CAPITALISM AND ITS DISCONTENTS

MASS LAYOFFS AND DEATHS OF DESPAIR

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Abstract. We observe a relationship between mass layoffs and *deaths of despair*. In particular, we use data from the BLS (Bureau of Labor Statistics), the CDC (Center for Disease Control), and the BEA (Bureau of Economic Analysis) to analyze how mass layoffs affect deaths from alcohol, drugs, and suicide at the county-year level. In agreement with previous literature, we find that naive income is a poor explanatory variable for these deaths of despair after controlling for mass layoffs. Contrasting with previous literature, we find that combining drugs and alcohol into one outcome variable is a flawed method of analysis. While the exact relationship between mass layoffs and deaths of despair is complicated, our analysis makes clear that there is a highly significant relationship between mass layoffs and deaths from alcohol, drugs, and suicide.

Contents

Date: June 12, 2020.
Key words and phrases. Health, labor, deaths of despair, mass layoffs.
Our code is available on GitHub.

1. Introduction

With the improvement of medical technology, overall mortality rates have been dropping since the beginning of the twentieth century. This reduction in mortality has come to be an expectation of modern day life for all age groups and all demographics. However, Case and Deaton (2015) documents a very strong counterfactual to this trend: they find that all-cause mortality among middle-aged non-Hispanic whites stopped making progress around the turn of the century and has been worsening since then. This peculiar fact is only observed in the United States, with midlife mortality decreasing for all peer countries of the United States.

The authors break down this death data further find that the culprit behind this rise in all-cause mortality is a rapidly ascending rate of what they call *deaths of despair* among middle-aged non-college-educated non-Hispanic whites. The term *deaths of despair* refers to deaths related to alcohol and drug overdoses, suicide, liver disease, and the such. More broadly, these are all deaths that can be attributed to a "lack of hope" in ones future. The sharp increase in these deaths, even in such a narrow demographic group of middle-aged non-Hispanic whites without a college degree, is enough to increase all cause mortality for all middle-aged non-Hispanic whites, even outweighing decreases in mortality due to advances in medical technology.

While Case and Deaton have no doubt that there are economic drivers behind this trend, they find that naive income explanations (in particular stagnating or even declining incomes) serve as poor explanatory variables for this rise in mortality (Case and Deaton, 2017). Instead, the authors propose a preliminary story of cumulative disadvantage. To elaborate, the level of labor market outcomes or income is not the primary factor behind this rise in "deaths of despair," but rather the fact that reality sharply falls short of expectations.

Why this impacts non-Hispanic whites in particular (in contrast with say African Americans or Hispanics) is that in the past, especially in the in twentieth century, non-Hispanic whites have had a very optimistic view of the future, with each generation doing better than the next. However, in recent years, this trend has reversed for white non-Hispanics without a college education, with children in this category finding themselves much worse off than their parents. Cruel reality becomes especially unbearable as members of this demographic approach midlife, leading to the aforementioned deaths of despair. Meanwhile, for African Americans, the decrease in economic and social inequality between them and Caucasians have given the hope. In a similar vein, many Hispanic Americans are finding themselves in a much better economic condition than their immigrant parents. For these reasons, this rise in deaths of despair is unique to white non-Hispanic males.

We explore this hypothesis further by studying the impact that mass layoffs have on deaths of despair. We believe that the number of mass layoffs on the county-year level is a particularly good explanatory variable for three reasons:

(1) They serve as an immediate shock on labor market outcomes relative to expectations
(2) These mass layoffs are mostly likely to be blue collar jobs, thus their impact is mostly felt by people without a college education, one important aspect of the target demographic of Case and Deaton (2017)
(3) Mass layoffs are symptoms of macroeconomic trends such as decreased global demand for a firm's products or the entry of competitors from China, rather than local economic conditions such as labor supply. Thus, we say that mass layoffs act as an exogenous shock to the local economy of the county.

We focus on three types of deaths of despair: deaths from drug abuse, deaths from alcohol abuse, and suicides. We chose these types of deaths of despair because Case and Deaton (2017) find that drug and alcohol deaths appear to show the most dramatic impacts and because suicide is a leading cause of death in the United States (National Institutes of Mental Health, 2020). We decided to not analyze deaths from liver disease because we expect that those results are closely related to the deaths from alcohol. We did not look at heart disease and lung cancer because medical advancements in those fields over our time frame might affect our results (particularly if they are distributed differently). We have panel data with a very high number of observations from all the counties in the United States over the years 1999-2012, as well as layoffs data from 1997-2012.

Much of the other literature that studies the economic causes of death is medical literature, which is largely focused on small samples and case studies. Catalano et al. (2012) study the impact of mass layoffs on *in utero* deaths (deaths of babies in the womb) in California. Dean and Kimmel (2019) study the impact of free trade on death in increasing opioid overdoses and find that the loss of 1,000 jobs due to free international trade led to 11.3% increase in opiod overdoses when fentanyl was present in the heroine supply. Lastly, Beale and Nethercott (1985) study the impact of a single factory closure on 125 families and finds an dramatic increase in morbidity among these families as a result of the mass layoff.

We add to the literature by conducting a large scale cross-country analysis on the relationship between mass layoffs and deaths of despair.

The paper proceeds as follows: Section 2 is a description of our data; Section 3 describes our regression models; Section 4 contains our analysis of drug and alcohol deaths; Section 5 contains our analysis of deaths from suicide; Section 6 contains some general discussion; and we conclude with Section 7. A note on our tables: the width of many of our tables caused us to place the majority of them in our appendix. When these tables are referenced in the body of the paper, there will be a link to the appropriate table.

2. Data

Our dataset comes from three sources: the Bureau of Labor Statistics' (henceforth BLS) Mass Layoff Statistics program (Bureau of Labor Statistics, 2012), the Center for Disease Control and Prevention's (henceforth CDC) Wonder Database (CDC Wonder, 2020), and the Bureau of Economic Analysis's (henceforth BEA) Regional Economic Accounts (Bureau of Economic Analysis, 2020). The BLS dataset documents mass layoffs in a given county for any given year between 1997 and 2012.[1] The CDC Wonder dataset documents deaths by cause of death (alcohol, drug, suicide, etc) for any given county from 1999 to the present. For our data analysis purposes, we merge the two datasets at the county year level. We examine county-year units from 1999 to 2012 and use the earlier years from the BLS to create lagged variables. For our outcome variables, we focus on alcohol deaths, drug overdoses, and suicides. Lastly, our income control data (per capita income by county by year) comes from the BEA.

It should be noted that while Case and Deaton study both mortality and morbidity, we study only mortality in our paper. This is because there is higher quality data on mortality, which is validated by death certificates, rather than morbidity data, which is mostly obtained through surveys and hence is usually self-reported. Moreover, we focus on alcohol and drug overdoses as well as suicide for our deaths of despair over alternative outcome variables such as liver disease, heart disease, and lung cancer studied in Case and Deaton for a few reasons: (1) trends in these variables are complicated by many other factors, such as advances made in medical technology; (2) the time horizon for these deaths are potentially much higher from onset of the mass layoff than the three outcome variables we chose to study; and (3) concerns about unobserved health data.[2]

Our data has some quirks that we should explain. For privacy reasons, CDC Wonder drops all rows of data with less than 10 observations. For example, if there are less than 9 alcohol related deaths in Cook County in the year 2020, our data set will simply ambiguously omit the row. Thus, when there is a county-year row missing in our mortality data set, there could be anywhere from 0-9 deaths in that county that year. This is obviously an issue that could bias our data but as an immediate solution we simply omit those county years from our analysis. Unfortunately, this does mean that we at most have only fourteen thousand observations out of the conceivable forty-eight thousand potential county-year combinations. Nonetheless, we stand by our decision to omit these county-years as including them would substantially bias our results because many counties would be recorded as going from zero to ten or ten to zero deaths in a given year. As a result of this data limitation, our results are

[1]At this point, the BLS Mass Layoff Statistics Program has unfortunately become a casualty of budget cuts.
[2]This has to do with CDC privacy guidelines. We explain in next paragraph.

probably most applicable to counties that begin with higher baseline deaths in the category we examine.

On the other hand, our BLS layoff data is comprehensive: if a row is missing, then there was no mass layoff that year. The BLS defines a mass layoff to be where 50 or more initial claims are filed against the same employer within a 5 week period and when an employer indicates 50 or more people were separated from their jobs for more than 31 days. This aligns with what one would imagine to be the traditional idea of a mass layoff: a separation event where many people lose their jobs at a certain firm for the long term.

We present a table and a figure to help the reader gain an impression of our data.

Table 1. Mortality Data Summary

Statistic	Alcohol/Drugs	Alcohol	Drugs	Suicide
Mean	53.75	38.622	44.493	36.034
Median	23	21	21	20
25%	14	13	14	13
75%	49	40	44	38
Max	1,990	1,148	867	808
N	14,125	6,818	9,611	11,471

The above table contains quantile information that motivate our concerns regarding CDC data. The fact that CDC reports NA for any subdivisions with count less than 10: our 25th quantile is rather close to ten for every category, combined with the fact that we generally only have observations for around a quarter of the possible county-year combinations, we expect that we lose a significant amount of data due to the CDC's privacy concerns. It is for this reason that we did not further break down our analysis by race or by age.

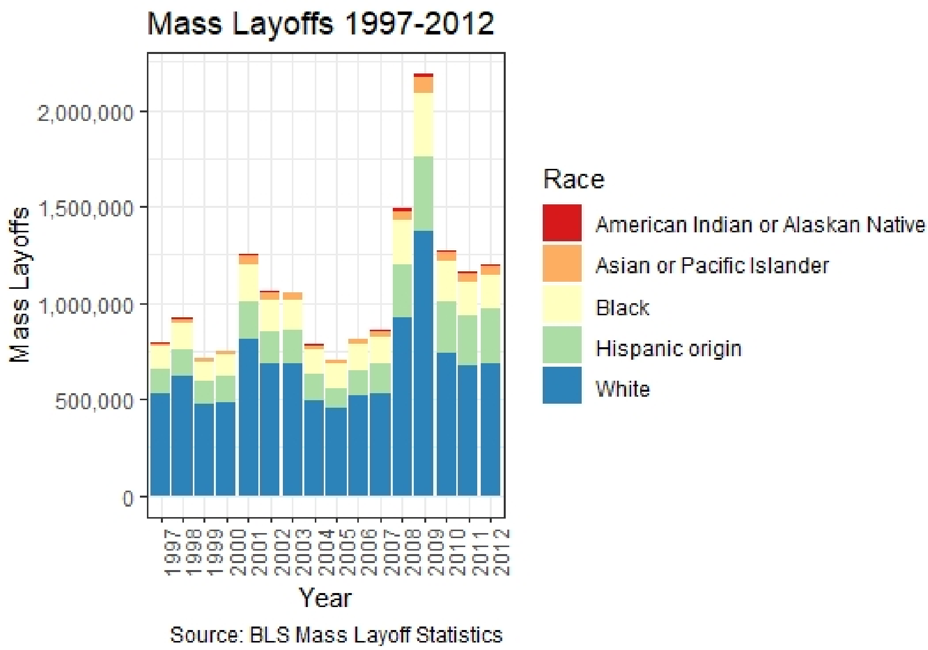

Figure 1. Mass Layoffs by Race, 1997-2012

Figure 1 depicts the distribution of mass layoffs across time and by race from 1997-2012. As expected, mass layoffs spiked during the recession following the 2008 Global Financial Crisis. In every year, the subset of Americans most impacted in raw number by mass layoffs is white Americans. However, this impact is not disproportionate to the population distribution of race.

3. Model

We began with a few variations on fixed-effects models and conducted LASSO regressions. The tables for our fixed-effects regressions we have put in the appendix because they are generally too large to fit in the body of the paper in a readable manner. Note that the table numbers are also links: if you click the number in "Table 4," you will go immediately to the location of the table in the appendix.

3.1. **Fixed Effects.**

Since we had data for multiple years by county across the entire United States, we began by using fairly standard methods of analyzing panel data, i.e. two-factor fixed-effects models. The first interesting question for our analysis was how many lags to put on the variables. As mortality is a prolonged/long-term outcome, we would not necessarily expect a large number of deaths to result from a layoff within the same year. If mass layoffs have any effect on deaths of despair, we would expect to see at least some results in the years after the layoff, not necessarily immediately.

