiple continuous (rather than categorical) measures of caring (and other) job attributes, and examines wage differentials associated with these measures in a comprehensive fashion.

2. Theoretical Rationales

There is a literature in sociology and economics in which researchers propose theories that might explain wage penalties for care work.[3] The mechanisms emphasized by sociologists, while not necessarily described using an economic framework, are largely compatible with economic theory once framed in language familiar to economists. In the remainder of this section, we use standard theory to discuss how systematic wage differentials for caring work may arise in the labor market.

The most obvious explanation for wage differentials associated with caring work is the theory of compensating differentials, whose sterling pedigree (i.e., Adam Smith's *Wealth of Nations*) is unrivaled. Some individuals will derive greater utility from work characterized by a high degree of caring for and helping others than from work that is not. And these workers may be disproportionately female. If such preferences are sufficiently widespread so that they are relevant at the margin (i.e., where labor supply and demand intersect) and not inframarginal, theory suggests that jobs involving high levels of caring will bear a wage penalty compared to jobs with otherwise similar working conditions and skills.

Compensating differentials are illustrated in Figure 1, which shows labor demand and supply for an occupation that involves a high level of caring. To illustrate our point, we show a diagram in which workers are equivalent except that one group prefers work in a caring job, while other workers are indifferent to (or dislike) caring tasks. The lower portion of the supply curve S_L represents occupation labor supply for the first group of workers, whose reservation wage is W_1. The upper portion of S_L

[3] See England and Folbre (1999); England et al. (2002); England (2005); and Barron and West (2013).

represents labor supply for the second group, whose reservation wage is W_2. In this simple case, if labor demand in the occupation is relatively low at D_1, we will see an equilibrium with wage W_1 and employment L_1, the latter including only workers who prefer caring jobs. At a high level of demand D_2, the equilibrium wage is W_2, a higher wage for both groups of workers. The more general case is that there is a continuum of preferences among workers leading to an upward sloping S_L.[4] The lower the level of demand, the lower the wage and thus "penalties" (negative compensating differentials) exist for caring work. At high levels of demand, "penalties" should decrease and eventually disappear with sufficiently high demand. If demand is high and workers at the margin dislike caring work, then we should see a wage "premium" (positive compensating differentials).

Researchers have referred to this "preference" argument as the "intrinsic rewards" or "prisoner of love" explanation (England and Folbre, 1999, and England, 2005, respectively). Economists are inclined to treat preferences as more or less freely chosen and deserving to be respected in markets. The concern is that selection into caring jobs may not fully reflect free choice, being seen instead as an obligation driven by societal expectations (hence the "prisoner of love" label).

"Devaluation" is a prevalent theory for a caring wage penalty emerging from sociology. It makes the assumption that society values whatever is produced by women less than what is produced by men; hence, caring labor pays less because women disproportionately work in caring jobs (England et al., 2002). A devaluation explanation can be reconciled with standard micro theory to the extent that devaluation means that individuals, in their roles as consumers, employers, voters, etc. have a lower willingness to pay for services typically provided by women. Combining lower labor demand with upward sloping long-run labor supply curves due to heterogeneous skill and job preferences can then produce wage differences between women and men and caring versus non-caring work.[5]

Independent of women's preferences for caring work, if there exists substantial employer-based discrimination against women in higher-paying non-caring jobs, women may be "crowded" into caring sectors, lowering equilibrium wages in caring jobs and denying women opportunities to accumulate human capital outside that sector. This characterization of the U.S. labor market may nicely fit the first three-quarters of the twentieth century, but over the last 40 years or so it has become less accurate.[6]

[4] In labor textbooks (e.g., Borjas, 2013, p. 213), the relationship between wages and job attributes is typically shown as a hedonic wage function formed by the tangencies of workers' indifference curves and firms' isoprofit curves, an approach developed by Thaler and Rosen (1976).

[5] Although gender discrimination in the workplace is illegal, lower wages resulting from labor supply preferences and "devalued" work would not typically be illegal.

[6] Women were also crowded into many low-pay, low-caring clerical and factory jobs.

An additional argument in the literature is that caring labor is disproportionately concentrated in the public sector (Barron and West, 2013; Folbre 2012), an outcome that we will subsequently document. If the political process produces a relatively low willingness to pay for public services that most involve caring, then low wages can result. In our empirical work, we separately examine how wage outcomes vary with respect to caring in the private and public sectors.

Prior studies have identified reasons one might see lower wages in caring jobs. One can also identify channels that might produce higher wages in caring jobs, or at least mitigate penalties. As mentioned in our discussion of compensating differentials, if demand for caring jobs is sufficiently high such that the marginal worker receives disutility for caring tasks, then we should see positive rather than negative compensating differentials. Efficiency-wage theory and theories of reciprocity and gift exchange suggest that caring jobs might have high rather than low wages. Measuring and monitoring the quality of care services provided by an employee can be difficult for employers or customers (e.g., parents selecting child care), so high wages may arise to attract more-able workers, reduce shirking, lower turnover rates, and foster gift-exchange between employees and the employer/customer (Fehr and Gächter 2000; Borjas 2013, pp. 484-493). It seems plausible to us that such forces might well mitigate to some (unknown) degree negative wage effects resulting from worker labor supply (i.e., intrinsic rewards for care work) and demand-side devaluation of caring jobs.

A final consideration is whether we should expect different wage-caring gradients for women and men, given that each group's selection into caring jobs can differ. Women bear a disproportionate share of caring, assisting, and teaching others within households. The acquired skills, preferences, and societal norms that accompany such a household division of labor make it more likely that in the labor market women sort into jobs requiring similar or complementary skills to those provided in the home. If women (on average) are particularly adept at caring tasks, we may observe smaller wage penalties for caring work among women than among men (i.e., biased estimates due to unmeasured productivity). A related argument stems from recent work by Heckman (e.g., Heckman and Kautz 2012) regarding the importance of noncognitive skills (e.g., conscientiousness) on success in the labor market and elsewhere. If women (on average) have higher levels of "people" skills valued in jobs involving high levels of caring, these unmeasured person-specific skills should lead to higher wages and weaker estimates of caring wage penalties for women than for men using cross-sectional analysis. As discussed subsequently, panel estimates, wherein caring wage differentials are measured by wage changes among workers switching between high and low caring jobs, should account for these person fixed effects.[7]

3. Previous Evidence

There is a limited number of empirical studies providing in depth analysis of caring wage differentials. We summarize two studies that are most similar to our work in terms of the research question being addressed. England et al. (2002) analyze the relative pay of caring labor in the U.S. using individual longitudinal data from the NLSY79 for the years 1982-1993. Their sample consists of 10,670 respondents for whom they had at least two years of detailed employment data. Respondents were ages 16-23 in the initial year of their sample (1982) and 28-35 in the final year (1993).[8] The authors create an indicator variable designating caring occupations, these being primarily in health care or education, plus a handful of other occupations (childcare workers, librarians, counselors, social workers, clergy and other religious workers, and recreation and fitness workers). An advantage of their data set is that they are able to construct measures of previous part-time and full-time work experience, job tenure, and breaks in employment. Such measures are particularly important for cross-sectional analysis, but effectively fall out in longitudinal analysis (through worker fixed effects or wage change analysis), the method favored in their study and in our subsequent analysis. In order to control for occupational skill, they use factor analysis to create a measure of cognitive skills demanded by an occupation based on job descriptors in the *Dictionary of Occupational Titles*.[9] Their fixed-effects wage regression models, with dummies for individuals and years, identify the wage effect of caring based on individuals who switch between care and non-care occupations. They perform their analysis separately for men and women, finding significant wage penalties of 5% for women and 6% for men.

When England et al. (2002) disaggregate care work into seven types, they find large heterogeneity in the estimated wage gaps. Female childcare workers were found to face large penalties. Surprisingly, doctors were found to suffer substantive wage penalties (men: 17%; women: 10%) while the category containing nurses, therapists, and medical assistants, referred to as 'other medical',

[7] We do not explore the possible effect of monopsonistic labor markets, where a limited number of employers and little worker mobility across firms leads to lower wages. As discussed in Manning (2003) and Webber (2013), if women have relatively less job-to-job mobility than do men, their wages are likely to be lower. Although empirical tests of monopsony models might help explain lower wages for women than men they do not necessarily explain lower wages for caring than non-caring jobs, absent evidence that job-to-job mobility is lower in high caring than in low caring jobs.

[8] They restricted their sample to respondents who worked either part- or full-time for at least two years during the sample period (person-years with missing values or extremely low or high hourly earnings were also dropped).

[9] The DOT was the precursor to O*NET, the latter being used in our analysis to construct job attribute indices using factor analysis. While the DOT included a small number of job descriptors with a limited range of integer coding, O*NET contains several hundred job skill/task and working condition attributes, each providing non-categorical continuous ratings. O*NET is discussed subsequently in our data section.

enjoyed a wage premium (men: 4%; women: 8%). The result for doctors is counterintuitive, but likely arises from age-truncation in the sample, as noted by the authors (England, et al. 2002, p. 468). The result regarding nurses is consistent with subsequent nursing studies, although Hirsch and Schumacher (2012) show that such estimates overstate relative nursing wages.[10]

The data and analysis in England et al. (2002) have advantages and limitations as compared to our work. The principal advantage is the NLSY longitudinal structure and the detailed information available on individuals and households over time. That said, the NLSY79 sample period covered 1983-1992, so all workers were under age 36 and were observed early in their careers, as noted by the authors. Their period of analysis, roughly twenty years earlier than in our study, may not reflect the experience of more recent cohorts, with occupational shifts among women due to evolving social norms and increased educational attainment, or the substantial changes in overall labor market rewards to skill and the skill content of jobs. And our CPS panels provide relatively larger samples of occupation switchers than does the NLSY, having roughly 19 and 22 thousand unique worker job switchers for women and men, respectively.

In a recent study, Barron and West (2013) analyze wage differentials for caring work in the British labor market. They use 17 waves of the British Household Panel Survey covering the years 1991 to 2007, consisting of annual accounts of an individual's education, employment, and family characteristics. They estimate a regression model that includes individual random effects (not fixed effects) and year fixed effects. Similar to England et al. (2002), Barron and West disaggregate care work into six specific types (doctors, nurses, teachers, childcare, nursing assistant, and welfare) by using self-reported job descriptions matched to occupation codes. Their empirical work combines men and women (a male dummy is included), thus not allowing for different caring penalties (rewards) for women and men. Barron and West rely on a Heckman selection correction procedure to account for the attrition of low-wage workers from the labor force, but do not discuss what exclusion restriction (if any) was used or how their selection results compare with OLS, thus making interpretation difficult. The authors construct different comparison groups based on broad occupation (described as socioeconomic groups) for each group of care workers.

Barron and West obtain wage differential estimates indicating that doctors earn 33% more, nurses 10% more, and teachers 5% more than their peers in non-caring occupations, while nursing

[10] Hirsch and Schumacher (2012) show that nursing/non-nursing wage gaps shrink substantially once one: (a) controls for occupation skill requirements and working conditions and, (b) accounts for bias in estimating log (percentage) wage differentials with OLS when comparing treatment groups with low wage dispersion (nurses) to broad comparison groups with much higher dispersion (all college-educated women). See Blackburn (2007).

assistants earn 6% less, welfare workers 18% less, and childcare workers 21% less than their peers in non-caring occupations. Unlike England et al. (2002) and our subsequent analysis, Barron and West do not include measures of occupational skills, nor do they account for worker fixed effects. We suspect that their large caring wage gap estimates (negative and positive) may reflect substantial skill differences between their caring and non-caring occupations and workers. And, as the authors point out, important differences exist between the U.S. and U.K. labor markets, in particular, the U.K.'s nationalized health care and education systems in which wages are set by national negotiations (Barron and West, 2013).

4. Data Sources and Descriptive Evidence on Caring Jobs

The data sets used in our analysis are constructed from two principal sources, the Current Population Survey Outgoing Rotation Group (CPS-ORG) monthly earnings files, containing worker-level data, and the Occupational Information Network (O*NET), providing occupational descriptors that can be matched to the CPS.[11] A cross-sectional data set is created by pooling 36 monthly CPS-ORG files for January 2006 through December 2008, with 166,009 women and 168,760 men included in the estimation sample. Since the CPS includes households in the same month in two consecutive years, we are able to construct a large panel data set consisting of about forty-thousand worker-year pairs of occupation switchers from 2003/4 to 2008/9 of which 18,981 are women and 21,689 men.[12]

An occupational-level data set constructed from a 2007 edition of O*NET provides several hundred job attributes. Most O*NET variables provide ratings of the skills and various tasks required to perform the job or the environment of a worker in the job. We use 206 O*NET variables, most measured on scale indicating the level to which a descriptor is required or needed to perform the occupation. Most O*NET variables are measured on a scale from 0-to-7 or 1-to-5, with reported values being a continuous number based on ratings provided by job analysts based on site visits and reports from job

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[11] The CPS-ORG data is jointly sponsored by the U.S. Census Bureau and the Bureau of Labor Statistics (BLS) while O*NET is sponsored by the Department of Labor's Employment and Training Administration (USDOL/ETA).

[12] The time period for the panel was determined by there being time-consistent detailed Census occupation codes in the CPS for the years 2003-2009. For details on the methods used to match individuals across years in CPS earnings files, see the appendix in Macpherson and Hirsch (1995) and Madrian and Lefgren (2000). Matching is conducted with the goal of including only pairs matched with near certainty (using household and person identifiers and demographic checks), even if it means excluding valid pairs that do not satisfy all match criteria. In addition, we exclude all individual observations with imputed earnings in the pooled cross section analysis and all earnings pairs with either or both years imputed in the panel analysis. In the CPS-ORG files, earnings non-respondents are assigned the earnings of a "similar" donor based on broad but not detailed occupation. Hence, the estimates of coefficients on caring or other occupation-based variables will be attenuated (so-called "match bias") if imputed earners are included. See Bollinger and Hirsch (2006) for a detailed discussion of CPS imputation methods, resulting biases, and alternative corrections for such biases. Simply omitting imputed earners avoids imputation match bias and provides estimates highly similar to more complex correction methods.

incumbents.[13] We scale all O*NET measures from zero to one to provide a comparable scale.[14]

In line with prior literature, we regard care work as involving activities and requirements in jobs characterized by high levels of non-routine interactive job tasks that directly foster recipients' social, emotional, intellectual, and/or physical well-being. Typically, the delivery and quality of caring job skills/tasks depend on workers providing individualized services and establishing a personal relationship with the recipient.[15] Consequently, we identify two O*NET occupational attribute variables as most directly measuring the level of caring work: 'assisting & caring for others' (A&C) and 'concern for others'. We examine these O*NET caring measures separately and jointly, using factor analysis to construct a latent factor combining the two measures, which we refer to as the 'caring' index. Table 1 provides the definition for the O*NET caring and developing/teaching attributes described below.

The 'assisting & caring for others' variable is designed to measure *job requirements*. A&C is included in a category of O*NET attributes labeled 'communicating and interacting with others', which is one of the multiple categories under the broader category of 'generalized work activities', all part of the larger content category 'occupational requirements'. The 'concern for others' measure, on the other hand, falls under the broad content category '*worker characteristics'*, with a sub-heading of 'work styles' and the more narrow sub-heading 'interpersonal orientation'. The 'A&C' and 'concern' measures have a high degree of statistical overlap. That said, A&C is a job descriptor designed to measure the level of required caring work activity in an occupation, whereas 'concern' is designed as a worker descriptor that identifies personal characteristics needed for job performance and for a good occupational match.

In addition to the caring and concern measures, we construct a 'developing/teaching' or D/T factor index, which loads four O*NET descriptors: 'developing & building teams', 'training & teaching others', 'coaching & developing others', and 'instructing'. As was the case for the A&C measure, the four D/T descriptors describe required occupational work activities. The D/T measures are not intended to directly measure caring wage effects. Because prior studies typically designate teaching jobs as caring jobs, it is important that we separately examine the relationship between wages and D/T tasks as well as

[13] We use the O*NET data set previously used in Hirsch and Schumacher (2012). They provide a more detailed description of its construction and merger with the CPS, Section 4 of their paper provides discussion of the selection of variables used to construct the skill and working condition indices. Most O*NET descriptors are measured by both required level and importance. The two rankings are highly collinear; we use levels.
[14] In order to normalize ratings for attributes using a different scale, we follow an approach similar to the one used by the USDOL; namely score $S = \left(\frac{O-L}{H-L}\right)$, where *O* is the original rating score on the rating scale used, *H* is the highest possible score on the rating scale used, and L is the lowest possible score on the rating scale used.
[15] Our definition is similar to England et al. (2002), but also incorporates the concepts of "routine versus nonroutine" and "interactive" job tasks developed in Autor et al. (2003) in their analysis of information technology (IT) on employment and wages. Each of these studies uses DOT occupation job descriptors to classify jobs.

wages and caring tasks. The advantage of our approach is that all occupations are included, each with distinct measures of levels of caring and D/T, allowing us to estimate separate wage gradients with respect to each.

