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The Role of Labor Market Inequalities in Explaining the Gender Gap in Depression Risk among Older US adults.

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Abstract

Background: We aim to investigate to what extent gender inequality at the labor market explains higher depression risk for older US women compared to men.

Methods: We analyze data from 35,699 US adults aged 50-80 years that participated in the Health and Retirement Study. We calculate the gender gap as the difference in prevalence in elevated depressive symptoms (>= 3, 8-item Center for Epidemiological Studies Depression Scale) between women and men. We employ a dynamic causal decomposition and simulate the life course of a synthetic cohort from ages 50-80 with the longitudinal g-formula. We introduce four nested interventions by assigning women the same probabilities of A) being in an employment category, B) occupation class, C) current income and D) prior income group as men, conditional on women's health and family status until age 70.

Findings: The gender gap in depression risk is 2.9%-points at ages 50-51 which increases to 7.6%-points at ages 70-71. Intervention A decreases the gender gap over ages 50-71 by 1.2%-points (95%CI for change: -2.81 to 0.4), intervention D by 1.64%-points (95%CI for change: -3.28 to -0.15) or 32% (95%CI: 1.39 to 62.83), and the effects of interventions B and C are in between those of A and D. The impact is particularly large for Hispanics and low educated groups.

Interpretation: Gender inequalities at the labor market substantially explain the gender gap in depression risk in older US adults. Reducing these inequalities has the potential to narrow the gender gap in depression.

Research in context

Evidence before this study

Many studies try to explain gender differences in depression and overall mental well-being. We searched PubMed (from database inception up until May 30 2022), Google Scholar and Web of Science. We included studies that investigated underlying pathways of the relationship between gender/sex and depression. We used combinations of the following search terms: “gender”, “sex”, “differences”, “inequality”, “inequity”, “depression”, “mental health”, “depressive disorder”, “mediation”, “decomposition”. We identified a review by Kuehner et al. (2017) that summarized reasons for the gender depression gap and highlights that changing socioeconomic trends in environmental factors, such as structural gender inequalities, are of importance. The identified studies face the limitation that they do not consider the bi-directional relationship of multiple determinants with depression and that gendered risk factors of depression such as employment, income, occupation, education, and overall health affect each other.

Added value of this study

We employ a counterfactual decomposition which allows all (time-varying) covariates, i.e. labor market characteristics, health and family status, and depression to affect each other. We furthermore attempt to assess the effect of structural gender inequalities at the labor market with a hypothetical policy intervention that equalizes opportunities across gender. We do this in older adults and run subgroup analyses by education and race/ethnicity.

Implications of all the available evidence

Policies that equalize opportunities at the labor market have the potential to reduce the gender depression gap. Reducing gender inequalities at the labor market, especially in terms of employment, reduces the gender depression gap most in groups with the largest gap, namely Hispanics and low educated groups. Labor market characteristics may explain part of the gender gap in depression because they relate to overall structural gender inequality at the labor market. Women are historically in a lower economic position than men due to gendered cultural norms. This disadvantage negatively affects their access to opportunities and resources to pursue goals, which might in turn affect their decisions regarding their health, including their mental health.

Introduction

Depression poses a major burden on the population and individual level.[1,2] In the US, women are twice as likely to suffer from depression than men[3], although the difference has narrowed in recent cohorts[3-6]. The gender depression gap is largest among the low-educated who also have a higher overall prevalence than the high-educated.[7]

Gendered cultural norms[8] which put women historically in a lower economic position than men[9-11] may contribute to the gender gap in depression. To date, women's employment rate and income levels are 17% and 21% lower than in men in the US, respectively.[10,12] Attitudes supporting gendered cultural norms are particularly common in older adults[13], suggesting that gendered labor market inequalities may be particularly important for the gender depression gap in older adults.

Socioeconomic characteristics play a role in explaining the gender depression gap[14], and both education and income are more important determinants for women than for men.[7,15] The gender depression gap becomes insignificant in highly educated individuals[7], and in women that earn more than their male counterparts, if matched on other socioeconomic and family characteristics.[15] Further, previous evidence suggests a beneficial link between employment and depression in men and specific female subgroups only, such as head-of-household or childless women.[16-18] Thus, traditional gender norms are at play in the link between employment and depression. While education plays a more important role in younger adults, employment status and income might be important factors in explaining the gender depression gap in middle and late adulthood.[4]

Available literature, however, does not consider the bi-directionality of multiple determinants with depression. For example, while unemployment is a risk factor for depression, depression acts as a risk factor for unemployment.[19] They also overlook that gendered risk factors of depression such as employment, income, occupation, education, and overall health affect each other.[20] The aim of this study is to address this bidirectionality and interdependence and assess to what extent the gender gap in depression changes if women would have the same employment, occupation and income opportunities as men from age 50 onwards.

Methods

Data source

We perform our analysis with the 2018 RAND HRS Longitudinal File of the Health and Retirement Study (HRS). The HRS is a nationally representative biannual longitudinal survey based in the US. It was established in 1992 and comprises data on over 37,000 adults over the age of 50 years.[21] The HRS data is sponsored by the National Institute on Aging (grant number U01AG009740) and conducted by the University of Michigan.

The flowchart illustrating sample selection can be found in supplementary Figure S.1. All covariates have less than 5% of missing observations except for occupation group (17%), mother's education (9%) and father's education (15%) which we imputed (supplement section 1). We do not allow the hypothetical interventions to affect the prevalence of retirement or disabled groups and therefore exclude them before aggregating the results by age and gender.

Outcome

We assess depressive symptoms in the past week with the 8-item Center for Epidemiological Studies – Depression scale (CES-D 8), which consists of dichotomous questions on six negative and two positive items resulting in a possible score of 0-8. A higher score indicates higher depressive symptomatology; a CES-D score of ≥3 suggesting elevated depressive symptoms [22]. We calculate the absolute gender gap in elevated depressive symptoms as the difference in the prevalence between women and men.

Time-invariant covariates

We stratify all analyses by gender (man/woman). Education level is categorized into less than high-school degree, high-school graduate, and some college and above. Race/ethnicity is classified into non-Hispanic Black, non-Hispanic White, Hispanic and other (other not shown due to small sample size). Education of the mother and father is categorized into low (<9 years of education), medium (9-12 years of education) and high (>12 years of education). Ever had psychological problems is defined as whether (yes/no) "the participant was ever told by a doctor to have emotional, nervous, or psychiatric problems".[23]

Time-varying covariates

We quantify employment status as employed full-time (>35h/week for >36 weeks/year), part-time, unemployed, part-time retired, full-time retired and homemaker (not working, not retired and not currently searching for a job). Participants are classified as part-time retired if they work part-time but mention retirement during the interview.[23]

Occupation group is assigned based on the 1980 Census codes and classified into "white collar/desk occupation", "pink collar/service-related occupation" and "blue collar/manual occupation" and "no occupation" for participants that are not currently employed, i.e. retired, disabled, unemployed or not in the labor force.

Personal income is the sum of "wage/salary income, bonuses/overtime pay/commissions/tips, 2nd job or military reserve earnings, and professional practice or trade income"[23] received last calendar year in nominal dollars. We adjust income for inflation with the consumer price index inflation calculator provided by the U.S. Bureau of Labor Statistics[24]. We calculate the inflation rate for June each year in reference to June 2006 and multiply individual earnings by the respective inflation rate to obtain inflation adjusted income.

We use the number of chronic conditions (whether a doctor diagnosed high blood pressure, diabetes, cancer, lung disease, heart disease, stroke and/or arthritis since the last wave) categorized into none, one, two, three and four or more chronic conditions as a proxy for physical health. We choose this proxy because there are known gender differences in the number of chronic conditions and physical health may affect employment levels.

We assume that family status affects both labor market outcomes and mental health, and we capture it with marital status (married/separated or divorced/widowed/not married), the number of household members (1/2/3/>3) as a proxy for whether children or elderly live in the house, and number of living and in-contact children at the household level (no child/one child/two children/>two children).

Statistical Analysis

We employ a dynamic causal decomposition using the longitudinal g-formula with Monte Carlo integration. We model the life course of a synthetic cohort from age 50 onwards in 2-year age groups to approximate the biannual data collection of the HRS.

The causal decomposition contains two essential steps: an estimation and a simulation step (supplement section 1). In the estimation step, we specify multivariable regression models for the time-varying covariates according to a directed acyclic graph (DAG). This DAG illustrates the theoretical framework of the interrelatedness of our covariates (Figure 1). We interact employment status with income and age to allow effects to vary by age and income. We lag all time-varying covariates by one wave (2 years). We do not allow covariates at time t to affect each other to avoid bias due to potential reverse causality. Time-invariant covariates are measured at age 50. We use logistic regression for depression, quantile regression for income and multinomial regression for employment status, occupation group, health status, marital status, number of household members and number of children.

For the simulation step, we use the steps of the g-formula (supplement section 1) and simulate depression risk in males and females without a hypothetical intervention (natural course approximation) and under our intervention scenarios. We introduce four interventions of which three are nested. For the nested interventions, we assign women the same probabilities of A) being in an employment category, B) occupation class and C) income as men, conditional on women's covariate values. To approximate the sample under these intervention scenarios, we simulate employment status, occupation group and income in women using the coefficients for estimating employment status and subsequently occupation group and income in men (supplement section 1). In the fourth intervention (D), we additionally intervene on prior income levels at age 50-51 (one wave before the intervention) by giving women the same mean income levels as men conditional on their employment and occupation group. We hypothesize that this intervention reflects prior socioeconomic status, which might attenuate the effect of our intervention on the gender gap in depression risk.

We calculate the absolute gender gap under natural course and each intervention scenario and compare the absolute change between both scenarios. We calculate the contribution as $1 - \frac{D_{w_{cf}} - D_{m_{nc}}}{D_{w_{nc}} - D_{m_{nc}}}$, where $D_{w_{cf}}$ is depression risk in women in the counterfactual scenario and $D_{w_{nc}}$ and $D_{m_{nc}}$ are depression risk in women and men in the natural course approximation.

We perform subgroup analyses by race/ethnicity and by education. Due to scarcity issues in the fourth intervention at age 50-51, we exclude 10 (0.2%) observations and 9 (0.2%) observations in the race/ethnicity and education subgroup analysis, respectively.

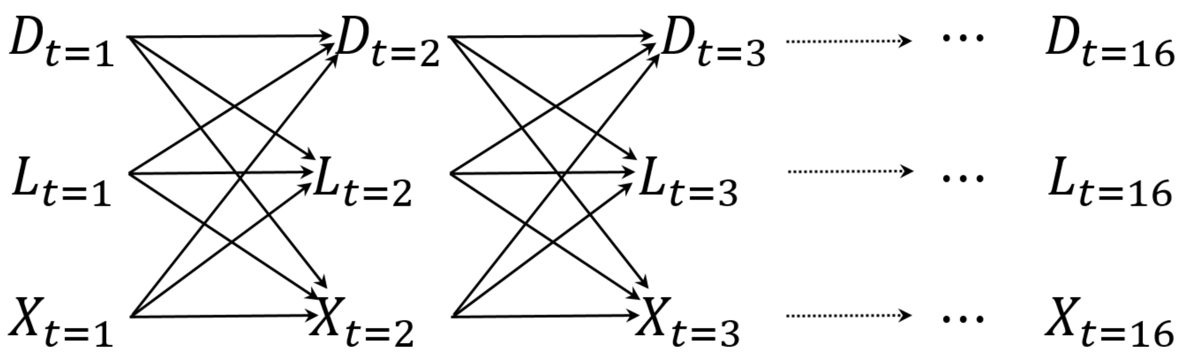

Figure 1 Simplified DAG which shows two-year cross-lagged structure. Depression risk (D), labor market variables (L) (employment status, occupation group, income) and time-varying covariates (X) are associated across (t) 1 to 16, which translates to 2-year age groups from 50 to 80. Time-varying covariates are: age, health status, marital status, N household members and N children in household. The DAG is simplified because it does not show time-invariant covariates. These are accounted for in all models.

Results

Sample characteristics

Mean age at observation is 65±8.24 years (Table 1). Both genders are mostly white (women: 68%, men: 71%). Women have a higher prevalence of elevated depressive symptoms, are less educated, less often full-time employed and more often part-time workers or homemakers than men in our sample. The proportion of desk worker occupation is similar across both genders (19%), but men are more often part of manual occupations (women: 2.5%, men: 13.5%) and women more often work in service-related occupations (women: 6%, men: 3%). Men more often earn more than 46,000 USD than women (women: 6%, men: 15%).

Table 1 Sample Characteristics across person years. Age inclusion 50-80. [a] Individual earnings is shown for 0-50th, 51-75th, 76-90th,91-95th,>95th percentile categories, which are the percentiles used for the quantile regression.

