Appendix

A1. Detailed Description of Data and Methodology

This appendix contains a more detailed description of the data and methods used in the paper. So that this appendix can stand alone, some material is repeated from the main text.

Data sources

We use data from decennial censuses from 1950 through 2000 and the 2011–2015 American Community Survey (ACS) to measure the distribution of occupations by sex, race, and education, and data from the American Time Use Survey (ATUS) to measure workers' feelings by occupation.

Occupation codes and distributions

Our estimation strategy requires a way to measure the distribution of occupations in a uniform way in data from both 1950 and the present day. We use the OCC1990 occupation coding produced by IPUMS[5] to do this. OCC1990 is based on the occupation codes used in the 1990 census; it maps occupation codes used in other years to the 1990 codes based on Census Bureau crosswalks, and aggregates some categories to make the coding more consistent over time. IPUMS includes the OCC1990 codes in its public use microdata samples for decennial censuses and the ACS. The ATUS data include only the current occupation coding scheme, which we map to OCC1990 ourselves.

The OCC1990 coding contains 389 occupation categories. Some of these categories are so narrow that we observe very few workers in them in the ATUS — too few to be able to estimate feelings precisely for these occupations. In addition, even though OCC1990 is harmonized, it is not entirely uniform over time because of changes in the level of detail in the census occupation variables. For example, in the 1950 census, almost all people in management jobs were recorded as "Managers, officials, and proprietors (not elsewhere classified)," which maps to the OCC1990 code "Managers and administrators, n.e.c." (code 022). But by the 1990 census, which forms the basis for the OCC1990 codes, some managers were recorded

[5] See `https://usa.ipums.org/usa-action/variables/OCC1990`.

as working in specialties, such as “managers of food-serving and lodging establishments” (code 017). Thus, a restaurant manager would be assigned the OCC1990 code 022 in the 1950 census but code 017 in the 1990 census or the 2011-2015 ACS. To improve the uniformity of the coding and to ensure a reasonably large number of people are used to calculate workers’ feelings in each occupation, we aggregate the occupations to 12 broad categories. (We exclude military occupations from the analysis.) Of course, aggregating occupations in this way poses the risk that the occupations categorized as, say, “sales occupations” in 1950 are quite different from those categorized as sales occupations in recent years. In analyses not reported here, we have found that we obtain similar overall results if we use the detailed OCC1990 codes, but the changes in the share of workers in each occupation become difficult to interpret (for example, because of the reclassification of restaurant managers between 1950 and 1990).

With this coding in hand, we estimate the distribution of occupations by race, sex, and education in the 1 percent sample of the 1950 census, the 5 percent samples of the 1960, 1980, 1990, and 2000 censuses; the 1 percent form 1 and form 2 state samples of the 1970 census; and the 2011-2015 five-year ACS sample. We obtain all datasets from IPUMS (Ruggles et al., 2015). We consider three education groups: a high school diploma or less, some college, and bachelor’s degree or more.

Feelings

The ATUS, produced by the U.S. Census Bureau, is a stratified random sample of the U.S. population ages 16 and older. ATUS respondents are a subset of respondents to the Current Population Survey. The ATUS asks respondents to report, in significant detail, how they spent each minute of a day. Respondents also report their occupation in their main job (but not in any other jobs they may have).

In 2010, 2012, and 2013, the ATUS contained a “well-being module” that randomly selected three activities during the day for each respondent and asked the respondents to report their feelings while engaged in these activities. Activities were eligible to be randomly selected for these questions if they lasted at least five minutes and were not categorized as sleeping, grooming, personal activities, refusal, or don’t know. For the chosen activities, respondents were asked:

> From 0 to 6, where a 0 means you were not happy at all and a 6 means you were very happy, how happy did you feel during this time?
>
> From 0 to 6, where a 0 means you were not sad at all and a 6 means you were very sad, how sad did you feel during this time?
>
> From 0 to 6, where a 0 means you were not stressed at all and a 6 means you were very stressed, how stressed did you feel during this time?
>
> From 0 to 6, where a 0 means you were not tired at all and a 6 means you were very tired, how tired did you feel during this time?
>
> From 0 to 6, where a 0 means you did not feel any pain at all and a 6 means you were in severe pain, how much pain did you feel during this time if any?
>
> From 0 to 6, how meaningful did you consider what you were doing? 0 means it was not meaningful at all to you and a 6 means it was very meaningful to you.

We use these data for respondents who were asked to report their feelings during the activity of working on their main job. We compute the mean response to each question within each occupation category listed in figure 1, adjusted for differences in demographics across occupations. Specifically, we regress self-reported feelings on dummy variables for single year of age, race, single year of education, and occupation categories:

$$z_i = \theta_0 + \sum_a \alpha_a + \sum_r \beta_r + \sum_e \gamma_e + \sum_o \delta_o + \epsilon_i, \tag{A1}$$

where z_i is respondent i's report of a particular feeling (such as meaningfulness, stress or sadness); a indexes age; r indexes race; e indexes education; o indexes occupation; and ϵ_i is an unobservable error, which we assume to be uncorrelated with the regressors. The adjusted mean feelings for a given occupation are the predicted value from the regression for the sample distribution of age, race, and education:

$$\bar{z}_o = \hat{\theta}_0 + \sum_a \hat{\alpha}_a s_a + \sum_r \hat{\beta}_r s_r + \sum_e \hat{\gamma}_e s_e + \hat{\delta}_o, \tag{A2}$$

where s_a is the fraction of the regression sample that is age a, s_r is the fraction that is race r, and s_e is the fraction that has e years of education. (The use of the regression sample to compute s_a, s_r and s_e is a normalization that affects only the overall level of mean feelings and not the differences between occupations, which are a function only of the estimated occupation effects $\hat{\delta}_o$. Thus, all of our estimates of the consequences of a changing occupation distribution would be unchanged if we computed s_a, s_r and s_e from the entire ATUS rather than the regression sample, or from a different dataset entirely.)

Because the occupation categories are quite broad, it is possible that people in different demographic groups typically perform different occupations within each category. For example, among people in managerial occupations, those with college degrees may be more likely to be chief executives while those with high school diplomas may be more likely to be restaurant managers. These differences could also affect people's feelings on the job, and removing demographic differences as in (A1) may be insufficient to control for these effects. Therefore, we also compute the adjusted mean feelings within each occupation category separately by demographic group (sex, sex $\times$ education, and sex $\times$ race $\times$ education) for use when we calculate changes over time by demographic group. We do this by running the regression in (A1) separately for each sub-group.

