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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

We aim to investigate to what extent gender inequality at the labor market explains higher depression risk for older US women compared to men. We analyze data from 35,699 US adults aged 50–80 years that participated in the Health and Retirement Study. The gender gap is calculated as the difference in prevalence in elevated depressive symptoms (score $\geq$ 3 on the 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 and 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. 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. 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.

## 1. Introduction

Depression poses a major burden on the population and individual level (Global Burden of Disease Collaborative Network, 2018; Plana-Ripoll et al., 2019). In the US, women are twice as likely to suffer from depression than men (Platt et al., 2021), although the difference has narrowed in recent cohorts (Platt et al., 2020, 2021; Oksuzyan et al., 2010). The gender depression gap is largest among the low-educated who also have a higher overall prevalence than the high-educated (Ross and Mirowsky, 2006).

Gendered cultural norms (Kuehner, 2017) which put women historically in a lower economic position than men (Haaland et al., 2018; Blau and Kahn, 2017; Cunningham, 2008) may contribute to the gender gap in depression. While women's labor force participation is increasing since the 1960s, 57.4% of women are in the labor force compared to 69.2% of men, and women earn 82% of what men earn (U.S. Bureau of Labor Statistics, 2021). Women may now face increased economic participation while still complying with expectations regarding traditional female gender norms (Campbell et al., 2021). This might be particularly important in older women (Bracke et al., 2020), because attitudes in favor of traditional gender norms are higher in this age group (Brooks and Bolzendahl, 2004), possibly driven by cohort effects. In fact, both, the gap in labor force participation across gender and the gender wage gap are larger in older adults: Among adults above the age of 55 years, 33% of women and 44% of men participate in the labor force, and women earn 75% of what men earn, whereas in adults aged 25 to 55, 75% of women and 88% of men participate in the labor force, and women earn 84% of what men earn (U.S. Bureau of Labor Statistics, 2022; U.S. Department of Labor Women's Bureau, 2022). Hence, 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

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depression gap (Van de Velde et al., 2010), and both education and income are more important determinants for women than for men (Ross and Mirowsky, 2006; Platt et al., 2016). The gender depression gap becomes insignificant in highly educated individuals (Ross and Mirowsky, 2006), and in women that earn more than their male counterparts, if matched on other socioeconomic and family characteristics (Platt et al., 2016). 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 (Plaisier et al., 2008; Yoo et al., 2016; Bijlsma et al., 2017). This beneficial link of employment with depression in women might be diluted by role overload or role conflict (Kuehner, 2017), which is reflected in women spending more time on unpaid care and household activities than men (Ortiz-Ospina et al., 2018; Ferrant et al., 2014). In turn, women get smaller labor market payoffs then men (Van de Velde et al., 2010) and are more often employed in flexible jobs with lower pay (Goldin, 2014; Civilian labor force participation rate by age et al., 2021; Ortiz-Ospina and Roser, 2018). Part-time employment, however, does not aid in addressing the potential role overload due to work-family conflict (Leupp, 2017). 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]

Hence, interventions that aim to equalize opportunities at the labor market across gender might aid in reducing the gender depression gap. This might be particularly beneficial in older adults as they have stronger attitudes in favor of traditional gender norms but lower potential role conflict than younger adults. This is due to increased compatibility of work and family at older ages (Leupp, 2017). Furthermore, specifically in older women, the beneficial link of employment or re-employment might be diluted by the duration of disadvantage at the labor market that women experienced in their life (Bracke et al., 2020). Therefore, such interventions need to account for this previous socioeconomic disadvantage.

This study implements a dynamic causal decomposition analysis that is based on the longitudinal g-formula which allows for introducing hypothetical interventions in a life course approach. We aim to assess to what extent the gender gap in depression changes if women would have the same labor market opportunities as men from age 50 onwards. We introduce four nested interventions, each building upon the previous one, and sequentially assign women: the same (A) employment, (B) occupation and (C) income opportunities, and (D) prior income at ages 50–51 as men (to account for previous socioeconomic status).