	Total		Women		Men	
N person-years	185,097		108,372		76,725	
N respondents	35,699		20,044		15,655	
Follow-up time (median (IQR))	5 (6)		5 (6)		4 (5)	
Outcome						
elevated depressive symptoms (yes N (%))	39,859	(21.5)	26,755	(24.7)	13,104	(17.1)
Confounders						
Age (mean (SD))	64.65	(8.24)	64.51	(8.32)	64.85	(8.13)
Race/ethnicity (%)						
Non-Hispanic White	127,531	(68.9)	73,272	(67.6)	54,259	(70.7)
Non-Hispanic Black	31,631	(17.1)	19,930	(18.4)	11,701	(15.3)
Hispanic	20,652	(11.2)	12,182	(11.2)	8,470	(11.0)
Other	5,283	(2.9)	2,988	(2.8)	2,295	(3.0)
Father's education						
Low	76,374	(48.6)	45,532	(49.8)	30,842	(46.8)
Middle	56,544	(36.0)	32,204	(35.2)	24,340	(37.0)
High	24,308	(15.5)	13,635	(14.9)	10,673	(16.2)
Mother's education						
Low	71,369	(42.4)	43,995	(44.5)	27,374	(39.4)
Middle	73,993	(44.0)	41,342	(41.8)	32,651	(47.0)
High	22,874	(13.6)	13,470	(13.6)	9,404	(13.5)
Ever reported psychological problems (Yes N (%))	27,205	(14.7)	19,180	(17.7)	8,025	(10.5)
Education N (%)						
High-school graduate	55,370	(29.9)	35,068	(32.4)	20,302	(26.5)
Lt High-school/GED	46,558	(25.2)	27,313	(25.2)	19,245	(25.1)
Some college or higher	83,169	(44.9)	45,991	(42.4)	37,178	(48.5)
Intervention variables						

Employment status N (%)							
	Full-time worker	52,165	(28.2)	25,820	(23.8)	26,345	(34.3)
	Part-time worker	11,435	(6.2)	8,631	(8.0)	2,804	(3.7)
	Unemployed	4,005	(2.2)	2,115	(2.0)	1,890	(2.5)
	Partly retired	15,522	(8.4)	7,663	(7.1)	7,859	(10.2)
	Retired	83,520	(45.1)	48,177	(44.5)	35,343	(46.1)
	Disabled	5,285	(2.9)	3,493	(3.2)	1,792	(2.3)
	Not in labor force/ Homemaker	13,165	(7.1)	12,473	(11.5)	692	(0.9)
Occupation group N (%)							
	Desk occupation	29,176	(19.1)	17,255	(19.0)	11,921	(19.2)
	Service-related occupation	7,204	(4.7)	5,250	(5.8)	1,954	(3.2)
	Manual occupation	10,636	(7.0)	2,281	(2.5)	8,355	(13.5)
	No occupation	105,975	(69.3)	66,258	(72.8)	39,717	(64.1)
Individual earnings[a]							
	0. no individual earnings	111,111	(60.0)	67,397	(62.2)	43,714	(57.0)
	1 to 18,233 USD	27,762	(15.0)	17,941	(16.6)	9,821	(12.8)
	18,234 to 46,354 USD	27,758	(15.0)	16,028	(14.8)	11,730	(15.3)
	46,355 to 67,679 USD	9,222	(5.0)	4,051	(3.7)	5,171	(6.7)
	more than 67,679 USD	9,244	(5.0)	2,955	(2.7)	6,289	(8.2)
Time-varying variables							
Marital status N (%)							
	Married	118,378	(64.0)	61,360	(56.6)	57,018	(74.3)
	Separated or divorced	29,727	(16.1)	18,997	(17.5)	10,730	(14.0)
	Widowed	27,465	(14.8)	22,509	(20.8)	4,956	(6.5)
	Not married	9,527	(5.1)	5,506	(5.1)	4,021	(5.2)
Number of persons in household N (%)							
	1	37,862	(20.5)	26,105	(24.1)	11,757	(15.3)
	2	97,262	(52.5)	54,175	(50.0)	43,087	(56.2)
	3	26,644	(14.4)	15,017	(13.9)	11,627	(15.2)
	>3	23,329	(12.6)	13,075	(12.1)	10,254	(13.4)
Number of living, in-contact children N (%)							
	no children	13,598	(7.3)	7,415	(6.8)	6,183	(8.1)
	1 child	18,562	(10.0)	11,486	(10.6)	7,076	(9.2)
	2 children	48,606	(26.3)	28,185	(26.0)	20,421	(26.6)
	more than 2 children	104,331	(56.4)	61,286	(56.6)	43,045	(56.1)
Number of chronic conditions N (%)							
	none	34,565	(18.7)	19,153	(17.7)	15,412	(20.1)
	1	50,929	(27.5)	29,867	(27.6)	21,062	(27.5)
	2	49,001	(26.5)	29,496	(27.2)	19,505	(25.4)
	3	30,722	(16.6)	18,043	(16.6)	12,679	(16.5)
	4+	19,880	(10.7)	11,813	(10.9)	8,067	(10.5)

Gender Gap in Depression Risk

Stratified by employment status, occupation group and income percentiles, women have a higher prevalence of elevated depressive symptoms than men in all categories except for the homemaker category (supplement section 2). The gender depression gap is smallest in part-time workers, the service-related occupation group, and the 90th-95th income percentile group.

Women have a higher prevalence of elevated depressive symptoms than men across all ages, with an absolute gender gap in elevated depressive symptoms of 2.9%-points at ages 50-51. This increases to 7.6%-points at ages 70-71 (Figure 2). The gender depression gap is largest in Hispanics and low educated groups, followed by non-Hispanic Blacks and middle educated groups (supplement section 2).

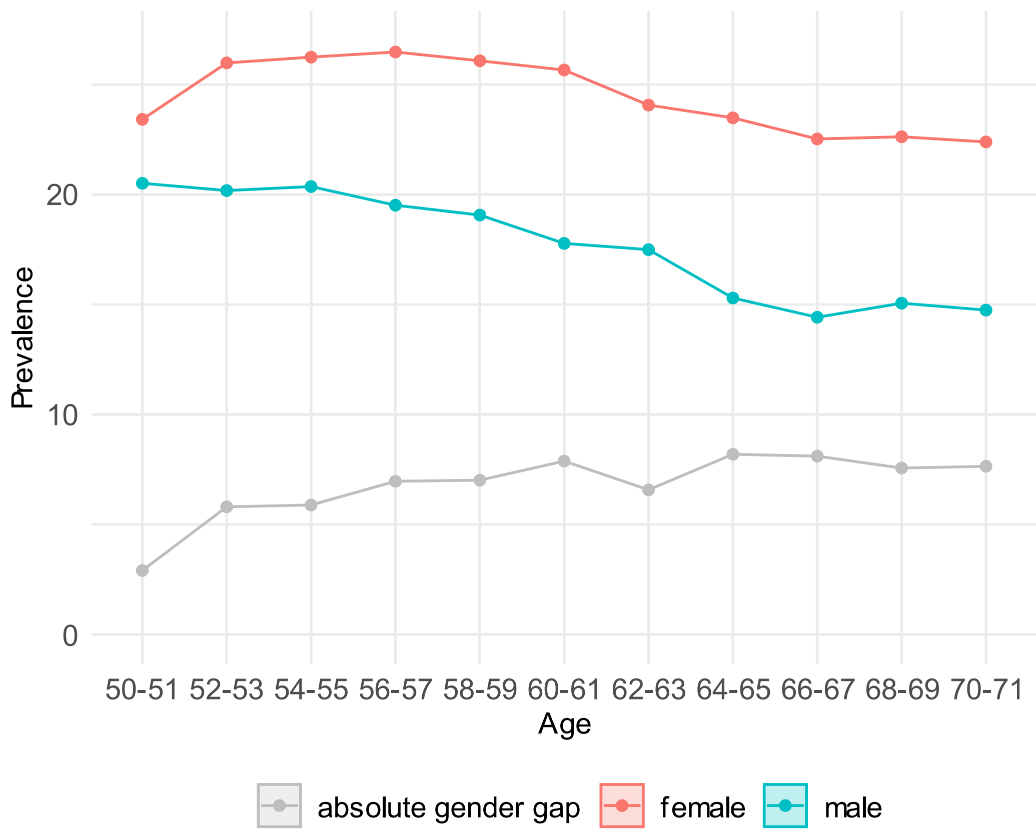

Figure 2 Depression prevalence (%) for females and males and absolute gender gap (%-point difference) in depression prevalence.

Effects of the interventions on labor market characteristics

Giving women the same employment outcomes as men (A) increases full-time employment on average by 10.19%-points (95%CI: 0.58 to 19.98) and decreases the homemaker group and part-time employed group on average by 9.54%-points (-15.56 to -4.92) and 6.10%-points (-11.22 to -0.56), respectively. Also equalizing occupation outcomes (B) increases the percentage of women in manual labor on average by 12.34%-points (7.52 to 17.12) and decreases service-related occupations on average by 3.98%-points (-7.85 to -0.24). The additional income intervention (C) increases annual income levels in women on average by 5,828 USD (95%CI: 2,957 to 8741), which results in only minor changes in employment status and occupation group compared to intervention B. Lastly, giving women the same mean income levels as men conditional on their employment and occupation group at age 50 (D) increases annual income levels in women on average by 10,967 USD (7,905 to 14,144). This leads to women's income being equal to men's (supplement section 4.1).

Effects of the interventions on the gender depression gap

The three nested interventions lead to a reduction in the absolute gender depression gap across ages 50-71, whereas the trend across age is attenuated in intervention D (Figure 3). Both, the employment (A) and additional occupation intervention (B) result in a mean decrease of 1.2%-points (-2.81 to 0.4) which translates to a median contribution to the gender depression gap of 27.69% (-6.84 to 58.52) and 26.61% (-7.2 to 60.58) (Table 2). Equalizing employment status, occupation and income opportunities between gender (C), reduces the gender depression gap across age by on average 1.35%-points (-3.01 to 0.15) with a median contribution of 29.03% (-2.49 to 62.82). Equalizing prior income in addition to the other interventions (D) reduces the gender depression gap on average by 1.64%-points (-3.28 to -0.15) resulting in a median contribution of 31.91% (1.39 to 62.83).

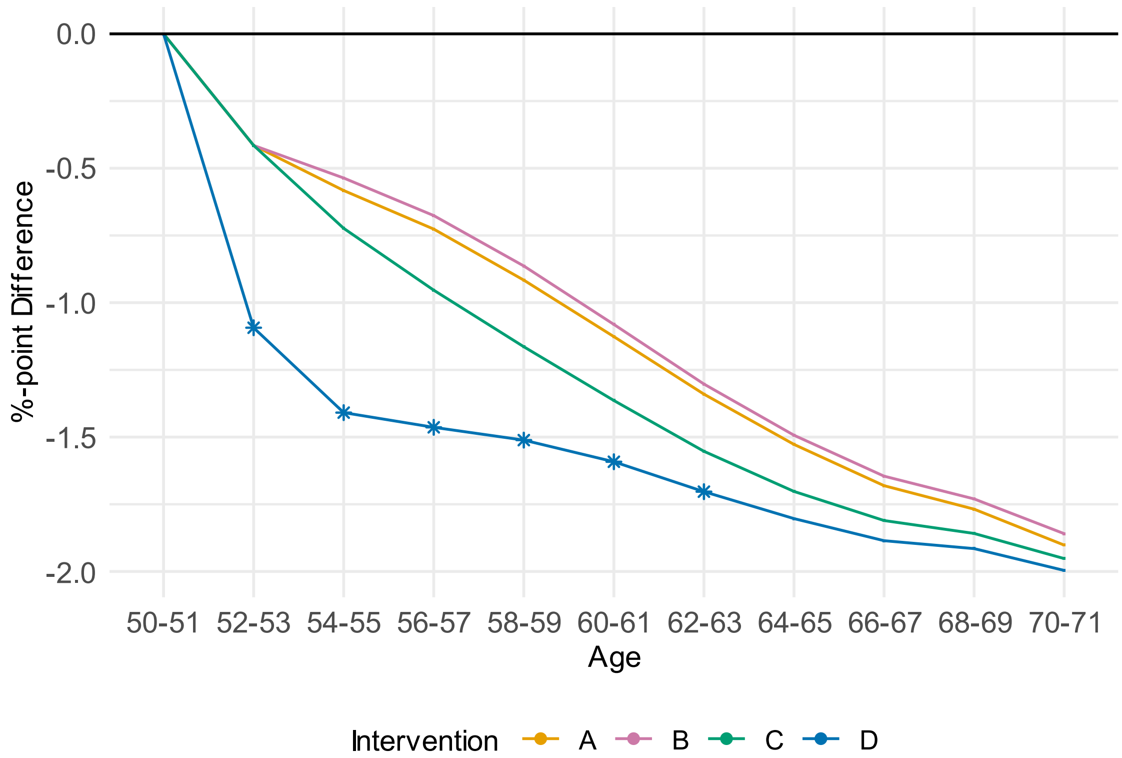

Figure 3 Absolute %-point change in the gender gap in elevated depressive symptoms from equalizing opportunities at the labor market across women and men. Highlighted points indicate a significant difference from the natural course (p<0.05). We exclude observations age 72-80 from the simulation step because from age 72, more than 50% of observations are from retired participants, leading to unstable estimates.

Subgroup Analysis

In the race/ethnicity subgroup analysis, we find that equalizing employment, occupation, income outcomes and previous income (intervention D) results in a pronounced decline in the absolute difference for Hispanics across age, while the non-Hispanic white and black groups follow a similar trend as the total population (supplement section 4.2). We find a mean decrease in the gender depression gap of 4.25%-points (-5 to -3.48) in Hispanics, 2.04%-points (-2.79 to -1.15) in the non-Hispanic Black group, 1.46%-points (-2.85 to 0.2) in non-Hispanic White group, which translates to median contributions of 36.83% (28.16 to 54.59), 30.33% (18.46 to 48.3) and 40.76% (-19.82 to 98.55), respectively (Table 2).

In the education subgroup analysis, we see a gradient in the decrease of the gender depression gap due to equalizing labor market outcomes in women, with the low education group showing the largest decrease (supplement section 4.3). Intervention D results in a mean reduction in the gender depression gap of 3.7%-points (-4.95 to -2.51) in low educated groups, 1.45%-points (-

2.15 to -0.7) in middle educated groups, and 1.11%-points (-1.95 to -0.37) in high educated groups, which translates to median contributions of 31.11% (20.65 to 47.94), 36.62% (17.05 to 90), 29.45% (7.36 to 51.84), respectively (Table 2).

