The Economic Impact of Mental Illness in Ohio

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Abstract

The costs associated with mental health issues are under examined and becoming increasingly relevant. Costs can broadly be organized into three groups: Foregone productivity, direct expenditure, and intangible quality of life costs. These costs are simultaneously large at the state level and appear to be growing over time. In 2023 mental health issues accounted for nearly $24 Billion dollars in lost productivity. We estimate an additional $6-7 Billion in direct medical expenditure associated with mental illness and nearly $50 billion in intangible quality of life damages. These costs stress a growing need to better understand the issue and to structure public policy to address it.

1 Introduction

Mental illness imposes costs that extend well beyond the individuals who directly experience it. These costs appear in labor markets through reduced employment, lower labor force participation, underemployment, and absenteeism; within households through uncompensated caregiving and lost employment; within the health care system through additional medical expenditures; and more broadly through interactions with homelessness, the criminal justice system, and premature mortality. Taken individually, each of these channels captures only one dimension of the burden associated with mental illness. Taken together, they suggest that mental illness has consequences not only for individual health and well-being, but also for economic activity and social welfare.

Measuring these costs is important for at least two reasons. First, many of the consequences of mental illness do not appear explicitly in government budgets or conventional measures of health care expenditure. A worker who leaves the labor force, works fewer hours, or earns less because of mental illness represents forgone economic activity even when no corresponding government expenditure occurs. Similarly, family members who reduce their own employment to provide care impose an economic cost that may never appear as a market transaction. A narrow focus on direct medical expenditures therefore understates the broader economic burden of mental illness. Second, credible estimates of these costs provide a basis for comparing the resources devoted to prevention and treatment with the economic and welfare losses that those interventions may avert.

This study estimates the economic burden of mental illness in Ohio by organizing costs into three broad categories: foregone economic production, direct expenditures, and intangible welfare losses associated with premature mortality and crime. This distinction is important because these measures describe conceptually different consequences and should not all be interpreted as changes in gross domestic product (GDP). Foregone production captures economic output that plausibly would have occurred in the absence of mental illness. Direct expenditures capture resources devoted to medical care and other services associated with

mental illness. Mortality-related welfare losses capture something broader: the value individuals place on reducing the risk of premature death and the emotional damages associated with crime.

The first category is based primarily on foregone labor income. The use of earnings as a measure of lost production follows from the income approach to measuring economic output. GDP reflects the income generated through production, including employee compensation, returns to capital, proprietors' income, and other components of value added. Foregone earnings therefore capture only one portion of the economic output that is lost when mental illness reduces employment, labor force participation, hours worked, or earnings. Because our estimates do not include employer-provided compensation or the non-labor income associated with the production that would otherwise have occurred, they should generally be interpreted as a conservative, lower-bound estimate of foregone GDP rather than as a complete measure of lost output i.e. $\Delta GDP \geq \Delta$forgone income . Throughout the analysis, we construct counterfactual employment and earnings outcomes by comparing individuals with mental illness to otherwise relevant populations without mental illness. The resulting differences are interpreted as forgone economic production attributable to mental illness, while recognizing that they do not capture the broader welfare losses associated with illness.

This distinction is especially important for premature mortality. The economic contribution lost when an individual dies can be approximated by the present discounted value of the earnings that individual would otherwise have generated. Such an estimate measures lost production, but it clearly does not capture the full social value of preventing a death. A life has value to the individual and to others that is not reflected in wages or GDP. We therefore report mortality-related welfare losses separately using the Value of a Statistical Life (VSL).

Despite its name, the VSL is not an estimate of the intrinsic or moral value of a particular person's life. It is an economic measure derived from individuals' willingness to pay for small reductions in mortality risk. When aggregated across a population, these willingness-to-pay

estimates provide a monetary measure of the welfare benefit associated with reducing the expected number of premature deaths. We therefore interpret the VSL estimates in this study as monetized welfare losses associated with premature mortality, rather than as lost GDP or as a literal valuation of the lives of individuals with mental illness.

Applying conventional VSL estimates to deaths associated with serious mental illness nevertheless raises important conceptual problems. Standard VSL estimates are largely derived from populations making relatively small and deliberate trade-offs between income and mortality risk. Those assumptions are less clearly applicable in the presence of severe mental illness and are particularly complicated in the case of suicide.

The remaining cost category consists of direct expenditures. These include medical resources devoted to individuals experiencing mental illness and, where measurable, other expenditures associated with consequences such as criminal justice involvement and homelessness. Unlike foregone production, these expenditures generally represent economic resources that are actually used and therefore may be recorded within conventional economic accounts. Their interpretation is consequently different: they represent resources devoted to responding to the consequences of mental illness rather than production that never occurs. All expenditure has an opportunity cost, these resources *could* have been applied to some other problem in the absence of mental illness.

Using this framework, we estimate the burden of mental illness across Ohio counties and over time. The analysis combines data on mental illness prevalence, employment and earnings, mortality, medical expenditures, caregiving, criminal justice involvement, and other outcomes to construct a set of complementary measures of economic burden. The objective is not to collapse every consequence of mental illness into a single dollar figure, but to provide a more complete accounting of where the burden occurs, how large its principal components are, and how those costs have changed over time. Due to resource and data limitations we focus our attention on working age individuals 18-64. This implies many **real** costs of mental illness went uncounted. This report should be interpreted as a start of a conversation to a

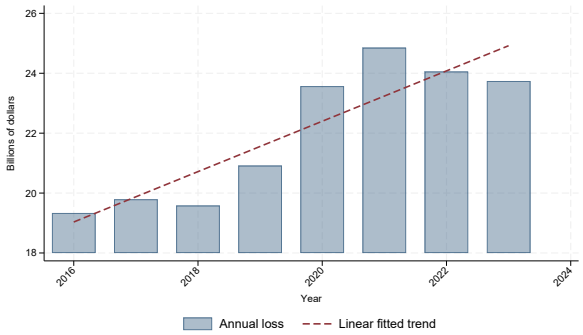
real problem, not as a comprehensive account of the magnitude of the issues involved. As with any assessment of economic outcomes assumptions must be made. We endeavored to stick to two principles; transparency about assumptions made, and reasonable decisions that are generally biased downward in costs. Estimates presented here should be considered at or near the lower bound in economic costs.

2 Summary of Results

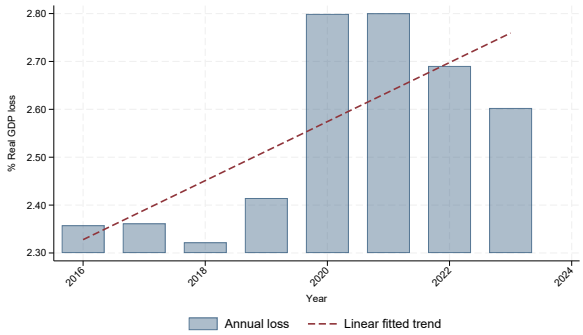
We estimate the total real forgone earnings (real GDP loss in 2025 dollars) to be around $20 billion in 2018 and about $24 billion in 2023. This increase is not purely driven by changes in population as the costs are growing as a share of GDP from around 2.4% to as high as 2.8% of GDP, see Figures 1a and 1b. These costs are comprised of (i) the foregone income from relatively higher unemployment rates and lower labor force participation rates, (ii) relatively lower wages and fewer working hours, (iii) the relatively lower household income of those households that must care for those with mental illness. The present discounted value of earning from premature death and suicide, and the lost production of incarceration.

Direct expenditures associated with mental illness typically sit somewhere between $6-8 billion dollars annually, see Figure 1c. These costs will include (i) medical expenditures associated with treatment of mental illness, (ii) expenditures toward treatment and housing of homeless individuals with MI, and (iii) expenditures for incarceration and damages related to criminal behavior.[1] Finally, in Figure 1d we present the intangible welfare losses associated with mental illness. These include the mortality-related welfare losses associated with suicide and premature death associated with mental illness as measured by VSL and the intangible (i.e. emotional pain and suffering) damages associated with crime that can be directly linked to mental illness. Finally we present an estimate of foregone tax revenue that is associated with the foregone productivity in Figure 1e.[2] Analogous estimates at the county level for

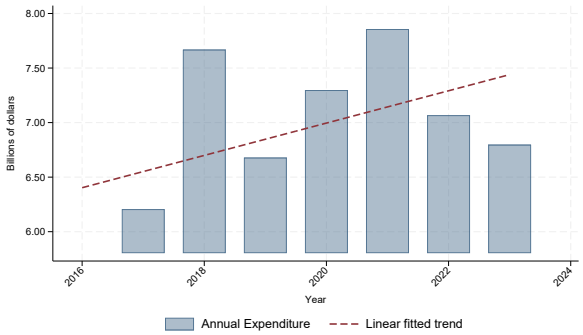
[1] Note that these do not include the emotional costs associated with mental illness e.g. pain and suffering.
[2] Foregone tax revenue is calculated as 5% of foregone wages.



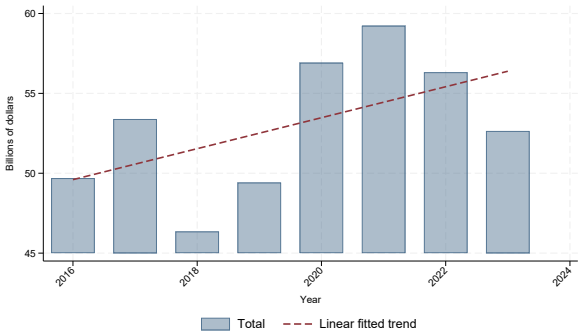
(a) Total Real GDP loss



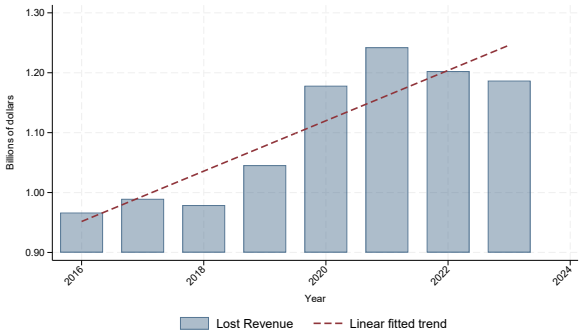
(b) %Real GDP Loss



(c) Direct Expenditures

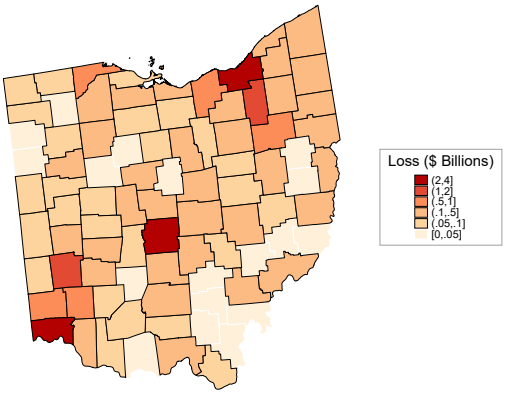


(d) Intangible Welfare Losses

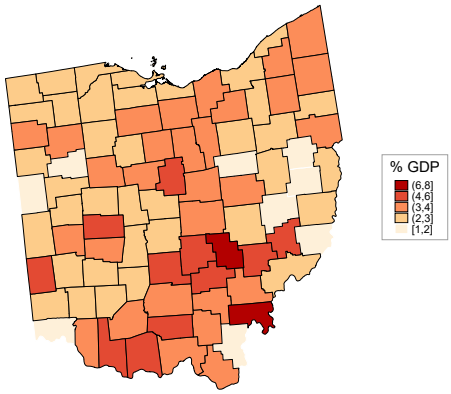


(e) Foregone Tax Revenue

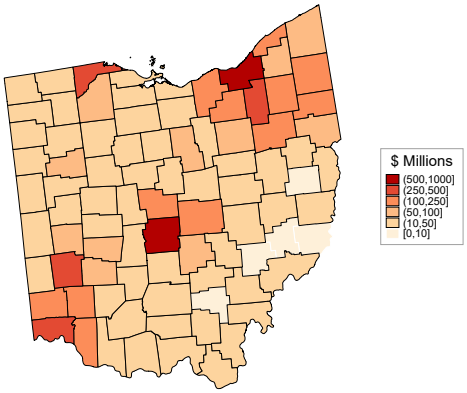
Figure 1: Total Direct and Indirect Costs by Year



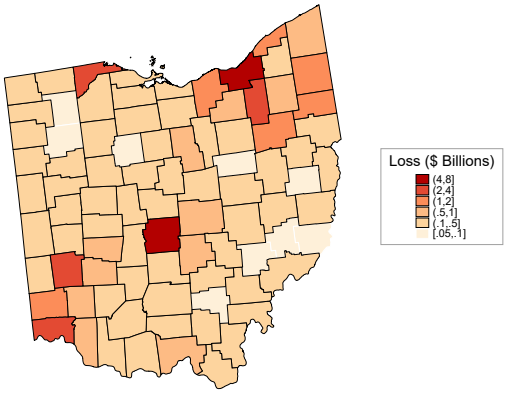
(a) Total Real GDP loss



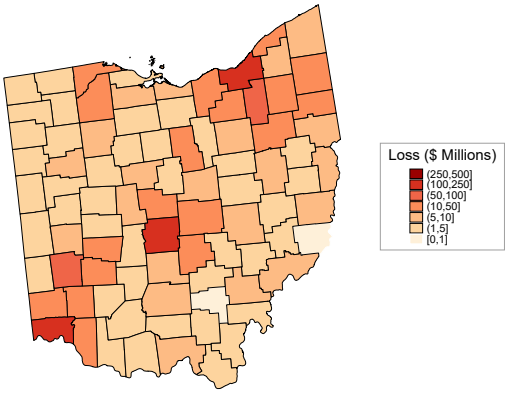
(b) %Real GDP Loss



(c) Direct Expenditures



(d) Intangible Welfare Losses



(e) Foregone Tax Revenue

Figure 2: Total Direct and Indirect Costs by County

2023 can be found in Figure 2 with exact calculations for each county in Table 1 in the appendix.

The remainder of this document will guide the reader through the process we used to calculate these costs, including our data sources, assumptions, and rationale.

3 Unemployment and Labor Force Participation

3.1 Data Sources

- American Community Survey (ACS)
- National Survey on Drug Use and Health (NSDUH)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

Adults with any mental illness (AMI) are more likely to be unemployed or not in the workforce. We estimate this economic loss by estimating the counterfactual employment if adults with AMI had similar labor force participation and unemployment rates as those without AMI. County estimates for the GDP loss due to mental illness are derived by first finding the estimated total number of adults between the ages of 18-64 with AMI. We take the total county population (ACS) in that age group and apply the rate of AMI for that population using the regional estimates in the SAMHSA Behavioral Health Barometer publications each year. This gives us the estimated total number of adults within the county with AMI for each year. The counterfactual GDP loss is the total number of unemployed adults, including those not in the labor force, with AMI who would otherwise be working, multiplied by their appropriate wage.