## 2. Methods

### 2.1. 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 (Sonnega et al., 2014). 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 S1. 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 for the hypothetical interventions to affect the prevalence of retirement or disabled groups and therefore exclude them before aggregating the results by age and gender.

### 2.2. 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 suggests elevated depressive symptoms (Steffick, 2000). We calculate the absolute gender gap in elevated depressive symptoms as the difference in the prevalence between women and men.

### 2.3. 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". (Bugliari et al., 2021).

### 2.4. Time-varying covariates

We quantify employment status as employed full-time (>35 h/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 (Bugliari et al., 2021).

Occupation group is assigned based on the 1980 Census codes and classified into "white collar/desk occupation" (Managerial specialty operations, professional specialty operations/technical support, clerical/administrative support, or sales), "pink collar/service-related occupation" (Service: private/household/cleaning/building service, Service: protection, Service: food preparation, Health service, or personal service) and "blue collar/manual occupation" (farming/forestry/fishing, mechanics/repair, construction trade/extractors, precision production, operators: machine, operators: transport etc., operators: handlers, etc., member of Armed Forces) (Bugliari et al., 2021) 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" (Bugliari et al., 2021) 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, 2022. 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).

### 2.5. Statistical analysis

We employ a dynamic causal decomposition using the longitudinal g-formula with Monte Carlo integration. The longitudinal g-formula has the advantage that we can account for time-varying covariates which might act as mediators in a longitudinal approach. Furthermore, in contrast to other causal inference methods, such as longitudinal propensity score matching, the g-formula is flexible in the type of hypothetical intervention that is introduced. 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 (Fig. 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 nested interventions, each building upon the previous one. In the first three interventions, we sequentially 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 the natural course and each intervention scenario and compare the absolute change between both scenarios. We calculate the contribution as $1 - \frac{D_{wcf} - D_{mnc}}{D_{wnc} - D_{mnc}}$ where $D_{wcf}$ is depression risk in women in the counterfactual scenario and $D_{wnc}$ and $D_{mnc}$ are depression risk in women and men in the natural course approximation. 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.

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.

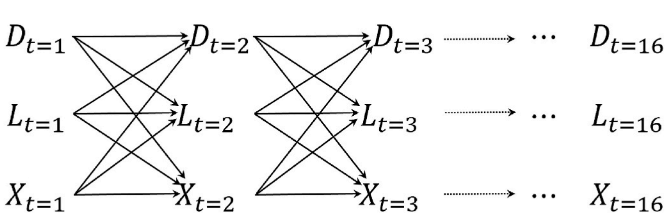


**Fig. 1.** Simplified DAG which shows two-year cross-lagged structure. Depression risk (D), labor market variables (L) (employment status, occupation group, income) and time-varying covariates (X) are associated across (t) 1 to 16, which translates to 2-year age groups from 50 to 80. Time-varying covariates 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.

## 3. Results

### 3.1. 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%).

### 3.2. 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 groups 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 (Fig. 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).

Our natural course approximation adequately predicts the observed mean percentage of women and men in each time-varying covariate group across age. This indicates adequate model fit (supplement section 3).

### 3.3. Effects of the interventions on labor market characteristics

The effects of the interventions on labor market characteristics can be found in Figs. 3–5. 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 (7.52–17.12) 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 5828 USD (95%CI: 2957 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 (7905 to 14,144). This leads to women's income being equal to men's.