We thus decided to repeat our analysis with different numbers of lags. We initially ran regressions of the following form:

$$Y_{i,t} = \sum_{j=0}^{J} \mu_j M_{i,t-j}, + \sum_{k=1}^{T} \alpha_k \mathbb{1}[t = k] + \sum_{l=1}^{N} \beta_l \mathbb{1}[i = l] + \epsilon_{i,t}$$

where $Y_{i,t}$ is the number of deaths (of whichever type of death of despair: i.e. alcohol/drug, alcohol, drug, or suicide) in county i in year t, $M_{i,t-j}$ is the number of people laid off in county i in year $t - j$, J varies from 0 to 5, and α_k and β_l represent the year and county fixed-effects respectively.

We considered scaling the number of deaths and the number of people laid off by the population of the county, but we then realized that since we would be scaling both numbers by the same population the regression should turn out the same either way, with the only potential difference being the coefficients on the fixed-effects.

We expected that holding years and counties fixed, mass layoffs would be relatively exogenous to a locality. Indeed, because a firm must be relatively large to even have a mass layoff in the first place by the definition of a mass layoff, we expect that mass layoffs are generally exogenous to the county and occur because of outside macroeconomic factors. To be precise, mass layoffs most likely result from outsourcing, increased automation, or decreased macro demand for the firm's product. All of these factors are exogenous to a particular county. However, we would still expect mass layoffs to be correlated with each other for several reasons. For example, a closed factory cannot lay off more people. On the other hand, (and more importantly) mass layoffs may be likely to come in waves. As fixed capital may take a while to build up, a firm that has a mass layoff one year may lay off more people the next as more of the technology for automation gets built or as an outsourced factory expands.

Although we would expect some counties to be more likely to experience deaths of despair from others – namely those with a higher proportion of non-Hispanic whites without a college degree (Case and Deaton, 2017) – the county fixed-effects will control for these kinds of demographic factors. Thus, once we control for county and year fixed-effects, we expect mass layoffs to be exogenous.

In addition to county-year fixed-effects, we also re-ran our regressions with the model:

$$Y_{i,t} = \sum_{j=0}^{J} \mu_j M_{i,t-j}, + \sum_{k=1}^{T} \alpha_k \mathbb{1}[t = k] + \sum_{l=1}^{N} \beta_l \mathbb{1}[i = l] + \sum_{r \in S} \sum_{q \in (0,T)} \gamma_{rq} \mathbb{1}[s = r, t = q] + \epsilon_{i,t}$$

where s refers to the state county i is in. That is to say, in order to allow different states to experience different macroeconomic effects, we also re-ran everything with state-year fixed-effects.

However, we might wonder whether the impact of mass layoffs on deaths are from the psychological effects of the shock on perception of disadvantage or whether the relationship we observe is just a matter of the economic covariates associated with mass layoffs. For example, mass layoffs might increase the local labor supply, decreasing wages which could be the true driver behind these deaths of despair. Thus we also repeated all of our analysis with income as an additional control variable.

We expected that adding income would not dramatically change our results for several reasons. First, the literature indicates that deaths of despair are not an income story. Case and Deaton (2017) explicitly rules out naive income as the cause of deaths of despair. In the literature from medicine, while the papers generally do not explicitly rule out income in the same way, they tend to point towards the existence of a stress-factor related to mass-layoffs and job loss beyond simply the decrease in income. We also expected the effects of mass layoffs to persist beyond the addition of an income control because of the time factor for deaths of despair. Finally, although we expect that income and mass layoffs will be related (in particular, low local income can result from mass layoffs through increased labor labor supply), we chose mass layoffs in the first place because we expected them to have a shock factor effect with regards to people's understandings of their own levels of labor market advantage or disadvantage.

Recently, literature has come out about a potential mathematical issue with two way fixed-effects documented in the working papers de Chaisemartin and D'Haultfœuille (npub) and Imai and Kim (npub).[3] Essentially, two-factor fixed-effects (in our case, county fixed-effects and year fixed-effects) produce estimates of average treatment effects via weighted sums. However, the interaction between the two-factors may cause negative weights to be placed on some observations when the effect is heterogeneous, which means that even if the average treatment effect is positive for every county, a two-factor fixed-effects regression can still output a negative estimate of the treatment effect manifested within the coefficient. We ultimately decided to continue with our analysis. First, we are not entirely certain that the issues with the interaction between the fixed-effects apply in this case after reading the papers in detail. Second, adding in the state-year fixed-effects did not significantly change our results, and if adding an entire additional set of fixed-effects did not change the results by much, then our results are probably not coming from some weird interaction between the fixed-effects. Most importantly, we found that running the regression with county fixed-effects only did not change the essence of our results (even if it changed the magnitude of our results), which lets us think that we mostly sidestep this issue.

3.2. **LASSO Models.** Ultimately, the differences between our analyses with the different numbers of lags were not particularly helpful in determining how far back we ought to go.

[3]This was brought to our attention by Paco.

In addition, some of our regressions brought up negative coefficients, which concerned us. Recent literature suggests that, with heterogeneous treatment effects, negative weights on some observations can give the appearance of a negative ATE. In hope of removing negative coefficients from our results and determining whether a particular number of lags is ideal, we ran a series of LASSO regressions.

Running a LASSO regression is essentially solving a quadratic programming problem:

$$\beta^* = \arg\min_{\beta} \|y - x\beta\|^2 + \lambda\|\beta\|$$

where $\lambda \in \mathbb{R}$ is an arbitrary penalty parameter that pushes the solution to have fewer nonzero coefficients (Tibshirani, 1996). The relationship between the penalty λ and the error generally depends on the topology of the data x as well as its relationship with the outcome y ; for our data, the optimal penalty[4] was $\lambda^* = 0.5012$ as for all our regressions, most reasonable penalty parameters resulted in the same variables being chosen, and 0.5012 was the smallest tested penalty.

We detail the exact results later in the following sections, but, importantly, every LASSO model we found dropped some lags and had positive coefficients on the non-removed layoffs.

4. Analysis of Drug and Alcohol Deaths

In this section and the following which contains analysis of deaths from suicide, we analyze our regression results in detail. The main takeaways are as follows:

(1) mass layoffs do appear to be a significant determinant of deaths of despair;
(2) our regression results within a particular outcome variable are extremely consistent between specifications: in general, the coefficients on the various mass layoff variables do not change that much;
(3) adding income effects likewise had little impact; and
(4) combining drug and alcohol deaths as one outcome for regressions is misleading.

Our analysis is rather granular. If you would like a broader summary of key results, please jump to the discussion section (section 6).

4.1. **Drug and Alcohol Deaths Combined.**
We started by examining deaths from drug and alcohol combined into a single category because Case and Deaton (2017) indicated that was where they found the strongest effects.

4.1.1. *Fixed Effects Analysis.*
Our results for the initial fixed-effects analysis for alcohol and drugs is in Table 6. This contains our six initial regressions, each with a different number of lags on the mass layoffs variable. Notably, one can observe that when we did the most naive

[4]Optimal in that, with this choice of λ^*, the LASSO-outputted regression coefficients β^* minimize the resulting mean square error.

regression, with just the total layoffs on deaths from drugs and alcohol that same year, we got a highly significant positive result, but that significance immediately disappears when adding more lags. This is an indication of just how related mass layoffs are between years. We do not expect that a mass layoff causes people to immediately die of drug or alcohol poisoning.

We see that all mass layoffs lags are significant in all of these specifications. Overall, the table (Table 6) points to mass layoffs being highly important for deaths of despair. For example, our sixth regression with all five lags indicates that for an increase of 1,000 mass layoffs in a given year, we would expect to see twelve additional deaths four years later from drugs and alcohol alone. Note that the correlation between mass layoffs in consecutive years probably biases the results of the last lag that we include in any given regression specification. This is most notable going from the first regression with no lags to the second regression with one lag, but most likely holds true throughout. Examining our results, one might wonder why we stopped at five years' worth of lags. Because each additional year of lags required dropping a year of data, we ultimately had to make a decision balancing the number of years we thought it worth to include. Because we were looking at drug and alcohol deaths, we thought that it is unlikely that a drug or alcohol death could reasonably be attributed to a layoff that happened six or more years ago.

We do have a few surprises in the table. The fourth regression, the one with the layoffs in the same year and the three lags, stands out as unusual. Not only is the only regression other than the first where layoffs in the same year are significant, but they have a negative impact, and layoffs three years ago, the longest lag in the fourth regression, are significant only at the 10% level. Another unusual thing is that the coefficient on the third lag flips to negative and highly significant in the fifth regression and then returns to being positive while retaining its significance in the sixth regression, while in the sixth regression the first lag suddenly becomes negative and slightly less significant than in the previous regressions.

There are a few possible explanations for these abnormalities. One possibility lies in the nature of mortality and the potential for unusual interplays between layoffs. Although we expect layoffs to be highly positively correlated in consecutive years, once a firm has closed down in an area, the number of firms that can even have mass layoffs has decreased, so a mass layoff five years ago may increase the likelihood of a mass layoff four years ago but decrease the likelihood of a mass layoff two years ago. Similarly, because people can only die once, if say, the effect of a mass layoff one year ago is very significant in both statistical significance and magnitude, (as it appears to be in both our second and third regressions in this table), then perhaps a mass layoff three years ago will increase deaths in the following year, but because those people have already died, it decreases deaths in future years. Alternatively, some of this weirdness may be due to the interaction between the two-factor fixed-effects, the combination of drug and alcohol deaths, or even some other explanation. To truly understand what is happening, we must delve deeper.

We next looked at total deaths from alcohol and drugs with county fixed-effects, year fixed-effects, and state-year fixed-effects. The results of these regressions are in Table 7. Notably the results of these regressions are extremely similar to the results from the previous regressions. The lags are almost always significant and positive, the coefficient on the layoffs three years ago flip back and forth between being positive and negative, and the magnitude of the coefficients generally remain pretty similar.

Next we repeated both of these regressions with county per-capita income as a control variable. The regressions with per-capita income and county and year fixed-effects are reported in Table 14, and the regressions with per-capita income, county, year, and state-year fixed-effects are reported in Table 15. First we consider the regular two-factor fixed-effects regressions with per capita income as a control (Table 14). Notably, per-capita income is never significant, and the coefficients on all the layoff variables look almost identical. In the first regression with just total layoffs, with and without income, the coefficient is 0.000394^{***}; in the second regression the coefficients without income are -0.000072 for contemporaneous layoffs and 0.001362^{***} for layoffs one year ago while with income the coefficients become -0.000071 and 0.001360^{***} respectively. These similarities persist throughout the two tables. Indeed, adding income barely changed the regressions at all. Not only was income not significant to alcohol and drug deaths in these regressions, but adding it as a control did not even change our coefficients on our other variables, indicating that we were not suffering from omitted variable bias from income in these regressions.

Moving to the table with the regressions where we also added state-year fixed-effects (Table 15) we see something very similar. Here income has gained in significance, becoming barely significant at the 10% level, but the coefficients on all our other variables remain almost unchanged (from the regressions without income, Table 7), with only the very last digit (the millionth's place) changing in the coefficients on our layoff variables. Not only that, but all the coefficients on income are positive. Then, the impact of income on these deaths being positive indicates that if anything, the fact that getting laid off lowers your income should actually decrease the likelihood of dying from alcohol or drugs. Thus, the fact that mass layoffs are still providing a significant increase in alcohol and drug deaths shows that they have an effect far beyond income on deaths of despair.

Of course, the possible interactions between multiple sets of fixed-effects remains a potential issue for our analysis. We thus analyzed deaths from alcohol and drugs first with just county fixed-effects (Table 22) and then with just year fixed-effects (Table 30) and then added income for both (Table 26 and Table 34). Going in, we would expect that the regressions with just county fixed-effects will generally be more informative than the regressions with just year fixed-effects as the regressions with just county fixed-effects de facto controls for county demographics, while the year fixed-effects do not.

Indeed, looking at our regressions with county fixed-effects only (Table 22) and comparing it to our initial regressions with county and year fixed-effects (Table 6), the two regressions are pretty similar. The coefficients appear larger in the regression with just county fixed-effects, but the signs of all the coefficients besides the contemporaneous total layoffs in the fifth regression remain the same between the two specifications. With regard to significance, the negative coefficient on layoffs three years ago in the fifth regression loses significance, the significance of layoffs one year ago in the fifth regression goes from 1% significance to 10% significance, and contemporaneous layoffs in the fourth regression, contemporaneous layoffs in the sixth regression, layoffs one year ago in the sixth regression, and layoffs three years ago in the fourth regression all gain significance, going from 5 or 10% significance to 1% significance. This makes sense because removing the year fixed-effects removes our time controls. In particular, both mass layoffs and alcohol and drug deaths have seen a general upwards trend; therefore, removing the year fixed effects biases the coefficients of the mass-layoffs upwards. Still, the overall similarity between the results indicates that we probably do not have a problem in this case with interactions between our two fixed-effects.

