The Impact of Job Loss on Self-injury Mortality in a Cohort of Autoworkers

Application of a Novel Causal Approach

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Background: Recent increases in national rates of suicide and fatal overdose have been linked to a deterioration of economic and social stability. The American auto industry experienced comparable pressures beginning in the 1980s with the emergence of a competitive global market.

Methods: Using the United Autoworkers-General Motors (GM) cohort as a case study, we examine the impact of employment loss on these self-injury mortality events. For 29,538 autoworkers employed on or after 1 January 1970, we apply incremental propensity score interventions, a novel causal inference approach, to examine how proportional shifts in the odds of leaving active GM employment affect the cumulative incidence of self-injury mortality.

Results: Cumulative incidence of self-injury mortality was 0.87% (255 cases) at the observed odds of leaving active GM employment ($\delta = 1$) over a 45-year period. A 10% decrease in the odds of leaving active GM employment ($\delta = 0.9$) results in an estimated 8% drop in self-injury mortality (234 cases) while a 10% increase ($\delta = 1.1$) results in a 19% increase in self-injury mortality (303 cases).

Conclusions: These results are consistent with the hypothesis that leaving active employment at GM increases the risk of death due to suicide or drug overdose.

Keywords: autoworkers; fatal drug overdose; incremental shifts; job loss; nonparametric; propensity score; suicide

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The data for this cohort may be available upon request to Ellen Eisen (eeisen@berkeley.edu). All analyses were performed with R and the analytical code can be found on GitHub (https://github.com/sdufault15/uaw-gm-ips).

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In their landmark paper, Case and Deaton observed that increased rates of suicide, fatal drug overdose, and alcoholic liver disease were responsible for an increase in all-cause mortality in midlife white Americans.[1] They attribute these distressing trends to "a long-term process of decline, rooted in the steady deterioration in job opportunities for people with low education," including increasingly limited access to defined benefit pension plans.[1,2] Analysis of the Health and Retirement Study reveals that midlife individuals are most likely to experience involuntary job separation in industries like manufacturing, mining, and construction, and only 10% of those who experienced involuntary separation ever reach the same weekly earnings they had prior to the separation.[3] Additionally, unemployment has been associated with up to a 16-fold increase in suicide risk,[4] and men who are not in the labor force experience "notably low levels of emotional well-being throughout their days," with nearly half taking pain medication.[5] With the current economic contraction and widespread unemployment related to the coronavirus disease 2019 (COVID-19) pandemic, the potential consequences of job loss on mental health are of increasing concern.

Few US industries have experienced rollercoaster growth and contraction quite like American auto manufacturers. Ford, Chrysler, and General Motors (GM), all headquartered in Michigan, dominated the industry for decades, hiring and manufacturing primarily within the United States. During confirmation hearings before the Senate Committee in 1952 (the heyday of American auto manufacturing), the soon-to-be United States. Secretary of Defense Charles E. Wilson famously stated "...what is good for the country is good for General Motors, and vice versa... It goes with the welfare of the country."[6] By the late 1970s, GM was the largest private American company, employing 618,365 workers,[7] and, due to gains made by the autoworkers union, was recognized as an extremely desirable company to work for, with good pensions and health care plans.

After the sustained growth leading up to the 1970s, the pressures of market globalization, climbing oil prices, and changes in politics and culture created an atmosphere in which foreign-produced automobiles outperformed American cars. In order to maintain a competitive profit margin, GM began exporting jobs to nonunion plants in the South and then offshore, resulting in nationwide plant closures. Michigan made excessive concessions, including unprecedented tax breaks, in an effort to keep their GM plants open.[8] From the late 1980s through the present, GM has continued to lay off its American workforce, putting 10s of 1,000s of workers at a time through forced job separation.[9,10] Amplifying the trauma experienced by workers during mass layoffs, the union was unable to protect the previously generous pensions and was forced to accept a drop in the hourly wage.[9]

This paper examines the accumulation of cases of suicide and drug overdose in relation to the growth and subsequent downsizing of three GM plants located in Michigan. Each plant had a unique impact on the landscape of Michigan manufacturing and a distinct role in the lifespan of GM. Plant 1, located in Hamtramck within the city limits of Detroit, began as Chevrolet's Gear and Axle plant in 1919. The plant was actively involved in the impactful 113-day strike beginning in 1945, which aimed to offset postwar changes to the cost of living. Although the union did not secure the full desired wage increase, this set the stage for future negotiations in the 1950s and 1970s that would make GM jobs so desirable.[11] In 1994, the plant was purchased by American Axle & Manufacturing, Inc, and was subsequently closed in 2012.[12]

Plant 2, originally known as Willow Run and located in Ypsilanti Township, received national attention in the 1990s.[8] In December 1991, GM's Chief Executive Officer Robert Stempel announced its intentions to close 21 plants and cut 70,000 jobs. Quickly, this plant of more than 4,000 workers found itself in a "whipsaw" competition with a similar plant located in Arlington, TX—a competition it ultimately lost. Within 2 months of the announcement of Willow Run's closure, there were five worker deaths—four heart attacks and an aneurysm all among 30- to 40-year-old workers.[8] The plant was eventually closed in 2010[13] after several legal battles against GM by Ypsilanti Township and the State of Michigan.[8]

