Employee Ownership and Worker Outcomes: Evidence from ESOPs

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Summary

This statistical analysis examines the effects of employee ownership on worker outcomes, and whether these effects are different for disadvantaged workers. While previous studies have established that ESOP firms exhibit productivity levels equal to or higher than conventional firms and that ESOP members tend to benefit from wealth building, there is limited research on worker experiences within ESOPs in general.

The analysis of self-reported attitudes and perceptions in two datasets, the General Social Survey and the National ESOP Employee Survey,[1] finds that ESOP membership is related with several outcomes: increased worker satisfaction, participation in decision-making, commitment to the firm, and less searching for alternative jobs. While the GSS data shows mixed results with only some findings remaining statistically significant after adjusting for multiple comparisons, the NEES data consistently indicates robust positive impacts of ESOP membership on job satisfaction, organizational commitment, and reduced intentions to seek new employment. However, the analysis also finds no significant evidence that these effects vary significantly between disadvantaged and non-disadvantaged workers.

These findings suggest that ESOP membership can enhance job quality and employee well-being in certain measures. However, given a modest sample size, these findings have limited precision, with insufficient data to draw firm conclusions about the experiences for disadvantaged workers.

This calls for further research with larger, more representative data to better understand the diverse impacts of ESOPs and to inform policies that support equitable benefits across different worker groups.

[1] The Rutgers Institute for the Study of Employee Ownership and Profit Sharing ran the National ESOP Employee Survey with funding from the Employee Ownership Foundation. The Rutgers Institute also added questions on employee ownership to the General Social Survey with financial support from the Employee Ownership Foundation from 2002 to 2018, and from Google.org in 2022. We appreciate both the Rutgers Institute and these donors for providing the data we analyze. We also thank Ed Carberry and Jungook Kim for their valuable efforts with data collection.

1. Introduction

A growing body of research has highlighted the potential benefits of Employee Stock Ownership Plans (ESOPs) for both firms and workers. Studies have found that ESOP firms exhibit productivity levels at least on par with conventional firms,[2] and that positive outcomes of ESOP membership are potentially mediated by psycological ownership.[3] Furthermore, ESOP companies are less likely to lay off workers during economic downturns,[4] suggesting greater employment stability. Evidence also indicates that ESOP participants accumulate higher levels of household wealth compared to non-ESOP employees.[5] However, despite these insights, a gap remains in our understanding of how ESOP membership relates to employees' self-reported attitudes, perceptions, and overall job quality experiences.

Examining the impact of ESOP membership on worker attitudes and perceptions is crucial for evaluating the merits of ESOPs as a means to promote job quality and employee well-being. Key questions arise: Does ESOP membership contribute to improved worker satisfaction, heightened organizational commitment, and reduced intentions to seek new employment opportunities? Moreover, do these potential benefits extend equitably to workers facing various forms of social disadvantage, such as those belonging to ethnic or racial minorities, immigrants, or individuals without a high school diploma? Addressing these questions is essential to assess ESOPs' ability to promote high-road employment.

We analyze two complementary datasets to address these questions: the General Social Survey (GSS) and the National ESOP Employee Survey (NEES). The GSS, conducted biennially by the National Opinion Research Center at the University of Chicago, provides a nationally representative sample of U.S. households and includes information on respondents' ESOP membership status, job characteristics, and various worker outcomes related to job satisfaction, decision-making, fairness perceptions, and experiences of discrimination. While the GSS offers a broad sample that is representative of the U.S. population, it has a relatively small number of ESOP worker observations, which limits the precision of statistical estimates for this subgroup. On the other hand, the NEES dataset, collected by Rutgers' Institute for the Study of Employee Ownership and Profit Sharing, has a sample that is more focused on ESOP firms and their employees. This dataset includes survey data from approximately 3,000 employees. These workers are either recruited from nine different ESOP firms, or are non-ESOP workers recruited

[2] Kurtulus and Kruse, 2017; Kim and Ouimet, 2014; Pendleton and Robinson, 2010.
[3] Carberry et al, 2024
[4] Blasi et al, 2021; Kurtulus & Kruse, 2017.
[5] Wiefek, 2017.

through Amazon Mechanical Turk, allowing for a comparison of worker experiences and perceptions between these two groups. However, a limitation of the NEES is that it is not nationally representative. The NEES also captures additional dimensions of the employee experience, such as organizational commitment, citizenship behavior, and perceptions of organizational justice, providing a nuanced understanding of the potential impact of ESOP membership. Importantly, these data are roughly representative of all ESOPs employees, but most ESOPs are not democratic, majority-owned ESOPs.

It is plausible that ESOP employees differ from non-ESOP employees in ways that correlate with the outcomes we study. If so, we might find a correlation between ESOP and outcomes that is not causal, but due to omitted factors that cause both. For example, workers with higher skills might be more likely to have employee ownership and also higher workplace satisfaction.

To evaluate the effects of ESOP participation on worker outcomes while accounting for endogeneity concerns, we employ a double machine learning technique.[6,7] This approach leverages machine learning algorithms to partial out the effects of various control variables from both the dependent (worker outcomes) and independent variables (ESOP membership and its interaction with worker disadvantage). Subsequently, we estimate the net effects of ESOP membership on worker outcomes using the residualized variables, ensuring that our estimates are adjusted for observable differences between ESOP and non-ESOP workers.

Intuitively, this method isolates the direct relationship between the worker outcomes and ESOP membership, while holding all other observable variables constant. It does this by first removing the influence of the control variables from both the outcome and treatment variables. This is achieved by regressing the outcomes and ESOP membership separately on the control variables and calculating the residuals. The residualized versions now have the variation explained by the controls removed. The effect of ESOP membership on outcomes is then estimated using just these residual components, capturing the relationship after taking out the “noise” from the other observable factors.

Our analysis of the GSS data reveals a positive association between ESOP membership and several indicators of job quality, such as participation in decision-making and good relations with management. However, after adjusting for the potential false discovery rate arising from multiple comparisons, the only result that remains statistically significant is the effect of ESOP membership on workers’ agreement with the statement “I take part in decision-making.” On a 1 to

[6] Chernozhukov et al, 2018.
[7] Our pre-analysis plan is at https://osf.io/jx8kd/.

10 agree-disagree scale, ESOP membership is associated with an increase of 1.3 in this worker outcome, suggesting that ESOP members tend to report higher levels of participation in decision-making processes. Despite the limited individually significant results, a joint significance test rejects the null hypothesis of no overall effect of ESOP membership on the examined worker outcomes. This further indicates a general positive association between ESOP membership and various measures of job quality and worker experiences, even if the individual effects do not all reach conventional levels of statistical significance after correcting for multiple comparisons.

In contrast, the results from the NEES dataset suggest statistically significant positive impacts of ESOP membership on various aspects of the employee experience. On a 1 to 10 agree-disagree scale, ESOP participation is associated with a 1.5 higher score on the level of satisfaction and pride in their company, a 1.9 higher score on commitment to the worker's firm, and a 1.2 higher score on organizational citizenship behavior. Participation in an ESOP is also associated with a 1.1 lower score on reporting being actively searching for new employment opportunities. These effects are substantial in magnitude and statistically significant after accounting for the potential false discovery rate. ESOP participation also has a statistically significant effect on all the outcomes when tested jointly. While our results point to a generally positive effect of ESOP membership on the whole sample of workers, we find no statistically significant evidence that this effect is heterogeneous between disadvantaged and non-disadvantaged workers (defined as workers who are either Black, Hispanic, immigrant, lacking a high school diploma, or earning in the bottom 30% of the dataset's income distribution).

To further understand the mechanisms through which ESOP membership affects worker outcomes, we conducted a mediation analysis using the NEES dataset. This analysis reveals that the positive effects of ESOP membership on worker outcomes are partially mediated by increased participation in decision-making, higher job satisfaction, and greater organizational commitment. For instance, we found that ESOP's negative association with job search intentions is primarily explained by increased job satisfaction and organizational commitment among ESOP members.