Using data from the National Survey on Drug Use and Health (NSDUH), conducted by the Substance Abuse and Mental Health Services Administration (SAMHSA) (henceforth NSDUH), we are able to find the difference in labor force participation rates and unemployment rates between those with and without AMI. An additional 9% of the total adult population with AMI would be working if they had similar labor force participation and

unemployment rates as those without AMI.[3] We apply the non-AMI employment rate to this share of the AMI adult population to represent the number of additional AMI adults who would be working if they experienced the same employment rate as adults without AMI. However we only observe one average wage for each county. We know that this wage is a composition of those with and without AMI and part/full time workers. Not every non-AMI worker is working full time. As we will discuss in Section 4 the population unemployment rate of those with AMI is slightly higher than those without AMI, but they are considerably more likely to be out of the labor force all together or underemployed (i.e. working part time). Because the part-time/full-time wage distinction must be made in Section 4 we opted to do it here as well for completeness. We use the NSDUH to find the proportions of employed workers that work full/part-time conditional on having AMI as well as the relative wages across the four groups: AMI-part-time, AMI-full time, non-AMI-part-time, non-AMI-full time. A full decomposition can be found in Appendix Section A.

We also calculate a separate estimate for wages. We follow Traynor (2025), in estimating forgone wages through median household income. One complication is that each household income estimate likely contains more than one earner. Median household income must be weighted by the number of workers per household before it can be multiplied by the estimated number of AMI individuals who should be working. The ACS provides county estimates for the total number of family and non-family households; as well as the total number of family households with one, two, and three earners. Assuming that non-family households have a single earner summing over the remainder of the households multiplied by the number of workers the total number of workers can be estimated. Dividing by the total number of households we are able to estimate the average number of workers per household.[4] Estimates for an individual salary are obtained by dividing median household income by the number of workers per household. We multiply that by our existing estimate of the number of

[3]This equates to approximately 700 and 1650 people per county year for the median and average Ohio county.

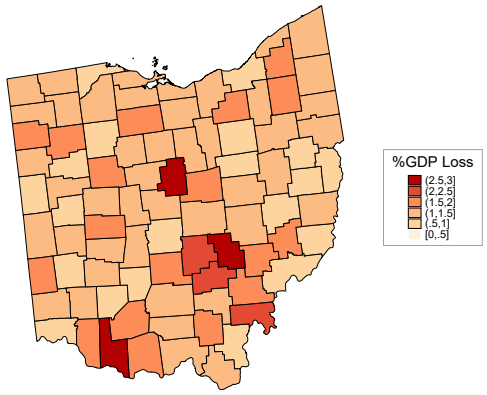
[4]Estimates are remarkably similar for the mean and median county at 1.29 workers per household. This is slightly higher than the estimates (1.2) used by Traynor.

people who would otherwise be working if they did not have mental illness. Finally, all nominal dollar amounts were translated to real 2025 real dollars using the C-CPI: All Urban Consumers, for all items published by FRED.

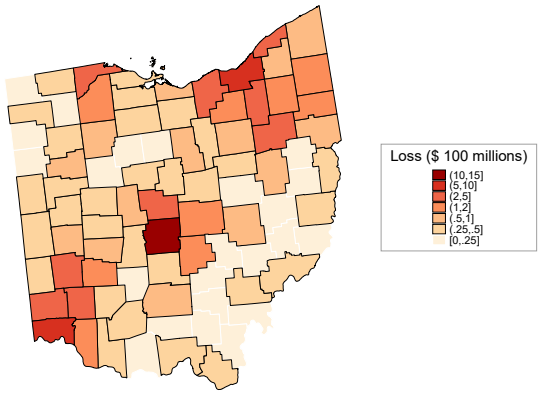
3.2 Results

Both income estimates give very similar results, so we present only the estimates from the wage decomposition described above. The median and average counties loose about 30 and 84 million dollars respectively in GDP loss, this translates to about 0.9-1% of GDP for most counties. Figures 3a and 3b present the percent and nominal losses to GDP in 2023 for each county. It is important to note that this cost has been growing since 2015. Figures 3c and 3d present the total statewide figures over time. The cost of unemployment associated with mental illness has been growing over time both as a percentage of, and in real, GDP. Reaching a total statewide cost of nearly 7.5 Billion in 2023 in real 2025 dollars. This translates to about 0.825% percent of total statewide GDP.[5]

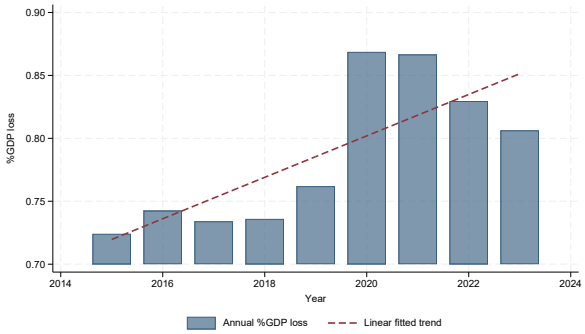
[5]Note that counties with the largest GDP tend to have GDP losses less than 1% which is how the average GDP loss can be over 1% for most counties but it be only about .825% statewide when aggregated in 2023.



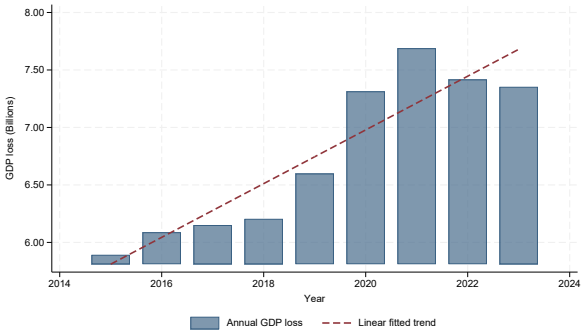
(a) Percent GDP loss



(b) Real GDP loss 2025 dollars



(c) Statewide Percent GDP loss



(d) Statewide real GDP loss 2025 dollars

Figure 3: GDP Losses Associated with Unemployment

4 Absenteeism/Underemployment

4.1 Data Sources

- American Community Survey (ACS):
- National Survey on Drug Use and Health (NSDUH)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

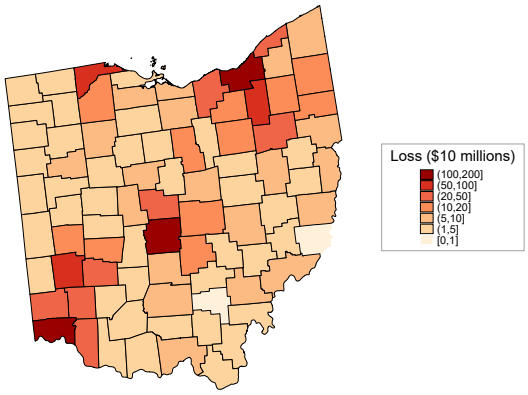
In the previous section we calculate the cost of higher unemployment and lower LFP of those with AMI. Adults with mental illness are also substantially more likely to be underemployed when they do work. This underemployment is reflected in lower annual earnings. To estimate this cost, we compare the observed income of employed adults with AMI to the hypothetical income they would have earned in the absence of AMI at similar employment rates as those without AMI.

Using the ACS, we identify the population of residents between the ages of 18 and 64 in each county. Using data from the NSDUH, we estimate the proportion of the county's working-age population that has AMI. NSDUH data also indicate that employed adults with AMI earn approximately 77% as much as adults without AMI. However, this is primarily driven by the fact that, conditional on being employed, the part-time unemployment rate for those with AMI is about eight percentage points higher. When investigated separately, those with AMI make about 87% and 83% of that made by those without AMI for both the full and part-time employed. The 77.4% is a product of the fact that part-time employed workers make considerably less than those employed full time. To estimate the cost we estimate the current contribution to GDP for those with AMI, at their current employment (full/part time) rates and wages, and subtract that from the counterfactual of those same

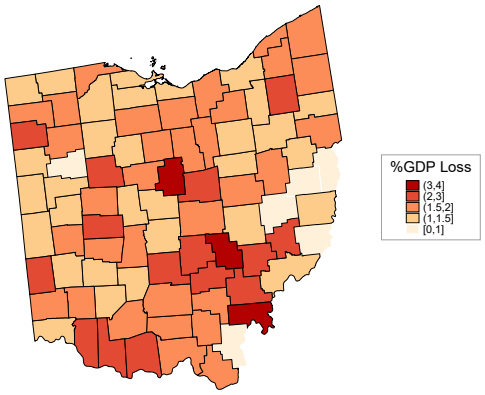
individuals working at the full/part time employment rates and wages of those without AMI. The difference would represent the foregone GDP.

5 Results

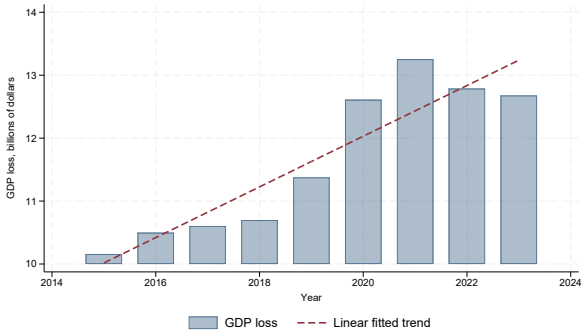
From Figure 4 we see the costs of underemployment are comparable to those of unemployment and lower labor force participation. There was also a major increase in both the level (Figure 4c) and percent (Figure 4d) of forgone productivity in the COVID and post-COVID era. This is likely due to the increased proportion of AMI workers being part-time; which were considerably more likely designated as "unessential" during the pandemic. There is also some evidence of an increase in some mental illness during the pandemic (Ettman et al., 2020), although the evidence is somewhat mixed, Penninx et al. (2022). The intersection of the ***causal*** implications of the pandemic, economic growth, and mental illness is not very well understood. Back of the envelope estimates put the *cost* of mental illness underemployment at somewhere between 11 and 13 billion dollars annually which translates to between 1.3 and 1.5% of GDP statewide.



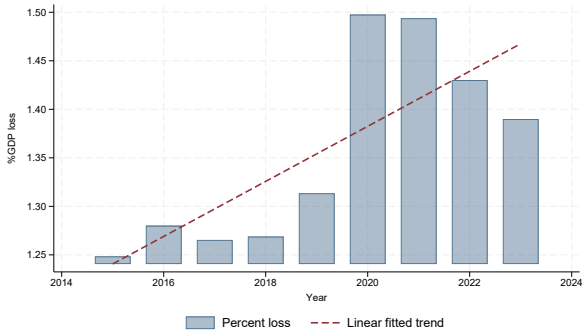
(a) Real GDP (2025 dollars)



(b) % Real GDP



(c) Real GDP loss



(d) Statewide % GDP loss

Figure 4: GDP losses associated with Absenteeism and Under Employment

6 Caregiving

6.1 Data Sources

- United for ALICE (ALICE)
- North Central Regional Center for Rural Development Stat Survey (NCR-STAT)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

One major cost of mental illness is the forgone productivity from missing work or under-employment associated with caring for those with mental illness. To estimate this cost we leverage the NCR-STAT Caregiving survey. We narrow our investigation to the North Central Region survey to ensure that results will be as representative of Ohio as possible.[6] Assuming the sample is representative, we are able to identify the percent of households that cared for an adult (18-64), who has some form of mental illness. This represents about 5% of households. However, we do not want to include households where the respondent caring for an adult is not in the labor force (retired, unemployed by choice, etc.), or is being compensated for caring for that adult with AMI, or is already working *full time*. The NCR-STAT survey defines full time as anything over 30 hours where the average worker in Ohio is working somewhere between 34 and 35 hours per week so there is a genuine argument for including and not including these households.[7] The estimated costs of caregiving are sensitive to these inclusions. Excluding families working full time reduces the proportion of relevant households to approximately 0.84% of total households. The survey also captures household income information. We are able to calculate that households that care for an adult with mental illness, where the household also satisfies the above criteria; makes on

[6] See Figure 20 for states involved.

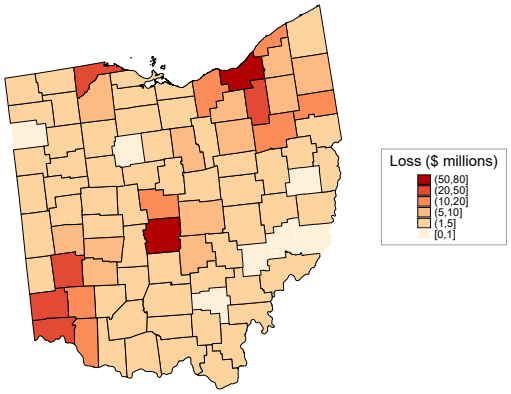
[7] https://fred.stlouisfed.org/series/SMU39000000500000002

average 75% of all other households, even those that must care for others without AMI.[8] The crucial assumption in this analysis is that the difference in household income is caused by the time required to care for someone with MI. This assumption is supported by other questions in the survey that indicate that the average respondent, who cares for a MI adult, and who is still in the labor force, dedicates almost three hours a week to that care or is under employed working part time. Including households where the respondent works full time increases the number of relevant households to 2.43% of all households, but due to that additional employment, those households make approximately 95% of all other households. When calculating those costs there is an increase in households but a decrease in the cost per household. In an effort for transparency and completeness we present both sets of estimates. With an estimate of the proportion of relevant households and their proportion of income relative to the typical household we need only the number of households and median household income by county. Both of which are published by United for ALICE in Ohio.[9].

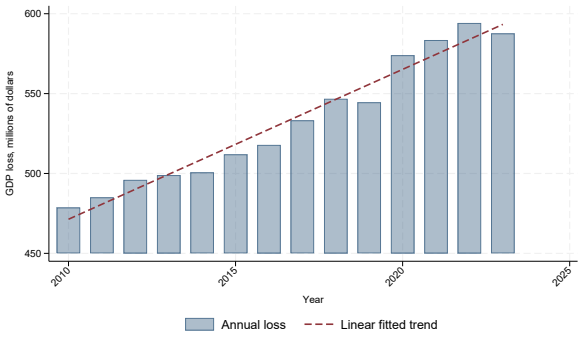
6.2 Results

There is a sizable difference in estimated costs depending on the inclusion of households where the respondent said that they work full time. Figures 5 and 6 present results excluding and including full time workers respectively. Excluding full time workers increases the estimates by about 40%. This is due to the percentage point change in estimated income being larger than the percentage point change in relevant households. Total state wide costs has increased considerably since 2010, Figures 5b and 6b. However, as a percent of GDP those increases appear to be considerably more modest, thought both estimates do show a slight increase primarily driven by the pandemic. More time will be required to ascertain if those increases will pe permanent.