Plant 3 was originally a Chevrolet steering manufacturing plant located in Saginaw. When it closed in 2014, it took with it the remaining 600 jobs, a mere fraction of the 1,000s it had employed at the peak of GM's US manufacturing.[14]

Using individual-level work histories and mortality records from unionized autoworkers at these plants, we examine the impact of leaving active GM employment on the risk of suicide and drug overdose. Job loss in this cohort was recently linked with increased risk of suicide and overdose, particularly for those who left work prior to retirement age.[15] We apply a novel nonparametric approach to examine the risk of suicide and fatal drug overdose that would have been observed if each employee's propensity for loss of active GM employment were altered by an odds ratio, δ. This approach is able to investigate the effects of more realistic, dynamic exposure scenarios than those traditionally analyzed in epidemiologic studies (e.g., average treatment effects) without needing to meet strict positivity assumptions for identifiability.[16,17]

METHODS

This research was approved by the Committee for the Protection of Human Subjects at the University of California, Berkeley (Protocol no. 2013-11-5825).

Study Population

The United Autoworkers-General Motors (UAW-GM) cohort includes nearly 39,000 autoworkers at three Michigan plants followed for mortality beginning in 1941.[18] Individuals hired after 1938 and employed a minimum of 3 years prior to 1 January 1985 were eligible. Employment records and job histories track workers through the end of 1994. We used these records to extract general demographic data as well as exposure histories based on time spent in machining, grinding, and assembly jobs. Due to administrative censoring of work records, almost 11,000 members of the original cohort were still employed at the end of 1994; their employment status from then through the end of follow-up remains unknown. We restrict the analytic cohort to those who were still at work in, or hired after, 1970 in order to capture the period of downsizing at the plants.

Outcome

Vital status follow-up covers 1941 to 2015. We extracted mortality status and cause of death from state vital records and the National Death Index. The International Classification of Disease codes for suicide and overdose are listed in the Appendix and are based on designations developed by the Centers for Disease Control and Prevention.[19,20]

Exposure

For the nonparametric approach described below, the exposure of interest (A_t) is a binary measure of whether the individual is an active (currently employed) or inactive (after the person has left employment) employee at one of three GM plants at time *t*. There are many reasons an employee may terminate employment; the data do not differentiate between voluntary and involuntary job loss. We focus on a period of GM's history during which automobile manufacturing in Michigan was declining; leaving work was thus more likely tied to plant downsizing and closure than other reasons. Individuals no longer actively employed at GM might find employment elsewhere. However, over this same period, finding new employment in a comparable job was increasingly unlikely. Ford, Chrysler, and GM lost considerable market share to foreign manufacturers[10] and entered a period of shock and slow recovery from the late 1970s through the 1980s. Between 1977 and 1987, the US auto industry cut nearly 500,000 jobs nationally, with more than 60,000 jobs lost in the counties where the UAW-GM cohort is located.[21]

Confounders

The UAW-GM records included information on a number of employee characteristics that may confound the exposure-outcome relationship of interest. We adjust for time-varying measures such as employee age, calendar year, pension eligibility, cumulative time off work, and proportion of the year spent in either machining or assembly or off work. Fixed characteristics such as year of hire, race, and sex are also incorporated in the IPS analysis. Unfortunately, this administrative dataset lacks information for many health-related factors, such as injury, drug abuse, or depression, that may further confound job loss and self-injury mortality. A directed acyclic graph (DAG) of the hypothesized causal relationships was provided in previous work.[15]

Missingness was handled as in previous studies of this cohort. The 8% of workers in the cohort with missing race were assumed to be white. Gaps in the employment record were interpolated when no more than half of the record was missing. Those missing more than half of their employment record were excluded from the analysis.[22,23]

Statistical Analyses

Incremental Propensity Score Method

We used a novel nonparametric approach, the incremental propensity score (IPS) method,[16] to examine the association of loss of active GM employment and self-injury mortality, a composite outcome consisting of cases of suicide or fatal drug overdose. Initially, we considered using standard marginal structural models[24] that would allow us to examine the average treatment effect comparing cumulative self-injury mortality when all employees are set to inactive status versus when none of the employees are set to inactive status. Upon further consideration, concerns about identifiability and about the utility of the parameter to be estimated (see below) motivated a new scientific question and necessitated the use of an alternate approach.

Propensity scores in marginal structural models are most commonly applied through variations of inverse propensity score weighting (IPW), a common causal inference technique that disrupts exposure-outcome confounding by generating a "pseudo-population" where exposure assignment is independent of measured covariates. To generate the pseudo-population, individuals are inverse weighted by the propensity of their received exposure. IPW methods are vulnerable to many threats common in observational data. For example, positivity violations, which are nearly certain to occur in longitudinal data like the UAW-GM cohort, can result in highly unstable weights. Furthermore, IPW methods are often applied to causal questions concerning deterministic exposure assignment, frequently relying on a comparison of counterfactual outcomes under an intervention in which all individuals receive one level of exposure to those under another in which all individuals receive an alternative level of exposure, regardless of how unrealistic such an intervention may be.