In addition to the job caring indices, we construct two broad factor indices, one reflecting occupation job skill and task requirements and a second reflecting job working conditions.[16] Our 'job skills index' includes 162 O*NET job skill/task variables and heavily loads cognitive skills. For example, heavily-loaded attributes include levels of critical thinking, judgment and decision making, monitoring, written expression, speaking, active listening, active learning, negotiation, and persuasion. A second factor index – a 'working conditions index' – is constructed by loading 38 O*NET variables measuring (mostly) physical working conditions. This index heavily loads attributes such as required types of strength, extreme temperatures, extremely bright or inadequate lighting, exposure to contaminants, cramped work space or awkward position, exposure to injuries, and exposure to hazardous equipment.

The skills index is a particularly important control variable in the wage analysis for two reasons. First, the job skills index is a strong correlate of wages and, second, caring jobs vary greatly in their required level of skill, some involving minimal training and low levels of cognitive skills, while others are among the most highly-skilled jobs in the economy. Caring jobs also vary with respect to working conditions, although these attributes have far weaker effects on wages than do skills. As recognized in the literature, it is difficult to identify compensable working conditions due to (a) heterogeneous preferences and sorting with respect to job attributes and (b) because job disamenities tend to be negatively correlated with unmeasured worker skills (Hwang, Reed, and Hubbard 1992).

The O*NET attributes and factor indices measuring occupation skills, working conditions, and the various measures of caring are matched by detailed occupation to both the 2006-2008 CPS cross-sections and the 2003/4-2008/9 CPS panel data sets. Table 2 provides the unweighted means and standard deviations for women and men for the O*NET measures and indices, plus the earnings measure used in the CPS, as described below.[17]

Our earnings measure is the natural log of average hourly earnings across all hours worked, with earnings inclusive of tips, overtime, and commissions, for individual worker *i*, in constant 2008 dollars. In our regression models (section 5), we include all non-student workers ages 18 to 65 with hourly wage values between three and one hundred fifty dollars. We exclude full-time students (reported for those

[16] Our approach in forming the O*NET skills and working condition indices follows Hirsch and Schumacher (2012). For further details on the O*NET to CPS match, see their paper.
[17] Differences between sample-weighted and unweighted descriptive statistics and regression analyses are trivial.

under age 25) and observations in which workers' earnings are not reported and instead imputed by Census, since workers' detailed occupation is not a hot deck match attribute used to assign donor earnings to non-respondents (Bollinger and Hirsch 2006, Table 1). The same sample exclusions are applied to the panel analysis covering 2003/4 – 2008/9, where the dependent variable is the one-year change in the log of average hourly earnings. Were imputed earners included, coefficient estimates regarding caring attributes in the wage level analysis would be attenuated, whereas panel estimates would be severely biased toward the cross-section results (see Bollinger and Hirsch 2006).[18]

Turning to Table 2, the raw gender gap is 0.19 log points (roughly 20%), with women's mean hourly earnings $4.38 less than that for men and somewhat less dispersed.[19] The other variables in Table 2 are occupation measures, with the means compiled across workers (i.e., equivalent to a sample-weighted mean across occupations). We use six 'caring' attributes from O*NET, measured in levels and each scaled between 0 and 1. The two attributes used to measure caring are 'assisting & caring for others' and 'concern for others'. Women have higher averages than do men for each, 0.46 versus 0.39 for the former and 0.78 versus 0.69 for the latter. Our 'caring' factor index that combines these two attributes has a substantially higher value for women than men, the difference exceeding a half standard deviation.

Table 2 also presents means for the four occupational measures emphasizing aspects of team development, training, coaching, and instructing. Here, women and men have highly similar levels for each. Even if these job attributes were associated with substantial differences in wages, this would produce minimal changes in the gender wage gap. We combine these four O*NET attributes into the factor index labeled 'developing/teaching' (D/T).

To get a feel for how various occupations are rated by O*NET with respect to 'assisting & caring for others' and 'concern for others', in Table 3 we provide ratings for selected occupations that have very high and low ratings, plus many of the larger occupations in the economy. What can be clearly seen in Table 3 is that many of the highest ranked occupations are health care jobs in which workers directly interact with individuals. Notable among the occupations ranked one-to-five in 'assisting & caring' (physician assistants, physicians and surgeons, LPN/LVNs, respiratory therapists, and registered nurses), are the substantial differences in required skills and pay. This reinforces our previous statement that in

[18] Inclusion of imputed earners does not correct for (possible) non-ignorable response bias, since included non-respondents are assigned the earnings of respondents. One can reweight the respondent sample by the inverse probability of response, which rebalances the sample based on measured attributes. But in practice IPW regression results are nearly identical to those using unweighted respondent samples. See Bollinger and Hirsch (2006, 2013).

[19] Throughout the paper we will treat log wage gaps as approximate percentage differentials, with the implicit wage base being in between the average for women and men (roughly the geometric mean).

order to measure wage differences associated with caring, it is essential to have good controls for individual worker skills and job skill requirements. Occupations requiring minimal levels of 'assisting & caring' include engineers, mathematicians, machinists, and sales representatives. Examining the rankings for 'concern for others' shows that there is a strong correlation with 'assisting & caring'' but that an occupation can be ranked high (or low) using one measure but not the other. The sales representatives occupation involves few 'assisting & caring' tasks, but 'concern for others' is a worker attribute that is helpful in performing a sales job. Ambulance drivers are ranked 8th highest in 'assisting & caring' but 71st in 'concern' for others.

A principal takeaway from Table 3 is that all jobs require tasks involving some degree of 'assisting & caring' and that adequate performance in all jobs requires that workers have some degree of 'concern' for others. Characterizing occupations as either caring or not provides a useful shorthand for discussion. But in order to statistically estimate the relationship between market wages and caring, it makes sense to examine multiple caring measures and explicitly account for the required levels of care for each. Rather than estimating wage differentials between jobs designated as caring or not, we estimate labor market wage gradients with respect to the degree of caring across all occupations.

Table 4 reports the simple pairwise correlations between earnings, gender, and the various O*NET job descriptors and indices. The O*NET descriptors 'assisting & caring for others' and 'concern for others' have a 0.71 correlation. The caring index combining these two caring measures is positively correlated with our comprehensive job skill index (0.39), negatively correlated with the index of physical working conditions (-0.21), positively but weakly correlated with the log wage (0.07), and strongly correlated with the share of women in an occupation (0.54). The developing/teaching index is positively correlated with wages and the caring measures, but largely uncorrelated with gender.

Figure 2 shows smoothed distributions of the indices for caring and developing/teaching across the labor market (absent smoothing one observes multiple "mini-peaks" at index values attached to large occupations). Recall that by construction, the means of the factor indices, constructed for women and men combined, have a zero mean and s.d. of 1.0. In Figure 2, the caring index distribution for women is everywhere to the right of the male distribution, demonstrating both higher and more dispersed levels of job caring than seen among men. By contrast, the D/T index, which combines the four pertinent O*NET measures, displays differences between women and men, but is not systematically higher for one group or the other. The left tails and peaks of the two distributions are similar, but beyond the peaks, men are more heavily represented in occupations requiring mid-to-high levels of D/T, while women are more heavily represented in occupations with the highest levels of D/T.

In order to use our 2007 version of O*NET, which is matched to the 2000 Census occupation codes (COC), to study measure trends in caring work over a long time period, it is necessary to approximate a time-consistent set of occupation codes. The 2000 COC codes, used in the CPS during 2003-2010, and the 1990 COC used in the CPS during 1992-2002, were converted back to 1980 COC codes using a probabilistic mapping provided by Census.[20] Beginning with the 2007 O*NET values matched to the 2000 COC codes for all wage and salary workers using the 2006-2008 CPS, we then recalculated each O*NET attribute value for the large 2006-2008 sample based on their 1980 COC codes. Once we had O*NET values based on the 1980 COC codes, we then calculated the means of our O*NET measures of caring and D/T for all wage and salary workers ages 16 and over from 1983 through 2010. We find no discontinuity in our series associated with occupational code breakpoints (1991 vs. 1992 and 2002 vs. 2003), thus enhancing our confidence in the series.

The matched CPS/O*NET data set allows us to examine changes in caring in the labor market over the 28 year period from 1983 to 2010. Note that the within-occupation O*NET ratings are not changing (they are fixed at 2007 values). Thus, the measured economy-wide changes in caring occur entirely from changes in the distribution of workers across occupations (all index values are employment weighted using CPS sample weights). Figure 3 shows the trends for the years 1983-2010 in the mean levels of 'assisting & caring for others' and 'concern for others' among both women and men. As evident in the figure, the levels of these caring tasks in the U.S. labor market has increased steadily over time for both women and men, but the overall change has been quite small and there is no evidence of a narrowing in the caring gap between women and men.

Similar descriptive data for 1983-2010 was also constructed for the four O*NET D/T attributes. In Figure 4, we show the means of each of these attributes for the years 1983 and 2010. In contrast to the evidence on caring, we find that the developing and teaching content of both women and men's jobs have increased over time, but substantially more so for women than men. By 2010, women's jobs involved slightly higher levels than did men's jobs of training and teaching, coaching and developing, and instructing others, and slightly lower levels of developing and building teams.

5. Measuring Wage Differentials for Caring Work: Methods

Our empirical approach is straightforward. We estimate standard Mincerian semilog earnings functions in which hourly earnings is a function of accumulated human capital (net of depreciation),

[20] We thank David Macpherson for providing programming code to convert 1990 and 2000 Census occupation codes back to 1980 codes. Note that the O*NET measures matched to 1980 COC codes are used exclusively for the historical series shown in Figures 3 and 4, but nowhere else in this paper.

proxied by time spent in schooling and the labor market. The human capital earnings function is augmented by inclusion of selected demographic controls, measures of location, and job attributes associated with wage differentials, including various measures of caring. We provide estimates from separate female and male earnings functions. This permits a straightforward way to examine how caring job attributes differently affect the wages of women and men, as emphasized in this literature. We provide estimates using panel as well as cross-section data, thus accounting for worker heterogeneity. And our large sample allows us to examine whether caring wage differentials differ across the private and public sectors, as well as among various worker characteristics.

To examine caring wage differentials across workers, we use the CPS/O*NET 2006-2008 sample and estimate wage level equations of the following form:

$$lnW_{iF} = \sum_{k=1}^{K}(\beta_{kF}X_{ikF}) + \gamma_F caring_{iF} + \varepsilon_{iF} \quad (1a)$$

$$lnW_{iM} = \sum_{k=1}^{K}(\beta_{kM}X_{ikM}) + \gamma_M caring_{iM} + \varepsilon_{iM} \quad (1b)$$

Here, subscripts *F* and *M* denote female and male, respectively; lnW_i is the natural log of hourly earnings for worker *i*; X_{ik} contains an intercept and *K*-1 independent variables measuring worker and job-related characteristics; β_k contains a constant and coefficients for covariates in *X*; $caring_i$ is the covariate(s) of interest measuring caring skills for each worker's detailed occupation; γ are the coefficients of interest measuring marginal wage effects of one standard deviation changes in the caring measures; and ε_i is an idiosyncratic error term. Estimates of γ_F and γ_M may be sensitive to the controls included in X_k, in particular measures of job skills and working conditions. And variants of equations (1a) and (1b) can be estimated within different sectors or for different groups of workers.

If employment in caring jobs is correlated with workers skills, motivation, etc. not reflected in measures of occupation skill requirements, wage level estimates may be biased. In order to account for worker heterogeneity, we use panel analysis, in this case longitudinal wage change equations that conform to the CPS sample structure. To examine wage differentials for caring among job switchers, we use our CPS/O*NET 2003/4–2008/9 panel sample, including only those workers who change occupations and, thus, have had changes in the O*NET caring measures.[21] We estimate the following wage change equations:

[21] More precisely, we include only those who have changed detailed occupation and industry in order to insure that we include mostly "true" job switchers. Worker descriptions of occupation are coded by Census employees and can be coded differently one year apart even when there has been no job change. Industry is reported with greater accuracy and restricting the sample to just those who report changes in occupation and industry insures a

$$\Delta lnW_{iF} = \sum_{k=1}^{K}(\beta_{kF}\Delta X_{ikF}) + \gamma_F \Delta caring_{iF} + \Delta\varepsilon_{iF} \quad (2a)$$

$$\Delta lnW_{iM} = \sum_{k=1}^{K}(\beta_{kM}\Delta X_{ikM}) + \gamma_M \Delta caring_{iM} + \Delta\varepsilon_{iM} \quad (2b)$$

where Δ denotes changes between year-pairs (i.e., 2004 minus 2003, etc.). Parameter estimates in equations (2a) and (2b) are based exclusively on occupation switchers and net out worker-specific fixed effects on wages. Two limitations in using the O*NET job skill/task measures warrant mention: (1) the O*NET values matched to each occupation are fixed over time, and (2) the value of each O*NET attribute does not vary across workers in a given occupation.[22] We are not concerned with the first issue – relative occupational differences in attributes change gradually and our analysis is for a relatively short time period. The measurement of job attributes at the occupation rather than individual worker level is a more serious concern. There is heterogeneity of job characteristics within detailed occupations and these may differ to some degree by gender as well as across individuals. It is not clear whether or to what extent measurement error in O*NET job attributes is mitigated in the panel analysis through differencing (i.e., where "two wrongs can make a right"). Because job attributes are at the occupation rather than individual level, we cluster standard errors by occupation in the wage level analysis and by occupation switching pairs in the longitudinal analysis.[23]

An important advantage of our CPS/O*NET data set is that we not only have continuous measures of caring intensity across all occupations, but also measures for a large array of detailed job tasks, skill requirements, and working conditions. Such data make it more likely that we can obtain relatively clean estimates of wage differentials associated with caring in the U.S. labor market. And because the analysis also is done using CPS longitudinal data, where we identify person-specific wage changes resulting from movement across years into or out of occupations with different levels of caring, we can account for bias due to worker heterogeneity correlated with caring.

We include additional independent variables to control for other important factors that may influence wages. When estimating wage level regression equations (1a and 1b), we use controls for

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high probability of true occupational change, thus avoiding attenuation of the caring coefficients. For a careful discussion of this approach, see Macpherson and Hirsch (1995).

[22] O*NET updates ratings for occupations on a rolling basis; it takes several years for all occupations to have revised ratings.

[23] Because there are such a large number of occupation-to-occupation combinations in the panel analysis, there are only trivial differences between non-clustered and clustered standard errors. An issue not addressed for the wage level analysis is that two observations exist for a sizable share of the workers, thus decreasing standard errors and slightly exaggerating significance levels. This is a standard issue when using full CPS samples for adjacent years. For those concerned, the typical approach is to cut the sample (roughly) in half using workers observed either in their first year (rotation group 4) or second year (rotation group 8). We know of no examples where results meaningfully differ between such samples.

potential experience (years since schooling completed or since age 16, whichever is less) in quartic form, dummies for gender, race, ethnicity, marital status, foreign-born, union, region (8 dummies for 9 regions), city size (6), year, broad industry (11), and broad occupation (9). Education dummies are included for the completed grades 9, 10, 11, and 12 (but no diploma), plus high school degree (including the GED), some college no degree, associate, bachelor, masters, professional, and doctorate degrees (those reporting 0-8 years are the omitted category). Dummies are also included for the public sector and the private-not-for-profit sector (private-for-profit being the reference group). Given that caring jobs are sometimes largely female jobs, we separately estimate wage equations including a sex composition variable to control for the ratio of the number of females to total workers in each occupation. Although this is not the focus of our study, we can observe the sensitivity of caring penalty estimates to the inclusion of gender composition (and vice-versa).

6. Caring Wage Differentials Using Wage Level Analysis

Table 5 provides wage level results for women and men, respectively, with different columns (specifications) including alternative measures or combinations of caring. Column 1 includes the single 'caring' index that loads the two O*NET descriptors measuring 'assisting & caring' and 'concern' for others. Column 2 includes the 'developing/teaching' index that loads the four relevant O*NET attributes; it excludes the caring index. Columns 3 includes both the 'caring' and 'D/T' factor indices. Column 4 regressions include the six separate O*NET measures (each normalized to zero mean and standard deviation of one) included in the caring and D/T indices, but we focus on (and show) only the O*NET measures 'assisting & caring' and 'concern' for others (coefficients on the other four are included in appendix Table A-1). Coefficients on the O*NET factor indices in columns 1-3 and normalized O*NET descriptors in column 4 can be interpreted as the partial effect of a one standard deviation change in the caring measure.

All specifications include a rich set of individual worker and location controls (see the text note) and, importantly, O*NET occupational skill and working condition indices. For reasons of space, we do not show coefficients for all our control variables. Tables in the appendix provide coefficients for most of the control variables not shown in Tables 5 and 7 (the wage level and wage change results, respectively). Table 6 is identical to Table 5, except that we omit the O*NET skill and working condition indices. Before turning to results with respect to the caring variables, we note that the skill (and to a lesser extent, working conditions) indices have large and highly significant coefficients and add 3-4 percentage points to the R^2 values. A one s.d. increase in the skill index is associated with a roughly 20 log point increase in wages for women and men. These large wage effects reflect the impact not only from job skill requirements but also from worker skills not fully captured by schooling, potential experience, and other CPS control variables. In our panel analysis (shown subsequently), which accounts for worker fixed effects, the skill index coefficients are only about one-fifth as large, but still highly significant. The estimated working conditions coefficients are positive, as predicted by theory, with larger coefficients (in cross-section analysis) for women than men, consistent with prior literature (Hersch 1998).