[8]The NCR-STAT Survey asks respondents to indicate the income bracket for the household. When calculating averages we give every respondent the midpoint of the bracket. The brackets are top coded at

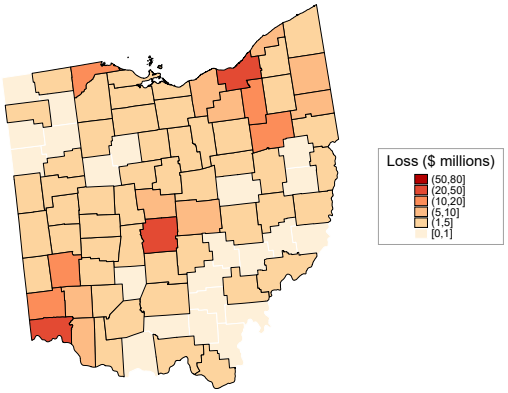


(a) Measured in Real 2025 Dollars

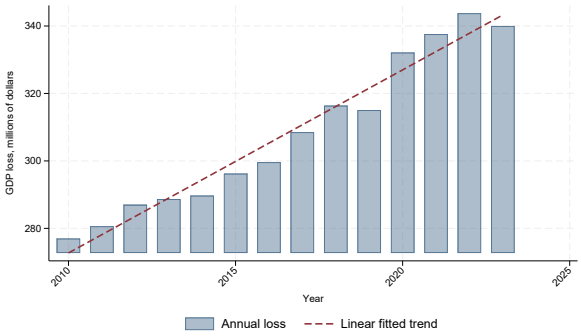


(b) Real GDP loss

Figure 5: GDP losses associated with Caregiving: Excluding Full-time

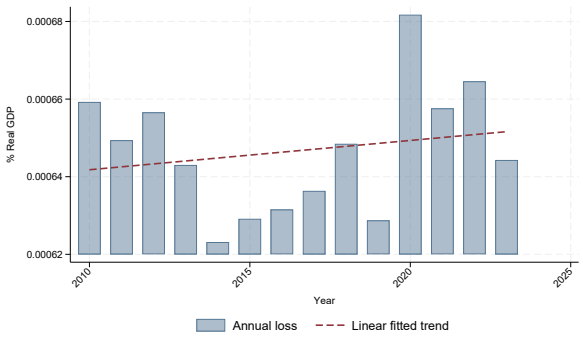


(a) Measured in Real 2025 Dollars

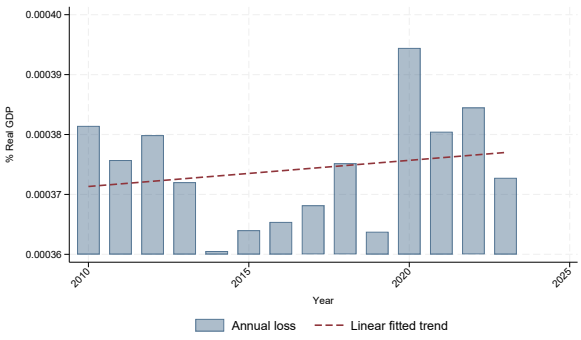


(b) Real GDP loss

Figure 6: GDP losses associated with Caregiving: Including Full-time



(a) Excluding Full-time



(b) Including Full-time

Figure 7: % of real GDP losses associated with Caregiving

7 Adult Crime, Criminal Justice, and Homelessness

7.1 Data Sources

- American Community Survey (ACS)
- National Survey on Drug Use and Health (NSDUH)
- Vera Institute of Justice (VIJ)
- Bureau of Justice Statistics (BJS)
- Ohio Department of Rehabilitation & Correction (ODRC)
- Department of Housing and Urban Development (HUD)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

The costs associated with the intersection of MI and crime are more nuanced than just lost productivity. Those costs can broadly be placed into three categories foregone GDP, the opportunity costs associated with measurable things in GDP, and the intangible costs to victims associated with crime. Foregone GDP can be measured by the lost productivity of incarcerated individuals that has heretofore not been captured. Expenditure within the criminal system typically contributes to GDP but is considered a *cost* here because of the opportunity cost of that spending. Mental illness is disproportionately prevalent among incarcerated populations relative to the general population (nearly double), with estimates ranging from 37% to 44% of jail and prison populations respectively, Bronson and Berzofsky (2017). However, prevalence alone does not establish that incarceration is *caused by* mental

$300,000+, in this instance we give the household an "income" of $350,0000.

[9] https://www.unitedforalice.org/county-reports/ohio

illness: a large share of individuals with a mental illness diagnosis would plausibly be incarcerated regardless of their diagnosis. To estimate the cost of mental illness attributable specifically to incarceration, we require an estimate of the share of mentally ill prisoners who are incarcerated *because of* their illness, rather than simply the share of prisoners who happen to have a diagnosis.

No single study directly estimates this attributable share for the full incarcerated population. We therefore present two bounding estimates drawn from distinct methodologies, and treat the true attributable share as bounded between them. The lower bound, 8%, comes from a clinical case-review study of arrestees with severe mental illness (schizophrenia spectrum or major mood disorder with co-occurring substance use disorder) enrolled in a Hawaii jail-diversion program, in which researchers directly assessed whether the underlying offense was attributable to illness-related behavior (Junginger et al., 2006).[10] A similar investigation into the criminalization hypothesis estimates this number at 7%, Peterson et al. (2010). However, these estimates are restricted to a narrow diagnostic band and a single, small program sample, we treat it as likely understating the true share across the broader population of prisoners with *any* mental illness diagnosis.

The upper bound, 27%, is derived from an odds ratio reported in a large-sample study of misdemeanor sentencing outcomes in New York State (Hall et al., 2019), which found that a major mental illness diagnosis was associated with a 52% increase in the odds of receiving a jail sentence, holding other case characteristics constant. This odds ratio reflects differential processing of individuals with a diagnosed major mental illness are more likely to be incarcerated for comparable underlying conduct.

With regard to the upper bound we are making a few crucial assumptions. We are assuming that the additional 52% increase estimate is not endogenous. We are also assuming that that increase in odds, *ceteris paribus*, represents the proportion of incarcerated that would not be incarcerated but for their mental illness. We convert this odds ratio into an

[10]The 8% is found by summing the direct and indirect effects. It's worth noting that this study can't perfectly disentangle the MI effect from the SUD effect, since by design every participant had both.

attributable-fraction estimate; the derivation is presented in Appendix G.

Because these two estimates capture conceptually different mechanisms, direct behavioral causation versus differential legal processing; and they are based on different populations (severe mental illness in a diversion program vs. major mental illness among misdemeanor arrestees statewide), we do not treat them as directly comparable point estimates. Rather, we present 8%–27% as a plausible bound on the population-wide share of mentally ill prisoners incarcerated because of their illness, and calculate the associated cost estimates across this full range in Section 7.2. In layman, we are assuming that of all the incarcerated individuals, with mental illness, somewhere between 8% and 27% of them would not be there if they did not have some mental illness.

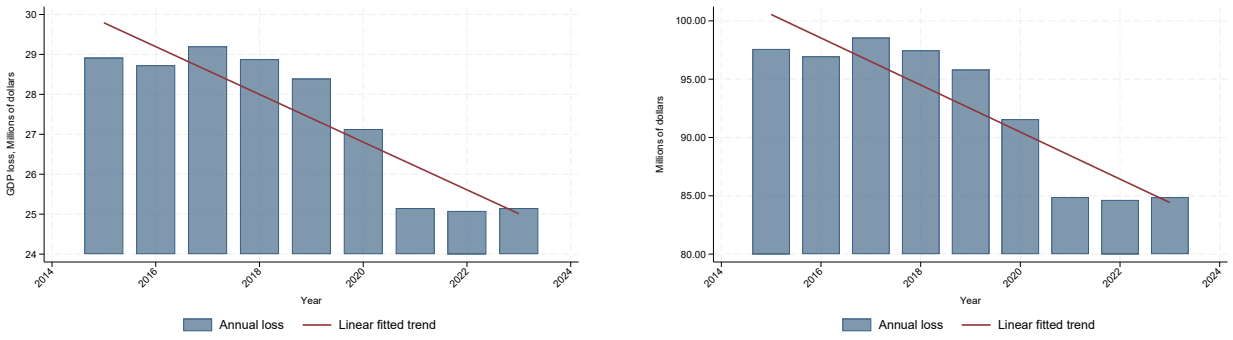
Beyond simply estimating how many individuals would otherwise not be in the criminal justice system we also need to estimate the costs associated with both their incarceration **and** their crimes. The logical implication of the assumptions above is that the crime from these individuals would never have taken place. The social cost of crime is notoriously difficult to estimate. McCollister et al. (2010) generate a comprehensive index of costs associated with criminal convictions. They break costs into two different categories, tangible which are: direct victim costs(economic/property damage, medical, etc.), criminal justice costs (spending on incarceration), and intangible costs that include the pain and suffering to victims. They also categorize the costs by type of crime. We use these costs estimates combined with estimates of local jail composition, James (2004); and state/federal criminal crime composition, Carson and Kluckow (2023). To find the total cost of mental illness associated with crime, we first find the total average daily population of criminals in both the local and state/federal system.[11] Identify the proportion of those that have mental illness. We apply the upper/lower bound proportions, and the composition by crimes in each population and then apply the appropriate costs from (McCollister et al., 2010). Finally we

[11]Data on incarcerated individuals is collected from three sources: Bureau of Justice Statistics, Vera Institute of Justice (2024), and Ohio Department of Rehabilitation and Correction. Local jail population from the BJS for years 2015-2019, and the Vera Institute for Justice for 2020-2023; State and federal prison counts are collected from the Ohio Department of Rehabilitation and Correction.

weight each crime by average length of tenure to avoid double counting the same prisoner each year. Average tenure by crime severity is published by Ohio Department of Rehabilitation and Correction (2022).

7.2 Results

Estimates for the tangible costs associated with crime for 2023 range between 25 million and 85 million statewide, see Figure 8. In both cases there has been a considerable decrease in the associated costs since 2015. This is primarily driven by a reduction in the number of incarcerated individuals. Depending on whether we use the lower or upper bounds the number of prisoners that meet the criteria has fallen somewhere between 328 to 1,107 from the peak in 2017 to 2023. Which represents about a 15% fall in total population. This generally coincides with a pattern of falling crime rates since the late 1980s. The GDP losses from forgone productivity have also fallen over the time period, upper and lower bounds found in Figure 9.[12]

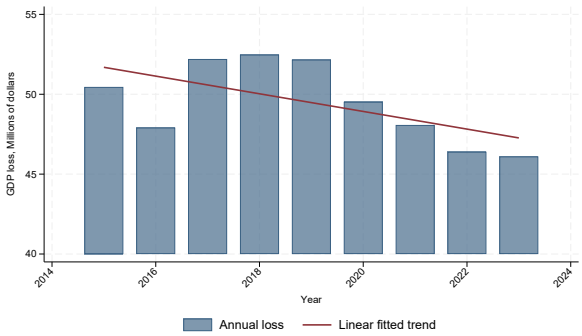


(a) Lower Bound (b) Upper Bound

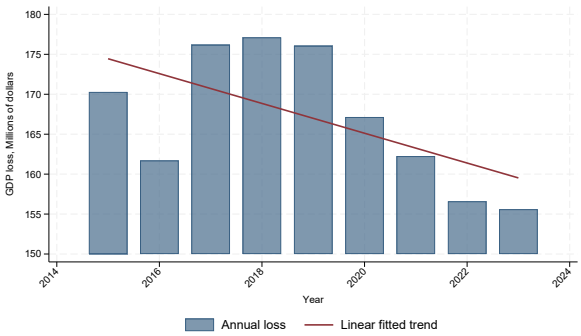
Figure 8: Tangible Costs associated with Crime

The intangible costs associated with crime are considerably larger reaching somewhere between 150 million and 500 Million dollars in 2023. It is important to note that these estimates reflect pain and emotional damage that is conceptually very different from, and should not be compared to, aggregates like GDP. Note that these costs are likely a lower

[12]We assume serious mental illness employment rates and wages (NSDUH) to calculate the loss of GDP.



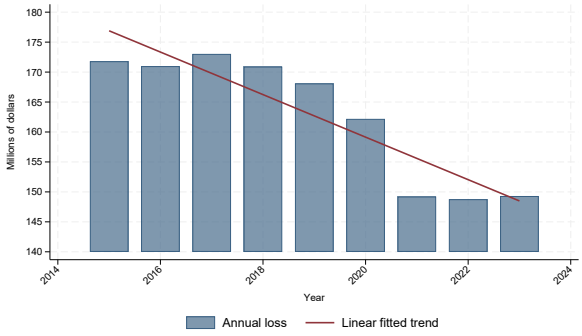
(a) Lower Bound



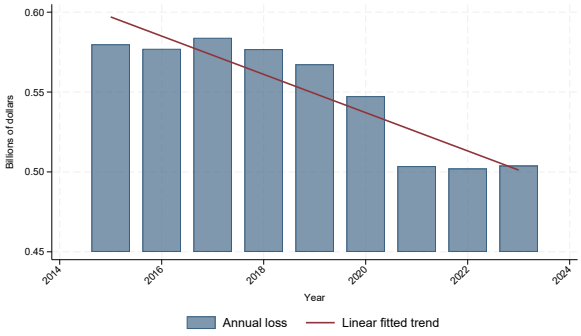
(b) Upper Bound

Figure 9: Forgone Productivity Costs Associated with Incarceration

bound on the true costs associated with MI. The costs outlined in McCollister et al. (2010) are per incident of crime. We are only calculating the cost per crime as captured by prisoner. Given that many crimes go unsolved/unpunished we are undoubtedly under-counting the true cost.



(a) Lower Bound



(b) Upper Bound

Figure 10: Intangible Costs associated with Crime

7.3 Complication of Homelessness

Over the same period there has been an increase in homelessness both in absolute levels (9%) and in percent of total population (about 7% increase) from 2015 to 2023, see Figure 11a.[13] However the total number of homeless with a serious mental illness diagnosis has stayed

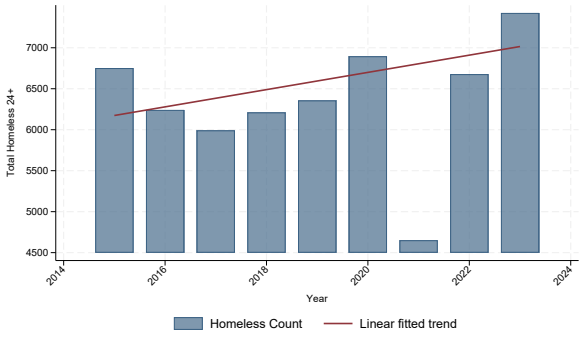
[13] U.S. Department of Housing and Urban Development, Office of Community Planning and Development (2024)

relatively flat over the period, Figure 11b.[14] Figure 11c presents the total costs associated with providing the most basic necessities for only those homeless suffering only from severe mental illness.[15] Culhane et al. (2002) estimated the total average cost of a homeless adult to be about $40,451 in 1999. This includes shelter, hospital services, Medicaid, Medicare and VA spending.[16] During the pandemic there were complications in estimating the total number of homeless individuals and the precipitous fall in 2021 (see Figure 11) should be interpreted with care, (U.S. Department of Housing and Urban Development, 2021). Figures 11c and 11d are best interpreted as an upper and lower bound on the costs depending on which services are utilized by homeless people with SMI, somewhere between 40-125 Million annually in 2025 dollars.

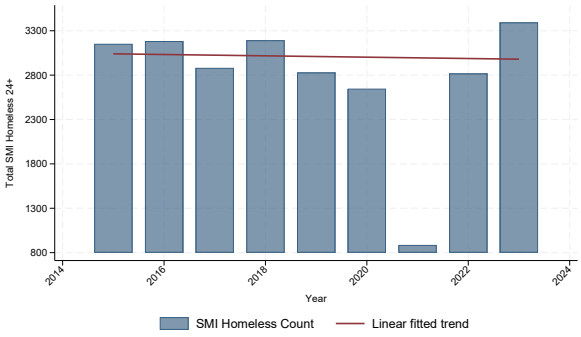
[14] Estimates collected from U.S. Department of Housing and Urban Development (2015–2023).

[15] Culhane and An (2021) estimate the daily cost of basic food and shelter to be approximately $38 per person, per day.