These drawbacks were avoided by instead estimating IPS effects, a "natural alternative" to the average treatment effect.[16,17] Instead of directly intervening on the exposure itself, the IPS method intervenes by shifting the propensity of exposure. The IPS method is described in detail elsewhere[16,17]; however, we highlight a few key components here for clarity. Using parametric or nonparametric estimation techniques, IPS replaces the observed propensity of exposure, π_t, with a shifted propensity of exposure, q_t, and then examines the impact on the outcome. Equation 1 demonstrates how the observed propensity, π_t, and the desired size of the intervention, δ, inform the shifted propensity, q_t. Both the observed and shifted propensities depend on the observed history of exposure and other measured covariates, h_t.

$$\delta = \frac{q_t(h_t)/\{1-q_t(h_t)\}}{\pi_t(h_t)/\{1-\pi_t(h_t)\}} \tag{1}$$

The IPS intervention can be thought of as applying a proportional shift (δ) to the observed odds of exposure. Unlike assigning all individuals to one level of exposure versus another, this intervention examines how outcomes would have changed with only slight, perhaps more realistic, adjustments to the observed exposure distribution. For example, consider two hypothetical employees with propensities of 3% and 50% of leaving employment in a given year. Applying an IPS intervention, we can examine what would happen to the risk of suicide and fatal drug overdose if each individual's propensity to lose employment were increased by 20% ($\delta = 1.2$). For these two employees, this is equivalent to now observing their counterfactual outcomes under propensities of 3.6% and 60% of leaving GM, respectively. Despite applying a fixed intervention ($\delta = 1.2$), the intervention effect is dynamic, as it depends on each individual's characteristics and exposure history.

With the IPS approach in mind, we asked the following question: if we changed the odds of leaving GM employment by a constant factor in every calendar year of follow-up from 1970 to 1994, how many self-injury deaths would we expect by 2015? Our outcome (Y) was self-injury death, either by suicide or overdose, by the end of follow-up in 2015. The exposure of interest (A_t) was having left GM employment at time t, where t denotes the years from 1970 until 1994; this whole exposure history is included in the outcome model. Figures A1 and A2 provide diagrams of the data and cohort. The IPS intervention shifted the annual observed odds of having left GM employment by a multiplicative factor of δ ranging from 0.75 (proportionally decreasing the odds of leaving work by 25%) to 1.25 (proportionally increasing the odds of leaving work by 25%). We summarized results using an incremental effect curve $\psi(\delta)$, which allows for a nuanced examination of "protective" ($\delta < 1$) and "harmful" ($\delta > 1$) interventions concurrently.

Over the years 1970 to 1994, we modeled propensity to leave work, π_t, using random forests based on time-varying measures (cumulative years of employment, proportion of year spent in machining or assembly, proportion of time spent off work, plant, calendar year, age, pension eligibility, and cumulative time off work) and baseline measures (year of hire, race, and sex). The outcome model uses random forests to recursively regress the outcome (observed in 2015) onto the covariate (year of hire, race, sex, and pension eligibility) and exposure histories (observed until the time of the event, the time of censoring, or the end of employment records in 1994, whichever comes first). Finally, we generate the expected outcomes under an IPS intervention by the fitted outcome model. Modeling is performed with sample splitting to avoid overfitting. See the Appendix and Algorithm 1 in Kennedy[16] for more detail. We estimate confidence intervals pointwise, via influence curve-based estimation, and uniformly, via the multiplier bootstrap.[16]

In addition to the advantage of estimating quantities of greater interest, identification relies solely on meeting consistency and exchangeability assumptions. Furthermore, nonparametric propensity estimation that is robust to model misspecification can be used instead of parametric propensity models, mitigating sources of inefficiency and bias in estimation.

Secondary analyses restricted follow-up to shorter periods. Specifically, we examined the effects of the same IPS interventions in relation to self-injury deaths by 1995 or 2005. These analyses examined whether the impact of job loss during a period of industry decline on self-injury mortality changes over time. Furthermore, by linking more temporally proximate self-injury mortality events to the period of recorded employment histories, we hoped to strengthen the validity of the statistical findings and mitigate potential exposure misclassification due to the subsequent unknown employment status of those still working at the end of 1994.

All analyses were carried out using R version 4.0.2 "Taking Off Again".[25] The plots relied on functions from the "tidyverse",[26] a collection of data science R packages with shared grammar and data structures, as well as general data management R packages.[27–29] The function *ipsi* from the "npcausal" package was used to estimate the effects of the IPS intervention.[30] The treatment and outcome models rely on the random forest implementation from the "ranger" package, using default settings for hyperparameter tuning.[31] All code necessary to reproduce these analyses can be found on GitHub (https://github.com/sdufault15/uaw-gm-ips).

RESULTS

The Table presents the characteristics for the cohort used in the IPS analysis. There were 201 suicides and 54 fatal overdoses by 2015 among the 29,538 UAW-GM employees who were actively employed on or after 1 January 1970. The majority of the cohort was white (72%) and male (87%), with men accounting for approximately 95% of all suicides and fatal overdoses.