In our year fixed-effects only regressions (Table 30), the magnitude of our coefficients and their significance become a lot larger. This makes sense because we expect that county-level factors, such as the proportion of non-college educated to college educated workers would be impactful both for deaths of despair and for the likelihood that a mass layoff will occur. The county-level fixed-effects allows us to essentially control for this demographic variable and others like it, but the year-fixed-effects do not, so our coefficients become larger by an order of magnitude (and in some cases two).

Adding income to the county fixed-effects regressions (Table 26), the coefficients change a little more than they did from adding them to the county and year fixed-effects regressions, but the overall patterns among the layoff variables remain the same. Notably, in this regression income is positive and significant. This is probably because without the year fixed-effects, we are no longer controlling for general macroeconomic conditions. Thus, this income effect reflects the pro-cyclicality of mortality.[5]

Adding income to the year fixed-effects regressions (Table 34) does not change the coefficients on the layoffs significantly from the regressions with just the year fixed-effects (Table 30). However, once again income is positive and significant. This is actually very curious, as one might expect that in the absence of county fixed-effects, income would absorb some county characteristics, such as the ratio of college educated to non-college educated workers in the county. Moreover, the coefficients on income are actually not that much smaller

[5]Eg. Catalano et al. (2012)

than in our regressions with income and county fixed-effects (Table 27). This implies that per capita income itself shares, if anything, a positive relationship with deaths from alcohol and drugs. There could be a number of reasons for this running from the pro-cyclicality of mortality to the fact that drugs and alcohol cost money. Overall, this implies that the positive relationship between mass layoffs and deaths of despair is, if anything, dampened by the income effects of deaths of despair.

4.1.2. *LASSO Analysis.* We ran a single LASSO regression for this category (Table 2), considering a regressand sum of alcohol and drug deaths with regressors total mass layoffs in the last 0-5 years, per-capita income, and county-year two-way fixed-effects. This regression also suggests that the effect of income on these deaths was not interesting or relevant: this LASSO regression gave a 0 coefficient on per capita income. Beyond that, the LASSO regression dropped layoffs in the current year, as well as layoffs three years prior. Notably, the layoffs three years prior and contemporaneous layoffs were the only variables that ever had a significant negative coefficient in our fixed-effects analysis. This implies that perhaps we do not actually need to be concerned about these negative coefficients.

Table 2. LASSO with 2FE, Alcohol/Drug Deaths

Variable	Coefficient
Intercept	$-3.626215 \cdot 10^{-16}$
Total layoffs (this year)	0
Total layoffs (last year)	0.01251376
Total layoffs (two years ago)	0.09568590
Total layoffs (three years ago)	0
Total layoffs (four years ago)	0.1120568
Total layoffs (five years ago)	0.08079525
Income (per capita, this year)	0
Note:	Value 0 suggests drop

4.2. **Drug and Alcohol Deaths Individually.** After analyzing the effects on drugs and alcohol together, we decided it was worthwhile to analyze the two separately in order to see if one or the other was particularly driving our effects. More specifically, we were concerned about the possibility of our effects being driven by opioids. If that were the case, while that would be interesting, we would be studying the effects of the opioid epidemic, rather than explicitly deaths of despair in and of itself.

4.2.1. *Fixed Effects Analysis.* First, we conducted the standard two-factor fixed-effects regressions on alcohol deaths and drug deaths separately with year and county fixed-effects, which can be seen in Table 8 and 10 respectively. These results are actually quite surprising because they do not share the significance patterns nor signs on coefficients with the combined alcohol and drug regression. In particular, while for the combined regression the current year mass layoff numbers were statistically insignificant once you included the first year lag, for alcohol deaths the current year layoffs are always very significant (i.e. significant at the one percent level), regardless of how many lags you include. It is also true that for drug deaths, the current year mass layoff is also very significant for drug deaths regardless of the number of lags. Even more puzzling, the coefficient on the current year lags are positive for alcohol but negative for drugs. That is, our data tells us that more mass layoffs in a year is associated with less drug deaths this year but more alcohol deaths. This implies that when looking at the standard regression, the two effects are actually counteracting each other resulting in the insignificance of the concurrent year layoffs. Moreover the general pattern of negative and positive coefficients and of significance among the coefficients is more mixed than in the combined regression and is different between the two.

Already, this demonstrates a problem with studying alcohol deaths and drug deaths as a single, combined category (and thus also a potential concern for Case and Deaton (2017)). Aggregating these two causes of death into one category would only make sense if they came from fundamentally similar sources, but if alcohol and drug deaths had similar stories behind them they should share similar patterns of significance and sign in their coefficients. However, as our regression demonstrates, this could not be farther from the truth. For the outcome variable that combines alcohol and drug deaths, the contemporaneous mass layoffs are not significant after including at least one lag. However, after running the alcohol and drug deaths separately, we can somewhat conclude that this insignificance in the aggregate regression is not because mass layoffs this year are irrelevant, but because there is a conflict of effects going on. Mass layoffs this year are significantly associated with an increase in alcohol deaths this year but are also significantly associated with a decrease in drug deaths this year. Thus, in our combined alcohol and drug analysis, it shows up as having no significant net effect on combined alcohol and drug deaths.

This conflict of effect also occurs in our other lags: the coefficient on the 5 year lag for alcohol deaths is very significant and negative, telling us that an increase of 1,000 mass layoffs 5 years ago should be an associated decrease of 7 alcohol related deaths in the current year. On the other hand the coefficient on the 5 year lag for drug deaths is very positive and significant, telling us that an increase of 1,000 mass layoffs 5 years ago is associated with an increase of 12 additional drug deaths in the current year. In the aggregate regression, the coefficient on the 5 year lag is still significant, but tells us that an increase of 1,000 mass layoffs 5 years ago is associated with 5 additional net alcohol and drug deaths this year. While this is technically consistent with our separate regressions, it is clear that by running an regression on alcohol and drug deaths combined, we are losing a lot of pertinent information.

We can then look at the regressions for alcohol and drugs with county, year, and state-year fixed-effects, which are given by Tables 9 and 11 respectively. To summarize, the patterns of significance do not change at all for the alcohol only regression while the significance does somewhat shift for the drug only regression, speaking further to the existence of fundamental differences between these two outcome variables. We add income controls in Tables 16 and 17 for alcohol deaths and Tables 18 and 19 for drug deaths without and with state-year fixed-effects respectively. We see that that adding income effects, similar to the previous case with analyzing drug and alcohol deaths together, changes the coefficients by less than 4 deaths per 1,000,000 layoffs. We see that, even when breaking down our analysis by regressing on two separate outcomes, pure income is almost entirely irrelevant.

Next, we address the potential issue with two way fixed-effects by regressing the two separate outcome variables on county fixed-effects only. For the alcohol deaths only outcome, we compare Tables 8, which contains results for the regression with two way fixed-effects and 23, the regression with county fixed-effects only. In terms of significance, we see only one change: when we run the regression with only county fixed-effects instead of two-way fixed-effects, we find that one of the previously significant but negative coefficients becomes positive. Otherwise, there is no substantial change in any of the significant coefficients. For the drugs-only outcome variable, we compare Table 10, two way fixed-effects, and Table 24 and see that there are more substantial changes in significance patterns among lags. This might be because drug deaths have changed more (nationally) over time than alcohol deaths. For alcohol, we take the very similar consistency of significance and magnitude of coefficients between the regression with two way fixed-effects and only county fixed-effects as evidence that we are not suffering from the two-way fixed effect issue. For drugs, although we see changes, we would expect to see these changes as given the opioid epidemic, drug deaths have changed more over this time frame than alcohol deaths have.

Lastly, looking at regressions with year fixed-effects demonstrates substantially different significance patterns and coefficients for both the alcohol-deaths outcome variable and drug-deaths outcome variable, once again hinting at the inadequacy of only year fixed-effects to account for heterogeneity within our analysis.

4.2.2. *LASSO Analysis.* We ran two LASSO regressions for this category (Tables 3 and 4), with different results.

The results from the LASSO regression focusing on deaths from alcohol abuse (Table 3) are fundamentally the same as the results from the LASSO regression incorporating deaths from both alcohol and drug abuse (Table 2): both drop layoffs in years t and $t-3$, as well as per-capita income. However, the LASSO regression on deaths from drug abuse (Table 4)

Table 3. LASSO with 2FE, Alcohol Deaths

Variable	Coefficient
Intercept	$2.822691 \cdot 10^{-15}$
Total layoffs (this year)	0
Total layoffs (last year)	0.1321004
Total layoffs (two years ago)	0.05705804
Total layoffs (three years ago)	0
Total layoffs (four years ago)	0.04871628
Total layoffs (five years ago)	0.08772960
Income (per capita, this year)	0
Note:	Value 0 suggests drop

Table 4. LASSO with 2FE, Drug Deaths

Variable	Coefficient
Intercept	$6.179984 \cdot 10^{-16}$
Total layoffs (this year)	0
Total layoffs (last year)	0
Total layoffs (two years ago)	0.02859054
Total layoffs (three years ago)	0
Total layoffs (four years ago)	0.1358690
Total layoffs (five years ago)	0.05596483
Income (per capita, this year)	0
Note:	Value 0 suggests drop

contains much more interesting results. In addition to the covariates that the other LASSO regressions suggested we drop, the drug death regression drops total mass layoffs in year $t-1$. Once again, this indicates that drug deaths and alcohol deaths have different determining factors, so combining them is a flawed method of analysis.

5. Analysis of Deaths from Suicide

We now turn to the ultimate death of despair: suicide. Like in Section 4, here we go into detail about our regression results. The key takeaway for this section would be that, once again, we observe that mass layoffs appear to be a significant determining factor and that income is not. Additionally, suicide appears to follow different patterns from the drug and alcohol deaths, pointing once more to the importance of disaggregating analyses of deaths of despair.

We began with alcohol and drug deaths because Case and Deaton (2017) indicated that that was where they saw the largest effects, but through our comparison of regressions with drug and alcohol deaths combined versus regressions with drug deaths and alcohol deaths as separate outcomes, we realized that looking at the combined drug and alcohol deaths is fraught with potential sources of error, and that the rising drug and alcohol deaths may be two separate (albeit perhaps related) stories. Thus, we decided to look at another outcome under deaths of despair, suicide.

Suicide was the tenth leading cause of death overall in the United States in 2017, the second among those ages 10-34, and the fourth among those aged 35-54 (National Institutes of Mental Health, 2020), thus demonstrating the relevance of this outcome variable to the population as a whole.

5.1. **Fixed Effects Analysis.** We began by using our basic two-factor fixed-effects regression with suicide as the outcome variable (Table 12). First, across the board, almost all the layoff variables are highly significant. In a notable difference from the alcohol and drug regressions, the concurrent year layoffs remains highly significant across the board, and although there is an initial drop in magnitude between regressions one and two as we add the first lagged layoff, once we get to regressions five and six, the magnitude of the concurrent year layoffs rise again. This fact indicates that suicide may be a more immediate outcome than drug or alcohol deaths. Moreover, this is another reminder that deaths of despair are not interchangeable phenomena, so analyzing them disaggregated by particular cause of death is not only a valuable addition but is entirely necessary. Notably, we once again have a few negative coefficients, but two of them are not significant at all. The third, layoffs three years ago in the regression with all five lags, is significant at the 5% level, and may relate to the previously discussed unusual nature of mortality as an outcome variable, namely that because people cannot die twice, having deaths as an outcome is really a question of moving deaths through time.

Once again, adding the state-year fixed-effects (Table 13) does not change much. Interestingly, here we no longer have any significant negative coefficients. Because adding state-year fixed-effects essentially allows for states to have separate macro-economies that are then controlled for, this means that we may be missing some unobserved economic variable that is dampening our effects.

Like before, we then re-did our analysis with county per-capita income as a control variable. We began by looking at just the year and county fixed-effects regressions with income (Table 20). Notably, income is not significant for any of these regressions. In addition, our actual regression coefficients barely change from our examination without income (Table 12). No coefficient changes by more than 3 deaths per 1 million mass layoffs. However, a couple coefficients do change in significance: the coefficient on layoffs two years ago in the third regression goes from 10% significance to insignificance and the coefficient on layoffs two years ago in the fifth regression goes from 5% significance to 10% significance. Nonetheless, the general story remains the same between the two regressions.