Table 2 Average absolute difference and median contribution by intervention for main and subgroup analyses over age range 50 to 71. We present the median contribution due to some skewness in the White race/ethnicity group.

		Intervention A		**Intervention B**		**Intervention C**		**Intervention D**	
		estimate	95% CI	estimate	95% CI	estimate	95% CI	estimate	95% CI
Main analysis									
Absolute Difference		-1.2	(-2.81, 0.4)	-1.16	(-2.82, 0.36)	-1.35	(-3.01, 0.15)	-1.64	(-3.28, -0.15)
Contribution		27.69	(-6.84, 58.52)	26.61	(-7.2, 60.58)	29.03	(-2.49, 62.82)	31.91	(1.39, 62.83)
By ethnicity									
Absolute Difference	White	-1.1	(-2.5, 0.65)	-0.98	(-2.38, 0.79)	-1.18	(-2.58, 0.5)	-1.46	(-2.85, 0.2)
	Black	-0.96	(-1.69, -0.05)	-1.27	(-2.02, -0.44)	-1.6	(-2.37, -0.75)	-2.04	(-2.79, -1.15)
	Hispanic	-4.24	(-5.05, -3.42)	-4.13	(-4.85, -3.36)	-4.22	(-4.96, -3.45)	-4.2	(-5, -3.48)
Contribution	White	30.35	(-40.55, 83.32)	26.72	(-46.42, 73.71)	32.25	(-34.95, 84.68)	40.76	(-19.82, 98.55)
	Black	13. 71	(0.1, 27.35)	17.71	(5.55, 32.72)	22.24	(10.03, 39.92)	30.33	(18.46, 48.3)
	Hispanic	37.03	(25.12, 56.05)	35.61	(26.99, 53.29)	36.6	(27.98, 53.73)	36.83	(28.16, 54.59)
By education									
Absolute Difference	Low	-3.39	(-4.71, -2.22)	-3.35	(-4.63, -2.12)	-3.64	(-4.93, -2.44)	-3.7	(-4.95, -2.51)
	Middle	-1.12	(-1.78, -0.44)	-0.87	(-1.6, -0.17)	-1.19	(-1.89, -0.43)	-1.45	(-2.15, -0.7)
	High	-0.63	(-1.45, 0.13)	-0.64	(-1.48, 0.13)	-0.81	(-1.66, -0.04)	-1.11	(-1.95, -0.37)
Contribution	Low	28.55	(17.39, 44.9)	28.16	(17.1, 43.75)	30.42	(19.62, 46.97)	31.11	(20.65, 47.94)
	Middle	25.91	(7.97, 79.54)	20.26	(2.16, 58.37)	27.97	(9.3, 77)	36.62	(17.05, 90)
	High	16.85	(-6.05, 36.51)	17.11	(-8.14, 37.42)	21.75	(-0.98, 42.63)	29.45	(7.26, 51.84)

Discussion

Our study finds that equalizing employment status, occupation and income opportunities across gender from age 50 onwards leads to an average reduction of 1.64%-points in the gender depression gap. Hence, on average, 32% of the gender depression gap can be explained by unequal opportunities at the labor market. Without accounting for women's prior socioeconomic disadvantage, we find a mean reduction in the gender depression gap of 1.35%-points, which translates to a contribution of 28%. Subgroup analyses reveal that equalizing labor market opportunities across gender reduce the gender depression gap most in Hispanics and low educated groups.

Comparison with the literature and interpretation of findings

We find that unequal labor market opportunities contribute to the gender depression gap. Equalizing employment opportunities across gender moves 9.54% of women from homemakers into full-time or part-time employment which reduces the gender depression gap by 1.2%-points. This reduction does not increase if we additionally equalize occupation and move 12.34% of women into manual labor occupations. This is not surprising because women that are employed in male-dominated (often manual) occupations report higher depressive symptoms than in female-dominated (often service-related) occupations.[25] However, while this suggests that increasing manual occupation levels in women increases their depression risk, we find that equalizing employment reduces the gender depression gap irrespective of occupation. The beneficial effect of re-employment on mental health[26] might therefore be independent of occupation. Intervention D, in which we additionally account for prior income, yields the largest reduction in the gender depression gap compared to the other interventions by closing the gender wage gap. This underlines previous findings that indicate that reductions in the gender wage gap reduce the gender depression gap in women.[15,27]

Our subgroup analysis shows that equalizing labor market opportunities across gender reduces the gender gap most in groups with the largest gender depression gap, namely Hispanic and low educated groups. While we find the depression gap to be largest in Hispanics, Hargrove et al[28] find no evidence for differences in the gender gap across race/ethnicity. Their study focusses on US adolescents and adults until age 42, while our study includes ages 50-71. It is therefore possible that the gender depression gap across race/ethnicity starts to emerge at older ages.

We also find differences in the gender depression gap across education groups, with the smallest gap in the highly educated groups. This is partially in line with Ross et al.[7] who suggest that the gender depression gap is closed in men and women with a college degree or higher, and therefore might be closed in future generations. This is only partially supported by Platt et al.[4] who found that the decreasing gender ratio in college attainment between men and women mediates 39% of the gender depression gap across cohorts. While the authors suggest that education contributes to the gender depression gap more so in younger working adults[4], we show that the persisting education differences in the gender depression gap in older adults are partly explained by inequalities at the labor market.

Even though our main analysis suggests that a comprehensive intervention, i.e. intervention D, yields the largest reduction in the gender depression gap, Hispanics and low educated groups benefit most from equalizing employment opportunities across gender (intervention A). Chen et al.[29] suggest that structural gender inequality does not affect women of different socioeconomic or race/ethnicity backgrounds differently. Indeed, our results might be driven by the larger difference in prevalence of female homemakers in Hispanics and low educated groups compared to other subgroups (supplement section 2). By giving Hispanic and low educated women the same employment opportunities as men in their group, this results in more women moving from homemakers back into employment, compared to other racial/ethnic and education groups (supplement section 4).

While the absolute change in the gender depression gap is largest in Hispanic and low educated groups, the relative change (contribution) for intervention D in the other subgroups are of similar size as for intervention A in Hispanics and low educated groups. This might be because the gender wage gap is largest among highly educated and White populations in our sample. Therefore, intervening on prior income (intervention D) raises women's income to that of men in white and high educated groups, and to a lesser extent in black and middle educated groups. Hence, while policies that address inequalities in employment opportunities, for example through improving affordability and access of childcare, will meaningfully reduce the gender depression gap in older Hispanic and low educated adults, policies that address the gender wage gap (intervention D in our study), for example through addressing the motherhood wage penalty, will reduce the gender depression gap in all subgroups.

Even though we attempt to capture the complex relationship between labor market opportunities and depression risk, we do not consider all factors which contribute to the gender gap in depression risk and may affect labor market decisions. Kuehner[8] summarized these into differences in individual susceptibility, such as genetic risk or physiological stress response; environmental factors, such as stressful life evens and structural gender inequities; and differences in reporting across gender. In addition to that, women tend to live longer but in worse health than men[30] and having one or more chronic health conditions is linked to increased depression risk.[31] Hence, mortality selection might play a crucial role in explaining the gender gap in depression in older adults.

Evaluation of Data and Methods

Our causal decomposition analysis is based on three core assumptions: SUTVA (stable unit treatment value assumption), positivity and no unmeasured confounding. The discussion of the SUTVA and positivity assumption can be found in supplement section 5. In terms of unmeasured confounding, the gender-labor market and gender-depression pathways cannot be confounded, because gender cannot be seen as a manipulable exposure. However, unmeasured confounding might be present for the labor market-depression pathway. This pathway might be confounded for example through attitudes towards gender norms, i.e. whether women experience role conflicts, or hours spent on unpaid household or care work, and employment histories, i.e. employment duration and the number of transitions in and out of employment during the life course. We attempt to account for employment histories by additionally intervening on prior income levels, which might not adequately capture it. Both employment history and attitudes towards gender norms may negatively affect employment decisions and mental health. Not including these factors may therefore lead to an overestimation of the positive effect of employment on mental health. We assess previous history of depression at baseline (age 50-51) by including the covariate "whether a participant ever was told by a doctor to have psychological problems". This covariate might be updated after baseline if the participant got diagnosed with a psychological disorder. While this might capture part of the effect of elevated depressive symptoms, exclusion of this covariate does not meaningfully affect our main results (supplement section 6).

Furthermore, we find evidence for differential attrition due to mortality and overall non-response in our sample with depressed men being more likely to leave the study than depressed women (supplement section 6). Therefore, part of the gender gap in depression risk in older adults might be explained by healthy selection of males that do not drop out due to mortality or overall non-response. This could lead to an overestimation of the causal effects of equalizing labor market opportunities.

An advantage of our study is that we use the HRS which is representative of US adults born 1916-1966, age 50-71, and allows us to generalize our conclusions towards that group of US adults.

Additionally, we employ a causal decomposition approach which allows all (time-varying) covariates and the outcome to affect each other and try to capture the complexity of how labor market inequalities contribute to the gender gap in depression risk.

Conclusion

Our study finds that 32% of the gender gap in depression risk in older US adults can be explained by unequal opportunities at the labor market. This indicates that policies that attempt to equalize labor market opportunities have the potential to narrow the gender gap in depression. Decreasing labor market inequalities, especially in employment opportunities, reduces the gender depression gap most in groups with the largest gender depression gap, namely Hispanics and low educated groups. Future research could benefit from studying the impact of labor market inequalities on the gender depression gap in younger adults.

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Supplement

Contents

Flowchart

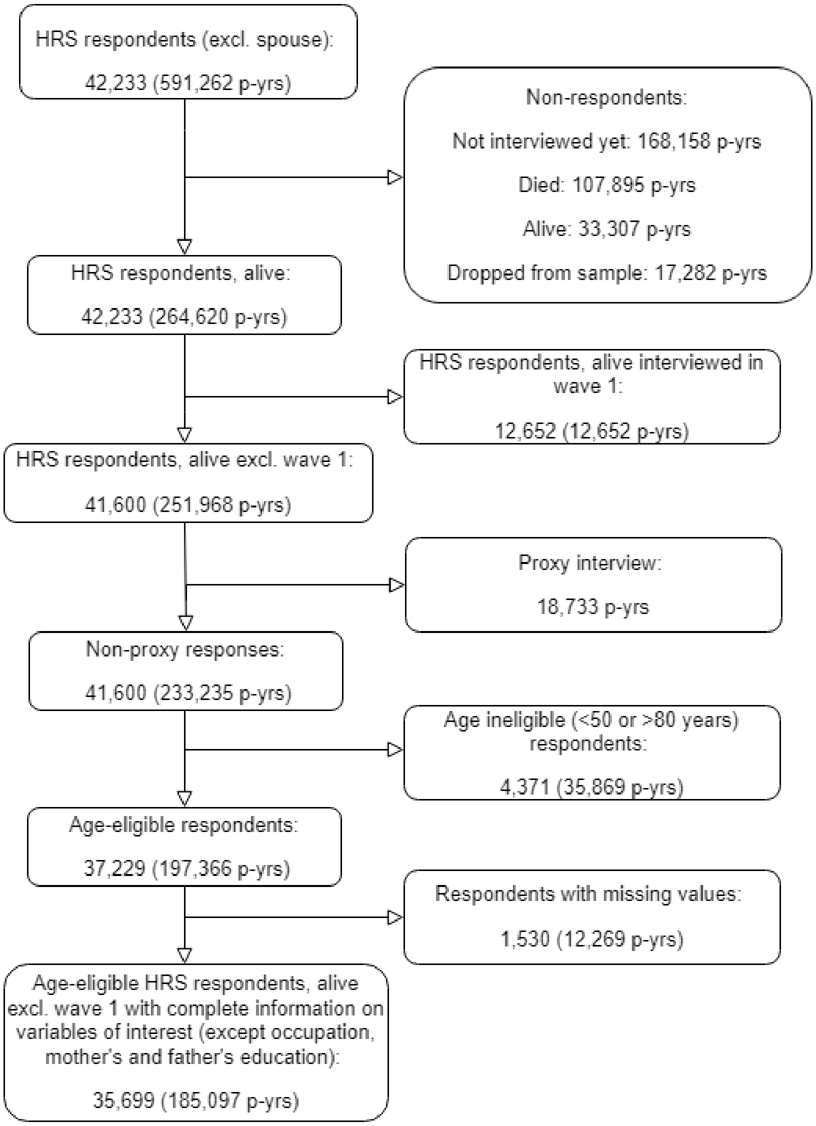

Figure S. 1 Flowchart of sample selection. p-yrs: person-years. Proxy interviews indicate that the responded was not able or willing to participate in the interview themselves so a proxy respondent (e.g. spouse, family member) conducted the interview for them.

Section 1: Additional information on causal decomposition analysis

Imputation of covariates

We use multivariate imputations chained equations (MICE) algorithm to impute the 4-category occupation class, and mother's and father's education class for our dataset at age 50-51 (M=100). This is the starting point of the simulation.

For the dataset that will be used for estimating the regression models, we impute mother's and father's education class and 3-category occupation group by fitting a multinomial model that is congenial with the estimation model as part of the bootstrapping step (see next section). Since occupation group is deterministically based on employment status, i.e. unemployed, homemakers, retired and disabled people will be in the "no occupation" group, we impute the 4-category occupation group based on the predictions of the fitted multinomial model and the reported employment status for ages 52 to 80 for every bootstrap iteration. We do this because ages 50-51 are imputed outside the g-formula (see paragraph above).