Figure 1 shows the annual counts of suicide and fatal overdose (bars) and the annual number of actively employed individuals (line) for the cohort from 1941 until 1994. Prior to 1980, the UAW-GM workforce exhibited primarily monotonic growth with approximately a 4% annual worker exit rate. After 1980, the annual worker exit rate increased to nearly 14% and the number of active employees was eventually reduced to quantities not seen since the late 1960s. In 1994, an estimated 60% of UAW-GM employees at Plant 1 left GM due to massive downsizing efforts. Plants 2 and 3 maintained similar worker exit rates as observed in previous years, although these plants would later undergo massive downsizing and layoffs in the late 1990s and early 2000s, after our employment records end.

TABLE. Characteristics of the Analytic Cohort, Suicide Cases, and Overdose Cases, UAW-GM Cohort 1970–2015

	Analytic Cohort	Suicide Cases	Fatal Overdose Cases
N (person–years)	29,538 (1,144,720)	201 (4,659)	54 (1,281)
Race, *n* (%)			
White	21,195 (72%)	154 (77%)	35 (65%)
Black	6,126 (21%)	25 (12%)	15 (28%)
Unknown	2,217 (8%)	22 (11%)	4 (7%)
Sex, *n* (%)			
Male	25,576 (87%)	191 (95%)	51 (94%)
Female	3,962 (13%)	10 (5%)	3 (6%)
Plant,[a] *n* (%)			
Plant 1	6,495 (22%)	29 (14%)	10 (19%)
Plant 2	12,277 (42%)	97 (48%)	36 (67%)
Plant 3	10,729 (36%)	75 (37%)	8 (15%)
Complete work records[b]	18,568 (63%)	167 (83%)	33 (61%)
Year of hire	1968 (1959–1976)	1968 (1962–1976)	1976 (1976–1977)
Age at hire	24 (20–31)	23 (20–28)	21 (20–24)
Year of birth	1943 (1929–1951)	1945 (1933–1953)	1954 (1950–1956)
Year of worker exit[c]	1983 (1977–1990)	1983 (1977–1988)	1985 (1980–1988)
Age at worker exit[c]	52 (37–60)	40 (32–52)	33 (26–37)
Length of follow-up	36.34 (30.39–42.69)	18.9 (9.85–28.39)	24.27 (13.68–31.49)
Age at death among deceased	69 (59–79)	51 (40–61)	52 (44–56)
Year of death among deceased	2000 (1990–2008)	1993 (1984–2003)	2003 (1993–2009)

Notes: Statistics shown are median (first quartile, third quartile), unless indicated otherwise.
[a]Some subjects worked at several sites; plant indicates the site of longest work record time.
[b]Employment records end on December 31, 1994.
[c]Among those with known date of worker exit.

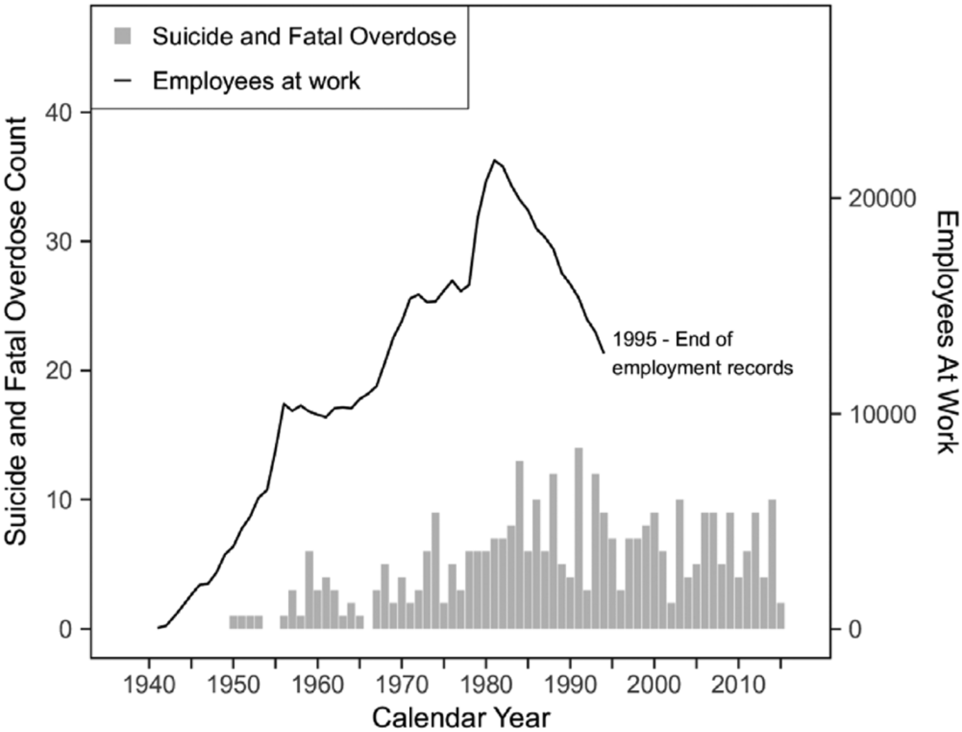

FIGURE 1. Annual counts of suicide and fatal overdose (bars) and the annual number of actively employed individuals (line) in the United Autoworkers-General Motors cohort 1941–1994.