The comparison between our analysis with county per-capita income as a control variable within our regressions including state-year effects on top of the year and county fixed-effects (Table 21) and without income (Table 13) is similar to the one without state-year fixed-effects. The coefficients on the layoff variables are extremely similar in magnitude, sign, and significance between the two sets of regressions. In this specification, income does become significant for the regression with just one lag and the regression with two lags, but only at the 5% level. These coefficients are still smaller in magnitude than those on the layoffs and, because they are positive, still indicate that, if anything, the lowered income from being laid off during a mass layoff should decrease deaths from suicide, and thus that the increase from deaths of despair related to mass layoffs is not a matter of income.

Out of concern for the potential for interaction effects resulting from our two-factor fixed-effects, we once again analyzed the relationship between suicide and mass layoffs with only one set of fixed-effects at a time.

Beginning with just the county fixed-effects (Table 25), we see that compared to the specifications with both county and year fixed-effects (Table 12), the results are pretty similar. The only difference is that the coefficients increase in magnitude and none of the coefficients (significant or insignificant) are negative. This increase in magnitude as a result of removing the year fixed-effects points to the possibility that while mortality is generally pro-cyclical, suicide may be counter-cyclical and exacerbated by mass layoffs.

Next, we can examine the relationship between mass layoffs and suicide with year fixed-effects (Table 33). The coefficients become much larger in magnitude, probably because, once again, county fixed-effects essentially function in place of a variety of demographic controls many of which are closely related to suicide. Notably, we now have two highly significant negative coefficients: mass layoffs one year ago in the fifth and sixth regressions. This is extremely curious. Not only are these coefficients now negative, they are larger in magnitude than they were when they were positive coefficients in our regressions with year and county fixed-effects (Table 12). This is particularly strange because the other two coefficients that switch sign, mass layoffs three years ago in the sixth regression and mass layoffs two years ago in the second regression, both go from negative to positive and increase in magnitude and significance. Moreover, all the other variables have coefficients that increase except for three: mass layoffs three years ago in the fifth regression (but this one is pretty small, negative, and insignificant in both regressions) and mass layoffs one year ago in regressions three and four. Thus the most anomalous movements occur in the one year lag, presenting an interesting puzzle.

This is highly unusual, as one would expect that county fixed-effects generally control for aspects of a county that do not change with time, such as county demographics or geography. This might imply that (like when looking at alcohol and drugs together) there are multiple stories hidden within our analysis of suicide. Perhaps different types of people are more or less likely to commit suicide different lengths of time after a mass layoff. Alternatively, perhaps this is a fluke in the data that is somehow related to some peculiarities of our time-frame of analysis. Regardless, the analysis with year fixed-effects only once again shows that looking at the effects of mass layoffs without county fixed-effects (or perhaps a significant suite of control variables in its place) is disingenuous.

Once again, we repeat our analysis with income. Looking at the relationship between suicide and mass layoffs with income as a control and county fixed-effects only (Table 29) we see that the coefficients on layoffs do not change significantly from the regressions with just county fixed-effects (Table 25). Notably, per capita income is significant and positive. This is notable because previously we considered the possibility that suicide, unlike other deaths, is counter-cyclical, but we would expect that the income variable is picking up a lot of the impact of the macro-economic environment more broadly that is no longer being controlled for without the year fixed-effects, so the fact that the per capita income coefficients are large and positive points against that possibility.

Examining our results for regressions relating suicide and mass layoffs with year fixed-effects with and without income as a control (Table 37 and Table 33 respectively), we observe that the coefficients on layoffs do not change significantly but that county per capita income has large, positive, and significant impacts across the board. Because the coefficients for layoffs do decrease (albeit not that much), this may indicate that per capita income is capturing a large effect from county fundamentals but does not capture everything. Once again, this points to year fixed-effects alone as being an insufficient tool of analysis.

Altogether, these results point to mass layoffs having an impact on suicide rates, and in particular, an impact outside of income.

5.2. **LASSO Analysis.** The LASSO results for suicides (Table 5) are rather interesting, in that they are actually not that different from our other LASSO results. This regression drops the same coefficients as the combined alcohol/drug regression, as well as the alcohol-only regression. This result points to an odd possibility that suicide and alcohol deaths may be more related than alcohol and drug deaths despite the links between both alcohol and drugs as being forms of substance abuse and suicide and drugs as a potential method of suicide. Moreover, the remaining coefficients are all positive.

Table 5. LASSO with 2FE, Suicide Deaths

Variable	Coefficient
Intercept	$-1.096870 \cdot 10^{-16}$
Total layoffs (this year)	0
Total layoffs (last year)	0.06248131
Total layoffs (two years ago)	0.03327658
Total layoffs (three years ago)	0
Total layoffs (four years ago)	0.05368127
Total layoffs (five years ago)	0.06892811
Income (per capita, this year)	0
Note:	Value 0 suggests drop

6. Discussion

There are three key findings we would like to discuss

(1) Income is not very impactful for any of our outcome variables, confirming that naive income in general is a poor explanatory variable for deaths of despair.
(2) The combining of alcohol and drug deaths into one outcome variable as done is Case and Deaton (2017) is quite problematic More broadly, combining different kinds of deaths of despair into one variable is potentially problematic
(3) There is a significant relationship between mass layoffs and deaths of despair, as demonstrated by the consistency within each outcome between different regression specifications

At the end of the discussion we include a section to address some of the limitations of this project and avenues for further research.

6.1. **Income Is Not a Predictor of Deaths of Despair.** Within our analysis of combined alcohol and drug deaths, alcohol deaths only, and drug deaths only, we found a very interesting pattern. After controlling for county - year fixed-effects, we find that adding income controls essentially does not change the coefficients on the mass layoff lags at all! This can be seen by comparing between Tables 6 and 14 for the combined outcome variable, by comparing Tables 8 and 16 for alcohol deaths only and by comparing Tables 10 and 18 for drug deaths only.

Numerically, we find that for both alcohol and drug deaths individually and as a combined outcome variable, adding income controls changes the coefficient on existing mass layoff lags by less than 4 deaths per 1,000,000 mass layoffs. Relative to the magnitude of our existing significant variables (which reach up to 14 deaths per 10,000 mass layoffs or 1,400 deaths per 1,000,000 mass layoffs), these changes are utterly insignificant.

Even more so, the coefficient on per capita income by county is also insignificant and gets dropped by the LASSO in almost all choices of the constraint. For the alcohol and drug deaths outcome variables (both individually and combined), we see that per capita income for the county is an irrelevant variable. Moreover, this is also great news for our assumption that mass layoffs are essentially exogenous from economic conditions at the county level (that is mass layoffs are not caused by decline in local demand or local supply).

As a sanity check, since these results seem too good to be true, we consider regressions with the three outcome variables (drug deaths only, alcohol deaths only, drug and alcohol deaths combined) with only county level fixed-effects (without controlling for year) and once again compare our regression results both with and without income controls. Here, we see that income is in fact significant and does change the coefficients on existing mass layoff lags in a not-insignificant manner. Moreover, the coefficients on per capita income on these regressions become very significant. This makes sense because per capita income is certainly closely related to macroeconomic trends. This leads us to believe that the strong results stated above are valid and not the result of, say, some coding or data cleaning error. For verification of the results mentioned in this paragraph, compare Tables 22 and 26 for combined deaths, Tables 23 and 27 for alcohol deaths, and Tables 24 and 28 for drug deaths.

Regressions on the suicide outcome variable with two way fixed-effects also confirms the above facts, which you can verify by comparing Tables 12 and 20 for income controls with two way fixed-effects and by comparing Tables 25 and 29 for income controls with county level fixed-effects only.

On top of all of our fixed effects analysis, every single LASSO regression drops income as a determinant of deaths of despair.

6.2. **Issues with a Combined Alcohol and Drug Death Outcome Variable.** Another key finding we stumble upon that it is potentially very problematic to combine both the alcohol and drug deaths into one outcome variable. This was made readily apparent when we studied the impacts of mass layoffs on drugs deaths and alcohol deaths separately.

The most concerning aspect was that corresponding coefficients for the alcohol deaths and drug deaths would both be significant, but have the opposite signs. To give a concrete example, the coefficient on current year layoffs for alcohol deaths within the 4 year lag regression was very significant and told us that 1,000 mass layoffs in the current year corresponds to an increase of 2.4 alcohol deaths in the current year. The coefficient on current year layoffs for drug deaths within the 4 year lag regression was also very significant but told us that an increase of 1,000 mass layoffs in the current year resulted in 2.5 less deaths in the current year. When we regress on the combined alcohol and drug death outcome variable with 4 year mass layoff lags, we find out that the current year layoffs are insignificant. However, by breaking this coefficient down, it is clear that this insignificance is actually the result of two conflicting significant effects in the opposite directions. See Tables 8 and 10 for documentation of these results.

In general, we find that the significance patterns and negative sign patterns on coefficient when regressing on the two separate outcome variables to be drastically different. For combining alcohol and drug deaths into one variable, it must be true that they are fundamentally similar, which we have shown to be clearly not true.

More broadly, the results we have for suicide also differ significantly from those with alcohol and/or drug deaths as outcomes. Although the coinage of the term ”deaths of despair” is useful in referring to the phenomena that are driving the observed unusual rises in mortality, the sources of these deaths are different enough to warrant separate analyses, and combining them into one variable opens many avenues for bias and error.

6.3. **Significant Relationship Between Mass Layoffs and Deaths.** Lastly we would like to point out that in all our regressions on suicide, alcohol, and drug deaths, we find a significant relationship between mass layoffs and these deaths of despair. This fact remains robust when considering state-year fixed-effects, only year fixed-effects, only county fixed-effects, and all of the above with income controls.

While perhaps it is difficult to make a causal statement in terms of our coefficients, there is no doubt that mass layoffs do have some sort of impact on these deaths of despair. Using mass layoffs as a shock to cumulative disadvantage (labor market outcome relative to expectation), we thus verify the claim made in Case and Deaton (2017) that changes in cumulative disadvantage could indeed be the driving force behind this increase in deaths of despair.

Moreover, our study has an even broader scope than this. While we agree with Case and Deaton (2017) that in the aggregate, deaths of despair should most heavily impact white non-Hispanics without a college degree, by isolating mass layoffs at the county level we find that surprising negative shocks to local labor markets impact deaths of despair on the population as a whole.

6.4. **Limitations of Our Analysis and Avenues for Further Research.** We had two main areas of concern in our analysis: understanding the role of the significant negative coefficients (although few, they were extremely puzzling), and the dropped data from the CDC.

6.4.1. *The Question of Negative Coefficients.* One persistent question throughout our analysis has been the role of negative coefficients. Throughout all of our regressions, some lagged mass layoff variables would have a negative coefficient, particularly in regressions that included four or five lags. This is particularly strange because all of our other coefficients are positive. It would be very strange if mass layoffs five years ago, four years ago, two years ago, and one year ago increased deaths this year, but mass layoffs three years ago decreased them. We explored several possible causes of this.

First we considered the possibility of the previously mentioned problem of negative weights from two way fixed-effects, but we quickly ruled out this possibility by running the regressions with just county or just year fixed-effects. Those regressions tended to have very similar results as our regressions with two-way fixed-effects. In particular, the problem of negative coefficients persisted in these single single factor fixed effects regression.

Next we wondered whether the pro-cyclical nature of mortality[6] was somehow causing this. However, we find this explanation similarly unsatisfactory, since we picked mass layoffs as an explanatory variable because at the county level, it essentially acts as an exogenous shock that is not particularly correlated with local economic conditions (eg. income) after controlling for broader macroeconomic trends in the fixed-effects.

Another possibility is that because each person can only die once, outcomes related to mortality are really a question of moving a person's death forward or backwards in time. Thus, for example, from the perspective of year t if a layoff in year $t-3$ causes a person to die in year $t-1$ or year $t-2$ who otherwise might have died in year t, that would register as a decrease in mortality caused by the layoff in year $t-3$. However, if this were a problem, we would also expect to sometimes see negative coefficients in the four year lags, but we never do.