Causal dynamic decomposition

To assess the effect of our hypothetical intervention, we employ a dynamic causal decomposition using the longitudinal g-formula with Monte Carlo integration. We employ the longitudinal parametric g-formula with the following steps:

1. Randomly draw women and men from the data with replacement
2. To the randomly drawn individuals:
    a. Fit regression models for men and women for imputing missing covariates for ages 52-80 (see *Imputation of covariates* section)
    b. After imputation, fit parametric models for men and women for time-varying covariates:
    $f(Y_{t,w}|C, X_{t-1}, D_{t-1}, L_{t-1}) = \beta_0 + C_w\beta_1 + A_w\beta_2 + D_{w,t-1}\beta_3 + L_{w,t-1}\beta_4 + Xw,_{t-1}\beta_5 + K_{w,t-1}\beta_6$ (Eq.1)
    $f(Y_{t,m}|C, X_{t-1}, D_{t-1}, L_{t-1}) = \theta_0 + C_m\theta_1 + A_m\theta_2 + D_{m,t-1}\theta_3 + L_{m,t-1}\theta_3 + X_{m,t-1}\theta_5 + K_{m,t-1}\theta_5$ (Eq.2)
    Where Y_t is the time-varying variable of interest at wave t, with w referring to observations for women and m for men, C is a matrix of time-invariant covariates, A a matrix of natural cubic spline basis functions for age with three degrees of freedom, D_{t-1} is depression at t-1, L_{t-1} is a matrix of labor market variables at t-1, X_{t-1} is a matrix of time-varying covariates at t-1, and K_{t-1} is a matrix of interaction between employment status at t-1 with income at t-1 and age. Note that each parameter other than the intercept represent vectors of coefficients. f refers to the link function: logistic regression for depression and multinomial regression for employment status, occupation group, health status, marital status, number of household members and number of children. The "no occupation" occupation group is deterministically based on employment status, so we fit the regression model for three categories of occupation group and exclude the "no occupation" group. We model income with quantile regression to account for zero-inflation and outliers.
3. Take the observed data at wave t1 with imputed missing values (see *Imputation of covariates* section) and simulate observations for t+1 (second wave of follow up).
    a. We obtain predicted probabilities based on the estimated regression models. Then we draw from either a binomial or multinomial distribution, depending on the class of the time-varying covariate, with the predicted probabilities as their parameters. For income, we estimate quantile models and assign the quantile predictions based on whether a random number drawn from a uniform distribution falls within the boundaries, akin to the inverse CDF sampling technique[1], where boundary values are set as $\frac{Quantile_{x-1} + Quantile_x}{2}$.
    b. Use those simulated observations to simulate observations for the next wave and continue until age group 79-80.
4. Save simulated outcomes from **step 3** for depression risk and other time-varying covariates for all waves/age-groups (natural course approximation)
5. **Repeat step 3**, but introduce the first hypothetical intervention. Assign women the same probability as males of being in an employment, occupation and/or income class. Interventions 1 to 3 can be expressed with the following formula:
$E[Y_{t,w}|C, X_{t-1}, D_{t-1}, L_{t-1}] = f^{-1}(\theta_0 + C_w\theta_1 + A_w\theta_2 + D_{w,t-1}\theta_3 + L_{w,t-1}\theta_4 + X_{w,t-1}\theta_5 + K_{w,t-2}\theta_5)$ (Eq.3)

Where $\theta_0, \theta_1, \theta_2, \theta_3, \theta_4$, and θ_5 are the vectors of coefficients of the equation for men (Eq.2) and $C_w, A_w, D_{w,t-1}, L_{w,t-1}$, and $X_{w,t-1}$ are women's covariate values.

6. Save simulated outcome from **step 5** for depression risk and other time-varying covariates for all simulated waves/age-groups.
7. Perform Monte Carlo error reduction by repeating **steps 2 to 6** 100 times and averaging simulated depression risk for both scenarios.
8. Calculate the absolute gender gap in depression risk between natural course and intervention scenario and contribution as $1 - \frac{D_{w_{cf}} - D_{m_{nc}}}{D_{w_{nc}} - D_{m_{nc}}}$ ($D_{w_{cf}}$ is depression risk in women in the counterfactual scenario, $D_{w_{nc}}$ and $D_{m_{nc}}$ are depression risk in women and men in the natural course approximation) and save those estimates.
9. Bootstrap: Perform **steps 1-8** 499 times. We calculate the 95% confidence intervals for the absolute difference and contribution by taking the mean effect and the 2.5 and 97.5% quantiles of the estimated effects across all bootstrap iterations. For calculating the mean absolute difference and median contribution across all ages, we take the average effect across age for each bootstrap iteration and calculate the 2.5 and 97.5% quantiles of the estimated effects across all bootstrap iterations.

We repeat steps 1-9 for each of the four intervention scenarios that are described in the methods section.

Section 2: Additional descriptive Tables and Figures

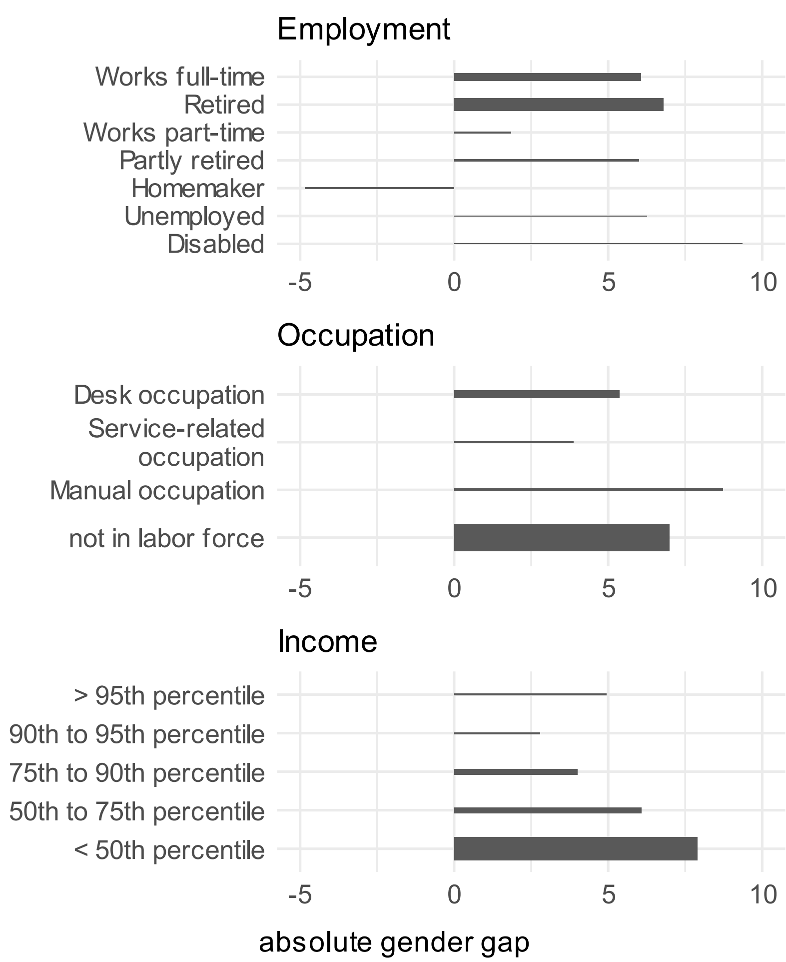

Figure S. 2 Gender depression gap by employment status, occupation group and income percentiles, US adults ages 50 to 80. Width of the bars represents relative group size. Gender depression gap is calculated as depression risk in females – depression risk in males. A gender gap >0 indicates that females are more depressed than males, while a gender gap <0 indicates that males are more depressed than females.

By race/ethnicity and education

Table S. 1 Sample characteristics by gender and race/ethnicity.

	NH White		NH Black		Hispanic		Other	
	female	male	female	male	female	male	female	male
N person-years	73272	54259	19930	11701	12182	8470	2988	2295
outcome								
eleveated depressive symptoms (yes N(%))	15545 (21.2)	7961 (14.7)	5940 (29.8)	2601 (22.2)	4387 (36.0)	2071 (24.5)	883 (29.6)	471 (20.5)
Confounders								
Age (mean (SD))	65.32 (8.37)	65.63 (8.11)	63.12 (7.94)	63.27 (7.85)	62.59 (7.95)	62.75 (7.81)	61.65 (8.03)	61.98 (7.90)
Father's education (mean (SD))								
low	29477 (45.1)	20623 (42.3)	7834 (55.6)	4446 (52.6)	7156 (75.4)	5094 (75.3)	1065 (43.6)	679 (36.8)
middle	24602 (37.6)	19087 (39.1)	5200 (36.9)	3339 (39.5)	1650 (17.4)	1224 (18.1)	752 (30.8)	690 (37.4)
high	11275 (17.3)	9085 (18.6)	1045 (7.4)	671 (7.9)	687 (7.2)	443 (6.6)	628 (25.7)	474 (25.7)
Mother's education (mean (SD))								
low	26532 (38.7)	16895 (33.7)	7804 (46.0)	4110 (41.3)	8454 (79.2)	5546 (75.8)	1205 (44.9)	823 (41.3)
middle	31103 (45.4)	25432 (50.7)	7475 (44.0)	4928 (49.5)	1716 (16.1)	1453 (19.8)	1048 (39.1)	838 (42.0)
high	10837 (15.8)	7829 (15.6)	1699 (10.0)	920 (9.2)	506 (4.7)	322 (4.4)	428 (16.0)	333 (16.7)
Ever reported psychological problems (Yes N(%))	13119 (17.9)	5540 (10.2)	2924 (14.7)	1298 (11.1)	2531 (20.8)	918 (10.8)	606 (20.3)	269 (11.7)
Education N(%)								
low	13071 (17.8)	9961 (18.4)	6599 (33.1)	4201 (35.9)	6917 (56.8)	4557 (53.8)	726 (24.3)	526 (22.9)
middle	26699 (36.4)	15118 (27.9)	5409 (27.1)	3166 (27.1)	2316 (19.0)	1615 (19.1)	644 (21.6)	403 (17.6)
high	33502 (45.7)	29180 (53.8)	7922 (39.7)	4334 (37.0)	2949 (24.2)	2298 (27.1)	1618 (54.1)	1366 (59.5)
Intervention variable								
Labor force status N(%)								
Full-time worker	16750 (22.9)	18243 (33.6)	5371 (26.9)	3756 (32.1)	2746 (22.5)	3368 (39.8)	953 (31.9)	978 (42.6)
Part-time worker	5630 (7.7)	1700 (3.1)	1438 (7.2)	502 (4.3)	1299 (10.7)	497 (5.9)	264 (8.8)	105 (4.6)
Unemployed	1041 (1.4)	980 (1.8)	592 (3.0)	418 (3.6)	369 (3.0)	389 (4.6)	113 (3.8)	103 (4.5)
Partly retired	5782 (7.9)	6327 (11.7)	1283 (6.4)	917 (7.8)	440 (3.6)	448 (5.3)	158 (5.3)	167 (7.3)
Retired	34276 (46.8)	25966 (47.9)	8797 (44.1)	5432 (46.4)	4047 (33.2)	3120 (36.8)	1057 (35.4)	825 (35.9)
Disabled	1453 (2.0)	765 (1.4)	1257 (6.3)	529 (4.5)	636 (5.2)	427 (5.0)	147 (4.9)	71 (3.1)
Not in labor force	8340 (11.4)	278 (0.5)	1192 (6.0)	147 (1.3)	2645 (21.7)	221 (2.6)	296 (9.9)	46 (2.0)
Occupation Class N(%)								
Desk occupation	14140 (22.2)	10244 (22.5)	1864 (11.9)	780 (8.8)	845 (8.9)	611 (10.2)	406 (18.4)	286 (18.0)
Service-related occupation	2980 (4.7)	1239 (2.7)	1450 (9.3)	432 (4.9)	687 (7.2)	234 (3.9)	133 (6.0)	49 (3.1)
Manual occupation	1439 (2.3)	6088 (13.4)	518 (3.3)	1087 (12.3)	267 (2.8)	972 (16.3)	57 (2.6)	208 (13.1)
Not in labor force	45110 (70.9)	27989 (61.4)	11838 (75.5)	6526 (73.9)	7697 (81.1)	4157 (69.6)	1613 (73.0)	1045 (65.8)
Individuals earnings								
no individual earnings	45934 (62.7)	30937 (57.0)	11536 (57.9)	6776 (57.9)	8255 (67.8)	4841 (57.2)	1672 (56.0)	1160 (50.5)
1 to 18,233 USD	11528 (15.7)	6492 (12.0)	3711 (18.6)	1626 (13.9)	2193 (18.0)	1400 (16.5)	509 (17.0)	303 (13.2)
18,234 to 46,354 USD	10720 (14.6)	7662 (14.1)	3464 (17.4)	2075 (17.7)	1371 (11.3)	1602 (18.9)	473 (15.8)	391 (17.0)
46,355 to 67,679 USD	2956 (4.0)	3921 (7.2)	709 (3.6)	675 (5.8)	221 (1.8)	373 (4.4)	165 (5.5)	202 (8.8)