The findings from these two datasets consistently point toward a positive association between ESOP membership and desirable worker outcomes, particularly in areas related to job satisfaction, decision-making involvement, and organizational commitment. Despite these insights, our analysis has several limitations. The lack of an experimental design or an opportunity in data for a causal identification strategy precludes us from establishing causal relationships between ESOP membership and worker outcomes. While our methodology attempts to account for observable differences between ESOP and non-ESOP workers, the potential for unobserved factors influencing both ESOP participation and worker attitudes cannot be ruled out.

Furthermore, our datasets suffer from sample size limitations, particularly concerning the representation of disadvantaged workers who are ESOP members. The relatively small number of observations in this subgroup restricts our ability to estimate the potentially heterogeneous effects of ESOP membership across different dimensions of disadvantage, such as race, ethnicity, immigration status, or educational attainment. This sampling limitation also prevents us from exploring how the impact of ESOP membership may vary over time, across economic cycles, or in different regional or industry contexts. Further, ESOPs participating in the National ESOP Employee Survey may not represent all ESOPs, and the non-ESOP workers recruited through Amazon Mechanical Turk may not represent the broader U.S. workforce.

Despite these limitations, our study contributes to the growing literature on employee ownership and its implications for workers' attitudes and perceptions. While previous research has examined the effects of ESOPs on firm performance, productivity, and employment stability (as summarized in the literature review), fewer studies have focused on employees' self-reported attitudes and perceptions. Our analysis provides new evidence on the positive association between ESOP membership and indicators of job quality, such as satisfaction, pride in the company, participation in decision-making, and organizational commitment.

Overall, our study reinforces the potential benefits of ESOPs for promoting desirable worker outcomes and job quality, while also underscoring the need for further research with larger and more representative samples to better understand the nuanced effects of ESOP participation across different contexts and subgroups of workers.

2. Data

We analyze two datasets: the General Social Survey (GSS) and the National ESOP Employee Survey (NEES). The GSS, conducted by the National Opinion Research Center (NORC) at the University of Chicago, has been carried out biennially since 1972. It collects information on social behaviors, civic engagement, and political opinions. Our analysis utilizes data from the 2014, 2019, and 2022 survey waves, which include information on ESOP membership. This data encompasses firm and worker characteristics and evaluates aspects of job quality, such as perceived discrimination, respect in the workplace, fairness of earnings, and job satisfaction – which we refer to as worker outcomes.

The National ESOP Employee Survey (NEES), conducted by Rutgers' Institute for the Study of Employee Ownership and Profit Sharing, surveys approximately 3,000 employees from ESOP and non-ESOP firms. ESOP worker respondents were recruited from nine different firms, while the data for non-ESOP workers was collected via Amazon Mechanical Turk (MTurk). In addition to exploring worker outcomes similar to those analyzed in the GSS, the NEES also examines additional dimensions such as the sense of ownership of the firm, commitment to it, and perceptions of organizational justice, offering a more nuanced view of the employee experience.

However, the NEES dataset has significant limitations. Firstly, it encompasses surveys from only nine ESOP firms. Should these firms diverge significantly from the typical U.S. ESOP firm, our findings might lack representativeness. Additionally, the comparison group of non-ESOP workers fails to reflect the broader U.S. workforce, consisting solely of "turkers" – individuals who undertake tasks online via MTurk. Lastly, although we excluded any respondents in this comparison group who failed an attention-assessment question, lingering concerns remain regarding the overall data quality collected through MTurk.[8]

We want to evaluate the impact of ESOP participation on worker outcomes. To accurately identify the effects of ESOP participation, we need comparable ESOP and non-ESOP worker samples. Therefore, we excluded categories of workers who significantly differ from typical ESOP participants, such as self-employed individuals, government employees, part-timers, and employees from firms with fewer than 50 employees. In addition, we removed low-quality responses in the NEES dataset, including those from participants failing an attention check, ESOP firm employees who denied ESOP participation, and non-ESOP workers recruited through MTurk who identified as ESOP members.

Table 1 presents the distribution of ESOP workers across each dataset, segmented by various strata of disadvantage. Within the GSS, which includes a total of 892 workers, there are only 12 ESOP workers in the lowest 30% income bracket of the sample. Additionally, the dataset contains only 36 workers that we identify as disadvantaged, i.e., workers that are in the lowest 30% income bracket, Black, Hispanic, immigrant, or high school dropouts.[9] Due to the limited number of observations among the income-poor and disadvantaged workers, we use the GSS data to explore only the main effects of ESOP membership on employees. The investigation into how these effects vary among disadvantaged workers is conducted with the NEES dataset, which

[8] Ahler et al, 2019.
[9] Our datasets do not allow for a more nuanced definition of the disadvantaged group. Thus, we define this group as workers with characteristics related to low socioeconomic status or that belong to ethno-racial minorities, following the literature on social disadvantage in Ayala-Mar´ın at al, 2020 and Goodman et al, 2005.

offers a larger sample size of 1,718 workers and a more substantial representation of ESOP members, totaling 855 workers.

Table 1: Number of ESOP members by socioeconomic, ethno-racial, and educational disadvantages in each dataset.

	GSS	NEES
Bottom 30% earnings	12	150
Black worker	10	14
Hispanic worker	14	22
Immigrant worker	13	.
High school dropout	3	5
Disadvantaged (any of the above)	36	180
Total ESOP members	80 (of 892)	855 (out of 1,718)

Notes: On the GSS data, we infer immigrant status when both the respondent and their parents were born outside the U.S. The NEES survey does not include immigration status or proxies. The GSS analysis utilizes surveys from 2014, 2019, and 2022, excluding self-employed, government, part-time workers, and those in firms with fewer than 50 employees. NEES data, collected in 2018-2020, omits respondents from small firms (less than 50 employees), those failing an attention test, Mturk respondents identifying as ESOP members, and ESOP firm respondents denying ESOP participation. The disadvantaged group includes workers in the bottom 30% of the dataset's income distribution or belong to one or more of the following categories: Black, Hispanic, immigrant workers, or those without a high school diploma.

Table 2 presents cross-sectional differences in mean outcomes for workers in non-ESOP and ESOP settings. For the General Social Survey (GSS) data, the table compares outcomes between all non-ESOP and ESOP workers, whereas the NEES data focuses on comparisons among disadvantaged non-ESOP and ESOP workers. These mean differences, which are not adjusted for characteristics of workers or firms, offer descriptive insights on ESOP workers compared to non-ESOP workers. The GSS data suggests that ESOP workers tend to feel more involved in the decision-making processes at their firms by 1.4 points in a 10-point agree-disagree scale. The remaining differences in outcomes have substantial standard errors, rendering the differences not statistically significant. These differences suggest a positive association between ESOP membership and workers' satisfaction and pride in their company, greater job autonomy, improved relations with management, reduced likelihood of searching for new employment opportunities, or perceiving their pay as fair.

The comparison of mean outcomes in the NEES data illustrates a similar trend for disadvantaged ESOP versus non-ESOP workers. Disadvantaged ESOP workers report higher levels of satisfaction and pride in their companies, and are less likely to seek new employment opportunities compared to their non-ESOP counterparts. Additionally, these workers indicate a greater involvement in decision-making processes within their firms and generally perceive their compensation as fairer than non-ESOP workers. Further comparisons of mean worker outcomes are detailed in Appendix A.1, with information on the survey questions that generated these outcomes available in Appendix A.3.