Lastly, the answer might lie in the high correlation between our explanatory variables. Mass layoffs 1 year ago is highly correlated with mass layoffs 2 years ago, and mass layoffs 3 years ago, and so forth. When we examine auto-correlation, we find this correlation to reach as high as 92% between layoffs in consecutive years (with the correlation decreasing with additional years of separation).[7] Generally speaking, when a regressor is highly correlated with another regressor, we expect that the coefficient on the correlated regressors to be smaller in regressions that include both regressors. While this is certainly true throughout our tables, it does not appear to always hold, and the effect is smaller than expected given just how high the correlation between layoffs in different years is.[8] The fact that all of the layoff variables are so highly correlated with each other makes the interpretation of our

[6]This is documented in many health and economics papers such as Stevens et al. (2015)

[7]This is why when reporting our LASSO results, we focused on sign and significance over magnitude as we are well aware that a major problem for LASSO can be omitted variable bias, but since the goal of the LASSO was primarily to determine the most important coefficients to deaths of despair, we determined that it was not necessary to run a double LASSO for each layoff variable

[8]For example, when looking at our simple two way fixed-effects regression for suicide (Table 12), between the second, third, and fourth regressions, the coefficient on layoffs one year ago drops by around 0.00005 between the second and third regressions but rises by around 0.000004 between the third and fourth regressions even though the correlation between regressions in consecutive years (i.e. one year ago and two years ago) is 92% and the correlation between regressions separated by a year (i.e. one year ago and three years ago) is around 85%. If anything, we might have expected the coefficient to drop more between the three regressions than it did.

coefficients very difficult and might explain why some of the coefficients are negative. Thus a clear next step for someone who wishes to do a similar analysis would be to examine the role of high correlation between the lagged variables and closely consider the literature on how that might affect the interpretation of coefficients.[9]

6.4.2. *Data Concerns.* Because of the CDC's privacy guidelines, we lost all observations for county-years with less than ten deaths. This was an enormous loss of data. If we had had observations for all county-years from 1999 to 2012 we would have had 44,058 observations. Instead, even for our largest regression (alcohol and drug deaths combined), we only had 14,125 observations. While this is still a large number of observations, it was highly disappointing to find out the amount of lost data. Further analysis, perhaps with the appropriate waivers signed, would be able to go more in depth.[10] Because of this data limitation, we did not break the results down by race, gender, or age. Moreover, this limitation implies that our analysis primarily applies to larger counties.

Aside from the CDC privacy guidelines, another limiting factor to our data was that the federal Mass Layoff Statistics Program was terminated in 2013 due to budget cuts, so our data ended in 2012. The WARN act still requires that states keep track of mass layoff data, but it is now in fifty different databases all with their own method of organization. With more time, researchers could also break this data barrier. However, this is a much less significant limitation than the one from the CDC.

7. Conclusion

Ultimately, each of the four outcome variables mentioned above (alcohol and drug deaths combined, alcohol deaths only, drug deaths only, suicides) tell their own story. The combined alcohol and drug deaths outcome variable is directly motivated by Case and Deaton (2017) and originally served as our base case. The combined alcohol and drug deaths outcome points to mass layoffs potentially being significant, as the coefficients on those regressions are consistently almost all positive and highly significant. The individual alcohol deaths only and drug deaths only outcome variables breaks down the driving forces behind the combined outcome variables and tells us that while both alcohol deaths and drug deaths appear to be impacted by mass layoffs, the stories behind them are probably quite different, so the two should not be analyzed as one combined variable. Using suicide as an outcome variable points to further differences between the different types of *deaths of despair* while also, once

[9]Unfortunately, we did not have enough time to do a close analysis of the econometric literature on regressors with high auto-correlation

[10]Alternatively, it appears that there is a potentially more comprehensive database from the National Vital Statistics Survey, but even processing the data from that required more computing power (or for much longer lengths of time) than we had access to at this time, so we are not even able to say whether or not that data would have been useful for this analysis.

again, indicating that mass layoffs share a significant relationship with deaths from suicide. The four different stories of the outcome variables point to the importance of avoiding over-aggregation, and a reminder that just because deaths that can be attributed to psychological factors are increasing simultaneously does not mean that they are increasing for the same reasons or in the same way. One fact that does, however, appear to be consistent across the board is that income is a poor explanatory variable for deaths of despair. Ultimately, our findings indicate that mass layoffs indeed provide a shock to local labor markets that increases deaths of despair as measured by drug deaths, alcohol deaths, and suicides (even if in different ways).

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Appendix A. Tables

A.1. **Regressions with Two-Factor Fixed Effects.** This section contains regression tables for two-factor effects. Note that the regressions with state-year fixed-effects are also here.

Table 6. Total Deaths from Alcohol and Drugs regressed on total layoffs with year and county fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000394***	−0.000072	−0.000042	−0.000151**	−0.000012	0.000123*
	(0.000070)	(0.000074)	(0.000074)	(0.000072)	(0.000080)	(0.000073)
Total layoffs 1 year ago		0.001362***	0.000994***	0.001082***	0.000386***	−0.000262**
		(0.000078)	(0.000111)	(0.000108)	(0.000111)	(0.000105)
Total layoffs 2 years ago			0.000613***	0.000391***	0.001064***	0.000617***
			(0.000131)	(0.000149)	(0.000150)	(0.000136)
Total layoffs 3 years ago				0.000230*	−0.000390***	0.000499***
				(0.000127)	(0.000149)	(0.000142)
Total layoffs 4 years ago					0.001081***	0.001243***
					(0.000142)	(0.000156)
Total layoffs 5 years ago						0.000542***
						(0.000147)
Observations	14,125	14,125	14,125	13,520	12,877	12,168
F Statistic	32.093150*** (df = 1; 12586)	169.584900*** (df = 2; 12585)	120.495900*** (df = 3; 12584)	93.256110*** (df = 4; 11980)	82.861530*** (df = 5; 11338)	76.072340*** (df = 6; 10629)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7. Total Deaths from Alcohol and Drugs regressed on total layoffs with year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000272***	−0.000114	−0.000088	−0.000188***	−0.000038	0.000058
	(0.000070)	(0.000074)	(0.000074)	(0.000072)	(0.000080)	(0.000073)
Total layoffs 1 year ago		0.001161***	0.000881***	0.000966***	0.000305***	−0.000304***
		(0.000078)	(0.000111)	(0.000108)	(0.000112)	(0.000107)
Total layoffs 2 years ago			0.000469***	0.000223	0.000886***	0.000512***
			(0.000134)	(0.000151)	(0.000153)	(0.000139)
Total layoffs 3 years ago				0.000283**	−0.000326**	0.000590***
				(0.000129)	(0.000151)	(0.000146)
Total layoffs 4 years ago					0.001099***	0.001225***
					(0.000143)	(0.000158)
Total layoffs 5 years ago						0.000543***
						(0.000148)
Observations	14,125	14,125	14,125	13,520	12,877	12,168
F Statistic	8.969889*** (df = 713; 11888)	3.615863*** (df = 700; 11887)	3.631627*** (df = 701; 11886)	3.819248*** (df = 653; 11331)	4.019964*** (df = 605; 10738)	3.896478*** (df = 556; 10079)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 8. Total Deaths from Alcohol regressed on total layoffs with year and county fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000530***	0.000337***	0.000353***	0.000288***	0.000240***	0.000291***
	(0.000039)	(0.000041)	(0.000041)	(0.000041)	(0.000047)	(0.000045)
Total layoffs 1 year ago		0.000559***	0.000347***	0.000323***	0.000247***	−0.000046
		(0.000043)	(0.000063)	(0.000061)	(0.000066)	(0.000066)
Total layoffs 2 years ago			0.000350***	0.000569***	0.000637***	0.000601***
			(0.000075)	(0.000086)	(0.000089)	(0.000085)
Total layoffs 3 years ago				−0.000146**	−0.000086	−0.000006
				(0.000072)	(0.000088)	(0.000089)
Total layoffs 4 years ago					−0.000038	0.000556***
					(0.000084)	(0.000098)
Total layoffs 5 years ago						−0.000681***
						(0.000091)
Observations	6,818	6,818	6,818	6,438	6,047	5,659
F Statistic	185.000800*** (df = 1; 6016)	177.883300*** (df = 2; 6015)	126.281700*** (df = 3; 6014)	106.192400*** (df = 4; 5638)	81.184040*** (df = 5; 5251)	69.243080*** (df = 6; 4868)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 9. Total Deaths from Alcohol regressed on total layoffs with year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000511***	0.000329***	0.000350***	0.000290***	0.000254***	0.000293***
	(0.000040)	(0.000042)	(0.000043)	(0.000042)	(0.000048)	(0.000046)
Total layoffs 1 year ago		0.000546***	0.000327***	0.000302***	0.000224***	−0.000071
		(0.000045)	(0.000065)	(0.000064)	(0.000069)	(0.000069)
Total layoffs 2 years ago			0.000364***	0.000591***	0.000668***	0.000624***
			(0.000079)	(0.000090)	(0.000095)	(0.000091)
Total layoffs 3 years ago				−0.000150**	−0.000112	−0.000003
				(0.000076)	(0.000093)	(0.000096)
Total layoffs 4 years ago					−0.000003	0.000593***
					(0.000088)	(0.000103)
Total layoffs 5 years ago						−0.000704***
						(0.000095)
Observations	6,818	6,818	6,818	6,438	6,047	5,659
F Statistic	3.628714*** (df = 706; 5325)	2.267100*** (df = 693; 5324)	2.303164*** (df = 694; 5323)	2.383048*** (df = 648; 4994)	2.342608*** (df = 600; 4656)	2.362103*** (df = 552; 4322)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 10. Total Drug Deaths regressed on total layoffs with year and county fixed-effects

	Dependent variable:					
	Total Drug Deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	-0.000165^{***}	-0.000397^{***}	-0.000393^{***}	-0.000408^{***}	-0.000257^{***}	-0.000196^{***}
	(0.000062)	(0.000066)	(0.000066)	(0.000064)	(0.000072)	(0.000065)
Total layoffs 1 year ago		0.000677^{***}	0.000618^{***}	0.000701^{***}	0.000178^{*}	-0.000165^{*}
		(0.000069)	(0.000099)	(0.000097)	(0.000100)	(0.000094)
Total layoffs 2 years ago			0.000097	-0.000180	0.000331^{**}	-0.000025
			(0.000118)	(0.000134)	(0.000135)	(0.000122)
Total layoffs 3 years ago				0.000158	-0.000374^{***}	0.000401^{***}
				(0.000114)	(0.000135)	(0.000128)
Total layoffs 4 years ago					0.000927^{***}	0.000538^{***}
					(0.000128)	(0.000140)
Total layoffs 5 years ago						0.001172^{***}
						(0.000132)
Observations	9,611	9,611	9,611	9,272	8,922	8,528
F Statistic	7.189544^{***} (df = 1; 8453)	51.307060^{***} (df = 2; 8452)	34.429930^{***} (df = 3; 8451)	25.238490^{***} (df = 4; 8113)	33.109820^{***} (df = 5; 7763)	57.418790^{***} (df = 6; 7369)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 11. Total Drug Deaths regressed on total layoffs with year, county, and state-year fixed-effects

	Dependent variable:					
	Total Drug Deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	-0.000278^{***}	-0.000440^{***}	-0.000442^{***}	-0.000465^{***}	-0.000293^{***}	-0.000266^{***}
	(0.000062)	(0.000066)	(0.000066)	(0.000064)	(0.000071)	(0.000065)
Total layoffs 1 year ago		0.000491^{***}	0.000521^{***}	0.000594^{***}	0.000076	-0.000200^{**}
		(0.000069)	(0.000100)	(0.000097)	(0.000101)	(0.000097)
Total layoffs 2 years ago			-0.000051	-0.000359^{***}	0.000171	-0.000102
			(0.000120)	(0.000136)	(0.000138)	(0.000126)
Total layoffs 3 years ago				0.000227^{*}	-0.000321^{**}	0.000459^{***}
				(0.000117)	(0.000137)	(0.000133)
Total layoffs 4 years ago					0.001000^{***}	0.000543^{***}
					(0.000129)	(0.000143)
Total layoffs 5 years ago						0.001204^{***}
						(0.000133)
Observations	9,611	9,611	9,611	9,272	8,922	8,528
F Statistic	8.089020^{***} (df = 687; 7781)	3.005756^{***} (df = 674; 7780)	3.001247^{***} (df = 675; 7779)	3.068056^{***} (df = 631; 7486)	3.288154^{***} (df = 587; 7181)	3.310489^{***} (df = 541; 6834)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 12. Total deaths from intentional self harm (suicide) regressed on total layoffs with year and county fixed-effects