more than 67,679 USD	2134 (2.9)	5247 (9.7)	510 (2.6)	549 (4.7)	142 (1.2)	254 (3.0)	169 (5.7)	239 (10.4)
Time-varying variables								
Marital status N(%)								
Married	45853 (62.6)	42282 (77.9)	7114 (35.7)	6659 (56.9)	6798 (55.8)	6362 (75.1)	1595 (53.4)	1715 (74.7)
Separated or divorced	10323 (14.1)	6342 (11.7)	5463 (27.4)	2750 (23.5)	2524 (20.7)	1306 (15.4)	687 (23.0)	332 (14.5)
Widowed	14871 (20.3)	3369 (6.2)	5009 (25.1)	1075 (9.2)	2126 (17.5)	392 (4.6)	503 (16.8)	120 (5.2)
Not married	2225 (3.0)	2266 (4.2)	2344 (11.8)	1217 (10.4)	734 (6.0)	410 (4.8)	203 (6.8)	128 (5.6)
Number of persons in household N(%)								
1	17765 (24.2)	7743 (14.3)	5733 (28.8)	2806 (24.0)	1977 (16.2)	934 (11.0)	630 (21.1)	274 (11.9)
2	41333 (56.4)	34321 (63.3)	7282 (36.5)	4692 (40.1)	4329 (35.5)	3064 (36.2)	1231 (41.2)	1010 (44.0)
3	8713 (11.9)	7342 (13.5)	3379 (17.0)	2131 (18.2)	2392 (19.6)	1715 (20.2)	533 (17.8)	439 (19.1)
>3	5461 (7.5)	4853 (8.9)	3536 (17.7)	2072 (17.7)	3484 (28.6)	2757 (32.6)	594 (19.9)	572 (24.9)
Number of children in household N(%)								
no children	5033 (6.9)	4474 (8.2)	1369 (6.9)	995 (8.5)	695 (5.7)	514 (6.1)	318 (10.6)	200 (8.7)
1 child	7397 (10.1)	5065 (9.3)	2742 (13.8)	1177 (10.1)	988 (8.1)	602 (7.1)	359 (12.0)	232 (10.1)
2 children	20939 (28.6)	15711 (29.0)	3965 (19.9)	2314 (19.8)	2463 (20.2)	1716 (20.3)	818 (27.4)	680 (29.6)
more than 2 children	39903 (54.5)	29009 (53.5)	11854 (59.5)	7215 (61.7)	8036 (66.0)	5638 (66.6)	1493 (50.0)	1183 (51.5)
Number of chronic conditions N(%)								
none	13963 (19.1)	10560 (19.5)	2235 (11.2)	2049 (17.5)	2277 (18.7)	2233 (26.4)	678 (22.7)	570 (24.8)
1	21115 (28.8)	15067 (27.8)	4630 (23.2)	2972 (25.4)	3312 (27.2)	2369 (28.0)	810 (27.1)	654 (28.5)
2	19651 (26.8)	13851 (25.5)	5912 (29.7)	3101 (26.5)	3178 (26.1)	2035 (24.0)	755 (25.3)	518 (22.6)
3	11273 (15.4)	9033 (16.6)	4132 (20.7)	2116 (18.1)	2219 (18.2)	1205 (14.2)	419 (14.0)	325 (14.2)
4+	7270 (9.9)	5748 (10.6)	3021 (15.2)	1463 (12.5)	1196 (9.8)	628 (7.4)	326 (10.9)	228 (9.9)

Table S. 2 Sample characteristics by gender and education.

	low		middle		high	
	female	male	female	male	female	male
N person-years	27313	19245	35068	20302	45991	37178
outcome						
eleveated depressive symptoms (yes N(%))	10244 (37.5)	5009 (26.0)	8176 (23.3)	3412 (16.8)	8335 (18.1)	4683 (12.6)
Confounders						
Age (mean (SD))	65.58 (8.28)	66.00 (8.19)	65.33 (8.30)	65.13 (8.15)	63.25 (8.19)	64.09 (8.00)
Race/ethnicity (%)						
White	13071 (47.9)	9961 (51.8)	26699 (76.1)	15118 (74.5)	33502 (72.8)	29180 (78.5)
Black	6599 (24.2)	4201 (21.8)	5409 (15.4)	3166 (15.6)	7922 (17.2)	4334 (11.7)
Hispanic	6917 (25.3)	4557 (23.7)	2316 (6.6)	1615 (8.0)	2949 (6.4)	2298 (6.2)
Other	726 (2.7)	526 (2.7)	644 (1.8)	403 (2.0)	1618 (3.5)	1366 (3.7)
Father's education (mean (SD))						
low	15151 (76.6)	10670 (75.1)	16386 (54.8)	9044 (52.1)	13995 (33.6)	11128 (32.4)
middle	4136 (20.9)	3081 (21.7)	11489 (38.4)	7245 (41.8)	16579 (39.8)	14014 (40.8)
high	491 (2.5)	448 (3.2)	2044 (6.8)	1059 (6.1)	11100 (26.6)	9166 (26.7)
Mother's education (mean (SD))						
low	16663 (74.4)	10249 (66.5)	15217 (47.3)	7755 (42.1)	12115 (27.4)	9370 (26.3)
middle	5288 (23.6)	4716 (30.6)	15186 (47.2)	9681 (52.6)	20868 (47.2)	18254 (51.3)
high	443 (2.0)	436 (2.8)	1779 (5.5)	980 (5.3)	11248 (25.4)	7988 (22.4)

Ever reported psychological problems (Yes N(%))	6188 (22.7)	2349 (12.2)	5316 (15.2)	1774 (8.7)	7676 (16.7)	3902 (10.5)
Intervention variable						
Labor force status N(%)						
Full-time worker	3791 (13.9)	4583 (23.8)	7539 (21.5)	6635 (32.7)	14490 (31.5)	15127 (40.7)
Part-time worker	1924 (7.0)	735 (3.8)	2726 (7.8)	616 (3.0)	3981 (8.7)	1453 (3.9)
Unemployed	478 (1.8)	554 (2.9)	610 (1.7)	384 (1.9)	1027 (2.2)	952 (2.6)
Partly retired	1258 (4.6)	1427 (7.4)	2413 (6.9)	1952 (9.6)	3992 (8.7)	4480 (12.1)
Retired	13114 (48.0)	10746 (55.8)	16603 (47.3)	10179 (50.1)	18460 (40.1)	14418 (38.8)
Disabled	1800 (6.6)	928 (4.8)	869 (2.5)	392 (1.9)	824 (1.8)	472 (1.3)
Not in labor force	4948 (18.1)	272 (1.4)	4308 (12.3)	144 (0.7)	3217 (7.0)	276 (0.7)
Occupation Class N(%)						
Desk occupation	1330 (5.4)	725 (4.4)	5352 (17.4)	1864 (11.1)	10573 (29.6)	9332 (32.6)
Service-related occupation	2088 (8.5)	572 (3.4)	2001 (6.5)	678 (4.1)	1161 (3.2)	704 (2.5)
Manual occupation	823 (3.3)	2803 (16.9)	968 (3.2)	3082 (18.4)	490 (1.4)	2470 (8.6)
Not in labor force	20340 (82.7)	12500 (75.3)	22390 (72.9)	11099 (66.4)	23528 (65.8)	16118 (56.3)
Individuals earnings						
no individual earnings	20792 (76.1)	13198 (68.6)	22643 (64.6)	11999 (59.1)	23962 (52.1)	18517 (49.8)
1 to 18,233 USD	4379 (16.0)	2786 (14.5)	6220 (17.7)	2651 (13.1)	7342 (16.0)	4384 (11.8)
18,234 to 46,354 USD	1950 (7.1)	2560 (13.3)	5263 (15.0)	3589 (17.7)	8815 (19.2)	5581 (15.0)
46,355 to 67,679 USD	126 (0.5)	434 (2.3)	654 (1.9)	1243 (6.1)	3271 (7.1)	3494 (9.4)
more than 67,679 USD	66 (0.2)	267 (1.4)	288 (0.8)	820 (4.0)	2601 (5.7)	5202 (14.0)
Time-varying variables						
Marital status N(%)						
Married	13074 (47.9)	13383 (69.5)	20688 (59.0)	14993 (73.8)	27598 (60.0)	28642 (77.0)
Separated or divorced	4856 (17.8)	2871 (14.9)	5210 (14.9)	2870 (14.1)	8931 (19.4)	4989 (13.4)
Widowed	7878 (28.8)	1837 (9.5)	7766 (22.1)	1450 (7.1)	6865 (14.9)	1669 (4.5)
Not married	1505 (5.5)	1154 (6.0)	1404 (4.0)	989 (4.9)	2597 (5.6)	1878 (5.1)
Number of persons in household N(%)						
1	6900 (25.3)	3248 (16.9)	8628 (24.6)	3258 (16.0)	10577 (23.0)	5251 (14.1)
2	11500 (42.1)	9462 (49.2)	18452 (52.6)	11744 (57.8)	24223 (52.7)	21881 (58.9)
3	4137 (15.1)	3109 (16.2)	4498 (12.8)	2990 (14.7)	6382 (13.9)	5528 (14.9)
>3	4776 (17.5)	3426 (17.8)	3490 (10.0)	2310 (11.4)	4809 (10.5)	4518 (12.2)
Number of children in household N(%)						
no children	1305 (4.8)	1398 (7.3)	1962 (5.6)	1378 (6.8)	4148 (9.0)	3407 (9.2)
1 child	2484 (9.1)	1473 (7.7)	3478 (9.9)	1935 (9.5)	5524 (12.0)	3668 (9.9)
2 children	4771 (17.5)	3673 (19.1)	9670 (27.6)	5556 (27.4)	13744 (29.9)	11192 (30.1)
more than 2 children	18753 (68.7)	12701 (66.0)	19958 (56.9)	11433 (56.3)	22575 (49.1)	18911 (50.9)
Number of chronic conditions N(%)						
none	3238 (11.9)	3357 (17.4)	5970 (17.0)	3683 (18.1)	9945 (21.6)	8372 (22.5)
1	6090 (22.3)	4753 (24.7)	9758 (27.8)	5478 (27.0)	14019 (30.5)	10831 (29.1)
2	7577 (27.7)	5010 (26.0)	9786 (27.9)	5395 (26.6)	12133 (26.4)	9100 (24.5)
3	5762 (21.1)	3469 (18.0)	5921 (16.9)	3499 (17.2)	6360 (13.8)	5711 (15.4)
4+	4646 (17.0)	2656 (13.8)	3633 (10.4)	2247 (11.1)	3534 (7.7)	3164 (8.5)

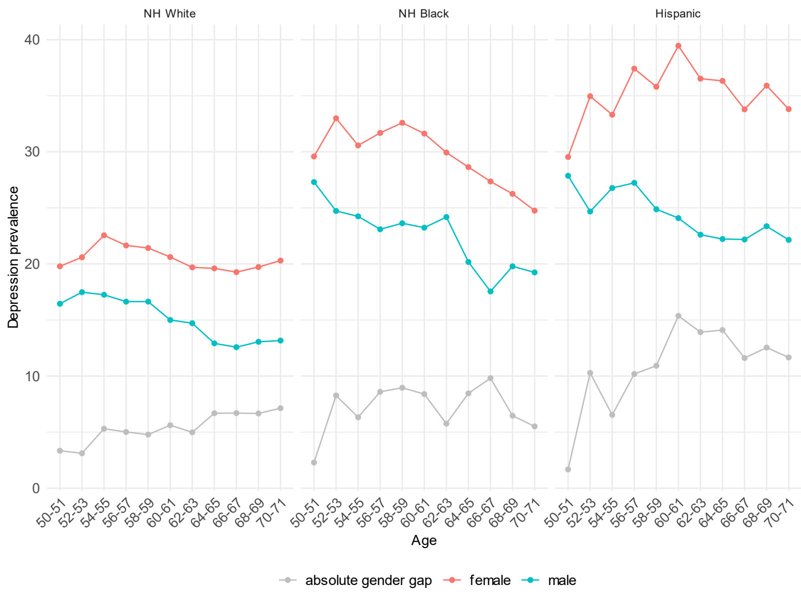

Figure S. 3 Depression prevalence by race/ethnicity per 100 for men and women over age and absolute gender gap in depression prevalence.

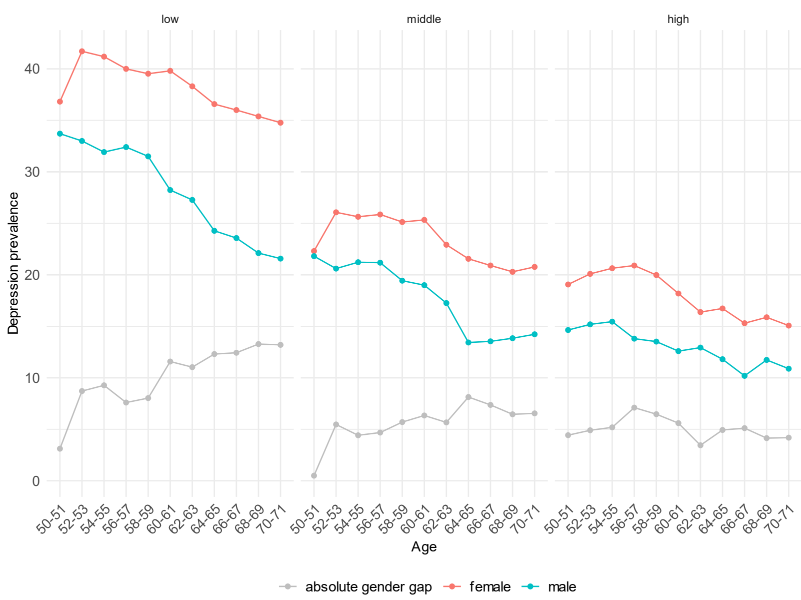

Figure S. 4 Depression prevalence by education per 100 for men and women over age and absolute gender gap in depression prevalence.

Section 3: Natural course predictions

Our natural course approximation adequately predicts the percentage of women and men in each time-varying covariate group in main and subgroup analyses.