Table 2: Mean worker outcomes: ESOP vs. non-ESOP workers

	GSS			NEES		
	Non-ESOP mean	ESOP mean	Diff	Disad Non-ESOP mean	Disad ESOP mean	Diff
Satisfaction and pride	7.43	7.86	0.43	6.70	8.29	1.59***
	(2.07)	(1.88)	(0.25)	(2.93)	(2.02)	(0.24)
Decision-making	7.00	8.42	1.42***	6.51	7.35	0.84**
	(2.96)	(2.01)	(0.35)	(3.19)	(2.96)	(0.28)
Freedom on job	7.71	7.75	0.04	7.25	7.58	0.34
	(2.71)	(2.65)	(0.33)	(2.58)	(2.63)	(0.23)
Good relation w/ mgt	7.14	7.34	0.20	3.67	3.24	-0.43
	(2.06)	(2.10)	(0.25)	(4.83)	(4.69)	(0.43)
Earnings are fair	6.15	5.78	-0.37	4.64	5.31	0.67**
	(2.10)	(1.89)	(0.25)	(2.80)	(2.78)	(0.25)
Searching for new job	2.91	2.23	-0.68	3.47	2.08	-1.39***
	(3.71)	(3.81)	(0.45)	(3.63)	(3.25)	(0.31)
Sample Size (N*)	692 to 727	73 to 74		425	179 to 180	

Note: Means scale is 1-Totally disagree to 10-Totally Agree. Sample size values depend on the number of missing variables in the outcome variable. For mean values, standard deviations are reported in parentheses; for differences, standard errors are reported in parentheses. The Disad ESOP column reports means for disadvantaged workers that are ESOP members, while the Disad Non-ESOP column reports means for disadvantaged workers who are not ESOP members.The disadvantaged workers group comprises workers who fall within the bottom 30% of the dataset's income distribution or belong to one or more of the following categories: Black, Hispanic, immigrant workers, or those without a high school diploma.
Significance levels: *p < 5%, **p < 1%, ***p < 0.1%.

3. Methods

3.3. Estimation Technique

Our analysis involves comparing the worker outcomes of ESOP and non-ESOP workers and disadvantaged ESOP and non-ESOP workers. The goal is to estimate the effect of ESOP membership on worker outcomes while controlling for the characteristics of the workers and their jobs. This implies estimating two models for a worker's outcome. One of these models is the following interaction specification (prespecified in a pre-analysis plan):

$$\text{outcome}_i^j = \beta 1^j ESOP_i + \beta_2^j(\text{ESOP*disadvantage})_i + \beta_3^j \text{disadvantage} + v_i^j + \epsilon_i^j, \quad (1)$$

where v is a nuisance parameter that is correlated with outcome j, with ESOP membership and with being disadvantaged (disadvantage), and ϵ is an error term conditionally independent of the outcome, i.e., $E[\epsilon|v] = 0$. The other model is similar to (1) except that we drop the independent variables ESOP*disadvantage and disadvantage from (1) to obtain the main effect of ESOP membership on the outcome.[10]

The potential endogeneity between worker outcomes and ESOP membership is a challenge in our analysis. For instance, the theory of compensating differences posits that workers enduring lower levels of respect at their workplace – one of the worker outcomes we examine – might receive higher compensation (such as ESOP membership) for these less favorable conditions.[11] The relationship can also operate in the opposite direction: Employees might secure high wages and benefits, including ESOP membership, as a result of their high skills, because their jobs entail significant responsibilities, which employers recognize through efficiency wages,[12] or due to the distribution of their firm's rents or quasi-rents resulting from market power.[13] Such compensation often correlates with tangible rewards, like high wages and stock ownership, and intangible ones, such as respect in the workplace.

To address this endogeneity issue, we would ideally conduct an experiment by randomly assigning similar workers into two groups: ESOP and non-ESOP workers. Such randomization would ensure that the nuisance v in (1) would be independent of ESOP and $\mathrm{ESOP*disadvantage}$. Consequently, this setting would allow us to measure the causal effects of ESOP participation on both general worker outcomes and the specific outcomes of disadvantaged workers.

Without an experimental design, our strategy involves leveraging all observed characteristics potentially affecting ESOP membership, disadvantage, and worker outcomes to control for v in (1). However, due to the extensive array of potential control variables[14], incorporating all controls and their two-way interaction into a standard econometric regression would lead to an overfitting issue. To circumvent this limitation, we employ a double machine learning technique.[15] This approach hinges on the principles of the Frisch–Waugh–Lovell theorem, which suggests that we can estimate the regression coefficients β_1 and β_2 in (1) by initially partialling out the effects of control variables from both the dependent (outcome) and independent variables (ESOP, $\mathrm{ESOP*disadvantage}$ and $\mathrm{disadvantage}$[16]). Subsequently, we regress the outcome's residuals

[10] We run both a main effect and an interaction specification to obtain estimates of the general effects of ESOP membership on the whole sample and its heterogeneous effects among disadvantaged and non-disadvantaged workers. By lapse, the main effects specification was not included in the pre-analysis plan.
[11] Lavetti, K., 2023.
[12] Katz, L. F., 1986.
[13] Blanchflower et al, 1996.
[14] There are 384 potential control variables and two-way interactions in the GSS dataset and 134 in the NEES dataset. The list of potential control variables is in appendix A.2.
[15] Chernozhukov et al, 2018.
[16] The partialling out of effects from ESOP*disadvantage and disadvantage is only done for the interaction specification.

on the residuals of the ESOP and ESOP*disadvantage variables to uncover the effects of ESOP membership on worker outcomes.

Consequently, we model the nuisance parameter v as an unknown function of a high-dimensional vector of control variables Z (which encompasses the feature 'disadvantage'), and we specify the following "partial-out models" to remove the effects of Z from ESOP, ESOP*disadvantage, disadvantage, and from each independent variable, outcome^j:

$$\mathrm{ESOP}_i = f(Z_i) + \varepsilon,\ E[\varepsilon|Z] = 0, \tag{2}$$

$$\mathrm{ESOP{*}disadvantage}_i = g(Z_i) + e_i,\ E[e_i|Z] = 0, \tag{3}$$

$$\mathrm{outcome}_i^j = h^j(Z) + \mu_i^j,\ E[\mu_i^j|Z] = 0, \tag{4}$$

$$\mathrm{disadvantage}_i = i(Z) + \rho_i,\ E[\rho_i|Z] = 0. \tag{5}$$

We estimate these models using an ensemble of machine learning methods[17], which are apt to handle the high-dimensional vector of controls Z.[18] The method that yields the best total validation score is then selected for our analysis.[19,20]

Let $\mathrm{ESOP}_i^{\sim}$ be the estimated residuals of (2), $\mathrm{ESOP\&disad}_i^{\sim}$ be the estimated residuals of (3), and $\mathrm{outcome}_i^{j\sim}$ be the estimated residuals for outcome j in (4). After obtaining these residuals, we estimate the following model, which yields the effects of ESOP membership on workers (β_1) and disadvantaged workers' ($\beta_1 + \beta_2$) outcomes:[21,22]

$$\mathrm{outcome}_i^{j\sim} = \beta_0^j + \beta_1^j ESOP_i^{\sim} + \beta_2^j (\mathrm{ESOP{*}disadvantage})_i^{\sim} + \beta_3^j \mathrm{disadvantage}_i^{\sim} + r_i^j \tag{6}$$

[17] Following Dube et al, 2020 we employ a range of machine learning algorithms to estimate these models, including Lasso, AdaBoost, Bagging, ExtraTrees, and Random Forest. All these algorithms are implemented using the scikit-learn package.

[18] Appendix A.2 lists the controls in Z and appendix A.3 details the construction of the outcomes..

[19] The total validation score we employed to measure model performance was the sum of the root mean square error (RMSE) across the estimations of ESOP, ESOP*disadvantage, and all the outcomes under investigation.

[20] We implement a cross-fitting strategy to mitigate the overfitting bias inherent in using the full sample to estimate the predicted outcome and the predicted independent variables. This involves partitioning the sample into a main subset and an auxiliary subset. The auxiliary subset is utilized to estimate $\hat{\mu}_i$, while the main subset is used for obtaining $\hat{r}_i$ and $\hat{e}_i$. We then reverse the roles of the subsets and derive the remaining fitted values.

[21] In our pre specification plan we had incorrectly included disadvantage (the original variable) in (6). Here we include disadvantage~ (the residualized variable resulting from the model (5) estimation) instead to make (6) consistent with the Frisch–Waugh–Lovell theorem.

[22] The effects of ESOP membership on disadvantaged workers' outcomes are only obtained with the NEES dataset.

A key advantage of this double machine learning technique is that it does not require us to make strong assumptions about which specific control variables should be included in the model. Instead, we can leverage a high-dimensional set of observable characteristics that could potentially relate to ESOP membership, worker disadvantage, and the outcomes of interest. The machine learning algorithms will then determine which variables from this larger set are most relevant for predicting the independent and dependent variables in the partialling out step. This approach mitigates the risk of omitted variable bias from inadvertently excluding relevant controls and avoids the overfitting issues that could arise from manually specifying a large number of controls and interactions in a standard regression model.