### 3.4. 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 (Fig. 6). 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

**Table 1**
Sample Characteristics across person years. Age inclusion 50–80.

| | 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) | 8470 (11.0) |
| Other | 5283 (2.9) | 2988 (2.8) | 2295 (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) | 9404 (13.5) |
| Ever reported psychological problems (Yes N (%)) | 27,205 (14.7) | 19,180 (17.7) | 8025 (10.5) |
| Education N (%) | | | |
| High-school graduate | 55,370 (29.9) | 35,068 (32.4) | 20,302 (26.5) |
| Less than 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) | 8631 (8.0) | 2804 (3.7) |
| Unemployed | 4005 (2.2) | 2115 (2.0) | 1890 (2.5) |
| Partly retired | 15,522 (8.4) | 7663 (7.1) | 7859 (10.2) |
| Retired | 83,520 (45.1) | 48,177 (44.5) | 35,343 (46.1) |
| Disabled | 5285 (2.9) | 3493 (3.2) | 1792 (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 | 7204 (4.7) | 5250 (5.8) | 1954 (3.2) |
| Manual occupation | 10,636 (7.0) | 2281 (2.5) | 8355 (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) | 9821 (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 | 9222 (5.0) | 4051 (3.7) | 5171 (6.7) |
| more than 67,679 USD | 9244 (5.0) | 2955 (2.7) | 6289 (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) | 4956 (6.5) |
| Not married | 9527 (5.1) | 5506 (5.1) | 4021 (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) | 7415 (6.8) | 6183 (8.1) |
| 1 child | 18,562 (10.0) | 11,486 (10.6) | 7076 (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) | 8067 (10.5) |

[a] Individual earnings are shown for 0–50th, 51–75th, 76–90th, 91–95th, >95th percentile categories, which are the percentiles used for the quantile regression.

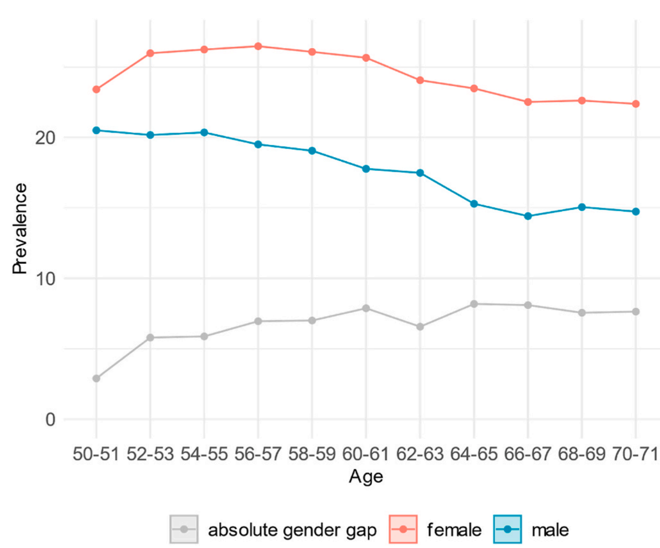


**Fig. 2.** Depression prevalence (%) for females and males and absolute gender gap (%-point difference) in depression prevalence.