We obtain the ATUS microdata from the American Time Use Survey Data Extract Builder at `http://www.atusdata.org` (Hofferth, Flood, and Sobek, 2015). We use the well-being module activity-level weights for estimation and normalize the weights such that the 2010, 2012, and 2013 samples receive equal weight in the calculations. Table 1 reports the mean adjusted feelings by sex and occupation.

Producing counterfactual estimates of aggregate feelings

Let $\bar{z}_{xo}$ be the demographically adjusted mean level of a particular feeling reported by workers with characteristics x in occupation o, according to the ATUS. Let $\pi_{xo,t}$ be the fraction of workers with characteristics x who are in occupation o in the year t census. We estimate the counterfactual mean feelings of workers with characteristics x in year t as the weighted average of occupation-specific feelings, weighting by the share of workers in each

Panel A: Women						
	Pain	Happiness	Sadness	Tiredness	Stress	Meaning
Managerial	0.54	4.07	0.69	2.22	2.68	4.45
Professional Specialty	0.85	4.25	0.55	2.68	2.75	4.99
Technicians	1.05	3.36	0.89	2.63	2.87	4.58
Sales	0.99	3.76	0.79	2.72	2.68	4.28
Admin/Clerical	0.85	3.80	0.62	2.48	2.73	4.08
Service	1.07	4.15	0.75	2.58	2.21	4.52
Farming/Forestry/Fishing	1.16	4.12	0.49	2.75	1.30	4.75
Precision Production	1.28	3.42	0.86	2.73	2.90	3.88
Repair	-0.67	5.07	-0.13	-0.09	0.31	5.75
Construction/Extractive	0.86	3.43	1.40	3.05	2.17	4.22
Operators/Assemblers	2.14	3.27	1.21	3.40	2.91	3.77
Transportation	1.09	4.56	1.00	2.36	1.64	4.16
Panel B: Men						
	Pain	Happiness	Sadness	Tiredness	Stress	Meaning
Managerial	0.59	3.81	0.58	2.19	2.52	4.38
Professional Specialty	0.61	3.93	0.56	2.24	2.45	4.56
Technicians	0.62	3.44	0.47	1.97	2.32	4.38
Sales	0.68	4.10	0.56	2.07	2.30	4.51
Admin/Clerical	0.69	3.66	0.90	2.31	2.12	3.91
Service	0.93	3.99	0.73	2.41	2.26	4.34
Farming/Forestry/Fishing	1.13	4.12	0.68	2.66	1.94	4.78
Precision Production	0.96	4.18	0.59	2.23	2.29	4.58
Repair	0.92	3.76	0.72	2.16	2.14	4.29
Construction/Extractive	1.30	4.22	0.40	2.24	2.00	4.70
Operators/Assemblers	0.78	4.19	0.68	2.20	2.04	4.57
Transportation	1.18	3.66	0.87	2.64	2.05	3.94

Table 1: Mean feelings by sex and occupation

Mean reported feelings by sex and occupation (scale 0 to 6), adjusted for age and education as described in text. Source: Authors' calculations from ATUS.

occupation in year t:

$$\hat{z}_{x,t} = \sum_o \pi_{xo,t} \bar{z}_{xo}. \tag{A3}$$

Note that estimation uncertainty in $\hat{z}_{x,t}$ arises both from uncertainty in the estimation of the occupation shares $\pi_{xo,t}$ and uncertainty in the estimation of the occupation adjusted mean feelings $\bar{z}_{xo}$. In practice, the Census and ATUS samples are so large that $\pi_{xo,t}$ is estimated very precisely. We return below to the implications of uncertainty in the estimation of $\bar{z}_{xo}$.

In principle, to compute aggregate mean feelings in the present era, we could directly calculate means of self-reported feelings on the job in the ATUS. However, because the ATUS is relatively small to begin with and because not all ATUS respondents are asked to report their feelings at their main job, the distribution of occupations among ATUS respondents who report feelings on their main job could randomly differ by a significant amount from the population distribution of occupations. Thus, if we found a difference between $\hat{z}_{x,1950}$ and the mean feelings in the ATUS, that difference could be caused by a failure of the ATUS sample to accurately reflect the current occupation distribution, and not by a change in the occupation distribution between 1950 and the present. To rule out this problem, we instead estimate aggregate mean feelings in the present era with a weighted average of occupation-specific feelings, weighted by the occupation distribution in the 2011–2015 ACS:

$$\hat{z}_{x,now} = \sum_o \pi_{xo,ACS} \bar{z}_{xo}, \tag{A4}$$

where $\pi_{xo,ACS}$ is the fraction of workers with characteristics x who are in occupation o in the 2011–2015 ACS. This approach is equivalent to reweighting the ATUS data so that the distribution of occupations among respondents who report feelings on the main job matches the distribution of occupations in the 2011–2015 ACS.

The change in feelings associated with the change in the occupation distribution is the difference between the year-t and present-day estimates:

$$\Delta\hat{z}_{x,t} = \hat{z}_{x,now} - \hat{z}_{x,t} = \sum_o (\pi_{xo,ACS} - \pi_{xo,t}) \bar{z}_{xo}. \tag{A5}$$

Observe that $\hat{z}_{x,now}$ and $\hat{z}_{x,t}$ are not independent because they are both functions of the same

ATUS estimates $\bar{z}_{xo}$. Thus, given the large Census samples and resulting precise estimation of $\pi_{xo,t}$, uncertainty in the estimates of mean feelings by occupation in the ATUS is the main source of uncertainty in our overall results.

A2. Controlling for Individual Fixed Effects

As noted in the text, our approach assumes that the estimated occupation coefficients are causal, so that we can use the coefficients to estimate workers' counterfactual feelings if they were in different occupations. This assumption will fail if occupation choices are correlated with other factors that affect a person's feelings. We can use the structure of the ATUS to partly control for these other factors. Each ATUS respondent reported his or her feelings in three randomly chosen activities, not all of which were necessarily work on the main job. Feelings in non-work activities might be viewed as an indicator of the respondent's baseline level of feelings that he would report regardless of occupation and thus control for non-occupation differences between respondents.