[16] Cost estimates are adjusted to 2025 dollars and discounted by 47% to reflect that their estimates are from NYC. The 47% reflects the reduced cost of living difference between NYC and Columbus. We also remove costs associated with Corrections to avoid double counting. The final per homeless SMI adult is $40,886.



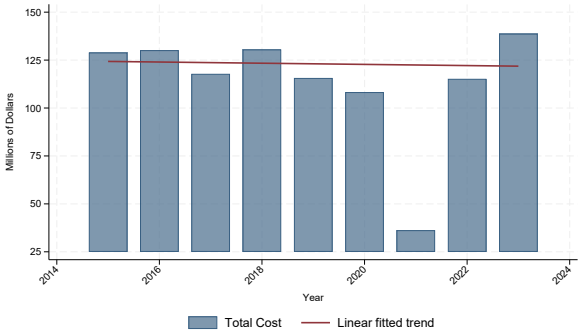
(a) Total Homeless



(b) Total Homeless SMI



(c) Total Cost of Basic Housing: SMI



(d) Total Cost: SMI

Figure 11: Statewide Homelessness with SMI

8 Suicide

8.1 Data Sources

- American Community Survey (ACS)
- National Survey on Drug Use and Health (NSDUH)
- Ohio Violent Death Reporting System (OVDRS)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

To estimate the economic cost of suicide in each county, we calculate the present discounted value (PDV) of lost earnings associated with each death. The forgone productivity of any given death is not just the loss in that year, but also the stream of future earnings that the person would likely have contributed to the economy over time. Yearly county suicide estimates are collected from the Ohio Department of Health[17]. We then weight those suicides by the percent of suicides in the demographic of interest, 18-64. We make one assumption that has meaningful influence in the remainder of the calculation. We assume that everyone who commits suicide has a serious mental illness (SMI). This affects two things; one, those with SMI are less likely to be employed; two, they also earn less than the typical worker. From the NSDUH survey, we estimate the population employment probability for those with SMI, in the appropriate age range, to be approximately 59.1%. On average SMI individuals also make about 66% of that of individuals with no mental illness when they are employed.[18] For each county-year, we begin with the SMI weighted county's wage as an

[17] https://odh.ohio.gov/

[18] We have no data on the full time/part time distinction for those who commit suicide, so we use the aggregates. We also opt to not use the wage decomposition income method here to avoid stacking assumptions. The counterfactual then is that this individual did not commit suicide **not** that this person did not commit suicide **and** is healthy, employed at non-AMI rates, etc.

estimate of annual per person average earnings published by the BLS. We then project that income forward over a 20-year period, allowing nominal wages to grow. Because income received in the future is worth less than income received today, future earnings are discounted back to present value using a standard discount rate. This produces a single present-value estimate of the lost future income associated with one death.

The present value calculation is:

$$PV_{ct} = \sum_{j=1}^{20} \frac{SMI\,Wage_{ct}(1+g)^{j-1}}{(1+r)^{j}} \tag{1}$$

where $SMI\,Wage_{ct}$ is the average nominal per person wage published by the BLS, weighted by 0.66, in county c in year t, g is the assumed annual wage growth rate, r is the discount rate, and the calculation is carried out over 20 years. The median age of most suicides is 45-46 years of age leaving an average of 20 remaining years of productive life.[19] In this analysis, we assume a wage growth rate of 3.5 percent and a discount rate of 3 and 5 percent.[20]

After calculating the present value of lost earnings for one individual in a county-year, we multiply that amount by the number of weighted suicide deaths in that county-year to reflect the labor force participation of those who suffer from SMI.

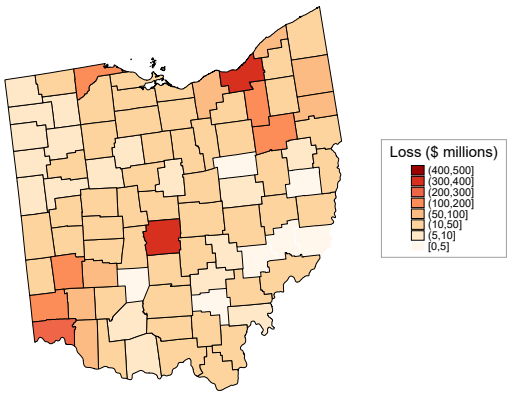
$$Cost_{ct} = Suicides_{ct} \times .591 \times PV_{ct} \tag{2}$$

[19] Traynor (2025)

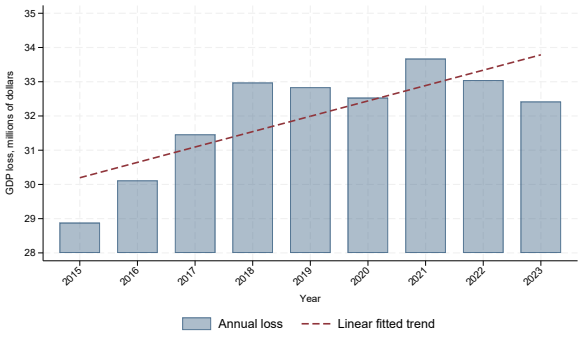
[20] Median annual nominal hourly wage growth has been approximately 3.5% in the period from 2015 to the pandemic, https://fred.stlouisfed.org/series/FRBATLWGT12MMAWMHWGO.

8.2 Results

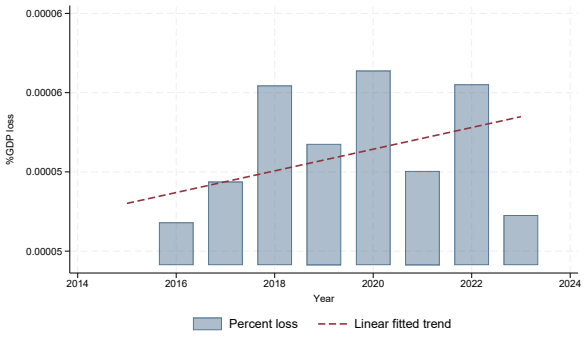
The cumulative present value of GDP loss varies considerably by county due to large variation in the amount of suicides. Estimates range anywhere from less than a million to nearly a half a billion dollars, see Figure 12a. Estimates in Figure 12a are the cumulative PDV of suicides from 2015-2023 calculated using a 3% discount rate. Estimates using the 5% rate can be found in Section C. Figure 12b presents the total annual real costs (2025 dollars) of suicide by year. Note that these are not cumulative costs or PDV cost, just those GDP losses due to suicides in that year. Costs have been growing since 2015, but so has population. In terms of total real GDP the cost of suicide is increasing slightly over time suggesting that the relationship in Figure 12b is not totally driven by population growth.



(a) Cumulative PDV



(b) Real GDP loss



(c) Statewide % GDP loss from suicide

Figure 12: Total Statewide GDP losses associated with Suicide

9 Premature Death and Overdose

- Center for Disease Control (CDC)
- National Survey on Drug Use and Health (NSDUH)
- Bureau of Labor Statistics (BLS)
- Bureau of Economic Analysis (BEA)
- Federal Reserve Bank of St. Louis (FRED)

Premature mortality from mental illness represents one of the most significant and irreversible components of the economic burden of mental illness in Ohio. To estimate the GDP loss attributable to non-suicide premature deaths associated with mental illness among working-age adults, we developed a multi-stage estimation procedure drawing on mortality data, labor market statistics, and clinical survey evidence.

We began by establishing the share of all-cause adult mortality in Ohio attributable to mental illness where mental illness is the underlying cause of death (UCD) or the multiple cause of death (MCD). Total all-cause deaths among Ohio residents aged 18-64 were obtained from the CDC WONDER Multiple Cause of Death database for each year from 2015 through 2023. From the same database, we identified the subset of deaths in this age group in which mental illness was recorded using ICD-10 diagnostic codes F20-F69 and F90-F98 as the UCD or MCD. Suicide-related causes of death, poisoning, and overdose and were explicitly excluded from this classification to ensure that the non-suicide/non-overdose premature-mortality channel was estimated independently.[21] Dividing the identified mental-illness-related death count by total all-cause deaths among adults aged 18-64 produced an annual state-level proportion of non-suicide adult mortality associated with mental illness that was applied to total county deaths.

[21] Codes:X40–X45, Y10, Y12, Y14, Y15 (overdose related codes) and U03.0, U03.9, X60-X84, Y87.0 (suicide-related causes of death).

This specification allows the underlying cause of death to be a physical disease, injury, or other non-overdose and non-suicide cause while requiring mental illness to appear as a contributing condition in the record. The resulting estimate is therefore interpreted as an upper bound: it captures deaths for which mental illness was documented as a contributing condition even when it was not itself the immediate or underlying cause of death. The distinction is important because the presence of a mental illness diagnosis on the death certificate does not necessarily imply that mental illness was the sole or proximate cause of death. Ultimately, we would like to know how many of these individuals would not have died had they not had mental illness, this however, is impossible to ascertain from the available data. So we present these estimates as deaths where mental illness is a contributing factor but they should be interpreted as an upper bound.

County-level all-cause mortality counts for Ohio adults aged 18-64 were obtained from CDC WONDER for the same years. Because CDC WONDER suppresses cell counts below a minimum threshold at the county level, it was not feasible to apply the complete ICD-10 filters directly to county-level data without incurring substantial suppression. Instead, the corresponding annual state-level mortality proportion was applied to each county's total all-cause adult death count to estimate the number of premature deaths associated with mental illness in each county-year. This approach assumes that the statewide relationship between qualifying mental-illness-related mortality and all-cause mortality provides a reasonable approximation of that relationship within individual counties. To the extent that the prevalence, severity, or mortality consequences of mental illness vary systematically across counties, individual county estimates may be over- or understated; however, when aggregated back to the state level, the estimates reproduce the statewide totals by construction.

To translate premature deaths into an estimate of economic output lost, it was necessary to account for the labor force participation and earnings characteristics of individuals living with mental illness. Drawing on the National Survey on Drug Use and Health (NSDUH), the population employment rate among adults with any mental illness (AMI) was identified

as 65.6%. This figure was applied separately to the county-level mental illness-attributable death estimates to identify the share of decedents who, in the absence of premature death, would have been expected to be employed and contributing to economic output. NSDUH data further indicated that adults with AMI earn approximately 77.4% of the average income of adults without a mental illness diagnosis. We applied this ratio to inflation-adjusted mean annual wages obtained from the Bureau of Labor Statistics for each year from 2015 through 2023 to produce a year-specific estimate of average income for AMI individuals, capturing both prevailing wage trends and the AMI earnings gap.

The overlapping nature of substance use and mental illness makes it difficult to assess either in isolation, particularly in the context of premature mortality. We therefore estimate non-suicide premature mortality associated with overdose as a separate mortality channel. The procedure is analogous to the preceding estimation of mental-illness-related premature mortality but uses the underlying and multiple causes recorded on the death certificate to distinguish the acute poisoning event, the substance involved, and documented substance-related mental or behavioral disorders.

Using the CDC WONDER Multiple Cause of Death database, we first identify qualifying non-suicide poisoning deaths through the underlying cause of death (UCD), using ICD-10 codes X40–X45 and Y10, Y12, Y14, Y15.[22] We then use the multiple-cause-of-death (MCD) record to identify the involvement of qualifying drugs using T40 codes, T42.4, and T43.6, as well as documented mental and behavioral disorders due to psychoactive substance use using F10-F19.

We construct two estimates to reflect uncertainty surrounding the documentation of substance-use disorders on death certificates. Our stricter specification requires the qualifying poisoning UCD together with both a qualifying drug code and a substance-related mental or behavioral disorder in the MCD record. This specification therefore identifies poisoning deaths for which the death certificate contains evidence of both the substance involved and

[22]X40-X45 identify accidental poisonings, while the selected Y-codes identify poisonings of undetermined intent included in our non-suicide overdose definition.

an associated substance-related behavioral disorder. It is important to emphasize that a behavioral disorder must be positively documented before it can appear on the death certificate, this requirement may omit overdose deaths involving individuals with an underlying mental disorder that was not known to, or documented by, the certifier. The absence of a behavioral-disorder code therefore cannot necessarily be interpreted as evidence that no such disorder existed.

For this reason, we also construct a broader specification in which a qualifying non-suicide poisoning UCD is retained when the MCD record contains either a qualifying drug code or a substance-related mental or behavioral disorder. The strict specification provides the more conservative estimate, while the broader specification captures deaths that may be excluded because one component of the underlying substance-use history or drug involvement was not documented. In the interest of transparency, results from both specifications are reported separately.

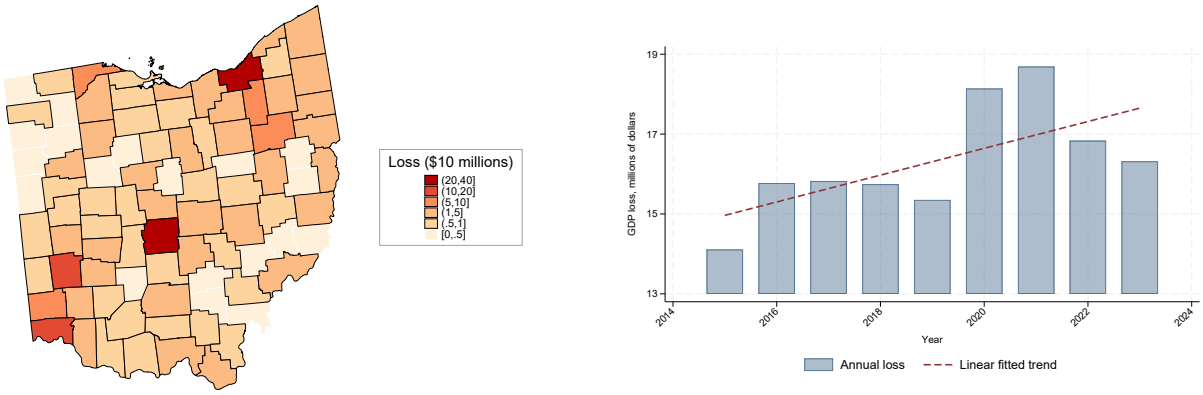
As with the mental-illness-related premature mortality estimates, the statewide annual overdose proportions are applied to county-level all-cause mortality among adults aged 18–64 to estimate qualifying overdose deaths for each county-year. The resulting county-level mortality estimates are then translated into forgone economic production using the same present-discounted-value framework described above but with different employment and wage ratio estimates from the NSDUH.[23] The resulting estimates represent the present value of future earnings that would otherwise have been expected from qualifying overdose decedents and are reported separately from the economic losses associated with non-overdose premature mortality related to mental illness.