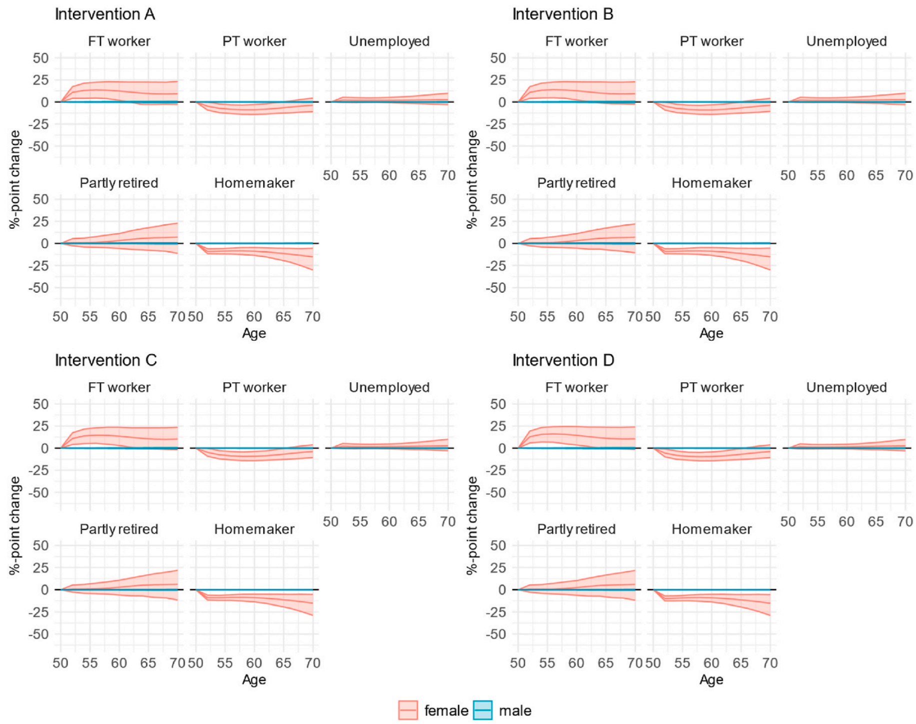


**Fig. 3.** %-Point change in employment status for men and women for each intervention scenario.

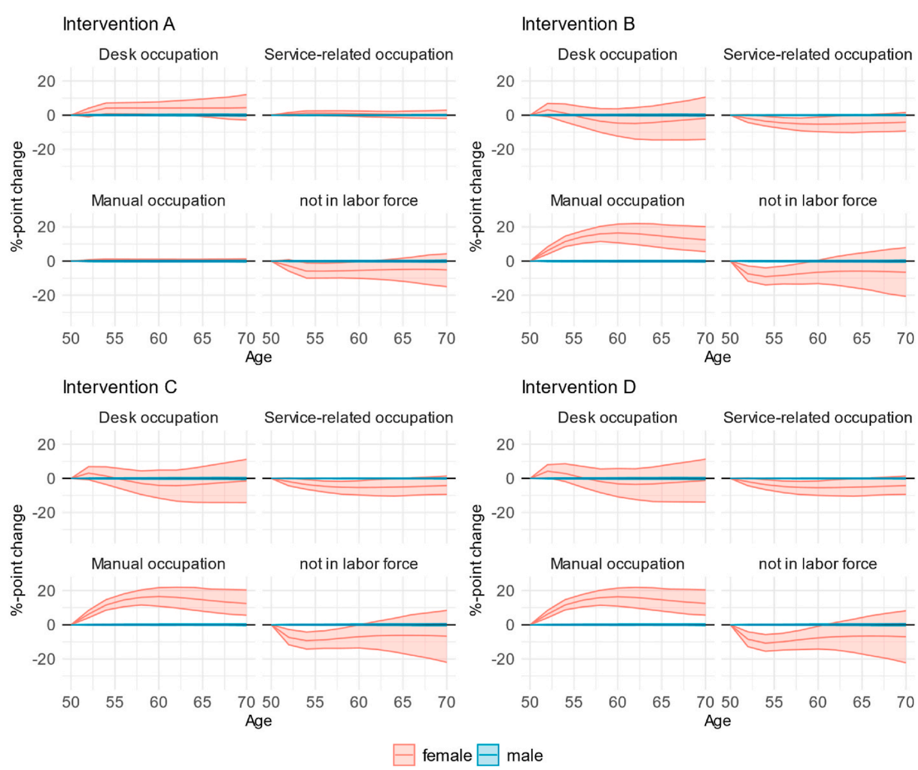


**Fig. 4.** %-Point change in occupation group for men and women for each intervention scenario.

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% (1.39–62.83).