Turning to the estimated effects of caring on wages in Table 5, we first focus on the estimated wage effects of the 'caring' index, absent control for the D/T index (column 1). For women, the estimate is a wage penalty of 0.04 log points, which is marginally significant. The coefficient for men is a more substantive and significant coefficient of -0.09, indicating a 9 percent lower wage with respect to a one s.d. increase in the level of caring. In column 2, we include the D/T but not caring index and in column 3 we include both. The caring coefficients change relatively little with the addition of D/T. The coefficients on D/T are negative and significant for both women and men. Focusing on the individual caring measures in column 4, it is readily evident that for women and men, the 'concern' measure is more strongly associated with wage penalties than is the 'assisting and caring' measure. Recall that the 'concern' measure is intended to measure needed worker attributes, whereas the A&C measure reflects required work activities. A possible interpretation of these results is that the negative concern coefficient captures penalties resulting from labor supply preferences (i.e., the prisoner of love theory).

Overall, the cross-section evidence in Table 5 provides support for the proposition that there are systematic nontrivial caring penalties in the labor market. It is important to note that the caring coefficient estimates are highly sensitive to inclusion of the skill index, consistent with the observation that high caring occupations include some of the highest (and lowest) skilled occupations in the labor market. Table 6 is identical to Table 5, except that each wage equation excludes the O*NET skill and working conditions indices. As evident in the Table 6 results, there is no longer clear evidence for caring wage penalties among women or men. Particularly notable is that the D/T coefficients turn from sharply negative to sharply positive once the job skills index is removed. As discussed subsequently, this change is due the exceptionally high skill requirement ratings attached to teaching occupations. A similar effect occurs with respect to the caring coefficients. Health professional occupations, nursing in particular, have high job skill requirements that we control for in Table 5 but not in Table 6. Similar effects no doubt are occurring to a lesser degree among numerous occupations, reinforcing the importance of controlling for occupational skill in the wage level analysis. Absent these controls, the only evidence we find for caring penalties is associated with the O*NET descriptor measuring workers' need to have concern for others, its coefficients being similar with or without inclusion of the skill index.

Our takeaway points from Tables 5 and 6 are twofold. First, evidence for penalties associated with caring jobs is stronger for men than for women and is rather mixed with respect to the types of caring attached to jobs. Second, skills matter. Worker and job skills have high payoffs in the labor market but are not typically well accounted for (controlled) in standard analyses. Caring jobs sometimes require highly skilled workers and tasks (e.g., registered nurses) and sometimes not. Because of the importance of skill, we place greater emphasis on our longitudinal estimates (shown below), which control both for worker heterogeneity (worker-specific fixed skills) and changes in job skill requirements.

7. Wage Equation Caring Results Using Longitudinal Analysis

As in England et al. (2002), our preferred approach for estimating caring wage differentials is longitudinal analysis that accounts for worker heterogeneity fixed over time (i.e., consecutive years using the CPS). There are potential downsides to using longitudinal data and, more narrowly, to using a sample that identifies wage gaps exclusively on job switchers (in this application, workers changing both occupation and industry). One concern is whether or not caring wage gaps for the job switcher sample are representative of the larger labor force. A second concern is whether selection into job change (i.e., endogenous job change) biases the longitudinal estimates. We address these issues below.

To examine the representativeness of the job switcher sample, we compare measurable worker characteristics for the two samples and estimate wage level equations for the job switcher sample identical to those shown in Table 5 (we show results using the initial year observation, but results are nearly identical using the second year). In comparing means of all variables for the two samples, we found no large or unusual differences (these results are available on request). The wage level regression results for the job switcher sample are shown in Appendix Table A-2. The results for the two samples are reasonably similar, although not identical. We see the same pattern of wage level caring penalties for both samples, the principal difference being that the caring penalties are somewhat higher for women and lower for men using the longitudinal rather than full samples. Indeed, the caring coefficients using the job switcher sample are quite similar for women and men, in contrast to those seen in Table 5. Our assessment is that the job switcher sample appears to be roughly representative, based both on similar measured characteristics and similar regression coefficients with comparable models.

The results from the longitudinal wage change analysis, shown in Table 7, are reasonably clear-cut. The magnitude of coefficients is substantially smaller using longitudinal rather than wage level analysis. Specifically, the coefficients on the 'caring' index (column 1 of Table 7) for women indicates a 1.4 log point decrease for a one s.d. increase in the caring index, while the estimate for men shows a 1.8 log point decrease. These coefficients are similar when the D/T index is included (column 3). Coefficients on the D/T index are effectively zero for women and men. In column (4) we break out the caring index into its component parts, obtaining negative but small wage effects for both 'caring & assisting' and 'concern' for others (the four D/T measures are also included, with coefficients shown in Appendix Table A-3). These caring estimates are tiny and not significant for women. They are somewhat more substantive for men, 1.1% and 0.8% wage decreases for one s.d. increases in 'caring &assisting' and 'concern' for others, respectively.

Overall, we regard the longitudinal evidence of wage penalties for caring work (measured by the narrow caring index) as plausible and reasonably convincing. That said, the magnitude of the estimated penalties is rather small, particularly so as compared to other wage gaps estimated in the larger literature (say, with respect to union status, city size, race/ethnicity, etc.).

A second concern pertinent for the longitudinal analysis is whether selection into job change (i.e., endogenous job change) biases the panel estimates. Selection of course has a bearing on the wage level analysis as well, but there the presumption was that wage differentials observed for caring work are "market prices" determined for marginal workers. Infra-marginal workers in caring jobs have a relatively stronger preference for caring and would have accepted lower wages (a larger penalty) to work in caring jobs. Infra-marginal workers in non-caring jobs would not be willing to work in caring jobs at current wage levels. Longitudinal analysis based on occupation switchers is likely to reflect wage changes among workers who tend to be closer to the margin and less likely to be inframarginal, an advantage of such analysis. The concern regarding the panel approach, however, is that even among such a group, job change is endogenous rather than random and likely to be correlated with wage changes. In our panel analysis, endogenous selection is likely to bias caring coefficients in opposite directions (as explained below) depending on whether workers move to occupations with lower or higher levels of caring. Thus, separate estimates for workers who "up-care" and "down-care" provide a useful robustness check on our results.

Workers are more likely to switch jobs the less attractive the wage in the current job relative to the wage in the destination job. This can affect measurement of the caring wage differential, as illustrated in Figure 5, which shows workers switching from job 1 with market wage W_1 to job 2 with market wage W_2. Job switchers who "down-care" (think of this as moving to a job disamenity or, equivalently, a loss in amenities) are more likely to do so if they have a relatively low wage draw on the current job (seen by the dotted line below market wage W_1) or high wage draw on the destination job (seen by the dotted line above market wage W_2). This leads to an *upward* bias in the caring wage gap seen among down-care movers in that the observed ΔW exceeds the market wage differential $W_2 - W_1$.

The same logic holds for “up-care” job switchers, who on average are more likely to have made the move if the wage on the lower-caring initial job was less than W_1 and/or there is a low wage penalty associated with the higher-caring destination job (i.e. a wage above W_2), thus leading to a *downward* bias in wage gaps seen between the low caring source job and high caring destination job. Imagine that the market equilibrium for a given difference in job caring is a 2% caring wage penalty. Our expectation is that estimates from those who “down-care” would exhibit average wage increases greater than 2%, while those who “up-care” will exhibit wage changes less than 2% in absolute value (i.e. wage decreases less than 2%). If we were to observe the predicted pattern with wide bounds around the average, it would suggest that such selection bias is substantive.

As seen in Table 8, longitudinal wage change equations providing separate estimates for those who up-care and down-care display fairly tight bounds, with similar coefficients for those who up-care and down-care (in no case are coefficients significantly different). For men, the separate coefficient estimates for “Up·ΔCare” and “Down·ΔCare” generally produce lower caring wage gap estimates (in absolute value) for workers who up-care and higher estimates for those who down-care, as expected based on selection. This pattern is not generally evident among women, suggesting any bias from selection is small, being more than offset by sample differences in wage changes among the “up” and “down” groups. The important point is that in all cases, coefficient differences between those moving toward more- and less-caring occupations are small, providing relatively tight bounds on our results. As an example, recall that in Table 7, column 3, we found statistically significant penalties of -0.014 for women and -0.022 for men. Estimating separate “up” and “down” care wage changes in column 3 of Table 8, we obtain estimates for men of -0.0135 and -0.030, symmetrically bounding the earlier -0.022 estimate and supporting the expected pattern of selection into job change. For women, we obtained “up” and “down” estimates of -0.017 and -0.011, which provides narrow bounds on the joint -0.014 estimate, but do not show the expected pattern of selection.[24]

8. Caring Penalties in the Public versus Private Sectors

Authors emphasizing the importance of caring wage penalties have stressed not only its disproportionate impact on women, but also that it may reflect a concentration of caring jobs in the public sector (e.g., Barron and West 2013). If caring jobs are concentrated in the public sector, a caring

[24] For both women and men and for all measures of caring, there were roughly equal numbers of workers “up-caring” and “down-caring” but with the number in the former group slightly exceeding that in the latter, consistent with the gradual upward trend in caring over time (see Figure 3). For both female and male job switchers, mean changes in caring magnitudes are nearly identical (in absolute value) for “up” versus “down” changes. For women, mean changes in the caring and developing/teaching indices are 0.67 and 0.86 standard deviations. For men, the equivalent means are 0.59 and 0.79.

penalty would mechanically arise if public workers are systematically paid less than are similar private sector workers in similarly demanding jobs. Analysis of public-private pay differences is beyond the scope of our paper, but our assessment of a now extensive literature is that estimated public/private wage differentials are typically small, sometimes negative and sometimes positive, and somewhat sensitive to inclusion of what have become controversial control variables (e.g., union status and employer size). More clear-cut is the finding of considerably greater pay compression and relatively higher non-wage benefits (pensions, health insurance) in the public sector.[25] Although not the focus of our study, in our regression analyses, a public sector dummy variable is systematically positive for women and men in the wage level analyses and effectively zero in the wage change analyses (shown in the Appendix Tables A-1 and A-3).

We do not focus on public/private pay differences, but instead examine how wages vary with respect to caring measures *within* the public and private sectors. Our principal focus is on results from wage level analyses for the two sectors. We do not examine wage changes among those switching occupations within the public sector because of measurement issues (discussed below). In addition to distinguishing between the public and private sectors, caring wage effects can differ across the private for-profit and private not-for-profit sectors, the latter including numerous health care workers employed by not-for-profit hospitals, as well as other caring workers employed by non-profits other than hospitals. As noted by a referee, public programs (e.g., Medicare and Medicaid) also can influence wage levels in the private sector. To preview our results, we find evidence consistent with caring penalties being more likely in the public than in the private sector, and (seen subsequently in section 10) with similar wages for caring work in the private for-profit and not-for-profit sectors.

Prior to turning to the wage evidence, we first examine the extent to which caring work is more prevalent in the public than in the private sector based on our multiple O*NET measures of caring. Figure 6 (as well as Table 9) shows the relative values for the six O*NET attribute measures. There is clear-cut evidence that for women and men, jobs in the public sector require considerably higher levels of caring, defined broadly or narrowly. Focusing on the O*NET factor indices (with mean 0 and s.d. 1 over the entire male/female, private/public sample), each is higher for women than men within the public sector, and each is higher in the public than in the private sector for women and for men. For example, the caring index for women in the public sector is 0.60 versus 0.21 in the private sector; for men, the public and private values are 0.22 and -0.35. For the D/T factor index, the value for women in

[25] Recent studies include Gittleman and Pierce (2011), Bender and Heywood (2012), and Lewin et al. (2012). The debate regarding inclusion of a union control can be traced back to Linneman and Wachter (1990).

the public sector is 0.62 versus -0.08 in the private sector; for men, the public and private values are 0.54 and -0.03. And as widely recognized, women are disproportionately employed in public sector jobs. The share of women in our public sector sample is 58.5%, as compared to 47.6% in the private sector. Using all CPS wage and salary workers for 2007 (i.e., no sample exclusions) and employing sample weights, the shares of women in the public and private sectors are 57% and 46%, respectively.[26]

Turning to the wage level results (Table 10), we provide separate estimates for caring wage penalties within the private and public sectors. In the private sector, results are similar to those seen previously in Table 5 for the full sample, where roughly five out of six workers are in the private sector. As before, evidence for caring penalties among women is weak; that for men is more clear-cut.

For the public sector (second page of Table 10), estimates for women and men suggest substantive caring penalties. Among women, a 5.7% penalty (column 3) is associated with a one s.d. change in the caring index. Among men, a 9.2% penalty (column 3) is found. For women and men, caring penalties in the public sector appear to be driven by jobs requiring 'concern' and not 'assisting & caring' for others (column 4). As noted previously, the 'concern' variable is intended to measure needed worker attributes, whereas the 'assisting and caring' variable measures job activities.

Notable in Table 10 are also the significantly negative coefficients attached to the D/T index, a result highly influenced by the large number of teachers in the sample. Our assessment is that these apparent penalties are overstated due to exceptionally high O*NET skill requirement ratings assigned to teaching occupations.[27]

Our wage level analysis in this section supports the thesis of larger caring penalties in the public than in the private sector. Because of unobserved worker heterogeneity, we have attached greater

[26] Men are slightly underrepresented in our estimation samples because they have higher rates of earnings non-response. As discussed previously, non-respondents are not matched to donors based either on public/private status or detailed occupation; their inclusion would attenuate estimated wage gaps (Bollinger and Hirsch 2006).
[27] The issue here is the impact of our occupational skills index. Note how the D/T index coefficients for our full sample turn from negative to positive when the skill index is excluded (Tables 5 versus 6). O*NET ratings of the skills involved in teaching are extremely high. Given the large market rewards associated with the job skill index, one finds that teachers are underpaid in the sense that their hourly earnings fall below the predicted wage. O*NET skill measures reflect the skills and tasks needed to perform a job well. They do not necessarily provide an accurate measure of the skills of workers hired in these jobs, although competitive market forces should limit discrepancies between worker skills and job skill ratings. It is quite possible that O*NET skill ratings for teaching jobs overstate the skill level of the average teacher. Thus, wage analyses controlling for job skill requirements understates relative pay for teachers. For example, Allegretto et al. (2004) use the CPS to compare hourly earnings for teachers with non-teachers, controlling for CPS worker attributes plus an occupational work level index derived from BLS data, similar in spirit to our O*NET skill index. Teachers were rated very high in required job skills and the authors concluded that teachers are substantially underpaid. Other analyses in the literature (e.g., Podgursky, Monroe, and Watson 2004; Scafidi, Sjoquist, and Stinebrickner 2006) fail to support the thesis of teacher underpayment, finding that those who leave teaching suffer substantive wage losses.

weight to the longitudinal than to the cross-section results. Economy-wide, the longitudinal evidence suggests much lower caring wage penalties than seen in the wage level analysis (Tables 5 and 7), indicating that worker heterogeneity is important. It is not obvious how to conduct meaningful longitudinal analysis within the public sector, however, because turnover is low and there are relatively few teachers, police, and firefighters (among others) switching both occupation and industry within the public sector. Were we to base such an analysis on changes in recorded occupation codes (but not require an industry change), the ratio of noise (i.e., reporting error) to true signal would be high and estimates would be severely attenuated.

9. Caring Penalties across the Earnings Distribution

Prior studies on caring wage differentials have focused on particular occupations, some requiring relatively low and some high skills. We examine how caring wage differentials vary across the earnings distribution using two approaches. First, we provide estimates using quantile regression, which provide caring coefficient estimates that vary across the wage distribution. Second, we divide our sample into quintiles based on their predicted earnings using only non-job attributes (schooling, demographics, location, etc.), which provides an index of earnings attributes or endowments, each weighted by its importance (coefficient) in the earnings function. We then provide OLS estimates within each of the quintiles. This latter approach can be used for our wage change analysis, where quantile regression is not appropriate.[28]

In Table 11, we show quantile regression results for women and men that correspond exactly to columns (1) through (3) shown previously in Table 5. These regressions include our full set of covariates, plus the caring index alone, the D/T index alone, and both the caring and D/T indices. We show our previous OLS results in the first column, followed by the quantile regression coefficients for percentiles 10, 25, 50, 75, and 90. The OLS results include clustered standard errors, while unclustered standard errors are provided for the quantile regression results. Given that standard errors in the quantile regression model should be less precise than with OLS, our guesstimate is that quantile regression coefficients need to exceed (in absolute value) roughly 0.05 to be significant at the standard 0.05 level.

The pattern of results in Table 11 is reasonably clear-cut. For women, the caring coefficients are remarkably stable across the wage distribution. The coefficient on the caring index (specification 1) indicates penalties of 0.05, 0.05, 0.04, 0.04, and 0.05 log points as one moves from the 10th to the 90th

[28] Quantile regression has been used in numerous applications. For examples and further details see Buchinsky (1998) and Koencker (2005). For an example of OLS log wage and wage change regressions for worker groups ordered by predicted wages, see Card (1996).

percentiles. Among men, there is the suggestion that penalties are somewhat higher in the bottom half the distribution, with caring penalties of 0.12, 0.11, 0.10, 0.07, and 0.05 log points as one move up the distribution. For all specifications, the median regression results are similar to the OLS mean regression seen previously in Table 5. In short, the quantile regression analysis for women suggests little difference in the wage-caring gradient across the distribution, while that for men suggests smaller penalties toward the top of the wage distribution. Although our principal focus is the wage effect of caring rather than of developing/teaching tasks in the labor market, the D/T coefficients are remarkably stable throughout the earnings distribution.