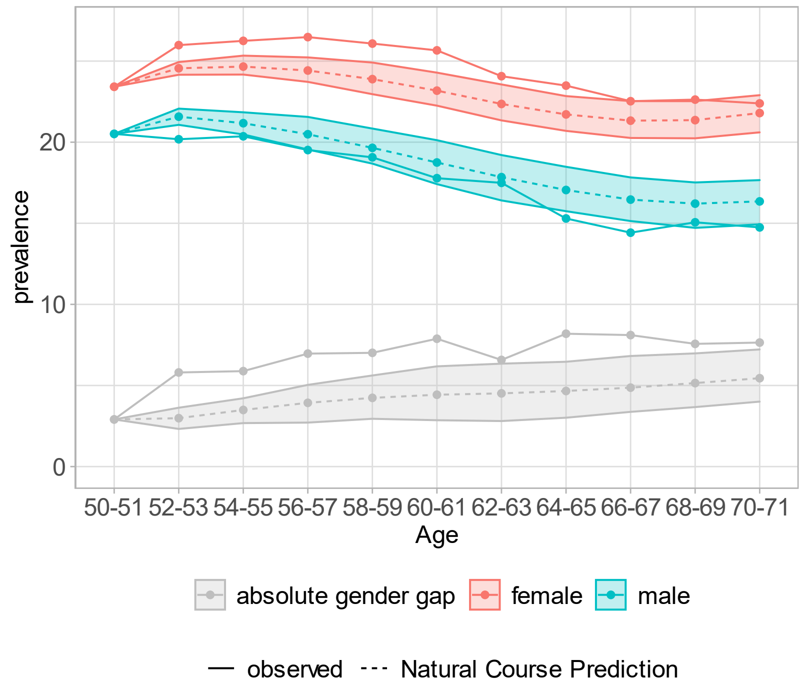

Figure S. 5 Natural course approximation of the gender depression gap and depression prevalence by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

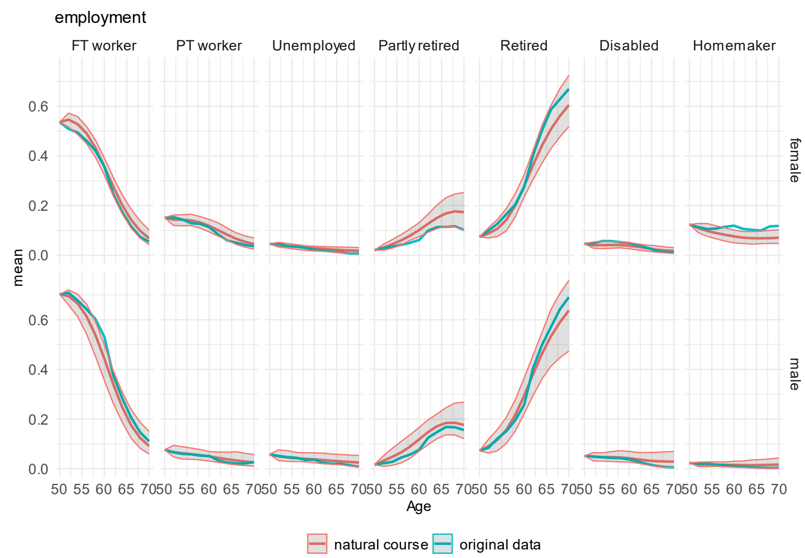

Figure S. 6 Natural course approximation of mean percentage in each employment group by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

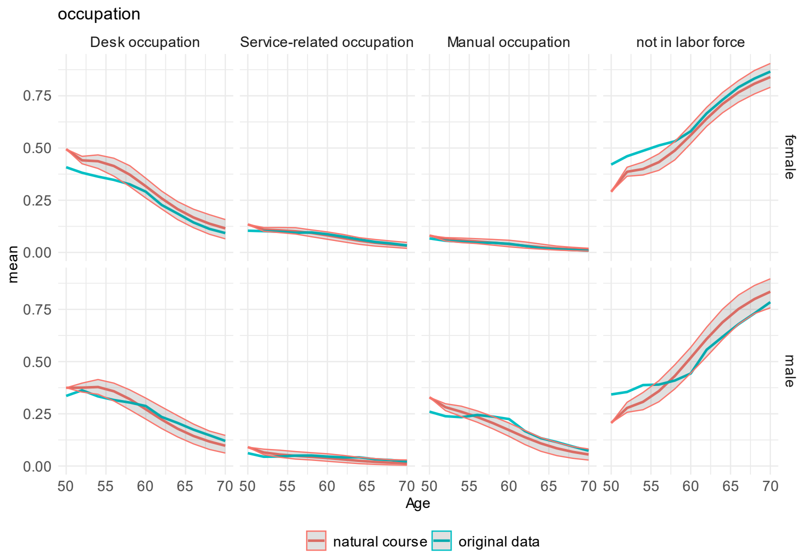

Figure S. 7 Natural course approximation of mean percentage in each occupation group by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

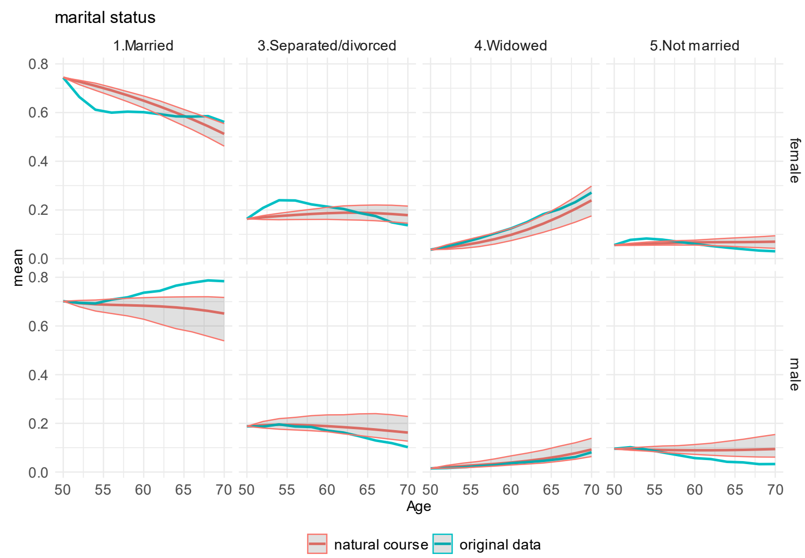

Figure S. 8 Natural course approximation of mean percentage in each marital status group by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

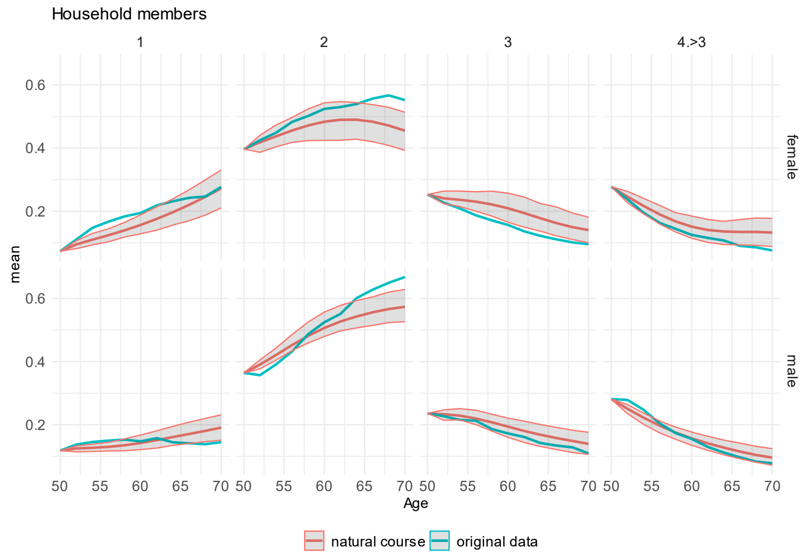

Figure S. 9 Natural course approximation of mean percentage in each household member group by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

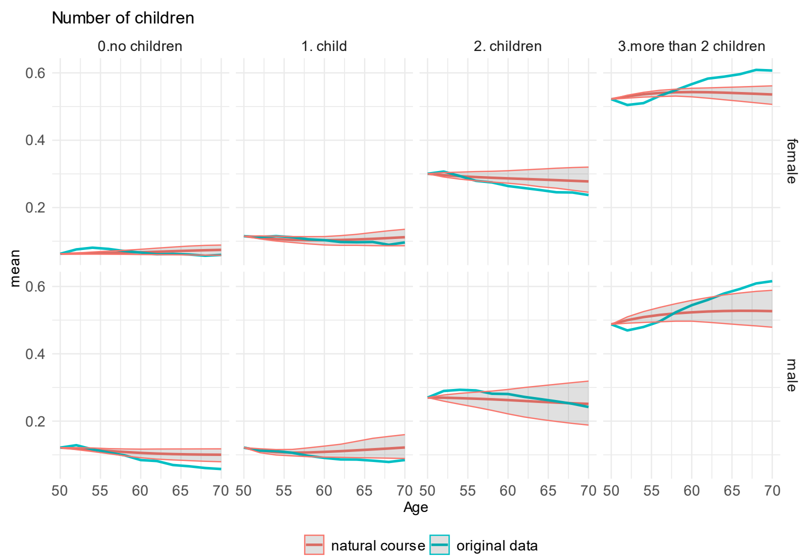

Figure S. 10 Natural course approximation of mean percentage for each number of children by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

Figure S. 11 Natural course approximation of mean percentage for number of chronic conditions by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

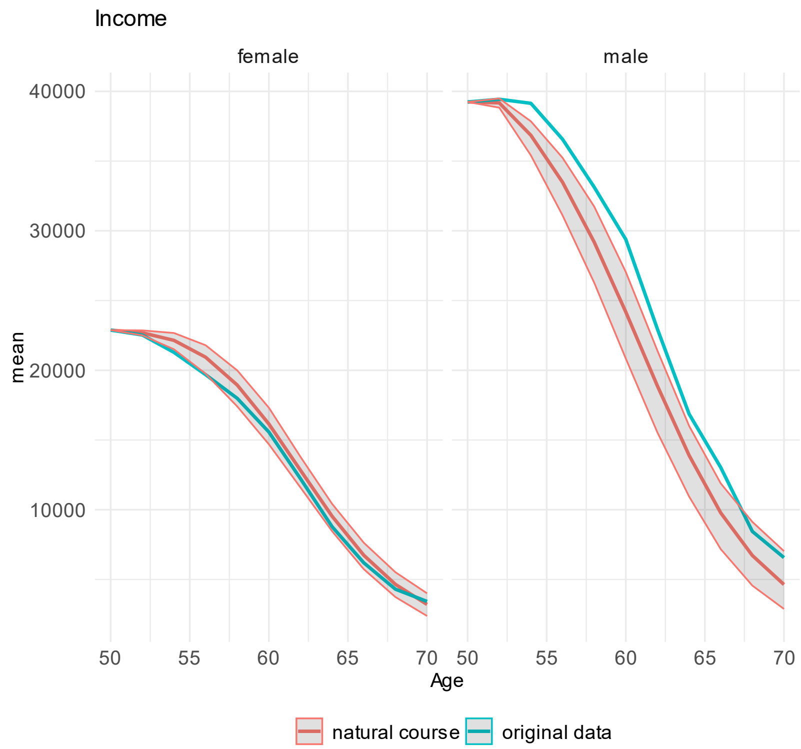

Figure S. 12 Natural course approximation of mean percentage for income by gender across age compared to observed data. Natural course approximation is calculated based on 60 bootstrap iteration without exclusion of retired or disabled groups.

Section 4: Intervention effects from equalizing labor market opportunities

Section 4.1: Main analysis

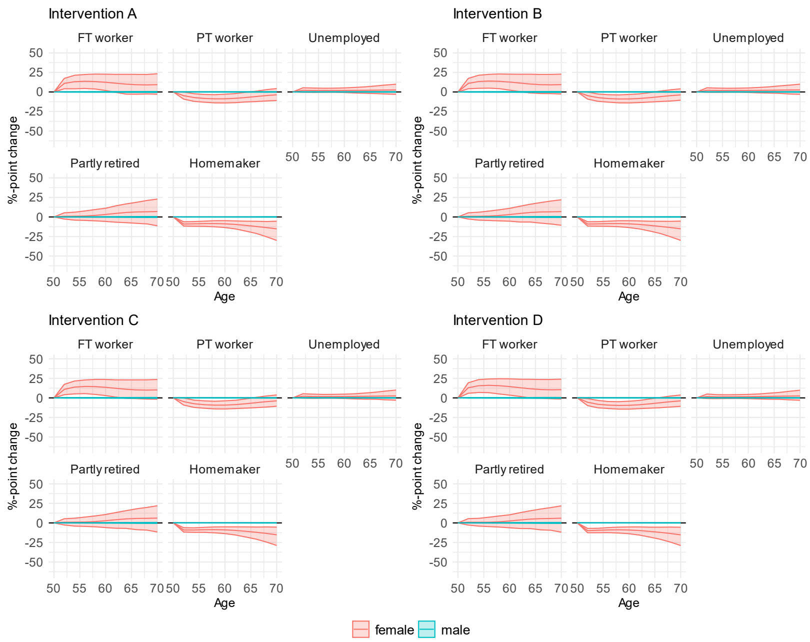

Figure S. 13 %-point change in employment status for males and females for each intervention scenario.