### 3.5. *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

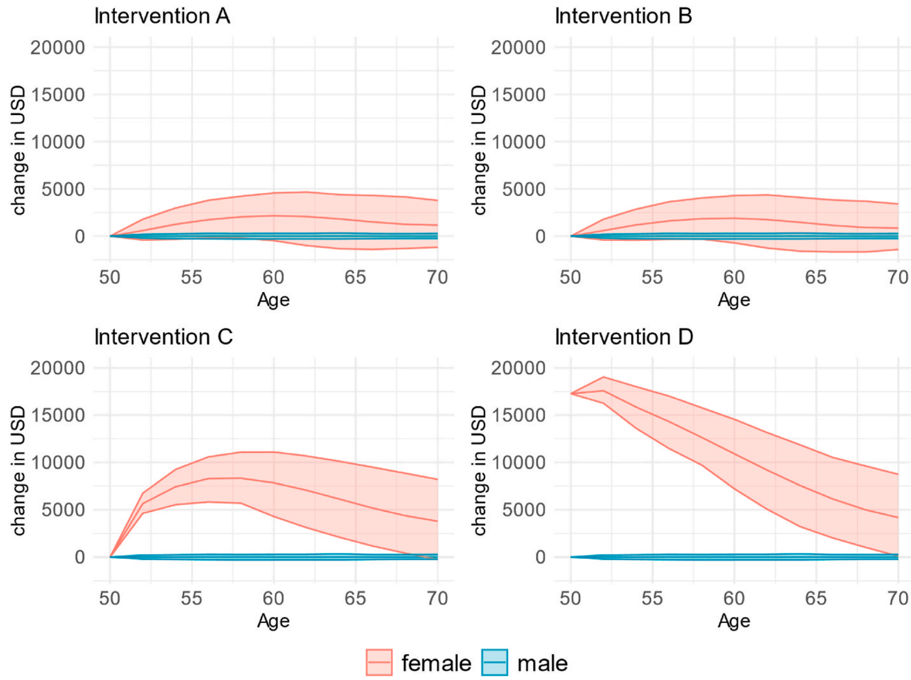


**Fig. 5.** %-Point change in income for men and women for each intervention scenario.

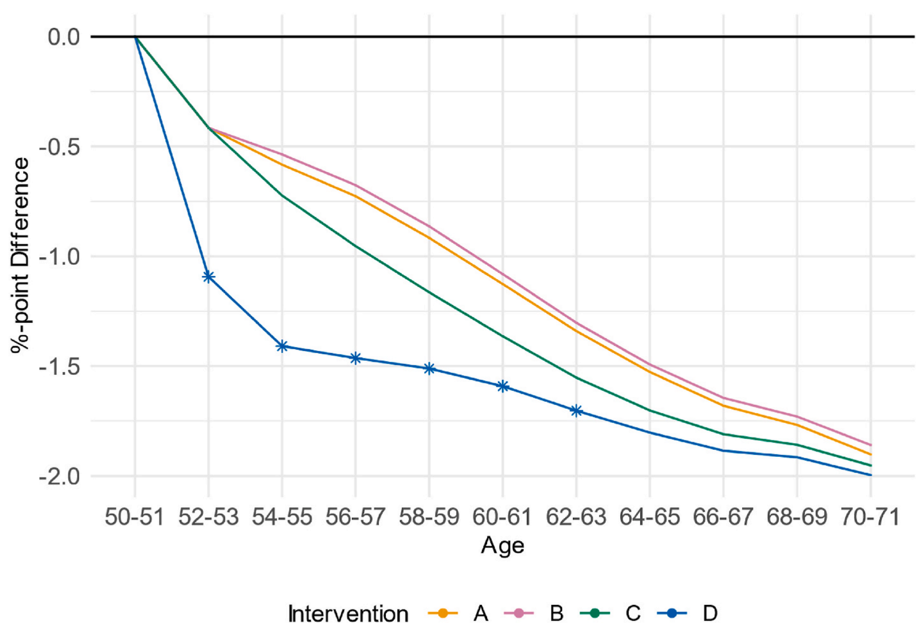


**Fig. 6.** Absolute %-point change in the gender gap in elevated depressive symptoms from equalizing opportunities at the labor market across women and men. Highlighted points indicate a significant difference from the natural course ($p < 0.05$).

groups follow a similar trend as the total population (supplement section 4.1). 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 and 1.46%-points (−2.85 to 0.2) in non-Hispanic White group, which translates to median contributions of 36.83% (28.16–54.59), 30.33% (18.46–48.3) 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 4.2). 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% (20.65–47.94), 36.62% (17.05–90), and 29.45% (7.36–51.84), respectively (Table 2).