In Table 12, we provide a distributional analysis of wage-caring gradients using both wage level and wage change analysis. Longitudinal (wage change) analysis does not lend itself to quantile regression; we are not asking how caring coefficients differ across the distribution of wage *changes* (i.e., the dependent variable). It is informative, however, to estimate OLS wage change (and wage level) equations within predicted wage percentile ranges, as seen in Card (1996). Here, we estimates OLS wage equations for each of the five quintiles of the predicted log wage, based on non-job attributes. The predicted wage provides a convenient index of compensable worker endowments and location wage differences. In the top half of Table 12, we show wage level results for women and men; in the bottom half we show wage change results.

The wage level results shown in the top half of Table 12 are roughly supportive of the pattern found using quantile regression, with OLS results at the middle quintile being very similar to median regression results. As with the quantile regression, we do not see systematic patterns of either increasing or decreasing caring wage penalties as we move across the distribution.

Our principal interest is the bottom half of Table 12, which provides OLS wage change results estimated separately by endowment quintiles; the results from the full sample, as shown previously in Table 7, are shown in the first column. For women, coefficient estimates on the caring index are negative and surprisingly similar in the lowest and highest quintiles (-0.015 and -0.017), while coefficients in the middle quintile are near zero. The caring coefficients for men are -0.016 and -0.024 in the lowest and highest quintiles, with near zero in the middle quintile. Because caring jobs are often concentrated among high and low skill workers, there may be too little variation in caring in the middle of the distribution to precisely estimate the wage-caring gradient.

We did not have strong priors that caring wage penalties should be systematically larger or smaller at different parts of the earnings and skill distributions. The quantile regression and wage quintile analyses presented in this section provide little evidence for either an upward- or downward-sloping wage-caring gradient over these distributions.

10. Linearity, Hours Worked, and Group Differences in Caring Wage Effects

In this section we address three issues. We first examine whether our (implicit) assumption of a linear relationship between wages and the level of caring is reasonable. Second, we ask how weekly hours worked for women and men vary with respect to levels of caring. And third, we examine whether there exist substantive group differences in the relationship between wages and caring.

In order to examine the linearity of the wage-caring gradient, we first extract the residuals from our female and male log wage regressions (specifically, column 3 from Table 5). We provide a scatterplot of these residuals with respect to the caring index that loads the O*NET measures 'assisting & caring' and 'concern' for others. By construction the regression residuals have mean zero. If the wage-caring relationship is truly linear, then the plot of mean residuals at each level of caring (in effect, the means for each of 501 occupations ordered by caring level), should be relatively flat at near-zero values. Figure 7 shows this relationship for women and men. The smoothed scatterplots are fitted from locally weighted regressions using the "lowess" command in Stata (Cleveland 1979).

What is readily evident for both women and men is that there is little slope over most of the distribution and minimal deviation from zero. Absence of substantial deviation from linearity provides support for our using simple and convenient linear specifications. That said, the figures are informative. The notable deviation from linearity is with respect to very high caring jobs (heavily dominated by health care jobs), with the upward slope more evident for women than men. The high-caring jobs are dominated by health care, all occupations with a caring index level above 2.0 being in health care, and those between 1.5 and 2.0 being mostly in health care. All else the same, workers in health care occupations are paid more than those outside the health sector. While there exist caring wage penalties in some sectors of the labor market, we find little evidence for such penalties in healthcare, the sector of the economy where jobs are evaluated as requiring the highest levels of assisting/caring and, to a somewhat lesser extent, concern for others.

Next we examine how hours worked vary with respect to caring work. Throughout the paper, we examine how average hourly earnings (i.e., wages) differ with respect to caring. If high-caring jobs had substantially higher (lower) weekly hours of work than did low-caring jobs, a substantive caring wage penalty would be associated with even larger (smaller) differences in weekly earnings. To examine the hours-caring relationship, Figure 8 provides a smoothed scatterplot (using the lowess procedure) showing the relationship between usual weekly hours and our O*NET caring index for women and men. Mean hours worked per week are 37.2 hours for women and 42.2 for men (Table 2). As seen in Figure 8, in some of the lowest-caring occupations mean weekly hours are close to 40 for women, but then decline with respect to caring over the lower and mid-caring portions of the distribution, remaining roughly constant at well under 40 hours per week in high-caring occupations. In contrast, men's average hours worked are relatively flat over the lower half of the caring distribution, but then turn up and are highest among those working in occupations with the highest levels of caring. Recall that health care occupations dominate the right tail of the caring distribution. Women are overrepresented in health care occupations where part-time work or low full-time hours are common; men are highly represented in health care occupations where long work hours are common.

Up to this point, we have estimated the wage-caring relationship separately for women and men, but have not examined differences across other groups of workers. Although such differences are not a focus of the paper, in Table 13 we provide caring level means and wage regression coefficients for selected demographic and worker groups. The caring coefficient for each group is from a wage level regression equivalent to that in column 3 of table 5.[29] Among both women and men, higher levels of caring are seen for part-time than full-time workers, for salaried versus hourly workers, for non-Hispanics than for Hispanics, for citizens than for non-citizens, among prime-age and older workers than among young workers, in the private not-for-profit and public sectors versus the private for-profit sector, and, most notably, among those with higher education levels.

Estimates of caring wage penalties (i.e., coefficients on the caring index) differ across groups, but often by little. Consistent with previous evidence for women, caring coefficients for most female groups are generally negative, but small and often insignificant. In contrast, all caring coefficients for men are negative, with most being statistically significant and substantive. Among the patterns observed are a tendency for more sizable caring penalties for full-time than for part-time work, increasing caring penalties with age, particularly large penalties for high school graduates and little evidence for penalties among those with graduate and professional degrees, and, as reported previously, more substantive penalties in the public than private sector, but with little difference between the private for-profit and not-for-profit sectors. Few differences are found with respect to race, ethnicity, foreign-born status, or marital status. The positive caring coefficients among women for part-time and private not-for-profit are driven primarily by the high wages seen for registered nurses. There is little if any part-time penalty

[29] This specification includes both the caring index and the developing/teaching (D/T) index. The choice of regressors is slightly modified as appropriate for each group. For example, the part-time dummy is excluded when we provide separate estimates for full- and part-time workers.

among RNs. Moreover, RNs employed in hospitals earn substantially more than do other RNs (Schumacher and Hirsch 1997) and about a third of hospital employees (using the 2008 CPS) work for private not-for-profit firms (Hirsch and Macpherson 2014, Table 7b, p. 97). More broadly, with RNs removed from all the analyses in this paper, one systematically finds more substantial evidence for caring wage penalties among women.

Previous literature has included dummy variables for selected occupations deemed as caring occupations. In practice, this approach leads to designating as caring jobs those who work as teachers, in health care occupations, and in child care and other caring occupations. Our concern about such an approach is twofold. First, such an approach fails to make distinctions between the level of caring required among occupations designated as caring and among those not designated as caring. Second, occupations designated as caring, say registered nurses and teachers, may require different types of caring and entail different types of job tasks. A virtue of our approach is that we use multiple measures – assisting and caring, concern for others, and developing/teaching tasks – each measured as continuous variables for all occupations. Such an approach allows one to distinguish between types of caring, to measure required levels of each task for all jobs, and to differentiate how these tasks are compensated in the labor market, conditional on other wage determinants.

We examine results using the dummy variable approach. Using wage level analysis and a single dummy variable for caring jobs (including health, teaching, and other caring occupations), we obtain negative and significant coefficients for women (-0.11) and men (-0.26). These results mask what are large positive and negative coefficients found when we break up the caring jobs into medical (2 categories), education (3), and other caring (2). For both women and men, we find large positive coefficients for the health care occupation dummies and large negative coefficients for the education and other caring dummies. When we shift to longitudinal analysis (similar to that in England et al. 2002), coefficients on the caring dummy change variable are virtually zero (-.0006 for women and -.0095 for men), neither being close to statistical significance. These results reinforce our earlier conclusion that accounting for individual worker heterogeneity is important.

11. Caring Penalties, Occupational Gender Composition, and the Gender Wage Gap

It is widely recognized that both women and men who work in occupations with high proportions of female workers tend to have lower wages (for comprehensive treatments, see Macpherson and Hirsch [1995], Bayard et al. [2003], and Ludsteck [2014]). Less clear are the reasons for these relationships, with it being some combination of sex-based discrimination, differences in job skill requirements and working conditions, unmeasured worker attributes correlated with the percent female (e.g., cumulative work experience), and difference in women's and men's occupational labor supply preferences. Because the sex composition of an occupation is highly correlated with occupational measures of caring (see Table 4), an important question to address is how addition of a sex composition variable (the %Female) to wage regressions affect the coefficients on the caring variables (and vice-versa). England et al. (2002) included %Female in their preferred specification. Given that it is negatively correlated with wages and positively correlated with caring work, they found that exclusion of %Female (as in our analysis) led to somewhat larger caring penalty estimates.

In order to save space, we summarize but do not report our results including %Female (they are available on request). Perhaps surprisingly, neither the cross-section nor longitudinal results are highly sensitive to inclusion of %Female in the wage equations. As expected, the wage level and wage change values of the caring coefficients become less negative after adding %Female, but the differences are modest and do not greatly change the interpretation of results. For example, in Table 5, the coefficients on the caring index for women and men (column 1) are -0.043 and -0.089; these decline (in absolute value) to -0.034 and -0.065 when %Female is added.

We also examine the reverse question. Do the estimated effects of %Female simply reflect wage differences associated with caring job attributes? Here we find that adding the caring attributes to wage level equations that include %Female does substantively decrease (in absolute value) the %Female coefficients, typically by about a third. As in Macpherson and Hirsch (1995), we find that %Female has a larger negative wage relationship for men than for women in wage level analysis, but that the magnitudes of the %Female coefficients drop sharply in longitudinal wage equations, being relatively small and similar for women and men. The longitudinal results indicate that a substantive portion of the wage effects associated with %Female stems for unobserved worker differences correlated with gender (e.g., cumulative work hours and experience). In a recent study, Ludsteck (2014) draws a similar conclusion using German administrative data that contain establishment as well as worker fixed effects.

In the larger academic and public discussion of gender wage differences, caring wage penalties are often proffered as an important (if not fundamental) determinant of the gender wage gap. Given the larger differences in levels of caring among jobs for women and men, such a focus would be appropriate if caring wage penalties were substantial (even more so if penalties were larger for women than men). That said, evidence in our paper indicates rather limited evidence for substantial market-wide caring penalties. Substantive estimates are found using wage level but not wage change analysis, yet the latter provides what are arguably more reliable results. The caring penalties that we do find are typically larger for men than for women.

How much might caring penalties narrow the gender wage gap? The difference in female and male means of the O*NET caring index is 0.56 (see Table 2). For sake of argument, assume that there exists a -0.02 wage penalty for a one standard deviation in caring. This roughly corresponds to the longitudinal estimates shown in Table 7 (column 3) showing caring coefficients of -0.014 for women and -0.022 for men. Multiplying 0.02 times the 0.56 caring difference indicates that the 0.190 gender wage gap in our sample (see Table 2) would be 0.011 or one log point lower absent the caring penalty, all else the same. Such a narrowing of the gender gap is not large. If one believes caring wage penalties are much larger, say, -0.05 rather than -0.02, the reduction in the gender gap would be less than 0.03 log points (0.05 times 0.56 = 0.028). Even if caring penalties were this large, policy implications are far from clear. What policies and shifts in attitudes might move us toward an alternative world in which we could eliminate caring wage differentials and/or differences in caring levels between women's and men's jobs? Are there not more feasible strategies through which gender equity can be enhanced and wage gaps narrowed?

12. Conclusion

Economists and sociologists have proposed plausible theories for why there may exist wage penalties for work involving helping and caring for others, jobs often performed by women. Previous evidence is mixed, but some studies have suggested wage penalties for women and men in caring jobs, on the order of 5%. Taken as a whole, the empirical evidence for caring wage penalties has been limited, varied, and not always convincing. Our expectation was that the use of large household samples of workers matched to multiple and varied measures of occupational "caring" would be likely to produce clear-cut and more compelling evidence of wage differentials associated with caring work.

Rather than designating occupations as caring or not, we use continuous measures from O*NET of 'assisting & caring for others' and 'concern for others', plus four measures of 'developing/teaching', in order to construct alternative measures of caring in the labor market. Our principal results focus on a caring factor index that loads the 'assisting & caring' and 'concern' for others variables. We also construct broad-based measures of job skills/tasks and physical working conditions. All these job descriptors are based on evaluations from job analysts and incumbents for detailed occupations across the U.S. workplace. We match these job descriptors to multiple years of the Current Population Survey (CPS) earnings files, which enables us to perform both standard cross-section wage level and longitudinal wage change analyses, the latter based on large panels with two observations per worker (one year apart). Because longitudinal analysis identifies the effects of caring based on wage changes among workers moving into and out of occupations involving different levels of caring, it accounts for otherwise unobserved worker heterogeneity correlated with wages.

Although we do find evidence of wage penalties for caring work, the magnitudes of the penalties are modest or small. Using wage level analysis, we obtain estimates of caring wage penalties of roughly 4 percent for women and 8 percent for men resulting from a one standard deviation change in the caring index (these estimates would be zero for women and about 5 percent for men absent inclusion of our occupational skill index). For both women and men, the caring penalty is more strongly associated with a measure of 'concern for others' than with the measure 'assisting and caring for others'. The former is intended to reflect needed worker attributes, whereas the latter reflects general work activities in the occupation. Our preferred estimates come from our longitudinal analysis (as in England et al. 2002), which accounts for worker heterogeneity. These estimates suggest caring penalties of 1.4 percent for women and 2 percent for men from a one standard deviation change in caring, with the 'concern' and 'assisting and caring' for others measures contributing similarly.

Jobs in the public sector involve substantially higher levels of caring for both women and men. When we provide separate wage level analyses for the public and private sectors, we find stronger evidence for caring penalties in the public than in the private sector for both women and men. That said, fewer than 1-in-6 wage and salary employees work in the public sector, although the rate is larger among women than men. We were unable to provide longitudinal analysis for the public sector given that occupation changes within the public sector are infrequent and would be poorly measured. Our expectation is that a substantive portion of the caring penalty estimates found in the public sector would reflect worker heterogeneity, just as we found for the economy-wide sample.

Also examined is how caring wage differentials vary across the earnings distribution. We do so using quantile regression and estimating OLS wage level and change equations across the quintiles of the predicted wage distribution. Although there are some differences in results between women and men based on the approach, the principal finding from the analysis is that caring wage effects are reasonably constant across the distribution.

There is a widespread belief among social scientists and the public that women are disproportionately employed in caring jobs and are penalized for doing so, receiving lower wages than they or similarly skilled workers would receive in jobs not requiring care. Our study confirms that the levels of 'assisting and caring' and 'concern' for others in the workplace are substantially higher for women than men. Estimates of caring wage penalties are sensitive to methods and specification, an expected result given that caring jobs include some of the most highly skilled and least skilled jobs in the economy. Although we find clear-cut evidence for lower wages in caring jobs using wage level analysis, the magnitude of these differences is sharply reduced using longitudinal analysis that accounts for worker heterogeneity. Our preferred estimates suggest caring wage penalties of about 2% for a one standard deviation increase in our caring index. Penalties are typically larger for men than for women, but fewer men work in high-caring jobs. We find little evidence for systematic differences in caring penalties across the wage distribution. The magnitude of estimated caring wage penalties is small as compared to other wage gaps in the labor market (e.g., union, industry, employer size, and city size wage differentials). Even were caring penalties erased from the labor market, there would be minimal closing of the gender wage gap.

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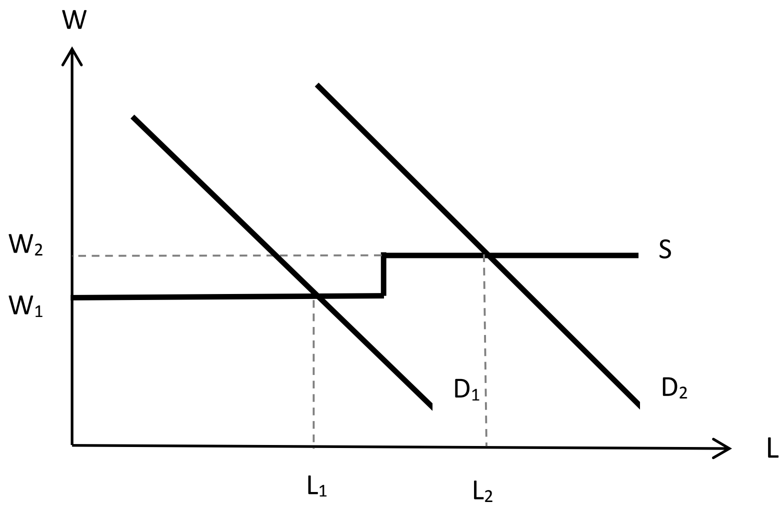
Figure 1

Labor Market Equilibria for Caring Occupations with Heterogeneous Preferences



W_1 represents the reservation wage for workers who prefer caring jobs and W_2 the reservation wage for those without such a preference. At low labor demand level D_1 the equilibrium wage for the caring job is W_1 with employment L_1. At the high level D_2 the equilibrium wage for both sets of workers is W_2 with employment L_2.