3.2. Cluster-Robust Standard Errors

The survey design behind the NEES dataset, where firms are selected first, and then workers within each firm are surveyed, suggests that regressors and errors might be correlated within each firm and that clustering the standard errors by firms is appropriate. Treating each firm and the group of MTurk respondents of the data as clusters presents a “few clusters” issue. This issue tends to bias downward the conventional errors in clustering, causing the Wald test to over-reject the null hypothesis of no significance.[23]

We used simulated data to assess the appropriateness of different types of cluster-robust standard errors. To do so, we first estimated the partialed-out models in (2), (3), (4), and (5) for each dataset using a suite of machine learning algorithms. We then picked the algorithm that achieved the best validation score, i.e., the lowest sum of root mean squared errors (RMSE) summed across all models. As depicted in Table 3, Lasso was the method that achieved the best score for both datasets.

Table 3: Sum of root mean squared errors across “Partial-out models” estimates with different algorithms

	AdaBoost	Bagging	ExtraTrees	Lasso	Random Forest
GSS	63.0	65.1	65.6	59.0	62.5
NEES	54.3	54.4	56.2	52.3	52.8

Once the partial-out models were estimated with the Lasso algorithm, we ran 500 simulations. In each, we created placebo residuals by randomly shuffling $\mathrm{ESOP}_{\mathrm{i}}\tilde{}$ and $\mathrm{ESOP\&disad}_{i}\tilde{}$, and ran an OLS regression of (6). This process breaks up any systematic association between outcome j and the variables ESOP and $\mathrm{ESOP*disadvantage}$, thus imposing the null hypothesis that

[23] Cameron and Miller, 2015.

there is no effect (i.e., $\beta_1^j = 0 \text{ and } \beta_2^j = 0$). We initially computed conventional cluster-robust standard errors in each simulation by clustering by the firm and treating the MTurk data as a single cluster. We considered clustering by firm and industry within the MTurk segment as an alternative approach. While this alternative method increased the number of clusters and promised to mitigate the "few clusters" issue, it was unclear whether regressors and errors were sufficiently correlated within industry groups in the MTurk data to justify this stratification.

Across our 500 simulations, where we imposed the null hypothesis of no effect, we anticipated that the p-value would be lower than 5% in exactly 5% of the simulations, reflecting the nominal test size. The first approach resulted in p-values lower than 5% in 20% of the simulations (reflecting the true test size), indicating a significant downward bias in standard errors due to the low number of clusters. The second approach, less affected by the "few clusters" issue, showed a true test size of 8%.

We also assess the true test size using the CRV3-Jackknife estimator for cluster-robust standard errors, as described in Mackinnon et al, 2023,[24] and implemented in the Python package wildboottest. This method produced an average true test size of approximately 5% for both the firm-only and firm-plus-industry clustering options across the various outcomes. Given that the CRV3-Jacknife true test size matches the nominal size, and that clustering solely by firm aligns more closely with the survey design, we opt to use the CRV3-Jackknife estimator and cluster by firm, treating the MTurk segment as a single cluster.

3.3. Controlling for False Positives, Joint Significance Test, and Power Analysis

We want to estimate the effect of ESOP membership on multiple worker outcome variables. This introduces a multiple comparison problem, which heightens the risk of false positives[25]. The more hypothesis tests we conduct, the greater the likelihood of inadvertently identifying at least one result as "statistically significant" due to chance. For instance, consider evaluating the impact of ESOP membership on 20 uncorrelated worker outcomes. If all null hypotheses – that ESOP membership has no effect – are true, conducting these 20 separate analyses would typically lead to one statistically significant result at a 5% significance level purely by random chance. This outcome would represent a false positive.

To manage the risk of false positives arising from our multiple comparisons, we employ the Benjamini-Hochberg method[26] to control the false discovery rate (FDR) – the proportion of false

[24] Mackinnon et al, 2023.
[25] For an overview of the issue of false positives in multiple comparisons, see Lindquist and Mejia, 2015.
[26] Benjamini and Hochberg, 1995.

positives among all detected statistically significant effects. This approach adjusts the significance threshold for each hypothesis test according to its rank when the hypotheses' p-values are ordered. Each p-value is compared to an increasing critical value, $i/m * \alpha$, where i is the rank, m is the total number of hypotheses tested, and α is the desired FDR.

Furthermore, we also run a joint significance test of β_1^j and β_2^j across all outcomes, to assess the combined significance of the effects of ESOP membership and its interaction with disadvantage $j \in 1, ..., J$ on all measured outcomes. We will estimate the equations as seemingly unrelated regressions (SUR) to accomplish this. We will then re-estimate this system under the constraint that $\beta_1^1 = \beta_2^1 = \beta_1^2 = \beta_2^2 = ...\beta_1^J = \beta_2^J = 0$ and conduct a likelihood ratio test.

Finally, in our pre-specified analysis, we used the simulations described in the previous subsection to run an exploratory power analysis. The findings from this analysis can be found in Appendix A.4. Notably, these power calculations were based on non-FDR adjusted p-values, as the actual values and their rank order could not be known before we conducted the regression analysis with the real data. Consequently, since these results do not account for the false discovery rate, they overestimate the true power of our tests.

4. Results

This section presents our estimates for the relationship of Employee Stock Ownership Plan (ESOP) membership and its interaction with worker disadvantage on various work-related outcomes using both the NEES and GSS datasets.

Table 6 presents the results using the GSS dataset. These results suggest a statistically significant positive effect of ESOP membership on workplace democracy: ESOP membership is associated with an increase of one point (roughly a third of a standard deviation) on a 10-point agree-disagree scale regarding participation in the worker firm's decision making. While the data suggests also a positive association between ESOP membership and several indicators of job quality, such as good relations with management and feeling treated with respect, there is also a suggestive association with higher reported rates of discrimination and harassment and a perception of less fair wages. None of these later results are statistically significant after adjusting for a 5% false discovery rate.

Table 6: Estimation results for the effect of ESOP membership on worker outcomes, GSS data.

	(1) Main effect
	ESOP
Satisfaction and pride about company	0.33
	(0.23)
I take part in decision-making	1.32***
	(0.32)
I have freedom to do my job	-0.05
	(0.30)
Good relation with management	0.25
	(0.24)
My earnings are fair	-0.32
	(0.23)
I am searching for a new job	-0.42
	(0.41)
I am treated with respect	0.28
	(0.25)
My coworkers care about me	-0.29
	(0.29)
Discriminated against due to age	0.35
	(0.31)
Discriminated against due to race†	0.81
	(0.63)
Discriminated against due to gender††	0.61
	(0.61)
Experienced sexual harassment at workplace	0.12
	(0.19)
Experienced non-sexual harassment at workplace	0.13
	(0.32)

Notes: All regressions but those on outcomes 'Discriminated against due to race' and 'Discriminated against due to gender' are run with N=892. †The regression for the outcome discriminated against due to race is run on the subsample of Black and Hispanic workers (N= 253). ††The regression for the outcome discriminated against due to gender is run on the subsample of female workers (N=385). These coefficients are from running regression 5 for all outcomes. $\widetilde{\mathrm{ESOP}}$, and $\widetilde{\mathrm{Outcome}}$ are the residuals of the Lasso estimation of equations (2), (3), and (4). The list of potential controls are in Appendix A.2. Outcomes are measured on a scale from 1 ('Totally disagree') to 10 ('Totally agree'). The number of selected control variables is in table 13. P-values: : *<5%, **<1%, ***<0.1% after adjusting for multiple tests using the Benjamini-Hochberg method to control the False Discovery Rate (FDR).