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000362***	0.000175***	0.000179***	0.000158***	0.000234***	0.000273***
	(0.000029)	(0.000031)	(0.000031)	(0.000031)	(0.000036)	(0.000035)
Total layoffs 1 year ago		0.000545***	0.000489***	0.000493***	0.000330***	0.000338***
		(0.000033)	(0.000047)	(0.000047)	(0.000050)	(0.000051)
Total layoffs 2 years ago			0.000093*	−0.000012	0.000134**	0.000120*
			(0.000056)	(0.000064)	(0.000068)	(0.000066)
Total layoffs 3 years ago				0.000167***	−0.000074	−0.000149**
				(0.000055)	(0.000067)	(0.000069)
Total layoffs 4 years ago					0.000379***	0.000250***
					(0.000064)	(0.000076)
Total layoffs 5 years ago						0.000261***
						(0.000072)
Observations	11,471	11,471	11,471	10,847	10,197	9,494
F Statistic	151.899800*** (df = 1; 10196)	216.200200*** (df = 2; 10195)	145.086700*** (df = 3; 10194)	106.172400*** (df = 4; 9571)	77.544760*** (df = 5; 8929)	60.089430*** (df = 6; 8234)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 13. Total Deaths from intentional self harm (suicide) regressed on total layoffs with year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000330***	0.000162***	0.000168***	0.000147***	0.000233***	0.000263***
	(0.000031)	(0.000032)	(0.000032)	(0.000032)	(0.000037)	(0.000037)
Total layoffs 1 year ago		0.000503***	0.000435***	0.000451***	0.000277***	0.000312***
		(0.000034)	(0.000049)	(0.000049)	(0.000053)	(0.000054)
Total layoffs 2 years ago			0.000113*	−0.000053	0.000113	0.000111
			(0.000059)	(0.000068)	(0.000072)	(0.000071)
Total layoffs 3 years ago				0.000259***	−0.000012	−0.000093
				(0.000058)	(0.000071)	(0.000074)
Total layoffs 4 years ago					0.000431***	0.000249***
					(0.000067)	(0.000080)
Total layoffs 5 years ago						0.000306***
						(0.000075)
Observations	11,471	11,471	11,471	10,847	10,197	9,494
F Statistic	5.357949*** (df = 714; 9497)	2.379384*** (df = 701; 9496)	2.381932*** (df = 702; 9495)	2.345358*** (df = 653; 8922)	2.279751*** (df = 605; 8329)	2.111541*** (df = 556; 7684)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 14. Total Deaths from Alcohol and Drugs regressed on total layoffs with Per Capita Income and year and county fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000394***	−0.000071	−0.000042	−0.000150**	−0.000011	0.000123*
	(0.000070)	(0.000074)	(0.000074)	(0.000073)	(0.000081)	(0.000073)
Per Capita Income	0.000097	0.000093	0.000094	0.000103	0.000119	0.000055
	(0.000083)	(0.000082)	(0.000082)	(0.000083)	(0.000083)	(0.000077)
Total layoffs 1 year ago		0.001360***	0.000994***	0.001082***	0.000389***	−0.000259**
		(0.000078)	(0.000111)	(0.000109)	(0.000112)	(0.000106)
Total layoffs 2 years ago			0.000608***	0.000389***	0.001061***	0.000614***
			(0.000132)	(0.000150)	(0.000150)	(0.000136)
Total layoffs 3 years ago				0.000226*	−0.000393***	0.000498***
				(0.000128)	(0.000150)	(0.000143)
Total layoffs 4 years ago					0.001076***	0.001237***
					(0.000143)	(0.000157)
Total layoffs 5 years ago						0.000542***
						(0.000148)
Observations	13,938	13,938	13,938	13,341	12,704	12,003
F Statistic	16.494480*** (df = 2; 12425)	112.001100*** (df = 3; 12424)	89.444290*** (df = 4; 12423)	73.890950*** (df = 5; 11826)	68.362890*** (df = 6; 11190)	64.309860*** (df = 7; 10489)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 15. Total Deaths from Alcohol and Drugs regressed on total layoffs with Per Capita Income and year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000272***	−0.000115	−0.000089	−0.000188***	−0.000039	0.000058
	(0.000070)	(0.000074)	(0.000075)	(0.000073)	(0.000080)	(0.000073)
Per Capita Income	0.000162*	0.000168*	0.000168*	0.000164*	0.000159*	0.000073
	(0.000091)	(0.000090)	(0.000090)	(0.000091)	(0.000090)	(0.000085)
Total layoffs 1 year ago		0.001162***	0.000883***	0.000967***	0.000307***	−0.000302***
		(0.000078)	(0.000112)	(0.000109)	(0.000113)	(0.000108)
Total layoffs 2 years ago			0.000467***	0.000223	0.000886***	0.000511***
			(0.000135)	(0.000152)	(0.000153)	(0.000140)
Total layoffs 3 years ago				0.000280**	−0.000328**	0.000588***
				(0.000130)	(0.000152)	(0.000147)
Total layoffs 4 years ago					0.001097***	0.001224***
					(0.000144)	(0.000159)
Total layoffs 5 years ago						0.000541***
						(0.000149)
Observations	13,938	13,938	13,938	13,341	12,704	12,003
F Statistic	8.853552*** (df = 714; 11727)	3.551454*** (df = 701; 11726)	3.566907*** (df = 702; 11725)	3.753957*** (df = 654; 11177)	3.948460*** (df = 606; 10590)	3.826423*** (df = 557; 9939)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 16. Total Deaths from Alcohol regressed on total layoffs with Per Capita Income and year and county fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000530***	0.000337***	0.000353***	0.000288***	0.000240***	0.000291***
	(0.000039)	(0.000041)	(0.000041)	(0.000041)	(0.000047)	(0.000045)
Per Capita Income	−0.000066	−0.000072	−0.000070	−0.000063	−0.000055	−0.000041
	(0.000060)	(0.000059)	(0.000059)	(0.000061)	(0.000062)	(0.000061)
Total layoffs 1 year ago		0.000560***	0.000348***	0.000324***	0.000247***	−0.000046
		(0.000044)	(0.000063)	(0.000061)	(0.000066)	(0.000066)
Total layoffs 2 years ago			0.000349***	0.000568***	0.000636***	0.000600***
			(0.000075)	(0.000086)	(0.000089)	(0.000086)
Total layoffs 3 years ago				−0.000146**	−0.000085	−0.000004
				(0.000073)	(0.000089)	(0.000090)
Total layoffs 4 years ago					−0.000039	0.000556***
					(0.000084)	(0.000098)
Total layoffs 5 years ago						−0.000681***
						(0.000091)
Observations	6,772	6,772	6,772	6,396	6,007	5,622
F Statistic	92.732440*** (df = 2; 5978)	118.543900*** (df = 3; 5977)	94.605490*** (df = 4; 5976)	84.787570*** (df = 5; 5603)	67.468730*** (df = 6; 5218)	59.100270*** (df = 7; 4837)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 17. Total Deaths from Alcohol regressed on total layoffs with Per Capita Income and year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Alcohol					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000511***	0.000329***	0.000350***	0.000290***	0.000254***	0.000293***
	(0.000040)	(0.000043)	(0.000043)	(0.000042)	(0.000048)	(0.000046)
Per Capita Income	−0.000027	−0.000025	−0.000025	−0.000007	0.000015	0.000038
	(0.000069)	(0.000068)	(0.000068)	(0.000070)	(0.000071)	(0.000070)
Total layoffs 1 year ago		0.000545***	0.000326***	0.000302***	0.000224***	−0.000072
		(0.000045)	(0.000065)	(0.000064)	(0.000069)	(0.000070)
Total layoffs 2 years ago			0.000364***	0.000591***	0.000668***	0.000625***
			(0.000079)	(0.000090)	(0.000095)	(0.000091)
Total layoffs 3 years ago				−0.000150**	−0.000113	−0.000005
				(0.000076)	(0.000093)	(0.000096)
Total layoffs 4 years ago					−0.000002	0.000595***
					(0.000088)	(0.000103)
Total layoffs 5 years ago						−0.000706***
						(0.000095)
Observations	6,772	6,772	6,772	6,396	6,007	5,622
F Statistic	3.603737*** (df = 707; 5287)	2.259127*** (df = 694; 5286)	2.295071*** (df = 695; 5285)	2.376603*** (df = 649; 4959)	2.335601*** (df = 601; 4623)	2.355095*** (df = 553; 4291)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 18. Total Drug Deaths regressed on total layoffs with Per Capita Income and year and county fixed-effects

	Dependent variable:					
	Total Drug Deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	−0.000166***	−0.000398***	−0.000393***	−0.000408***	−0.000258***	−0.000196***
	(0.000062)	(0.000066)	(0.000066)	(0.000065)	(0.000072)	(0.000065)
Per Capita Income	−0.000122	−0.000126	−0.000126	−0.000063	−0.000058	−0.000095
	(0.000087)	(0.000087)	(0.000087)	(0.000087)	(0.000085)	(0.000080)
Total layoffs 1 year ago		0.000675***	0.000618***	0.000700***	0.000178*	−0.000166*
		(0.000070)	(0.000100)	(0.000097)	(0.000101)	(0.000095)
Total layoffs 2 years ago			0.000094	−0.000182	0.000327**	−0.000028
			(0.000118)	(0.000135)	(0.000136)	(0.000122)
Total layoffs 3 years ago				0.000158	−0.000371***	0.000405***
				(0.000115)	(0.000135)	(0.000128)
Total layoffs 4 years ago					0.000925***	0.000537***
					(0.000128)	(0.000141)
Total layoffs 5 years ago						0.001171***
						(0.000132)
Observations	9,530	9,530	9,530	9,193	8,846	8,455
F Statistic	4.571840** (df = 2; 8385)	34.509360*** (df = 3; 8384)	26.039450*** (df = 4; 8383)	20.056080*** (df = 5; 8047)	27.354300*** (df = 6; 7700)	49.010310*** (df = 7; 7309)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 19. Total Drug Deaths regressed on total layoffs with Per Capita Income and year, county, and state-year fixed-effects

	Dependent variable:					
	Total Drug Deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	−0.000278***	−0.000439***	−0.000442***	−0.000465***	−0.000293***	−0.000265***
	(0.000062)	(0.000066)	(0.000066)	(0.000065)	(0.000072)	(0.000066)
Per Capita Income	0.000003	0.000009	0.000009	−0.000001	−0.000028	−0.000106
	(0.000096)	(0.000096)	(0.000096)	(0.000096)	(0.000093)	(0.000088)
Total layoffs 1 year ago		0.000491***	0.000521***	0.000594***	0.000075	−0.000203**
		(0.000069)	(0.000100)	(0.000098)	(0.000102)	(0.000097)
Total layoffs 2 years ago			−0.000050	−0.000360***	0.000170	−0.000103
			(0.000121)	(0.000137)	(0.000139)	(0.000126)
Total layoffs 3 years ago				0.000228*	−0.000320**	0.000463***
				(0.000117)	(0.000138)	(0.000134)
Total layoffs 4 years ago					0.000999***	0.000544***
					(0.000130)	(0.000143)
Total layoffs 5 years ago						0.001203***
						(0.000134)
Observations	9,530	9,530	9,530	9,193	8,846	8,455
F Statistic	8.011429*** (df = 688; 7713)	2.959594*** (df = 675; 7712)	2.955158*** (df = 676; 7711)	3.021066*** (df = 632; 7420)	3.245339*** (df = 588; 7118)	3.276654*** (df = 542; 6774)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 20. Total deaths from intentional self harm (suicide) regressed on total layoffs with Per Capita Income and year and county fixed-effects

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000363***	0.000176***	0.000180***	0.000159***	0.000235***	0.000274***
	(0.000029)	(0.000031)	(0.000031)	(0.000031)	(0.000036)	(0.000035)
Per Capita Income	0.000046	0.000044	0.000044	0.000054	0.000058	0.000049
	(0.000037)	(0.000037)	(0.000037)	(0.000039)	(0.000040)	(0.000041)
Total layoffs 1 year ago		0.000544***	0.000490***	0.000494***	0.000332***	0.000341***
		(0.000033)	(0.000047)	(0.000047)	(0.000050)	(0.000052)
Total layoffs 2 years ago			0.000090	−0.000014	0.000131*	0.000117*
			(0.000056)	(0.000065)	(0.000068)	(0.000066)
Total layoffs 3 years ago				0.000166***	−0.000077	−0.000151**
				(0.000055)	(0.000068)	(0.000070)
Total layoffs 4 years ago					0.000380***	0.000249***
					(0.000064)	(0.000076)
Total layoffs 5 years ago						0.000263***
						(0.000072)
Observations	11,319	11,319	11,319	10,702	10,062	9,369
F Statistic	76.347500*** (df = 2; 10063)	143.664700*** (df = 3; 10062)	108.421500*** (df = 4; 10061)	84.758130*** (df = 5; 9445)	64.593070*** (df = 6; 8813)	51.458060*** (df = 7; 8127)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 21. Total Deaths from suicide) regressed on total layoffs with Per Capita Income and year, county, and state-year fixed-effects

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000330***	0.000162***	0.000168***	0.000147***	0.000233***	0.000262***
	(0.000031)	(0.000032)	(0.000033)	(0.000033)	(0.000038)	(0.000037)
Per Capita Income	0.000070	0.000073*	0.000073*	0.000071	0.000068	0.000064
	(0.000043)	(0.000042)	(0.000042)	(0.000044)	(0.000046)	(0.000047)
Total layoffs 1 year ago		0.000503***	0.000436***	0.000451***	0.000278***	0.000314***
		(0.000034)	(0.000049)	(0.000049)	(0.000053)	(0.000055)
Total layoffs 2 years ago			0.000112*	−0.000053	0.000112	0.000110
			(0.000059)	(0.000068)	(0.000072)	(0.000071)
Total layoffs 3 years ago				0.000259***	−0.000011	−0.000094
				(0.000058)	(0.000072)	(0.000075)
Total layoffs 4 years ago					0.000429***	0.000247***
					(0.000068)	(0.000080)
Total layoffs 5 years ago						0.000306***
						(0.000075)
Observations	11,319	11,319	11,319	10,702	10,062	9,369
F Statistic	5.300992*** (df = 715; 9364)	2.368014*** (df = 702; 9363)	2.370491*** (df = 703; 9362)	2.332851*** (df = 654; 8796)	2.271142*** (df = 606; 8213)	2.100190*** (df = 557; 7577)
Note:						*p<0.1; **p<0.05; ***p<0.01

A.2. **Regressions with Only County Fixed Effects.** This section contains regression tables for regressions with just county fixed-effects.