Figure 2. Density Plots of O*NET 'Caring' and 'Developing/Teaching' Factor Indices

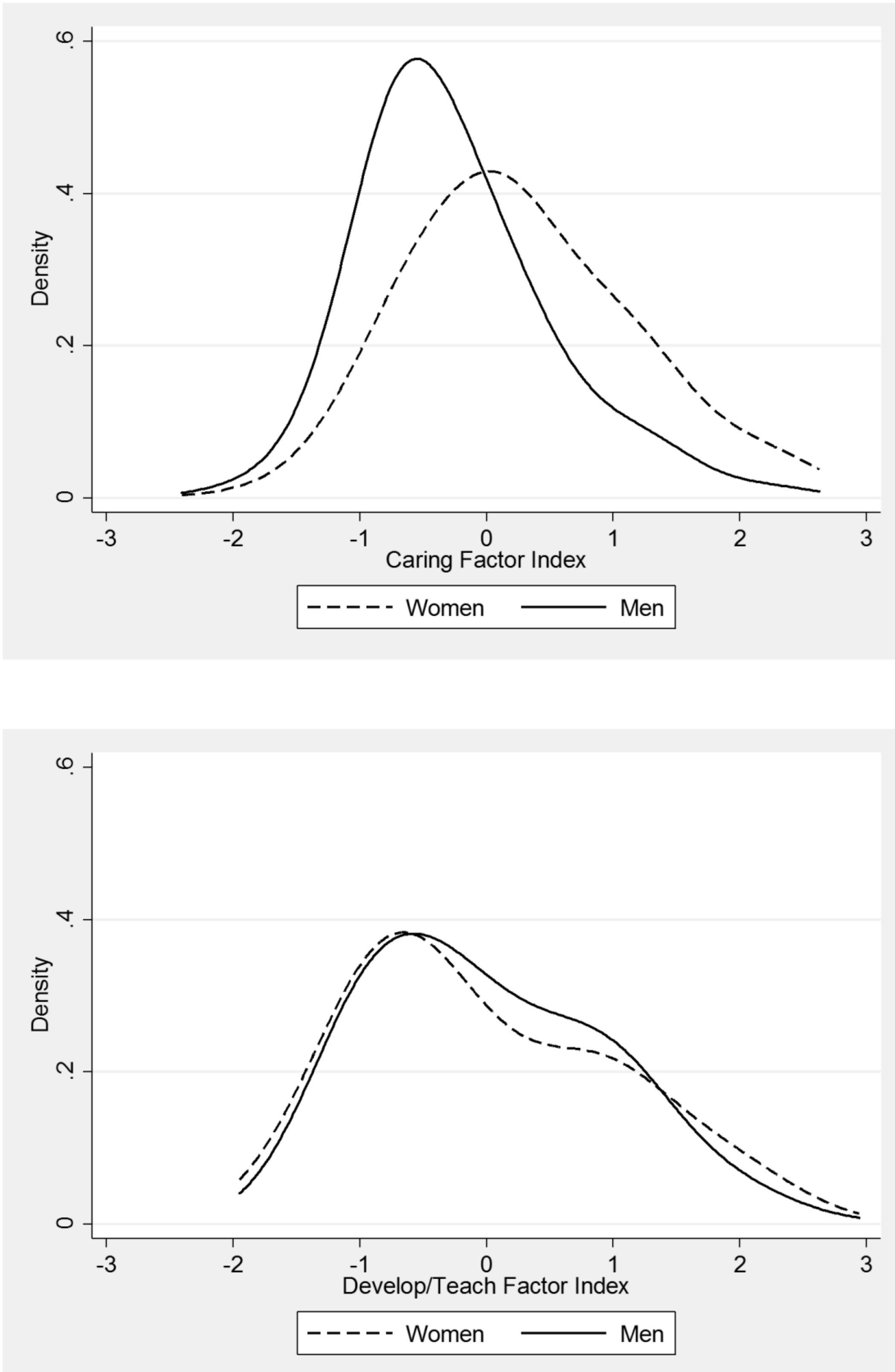
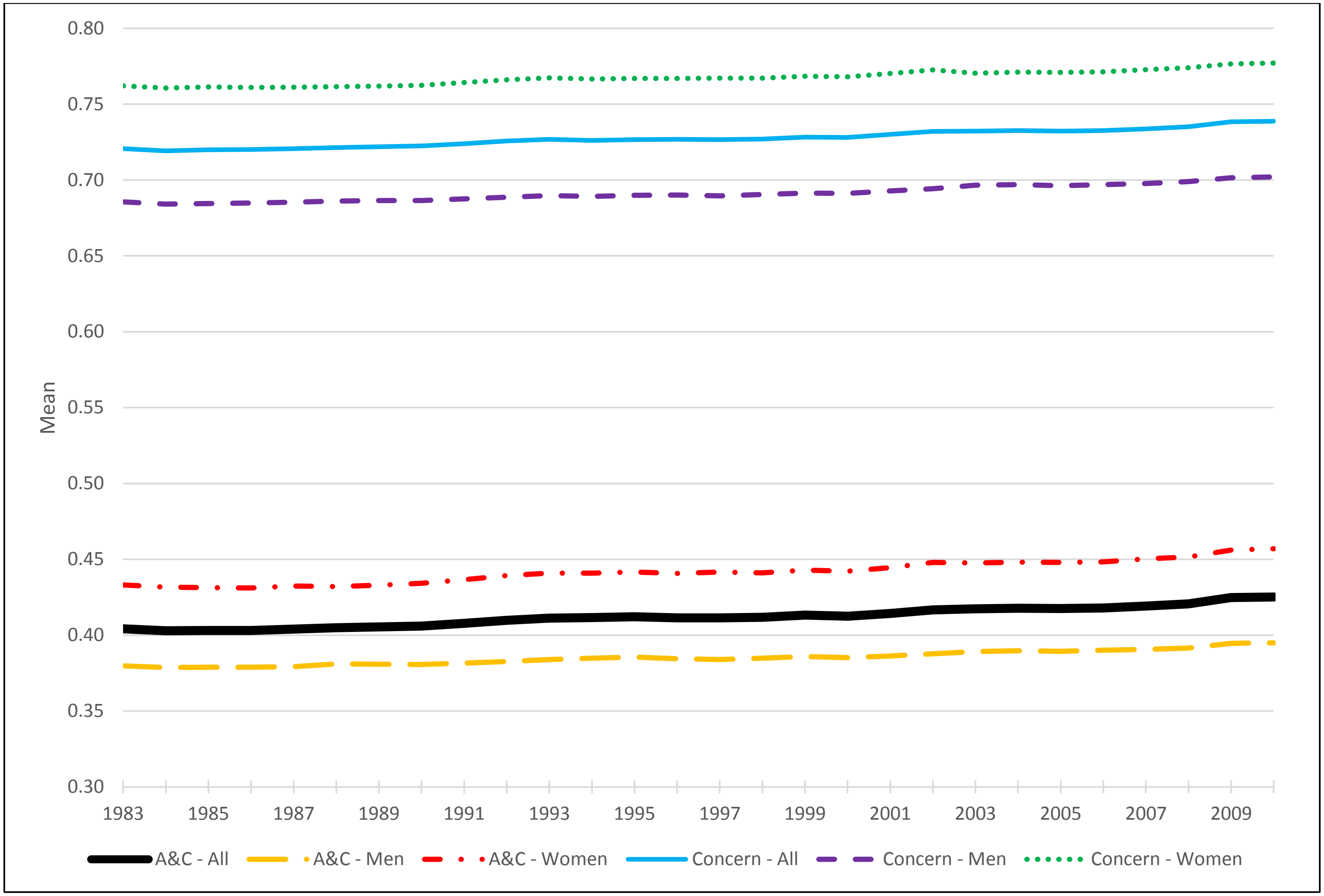
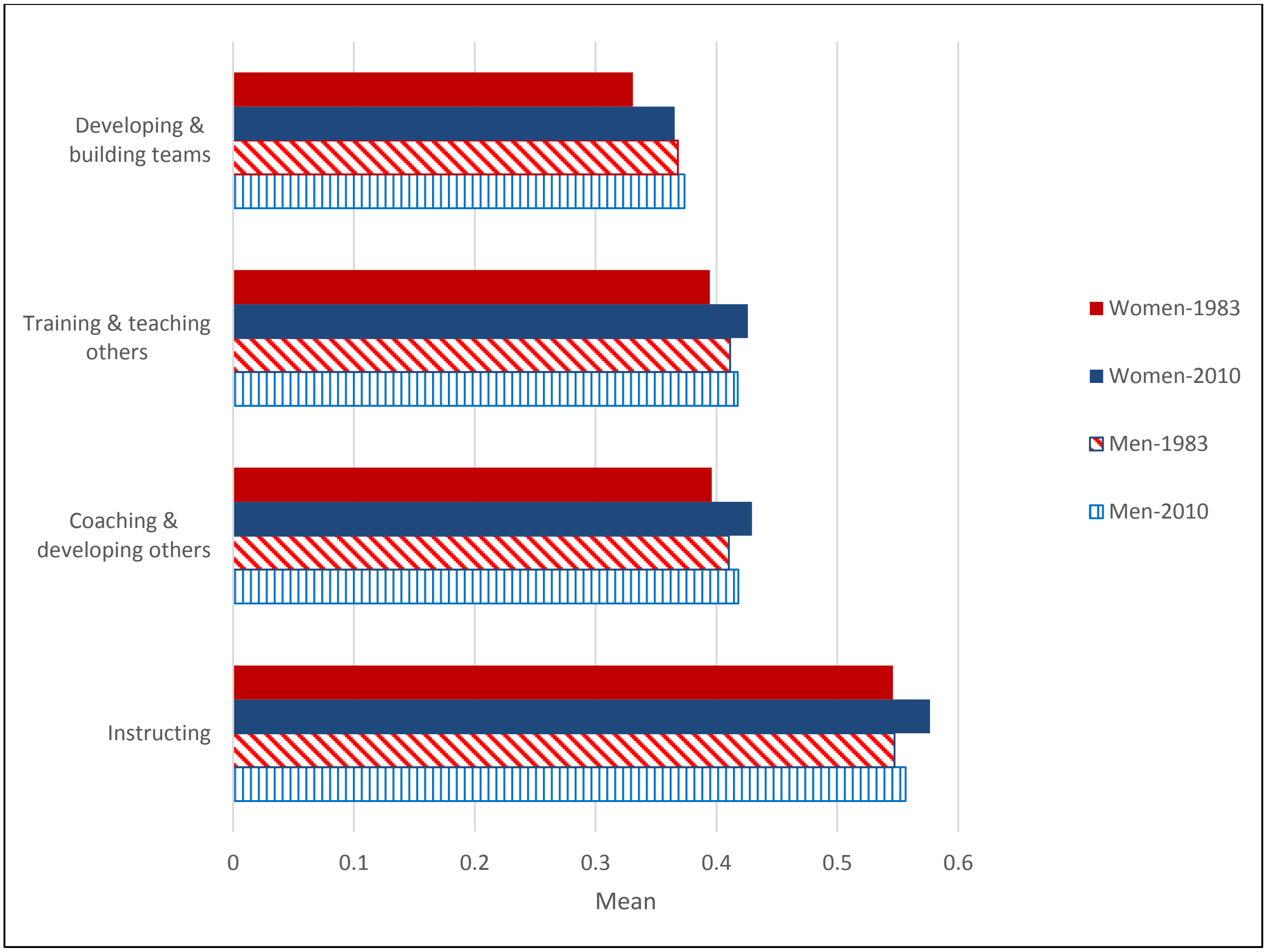


Figure 3. Trends in Means of O*NET 'Caring' Variables by Gender, 1983–2010



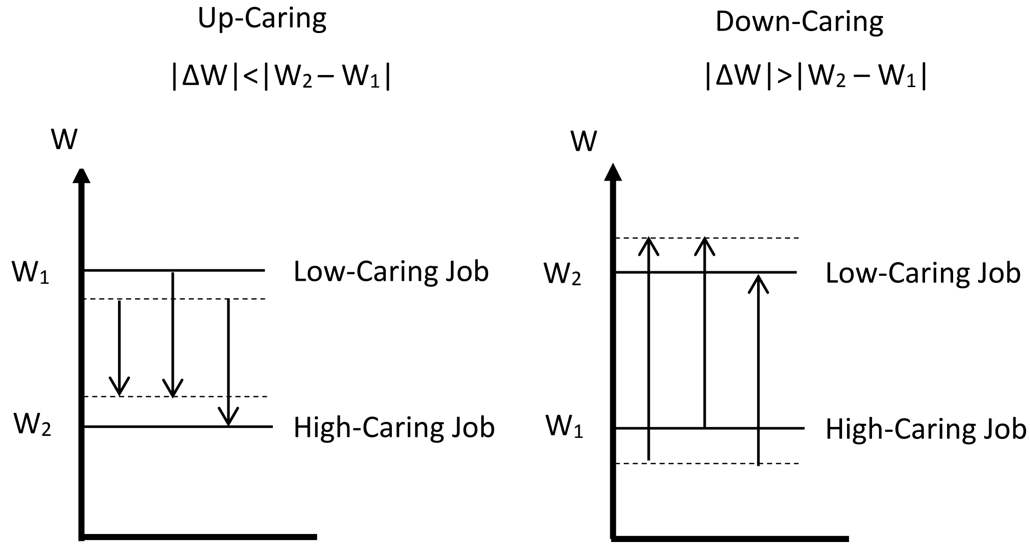
'A&C' and 'Concern' denote O*NET caring attributes 'assisting & caring for others' and 'concern for others' measured in levels and scaled [0,1]. Weighted means are calculated using all wage & salary workers, ages 16+. Caring measures are from the 2007 O*NET version 12, matched to the 2006-2008 CPS using 2000 COC codes, recalculated for that sample using 1980 COC codes, and then matched to workers for 1983-2010 using probabilistic time-consistent 1980 COC codes. The O*NET values by occupation are fixed. Changes over time are determined by changes in occupational employment. The 'A&C' and 'Concern' measures linked to 1980 COC codes are used in Figures 3 and 4, but nowhere else in the paper. See text for details.

Figure 4. Means of Developing/Teaching O*NET Variables, by Sex for 1983 and 2010



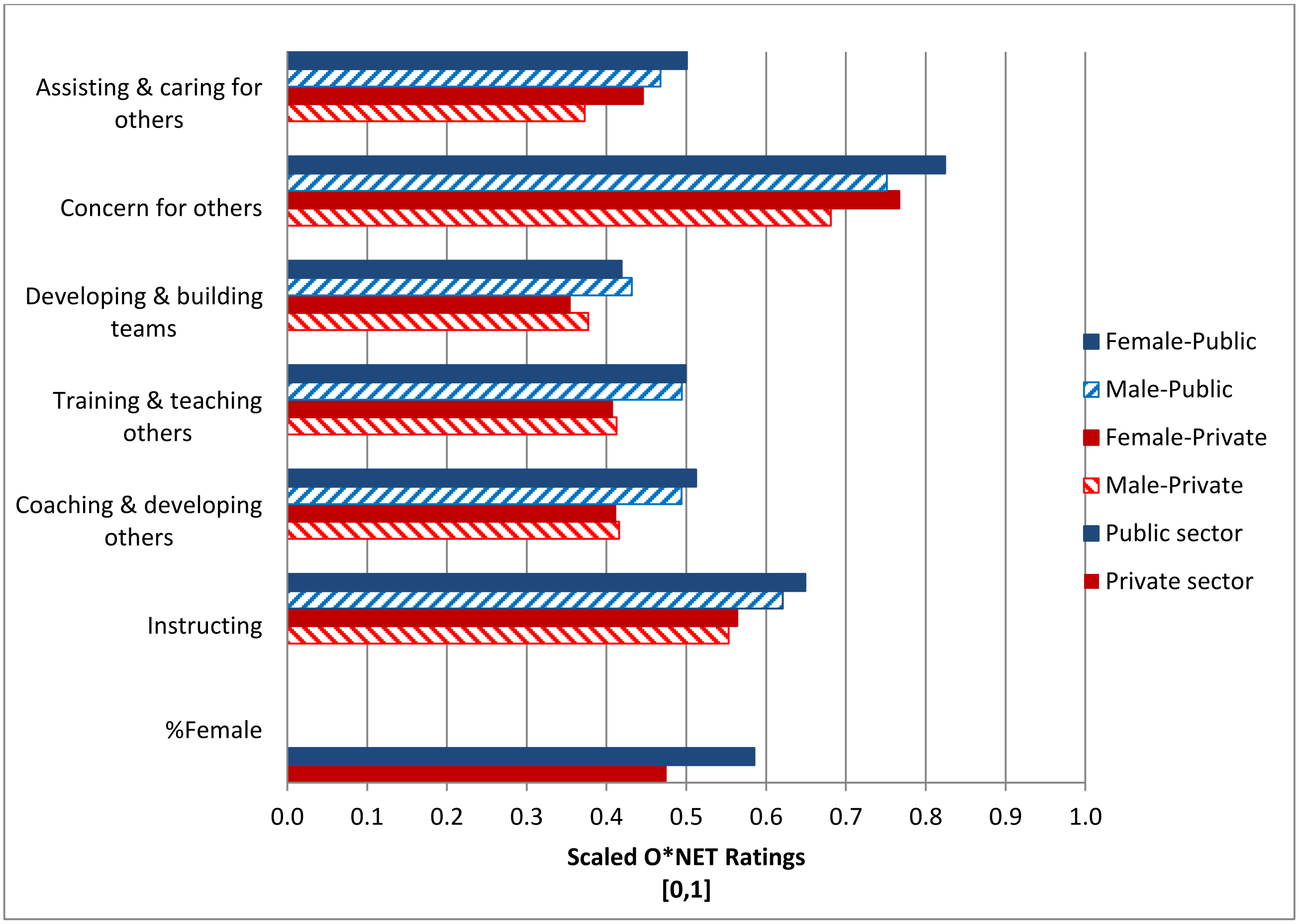
Weighted means are calculated using the full CPS sample for each year excluding only workers under age 16. CPS data are matched based on 1980 Census occupation codes and 2007 O*NET (version 12.0) values. O*NET variables are measured in levels and scaled on [0,1]. See text for further discussion.