9.1 Results

We begin by presenting the results for premature deaths where a mental illness code was in the UCD or MCD that **was not** categorized as a suicide or overdose death. Figure 13a

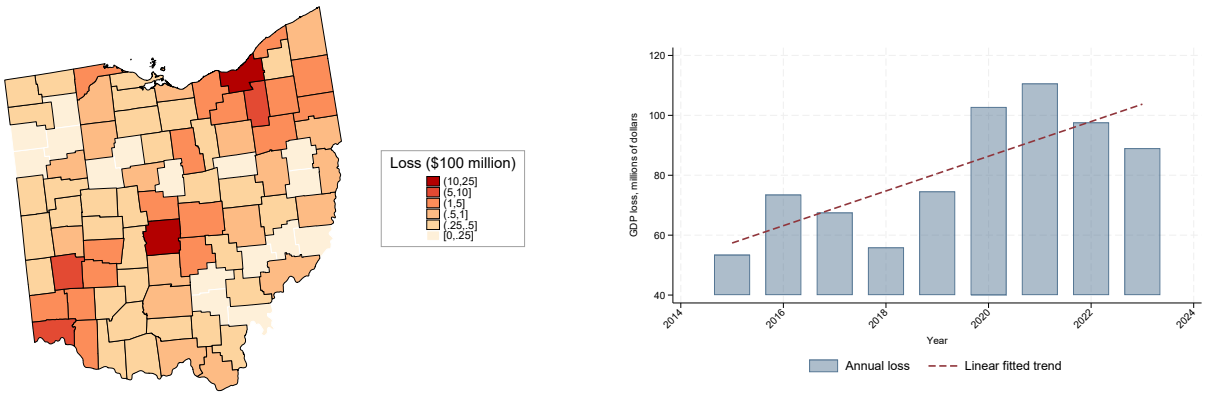
[23]Estimated using the illicit drug use variable in the NSDUH survey.

presents the cumulative PDV of GDP loss and the annual loss of these deaths. Recall that when evaluating overdose deaths, whether a mental illness code in the MCD is a precondition for inclusion has a non-trivial effect on the overall estimate of the costs of overdoses. In Figure 14 we see the annual costs of these overdose deaths reached over $100 million at its peak in 2021. However, those estimates just measure a single year. The present value of those accumulated losses from 2015-2023 vary by county but are as high as 2 billion for some counties.



(a) Cumulative PV GDP Loss by County (b) Statewide Annual GDP Loss

Figure 13: Any MI Related Death

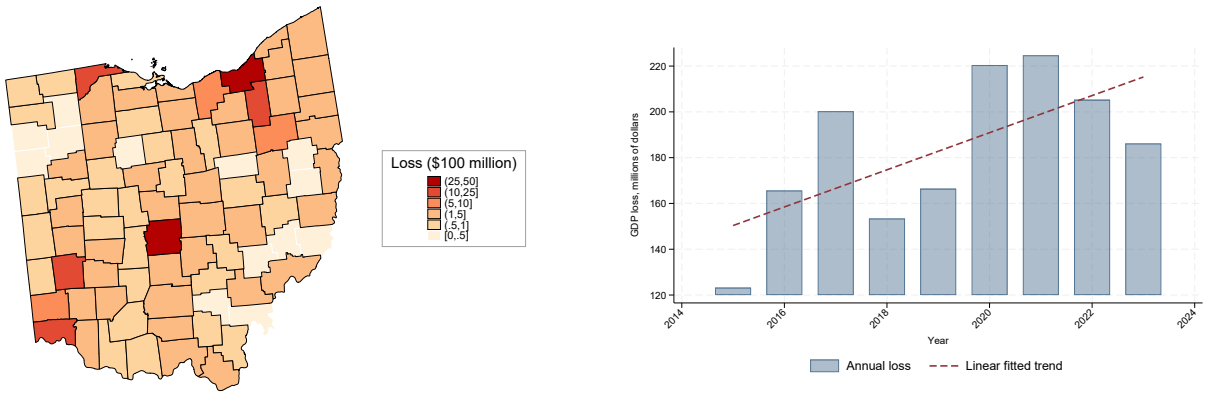


(a) Cumulative PV GDP Loss by County (b) Statewide Annual GDP Loss

Figure 14: MI Related Overdose Death

If we remove the precondition of a mental illness MCD code as a precondition of inclusion then the costs more than double in most cases. Figure 15 presents these updated estimates.

In both cases we see a large spike in 2020 and considerable growth over time. Cumulative estimates of GDP loss reach as high as 5 billion in some counties with state wide annual losses typically between 160-200 million for the time period.



(a) Cumulative PV GDP Loss by County

(b) Statewide Annual GDP Loss

Figure 15: Overdose Death

10 Intangible Losses from Suicide and Premature Death

The preceding sections quantified the economic costs of mental illness through its effects on GDP: earnings lost to premature death, reduced labor force participation, and forgone productivity. These are marginal measures. They capture the incremental output the economy forfeits when a life is cut short. GDP asks, in effect, "what would this person have produced?"

Value of Statistical Life (VSL) answers a fundamentally different question. Rather than measuring what a life contributes at the margin, VSL estimates the total value that individuals and society place on avoiding mortality risk, derived from revealed and stated preferences for small reductions in the probability of death (for example, wage premiums for risky occupations, or willingness to pay for safety improvements). It is not a measure of productive output; it is a measure of how much welfare, broadly construed, a life is worth to the people living it and to those around them. This distinction matters because GDP and VSL are not

simply two estimates of the same underlying quantity. They are answers to different questions, and conflating them understates the true cost of mortality by an order of magnitude or more.

A useful way to see why is to consider water. Water has an enormous, arguably near infinite, total value: without it, human life is impossible, so its total contribution to welfare is almost unbounded. Yet the marginal value of water, what a consumer will pay for one additional liter, or what a market will pay for the last unit sold, is very low, because water is abundant relative to the demand for any single additional unit at the margin. This is the classic diamond water paradox: total value and marginal value can diverge enormously for the same good, and it is marginal value, not total value, that governs market prices.

GDP based estimates of mortality cost are, in this sense, analogous to pricing water at its marginal value. They capture what a life contributes at the margin of economic production, not what that life is worth in total. VSL, by contrast, is closer to an estimate of water's total value: it attempts to capture the full welfare significance of a life, independent of that person's marginal contribution to output.

That total value framing, however, is not simply a number to be looked up and applied. The standard VSL figure is estimated from a specific population, largely employed workers making marginal tradeoffs between wages and workplace risk, under an implicit assumption that the people whose preferences generate the estimate are exercising stable, deliberative judgment about their own survival. Neither condition holds cleanly for the population that commits suicide or dies early from SMI.

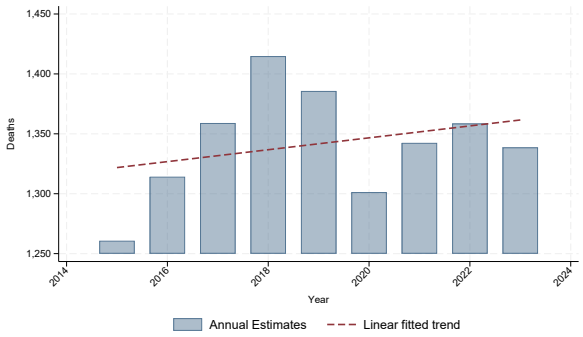
Appendix F works through why this matters in two respects. First, it addresses a conceptual problem: the standard economic model underlying VSL assumes individuals place higher value on being alive than on being dead, an assumption that suicide appears, at face value, to violate. We argue that this apparent preference reversal reflects the temporary, illness driven distortion of judgment associated with acute suicidal crisis rather than a stable preference for death, and that the standard VSL model was not calibrated for individuals

in that state. Second, it addresses an empirical problem: VSL rises with income, and serious mental illness substantially suppresses earnings of the individual. Appendix F develops an adjustment, grounded in the established income elasticity of VSL, that corrects for this illness induced income suppression while leaving the more difficult preference and agency questions conservatively unresolved.

The result is not a claim that any life is worth more or less than another. It is an attempt to estimate, as closely as the data allow, what this population's willingness to pay for survival would be absent the income suppressing effects of the illness itself. The full derivation, including the underlying utility framework and sensitivity of the estimate to alternative elasticity assumptions, appears in Appendix F. We preform VSL calculations using a weighted VSL of $10.88 million (2025 dollars) and as robustness we include estimates at $8.73 million and $12.34 million.

10.1 Results: Suicide

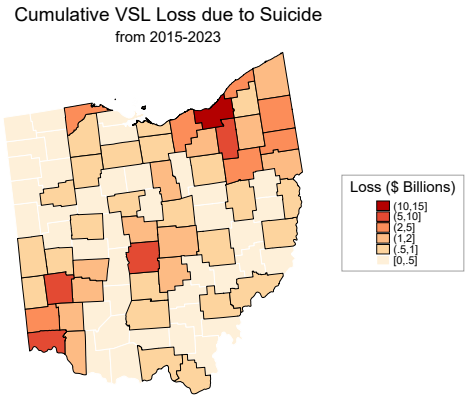
Suicide deaths amount to about 1350 people die each year, see Figure 16a. Using the middle VSL estimate of 10.88 million per death this translates to about 14.5 billion annually in VSL losses, Figure 16b. The upper and lower bound estimates range between 11.7 and 16.5 billion annually. We also present the cumulative lower and upper VSL estimates by county in Figures 16c and 16d.



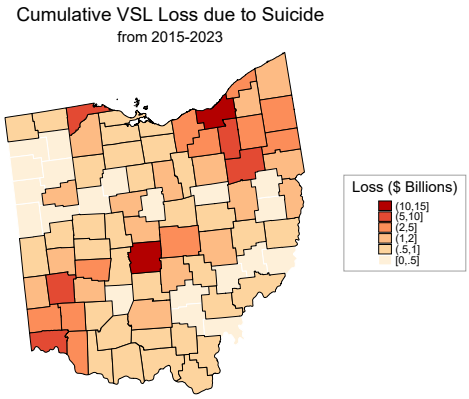
(a) Statewide Annual Suicide Deaths



(b) Statewide VSL Estimates



(c) VSL:$8.73 Million

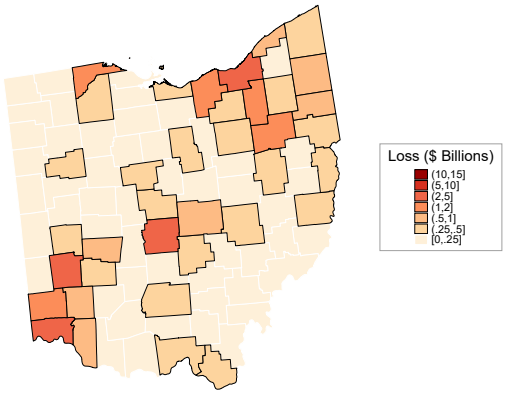


(d) VSL:$12.34 Million

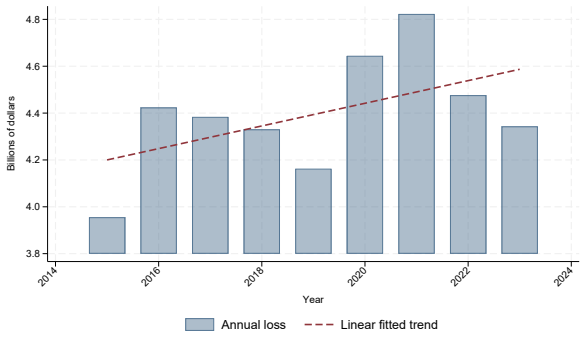
Figure 16: VSL Losses Related to Suicide

10.2 Results: Premature Death and Overdose

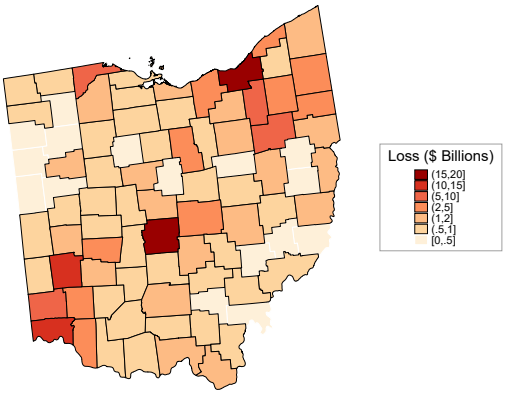
Figures 17a and 17b present the cumulative and annual VSL loses from mental illness related deaths. Recall that these include any cause of death that is not suicide or overdose that has some mental illness designation in the multiple cause of death. These costs amount to about $4.5 billion annually. Further recall from Section 9 that there were considerable differences in estimates depending on if we force the inclusion of any mental illness codes in the MCD as a precondition for a qualifying overdose, or if we just considered overdoses in general. In order to avoid inundating the reader with all possible combinations of VSL values/MCD codes we opt to stick with the midpoint VSL of $10.88 million outlined in Section 10 above with the estimate of overdoses in general and that in which some mental illness code in the MCD is a precondition for inclusion. Total *annual* VSL losses for any overdose and those for which a mental illness code is in the MCD can be seen in Figures 17c and 17d respectively. Even in the more restrictive specification, the VSL costs are estimated at around 20 billion on average annually. Figures 17e and 17f show the cumulative VSL costs of overdoses for each specification by county from 2015 to 2023. Even in the most rural counties the cumulative costs are in the billions. These figures should not be interpreted in the context of GDP, and are better thought of as the accumulated anguish of family and friends each time someone dies prematurely or overdoses.



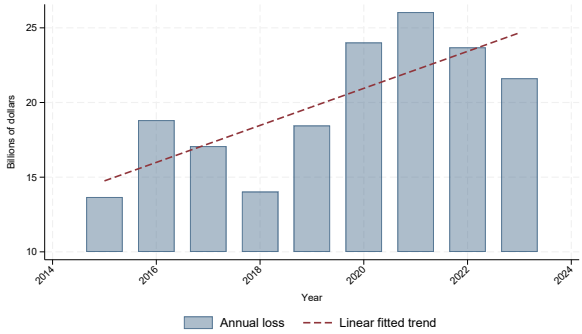
(a) Cumulative VSL - MI in UCD or MCD



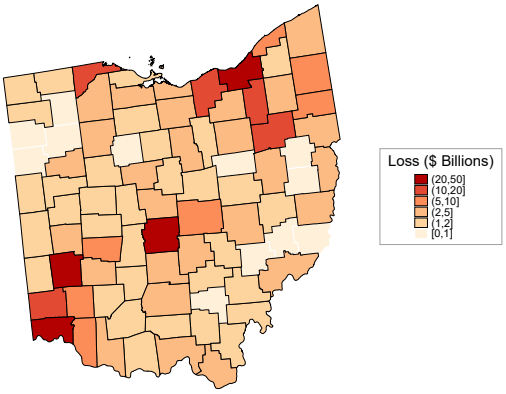
(b) Annual VSL - MI in UCD or MCD



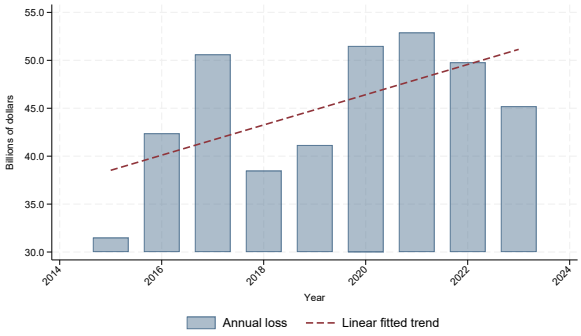
(c) Cumulative VSL from O.D. - MI in MCD



(d) Statewide VSL from O.D MI in MCD



(e) Cumulative VSL - All Overdoses



(f) Cumulative VSL - All O.D. with MI MCD

Figure 17: VSL Losses Related to Overdose and Premature Death: 2015-2023

11 Direct Medical Expenditures Associated with Mental Illness

The preceding sections estimate the economic costs of mental illness through forgone production resulting from unemployment, underemployment, and caregiving. Mental illness also imposes direct economic costs through the utilization of medical care. To estimate these expenditures, we use data from the Medical Expenditure Panel Survey (MEPS) Household Component and Medical Conditions files for the years 2016-2023. MEPS provides nationally representative information on medical conditions, health care utilization, expenditures, sources of payment, insurance coverage, and other health and socioeconomic characteristics for the U.S. civilian noninstitutionalized population.