Figure 7 provides some intuition for how this approach might work by showing the distribution across respondents of the difference in raw reported feelings between work and non-work activities. For each respondent who reported feelings in both work and non-work activities, we calculate the difference between the reported feelings at work and the reported feelings not at work (taking an average if there are two work reports or two non-work reports), then plot the histogram of these differences. We make no adjustments for demographics at this stage in order to exhibit the raw data. Respondents tend to report higher stress levels and lower happiness levels at work than at other activities, as well as slightly higher sadness and pain levels. The fixed effects estimator will identify the causal effect of occupations on feelings by examining how these differences in work vs. non-work feelings vary across people who have different occupations.

Specifically, we run the regression in (A1) on all of the observations for each respondent, not just the observations from work on the main job, and controlling for individual fixed effects as well as for the nature of the other activities that are the source of the additional

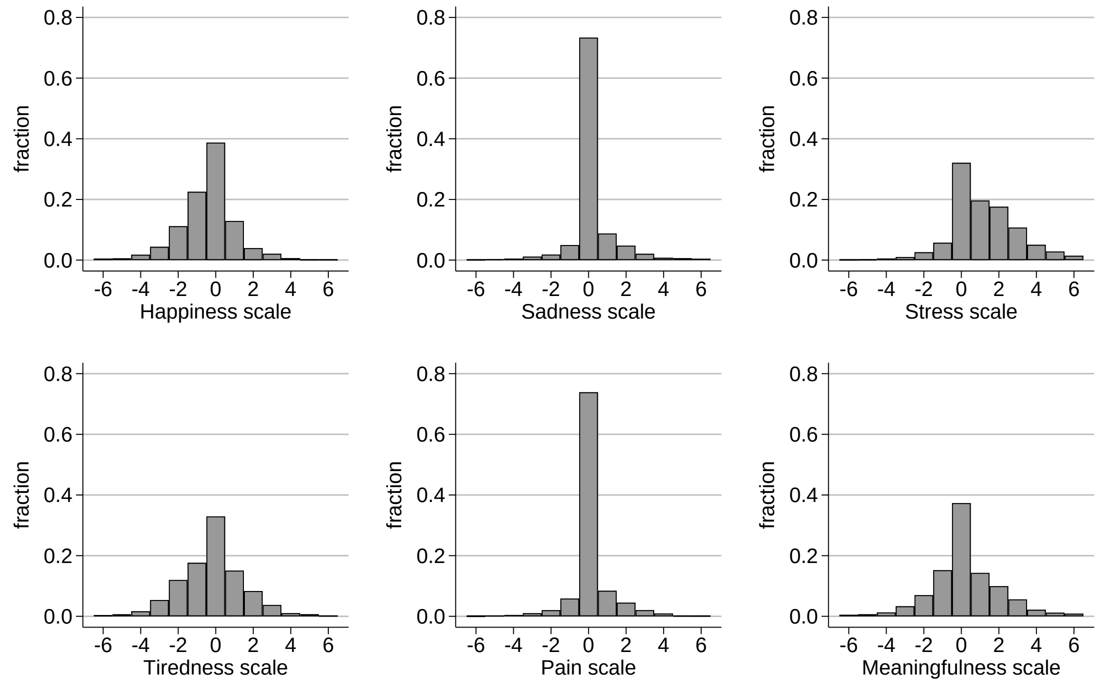


Figure 7: Differences in raw reported feelings between work and non-work activities

Source: Authors' calculations from census, ACS, and ATUS.

observations:

$$z_{ij} = \eta_i + w_{ij} \sum_o \delta_o + (1 - w_{ij}) \sum_n \zeta_n + (1 - w_{ij}) \left(\sum_a \alpha_a + \sum_r \beta_r + \sum_e \gamma_e \right) + \epsilon_{ij}, \quad \text{(A6)}$$

where $j \in \{1, 2, 3\}$ indexes observations within a respondent; $w_{ij} = 1$ if activity j is work at the main job and 0 otherwise; and n indexes types of activity other than work on the main job. The main effect of all of the demographics in (A1) is now absorbed into the fixed effect η_i, but we interact the demographics with w_{ij} to allow the possibility that the general difference between feelings at work and away from work differs by demographic group. The fixed-effects-adjusted mean feelings in occupation o are then:

$$\bar{z}_o^{FE} = \bar{\eta} + \hat{\delta}_o^{FE}, \quad \text{(A7)}$$

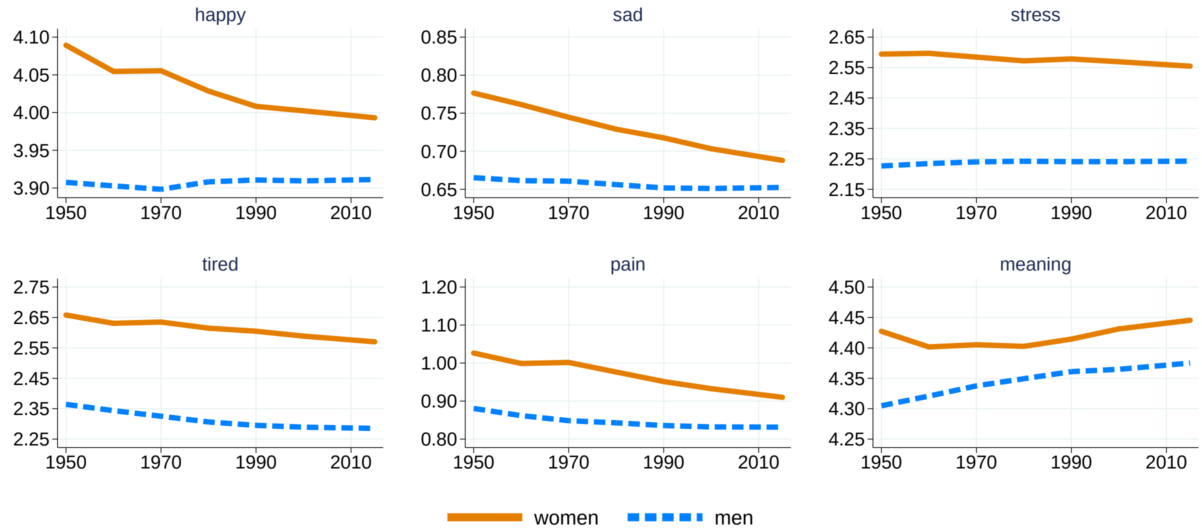


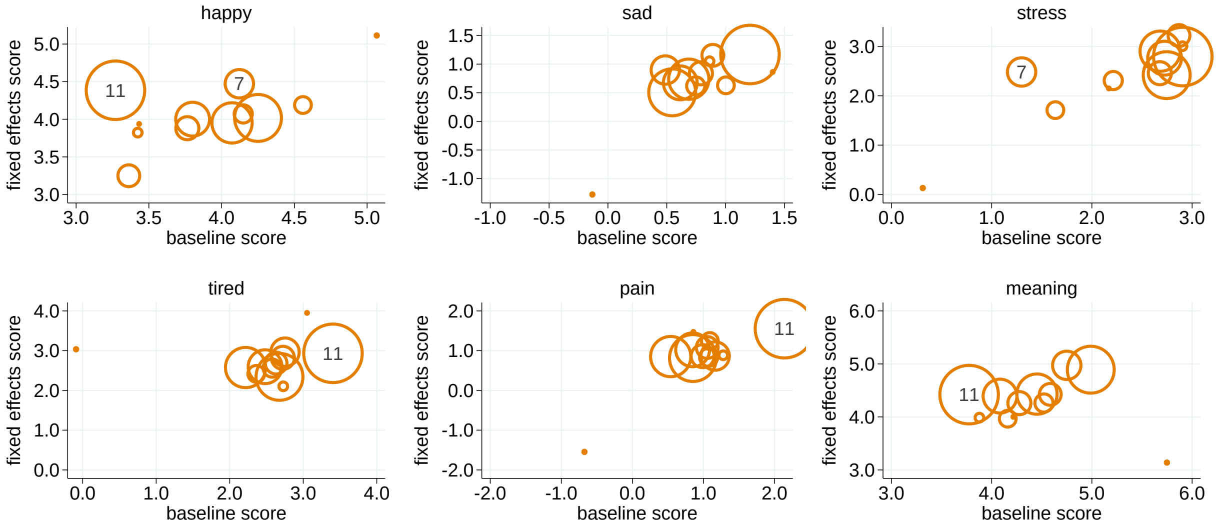
Figure 8: Changes in aggregate feelings at work by sex, fixed-effects-adjusted, 1950-present

Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated separately by sex; occupation scores estimated from fixed effects model. Source: Authors' calculations from census, ACS, and ATUS.

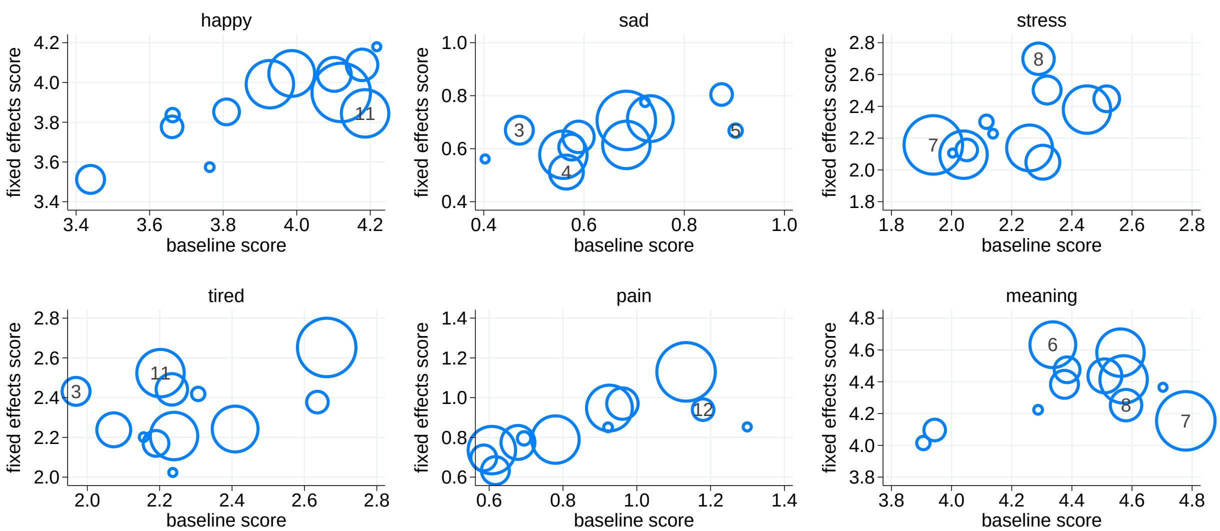
where $\bar{\eta}$ is the mean of the estimated individual fixed effects, and we can use $\bar{z}_o^{FE}$ in place of $\bar{z}_o$ in all of our calculations.

A drawback to the fixed effects strategy is that it assumes the effect of work on a worker's feelings is limited to his or her time at work. If feelings caused by work spill over into non-work activities, the fixed effects estimates could be biased either upward or downward. For example, if having a good job also makes people feel good at home, then we would estimate little or no effect of occupation on individual feelings in (A6) and correspondingly little or no effect of a changing occupation distribution on aggregate feelings. Therefore, if there are positive spillovers from work to home, estimates based on the fixed effects strategy provide a lower bound on how changes in the occupation distribution have changed aggregate feelings. On the other hand, negative spillovers are possible if people who have bad jobs are particularly happy to go home from them or people who have good jobs miss their work when they are at home; in these cases, the fixed-effects estimates would be biased upward.

Figure 8 shows the fixed effects estimates for men and women. The fixed effects estimates often show different trends from the baseline estimates. For example, happiness fell for women in the fixed effects estimates, compared with a rising trend in the baseline estimates without fixed effects; meaningfulness rose for men in the fixed effects estimates but fell in the baseline estimates. But the fixed effects estimates confirm the finding of a decreased physical toll of work — less pain and less tiredness — for both men and women.