Figure 5. Bounds for Selection Bias in Estimates of a Wage Penalty for Care Work



W_1 and W_2 are mean market wages for low- and high-caring jobs. The arrows designate the range of wage changes most likely seen among job switchers, and ΔW represents the mean of observed wage changes among the movers. Selection should lead to smaller observed wage changes (in absolute value) among those who "up-care" than among those who "down-care".

Figure 6. O*NET Ratings of Caring Attributes by Gender and Public/Private Sectors



Figures reflect the means shown in Table 9, which are based on the CPS/O*NET 2006-2008 sample. The %Female for public is 58.5% and for private 47.6% in our 2006-2008 sample.

Figure 7. Scatterplot of Wage Residuals and Occupational Levels of Caring for Women and Men

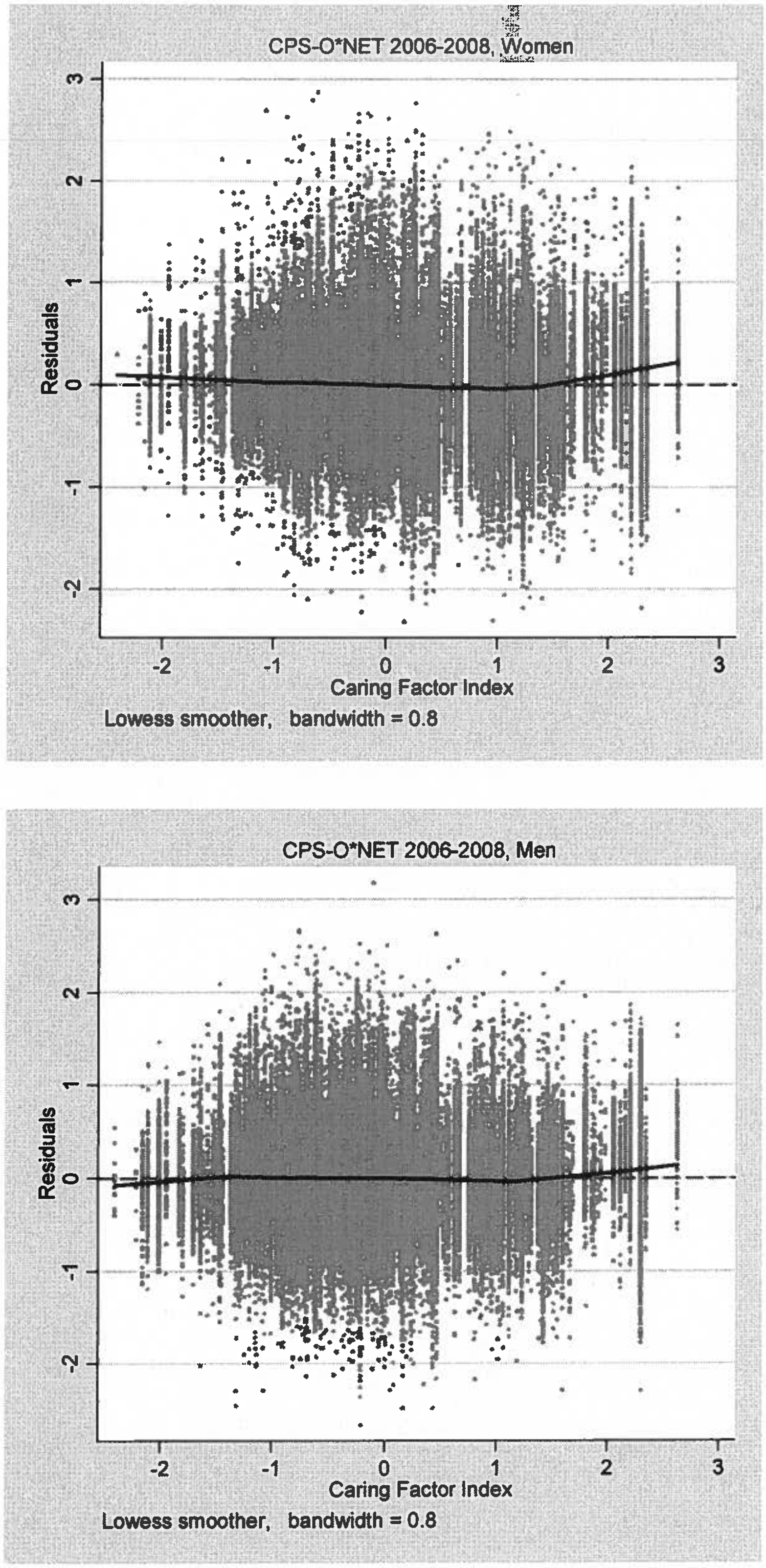
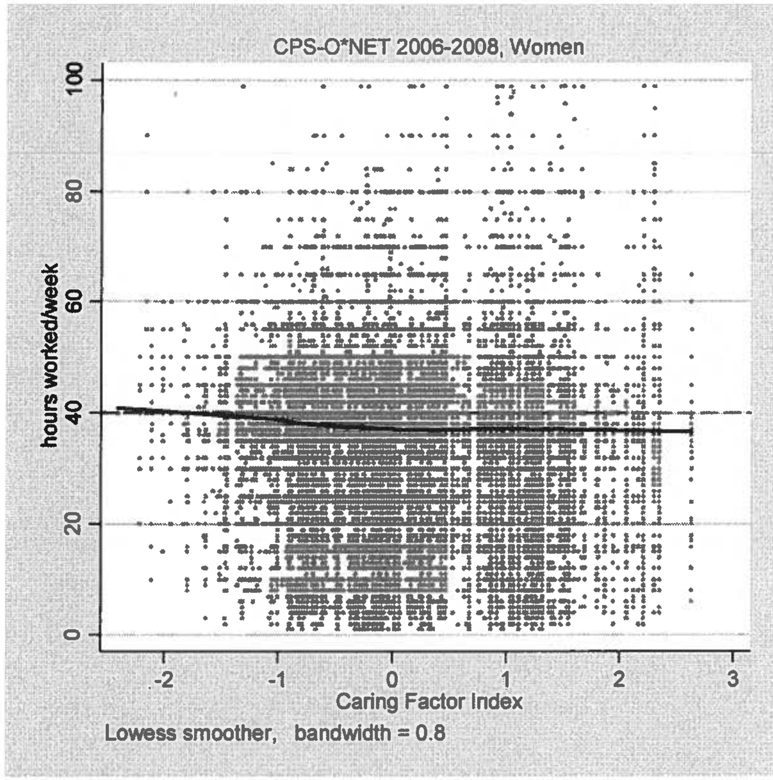


Figure 8. Scatterplot of Hours Worked and Occupational Levels of Caring for Women and Men



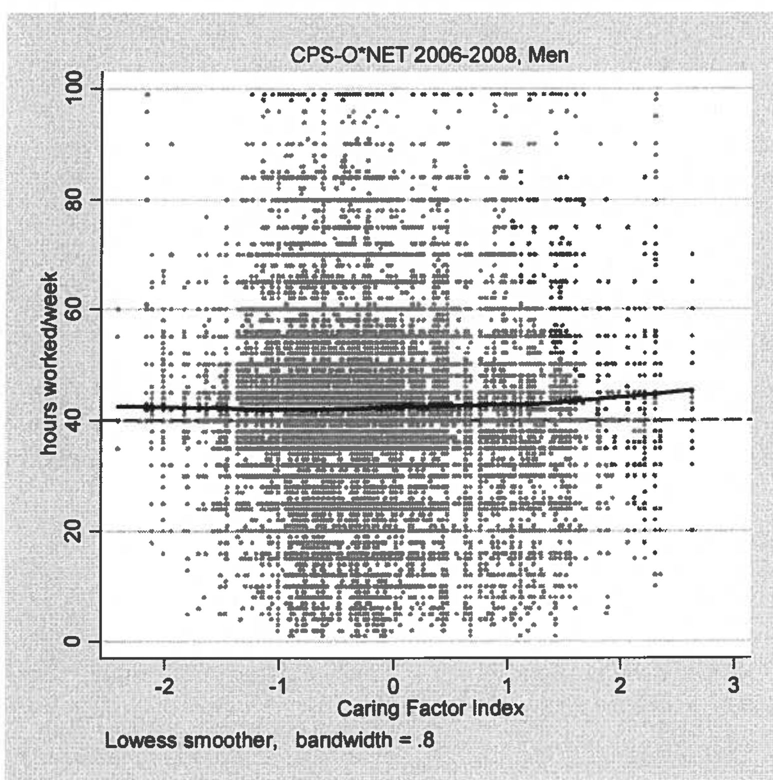


Table 1. O*NET Job Level Attributes Describing Care Work

	O*NET attribute label	O*NET attribute description	O*NET variable	Possible score range
Caring	Assisting and caring for others	Providing personal assistance, medical attention, emotional support, or other personal care to others such as coworkers, customers, or patients	4.a.4.a.5	[0, 7]
	Concern for others	Job requires being sensitive to others' needs and feelings and being understanding and helpful on the job	1.c.3.b	[1, 5]
Develop/Teach	Developing and building teams	Encouraging and building mutual trust, respect, and cooperation among team members	4.a.4.b.2	[0, 7]
	Training and teaching others	Identifying the educational needs of others, developing formal educational or training programs or classes, and teaching or instructing others	4.a.4.b.3	[0, 7]
	Coaching and developing others	Identifying the developmental needs of others and coaching, mentoring, or otherwise helping others to improve their knowledge or skills	4.a.4.b.5	[0, 7]
	Instructing	Teaching others how to do something	2.b.1.e	[0, 7]

Source: Author created using information from http://www.onetonline.org/. Original score range refers to the minimum and maximum score values in our sample before rescaling all O*NET attributes on [0, 1] using the formula $S = \left(\frac{O-L}{H-L}\right)$, where *O* is the original rating score on the rating scale used, *H* is the highest possible score on the rating scale used, and *L* is the lowest possible score on the rating scale used. The caring variables are normalized to mean zero and s.d. equal 1 when included in wage regressions (column 4 of the regression tables) so coefficients can measure the log wage effect of a one s.d. change in the O*NET measure.

Table 2. Summary Statistics for CPS and O*Net Attributes, by Gender, 2006-2008

	Women		Men		$\bar{X}_F - \bar{X}_M$
Variables	mean	s.d.	mean	s.d.	
Hourly earnings	18.83	13.51	23.21	17.59	-4.38
Ln(hourly earnings)	2.7635	0.5602	2.9531	0.5931	-0.1896
Usual hours worked per week	37.2	9.7	42.2	9.3	-5.0
Individual O*NET attributes (scaled 0-1):					
Concern for others	0.7793	0.1124	0.6916	0.1102	0.0877
Assisting & caring for others	0.4576	0.1625	0.3869	0.1281	0.0707
Developing & building teams	0.3681	0.1321	0.3854	0.1281	-0.0173
Training & teaching others	0.4269	0.1358	0.4249	0.1219	0.0020
Coaching & developing others	0.4331	0.1510	0.4274	0.1450	0.0057
Instructing	0.5822	0.1252	0.5633	0.1088	0.0189
O*NET Indices (using factor analysis):					
Caring index (loads concern and asst/caring above)	0.2950	0.8748	-0.2622	0.7420	0.5572
Developing/Teaching index (loads other 4 attributes)	0.0722	1.0062	0.0540	0.9201	0.0182
Job skills index (loads 162 O*NET attributes)	0.1157	0.9632	0.0332	1.0161	0.0825
Working conditions index (loads 38 O*NET attributes)	-0.4124	0.6790	0.3554	1.1155	-0.7678
Sex composition (%Female, from CPS)	0.6761	0.2332	0.3074	0.2468	0.3687
N	166,009		168,760		

Variable means and s.d. created from the CPS are unweighted (weighted means are highly similar). Hourly earnings are measured using implicit hourly wage (usual weekly earnings/usual weekly hours worked). All indices formed from factor analysis are compiled using the combined female and male sample and, by construction, have mean 0 and s.d. 1.0. The job skills index loads 162 O*NET job attributes and does not include the 6 O*NET 'caring' attributes. See the text for further details.

Table 3. Measures of Caring for Occupations with High or Low Caring Ratings and Selected Large Occupations

COC	Occupation Name (Standard Occupational Classification)	A&C rank	A&C value	Concern rank	Concern value
3110	Physician assistants	1	0.961	2	0.983
3060	Physicians and surgeons	2	0.961	12	0.945
3500	Licensed practical nurses & licensed vocational nurses	3	0.886	6	0.970
3220	Respiratory therapists	4	0.886	22	0.923
3130	Registered nurses	5	0.876	13	0.943
9110	Ambulance drivers & attendants, exc. emergency med. tech.	8	0.823	71	0.835
2040	Clergy	12	0.799	103	0.800
3160	Physical therapists	15	0.781	4	0.978
3850	Police and sheriff's patrol officers	18	0.771	75	0.831
3640	Dental assistants	22	0.743	73	0.833
3630	Massage therapists	36	0.679	7	0.965
2010	Social workers	40	0.666	25	0.921
3650	Medical assistants and other healthcare support occupations	45	0.644	60	0.859
4600	Child care workers	46	0.642	34	0.898
2310	Elementary and middle school teachers	73	0.571	19	0.931
3600	Nursing, psychiatric, and home health aides	79	0.554	54	0.865
620	Human resources, training, and labor relations specialists	104	0.525	59	0.860
2200	Postsecondary teachers	115	0.500	121	0.783
5700	Secretaries and administrative assistants	153	0.433	116	0.790
4110	Waiters and waitresses	165	0.420	101	0.745
5240	Customer service representatives	190	0.403	117	0.785
4720	Cashiers	195	0.401	152	0.754
1340	Biomedical engineers	202	0.393	272	0.670
120	Financial managers	253	0.366	301	0.651
9130	Driver/sales workers and truck drivers	266	0.359	341	0.623
9620	Laborers and freight, stock, and material movers, hand	270	0.356	402	0.583
10	Chief executives	293	0.346	176	0.738
5620	Stock clerks and order fillers	299	0.343	265	0.673
4760	Retail salespersons	301	0.341	183	0.733
2100	Lawyers, Judges, magistrates, and other judicial workers	310	0.337	349	0.620
7200	Automotive service technicians and mechanics	332	0.328	419	0.574
6230	Carpenters	355	0.315	385	0.600
5120	Bookkeeping, accounting, and auditing clerks	367	0.306	227	0.700
4220	Janitors and building cleaners	377	0.301	167	0.745
4020	Cooks	390	0.294	260	0.676
800	Accountants and auditors	400	0.287	329	0.630
1020	Computer software engineers	457	0.228	413	0.577
8030	Machinists	471	0.211	500	0.380
4850	Sales representatives, wholesale and manufacturing	472	0.210	203	0.720
1300	Architects, except naval	490	0.176	473	0.506
1210	Mathematicians	495	0.143	501	0.333
300	Engineering managers	499	0.103	308	0.645
1320	Aerospace engineers	501	0.019	373	0.613

'A&C' and 'Concern' denote O*NET attributes 'assisting & caring for others' and 'concern for others', respectively. COC denotes the 2002 Census occupation codes adopted in the CPS beginning in 2003. Value refers to the rescaled score of an occupation's corresponding O*NET attribute ranking on a [0,1] scale. See details in the note to Table 1.