Table 22. Total Deaths from Alcohol and Drugs regressed on total layoffs with county fixed-effects only

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000470***	−0.000103	−0.000046	−0.000234***	0.000015	0.000213***
	(0.000078)	(0.000082)	(0.000082)	(0.000080)	(0.000087)	(0.000079)
Total layoffs 1 year ago		0.001687***	0.000998***	0.001171***	0.000216*	−0.000487***
		(0.000087)	(0.000122)	(0.000118)	(0.000120)	(0.000112)
Total layoffs 2 years ago			0.001146***	0.000482***	0.001415***	0.000839***
			(0.000144)	(0.000162)	(0.000160)	(0.000144)
Total layoffs 3 years ago				0.000805***	−0.000226	0.000763***
				(0.000138)	(0.000160)	(0.000150)
Total layoffs 4 years ago					0.001594***	0.001658***
					(0.000153)	(0.000167)
Total layoffs 5 years ago						0.000659***
						(0.000159)
Observations	14,125	14,125	14,125	13,520	12,877	12,168
F Statistic	36.600130*** (df = 1; 12600)	206.857600*** (df = 2; 12599)	159.711700*** (df = 3; 12598)	126.914500*** (df = 4; 11993)	121.672200*** (df = 5; 11350)	116.041800*** (df = 6; 10640)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 23. Total alcohol deaths regressed on total layoffs with county fixed-effects only

	Dependent variable:					
	Total alcohol deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000532***	0.000294***	0.000322***	0.000237***	0.000255***	0.000327***
	(0.000041)	(0.000043)	(0.000043)	(0.000043)	(0.000049)	(0.000047)
Total layoffs 1 year ago		0.000698***	0.000370***	0.000378***	0.000202***	−0.000111
		(0.000046)	(0.000065)	(0.000064)	(0.000068)	(0.000068)
Total layoffs 2 years ago			0.000543***	0.000569***	0.000733***	0.000663***
			(0.000077)	(0.000088)	(0.000091)	(0.000088)
Total layoffs 3 years ago				0.000121	0.000001	0.000112
				(0.000075)	(0.000091)	(0.000092)
Total layoffs 4 years ago					0.000232***	0.000802***
					(0.000087)	(0.000102)
Total layoffs 5 years ago						−0.000648***
						(0.000097)
Observations	6,818	6,818	6,818	6,438	6,047	5,659
F Statistic	166.921300*** (df = 1; 6030)	202.061100*** (df = 2; 6029)	152.446500*** (df = 3; 6028)	124.682800*** (df = 4; 5651)	96.029200*** (df = 5; 5263)	84.461840*** (df = 6; 4879)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 24. Total Drug deaths regressed on total layoffs with county fixed-effects only

	Dependent variable:					
	Total Drug deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	−0.000060	−0.000392***	−0.000363***	−0.000462***	−0.000236***	−0.000108
	(0.000071)	(0.000075)	(0.000075)	(0.000072)	(0.000079)	(0.000070)
Total layoffs 1 year ago		0.000977***	0.000637***	0.000797***	0.000019	−0.000376***
		(0.000079)	(0.000112)	(0.000108)	(0.000109)	(0.000100)
Total layoffs 2 years ago			0.000565***	−0.000094	0.000679***	0.000177
			(0.000132)	(0.000148)	(0.000145)	(0.000128)
Total layoffs 3 years ago				0.000644***	−0.000251*	0.000627***
				(0.000126)	(0.000145)	(0.000134)
Total layoffs 4 years ago					0.001337***	0.000859***
					(0.000139)	(0.000149)
Total layoffs 5 years ago						0.001279***
						(0.000142)
Observations	9,611	9,611	9,611	9,272	8,922	8,528
F Statistic	0.711636 (df = 1; 8467)	75.981110*** (df = 2; 8466)	56.836700*** (df = 3; 8465)	46.244660*** (df = 4; 8126)	59.730720*** (df = 5; 7775)	82.227010*** (df = 6; 7380)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 25. Total Deaths from intentional self harm (suicide) regressed on total layoffs with county fixed-effects only

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000394***	0.000163***	0.000177***	0.000133***	0.000244***	0.000297***
	(0.000032)	(0.000034)	(0.000034)	(0.000033)	(0.000039)	(0.000038)
Total layoffs 1 year ago		0.000679***	0.000512***	0.000544***	0.000298***	0.000270***
		(0.000035)	(0.000050)	(0.000050)	(0.000053)	(0.000054)
Total layoffs 2 years ago			0.000277***	0.000020	0.000251***	0.000199***
			(0.000059)	(0.000068)	(0.000071)	(0.000069)
Total layoffs 3 years ago				0.000382***	0.000022	0.000007
				(0.000058)	(0.000071)	(0.000072)
Total layoffs 4 years ago					0.000538***	0.000415***
					(0.000067)	(0.000080)
Total layoffs 5 years ago						0.000256***
						(0.000077)
Observations	11,471	11,471	11,471	10,847	10,197	9,494
F Statistic	153.672800*** (df = 1; 10210)	262.652800*** (df = 2; 10209)	182.854300*** (df = 3; 10208)	139.674800*** (df = 4; 9584)	105.718300*** (df = 5; 8941)	77.026260*** (df = 6; 8245)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 26. Total Deaths from Alcohol and Drugs regressed on total layoffs with Per Capita Income county fixed-effects only

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000406***	−0.000079	−0.000044	−0.000165**	−0.000001	0.000158**
	(0.000071)	(0.000075)	(0.000075)	(0.000073)	(0.000082)	(0.000074)
Per Capita Income	0.001944***	0.001902***	0.001889***	0.001830***	0.001687***	0.001494***
	(0.000037)	(0.000037)	(0.000037)	(0.000039)	(0.000039)	(0.000038)
Total layoffs 1 year ago		0.001430***	0.001013***	0.001125***	0.000375***	−0.000258**
		(0.000080)	(0.000112)	(0.000109)	(0.000112)	(0.000106)
Total layoffs 2 years ago			0.000698***	0.000432***	0.001175***	0.000708***
			(0.000132)	(0.000149)	(0.000149)	(0.000135)
Total layoffs 3 years ago				0.000264**	−0.000460***	0.000441***
				(0.000128)	(0.000149)	(0.000142)
Total layoffs 4 years ago					0.001191***	0.001291***
					(0.000143)	(0.000157)
Total layoffs 5 years ago						0.000606***
						(0.000150)
Observations	13,938	13,938	13,938	13,341	12,704	12,003
F Statistic	1,379.673000*** (df = 2; 12439)	1,051.282000*** (df = 3; 12438)	797.167800*** (df = 4; 12437)	564.856600*** (df = 5; 11839)	422.718700*** (df = 6; 11202)	330.077900*** (df = 7; 10500)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 27. Total alcohol deaths regressed on total layoffs with Per Capita Income county fixed-effects only

	Dependent variable:					
	Total alcohol deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000505***	0.000299***	0.000319***	0.000259***	0.000248***	0.000301***
	(0.000039)	(0.000041)	(0.000041)	(0.000040)	(0.000047)	(0.000045)
Per Capita Income	0.000728***	0.000698***	0.000687***	0.000716***	0.000724***	0.000731***
	(0.000027)	(0.000027)	(0.000027)	(0.000029)	(0.000030)	(0.000031)
Total layoffs 1 year ago		0.000607***	0.000368***	0.000355***	0.000258***	−0.000016
		(0.000044)	(0.000062)	(0.000061)	(0.000065)	(0.000065)
Total layoffs 2 years ago			0.000398***	0.000552***	0.000641***	0.000608***
			(0.000073)	(0.000084)	(0.000087)	(0.000083)
Total layoffs 3 years ago				−0.000065	−0.000087	−0.000032
				(0.000071)	(0.000087)	(0.000088)
Total layoffs 4 years ago					0.000079	0.000649***
					(0.000083)	(0.000097)
Total layoffs 5 years ago						−0.000682***
						(0.000092)
Observations	6,772	6,772	6,772	6,396	6,007	5,622
F Statistic	455.843400*** (df = 2; 5992)	377.867900*** (df = 3; 5991)	292.139900*** (df = 4; 5990)	236.711900*** (df = 5; 5616)	183.557300*** (df = 6; 5230)	157.236300*** (df = 7; 4848)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 28. Total Drug deaths regressed on total layoffs with Per Capita Income county fixed-effects only

	Dependent variable:					
	Total Drug deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	−0.000118*	−0.000373***	−0.000364***	−0.000405***	−0.000251***	−0.000154**
	(0.000064)	(0.000068)	(0.000068)	(0.000067)	(0.000074)	(0.000066)
Per Capita Income	0.001819***	0.001788***	0.001784***	0.001699***	0.001487***	0.001249***
	(0.000041)	(0.000041)	(0.000041)	(0.000043)	(0.000043)	(0.000041)
Total layoffs 1 year ago		0.000752***	0.000642***	0.000752***	0.000146	−0.000202**
		(0.000072)	(0.000102)	(0.000099)	(0.000101)	(0.000095)
Total layoffs 2 years ago			0.000185	−0.000130	0.000487***	0.000081
			(0.000120)	(0.000136)	(0.000135)	(0.000121)
Total layoffs 3 years ago				0.000179	−0.000443***	0.000376***
				(0.000116)	(0.000135)	(0.000127)
Total layoffs 4 years ago					0.001005***	0.000569***
					(0.000130)	(0.000141)
Total layoffs 5 years ago						0.001237***
						(0.000134)
Observations	9,530	9,530	9,530	9,193	8,846	8,455
F Statistic	980.995500*** (df = 2; 8399)	698.606500*** (df = 3; 8398)	524.630800*** (df = 4; 8397)	359.800700*** (df = 5; 8060)	260.492000*** (df = 6; 7712)	214.773600*** (df = 7; 7320)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 29. Total Deaths from intentional self harm (suicide) regressed on total layoffs with Per Capita Income county fixed-effects only

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.000372***	0.000171***	0.000178***	0.000158***	0.000239***	0.000274***
	(0.000030)	(0.000031)	(0.000031)	(0.000031)	(0.000036)	(0.000036)
Per Capita Income	0.000665***	0.000646***	0.000644***	0.000656***	0.000637***	0.000644***
	(0.000016)	(0.000016)	(0.000016)	(0.000017)	(0.000019)	(0.000020)
Total layoffs 1 year ago		0.000591***	0.000515***	0.000526***	0.000356***	0.000366***
		(0.000033)	(0.000047)	(0.000046)	(0.000050)	(0.000051)
Total layoffs 2 years ago			0.000126**	0.000002	0.000160**	0.000144**
			(0.000055)	(0.000064)	(0.000067)	(0.000065)
Total layoffs 3 years ago				0.000192***	−0.000064	−0.000130*
				(0.000054)	(0.000067)	(0.000069)
Total layoffs 4 years ago					0.000389***	0.000263***
					(0.000064)	(0.000076)
Total layoffs 5 years ago						0.000230***
						(0.000072)
Observations	11,319	11,319	11,319	10,702	10,062	9,369
F Statistic	928.633800*** (df = 2; 10077)	745.013800*** (df = 3; 10076)	560.319200*** (df = 4; 10075)	410.081400*** (df = 5; 9458)	291.985300*** (df = 6; 8825)	223.121500*** (df = 7; 8138)
Note:						*p<0.1; **p<0.05; ***p<0.01

A.3. **Regressions with Only Year Fixed Effects.** This section contains regression tables for annual fixed-effects.