To assess the overall impact of ESOP membership on the set of worker outcomes, we conducted a joint significance test. The test examines whether the coefficients on ESOP membership are simultaneously equal to zero across all outcome models. With a p-value of 0.03 (Likelihood Ratio Statistic = 23.8, df=13), we reject the null hypothesis of no joint effect at the 5% significance level. This result suggests that there is indeed an overall influence of ESOP membership on worker outcomes, even after considering multiple testing. While we observed a significant effect of ESOP membership on workplace democracy individually, the joint test provides further evidence of a broader impact across various worker outcomes. However, it's worth noting that this effect is not significant at the stricter 1% level. Additional research with larger sample sizes may be beneficial to increase statistical power and draw stronger inferences about the specific impacts of ESOP participation on individual worker outcomes.

Table 7: Estimation results for the effect of ESOP membership and its interaction with disadvantage on worker outcomes (all partialed out). NEES data.

	(1) Main effect	(2) Interaction	
	1.1 ESOP	2.1 ESOP	2.2 ESOP&disad
Satisfaction and pride about company	1.54***	1.47	0.21
	(0.27)	(0.57)	(0.42)
I take part in decision-making	1.45	1.61	-0.36
	(0.95)	(0.95)	(0.88)
I have freedom to do my job	0.73	0.87	-0.29
	(0.41)	(0.39)	(0.46)
Good relation with management	0.51	0.35	0.26
	(1.47)	(1.61)	(0.48)
My earnings are fair	1.55	1.41	0.28
	(1.64)	(2.03)	(0.80)
I am searching for a new job	-1.13***	-1.21*	0.18
	(0.27)	(0.37)	(0.15)
Level of commitment to the firm	1.91***	1.85	0.22
	(0.37)	(0.78)	(0.66)
Organizational citizenship behavior	1.17***	1.11	0.22
	(0.31)	(0.56)	(0.36)
Organizational justice	1.19	1.08	0.23
	(1.33)	(1.65)	(0.63)
Perceived probability of losing job	-0.38	-0.48	0.23
	(0.42)	(0.49)	(0.30)

Notes: All regressions N=1,718. The main effect specification estimates equation 5 with ESOP~ as the sole regressor. The interaction specification estimates equation (6) with ESOP~, ESOP&disad~ and disadvantage (coefficient omitted) as regressors. ESOP~, ESOP&disad~, and Outcome~ are the residuals of the Lasso estimation of equations 2, 3, and 4. The list of potential controls are in Appendix A.2. Outcomes are measured on a scale from 1 ('Totally disagree') to 10 ('Totally agree'). The disadvantaged workers group comprises anyone who is Black, Hispanic, immigrant, lacking a high school diploma, or earning in the bottom 30% of the dataset's income distribution. Standard errors (in parentheses) clustered at the firm level using the CRV3-Jackknife method. The number of selected control variables is in table 14. P-values: *<5%, **<1%, ***<0.1% after adjusting for multiple tests using the Benjamini- Hochberg method to control the False Discovery Rate (FDR).

Table 7 presents the estimation results for the effect of ESOP membership and its interaction with worker disadvantage status on various worker outcomes using the NEES dataset. The main effect specification (column 1.1) estimates the overall impact of ESOP membership by including only the ESOP residual variable in the controls of equation (6), and excluding the interaction term (ESOP&disad~) and the disadvantaged worker control (disadvantaged~).

The results from this specification show that ESOP membership has a highly statistically significant positive effect on several worker outcomes. ESOP membership is associated with an increase of 1.5 points on a 10-point agree-disagree scale measuring satisfaction and pride about the company (significant at the 0.1% level). Similarly, it is linked to an increase of 1.9 points in the level of commitment to the firm, and of 1.2 points in workers' reported organizational citizenship behavior, all on the 1-10 point scale and significant at the 0.1% level. ESOP membership is also associated with a decrease of 1.1 points (significant at the 1% level) in the self-reported likelihood of searching for a new job.

The interaction specification (columns 2.1 and 2.2) estimates the full model in equation (6), including the ESOP main effect, the interaction term ESOP&disad, and the disadvantaged worker control. The ESOP coefficients in column 2.1, representing the impact of ESOP membership for non-disadvantaged workers, are similar to the main effects in column 1.1, although the estimates lost precision with the inclusion of the interaction term.

The ESOP&disad coefficients in column 2.2 show the difference in the ESOP effect between disadvantaged and non-disadvantaged workers. For instance, the coefficient for participation in decision-making is -1.0, suggesting that the positive effect of ESOP membership on this outcome might be smaller for disadvantaged workers. However, none of the coefficients in column 2.2 are statistically significant. This indicates that while the effects of ESOP membership appear to be somewhat smaller in magnitude for disadvantaged workers, our methods do not detect a statistically significant difference in ESOP effects between disadvantaged and non-disadvantaged workers.

Finally, we run a joint significance test for the main effect specification using the NEES dataset. We test the null hypothesis that the ESOP effects on all worker outcomes are jointly not significant. The test strongly rejects this null hypothesis (Likelihood Ratio Statistic = 748.4, df=10, p-value < 0.001), providing further evidence of generally positive effects of ESOP membership on job quality, decision-making influence, and other worker experiences captured in the NEES survey.

These results suggest that ESOP workers’ perception and attitudes towards their workplace confirm a positive effect of ESOPs, and find no statistically significant evidence of different impacts for disadvantaged workers. ESOP workers tend to feel more satisfied, committed and proud of working for their firm and tend to demonstrate more organizational citizenship behavior. Furthermore, while ESOP firms' administrators may be more reluctant to lay off workers, our results suggest that ESOP stability is, at least partially, driven by workers’ commitment to the firm and reduced desire to search for new jobs.

5. Mediation Analysis

To further understand the mechanisms through which ESOP membership affects worker outcomes, we conducted a mediation analysis with the NEES dataset. This analysis tests for potential indirect effects of ESOP membership on outcomes through mediating variables, answering questions as: Is the positive association between ESOP membership and satisfaction and pride about the firm linked to ESOP workers participating more in decision-making?

To study these mediation relations, we focused on the outcomes on which the ESOP variable has statistically significant main effects (depicted in column 1.1 of table 7): satisfaction and pride about the company, level of commitment to the firm, searching for a new job, and organizational citizenship behavior. Additionally, we included participation in decision-making due to the statistically significant impact of ESOP on this outcome in the GSS dataset.

The following nine models are the mediation hypothesis we test:

Participation in decision-making mediates the effect of ESOP membership on:

1. Satisfaction and pride about the company
2. Level of commitment to the firm
3. Searching for a new job
4. Organizational citizenship behavior

Satisfaction and pride about the company mediates the effect of ESOP membership on:

5. Level of commitment to the firm
6. Searching for a new job
7. Organizational citizenship behavior

Level of commitment to the firm mediates the effect of ESOP membership on:

8. Searching for a new job
9. Organizational citizenship behavior

These hypotheses were based on plausible causal chains. For instance, searching for a new job is likely an outcome of the level of satisfaction about the company rather than a driver of it.

Similarly, participation in decision-making may influence job satisfaction and commitment to the firm, while the act of searching for a new job is unlikely to be a primary driver of these attitudes.

To test these mediation hypotheses, we estimated the following set of equations for each mediation model:

$$\text{outcome}_{im}^{\sim} = \alpha_{0m} + c_m ESOP_i^{\sim} + \epsilon_1 \quad (7)$$

$$\text{mediator}_{im}^{\sim} = \alpha_{1m} + a_m ESOP_i^{\sim} + \epsilon_2 \quad (8)$$

$$\text{outcome}_{im}^{\sim} = \alpha_{2m} + c'_m ESOP_i^{\sim} + b_m \text{mediator}_{im}^{\sim} + \epsilon_3 \quad (9)$$

where the superscript ~ indicates that the variable it's attached to has been partialled-out, m=1,..., 9 denotes the mediation model subscript, and:

- c is the total effect of ESOP on the outcome (the same as the main effect in Table 7)
- a is the effect of ESOP on the mediator
- b is the effect of the mediator on the outcome, controlling for ESOP
- c' is the direct effect of ESOP on the outcome, controlling for the mediator

This mediation model decomposes the main effect (c) into direct (c') and indirect (a*b) effects of ESOP on a given outcome. The indirect effect represents the portion of ESOP's relationship with the outcome that is associated with the mediator. For instance, in the mediation hypothesis 1 a) above, the indirect effect would indicate how much of ESOP's relationship with satisfaction and pride is linked to ESOP workers' higher participation in decision-making.