Table 4. Pairwise Correlations of Earnings, Gender, and O*NET Occupational Attributes

	Ln(hourly earnings)	Female	Occupation %Female	Concern For others	Assist and Caring	Caring factor index	Develop/ Teach index	Job skills index	Work cond index
Ln(hourly earnings)	1.0								
Female	-0.16	1.0							
Occupation %Female	-0.13	0.61	1.0						
Concern for others	0.04	0.37	0.60	1.0					
Assisting & caring for others	0.08	0.24	0.39	0.71	1.0				
Caring factor index	0.07	0.33	0.54	0.93	0.93	1.0			
Developing/Teaching (D/T) factor index	0.35	0.01	0.02	0.37	0.49	0.47	1.0		
Job skills factor index	0.53	0.04	0.08	0.36	0.36	0.39	0.75	1.0	
Working conditions factor index	-0.20	-0.38	-0.63	-0.32	-0.08	-0.21	-0.20	-0.49	1.0

These correlations are calculated using a pooled sample of 36 CPS-ORG monthly earnings files for female and male workers covering January 2006 to December 2008 merged with O*NET job attributes. Sex composition is calculated as the ratio of the mean number of females to mean total workers in a given occupation. Observations are not weighted by CPS sampling weights. Hourly wage is an implicit measure based on worker self-reports of usual weekly earnings divided by usual weekly hours worked. See text for details.

Table 5. Wage Level Regression Estimates for Care Work Effects, by Gender, 2006 – 2008

	Women			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0431*		-0.0259	
	(0.0223)		(0.0220)	
Develop/Teach Index		-0.0967***	-0.0908***	
		(0.0211)	(0.0229)	
Assisting and Caring for Others				0.0459**
				(0.0227)
Concern for Others				-0.0685***
				(0.0155)
Job Skills Index	0.1939***	0.2638***	0.2683***	0.2683***
	(0.0233)	(0.0342)	(0.0330)	(0.0311)
Working Conditions Index	0.0800**	0.0882**	0.0961***	0.0829***
	(0.0373)	(0.0375)	(0.0356)	(0.0288)
CPS controls	Y	Y	Y	Y
Observations	166,009	166,009	166,009	166,009
R-squared	0.4748	0.4813	0.4820	0.4878
	Men			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0885***		-0.0732***	
	(0.0163)		(0.0150)	
Develop/Teach Index		-0.0696***	-0.0455***	
		(0.0161)	(0.0123)	
Assisting and Caring for Others				-0.0149
				(0.0172)
Concern for Others				-0.0490***
				(0.0118)
Job Skills Index	0.1775***	0.2039***	0.2094***	0.2134***
	(0.0121)	(0.0177)	(0.0154)	(0.0159)
Working Conditions Index	0.0062	0.0102	0.0132	0.0100
	(0.0142)	(0.0150)	(0.0141)	(0.0144)
CPS controls	Y	Y	Y	Y
Observations	168,760	168,760	168,760	168,760
R-squared	0.4971	0.4945	0.4989	0.4993

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is ln(hourly earnings). Regression coefficients measure the wage effects of one standard deviation changes. CPS controls consist of detailed education attainment dummies, demographics (potential experience and its square, cubic, and quartic terms); dummies for marital status, race, ethnicity, foreign-born citizen, non-citizen), geographic dummies for region (8) and MSA size (6), broad industry (11) and broad occupation (9) dummies, year dummies, and dummies for union membership, public sector, and private nonprofit sector. Col (4) includes the four developing/teaching measures. See text for further details.

Table 6. Wage Level Regression Estimates for Care Work Effects by Gender, Absent O*NET Skill & Working Conditions Indices

	Women			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	0.0181		0.0010	
	(0.0349)		(0.0375)	
Develop/Teach Index		0.0404*	0.0401*	
		(0.0209)	(0.0213)	
Assisting and Caring for Others				0.0798*
				(0.0406)
Concern for Others				-0.0849***
				(0.0224)
Job Skills Index	N	N	N	N
Working Conditions Index	N	N	N	N
CPS controls	Y	Y	Y	Y
Observations	166,009	166,009	166,009	166,009
R-squared	0.4415	0.4439	0.4439	0.4598
	Men			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0313		-0.0630***	
	(0.0203)		(0.0203)	
Develop/Teach Index		0.0333**	0.0564***	
		(0.0162)	(0.0172)	
Assisting and Caring for Others				-0.0096
				(0.0223)
Concern for Others				-0.0457**
				(0.0183)
Job Skills Index	N	N	N	N
Working Conditions Index	N	N	N	N
CPS controls	Y	Y	Y	Y
Observations	168,760	168,760	168,760	168,760
R-squared	0.4686	0.4693	0.4726	0.4771

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is ln(hourly earnings). The regressions in this table are identical to those shown in Table 5, except for the exclusion of the Job Skills and Working Condition indices. See Table5 notes.

Table 7. Wage Change Estimates for Care Work—Ind/Occ Switchers Only, by Gender, 2003/4 – 2008/09

	Women			
Δ O*NET Variables/Indices	(1)	(2)	(3)	(4)
Δ Caring Index	-0.0137***		-0.0140***	
	(0.0043)		(0.0045)	
Δ Develop/Teach Index		-0.0016	0.0017	
		(0.0049)	(0.0051)	
Δ Assisting & caring for others				-0.0058
				(0.0039)
Δ Concern for others				-0.0055
				(0.0040)
Δ Job Skills Index	0.0448***	0.0423***	0.0435***	0.0433***
	(0.0048)	(0.0061)	(0.0062)	(0.0073)
Δ Working Conditions Index	-0.0056	-0.0077	-0.0060	-0.0029
	(0.0060)	(0.0060)	(0.0061)	(0.0061)
Δ CPS controls	Y	Y	Y	Y
Observations	18,981	18,981	18,981	18,981
R-squared	0.0219	0.0213	0.0219	0.0225
	Men			
Δ O*NET Variables/Indices	(1)	(2)	(3)	(4)
Δ Caring Index	-0.0184***		-0.0217***	
	(0.0046)		(0.0047)	
Δ Develop/Teach Index		0.0040	0.0097**	
		(0.0039)	(0.0040)	
Δ Assisting & caring for others				-0.0106**
				(0.0041)
Δ Concern for others				-0.0080**
				(0.0035)
Δ Job Skills Index	0.0407***	0.0331***	0.0346***	0.0302***
	(0.0043)	(0.0048)	(0.0049)	(0.0057)
Δ Working Conditions Index	-0.0009	-0.0021	-0.0021	-0.0020
	(0.0049)	(0.0049)	(0.0049)	(0.0049)
Δ CPS controls	Y	Y	Y	Y
Observations	21,689	21,689	21,689	21,689
R-squared	0.0257	0.0249	0.0259	0.0263

Standard errors in parentheses, clustered by occupation pair. *** p<0.01, ** p<0.05, * p<0.10. Regression coefficients measure the wage effects of one standard deviation changes. ΔCPS controls consist of first differences in higher order terms of experience (square, cubic, and quartic), changes in union membership, public sector, private nonprofit sector, broad industry and broad occupation, and dummies for year pairs. All O*NET variables and indices are differenced. Dependent variable is Δln(hourly earnings).

Table 8. Separate Wage Change Estimates for Care Work for Up-Caring and Down-Caring Ind/Occ Switchers, by Gender, 2003/4 – 2008/09

	Women		
Δ Independent Variables	(1)	(2)	(3)
Up·ΔCaring index	-0.0158**		-0.0166**
	(0.0074)		(0.0075)
Down·ΔCaring index	-0.0115		-0.0114
	(0.0074)		(0.0075)
Up·ΔDevelop/Teach index		0.0008	0.0044
		(0.0067)	(0.0068)
Down·ΔDevelop/Teach index		-0.0040	-0.0011
		(0.0071)	(0.0072)
Δ Job Skills Index	0.0448***	0.0423***	0.0435***
	(0.0048)	(0.0061)	(0.0062)
Δ Working Conditions Index	-0.0057	-0.0078	-0.0060
	(0.0060)	(0.0060)	(0.0061)
Δ CPS controls	Y	Y	Y
Observations	18,981	18,981	18,981
R-squared	0.0220	0.0214	0.0220
	Men		
	(1)	(2)	(3)
Up·ΔCaring index	-0.0129		-0.0135
	(0.0081)		(0.0082)
Down·ΔCaring index	-0.0240***		-0.0299***
	(0.0087)		(0.0088)
Up·ΔDevelop/Teach index		-0.0035	0.0007
		(0.0070)	(0.0071)
Down·ΔDevelop/Teach index		0.0114*	0.0186***
		(0.0068)	(0.0070)
Δ Job Skills Index	0.0407***	0.0332***	0.0347***
	(0.0043)	(0.0048)	(0.0049)
Δ Working Conditions Index	-0.0008	-0.0019	-0.0019
	(0.0049)	(0.0049)	(0.0049)
Δ CPS controls	Y	Y	Y
Observations	21,689	21,689	21,689
R-squared	0.0262	0.0255	0.0266

Standard errors in parentheses, clustered by occupation pair. *** p<0.01, ** p<0.05, * p<0.10. No differences between Up and Down Care coefficients are significant at standard levels. Regression coefficients measure the wage effects of one standard deviation changes. See Table 6 for ΔCPS controls; see text for a detailed discussion of variables including interaction terms.

Table 9. O*NET Caring Attribute/Index Means in the Private and Public Sectors, by Gender

	Women		Men		
Private Sector Means:	mean	s.d.	mean	s.d.	$\bar{X}_F - \bar{X}_M$
Hourly earnings	18.22	13.66	22.75	17.96	-4.53
Log hourly earnings	2.7237	0.5648	2.9240	0.6022	-0.2003
Individual O*NET attributes (scaled 0-1):					
Concern for others	0.7668	0.1105	0.6809	0.1045	0.0859
Assisting & caring for others	0.4456	0.1657	0.3725	0.1156	0.0731
Developing & building teams	0.3540	0.1283	0.3772	0.1258	-0.0232
Training & teaching others	0.4069	0.1218	0.4125	0.1119	-0.0056
Coaching & developing others	0.4111	0.1392	0.4156	0.1388	-0.0045
Instructing	0.5636	0.1135	0.5531	0.1001	0.0105
O*NET Indices (using factor analysis):					
Caring index (loads concern and asst/caring above)	0.2097	0.8753	-0.3476	0.6769	0.5573
Developing/Teaching index (loads remaining 4 attributes)	-0.0790	0.9114	-0.0321	0.8629	-0.0469
N	129,987		143,228		
	Women		Men		
Public Sector Means:	mean	s.d.	mean	s.d.	$\bar{X}_F - \bar{X}_M$
Hourly earnings	21.03	12.74	25.77	15.09	-4.74
Log hourly earnings	2.9070	0.5184	3.1164	0.5093	-0.2094
Individual O*NET attributes (scaled 0-1):					
Concern for others	0.8244	0.1076	0.7512	0.1221	0.0732
Assisting & caring for others	0.5009	0.1424	0.4676	0.1610	0.0333
Developing & building teams	0.4188	0.1330	0.4316	0.1309	-0.0128
Training & teaching others	0.4991	0.1573	0.4943	0.1490	0.0048
Coaching & developing others	0.5125	0.1644	0.4941	0.1600	0.0184
Instructing	0.6493	0.1414	0.6209	0.1345	0.0284
O*NET Indices (using factor analysis):					
Caring index (loads concern and asst/caring above)	0.6029	0.8010	0.2172	0.8934	0.3857
Developing/Teaching index (loads remaining 4 attributes)	0.6180	1.1351	0.5374	1.0692	0.0806
N	36,022		25,532		

All means are calculated from the merged 2006-2008 merged CPS/O*NET data set described in the text.

Table 10. Wage Level Estimates for Care Work in Public and Private Sectors by Gender, 2006 – 2008

	Women in the private sector			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0181		-0.0090	
	(0.0225)		(0.0229)	
Develop/Teach Index		-0.0700***	-0.0685***	
		(0.0207)	(0.0219)	
Assisting and Caring for Others				0.0479*
				(0.0252)
Concern for Others				-0.0546***
				(0.0175)
Job Skills Index	0.1909***	0.2452***	0.2474***	0.2528***
	(0.0228)	(0.0344)	(0.0318)	(0.0331)
Working Conditions Index	0.0509	0.0620	0.0653*	0.0604**
	(0.0340)	(0.0391)	(0.0342)	(0.0290)
CPS controls	Y	Y	Y	Y
Observations	129,987	129,987	129,987	129,987
R-squared	0.4804	0.4842	0.4842	0.4892
	Men in the private sector			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0640***		-0.0539***	
	(0.0183)		(0.0171)	
Develop/Teach Index		-0.0487***	-0.0354***	
		(0.0146)	(0.0116)	
Assisting and Caring for Others				-0.0199
				(0.0194)
Concern for Others				-0.0289***
				(0.0108)
Job Skills Index	0.1706***	0.1921***	0.1966***	0.1944***
	(0.0141)	(0.0183)	(0.0166)	(0.0170)
Working Conditions Index	-0.0067	-0.0018	-0.0005	-0.0009
	(0.0144)	(0.0145)	(0.0143)	(0.0143)
CPS controls	Y	Y	Y	Y
Observations	143,228	143,228	143,228	143,228
R-squared	0.5066	0.5056	0.5076	0.5077

(continued on next page)

Table 10 (continued). Wage Level Estimates for Care Work in Public and Private Sectors by Gender

	Women in the public sector			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0844***		-0.0572***	
	(0.0213)		(0.0192)	
Develop/Teach Index		-0.1196***	-0.0970***	
		(0.0190)	(0.0224)	
Assisting and Caring for Others				0.0133
				(0.0192)
Concern for Others				-0.0712***
				(0.0140)
Job Skills Index	0.1996***	0.2804***	0.2799***	0.2582***
	(0.0298)	(0.0370)	(0.0368)	(0.0389)
Working Conditions Index	0.1312***	0.1410***	0.1507***	0.1282***
	(0.0370)	(0.0330)	(0.0332)	(0.0303)
CPS controls	Y	Y	Y	Y
Observations	36,022	36,022	36,022	36,022
R-squared	0.4512	0.4556	0.4599	0.4636

	Men in the public sector			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.1058***		-0.0916***	
	(0.0128)		(0.0131)	
Develop/Teach Index		-0.0912***	-0.0344**	
		(0.0173)	(0.0160)	
Assisting and Caring for Others				-0.0113
				(0.0149)
Concern for Others				-0.0657***
				(0.0117)
Job Skills Index	0.1882***	0.2222***	0.2122***	0.2052***
	(0.0132)	(0.0189)	(0.0191)	(0.0167)
Working Conditions Index	0.0303**	0.0346*	0.0355**	0.0231
	(0.0153)	(0.0193)	(0.0163)	(0.0143)
CPS controls	Y	Y	Y	Y
Observations	25,532	25,532	25,532	25,532
R-squared	0.4355	0.4245	0.4366	0.4397

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. Regression coefficients measure the wage effects of one standard deviation changes. CPS controls consist of detailed education attainment dummies, demographics (potential experience and its square, cubic, and quartic terms; dummies for marital status, race, ethnicity, foreign-born citizen, non-citizen), geographic dummies for region (8) and size (6), broad industry (11; private sector only) and broad occupation (9) dummies, and private non-profit (private sector only). Dependent variable is ln(hourly earnings), see text for a detailed description of variables.

Table 11. Quantile Regression Wage Level Estimates for Care Work—by Gender, 2006 – 2008

		Women, N=166,009				
O*NET Caring Indices	OLS/Table 5	QR-p10	QR-p25	QR-p50	QR-p75	QR-p90
Caring Index	-0.0431*	-0.0522	-0.0500	-0.0434	-0.0437	-0.0458
	(0.0223)	(0.0027)	(0.0019)	(0.0018)	(0.0022)	(0.0031)
Develop/Teach Index	-0.0967***	-0.0787	-0.0898	-0.0954	-0.0998	-0.1031
	(0.0211)	(0.0028)	(0.0020)	(0.0020)	(0.0024)	(0.0033)
Caring Index	-0.0259	-0.0372	-0.0348	-0.0284	-0.0289	-0.0296
	(0.0220)	(0.0026)	(0.0018)	(0.0019)	(0.0023)	(0.0032)
Develop/Teach Index	-0.0908***	-0.0693	-0.0818	-0.0890	-0.0944	-0.0965
	(0.0229)	(0.0029)	(0.0020)	(0.0021)	(0.0025)	(0.0035)
		Men, N=168,760				
O*NET Caring Indices	OLS/Table 5	QR-p10	QR-p25	QR-p50	QR-p75	QR-p90
Caring Index	-0.0885***	-0.1182	-0.1084	-0.0964	-0.0722	-0.0473
	(0.0163)	(0.0029)	(0.0022)	(0.0020)	(0.0023)	(0.0034)
Develop/Teach Index	-0.0696***	-0.0637	-0.0692	-0.0690	-0.0646	-0.0588
	(0.0161)	(0.0030)	(0.0022)	(0.0020)	(0.0023)	(0.0033)
Caring Index	-0.0732***	-0.1071	-0.0957	-0.0819	-0.0577	-0.0327
	(0.0150)	(0.0031)	(0.0023)	(0.0021)	(0.0024)	(0.0036)
Develop/Teach Index	-0.0455***	-0.0305	-0.0384	-0.0434	-0.0475	-0.0494
	(0.0123)	(0.0030)	(0.0023)	(0.0021)	(0.0024)	(0.0036)

*** p<0.01, ** p<0.05, * p<0.10 for OLS only. Standard errors for OLS are clustered by occupation. QR standard errors not clustered and QR significance levels not shown. "QR-pN" designates quantile regression results at the N^{th} percentile. See Table 5 notes for independent variables.