## 4. 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

**Table 2**
Average absolute difference in %-points and median contribution in % by intervention for main and subgroup analyses over ages 50 to 71. We present the median contribution due to skewness in the bootstrap estimation for 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) |

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.

### 4.1. 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. Policy regimes that do not consider the social and economic context and differences between genders might increase or reinforce gender inequalities. Hence, unequal opportunities in employment across gender might explain part of the gender depression gap because of social regimes that indirectly reinforce traditional gender roles (Bird and Rieker, 2008). This may inhibit women from entering the labor market or result in reduced payoffs from being in employment (Van de Velde et al., 2010; Bird and Rieker, 2008).

This reduction from equalizing employment opportunities 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 (Tophoven et al., 2015). 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 (van der Noordt et al., 2014) 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) through 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 (Platt et al., 2016; Loret de Mola et al., 2020). Closing the gender wage gap might play a role in explaining the gender depression gap among US older adults because many policies are tied to income in the US, for example social security, which is intended as a safety net against poverty in older adults. However, due to women's lower pay and average longer lifespan, women face lower payments over a longer period of time than men, which might affect their opportunities and choices regarding their (mental) health (Bird and Rieker, 2008).

Our subgroup analyses show 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. (2020) 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 and Mirowsky (2006) 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. (2020) 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 (Platt et al., 2020), 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. (2005) 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. These results suggest that (1) introducing policies to address inequalities in employment opportunities, for example through improving affordability and access of childcare, paid parental leave, paid sick and vacation days and more flexible work hours (Simon, 2020), will especially reduce the gender depression gap in older Hispanic and low educated adults and (2) 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.

We highlight that gender inequality at the labor market explains part of the gender depression gap among older US adults. These inequalities are interrelated with traditional gender norms and definitions of gender roles. The way how role definitions, identity and role overload explain the gender depression gap may be due to women being more exposed and/or vulnerable to role-related stressors compared to men. On the other hand, women and men may equally suffer from role-related stressors but exhibit mental health problems differently, with women more likely to develop internalizing disorders, e.g. depression, and men more likely to develop externalizing disorders, e.g. substance abuse (Simon, 2020).

Hence, while we highlight that the gender depression gap is driven by women being more depressed than men, it is important to highlight that men are more likely to exhibit externalizing disorders and to die by suicide than women (Simon, 2020). To what extent these differences can be explained by gender inequalities at the labor market may be explored in future research.

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 (2017) 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 (Bird and Rieker, 2008) and having one or more chronic health conditions is linked to increased depression risk (Read et al., 2017). Hence, mortality selection might play a crucial role in explaining the gender gap in depression in older adults.

### 4.2. 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. 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. We rather introduce a counterfactual world in which gender inequality at the labor market does not exist. Interference is possible for women with partners: Equalizing labor market opportunities might lead to a shift in gender norms, the labor market or other decisions at the household level, which might in turn affect their partner's mental health (Kuehner, 2017). 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 (Tophoven et al., 2015). 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 5).

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 5). 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 dynamic causal decomposition approach which accounts for bidirectionality and interrelatedness of depression and its determinants by allowing all (time-varying) covariates and the outcome to affect each other using a cross-lagged design. This provides a more valid understanding of how labor market inequalities contribute to the gender gap in depression risk.

### 4.3. 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.

## Data sharing statement

The Health and Retirement Study data is accessible at (http://hrsonline.isr.umich.edu/). The R code for reproducing our analysis is available on https://github.com/mariagltzw/gender-gaps-depression.

## Declaration of competing interest

None.

## Data availability

The Health and Retirement Study data is accessible at (http://hrsonline.isr.umich.edu/). The R code for reproducing our analysis is available on https://github.com/mariagltzw/gender-gaps-depression.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2023.116100.

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