We first use the annual MEPS Medical Conditions files to identify individuals with reported mental health conditions. The Medical Conditions file is organized at the condition level, with each observation representing a medical condition reported for a survey participant. Consequently, an individual reporting multiple medical conditions may be represented by multiple condition records. Medical conditions are identified using the ICD-10-CM diagnosis codes assigned to respondent reported medical conditions.

For this analysis, mental illness is identified using selected ICD-10-CM F codes. F03, F19, and F84 are excluded from the mental illness classification.[24] The resulting condition records are used to identify the individuals belonging to the mental illness population in each year.

Individuals identified in the Medical Conditions file are then matched by year to the corresponding MEPS Full Year Consolidated file using DUPERSID, the MEPS person level identifier. DUPERSID combines the dwelling unit and person identifiers and identifies the individual within the survey year.

Annual medical expenditure is measured using the corresponding MEPS total expen-

[24] F03: Unspecified Dementia, F19: Psychoactive substance-related disorders, F84: Pervasive developmental disorders.

diture variable. MEPS defines medical expenditures as actual payments made for health care services rather than the amounts initially charged. Total expenditures include payments made out of pocket and by private insurance, Medicare, Medicaid, and other payment sources. Thus, the expenditure measure used in the present analysis represents total medical expenditures incurred among the population included in the analysis.

Medical Condition Groups and Expenditure Estimates

To distinguish expenditures associated with mental illness from expenditures associated with other medical conditions and comorbidity, the analysis is conducted separately for three condition groups. The first group consists of individuals identified with mental illness but without another identified non mental medical condition (MI only). The second consists of individuals with identified medical conditions but without the mental illness conditions included in the analysis (non MI conditions only). The third consists of individuals identified with both mental illness and at least one other medical condition (MI and other conditions).

For each condition group and year, annual medical expenditures are weighted using the corresponding MEPS full year person weight.[25] For each year and condition group, we calculate the weighted mean of annual medical expenditures. Let $\bar{E}_{MI,t}, \bar{E}_{NMI,t}$ and $\bar{E}_{Both,t}$ represent the weighted mean annual medical expenditure among individuals with mental illness, non mental medical conditions only, and individuals identified with both mental illness and other medical conditions, in year t;

We calculate an excess comorbidity expenditure measure as

$$E_t^{Excess} = \bar{E}_{Both,t} - \bar{E}_{MI,t} - \bar{E}_{NMI,t}$$

This measure captures the portion of medical expenditure observed among individuals with both categories of conditions that exceeds the sum of the mean expenditures observed

[25]Equivalent year specific person weights are used for each year from 2016 through 2023.

separately among the MI only and non MI condition populations.[26]

This measure does not establish that mental illness itself causes the additional expenditure. Individuals with comorbid conditions may differ from either comparison group in the severity or number of their conditions, health care utilization, demographic characteristics, or other factors. The measure is therefore interpreted as *excess expenditure associated with the coexistence of mental illness and other medical conditions*, rather than a causal estimate of medical expenditure attributable to mental illness. The presence of mental illness undoubtedly contributes to the severity of other conditions which should translate as additional expenditure. Indeed, empirically this is what we find; on average, those with mental illness and some other condition spend more than those with just the other condition. We do our best to isolate the additional expenditure by subtracting out the average of mental illness only and no mental illness expenditure.

11.1 Estimating the Population Affected by Mental Illness

The MEPS analysis provides estimates of medical expenditure per person. To translate these estimates into aggregate expenditures for Ohio, we additionally use the National Survey on Drug Use and Health (NSDUH) to estimate characteristics of the population potentially subject to these expenditures.

Among adults ages 18-64 with AMI and valid responses to the health insurance measure, approximately 84.5 percent are estimated to have some form of health insurance (private, Medicaid, Medicare, etc.), while approximately 15.5 percent are uninsured. The insured AMI population can therefore be represented as

$$AMI_{ct}^{Insured} = Population_{ct} \times \alpha_t \times 0.845$$

where $Population_{ct}$ represents the relevant population in county c and year t, and α_t

[26] We estimate $\bar{E}_{MI,t}$, $\bar{E}_{NMI,t}$, and $\bar{E}_{Both,t}$ in 2023 (2025 real dollars) to be \$3,098, \$9,511, and \$16,602 respectively per person. Note that this includes both insurance and out of pocket expenditure.

represents the estimated prevalence of AMI. Just because a respondent has health insurance does not mean they necessarily utilize it. Evidence of this can be seen in the NSDUH survey, respondents are asked if they had an unmet perceived need for mental health treatment or counseling on the health insurance indicator. This demonstrates that some proportion of respondents, that are covered by *some* health insurance, did not utilize it. Among insured adults ages 18-64 with AMI and valid responses to the unmet need measure, approximately **23.5 percent** reported that they perceived a need for mental health treatment or counseling that was not met. Assuming the complimentary proportion of respondents both had a need, and had it met, then this implies that, $1 - 0.235 = 0.765$ utilized some sort of healthcare spending.

11.2 Estimating Direct Medical Expenditures

The weighted MEPS expenditure estimates are subsequently combined with the estimated population affected by mental illness, that is covered by some form of insurance and actually utilized it, to approximate direct medical expenditures across Ohio counties we first find the proportion of the total population that suffers from mental illness from the NSDUH (α_t). Using the MEPS we estimate the proportion of MI only (ϕ) and MI and some other condition ($\alpha_{ct} - \phi_{ct}$) within the population of those with MI. Total direct expenditure can be represented as,

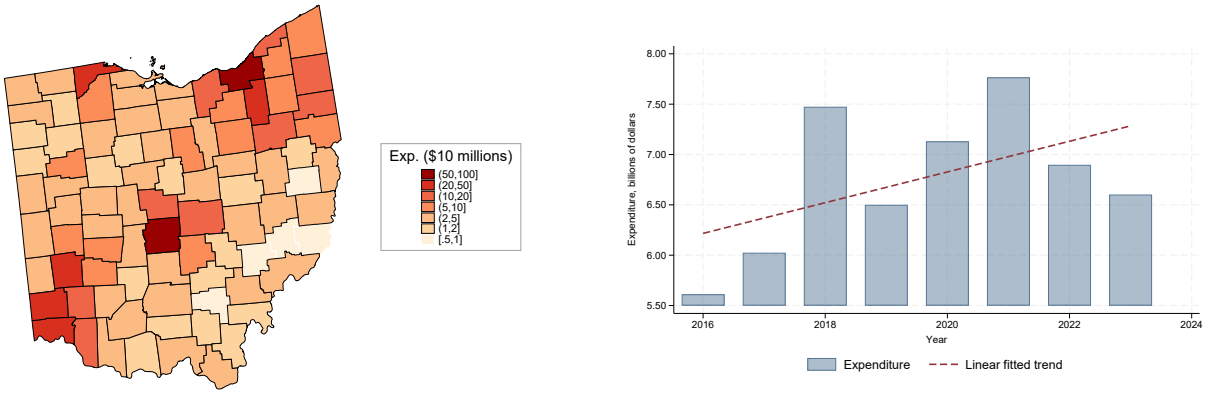
$$TDE_{ct} = AMI_{ct}^{insured} \times 0.765 \times (\bar{E}_{MI,t} + (\alpha_{ct} - \phi_{ct})E^{Excess}).$$

Total direct expenditure for each county c in year t is the estimated number of those with mental illness who are insured and actually use that insurance weighted by the average expenditure of those with only mental illness $\bar{E}_{MI,t}$ plus the insured proportion who also have some other ailment times the excess expenditure that applies to that subgroup.[27]

[27]We estimate ϕ_{ct} to be on average 0.03. About 20% of the population has some form of mental illness and those with **only** mental illness makes up about 3 percentage points.

11.3 Results

Consistent with many of the other results in previous sections there has been considerable growth in total real statewide medical expenditure related to mental illness. Much of that driven by the pandemic, although spending has fallen since its peak in 2021 (see Figure 18b) it is still nearly a billion dollars higher in real terms than in 2016. This is about an 18% increase in expenditure over a period where population grew by only (approximately) 2.4%. This accounts for a little over 5% of all private insurance/out of pocket and government medical expenditure in the state (U.S. Bureau of Economic Analysis, 2024). These expenditures are sizable but they should be interpreted with some caution, we are unable to identify the *causal* expenditure due to only mental illness and its contribution to the severity of other ailments.



(a) County Expenditure in 2023

(b) Statewide Annual Expenditure

Figure 18: Direct Medical Expenditures (Real 2025 Dollars)

Appendix A Decomposing the Observed Average Wage

The observed average wage reflects differences in both mental illness status and employment status. Workers are divided into four groups: workers with and without AMI; who work full and part time.

Let

- $\bar{w}$ = observed average wage across all workers;
- w_{NF} = average wage of full-time workers without AMI;
- $\alpha = \Pr(\text{AMI})$;
- $\phi_A = \Pr(\text{Full Time} \mid \text{AMI}, \text{working})$;
- $\phi_N = \Pr(\text{Full Time} \mid \text{No AMI}, \text{working})$;
- $\rho_F = \dfrac{w_{AF}}{w_{NF}}$, the wage ratio of full-time workers with AMI to full-time workers without AMI;
- $\rho_P = \dfrac{w_{AP}}{w_{NP}}$, the wage ratio of part-time workers with AMI to part-time workers without AMI;
- $\lambda = \dfrac{w_{NP}}{w_{NF}}$, the wage ratio of part-time to full-time workers without AMI.

Here, ρ_F represents the wage earned by a full-time worker with AMI relative to a full-time worker without AMI, while ρ_P represents the wage earned by a part-time worker with AMI relative to a part-time worker without AMI. The parameter λ represents the annual wage of a part-time worker without AMI relative to a full-time worker without AMI.

The four groups and their wages can therefore be written as follows:

Group	Population share	Average wage
No AMI, full time	$(1-\alpha)\phi_N$	w_{NF}
No AMI, part time	$(1-\alpha)(1-\phi_N)$	λw_{NF}
AMI, full time	$\alpha\phi_A$	$\rho_F w_{NF}$
AMI, part time	$\alpha(1-\phi_A)$	$\rho_P \lambda w_{NF}$

Because the observed average wage is a weighted average of the wages of these four groups, it can be expressed as

$$\bar{w} = (1-\alpha)\phi_N w_{NF} + (1-\alpha)(1-\phi_N)\lambda w_{NF} \qquad +\alpha\phi_A\rho_F w_{NF} + \alpha(1-\phi_A)\rho_P\lambda w_{NF}.$$

Factoring out w_{NF} gives

$$\bar{w} = w_{NF}\Big[(1-\alpha)\left(\phi_N + (1-\phi_N)\lambda\right) + \alpha\left(\phi_A\rho_F + (1-\phi_A)\rho_P\lambda\right)\Big]. \tag{3}$$

Solving for the average wage of full-time workers without AMI yields

$$w_{NF} = \frac{\bar{w}}{(1-\alpha)\left[\phi_N + (1-\phi_N)\lambda\right] + \alpha\left[\phi_A\rho_F + (1-\phi_A)\rho_P\lambda\right]} \tag{4}$$

Equation 4 allows the full-time wage of workers without AMI to be recovered from the observed average wage. The denominator adjusts the observed average for the proportion of workers with AMI, the full-time employment rates of workers with and without AMI, the wage difference associated with AMI, and the wage difference between part-time and full-time employment. Using the NSDUH survey we are able to estimate the parameters: $\alpha, \phi_A, \phi_N, \rho_F, \rho_P$ and λ.[28] Finding the cost of unemployment and lack of labor force participation for each county is relatively straightforward. We take the 9% of adults with AMI who would otherwise be working if those with AMI had similar unemployment and LFP rates as those without AMI and apply the population full time and part time employment rates of

[28]We assume λ to be equal across groups for analytical convenience and their estimated values in the actual survey are almost identical.

non-AMI people at the appropriate wages from above.[29]

Appendix B Total County Estimates for 2023

Table 1: County-Level Economic Costs

County	Forgone GDP ($ millions)	Forgone GDP (% GDP)	Forgone Tax Revenue ($ millions)	Direct Cost ($ millions)	Direct Cost (% GDP)	Indirect Cost ($ millions)
Adams	47.1	4.86	3.3	15.4	1.59	162.0
Allen	186.6	1.61	13.1	56.9	0.49	454.6
Ashland	75.8	3.19	5.3	28.1	1.18	218.5
Ashtabula	145.1	3.42	10.2	53.5	1.26	530.7
Athens	104.0	3.87	7.3	38.2	1.42	251.6
Auglaize	78.7	2.31	5.5	25.7	0.75	136.3
Belmont	102.9	2.86	7.2	37.2	1.03	291.5
Brown	65.5	5.58	4.6	25.2	2.15	266.8
Butler	807.7	2.82	56.5	229.4	0.80	1493.1
Carroll	39.0	1.94	2.7	14.5	0.72	118.2
Champaign	65.7	4.17	4.6	22.2	1.41	180.9
Clark	231.0	3.79	16.2	76.0	1.25	667.2
Clermont	396.9	3.97	27.8	122.8	1.23	796.6
Clinton	86.4	2.77	6.0	24.0	0.77	189.5
Columbiana	153.5	3.19	10.7	55.8	1.16	423.5
Coshocton	55.8	3.32	3.9	19.9	1.19	166.7
Crawford	67.0	3.89	4.7	23.0	1.33	235.7
Cuyahoga	2769.1	2.07	193.8	691.5	0.52	5308.4

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[29]Even non-AMI have some portion of their population unemployed or not in the labor force.