(a) Women



(b) Men

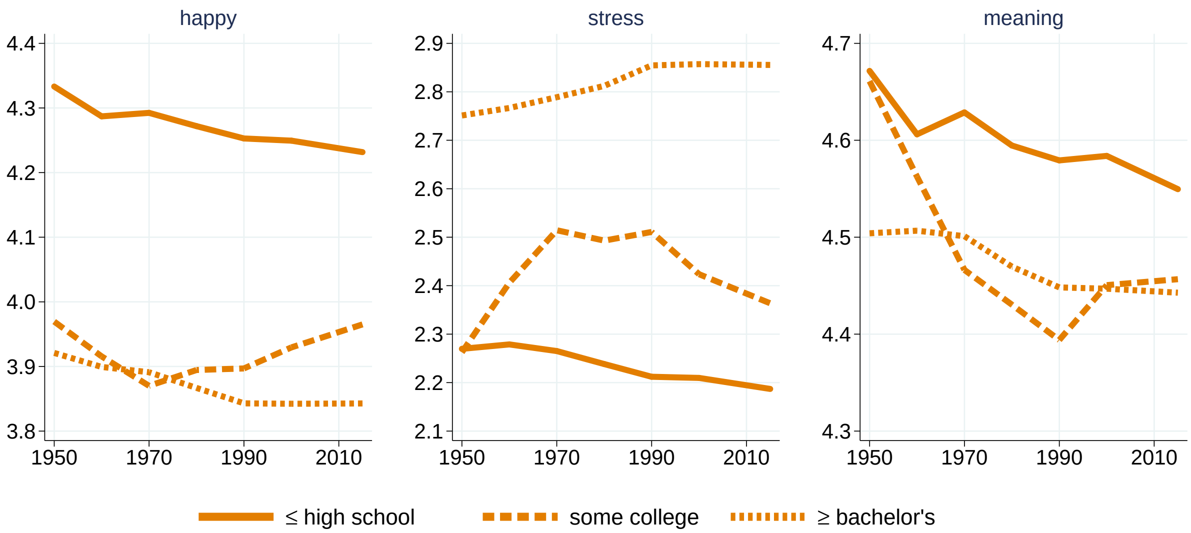
Figure 9: Relationship between fixed-effects and baseline occupation scores

Area of circle is proportional to absolute value of change between 1950 and 2015 in the share of workers in each occupation. Occupation scores and occupation distributions calculated separately by sex. Numbers centered in markers are codes for selected occupations. Codes: 3 = technicians and related support; 4 = sales; 5 = administrative support and clerical; 6 = service; 7 = farming, forestry, and fishing; 8 = precision production; 11 = machine operators, assemblers, and inspectors; 12 = transportation and material moving. Source: Authors' calculations from census, ACS, and ATUS.

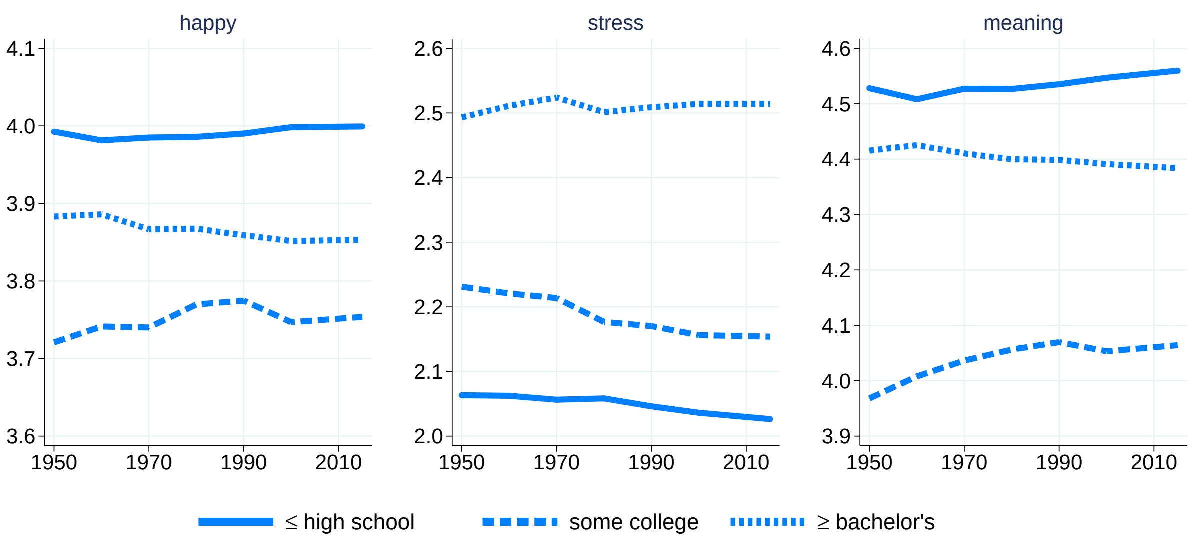
An occupation's score affects the trend for a given feeling only to the extent that the occupation's share of the work force changed substantially over time. Thus, to understand why the trends using fixed effects estimates are sometimes different from the baseline results, we examine how the difference between the fixed effects and baseline score for each occupation relates to the change in the occupation's share of the work force.

Figure 9 plots the fixed effects score against the baseline score for each occupation and uses the size of the markers to highlight occupations whose population shares changed the most between 1950 and 2015. For most occupations whose shares changed substantially, and for most of the types of feelings that we measure, the fixed-effects and baseline occupation scores are closely correlated. This correlation gives some confidence that our basic approach to measuring the feelings induced by an occupation is reasonable. However, there are a few outliers, and these outliers appear to drive the cases where we see different trends in the fixed effects and baseline estimates. For example, among women, the fixed-effects score for machine operators often differs substantially from the baseline score. This occupation was one of the lowest scoring on happiness for women in the baseline but one of the highest scoring on happiness for women in the fixed effects estimates, and it shrank substantially from 1950 to 2015, explaining why women had a downward trend in happiness according to the fixed effects estimates but an upward trend according to the baseline estimates. For men, farming, forestry and fishing were rated very high in meaning in the baseline estimates but quite low in the fixed effects estimates, while service occupations received a moderate meaning score in the baseline and a high score with fixed effects. Thus, the shrinkage of the agricultural sector and the growth of service work implied decreasing meaningfulness for men according to the baseline estimates but rising meaningfulness according to the fixed effects estimates.

Figure 10 breaks the fixed effects estimates down by education level. The differences in trends between the fixed effects estimates and the baseline estimates appear to be concentrated at lower education levels — women with no more than a high school education and men with a high school education or some college. At higher education levels, the fixed effects estimates are similar to the baseline. This result is perhaps unsurprising given that the largest differences between the fixed effects and baseline occupation scores appeared in occupations that have relatively lower average education levels.



(a) Women



(b) Men

Figure 10: Changes in aggregate feelings at work by sex and education, fixed-effects-adjusted, 1950-present

Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated separately by sex and education; occupation scores estimated from fixed effects model. Source: Authors' calculations from census, ACS, and ATUS.