Figure 2 displays a deeper investigation into the effects of the declining American auto manufacturing industry. The presented IPS curve shows the effect of proportionally shifting the odds of leaving work for all individuals over the entire range δ. Under no intervention effect (δ = 1.0), there were 255 observed self-injury mortality cases by 2015, corresponding to a cumulative incidence of 0.87%. A 10% shift in the odds of leaving work had larger estimated impact on overall self-injury mortality when increasing the odds of leaving work (303 cases; 95% confidence interval [CI] = 247.1, 358.8) compared to decreasing the odds of leaving work (234 cases; 95% CI = 207.1, 261.4). Stated another way, a 10% decrease in the odds of leaving work (δ = 0.9) results in only a 8% drop in self-injury mortality by 2015 while a 10% increase (δ = 1.1) results in a 19% increase in self-injury mortality by 2015.

Figure 3 contains the results from the secondary analysis and presents the overlaid IPS curves when self-injury mortality cumulative incidence is measured by 1995 and 2015. Furthermore, although there are fewer self-injury deaths when follow-up ends earlier, the point estimates suggest that the effect of an incremental shift in the odds of leaving employment may decrease over time. For example, when the odds of leaving work are decreased by 10%, the expected cumulative self-injury mortality by 1995 drops by 16.1% (114 cases; 95% CI = 95.95, 132.3), approximately double the effect that was estimated for cumulative self-injury mortality by 2015. Such trends are also observed when the odds of leaving work are increased. When the odds of leaving work are increased by 10%, the expected cumulative self-injury mortality by 1995 increases nearly 41% (191 cases; 95% CI = 142.5, 240.2) from what was observed. Individual IPS curves for 1995, 2005, and 2015 can be found in the Supplemental Figure 1; http://links.lww.com/EDE/B896.

DISCUSSION

This analysis of the UAW-GM cohort provides evidence of an association between job loss and self-injury mortality. Assuming consistency and no unmeasured confounding, increases in self-injury mortality in this cohort are consistent with the hypothesis of a role played by rampant loss of employment. Furthermore, IPS analyses provide a nuanced view of how a shift in the odds of leaving work might impact self-injury mortality in this cohort, and how that effect may change over time.

The estimated effect was stronger for increasing the propensity of leaving work than it was for decreasing it. This asymmetry may reflect a threshold effect: increasing the odds of job loss beyond a certain level (or actually losing one's job) creates a stressor, a psychological burden that becomes increasingly difficult to bear, leading to much higher risk of self-injury mortality. However, feeling moderately secure in one's employment is the absence of a stressor. Decreasing propensity for leaving work has only a small impact because it still corresponds to the absence of the stressor.

This is one of the first applications of the IPS method. In a standard analysis of these data, there would be two major barriers to identifiability. First, positivity would almost certainly be violated in this observational setting. For example, due to "last in, first out" agreements, recent hires would have a near zero probability of

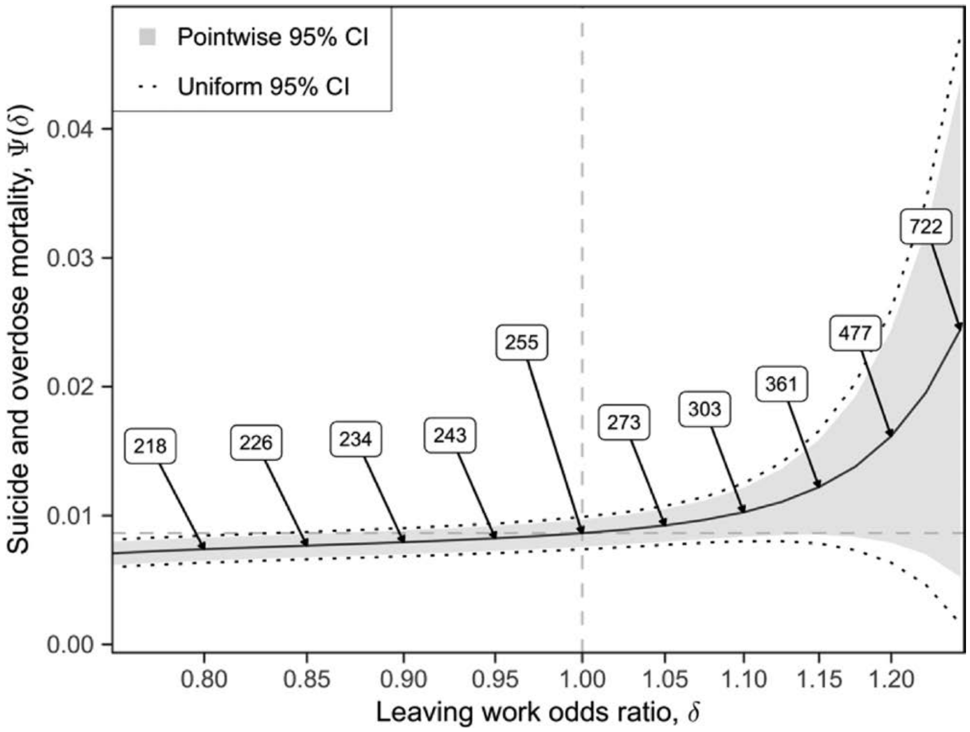

FIGURE 2. Risk of self-injury mortality by 2015 if the odds of leaving work were multiplied by a factor δ, with pointwise and uniform 95% confidence bands. The corresponding number of observed ($\delta = 1$) and expected ($\delta \neq 1$) mortality events in this cohort are noted in the labeled bubbles.