Table 1 – continued from previous page

County	Forgone GDP ($ millions)	Forgone GDP (% GDP)	Forgone Tax Revenue ($ millions)	Direct Cost ($ millions)	Direct Cost (% GDP)	Indirect Cost ($ millions)
Darke	79.8	2.75	5.6	28.1	0.97	225.1
Defiance	60.9	2.73	4.3	21.4	0.96	109.1
Delaware	462.1	2.45	32.4	125.0	0.66	452.1
Erie	121.6	2.22	8.5	42.8	0.78	329.6
Fairfield	265.8	4.11	18.6	92.9	1.44	615.7
Fayette	47.8	2.30	3.3	16.4	0.79	183.7
Franklin	3493.1	2.49	244.5	847.2	0.60	5098.9
Fulton	72.9	2.70	5.1	23.6	0.87	145.6
Gallia	43.7	1.59	3.1	16.2	0.59	121.1
Geauga	168.3	3.01	11.8	53.6	0.96	234.6
Greene	384.1	2.66	26.9	98.1	0.68	534.1
Guernsey	64.5	1.78	4.5	21.4	0.59	213.0
Hamilton	2150.3	1.97	150.5	499.8	0.46	3055.9
Hancock	152.4	2.19	10.7	42.7	0.61	314.5
Hardin	49.2	3.80	3.4	17.4	1.35	144.3
Harrison	26.4	1.87	1.8	7.7	0.55	75.1
Henry	44.0	2.75	3.1	15.2	0.95	86.5
Highland	61.3	3.53	4.3	24.2	1.39	224.7
Hocking	35.9	4.41	2.5	15.7	1.92	165.5
Holmes	64.0	1.90	4.5	22.9	0.68	89.3
Huron	96.4	3.26	6.7	32.1	1.09	241.2
Jackson	47.8	3.66	3.3	18.5	1.42	128.9
Jefferson	106.9	1.99	7.5	35.7	0.67	408.6

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Table 1 – continued from previous page

County	Forgone GDP ($ millions)	Forgone GDP (% GDP)	Forgone Tax Revenue ($ millions)	Direct Cost ($ millions)	Direct Cost (% GDP)	Indirect Cost ($ millions)
Knox	110.2	3.79	7.7	35.0	1.20	251.4
Lake	465.4	2.97	32.6	138.5	0.88	965.2
Lawrence	94.4	3.80	6.6	33.1	1.33	327.5
Licking	322.6	3.12	22.6	104.1	1.01	649.6
Logan	79.3	2.94	5.6	26.1	0.97	201.5
Lorain	511.9	3.56	35.8	168.9	1.18	1363.3
Lucas	949.7	2.83	66.5	262.2	0.78	1829.6
Madison	78.8	2.83	5.5	27.3	0.98	185.9
Mahoning	352.6	2.93	24.7	120.7	1.00	1194.6
Marion	115.9	3.39	8.1	37.4	1.09	347.1
Medina	309.0	3.06	21.6	101.1	1.00	491.9
Meigs	31.1	6.14	2.2	12.5	2.48	116.3
Mercer	63.7	1.90	4.5	22.5	0.67	129.5
Miami	190.1	3.12	13.3	61.4	1.01	426.9
Monroe	19.0	1.47	1.3	7.1	0.55	62.8
Montgomery	1036.1	2.59	72.5	296.3	0.74	2710.1
Morgan	21.3	4.41	1.5	7.5	1.56	67.6
Morrow	48.8	5.60	3.4	19.8	2.27	101.2
Muskingum	147.1	2.80	10.3	49.2	0.94	409.2
Noble	21.7	4.01	1.5	7.5	1.39	59.9
Ottawa	67.5	2.46	4.7	22.3	0.81	157.5
Paulding	31.7	3.98	2.2	10.4	1.30	111.3
Perry	56.5	6.04	4.0	19.9	2.13	138.9

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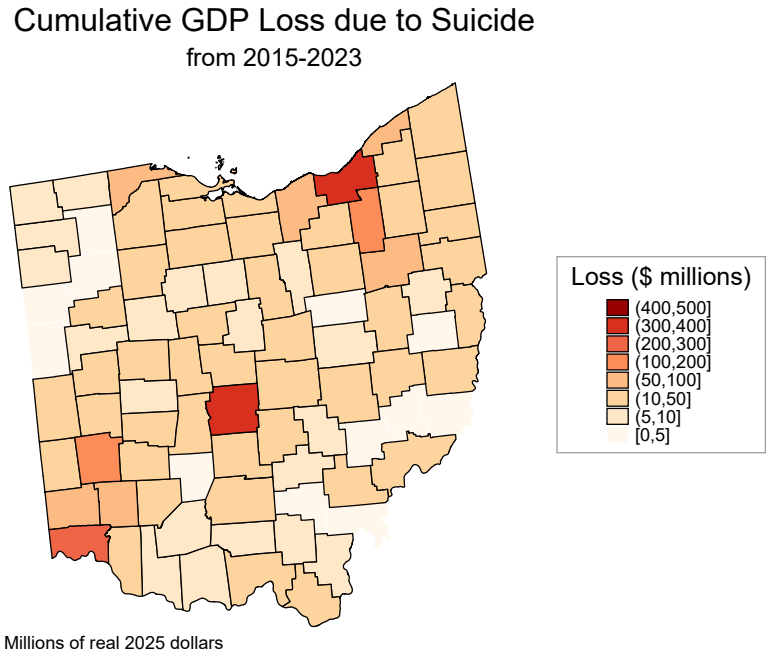
County	Forgone GDP ($ millions)	Forgone GDP (% GDP)	Forgone Tax Revenue ($ millions)	Direct Cost ($ millions)	Direct Cost (% GDP)	Indirect Cost ($ millions)
Pickaway	116.2	4.35	8.1	35.5	1.33	212.9
Pike	58.0	4.04	4.1	15.2	1.06	183.6
Portage	327.7	3.75	22.9	100.8	1.15	644.7
Preble	72.0	4.65	5.0	22.8	1.47	235.5
Putnam	50.0	2.99	3.5	18.6	1.11	73.0
Richland	203.9	3.37	14.3	69.6	1.15	599.5
Ross	150.1	3.77	10.5	45.3	1.14	386.9
Sandusky	104.2	2.76	7.3	34.3	0.91	231.0
Scioto	128.8	3.62	9.0	42.4	1.19	469.1
Seneca	89.2	3.38	6.2	32.1	1.22	219.1
Shelby	89.9	2.15	6.3	27.0	0.65	142.1
Stark	592.0	2.62	41.4	199.7	0.88	1459.4
Summit	1092.5	2.72	76.5	310.1	0.77	2365.7
Trumbull	319.6	3.46	22.4	109.1	1.18	1023.5
Tuscarawas	141.1	2.85	9.9	49.8	1.01	394.5
Union	137.9	2.29	9.7	38.7	0.64	164.1
Van Wert	44.7	2.58	3.1	16.0	0.92	96.1
Vinton	18.9	3.33	1.3	7.2	1.26	63.1
Warren	523.2	2.85	36.6	145.4	0.79	616.7
Washington	110.2	2.30	7.7	32.6	0.68	299.5
Wayne	193.1	2.21	13.5	61.7	0.71	391.7
Williams	59.8	2.71	4.2	20.7	0.94	160.2
Wood	248.0	2.37	17.4	80.5	0.77	391.5

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Table 1 – continued from previous page

County	Forgone GDP ($ millions)	Forgone GDP (% GDP)	Forgone Tax Revenue ($ millions)	Direct Cost ($ millions)	Direct Cost (% GDP)	Indirect Cost ($ millions)
Wyandot	38.6	2.73	2.7	12.4	0.88	88.6

Appendix C Suicide



(a) Measured in Nominal GDP

Figure 19: Total Statewide GDP losses associated with Suicide using 5% discount

Appendix D The NSDUH Survey

Mental illness prevalence, employment rates, income estimates, insurance coverage, and unmet treatment need figures used in this study were derived from the National Survey on Drug Use and Health (NSDUH) Combined Public-Use File, 2002-2019. The NSDUH is sponsored and published by the Substance Abuse and Mental Health Services Administration (SAMHSA), an agency within the U.S. Department of Health and Human Services. It

is a nationally representative annual household survey of the civilian, noninstitutionalized population of the United States aged 12 and older and is the primary federal data source for estimating the prevalence of mental illness, substance use, and treatment need at the national level. All analyses in this study were restricted to adults aged 18–64.

D.1 Survey and Limitations

The NSDUH samples the civilian, noninstitutionalized population, which explicitly excludes active-duty military personnel, residents of institutional group quarters including hospitals, prisons, nursing homes, and residential treatment centers, and homeless individuals not residing in shelters. While community-dwelling SSI and SSDI beneficiaries are captured within the NSDUH frame, those residing in institutional settings are not. This is a substantively important limitation for a mental illness burden study: individuals with the most severe illness burden are disproportionately represented in both institutionalized and disability-program populations, and mental illness is the primary diagnosis for one in three persons receiving disabled worker benefits under the age of 50. Because the NSDUH systematically undersamples this population, all prevalence, employment, and income estimates derived from it are conservative, they understate the true burden of mental illness in Ohio.

To assess whether SSI recipient status could be used to characterize this marginalized subgroup within the NSDUH sample, the variable IRPSSI (family receipt of SSI) was examined. However, IRPSSI was found to contain no valid data for any year in the 2011-2019 analytical window, all observations were coded as not collected for this period. The SSI subgroup analysis was therefore not feasible from this dataset, and the characterization of SSI and SSDI recipients as a distinct burden population relies instead on external SSA administrative data as described in the limitations section of the main paper.

D.2 Comparability and Pooling

The NSDUH underwent a partial questionnaire redesign in 2015, which affected the comparability of several variables across that year, and a complete methodological break in 2020 due to the introduction of web-based data collection that renders post-2019 data non-comparable with and non-poolable with the 2002-2019 series. The 2002-2019 Combined Public-Use File is accordingly the appropriate and final source for this study's estimation period.

Prior to pooling, the two key variables used in the income and prevalence analyses: MI_CAT_U (mental illness severity classification) and $IRPINC3$ (imputed personal income) were verified against the SAMHSA PUF Variable Crosswalk Chart for the 2002-2019 series. MI_CAT_U carried a consistent comparability code across all years from 2011 through 2019, indicating no break at the 2015 redesign. $IRPINC3$ showed a single comparability break in 2004 and a consistent code from 2004 through 2019, placing the entire 2011-2019 analytical window within a single comparable generation of the variable. Pooling across 2011-2019 is therefore methodologically supported for both variables.

As public-use files, the NSDUH data have been treated with disclosure-avoidance methods to protect respondent confidentiality, including the removal of most geographic variables. Estimates derived from the public-use file are comparable to but not identical to SAMHSA's officially published figures.

D.3 Mental Illness Classification

Mental illness severity was classified using MI_CAT_U, a four-level ordinal categorical variable derived from a logistic regression model revised by SAMHSA in 2012. The model estimates the predicted probability of Serious Mental Illness for each respondent using two underlying scale scores: the worst K6 psychological distress score ($WSPDSC2$) and the World Health Organization Disability Assessment Schedule score ($WHODASC3$). The four severity levels are mutually exclusive and collectively exhaustive:

- 0 = No past-year mental illness,
- 1 = Past-year mild mental illness,
- 2 = Past-year moderate mental illness,
- 3 = Past-year serious mental illness.

For analyses pertaining to any mental illness (AMI), respondents in categories 1, 2, and 3 were combined. For analyses specific to serious mental illness (SMI), only category 3 respondents were included.

D.4 Substance Use Disorder Classification

For the overdose-related premature mortality analysis in Section 9, adults with substance use disorder (SUD) were identified using UDPYILAL, the NSDUH recode for past-year illicit drug or alcohol dependence or abuse. Respondents coded UDPYILAL = 1 were classified as having SUD. This definition was selected to parallel the substance-related behavioral-disorder population represented by the F10-F19 ICD-10 codes used in the overdose mortality analysis. All SUD estimates were restricted to adults aged 18-64.

D.5 Employment Analysis

Employment rates among adults with AMI and SMI aged 18-64 were estimated from the pooled 2015-2019 sample. This window was dictated by data availability, the employment variable used in the analysis ($IRWRKSTAT18$) was not collected prior to 2015, when employment questions were restructured as part of the partial redesign. The five-year pooled adult analysis weight ($analwc5$) was applied to produce nationally representative weighted estimates of employment probability within each mental illness severity group. For the overdose analysis, the same pooled sample and weighting procedure were used to estimate the employment probability among adults aged 18-64 classified as having SUD.

D.6 Income Analysis

Income estimation drew on the broader 2011-2019 pooled sample to maximize sample size and precision, using the nine-year pooled adult analysis weight (analwc9). Individual income was measured using IRPINC3, NSDUH's imputed personal income variable, classified into seven bands with midpoint values assigned as follows:

Table 2: Income Bands and Assigned Midpoints

Income Band	**Assigned Midpoint**
Less than $10,000	$5,000
$10,000–$19,999	$15,000
$20,000–$29,999	$25,000
$30,000–$39,999	$35,000
$40,000–$49,999	$45,000
$50,000–$74,999	$62,500
$75,000 or more	$87,500

Weighted mean income was calculated separately for the AMI population, the SMI population, and the no mental illness population, each restricted to adults aged 18–64. The AMI-to-no-MI and SMI-to-no-MI income ratios were computed as the ratio of each group's weighted mean income to that of the no mental illness group. For the overdose analysis, the SUD income ratio was calculated as the weighted mean income of adults with SUD relative to adults without SUD. These ratios were subsequently applied to year-specific mean annual wages from the Bureau of Labor Statistics to produce year-specific estimated average incomes for AMI and SMI individuals across the 2015-2023 study period.

D.7 Insurance Coverage and Unmet Treatment Need

Two additional parameters used in the direct medical expenditure component of the burden model were estimated from the 2011-2019 pooled sample using analwc9. Health insurance coverage among AMI adults aged 18-64 was measured using IRINSUR4, a composite variable that classifies a respondent as insured if they are covered by any of the following: Medicare (IRMEDICR), Medicaid or CHIP (IRMCDCHP), Tricare, CHAMPUS, ChampVA, VA, or

military coverage (IRCHMPUS), private health insurance (IRPRVHLT), or any other health insurance (IROTHHLT). A respondent is classified as uninsured only if they report no coverage under any of these sources. This composite classification provides more comprehensive coverage of insurance status than single-source insurance variables. Approximately 84.5% of AMI adults aged 18-64 reported having any health insurance coverage and 15.5% were uninsured.

Unmet perceived need for mental health treatment or counseling was measured using AUUNMTYR among the insured AMI population. Approximately 23.5% of insured AMI adults reported unmet perceived need for mental health treatment or counseling in the past 12 months.

D.8 Sub-State Prevalence Estimates

County-level variation in AMI and SMI prevalence was estimated using the SAMHSA Behavioral Health Barometers, which draw on NSDUH data and provide state-level behavioral health estimates for adults aged 18 and older. Available volumes were used for each year across the 2015-2023 study period. Board-level prevalence estimates for Ohio were extracted from each respective volume and mapped to individual Ohio counties through a geographic crosswalk linking each county to its respective behavioral health board jurisdiction.

Appendix E The NCR-STAT Survey

The analysis of informal caregiving associated with mental illness uses data from the NCR-STAT Caregiving Survey, administered by the North Central Regional Center for Rural Development in collaboration with Ohio State University. The survey examines child, adult, and elder caregiving and the ways in which caregiving affects household, economic, health, and community well-being. Participation was limited to adults aged 18 years or older, and respondents completed the survey electronically.

E.0.1 Identification of Adult Caregivers

The caregiving analysis begins with respondents who reported providing paid or unpaid care to an adult aged 18 years or older during the preceding 12 months. Adult caregiving is identified using $SC2$. The survey defines caregiving broadly to include assistance with personal needs, household activities, finances or medication, transportation and medical appointments, meals and errands, regular monitoring, and emotional support.

Because the economic analysis focuses on the working-age population, caregiving for adults aged 65 years and older was excluded. Among respondents reporting adult caregiving, a working-age adult caregiving indicator was constructed from $AC1_A$, $AC1_B$, and $AC1_C$, which identify the number of adults cared for in the age groups 18–26, 27–49, and 50–64, respectively. $AC1_D$, which identifies care provided to adults aged 65 years and older, was not included in the working-age measure.

The working-age adult caregiver indicator can be written as

$$Caregiver_i^{18-64} = \mathbf{1}\left(SC2_i = 1 \ \wedge \ (AC1_A_i > 0 \ \vee \ AC1_B_i > 0 \ \vee \ AC1_C_i > 0)\right)$$

where $\mathbf{1}(\cdot)$ denotes an indicator function equal to one when the stated condition is satisfied and zero otherwise.