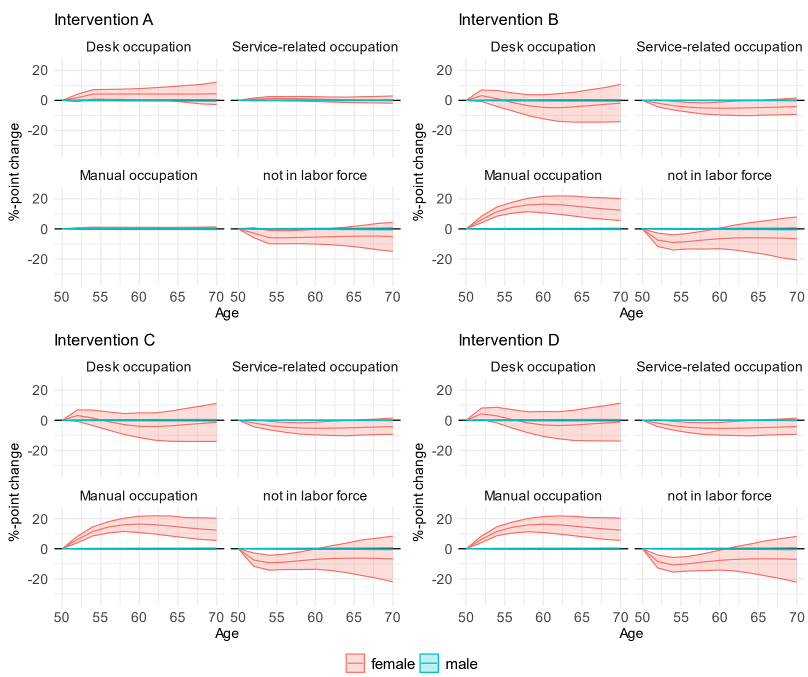

Figure S. 14 %-point change in occupation status for males and females for each intervention scenario.

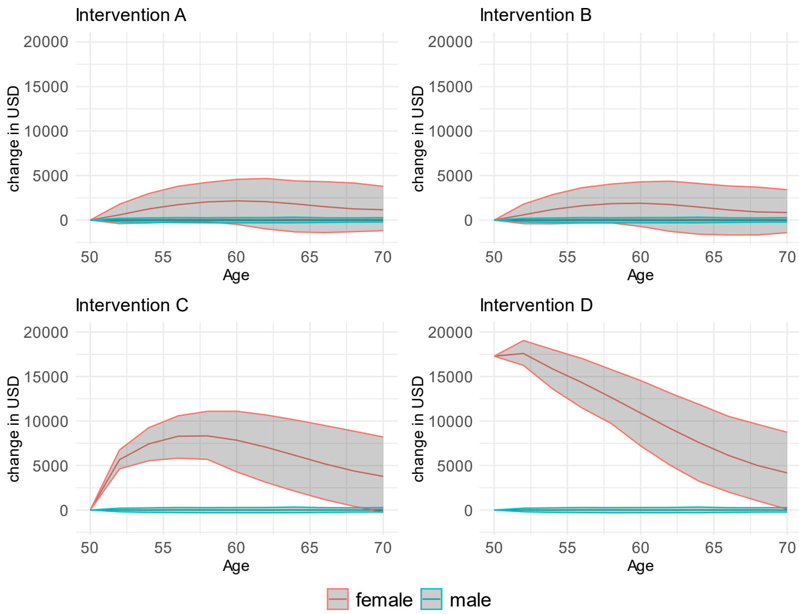

Figure S. 15 %-point change in income for males and females for each intervention scenario.

Section 4.2: Race/ethnicity

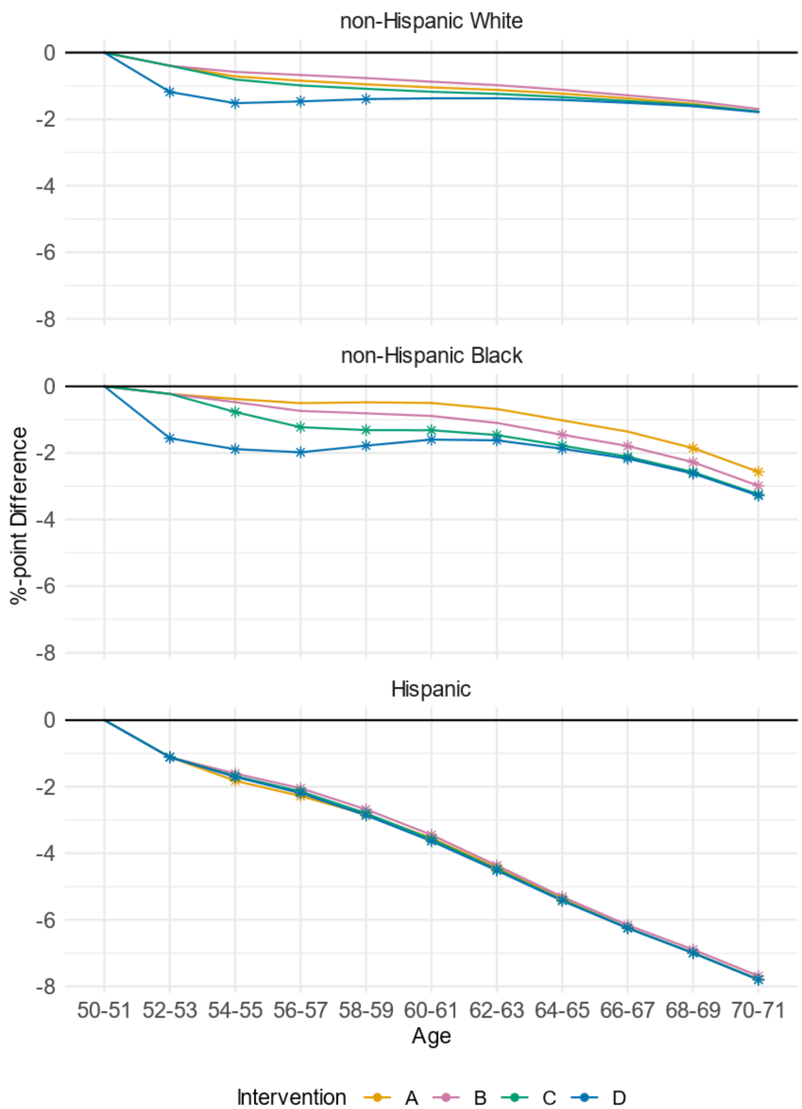

Figure S. 16 Absolute %-point change in the gender gap in elevated depressive symptoms from equalizing opportunities at the labor market across women and men stratified by race/ethnicity. Highlighted points indicate a significant difference from the natural course (p<0.05). We exclude observations age 72-80 from the simulation step because from age 72, more than 50% of observations are from retired participants

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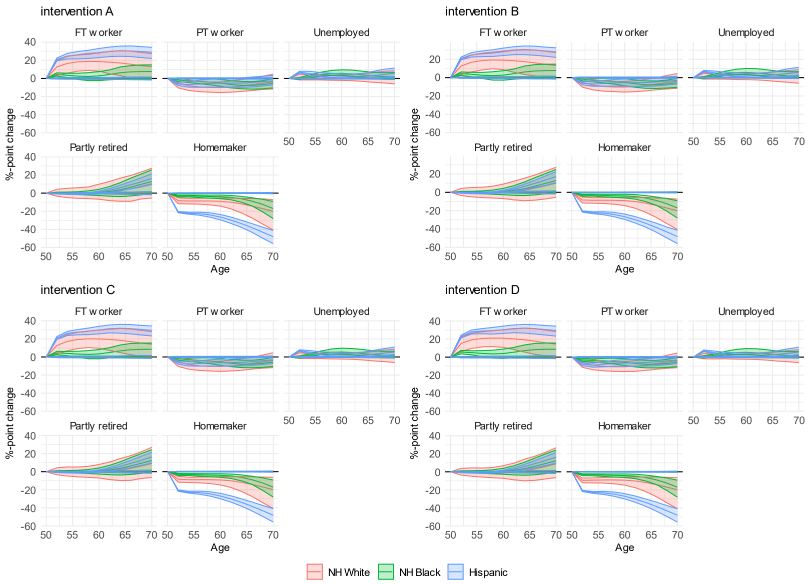

Figure S. 17 %-point change in employment status for males and females by race/ethnicity for each intervention scenario. NH = non-Hispanic

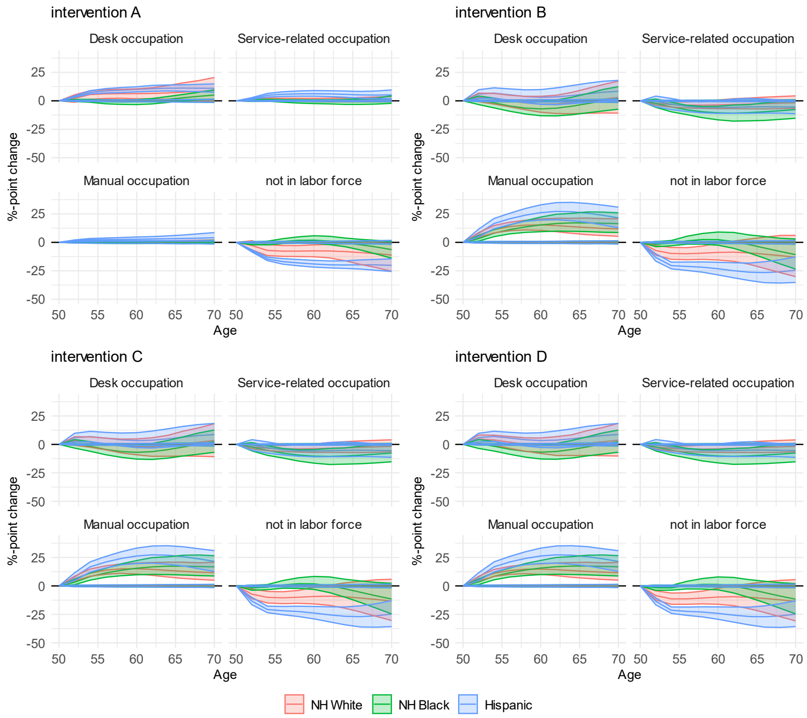

Figure S. 18 %-point change in occupation class for males and females by race/ethnicity for each intervention scenario. NH = non-Hispanic.

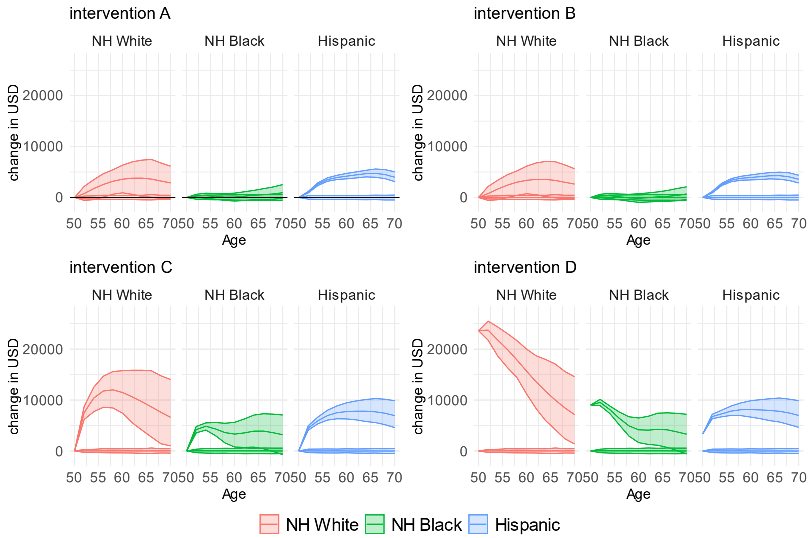

Figure S. 19 %-point change in income for males and females by race/ethnicity for each intervention scenario. NH = non-Hispanic.

Section 4.3: By Education

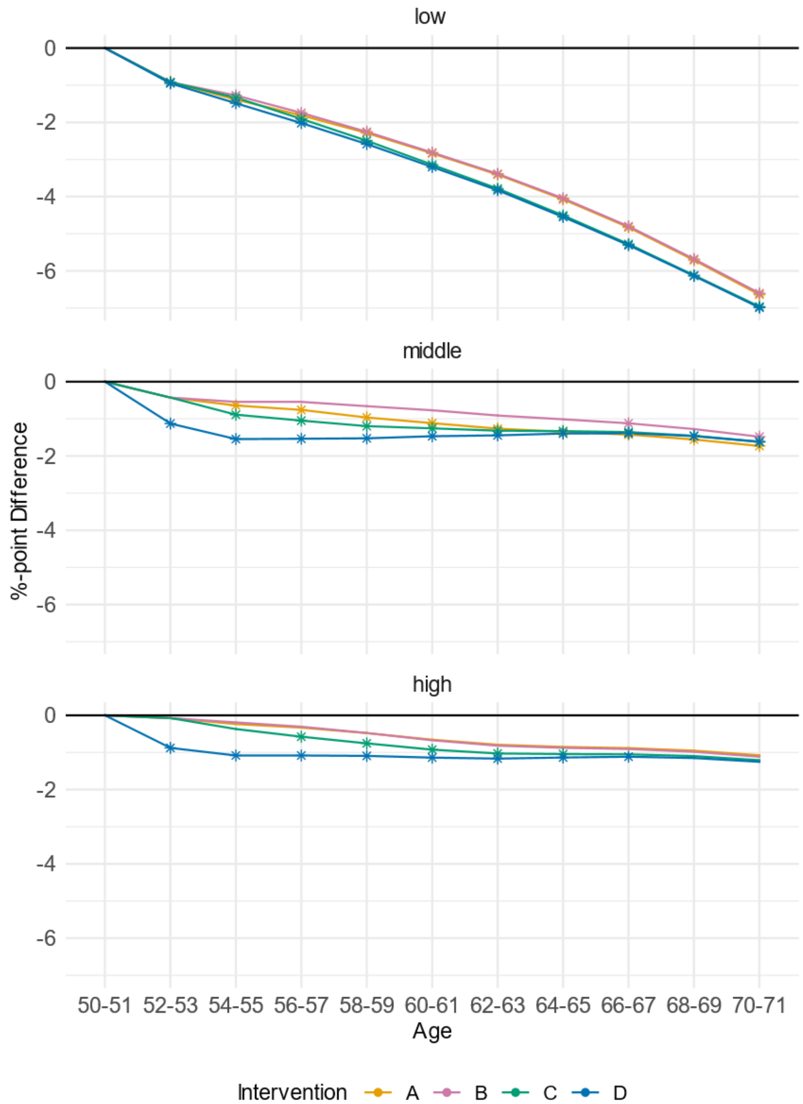

Figure S. 20 Absolute %-point change in the gender gap in elevated depressive symptoms from equalizing opportunities at the labor market across women and men stratified by education level at age 50. Highlighted points indicate a significant difference from the natural course (p<0.05). We exclude observations age 72-80 from the simulation step because from age 72, more than 50% of observations are from retired participants, leading to unstable estimates.