staying employed as extreme downsizing efforts swept the plants. Even near-violations of positivity can render classical causal inference estimation nonidentifiable or inefficient.[16] The IPS approach is one of few that avoids positivity assumptions entirely.

Second, the extended follow-up of this longitudinal dataset carries with it the curse of dimensionality. Parametrically specifying a propensity model is a common solution to this dilemma but would be ill-advised here. Instead, the IPS approach employed here uses machine learning techniques to model the treatment and outcome nonparametrically, relying less on assumptions of model specification while still returning estimates with desirable statistical properties.

Consistency, Kennedy points out, can be violated in settings with interference.[16] Interference is possible here, since the disruption to social networks and heightened worker anxiety may cause an individual's self-injury mortality to be influenced by a coworker's job status. It is unclear how substantial this effect would be on the estimates, although it would likely bias the results towards the null due to increased similarities in outcomes between those still at work and those separated from work.

A further threat to consistency is our inability to distinguish forced job separation (e.g., layoffs) from voluntary job separation (e.g., retirement). Specifically, this relates to the treatment version irrelevance assumption, also referred to as stable unit treatment value assumption (SUTVA), which assumes there is a single version of the exposure present. In this setting, there may be many reasons an employee leaves work (e.g., retirement, layoff, etc.), which could have different effects on potential outcomes and hence violate SUTVA. In a recent analysis of suicide in the same cohort using Cox models, we distinguished retirement from involuntary job loss by defining exposure as age at leaving and comparing hazards between those who left before and after retirement age (age 55). Those who left work at 19 to 29, 30 to 39, and 40 to 54 years of age had hazard ratios for suicide or overdose of 2.2, 2.4, and 1.5, respectively, compared to those who left after age 55.[15]

Exchangeability depends on the identification and measurement of an adequate set of confounders such that leaving work is essentially randomized within strata of the UAW-GM employees. In this analysis, there are lingering threats to exchangeability. While there are extensive employment and death records, we lack data on many health-related factors, such as injury, drug abuse, or depression, that may confound job loss and self-injury mortality, the relationships of which have been proposed via DAG in previous work.[15] However, there is a robust literature on economic decline and deaths by suicide.[32]

Job loss may also increase risk of other outcomes, such as deaths from cardiovascular disease or stroke, which could result in informative censoring in this cohort. A person who died of another cause was coded as not having died of self-injury, but perhaps if they had not died of something else, they would have died of self-injury. Our analysis did not adjust for this, but we believe any resulting bias is likely to be towards the null; secondary analyses with shorter follow-up (and thus less censoring by mortality from other causes) showed stronger effects.

Nearly two-thirds of the IPS analytic cohort left work by the end of employment records in 1994. All three of the study plants were closed by 2015.[12–14] Thus, we know that those still employed in 1994 had all left employment by the end of follow-up. What remains unknown is exactly when they became inactive, posing a threat to exposure classification. Thus, our