To test for the presence of mediation effects, which involves assessing the significance of the indirect effect, we employed the bootstrapping method of Preacher and Hayes (2004). This approach is preferred over the Sobel test as it does not assume normality in the sampling distribution of the indirect effect. We used 5,000 bootstrap samples to generate 99.9%, 99%, and 95% confidence intervals for the indirect, direct, and total effects. The results are depicted in Table 8, and the significance levels of the estimates were derived from the confidence intervals.

The total effects reported in Table 8 are the main effects of ESOP membership on these outcomes (as shown in column 1.1 of Table 7). The results in Table 8 suggest that ESOPs' relationship with positive workers' outcomes are partially explained by ESOPs having more increased participation in decision-making, higher job satisfaction, and greater organizational commitment.

Participation in decision-making is a statistically significant mediator for all outcomes examined. However, the magnitude of this mediation is relatively modest, as evidenced by the small differences between the total and direct effects. For instance, the indirect effect of ESOP on satisfaction through decision-making (0.3) is much smaller than the direct effect (1.2). This result suggests that while workplace democracy may play a role, it only partially explains the relationship between ESOP and positive workers' outcomes.

Table 8: Mediation Analysis Results

Model	Outcome	Mediator	Indirect	Direct	Total
1	Job search	Commitment	-1.11***	-0.02	-1.13***
2	Job search	Decision-making	-0.15***	-0.98***	-1.13***
3	Job search	Satisfaction	-0.99***	-0.14	-1.13***
4	OCB	Commitment	0.81***	0.36***	1.17***
5	OCB	Decision-making	0.32***	0.85***	1.17***
6	OCB	Satisfaction	0.59***	0.58***	1.17***
7	Commitment	Decision-making	0.29***	1.62***	1.91***
8	Commitment	Satisfaction	1.19***	0.71***	1.91***
9	Satisfaction	Decision-making	0.30***	1.24***	1.54***

*Note: All regressions N=1,718. For each row, we estimate the set of equations (7), (8) and (9). The total effect corresponds to coefficient c in (7) (with no mediation variables), the direct effect is the coefficient c' in (9) (with the listed mediating variables), and the indirect effect corresponds to the product of coefficients a*b obtained from (8) and (9). The outcome variables are measured on a scale from 1 ('Totally disagree') to 10 ('Totally agree'). OCB stands for Organizational Citizenship Behavior, Satisfaction stands for satisfaction and pride about a company, Decision-making stands for "I take part in decision-making," Commitment stands for Level of commitment to the firm, and Job search stands for "I am searching for a new job." The indirect, direct, and total effects are derived from bootstrapping with 5,000 samples. Significance levels: *p<5%, **p<1%, ***p<0.1%, derived from the bootstrapped 95%, 99%, and 99.9% confidence intervals, respectively.*

In contrast, satisfaction and commitment as mediators demonstrate stronger mediation effects. For example, when satisfaction mediates the relationship between ESOP and commitment, the indirect effect (1.2) is larger than the direct effect (0.7), indicating that a substantial portion of ESOP's association with commitment may operate by increased job satisfaction.

Finally, satisfaction and commitment as mediators render the direct effect of ESOP on job search intentions statistically insignificant (direct effect coefficients are -0.1 and 0.0, respectively). This suggests that ESOP's negative association with job search intentions is primarily explained by increased job satisfaction and organizational commitment among ESOP members.

These results paint a nuanced picture of how ESOP membership relates to positive worker outcomes. While workplace democracy plays a role, the stronger mediators of ESOP relationship with positive worker's outcomes are satisfaction and commitment. Further, these findings also hint at a potential chain of effects: ESOP membership appears to be associated with increased satisfaction, which in turn is linked to higher commitment, and these factors together are linked to reduced job search intentions and increased organizational citizenship behavior.

6. Conclusion

In this study, we investigate the relationship between employee stock ownership plan (ESOP) membership and workers' self-reported attitudes, perceptions, and overall job quality experiences. Drawing from two complementary datasets – the nationally representative General Social Survey (GSS) and the focused National ESOP Employee Survey (NEES) – we employed a double machine learning approach to account for potential endogeneity concerns while estimating the effects of ESOP participation.

Our analysis of the GSS data revealed a positive association between ESOP membership and several indicators of job quality, such as involvement in decision-making and good relations with management. However, except for the relation between ESOP membership and workplace democracy, these associations did not remain statistically significant after adjusting for the potential false discovery rate arising from multiple comparisons.

In contrast, the results from the NEES dataset suggested robust positive impacts of ESOP membership on various aspects of the employee experience, including higher levels of job satisfaction, pride in the company, and organizational commitment. ESOP workers were also less likely to be actively searching for new employment opportunities. Furthermore, we assessed whether these effects varied between the group of workers who may have historically faced systemic barriers or marginalization, namely those who identify as Black, Hispanic, or immigrant, those without a high school diploma, or those earning in the bottom 30% of the dataset's income distribution, a group we called "disadvantaged" for brevity, and workers who have not faced such barriers. We could not find statistically significant evidence that the ESOP membership effects differed between these two groups. Finally, a mediation analysis revealed that the positive effects of ESOP membership on worker outcomes are mediated by increased participation in decision-making, higher job satisfaction, and greater organizational commitment.

These results suggest that ESOP workers' perception and attitudes towards their workplace confirm positive effects of a firm having an ESOP structure. However, while our findings consistently pointed toward a positive association between ESOP membership and desirable worker outcomes, several limitations should be acknowledged. The lack of an experimental design or a clear identification strategy precluded us from establishing causal relationships. Additionally, our datasets suffered from sample size limitations, particularly concerning the representation of disadvantaged workers who are ESOP members, restricting our ability to precisely estimate heterogeneous effects across different dimensions of disadvantage. Future research with larger sample sizes could allow for more nuanced examination of distinct disadvantaged groups, such as analyzing Black, Hispanic, immigrant, and low-income workers separately, which may uncover important differences masked by combining them into a single category.

Notwithstanding these limitations, our study contributes to the growing literature on employee ownership by providing new evidence on the positive association between ESOP membership and indicators of job quality. Furthermore, it sheds light on workers' perceptions and attitudes towards the firm as possible drivers for differences between ESOP and non-ESOP firms. For instance, our findings suggest that the enhanced satisfaction and commitment among ESOP members may drive the generally favorable outcomes associated with ESOPs founded in literature.

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Appendix

A.1 Mean-differences in workers outcomes

Table 8: GSS data: Non-ESOP vs. ESOP. Means on a 1-Totally Disagree to 10-Totally Agree scale.

	Non-ESOP mean	ESOP mean	Difference
Satisfaction and pride about company	7.43	7.86	-0.43
	(2.07)	(1.88)	(0.25)
Participation in decision-making	7.00	8.42	-1.42***
	(2.96)	(2.01)	(0.35)
Freedom to do job	7.71	7.75	-0.04
	(2.71)	(2.65)	(0.33)
Good relation with management	7.14	7.34	-0.20
	(2.06)	(2.10)	(0.25)
Earnings fairness	6.15	5.78	0.37
	(2.10)	(1.89)	(0.25)
Searching for new job	2.91	2.23	0.68
	(3.71)	(3.81)	(0.45)
Treated with respect	7.38	7.66	-0.27
	(2.21)	(2.19)	(0.27)
Coworkers' care	2.95	2.57	0.38
	(2.61)	(2.31)	(0.32)
Age discrimination	0.81	1.35	-0.54
	(2.73)	(3.44)	(0.34)
Race discrimination	0.50	0.68	-0.18
	(2.17)	(2.53)	(0.27)
Gender discrimination	0.63	0.95	-0.31
	(2.44)	(2.95)	(0.30)
Sexual harassment	0.29	0.41	-0.12
	(1.68)	(1.99)	(0.21)
Non-sexual harassment	0.92	1.08	-0.16
	(2.90)	(3.13)	(0.36)
Sample Size (N*)	692 to 727	73 to 74	

Note: Means scale is 1-Totally disagree to 10-Totally Agree. Sample size values depend on the number of missing variables in the outcome variable. For mean values, standard deviations are reported in parentheses; for differences, standard errors are reported in parentheses.
Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

Table 9: NEES data: Disad Non-ESOP vs. Disad ESOP. Means in 1-10 scale for intersectionally disadvantaged workers.