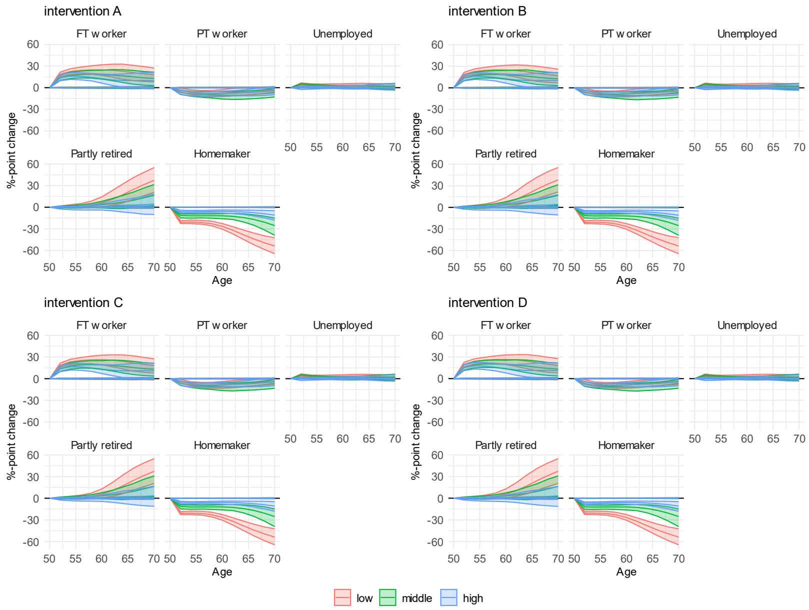

Figure S. 21 %-point change in employment status for males and females by education for each intervention scenario.

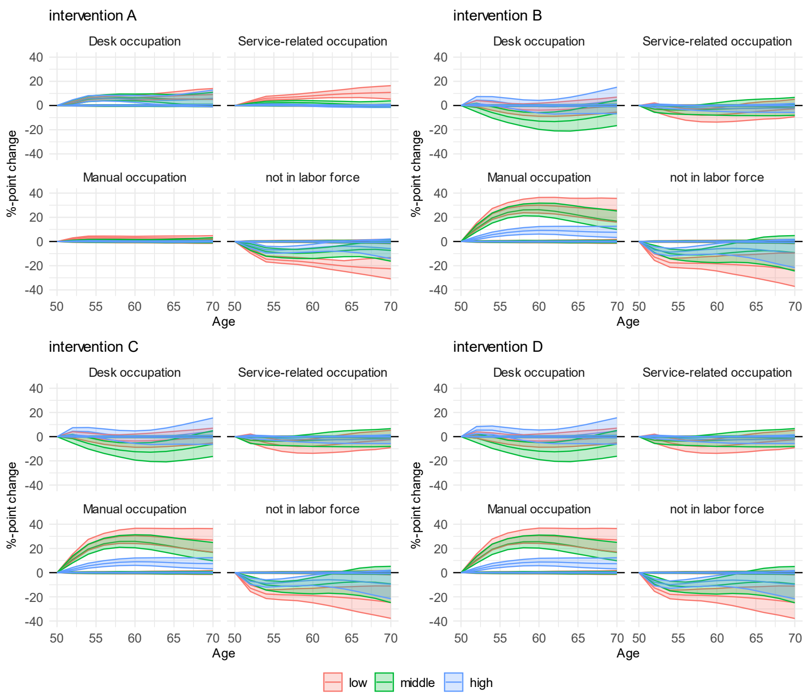

Figure S. 22 %-point change in occupation class for males and females by education for each intervention scenario.

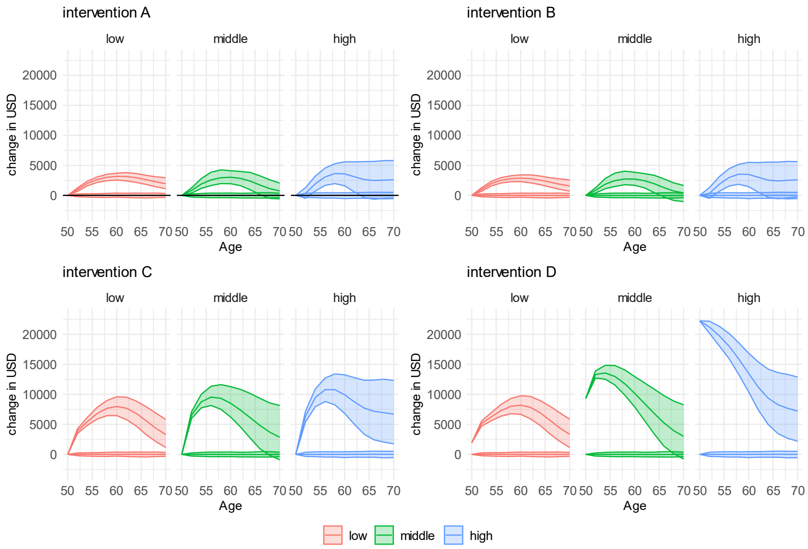

Figure S. 23 %-point change in employment status for males and females by education for each intervention scenario.

Section 5: Underlying assumptions of our causal decomposition

SUTVA requires that the intervention is well-defined (consistency) and that there is no interference. Even though we assume a policy intervention that equalizes the opportunities across gender at the labor market, our intervention cannot be classified as well-defined because we do not make specific claims about how the change in labor force, occupation or income opportunity is achieved. Interference is possible for women with partners: Equalizing labor market opportunities might lead to a shift in gender norms and labor market and other decisions at the household level, which might in turn affect their partner's mental health.[2]

Positivity requires that it must be possible for all individuals across all strata that are intervened on to be exposed. This is theoretically possible, which fulfills the deterministic positivity assumption.[3]

Section 6: Sensitivity analysis

Excluding the baseline covariate "ever reported psychological problems"

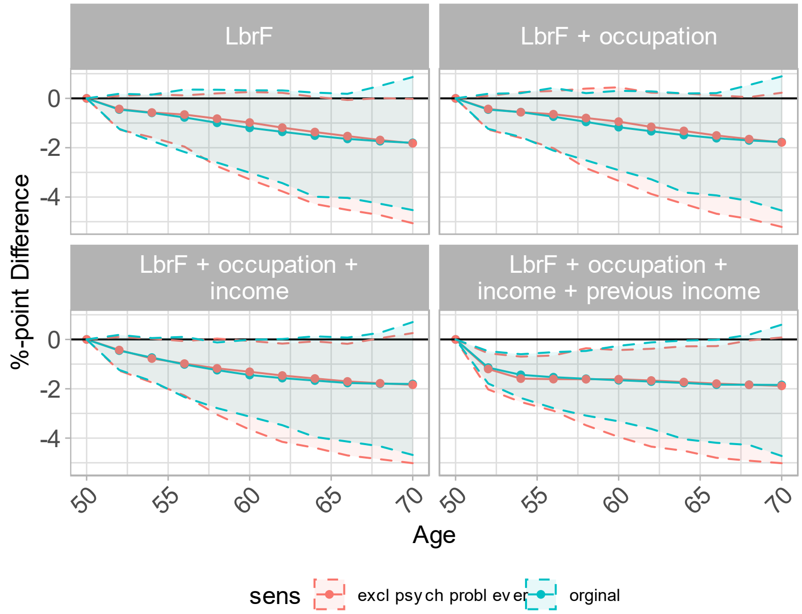

Figure S. 24 %-point change in the gender depression gap for each intervention for the main (in blue) and sensitivity analysis (in red).

Differential attrition due to mortality and overall non-response by gender

To assess whether attrition in the HRS differs by gender, we created two variables: One which indicates whether the respondent does not respond in the coming wave and one that indicates whether the respondent passes away in the coming wave. We fit the following regression model:

y ~ gender*depress + ns(AGEY_E,3) + education + race/ethnicity + wave

Where Y represents the indicator of whether the respondent leaves the study in the next wave. We interact gender with depression to test for differential attrition of depression by gender.

	Dependent variable:	
	non-response next wave	mortality next wave
	(1)	(2)
gender:male	0.097***	0.191***
	(0.036)	(0.041)
elevated depressive symptoms:yes	0.308***	0.429***
	(0.044)	(0.049)
ns(AGEY3)1	-0.161**	0.048
	(0.064)	(0.073)
ns(AGEY3)2	0.138	0.432*
	(0.191)	(0.221)
ns(AGEY3)3	0.241***	0.322***
	(0.048)	(0.054)
middle education	0.062	0.072*
	(0.038)	(0.043)
high education	-0.072**	-0.027
	(0.036)	(0.040)
non-Hispanic black	0.220***	0.190***
	(0.042)	(0.047)
Hispanic	0.108*	-0.003
	(0.059)	(0.068)
Other	0.304***	0.063
	(0.107)	(0.124)
wave	0.235***	0.296***
	(0.005)	(0.006)
gender*depression	0.246***	0.173**
	(0.064)	(0.071)
Constant	-3.470***	-4.438***
	(0.094)	(0.111)
Observations	40,339	40,339
Log Likelihood	-15,209.730	-12,538.030
Akaike Inf. Crit.	30,445.450	25,102.060
Note:		*p<0.1; **p<0.05; ***p<0.01

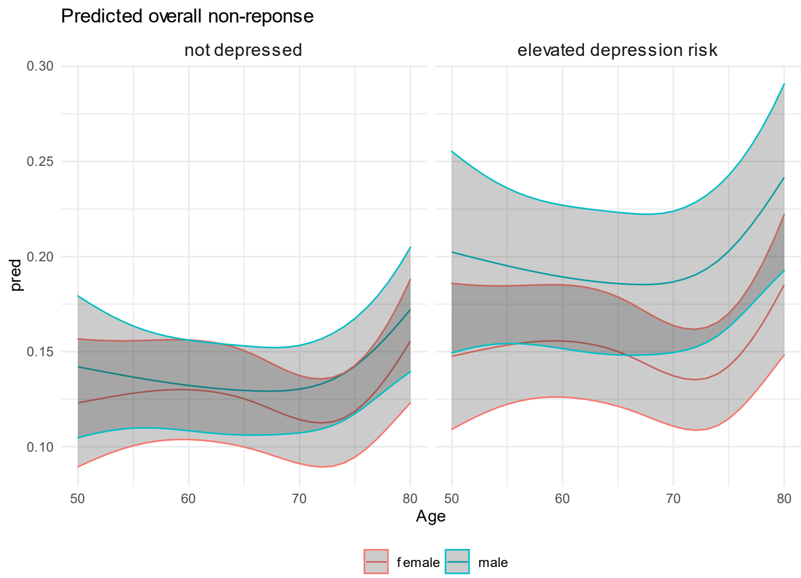

Figure S. 25 Predicted probability due to overall non-response in non-depressed and depressed groups across age and gender.

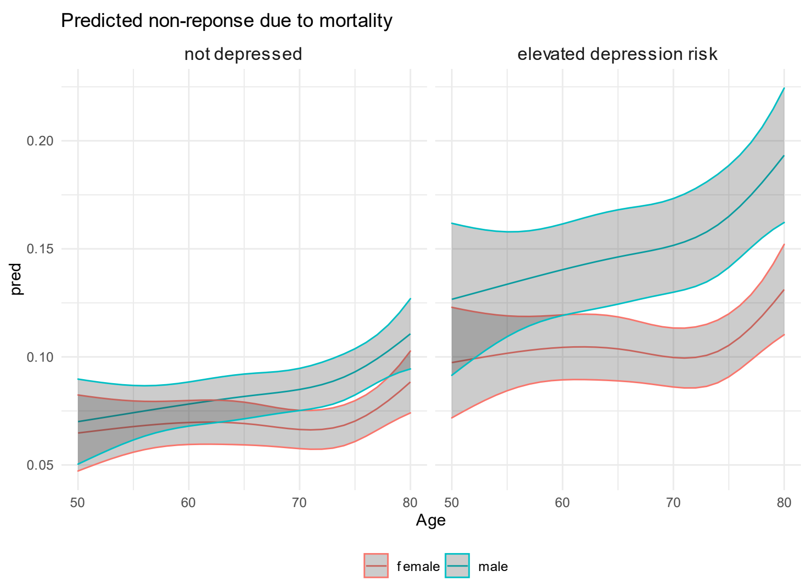

Figure S. 26 Predicted probability due to non-response because of mortality in non-depressed and depressed groups across age and gender.

References

1. Ross SM. Random Numbers. In: *Simulation*. 5th Edition ed.: Academic Press; 2013.
2. Kuehner C. Why is depression more common among women than among men? *The Lancet Psychiatry*. 2017;4(2):146-158.
3. Westreich D, Cole SR. Invited Commentary: Positivity in Practice. *American Journal of Epidemiology*. 2010;171(6):674-677.