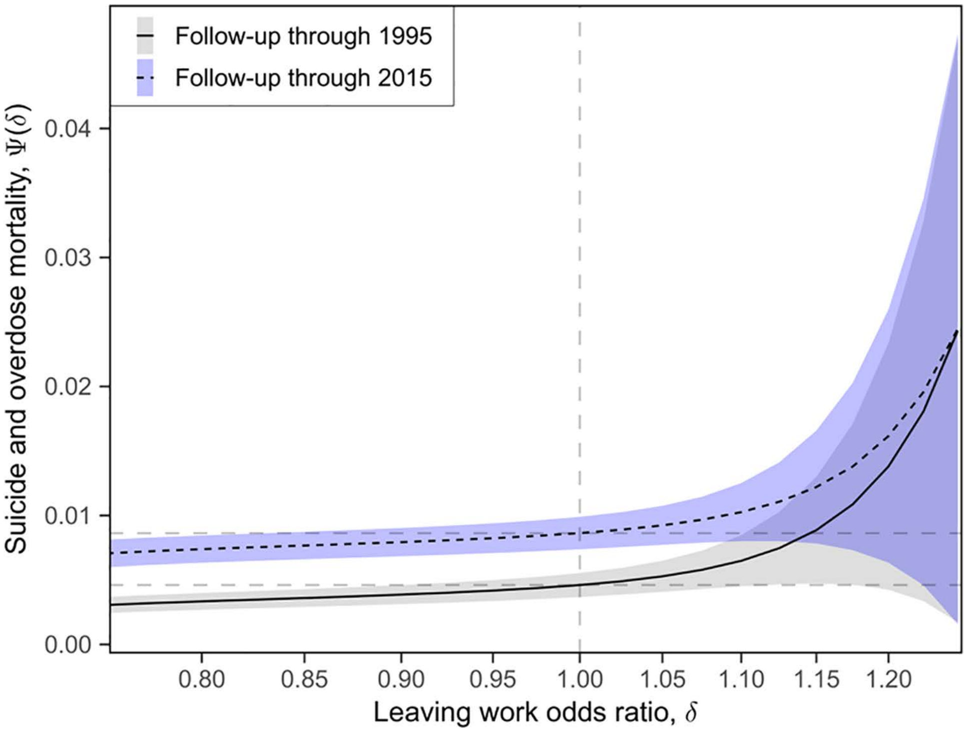

FIGURE 3. The estimated risk of self-injury mortality by 1995 (solid line) and 2015 (dashed line) if the odds of leaving work were multiplied by a factor δ, with uniform 95% confidence bands.

analysis explicitly targets interventions on propensity to leave work during 1970 to 1994. The stronger effect observed when follow-up was truncated earlier might imply that some self-injury mortality later in follow-up resulted from later job losses not affected by the intervention. The absolute change in number of self-injury deaths was similar for the main and secondary analyses, making the relative change greater for the shorter follow-up. Moreover, we examine employment status prior to 1994 with outcomes observed through the end of follow-up in 2015. Although long-term impacts of job loss on depression have been described,[33] the potential discrepancy between timing of exposure and outcome may have biased our results towards the null by dampening the signal between the propensity to leave work and self-injury mortality in the outcome model. The stronger effect sizes observed in the secondary analysis might also support this hypothesis. The lack of detail on reasons for leaving work and the ensuing difficulty in conceptualizing a "well-defined" intervention that would be both feasible and clearly represent the causal effect of interest in this study, may limit the direct applicability of the estimated effects to policy. However, as Pearl notes, causal effects are not limited to variables or causes that we can manipulate or those for which we can conceive feasible interventions.[34] The estimated parameters in this study may be more relevant in the realized causal effect framework[35] where causal contrasts can be defined without necessarily representing a (feasible) intervention.

Understanding the relationship between job loss and self-injury mortality is now more critical than ever. Historical data from industries that have experienced rapid growth and subsequent decline can provide insight to inform labor policy and improve work culture. This work will continue to be relevant as many American industries and their workers continue to feel the pressures of the current pandemic and the ever-changing global economy.

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APPENDIX

Outcome definitionsSuicide was defined by ICD-9 codes E950-E959 and ICD-10 codes X60-X84, Y87, and U03. Overdose was defined by ICD-9 codes E850-E858, E980.0-E980.5 and ICD-10 codes X40-X44 and Y10-Y14.

Data Structure

Cohort Diagram

IPS Estimation

Using the IPS method, we apply a stochastic dynamic intervention that shifts the odds of leaving work within a given year of employment by a multiplicative factor δ. This approach allows us to qualitatively assess the impact of leaving employment on suicide and fatal drug overdose deaths while relying solely on the assumptions of consistency and exchangeability.More technical information about the implementation of this method can be found in Algorithm 1.[16] Briefly, to implement the IPS method requires estimating two nuisance functions: (1) the propensity of exposure at each time *t*, and (2) pseudo-outcome models under the observed covariate history when the exposure is set to 1 or 0. Roughly, these steps are as follows for each incremental intervention δ:

Exposure

1. Split the sample. Separate the data into training and testing subsets.
2. Using the training data, model the propensity for employment termination by regressing the observed employment status at each time *t* on the observed covariate history. In this analysis, this regression was performed by nonparametric random forests.
3. For everyone in the sample (training and testing), predict the propensity of employment termination for each individual at each time *t* using the model from the previous step. These predicted propensities are used to establish the exposure distribution at each time *t*.
4. For those in the testing subset, apply the incremental intervention: multiplicatively shift the observed exposure distribution of propensity scores such that the odds of employment termination for each individual at each time *t* is shifted by δ.

Outcome

5. Using the training subset, recursively regress the observed outcome (fatal drug overdose or suicide) on the observed covariate history and observed employment status at each time *t*. In this analysis, this regression was also performed by nonparametric random forests.For everyone in the sample (training and testing) and at each time *t*, using the model from the previous step, predict the expected "pseudo-outcomes" using the observed covariate history, but setting employment termination to 1 and then to 0.

Relating the Outcomes to the Shifted Exposure Distribution

Combining the shifted exposure distribution and the predicted pseudo-outcomes, estimate the impact of the incremental shift in the propensity of employment termination in each year *t* on suicide and fatal drug overdose by the end of the study period.