	Disad Non-ESOP mean	Disad ESOP mean	Difference
Level of commitment to the firm	5.32	7.28	-1.96***
	(2.48)	(2.01)	(0.21)
Good relation with management	3.74	3.14	0.60
	(4.84)	(4.65)	(0.42)
Organizational citizenship behavior	6.64	7.65	-1.00***
	(2.40)	(1.76)	(0.19)
Intention to stay	5.50	7.39	-1.89***
	(2.80)	(2.33)	(0.23)
Work conflicts with family life	4.19	3.87	0.31
	(2.91)	(2.90)	(0.25)
Organizational justice	5.26	5.62	-0.35
	(2.25)	(2.40)	(0.20)
Burnout index	3.82	3.14	0.67**
	(2.99)	(2.52)	(0.25)
Probability of losing job	4.00	3.26	0.74***
	(1.96)	(1.34)	(0.16)
Sample Size (N*)	425	179 to 180	

Note: Means scale is 1-Totally disagree to 10-Totally Agree. Sample size values depend on the number of missing variables in the outcome variable. For mean values, standard deviations are reported in parentheses; for differences, standard errors are reported in parentheses. The Disad ESOP column reports means for disadvantaged workers that are ESOP members, while the Disad Non-ESOP column reports means for disadvantaged workers who are not ESOP members.The disadvantaged workers group comprises workers who fall within the bottom 30% of the dataset's income distribution or belong to one or more of the following categories: Black, Hispanic, immigrant workers, or those without a high school diploma.
Significance levels: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

A.2 Control Variables

For the analysis of the GSS dataset, the following control variables are as follows:

Demographics and Household Composition:

- Age
- Presence of minors in household
- Household size
- Marital status: Married, Widowed, Separated/Divorced
- Gender: Female

Economic and Work Characteristics:

- Tenure in job
- Number of workers in the entire firm
- Respondent's real income (adjusted to 2022 Prices)
- Whether the respondent usually works more than 45 hours
- The degree to which the worker is highly supervised

Ethnicity and Education:

- Ethnic background: Nonwhite, Black, Hispanic
- Educational background: Less than High school diploma, High school or equivalent degree, Associate/junior college degree, Bachelor's degree, Graduate degree

Health and Job Involvement:

- Whether the respondent has an impairing health issue
- Whether involved in any task force for decision-making

Fixed Effects:

- Industry (9 groups) fixed effects
- Occupation (6 groups) fixed effects Additional Variables:
- Indicator of disadvantage

For the NEES dataset, control variables are as follows:

Demographics and Household Composition:

- Age
- Presence of minors in household
- Household size
- Marital status: Married, Widowed, Separated/Divorced
- Gender: Female

Economic and Work Characteristics:

- Tenure in job
- Number of workers in the entire firm
- Respondent's real income (adjusted to 2022 Prices)
- Whether the respondent usually works more than 45 hours
- The degree to which the worker is highly supervised
- Ethnic background: Nonwhite, Black, Hispanic
- Educational background: Less than High school diploma, High school or equivalent degree, Associate/junior college degree, Bachelor's degree, Graduate degree

Health and Job Involvement:

- Whether the respondent has an impairing health issue
- Whether involved in any task force for decision-making Fixed Effects:
- Industry (9 groups) fixed effects
- Occupation (6 groups) fixed effects Additional Variables:
- Indicator of disadvantage

A.3 Construction of Outcomes

Table 10: Outcome variables and original variables in the GSS dataset.

Outcome	Original Variables	Original survey question
Satisfaction and pride about company index	satjob1	All in all, how satisfied would you say you are with your job?
	proudemp	Agree/Disagree: I am proud to be working for my employer
	respect	Agree/Disagree: At the place where I work, I am treated with respect
I take part in decision-making	wkdecide	In your job, how often do you take part with others in making decisions that affect you?
I have freedom to do my job	wkfreedm	Agree/Disagree: I am given a lot of freedom to decide how to do my own work
Good relation with management	promtefi	Agree/Disagree: Promotions are handled fairly
	manvsemp	In general, how would you describe relations in your workplace between management and employees?
	spvtrtair	Agree/Disagree: My supervisor treats me fairly.
My earnings are fair	fairearn	How fair is what you earn on your job in comparison to others doing the same type of work you do?
I am searching for a new job	trynewb	Taking everything into consideration, how likely is it that you will make a genuine effort to find a new job with another employer within the next year?
I am treated with respect	respect	Agree/Disagree: At the place where I work, I am treated with respect
My coworkers care about me	cowrkint	Agree/Disagree: The people I work with take a personal interest in me
Discriminated against due to age	wkageism	Do you feel in any way discriminated against on your job because of your age?
Discriminated against due to race	wkracism	Do you feel in any way discriminated against on your job because of your race or ethnic origin?
Discriminated against due to gender	wksexism	Do you feel in any way discriminated against on your job because of your gender?
Experienced sexual harassment at workplace	wkharsex	In the last 12 months, were you sexually harassed by anyone while you were on the job?
Experienced non-sexual harassment at workplace	wkharoth	In the last 12 months, were you threatened or harassed in any other way by anyone while you were on the job?

Note: Outcomes were bundled based on correlations and thematic consistency. Variables with strong correlations and overlapping concepts were combined into single indices, as they likely represent a single construct.

Table 11: Outcome variables and original variables in the NEES dataset.

Outcome	**Original Variables**
Satisfaction and pride about company index	affcomm2, affcomm5
I take part in decision-making	wp1
I have freedom to do my job	jobsat2
Good relation with management	lmx7
My earnings are fair	ojdist1, ojdist2, ojdist3, ojdist4
I am searching for a new job	tovint4
Level of commitment to the firm	loyal, psyown, commi
Organizational citizenship behavior	all OCB vars Intention to stay
	all TOVint vars
Work conflicts with family life	wfconf1, wfconf2
Organizational justice	all Ojdist, Ojprcd, and futil vars
Burnout index	all BO vars
Probability of losing job	jobsec

Note: Outcomes were bundled based on correlations and thematic consistency. Variables with strong correlations and overlapping concepts were combined into single indices, as they likely represent a single construct. For as much as the variables allowed, we reproduced the GSS survey construct for comparison purposes. Since the NEES data has not been made public, we refrain from sharing the original survey questions.

A.4 Power Analysis

We obtained estimates of effect sizes we will be powered to detect. This was done by simulating the model in (6) with placebo explanatory residuals. Note, however, that if we only have a few significant effects in our multiple comparison problem, the 5% FDR adjustment will yield a very stringent threshold for significance, which may render the whole analysis underpowered. As a result, this power analysis, which was part of the pre-specification plan, was only exploratory.

Table 4: Minimum detectable effects of ESOP membership on worker outcomes, GSS data.

	Mean	Std Dev	MDE ESOP
Satisfaction and pride about company	7.51	1.94	0.59
I take part in decision-making	7.17	2.76	0.75
I have freedom to do my job	7.70	2.56	0.80
Good relation with management	6.86	2.05	0.57
My earnings are fair	6.10	1.96	0.58
I am searching for a new job	2.80	3.52	1.07
I am treated with respect	7.41	2.09	0.63
My coworkers care about me	2.91	2.44	0.73
Discriminated against due to age	0.86	2.66	0.80
Discriminated against due to race†	0.95	2.87	1.63
Discriminated against due to gender††	1.10	3.04	1.46
Experienced sexual harassment at workplace	0.30	1.62	0.47
Experienced non-sexual harassment at workplace	0.94	2.76	0.79

Notes:†The regression for the outcome discriminated against due to race is run on the subsample of Black and Hispanic workers.
††The regression for the outcome discriminated against due to gender is run on the subsample of female workers.
The outcomes are measured on a scale from 1 ('Totally disagree') to 10 ('Totally agree').