Identification of Caregiving Associated with Mental Illness

The working-age adult caregiver sample was further restricted according to the reported health condition of the adult receiving care. $AC3$ asks caregivers to identify the health conditions affecting the adults for whom they provide care and allows multiple responses. Caregiving was classified as associated with mental illness when the respondent reported either a short-term emotional, behavioral, or mental health condition through $AC3_4$ or a long-term emotional, behavioral, or mental health condition through $AC3_5$.

The mental-health caregiving indicator was therefore defined as

$$MHCare_i = \mathbf{1}\left(Caregiver_i^{18-64} = 1 \ \wedge \ (AC3_4_i = 1 \ \vee \ AC3_5_i = 1)\right)$$

This classification distinguishes the mental-health categories from short- and long-term physical health conditions, COVID-related conditions, learning disabilities, developmental or intellectual disabilities, memory problems, and other reported reasons for care.

Approximately 30 percent of caregivers of working-age adults met this mental-health criterion. This corresponded to approximately 17.7 percent of respondents providing adult care and approximately 5.2 percent of the overall survey sample before the subsequent compensation and employment restrictions were imposed.

E.0.2 Restriction to Uncompensated Caregiving

To isolate informal, uncompensated caregiving, respondents reporting compensation for the care they provided were removed from the mental-health caregiving group. Compensation is identified using $ALC6$, which asks whether the respondent received compensation during the previous 12 months and defines compensation broadly to include cash payments, stocks, education, room and board, tax credits, and other forms of remuneration. Accordingly, respondents with ALC6 equal to 1 were excluded from the final mental-health caregiving indicator. This step was intended to distinguish unpaid household caregiving from caregiving for which the respondent received compensation.

E.0.3 Employment Restriction

The final analytic definition additionally applies restrictions based on the caregiver's employment status. The NCR-STAT survey permits respondents to report multiple employment categories through HD7, including full-time employment, part-time employment, full- and part-time self-employment, unemployment, retirement, homemaking, student status, and nonemployment.

Respondents were removed (in some specifications see Section 6) from the mental-health caregiving indicator if they reported full-time employment through $HD7_1$, full-time self-employment through $HD7_3$, unemployment while between jobs through $HD7_6$, unemployment while not currently looking for work through $HD7_7$, retirement through $HD7_8$, or full-time homemaker status through $HD7_9$.

Household Income and Caregiving Intensity

Household income is reported through HD10 as combined household income in 2022 across eight categorical ranges, from less than $25,000 to $300,000 or more. For descriptive analysis, the categorical income variable was converted into an approximate continuous measure using midpoints of $20,000, $37,500, $62,500, $87,500, $125,000, $175,000, $250,000, and $350,000 for the eight categories, respectively. Responses coded as 666, indicating "I do not know," and 999, indicating refusal to answer, were treated as missing. These representative income values are analytical recodes to calculate averages.

Caregiving intensity was examined using AC5, which measures the average number of hours per week spent providing adult care. The response categories are less than one hour per week, 1–4 hours, 5–19 hours, 20–40 hours, and constant or around-the-clock care. The analysis uses this variable to compare the distribution and summary characteristics of caregiving intensity between the identified mental-health caregiving group and other caregivers of working-age adults.

Appendix F Why Standard VSL Estimates Are Ill-Suited for Measuring the Costs of Suicide and Premature Death

F.1 What VSL Measures and Where It Comes From

Economists measure the cost of a premature death using a quantity called the *value of a statistical life* (VSL). The VSL is not a claim about what any particular life is "worth" in a moral sense. It is instead an answer to a narrower empirical question: *how much are people willing to pay, in aggregate, for small reductions in the risk of dying?*

The logic is easiest to see with an example. Suppose a workplace safety improvement reduces each worker's annual probability of death by 1 in 10,000. If each of 10,000 workers is willing to pay $500 for that improvement, their total willingness to pay is $5,000,000—and on average one statistical death has been averted. The VSL is therefore $5,000,000: the rate at which this group of workers trades money for mortality risk, scaled to a full unit of risk.

F.2 The Rationality Problem

The standard VSL model can be stated simply. An individual derives utility—a measure of wellbeing—from two things: consumption (financed by wealth w) and being alive. Let $U(w)$ denote the utility of being alive with wealth w, and $V(w)$ denote whatever value the individual places on their estate after death. We assume $U(w) > V(w)$: the individual prefers to be alive. Faced with a probability of death p, their expected wellbeing is:

$$EU \;=\; (1-p)\,U(w) \;+\; p\,V(w). \tag{5}$$

VSL is then derived as the rate at which this individual willingly exchanges wealth for reductions in p. The key result is:

$$\text{VSL} \;=\; \frac{U(w) - V(w)}{(1-p)\,U'(w) \;+\; p\,V'(w)}, \tag{6}$$

where $U'(w)$ is the marginal utility of an additional dollar of wealth. The numerator is the utility gap between being alive and being dead; the denominator converts that gap into dollar terms. Because the individual prefers life—$U(w) > V(w)$—VSL is positive: they are willing to pay to reduce mortality risk.

This derivation breaks down in at least two distinct ways when applied to suicide.

The preference reversal problem. Equation (6) assumes $U(w) > V(w)$: the individual values being alive more than being dead. A person who dies by suicide has, at the moment of the act, revealed the opposite preference ordering—they have chosen death over continued life. If we take that revealed preference at face value, the VSL formula assigns a *negative* value to their survival, which is both ethically unacceptable and theoretically incoherent as a basis for policy analysis.

One response is to simply take suicide seriously as a preference: if someone prefers death, then preventing their death imposes a welfare loss, not a welfare gain. Most economists and policymakers reject this conclusion, for good reason. The clinical evidence strongly suggests that suicidal preference reversals are transient. Studies of individuals who survived near-lethal attempts find that the overwhelming majority—often cited at greater than 90 percent—do not go on to die by suicide and report being glad they survived (Haw et al., 2012). This is inconsistent with a stable, considered preference for death. It is instead consistent with a temporary state in which the individual's capacity for preference formation is severely compromised.

The compromised agency problem. The deeper issue is not merely that suicide preferences are unstable, but that they arise under conditions that the standard model explicitly

assumes away. Severe mental illness— present in the large majority of suicide decedents (Cavanagh et al., 2003)—distorts the cognitive processes through which preferences are formed and acted upon. Depression, for instance, systematically biases the evaluation of future states: individuals in a depressive episode underweight future positive experiences and overweight current pain, in ways they themselves often recognize as distorted in retrospect. Acute suicidal crisis is frequently accompanied by cognitive constriction—a narrowing of perceived options that precludes the kind of deliberative weighing of alternatives the VSL model requires.

These are not minor deviations from perfect rationality of the kind behavioral economics routinely accommodates. They represent a categorical failure of the preference-formation process that generates VSL in the first place. To apply a VSL derived from workers making marginal risk tradeoffs in labor markets to individuals in acute suicidal crisis is to use a measuring instrument outside the conditions for which it was calibrated. We observe similar compromises while estimating the VSL of non-suicide premature deaths due to mental illness and substance use disorder. The standard VSL does not conform well to the underlying risky behavior exhibited by individuals with mental illness and substance abuse issues. For this reason we will be using the same underlying VSL calculations for all decedents.

Implications for cost estimation. These two problems do not simply introduce noise into VSL-based cost estimates for suicide—they introduce systematic bias of indeterminate sign and potentially large magnitude. If suicidal preferences reflect temporary, illness-induced distortions rather than stable underlying preferences, then the welfare-relevant VSL for this population is not the observed market VSL, nor zero, but something closer to the VSL that would be revealed by the individual's own preferences absent the episode of illness. That counterfactual quantity is not directly observable, which is precisely why applying the standard VSL figure requires stronger assumptions than are typically acknowledged.

For these reasons, VSL-based estimates of the cost of suicide should be interpreted with significant caution. They provide a useful benchmark and facilitate comparisons with cost

estimates for other causes of death, but they do not have the welfare-theoretic foundations that VSL estimates carry in the contexts for which they were designed.

F.3 A Tractable Adjustment: Illness-Induced Income Suppression

The preceding sections establish that the standard VSL is theoretically ill-suited to suicide deaths among individuals with mental illness. They do not, however, point to a single corrected VSL figure. The welfare-relevant VSL for this population is a counterfactual that cannot be directly observed. We therefore adopt a more conservative approach: rather than attempting to correct for the full set of complications identified above, we adjust the standard VSL for a single, well-grounded, and empirically tractable source of divergence between this population and the general workforce.

As established in equation (6), VSL is increasing in wealth. This is one of the most robust predictions of the theoretical framework and one of the best-documented findings in the empirical literature (Viscusi and Aldy, 2003). Wealthier individuals have more resources to allocate toward safety and therefore reveal higher willingness to pay for mortality risk reductions. The standard VSL figure (approximately $12 million) reflects the income distribution of the study populations from which it is estimated, predominantly employed workers in the general labor force.

Individuals with serious mental illness have substantially lower incomes than the general population, not because of pre-existing differences in preferences or productivity, but because mental illness itself suppresses labor market participation and earnings (Insel, 2008). Depression, schizophrenia, bipolar disorder, and related conditions reduce the capacity to maintain steady employment, advance in careers, and accumulate wealth over the life cycle. The income gap between individuals with serious mental illness and the general population is therefore better understood as a consequence of illness than as a fixed characteristic of the individuals themselves. We refer to this as *illness-induced income suppression*.

The distinction between illness-induced income suppression and simple poverty is not

merely semantic. When VSL is adjusted for income differences across countries, which is standard practice in international cost–benefit analysis (Viscusi and Aldy, 2003), the adjustment reflects genuine cross-national differences in economic development and preferences. Applying the same adjustment within a country to a population defined by illness carries a different interpretation: we are not asserting that the lives of individuals with mental illness are worth less. We are instead correcting for the fact that their income, and therefore their revealed willingness to pay for safety, has been artificially compressed by illness. The adjusted VSL is an estimate of what their willingness to pay would be, absent the income-suppressing effects of mental illness, not a claim about the intrinsic value of their lives.

The adjustment procedure. We modify the traditional cross nation VSL valuation to mental illness. Denoting the population mean income as $\bar{y}$ and the mean income of individuals with serious mental illness as y_{MI}, the adjusted VSL is:

$$\text{VSL}_{MI} \;=\; \text{VSL} \times \left(\frac{y_{MI}}{\bar{y}}\right)^{\epsilon}, \tag{7}$$

where $\epsilon \in [0.4, 1.5]$ is the income elasticity of VSL. The income elasticity of VSL is estimated in the literature at approximately 0.5 to 0.6, meaning that a one percent difference in income corresponds to a 0.5 to 0.6 percent difference in VSL (Viscusi and Aldy, 2003). However, (Boardman et al., 2018) argue for a value around 0.8 with robustness in ranges of 0.4 and 1.5. We estimate y_{MI} and $\bar{y}$ directly from our data (see Section A), allowing the adjustment to reflect the actual income gap in our study population rather than a generic assumption.[30] This approach is conservative in two respects. First, it corrects only for the income channel, leaving the preference and agency problems identified in Sections A.2 and A.3 unaddressed—meaning our adjusted VSL likely still overstates the true welfare-consistent value for this population. Second, by treating the income gap as illness-induced rather than intrinsic, it implicitly asks what individuals with serious mental illness *would* pay for survival if their

[30]We just use the ratio of average wages to avoid the part-time/full-time distinction, on average the ratio is 0.73 for those who suffer from severe mental illness.

earning capacity were not suppressed by illness—a question that is both welfare-theoretically appropriate and empirically tractable given our data. Several government agencies attempt to calculate VSL estimates: U.S. Department of Transportation (2026), Kearsley (2026), and U.S. Environmental Protection Agency (2026). Central estimates suggest a VSL for 2025 at approximately 14 million. See Table 3 for estimates under different elasticities.

Table 3: Value of a Statistical Life Under Alternative Income Elasticities

Income elasticity, ϵ	Calculation	VSL_{MI}
0.4	$\$14{,}000{,}000(0.73)^{0.4}$	\$12.34 million
0.8	$\$14{,}000{,}000(0.73)^{0.8}$	\$10.88 million
1.5	$\$14{,}000{,}000(0.73)^{1.5}$	\$8.73 million

Appendix G Deriving the 27% Attributable-Fraction Estimate

Hall et al. (2019) report two relevant summary statistics for misdemeanor arrestees in New York State (2010–2013, $N \approx 600{,}000$): (1) an overall jail-sentence rate of 20% across all misdemeanor arrestees, and (2) that 6% of arrestees had a documented major mental illness (MMI) diagnosis in the year prior to arrest. The study additionally reports an adjusted odds ratio of 1.52 (95% CI: 1.47–1.57) for the association between MMI diagnosis and receiving a jail sentence, controlling for offense characteristics, sex, and race.

The paper does not report the jail-sentence probability separately for the MMI and non-MMI groups. We back-solve for these group-specific probabilities using the two reported summary statistics together with the reported odds ratio.

Let p_0 denote the jail-sentence probability for arrestees without an MMI diagnosis, and p_1 the corresponding probability for arrestees with an MMI diagnosis. The odds ratio relationship implies

$$p_1 = \frac{1.52 \cdot \dfrac{p_0}{1-p_0}}{1 + 1.52 \cdot \dfrac{p_0}{1-p_0}} = \frac{1.52\,p_0}{1 + 0.52\,p_0}. \tag{8}$$

The overall 20% jail-sentence rate is a weighted average of the two group-specific rates, weighted by the 6%/94% MMI/non-MMI split:

$$0.06\,p_1 + 0.94\,p_0 = 0.20. \tag{9}$$

Substituting the first equation into the second and solving numerically yields $p_0 \approx 0.196$ and $p_1 \approx 0.270$.

The attributable fraction — the share of MMI-diagnosed prisoners who would not have received a jail sentence had they faced the non-MMI probability p_0 — is then

$$\mathrm{AF} = 1 - \frac{p_0}{p_1} = 1 - \frac{0.196}{0.270} \approx 0.27. \tag{10}$$

Limitations. This derivation combines an adjusted odds ratio (which controls for case covariates) with unadjusted marginal rates (which do not), and is therefore an approximation rather than a quantity directly reported by the study. It applies only to misdemeanor sentencing outcomes: Hall et al. (2019) explicitly found no comparable association between MMI diagnosis and incarceration for felony arrestees, this is likely due to the base probability of conviction (conditional on a charge) for felony arrest to be much greater than that of misdemeanor. This would almost certainly reduce the odds ratio 1.52 to something closer to one.

Appendix H Additional Figures

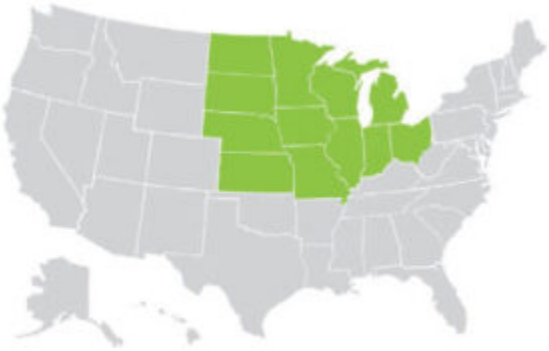


Figure 20: North Central Region

Source: North Central Regional Center for Rural Development, https://ncrcrd.ag.purdue.edu/ncr-stat/

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