Table 30. Total Deaths from Alcohol and Drugs regressed on total layoffs with year fixed-effects only

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.017252***	0.007713***	0.006738***	0.005288***	0.007474***	0.005172***
	(0.000159)	(0.000231)	(0.000221)	(0.000222)	(0.000223)	(0.000236)
Total layoffs 1 year ago		0.011863***	0.000882**	0.001293***	−0.002710***	−0.001604***
		(0.000223)	(0.000362)	(0.000355)	(0.000367)	(0.000377)
Total layoffs 2 years ago			0.014408***	0.005699***	0.007391***	0.005302***
			(0.000385)	(0.000487)	(0.000490)	(0.000486)
Total layoffs 3 years ago				0.011366***	−0.000717	0.003123***
				(0.000384)	(0.000497)	(0.000513)
Total layoffs 4 years ago					0.014947***	0.005098***
					(0.000389)	(0.000561)
Total layoffs 5 years ago						0.012149***
						(0.000453)
Observations	14,125	14,125	14,125	13,520	12,877	12,168
F Statistic	11,831.930000*** (df = 1; 14109)	8,513.653000*** (df = 2; 14108)	6,708.186000*** (df = 3; 14107)	5,270.427000*** (df = 4; 13502)	4,738.783000*** (df = 5; 12859)	4,140.743000*** (df = 6; 12150)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 31. Total alcohol deaths regressed on total layoffs with year fixed-effects only

	Dependent variable:					
	Total alcohol deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.008350***	0.003920***	0.003512***	0.002982***	0.004079***	0.003114***
	(0.000095)	(0.000134)	(0.000128)	(0.000129)	(0.000130)	(0.000139)
Total layoffs 1 year ago		0.005533***	0.000753***	0.000987***	−0.000180	0.000721***
		(0.000129)	(0.000211)	(0.000209)	(0.000217)	(0.000225)
Total layoffs 2 years ago			0.006276***	0.002655***	0.002800***	0.002216***
			(0.000226)	(0.000290)	(0.000293)	(0.000293)
Total layoffs 3 years ago				0.004539***	−0.001053***	−0.000070
				(0.000227)	(0.000295)	(0.000308)
Total layoffs 4 years ago					0.006455***	0.001866***
					(0.000230)	(0.000336)
Total layoffs 5 years ago						0.005087***
						(0.000269)
Observations	6,818	6,818	6,818	6,438	6,047	5,659
F Statistic	7,675.585000*** (df = 1; 6802)	5,787.342000*** (df = 2; 6801)	4,553.299000*** (df = 3; 6800)	3,455.658000*** (df = 4; 6420)	3,003.238000*** (df = 5; 6029)	2,487.569000*** (df = 6; 5641)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 32. Total Drug deaths regressed on total layoffs with year fixed-effects only

	Dependent variable:					
	Total Drug deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.008164***	0.003461***	0.002957***	0.002136***	0.003203***	0.001955***
	(0.000116)	(0.000174)	(0.000169)	(0.000171)	(0.000173)	(0.000182)
Total layoffs 1 year ago		0.005862***	0.000077	0.000293	−0.002318***	−0.002051***
		(0.000168)	(0.000278)	(0.000274)	(0.000286)	(0.000292)
Total layoffs 2 years ago			0.007595***	0.002856***	0.004298***	0.002848***
			(0.000296)	(0.000378)	(0.000383)	(0.000377)
Total layoffs 3 years ago				0.006264***	0.000014	0.002753***
				(0.000297)	(0.000389)	(0.000399)
Total layoffs 4 years ago					0.008067***	0.002893***
					(0.000304)	(0.000436)
Total layoffs 5 years ago						0.006799***
						(0.000351)
Observations	9,611	9,611	9,611	9,272	8,922	8,528
F Statistic	4,915.635000*** (df = 1; 9595)	3,375.215000*** (df = 2; 9594)	2,623.386000*** (df = 3; 9593)	2,068.486000*** (df = 4; 9254)	1,900.244000*** (df = 5; 8904)	1,752.809000*** (df = 6; 8510)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 33. Total Deaths from intentional self harm (suicide) regressed on total layoffs with year fixed-effects only

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.007439***	0.003477***	0.003063***	0.002405***	0.003307***	0.002206***
	(0.000085)	(0.000127)	(0.000123)	(0.000124)	(0.000127)	(0.000137)
Total layoffs 1 year ago		0.004933***	0.000261	0.000443**	−0.001268***	−0.000598***
		(0.000122)	(0.000202)	(0.000200)	(0.000210)	(0.000219)
Total layoffs 2 years ago			0.006137***	0.002291***	0.003059***	0.002262***
			(0.000215)	(0.000274)	(0.000281)	(0.000283)
Total layoffs 3 years ago				0.005020***	−0.000083	0.001414***
				(0.000216)	(0.000284)	(0.000299)
Total layoffs 4 years ago					0.006282***	0.001957***
					(0.000223)	(0.000327)
Total layoffs 5 years ago						0.005078***
						(0.000263)
Observations	11,471	11,471	11,471	10,847	10,197	9,494
F Statistic	7,642.829000*** (df = 1; 11455)	5,174.199000*** (df = 2; 11454)	3,968.395000*** (df = 3; 11453)	3,061.801000*** (df = 4; 10829)	2,643.090000*** (df = 5; 10179)	2,170.764000*** (df = 6; 9476)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 34. Total Deaths from Alcohol and Drugs regressed on total layoffs with Per Capita Income and year fixed-effects only

	Dependent variable:					
	Total Deaths from Alcohol and Drugs					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.016704***	0.007462***	0.006536***	0.005163***	0.007334***	0.005115***
	(0.000157)	(0.000226)	(0.000217)	(0.000218)	(0.000219)	(0.000232)
Per Capita Income	0.001939***	0.001765***	0.001655***	0.001561***	0.001467***	0.001392***
	(0.000071)	(0.000065)	(0.000062)	(0.000061)	(0.000059)	(0.000059)
Total layoffs 1 year ago		0.011554***	0.000966***	0.001354***	−0.002482***	−0.001371***
		(0.000219)	(0.000355)	(0.000349)	(0.000361)	(0.000371)
Total layoffs 2 years ago			0.013918***	0.005498***	0.007056***	0.005068***
			(0.000378)	(0.000479)	(0.000482)	(0.000478)
Total layoffs 3 years ago				0.010983***	−0.000878*	0.002765***
				(0.000377)	(0.000489)	(0.000505)
Total layoffs 4 years ago					0.014651***	0.004985***
					(0.000383)	(0.000552)
Total layoffs 5 years ago						0.011910***
						(0.000446)
Observations	13,938	13,938	13,938	13,341	12,704	12,003
F Statistic	6,521.930000*** (df = 2; 13921)	6,144.174000*** (df = 3; 13920)	5,396.144000*** (df = 4; 13919)	4,493.399000*** (df = 5; 13322)	4,184.436000*** (df = 6; 12685)	3,742.892000*** (df = 7; 11984)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 35. Total alcohol deaths regressed on total layoffs with Per Capita Income and year fixed-effects only

	Dependent variable:					
	Total alcohol deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.008278***	0.003891***	0.003490***	0.002969***	0.004065***	0.003112***
	(0.000095)	(0.000133)	(0.000127)	(0.000129)	(0.000130)	(0.000139)
Per Capita Income	0.000478***	0.000404***	0.000365***	0.000326***	0.000292***	0.000272***
	(0.000054)	(0.000048)	(0.000046)	(0.000046)	(0.000044)	(0.000045)
Total layoffs 1 year ago		0.005493***	0.000760***	0.000990***	−0.000158	0.000742***
		(0.000129)	(0.000211)	(0.000209)	(0.000217)	(0.000225)
Total layoffs 2 years ago			0.006220***	0.002632***	0.002763***	0.002190***
			(0.000226)	(0.000289)	(0.000293)	(0.000293)
Total layoffs 3 years ago				0.004499***	−0.001070***	−0.000111
				(0.000227)	(0.000295)	(0.000309)
Total layoffs 4 years ago					0.006427***	0.001858***
					(0.000230)	(0.000336)
Total layoffs 5 years ago						0.005064***
						(0.000269)
Observations	6,772	6,772	6,772	6,396	6,007	5,622
F Statistic	3,892.894000*** (df = 2; 6755)	3,893.712000*** (df = 3; 6754)	3,438.304000*** (df = 4; 6753)	2,777.460000*** (df = 5; 6377)	2,510.241000*** (df = 6; 5988)	2,136.705000*** (df = 7; 5603)
Note:						*p<0.1; **p<0.05; ***p<0.01

TABLE 36. Total Drug deaths regressed on total layoffs with Per Capita Income and year fixed-effects only

	Dependent variable:					
	Total Drug deaths					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.007888***	0.003339***	0.002857***	0.002077***	0.003135***	0.001929***
	(0.000115)	(0.000171)	(0.000166)	(0.000168)	(0.000170)	(0.000179)
Per Capita Income	0.001255***	0.001166***	0.001111***	0.001067***	0.001015***	0.000969***
	(0.000058)	(0.000055)	(0.000053)	(0.000053)	(0.000052)	(0.000051)
Total layoffs 1 year ago		0.005695***	0.000112	0.000313	−0.002196***	−0.001921***
		(0.000165)	(0.000273)	(0.000270)	(0.000281)	(0.000287)
Total layoffs 2 years ago			0.007340***	0.002751***	0.004102***	0.002715***
			(0.000291)	(0.000371)	(0.000377)	(0.000371)
Total layoffs 3 years ago				0.006057***	−0.000080	0.002535***
				(0.000292)	(0.000382)	(0.000392)
Total layoffs 4 years ago					0.007911***	0.002836***
					(0.000299)	(0.000429)
Total layoffs 5 years ago						0.006666***
						(0.000345)
Observations	9,530	9,530	9,530	9,193	8,846	8,455
F Statistic	2,783.882000*** (df = 2; 9513)	2,483.096000*** (df = 3; 9512)	2,145.549000*** (df = 4; 9511)	1,792.744000*** (df = 5; 9174)	1,701.791000*** (df = 6; 8827)	1,604.063000*** (df = 7; 8436)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 37. Total Deaths from intentional self harm (suicide) regressed on total layoffs with Per Capita Income and year fixed-effects only

	Dependent variable:					
	Total Deaths from Suicide					
	(1)	(2)	(3)	(4)	(5)	(6)
Total layoffs this year	0.007226***	0.003379***	0.002984***	0.002355***	0.003251***	0.002187***
	(0.000084)	(0.000124)	(0.000121)	(0.000122)	(0.000125)	(0.000135)
Per Capita Income	0.000949***	0.000880***	0.000839***	0.000792***	0.000745***	0.000715***
	(0.000041)	(0.000039)	(0.000037)	(0.000037)	(0.000037)	(0.000037)
Total layoffs 1 year ago		0.004809***	0.000289	0.000462**	−0.001184***	−0.000513**
		(0.000120)	(0.000198)	(0.000196)	(0.000207)	(0.000216)
Total layoffs 2 years ago			0.005945***	0.002212***	0.002929***	0.002169***
			(0.000211)	(0.000270)	(0.000277)	(0.000279)
Total layoffs 3 years ago				0.004872***	−0.000140	0.001276***
				(0.000213)	(0.000280)	(0.000295)
Total layoffs 4 years ago					0.006160***	0.001908***
					(0.000219)	(0.000322)
Total layoffs 5 years ago						0.004987***
						(0.000259)
Observations	11,319	11,319	11,319	10,702	10,062	9,369
F Statistic	4,222.137000*** (df = 2; 11302)	3,743.708000*** (df = 3; 11301)	3,202.915000*** (df = 4; 11300)	2,617.319000*** (df = 5; 10683)	2,338.580000*** (df = 6; 10043)	1,967.758000*** (df = 7; 9350)

Note: *p<0.1; **p<0.05; ***p<0.01