The MDE are obtained from the 10th to 90th percentile range of the distribution of coefficients β_1 and β_2 from our shuffled residuals, $\tilde{\mathrm{ESOP}_i}$ and $\tilde{\mathrm{ESOP\&disad}_i}$. Table 4 depicts the MDE for the impact of ESOP membership on various worker outcomes using GSS data. This table suggests that assuming the FDR adjustment is modest enough not to affect the power, we are powered to detect increases of approximately a quarter of a standard deviation increase from the outcomes sample mean resulting from the worker being an ESOP member. Finally, Table 5 shows a similar table with the minimum detectable effect for the impact of ESOP membership on worker outcomes. This table suggests that, assuming the FDR adjustment is modest enough not to affect the power, we are powered to detect increases of approximately a twelfth of a standard deviation from the outcomes sample mean resulting from the worker being an ESOP member. Similarly, we are powered to detect increases of a sixth of a standard deviation from the outcome sample resulting from the worker being disadvantaged and an ESOP member.

Table 5: Minimum detectable effects of ESOP membership on worker outcomes. NEES data. The “partial-out models” were estimated with Lasso.

	Mean	Std Dev	MDE ESOP	MDE ESOP*disad
Satisfaction and pride about company	7.93	2.40	0.20	0.35
I take part in decision-making	7.58	2.92	0.25	0.41
I have freedom to do my job	7.63	2.54	0.19	0.36
Good relation with management	4.10	4.91	0.38	0.69
My earnings are fair	6.02	2.70	0.21	0.36
I am searching for a new job	2.23	3.27	0.24	0.45
Level of commitment to the firm	6.85	2.39	0.20	0.34
Organizational citizenship behavior	7.49	2.04	0.17	0.30
Organizational justice	6.20	2.20	0.18	0.32
Perceived probability of losing job	3.51	1.70	0.13	0.23

Note: The outcomes are measured on a scale from 1 ('Totally disagree') to 10 ('Totally agree').

A.5 Joint significance test with SUR models in Python

To perform the joint significance test mentioned in subsection 2.2, we utilize the “linear-models” Python package to estimate both an unrestricted and a restricted SUR model. The unrestricted model incorporates vectorized outcome variables and coefficients to assess the impacts of ESOP membership and its interaction with disadvantage across multiple job- related outcomes:

$$\textbf{outcome} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1\textbf{ESOP} + \boldsymbol{\beta}_2\textbf{ESOP\&disad} + \boldsymbol{\beta}_3\textbf{disadvantage} + \boldsymbol{r} \tag{A.1}$$

Here, **outcome** is a vector containing various measurements of worker outcomes. **ESOP**, **ESOP&disad**, and **disadvantage** are vectors of the original variables stacked for each outcome. The vectors of coefficients $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$ represent the effects of the intercept, ESOP membership, its interaction with disadvantage, and the effects of being disadvantaged across all considered outcomes. The residual vector $\boldsymbol{r}$ is assumed to follow a multivariate normal distribution, $\boldsymbol{r} \sim N(0, \Sigma \otimes I_T)$, where Σ is the covariance matrix representing the covariances between equations in the model. I_T is an identity matrix, and T denotes the number of observations per equation.

The restricted model is formulated similarly to (A.1) but excludes the **ESOP** and **ESOP&disad** vectors. To calculate the likelihood ratio for the joint significance test, we compute the likelihood for both the unrestricted and restricted SUR models. Since the linearmodels Python package does not provide a method to directly obtain the log likelihood, we extract the estimated coefficients $\boldsymbol{\beta}_0$, $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$, and $\boldsymbol{\beta}_3$ and the estimated covariance matrix of errors Σ for both models. These estimates are then used to calculate the likelihood of each model.

The log-likelihood function for the SUR model, considering the multivariate normal distribution of errors, is given by:

$$\mathrm{Log}L = -\left(\frac{nT}{2}\right)\ln(2\pi) - \frac{1}{2}\ln(\det(\Sigma \otimes I_T)) - \frac{1}{2}(r)'(\Sigma^{-1} \otimes I_T)(r) \qquad \text{(A.1)}$$

For efficient implementation in Python, we rewrite (A1) as[27]

$$\mathrm{Log}L = -\frac{nT}{2}\ln(2\pi) + \frac{T}{2}\ln(\det(\Sigma^{-1})) - \frac{1}{2}\sum_{i=1}^{M}\sigma^{ii}(r_i)'(r_i) - \sum_{i=1}^{M}\sum_{j<i}\sigma^{ij}(r_i)'(r_j) \qquad \text{(A.2)}$$

where σ^{ij} is the (i,j) element of Σ^{-1}, T represents the number of observations per equation, M is the number of equations in the model, and n is the total number of individuals. Each $\boldsymbol{r}_i$ vector contains residuals for the i-th equation. Thus, we use (A.2) to obtain the log likelihood of the unrestricted and restricted models, and test the null hypothesis that $\boldsymbol{\beta}_1 = \boldsymbol{\beta}_2 = 0$ by doing:

$$LR = 2 \times (\mathrm{Log}L_{\text{unrestricted}} - \mathrm{Log}L_{\text{restricted}}) \sim \chi^2_{df} \qquad \text{(A.3)}$$

where $\mathrm{LogL}_{\text{unrestricted}}$ and $\mathrm{LogL}_{\text{restricted}}$ are the log-likelihoods of the unrestricted and restricted models, respectively. The likelihood ratio statistic *LR* follows a chi-squared distribution with degrees of freedom *df* , which equals the number of restrictions imposed by the null hypothesis. In this case, the degrees of freedom are 2**M* , reflecting that two coefficients ($\boldsymbol{\beta}_1$ and $\boldsymbol{\beta}_2$) are being tested for each of the *M* equations in the model.

[27] As derived in the class notes of Seung Ahn. https://www.public.asu.edu/~miniahn/ecn726/cn_sur.pdf, last accessed on May 7, 2024.

Table 13: Number of covariates used by the LASSO regression to residualize the dependents (ESOP) and independent variables with the GSS dataset.

Variable	**Covariates No.**
ESOP	25
Satisfaction and pride about company	10
I take part in decision-making	16
I have freedom to do my job	12
Good relation with management	20
My earnings are fair	10
I am searching for a new job	24
I am treated with respect	15
My coworkers care about me	15
Discriminated against due to age	1
Discriminated against due to race	17
Discriminated against due to gender	15
Experienced sexual harassment at workplace	2
Experienced non-sexual harassment at workplace	2

Note: The dummy variable ESOP is estimated with a Cross-fit Logistic Regression (L1 Penalty), which extends the LASSO method to classification problems. The remaining variables, measured on a 1 to 10 agree/disagree scale, are estimated with a Cross-fit Lasso Regression. Covariates No. represents the number of variables that were picked at least once for the LASSO regression across the two folds of the cross-fit. The disadvantaged workers group comprises anyone who is Black, Hispanic, immigrant, lacking a high school diploma, or earning in the bottom 30% of the dataset's income distribution. There were a total of 384 potential covariates in the GSS dataset.

Table 14: Number of covariates used by the LASSO regression to residualize the dependents (ESOP, ESOP*disad, Disadvantaged) and independent variables with the NEES dataset.

Variable	**Covariates No.**
Esop	44
Esop*disad	24
Disadvantaged	24
Satisfaction and pride about company	13
I take part in decision-making	10
I have freedom to do my job	15
Good relation with management	6
My earnings are fair	12
I am searching for a new job	4
Level of commitment to the firm	7
Organizational citizenship behavior	7
Organizational justice	15
Perceived probability of losing job	25

Note: The dummy variables ESOP, ESOP*disad, and Disadvantaged are estimated with a Cross-fit Logistic Regression (L1 Penalty), which extends the LASSO method to classification problems. The remaining variables, measured on a 1 to 10 agree/disagree scale, are estimated with a Cross-fit Lasso Regression. Covariates No. represents the number of variables that were picked at least once for the LASSO regression across the two folds of the cross-fit. ESOP*disad corresponds to the interaction of ESOP membership and being part of the disadvantaged group. The disadvantaged workers group comprises anyone who is Black, Hispanic, immigrant, lacking a high school diploma, or earning in the bottom 30% of the dataset's income distribution. There were a total of 134 potential covariates in the NEES dataset.