The differences between the fixed effects and baseline estimates suggest a need for caution in interpreting the overall results. As we noted earlier, though, the fixed effects estimates are not a panacea for potential biases in the baseline estimates. The fixed effects estimates themselves may be biased either upward or downward there are any spillovers from what happens at work to how someone feels at home.

A3. Controlling for the Interaction of Age and Education

Controlling for age and education separately when we estimate occupation scores might be insufficient to remove the effects of age and education on feelings if the effect has differed across cohorts, for example if the education system gave different messages to different cohorts about what types of work were meaningful.

As a robustness check, we therefore reestimate the occupation scores with additional controls for the interaction of single year of age and single year of education in (A1). Figures 11 through 15 reproduce the estimates shown in Figures 2 through 6, respectively, using these additional controls. The results with the additional controls are quite similar to those obtained in the baseline estimates.

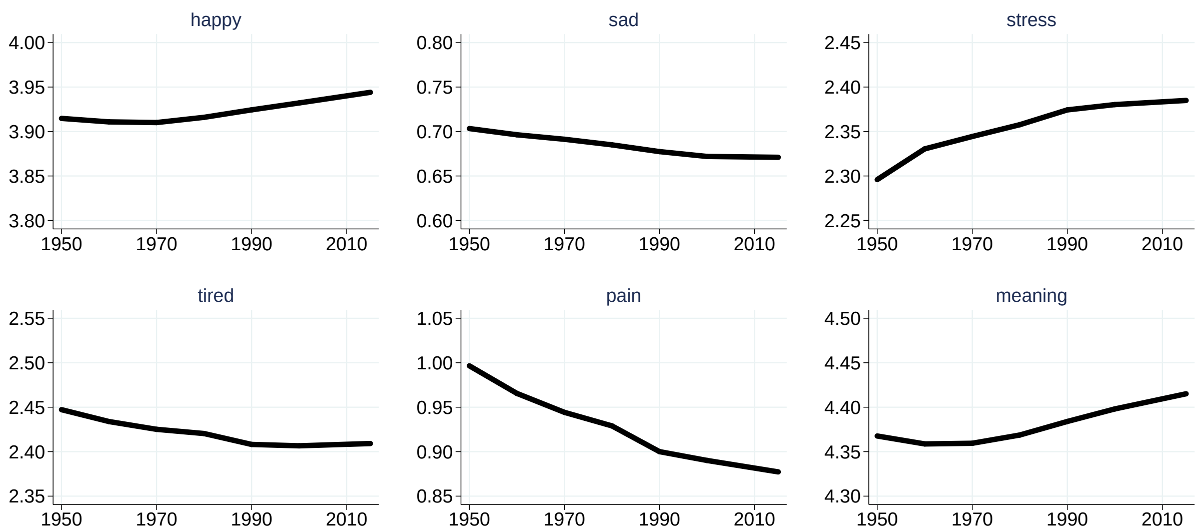


Figure 11: Changes in aggregate feelings at work, 1950-present

Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated for full population; occupation scores adjusted for age, race, sex, years of education, and interaction of age and education. Source: Authors' calculations from census, ACS, and ATUS.

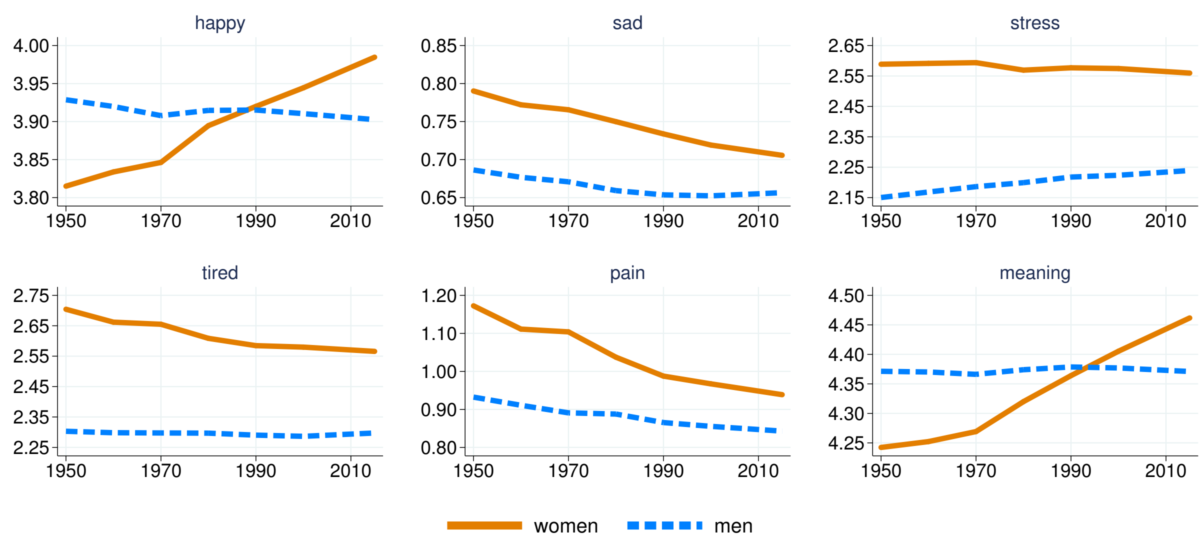
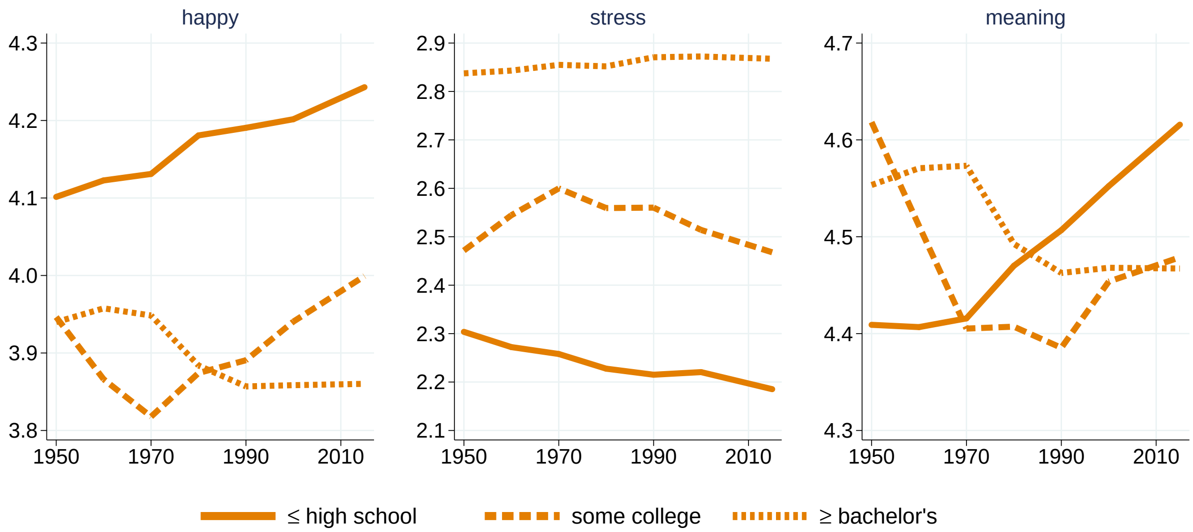
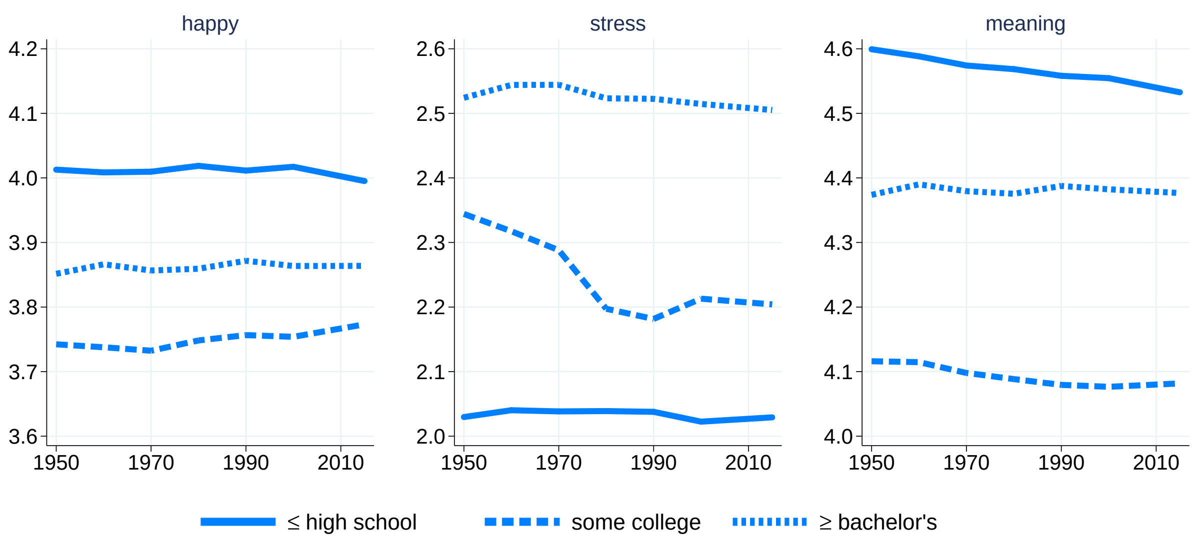