Table 12. Wage Level and Wage Change Estimates for Care Work by Predicted Wage Quintile

	Wage Level Regression Estimates, 2006-2008 Women					
O*NET Caring Indices	Table 5	Q1	Q2	Q3	Q4	Q5
Caring Index	-0.0431*	-0.0301	-0.0472**	-0.0413*	-0.0441**	-0.0430**
	(0.0223)	(0.0183)	(0.0202)	(0.0245)	(0.0215)	(0.0175)
Develop/Teach Index	-0.0967***	-0.0156	-0.0625***	-0.0939***	-0.1138***	-0.1239***
	(0.0211)	(0.0213)	(0.0208)	(0.0216)	(0.0246)	(0.0255)
Caring Index	-0.0259	-0.0310*	-0.0441**	-0.0293	-0.0143	0.0004
	(0.0220)	(0.0184)	(0.0203)	(0.0243)	(0.0223)	(0.0168)
Develop/Teach Index	-0.0908***	-0.0175	-0.0598***	-0.0892***	-0.1092***	-0.1240***
	(0.0229)	(0.0197)	(0.0192)	(0.0221)	(0.0281)	(0.0285)
Observations	166,009	33,202	33,202	33,202	33,202	33,201
	Men					
Caring Index	-0.0885***	-0.0302**	-0.0768***	-0.0818***	-0.0916***	-0.0686***
	(0.0163)	(0.0127)	(0.0143)	(0.0140)	(0.0192)	(0.0192)
Develop/Teach Index	-0.0696***	-0.0140	-0.0341***	-0.0440***	-0.0818***	-0.1019***
	(0.0161)	(0.0127)	(0.0113)	(0.0120)	(0.0177)	(0.0180)
Caring Index	-0.0732***	-0.0288**	-0.0718***	-0.0743***	-0.0719***	-0.0330*
	(0.0150)	(0.0130)	(0.0146)	(0.0140)	(0.0176)	(0.0177)
Develop/Teach Index	-0.0455***	-0.0114	-0.0201**	-0.0243**	-0.0542***	-0.0854***
	(0.0123)	(0.0127)	(0.0101)	(0.0094)	(0.0142)	(0.0192)
Observations	168,760	33,752	33,752	33,752	33,752	33,752
	Wage Change Estimates for Ind/Occ Switchers, 2003/4 - 2008/9 Women					
O*NET Caring Indices	Table 7	Q1	Q2	Q3	Q4	Q5
Δ Caring Index	-0.0137***	-0.0148	-0.0066	0.0013	-0.0223***	-0.0171*
	(0.0043)	(0.0096)	(0.0104)	(0.0094)	(0.0086)	(0.0090)
Δ Develop/Teach Index	-0.0016	0.0301***	-0.0026	-0.0095	-0.0020	-0.0125
	(0.0049)	(0.0107)	(0.0104)	(0.0100)	(0.0101)	(0.0103)
Δ Caring Index	-0.0140***	-0.0164*	-0.0064	0.0033	-0.0236***	-0.0148
	(0.0045)	(0.0097)	(0.0104)	(0.0098)	(0.0091)	(0.0096)
Δ Develop/Teach Index	0.0017	0.0310***	-0.0020	-0.0101	0.0047	-0.0063
	(0.0051)	(0.0108)	(0.0105)	(0.0104)	(0.0107)	(0.0110)
Observations	18,981	3,797	3,796	3,796	3,796	3,796
	Men					
Δ Caring Index	-0.0184***	-0.0157	-0.0430***	0.0020	-0.0102	-0.0236**
	(0.0046)	(0.0108)	(0.0105)	(0.0106)	(0.0097)	(0.0100)
Δ Develop/Teach Index	0.0040	0.0057	-0.0129	0.0164*	0.0004	0.0074
	(0.0039)	(0.0083)	(0.0093)	(0.0091)	(0.0087)	(0.0099)
Δ Caring Index	-0.0216***	-0.0168	-0.0416***	-0.0036	-0.0119	-0.0326***
	(0.0047)	(0.0107)	(0.0109)	(0.0108)	(0.0105)	(0.0105)
Δ Develop/Teach Index	0.0096**	0.0074	-0.0051	0.0173*	0.0042	0.0207**
	(0.0040)	(0.0083)	(0.0098)	(0.0094)	(0.0094)	(0.0103)
Observations	21,689	4,338	4,338	4,338	4,338	4,337

Standard errors in parentheses, clustered by occupation in wage level results (top half of table) and by occupation-pair in wage change results (bottom half). *** p<0.01, ** p<0.05, * p<0.10. Wage quintiles are based on predicted log wage from wage level estimates (excluding job attributes) using the 2006-2008 CPS sample in the top half of the table and in the bottom half the initial CPS panel year samples, 2003/4-2008/9. Covariates include demographic, education, and geographic variables, plus year dummies. All estimates are OLS.

Table 13. Wage Level Estimates for Care Work Effects for Selected Groups, 2006 – 2008

	Women, N=166,009			Men, N=168,760		
Group	N	mean caring	caring estimate	N	mean caring	caring estimate
Full-time	130,924	0.2690	-0.0383*	157,672	-0.2696	-0.0741***
Part-time	35,085	0.3920	0.0284	11,088	-0.1566	-0.0364*
Hourly workers	99,951	0.2480	-0.0015	93,086	-0.3760	-0.0489***
Salaried workers	66,058	0.3662	-0.0392**	75,674	-0.1222	-0.0647***
Non-Hispanic white	123,125	0.3333	-0.0193	123,963	-0.2402	-0.0697***
Non-Hispanic Black	15,199	0.2944	-0.0484***	11,101	-0.1778	-0.0896***
Non-Hispanic other	10,519	0.2087	-0.0281	10,625	-0.2723	-0.0746***
Hispanic	17,166	0.0738	-0.0469**	23,071	-0.4162	-0.0578***
Native citizen	147,637	0.3232	-0.0245	143,851	-0.2354	-0.0711***
Foreign-born citizen	8,208	0.2190	-0.0345	8,207	-0.2889	-0.0666***
Foreign-born non-citizen	10,164	-0.0527	-0.0290	16,702	-0.4793	-0.0728***
Ages 18-24	15,638	0.1684	-0.0133	17,230	-0.3925	-0.0419***
Ages 25-34	38,197	0.3089	-0.0146	41,327	-0.2804	-0.0560***
Ages 35-44	41,823	0.2906	-0.0234	43,532	-0.2469	-0.0555***
Ages 45-54	44,166	0.3076	-0.0389	41,707	-0.2511	-0.0764***
Ages 55-65	26,185	0.3361	-0.0286	24,964	-0.1870	-0.0929***
Never married	38,147	0.2125	-0.0232	43,869	-0.3124	-0.0662***
Ever-married	127,862	0.3196	-0.0278	124,891	-0.2445	-0.0738***
HS dropout	10,745	-0.1642	-0.0476**	17,840	-0.5394	-0.0332***
HS graduate –no college	45,311	0.0452	-0.0653***	51,936	-0.4125	-0.0667***
Some college	52,555	0.3351	-0.0228	46,348	-0.2507	-0.0607***
BA/BS degree	38,142	0.4614	-0.0023	34,787	-0.1369	-0.0614***
Graduate/professional/doctoral degree	19,256	0.7003	0.0122	17,849	0.1784	-0.0131
Large metro (pop ≥ million)	20,426	0.2781	-0.0449*	21,258	-0.2464	-0.0818***
Small metro (100K ≤ pop < 5million)	99,490	0.2862	-0.0247	101,266	-0.2601	-0.0745***
CPS non-metro	46,093	0.3215	-0.0095	46,236	-0.2739	-0.0552***
Private for-profit	111,600	0.1088	-0.0138	135,439	-0.3994	-0.0396***
Private not-for-profit	18,387	0.8221	0.0097	7,789	0.5527	-0.0432*
Public	36,022	0.6029	-0.0572***	25,532	0.2172	-0.0916***

*** p<0.01, ** p<0.05, and * p<0.01 using standard errors clustered on occupation. “Mean caring” is mean of the O*NET caring index. “Caring estimate” is the wage regression coefficient on the caring index. Regression model used is similar to Table 5 Column 3. See Table 5 notes.

Appendix Tables

Table A-1. Coefficients (s.e.) for O*NET D/T Attributes and Selected Control Variables to Accompany Table 5 Regression Results for Women and Men

	Women			
Independent Variables	(1)	(2)	(3)	(4)
Developing and Building Teams				-0.0185
				(0.0205)
Training and Teaching Others				-0.0745***
				(0.0204)
Coaching and Developing Others				0.0164
				(0.0250)
Instructing				-0.0466***
				(0.0169)
Married, spouse present	0.0407***	0.0416***	0.0422***	0.0428***
	(0.0054)	(0.0048)	(0.0048)	(0.0044)
Separated/widowed/divorced	0.0116***	0.0099**	0.0107***	0.0111***
	(0.0041)	(0.0041)	(0.0039)	(0.0039)
Black	-0.0718***	-0.0752***	-0.0741***	-0.0727***
	(0.0095)	(0.0090)	(0.0093)	(0.0083)
Other race	-0.0155*	-0.0189**	-0.0192***	-0.0217***
	(0.0082)	(0.0073)	(0.0072)	(0.0066)
Hispanic	-0.0803***	-0.0788***	-0.0779***	-0.0767***
	(0.0070)	(0.0069)	(0.0071)	(0.0068)
Foreign-born citizen	-0.0367***	-0.0400***	-0.0399***	-0.0394***
	(0.0079)	(0.0077)	(0.0077)	(0.0075)
Foreign-born noncitizen	-0.1313***	-0.1301***	-0.1316***	-0.1287***
	(0.0125)	(0.0125)	(0.0127)	(0.0126)
Experience	0.0381***	0.0384***	0.0382***	0.0377***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Experience^2	-0.0017***	-0.0017***	-0.0017***	-0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Part-time (hours<35)	-0.0966***	-0.1005***	-0.0975***	-0.0961***
	(0.0150)	(0.0166)	(0.0150)	(0.0144)
Public	0.0363	0.0743***	0.0672***	0.0901***
	(0.0296)	(0.0245)	(0.0254)	(0.0268)
Private not-for-profit	-0.0207	-0.0112	-0.0129	-0.0157
	(0.0221)	(0.0202)	(0.0213)	(0.0200)
Union member	0.1185***	0.1283***	0.1301***	0.1376***
	(0.0100)	(0.0103)	(0.0100)	(0.0113)

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. See Table 5 notes.

(Table A-1 continued on next page)

Table A-1 (continued). Coefficients (s.e.) for O*NET D/T Attributes and Selected Control Variables to Accompany Table 5 Regression Results Women and Men

	Men			
Independent Variables	(1)	(2)	(3)	(4)
Developing and Building Teams				-0.0069
				(0.0120)
Training and Teaching Others				-0.0183
				(0.0190)
Coaching and Developing Others				-0.0172
				(0.0192)
Instructing				-0.0184
				(0.0139)
Married,spouse present	0.1249***	0.1252***	0.1244***	0.1241***
	(0.0051)	(0.0054)	(0.0052)	(0.0052)
Separated/widowed/divorced	0.0416***	0.0405***	0.0409***	0.0409***
	(0.0054)	(0.0055)	(0.0054)	(0.0054)
Black	-0.1319***	-0.1370***	-0.1311***	-0.1312***
	(0.0074)	(0.0077)	(0.0075)	(0.0075)
Other race	-0.0421***	-0.0425***	-0.0433***	-0.0437***
	(0.0104)	(0.0106)	(0.0100)	(0.0097)
Hispanic	-0.1149***	-0.1172***	-0.1136***	-0.1132***
	(0.0075)	(0.0077)	(0.0075)	(0.0075)
Foreign-born citizen	-0.0464***	-0.0465***	-0.0471***	-0.0475***
	(0.0087)	(0.0083)	(0.0084)	(0.0083)
Foreign-born noncitizen	-0.1325***	-0.1292***	-0.1317***	-0.1316***
	(0.0112)	(0.0115)	(0.0109)	(0.0109)
Experience	0.0350***	0.0349***	0.0350***	0.0351***
	(0.0021)	(0.0022)	(0.0022)	(0.0021)
Experience^2	-0.0011***	-0.0011***	-0.0011***	-0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Part-time (hours<35)	-0.1588***	-0.1647***	-0.1569***	-0.1562***
	(0.0147)	(0.0154)	(0.0149)	(0.0151)
Public	0.0937**	0.0945*	0.0967**	0.1023**
	(0.0468)	(0.0487)	(0.0437)	(0.0440)
Private not-for-profit	-0.1023***	-0.1072***	-0.0961***	-0.0989***
	(0.0352)	(0.0372)	(0.0324)	(0.0331)
Union member	0.1886***	0.1839***	0.1907***	0.1926***
	(0.0136)	(0.0142)	(0.0131)	(0.0127)

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. See Table 5 notes.

Table A-2. Wage Level Regression Estimates for Care Work Effects Using the Longitudinal Sample of Ind/Occ Switchers, Initial Year of 2003/4 – 2008/09 Panels

	Women			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0604***		-0.0523***	
	(0.0126)		(0.0126)	
Develop/Teach Index		-0.0507***	-0.0362***	
		(0.0121)	(0.0114)	
Assisting and Caring for Others				-0.0102
				(0.0136)
Concern for Others				-0.0330***
				(0.0108)
Job Skills Index	0.1580***	0.1843***	0.1872***	0.1889***
	(0.0112)	(0.0170)	(0.0159)	(0.0187)
Working Conditions Index	-0.0131	-0.0132	-0.0044	-0.0035
	(0.0173)	(0.0165)	(0.0174)	(0.0178)
CPS controls	Y	Y	Y	Y
Observations	18,981	18,981	18,981	18,981
R-squared	0.4215	0.4194	0.4229	0.4236

	Men			
O*NET Variables/Indices	(1)	(2)	(3)	(4)
Caring Index	-0.0661***		-0.0621***	
	(0.0090)		(0.0088)	
Develop/Teach Index		-0.0303***	-0.0112	
		(0.0092)	(0.0073)	
Assisting and Caring for Others				-0.0329***
				(0.0083)
Concern for Others				-0.0203***
				(0.0072)
Job Skills Index	0.1303***	0.1357***	0.1382***	0.1408***
	(0.0086)	(0.0110)	(0.0100)	(0.0112)
Working Conditions Index	-0.0140	-0.0118	-0.0121	-0.0129
	(0.0100)	(0.0103)	(0.0100)	(0.0098)
CPS controls	Y	Y	Y	Y
Observations	21,689	21,689	21,689	21,689
R-squared	0.4780	0.4750	0.4782	0.4783

Standard errors in parentheses, clustered by occupation. *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is ln(hourly earnings). See Table 5 notes for CPS controls; see text for a detailed description of variables.

Table A-3. Coefficients (s.e.) for O*NET D/T Attributes and Selected Control Variables to Accompany Table 7 Wage Change Regression Results—Ind/Occ Switchers (Women)

	Women			
Δ Independent Variables	(1)	(2)	(3)	(4)
Δ Developing & building teams				-0.0034
				(0.0050)
Δ Training & teaching others				-0.0136**
				(0.0054)
Δ Coaching & developing others				0.0147**
				(0.0057)
Δ Instructing				0.0030
				(0.0047)
Δ $experience^2$	-0.0031***	-0.0031***	-0.0031***	-0.0031**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Δ part-time (hours<35)	-0.0078	-0.0081	-0.0078	-0.0076
	(0.0075)	(0.0075)	(0.0075)	(0.0075)
Δ union	0.0740***	0.0734***	0.0740***	0.0737***
	(0.0140)	(0.0140)	(0.0140)	(0.0140)
Δ public sector	-0.0012	0.0007	-0.0015	-0.0020
	(0.0164)	(0.0164)	(0.0164)	(0.0164)
Δ private not-for-profit	-0.0181	-0.0180	-0.0182	-0.0186*
	(0.0111)	(0.0111)	(0.0111)	(0.0111)
	Men			
Δ Developing & building teams				0.0060
				(0.0040)
Δ Training & teaching others				-0.0068
				(0.0050)
Δ Coaching & developing others				0.0094*
				(0.0053)
Δ Instructing				0.0041
				(0.0043)
Δ $experience^2$	-0.0024**	-0.0024**	-0.0024**	-0.0024*
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Δ part-time (hours<35)	-0.0263***	-0.0262***	-0.0263***	-0.0263***
	(0.0083)	(0.0083)	(0.0083)	(0.0083)
Δ union	0.0835***	0.0826***	0.0830***	0.0831***
	(0.0123)	(0.0123)	(0.0123)	(0.0123)
Δ public sector	0.0118	0.0077	0.0108	0.0118
	(0.0176)	(0.0176)	(0.0176)	(0.0176)
Δ private not-for-profit	-0.0234	-0.0279	-0.0238	-0.0235
	(0.0174)	(0.0174)	(0.0174)	(0.0174)

*** p<0.01, ** p<0.05, * p<0.10. See detailed notes for Table 7. Results for Δ$experience^3$, Δ$experience^4$, broad industry and occupation changes, and year-pairs are not shown.