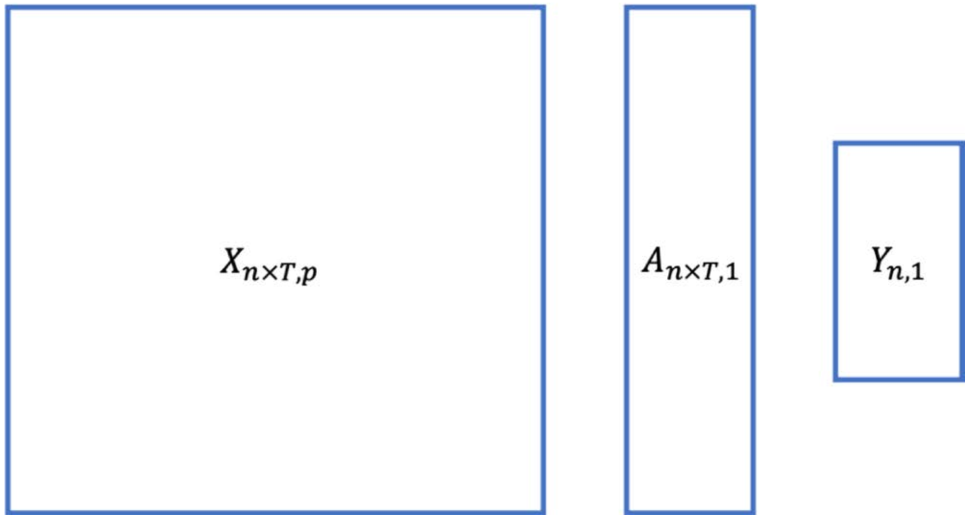

FIGURE A1. A generalization of the data necessary for IPS analysis. Covariate data (X) and exposure (A) are expected to be time-varying and measured throughout the course of the study. For a sample of size *n* with study length *T*, X should be a matrix with $n \times T$ person-year rows and *p* covariate columns. In this analysis, this means each individual will have a person-year row from 1970 to 1994. The exposure, A is a {0,1} vector of length $n \times T$ that captures the active (A = 0) or inactive (A = 1) employment status in each year for each individual. The outcome (Y), unlike X and A, is only measured at the end of the study. Therefore, Y is a {0,1} vector of length *n*. More information can be found in the "npcausal::ipsi" documentation.[30]

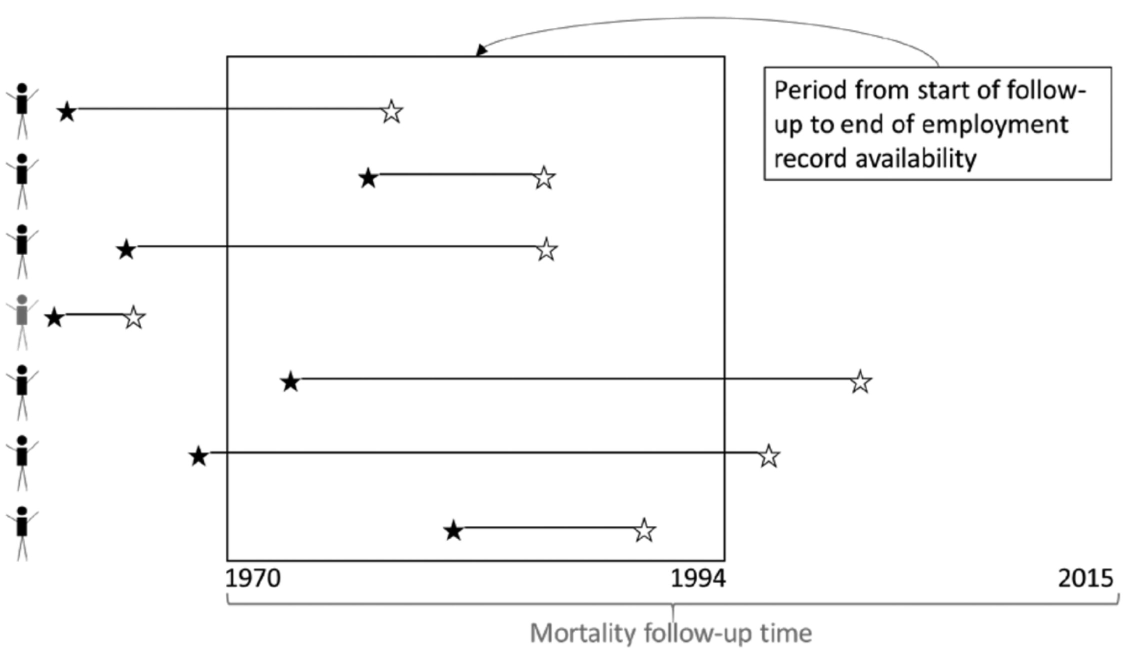

FIGURE A2. Diagram illustrating a few examples of workers in the cohort. Black stars represent hire and white stars represent end of employment at GM. The large rectangle represents the period from start of follow-up to end of employment records, 1970–1994, which is also the period of the hypothetical IPS intervention on employment. Mortality follow-up time goes from 1970 to 2015. Workers 1, 3, 4, and 6 were hired before 1970. Workers 2, 5, and 7 were hired after 1970. Person 4 (gray figure) left GM before 1970 and is therefore excluded from the cohort; everyone else is included. Workers 1, 2, 3, and 7 left GM during the period when employment records were available, while workers 5 and 6 left after 1994 and thus have incomplete exposure information. The analysis considers an intervention on propensity to leave employment only during the period in which employment data are available, but the outcome of self-injury mortality is assessed for everyone through 2015.