Figure 12: Changes in aggregate feelings at work by sex, 1950-present

Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated separately by sex; occupation scores adjusted for age, race, and years of education. Source: Authors' calculations from census, ACS, and ATUS.



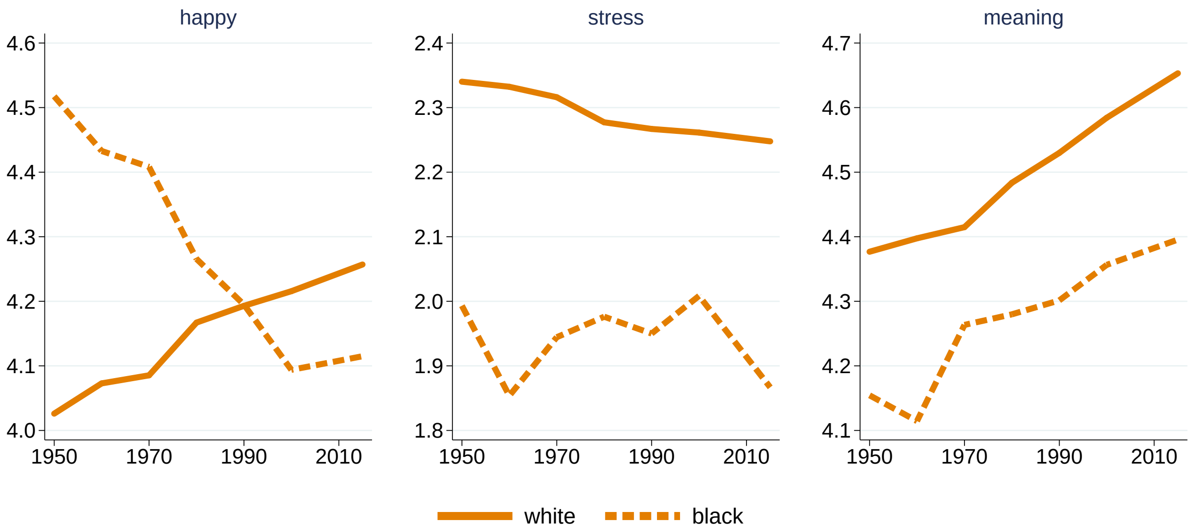
(a) Women



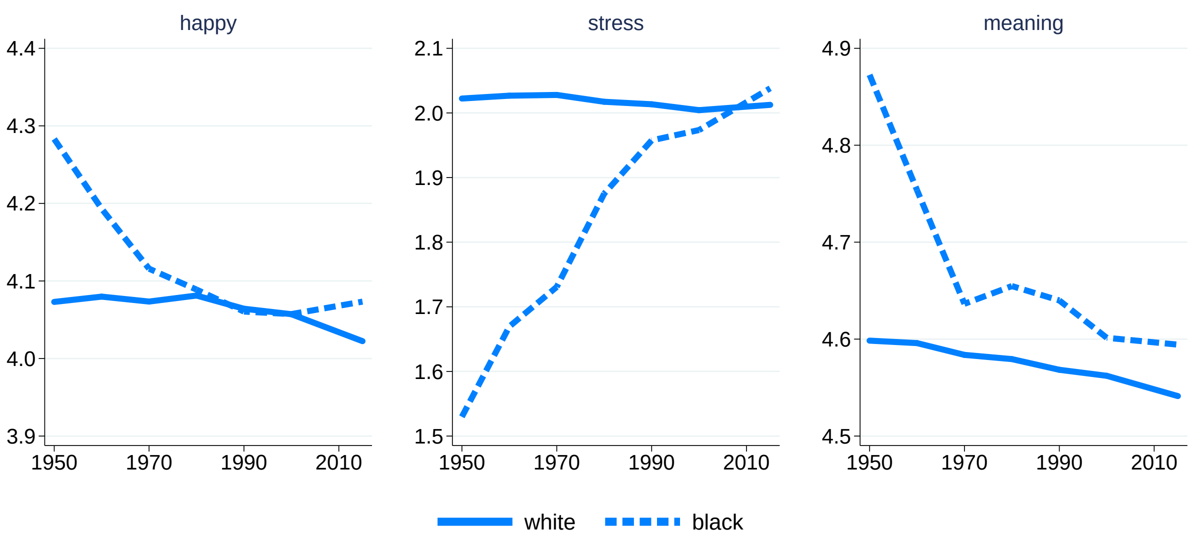
(b) Men

Figure 13: Changes in aggregate feelings at work by sex and education, 1950-present

Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated separately by sex and education; occupation scores adjusted for age, race and years of education. Source: Authors' calculations from census, ACS, and ATUS.



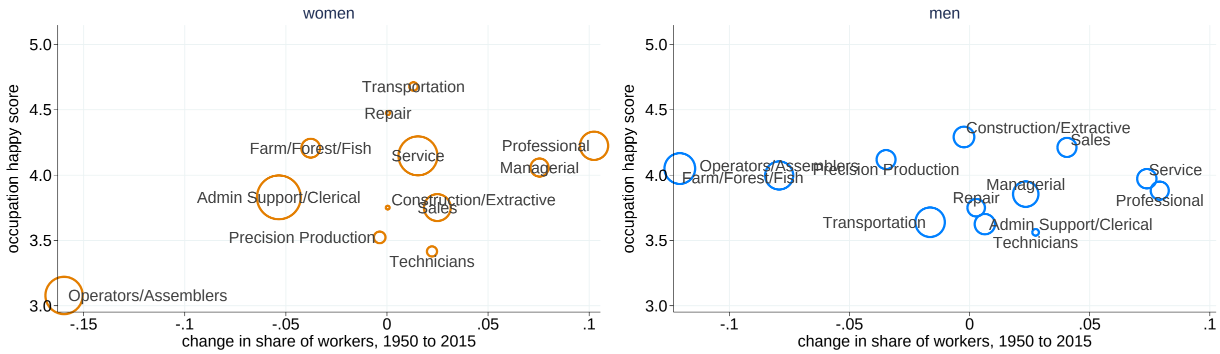
(a) Women



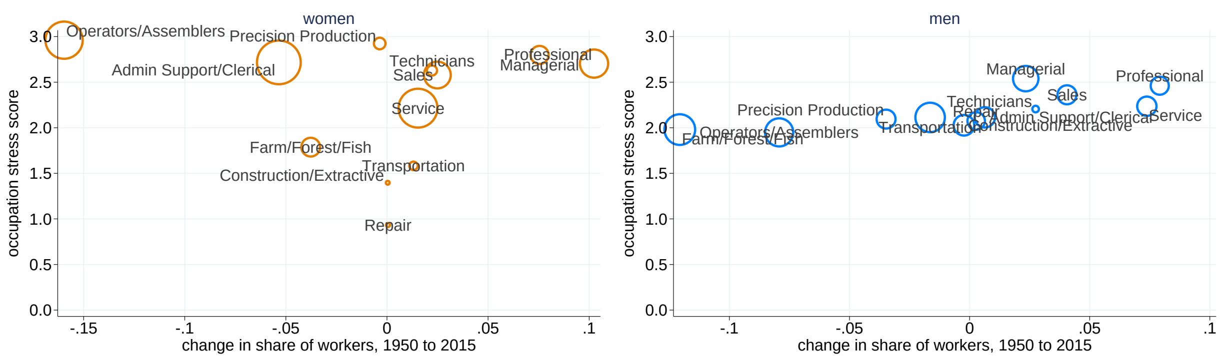
(b) Men

Figure 14: Changes in aggregate feelings at work by sex and race (education $\leq$ high school), 1950-present

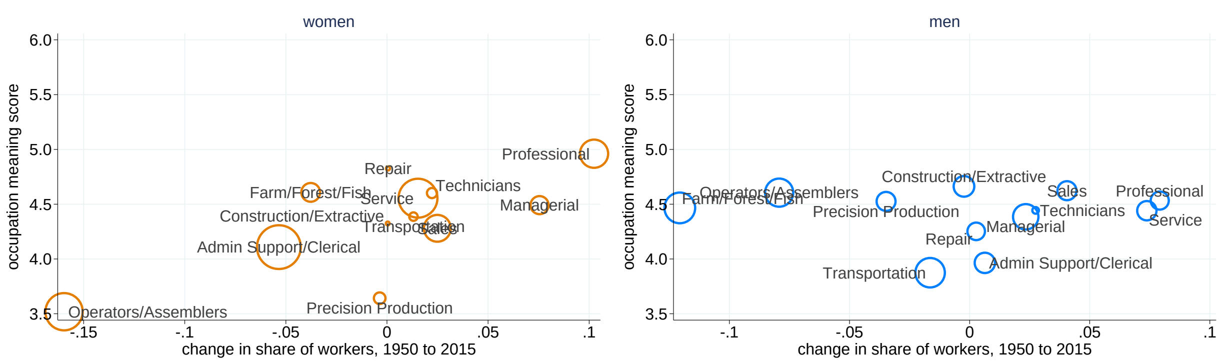
Lines show average of occupation scores weighted by distribution of occupations in each year. Occupation scores and occupation distributions calculated for black and white respondents with no more than a high school education, separately by race and sex; occupation scores adjusted for age and years of education. Other races excluded from calculation. Source: Authors' calculations from census, ACS, and ATUS.



(a) Happy



(b) Stress



(c) Meaning

Figure 15: Changes in occupation share and average feelings by occupation

Area of circle is proportional to share of workers in each occupation in 1950, by sex. Occupation scores and occupation distributions calculated separately by sex; occupation scores adjusted for age, race, and education. Source: Authors' calculations from census, ACS, and ATUS.

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