Online Appendix for

"When Innovation Goes Wrong: Technological Regress and the Opioid Epidemic"

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This appendix describes the data and provides fuller results for the above article, published in the Journal of Economic Perspectives. All the program used, along with instructions to replicate the results are available at http://doi.org/10.3886/E138262.

I. Aggregate Trends in Mortality and Drug Shipments

Data on opioid shipments are from the Drug Enforcement Administration's **Automated of Reports and Consolidated Order System (ARCOS) (DEA, 1999-2017)**. ARCOS reports shipments by product and three-digit zip code. We aggregate the ARCOS data to counties or the nation as appropriate. When a three-digit zip code spans multiple counties, we split shipments based on the share of the population in each county using data from the U.S. Census Bureau (U.S. Census Bureau, 2010a). We convert drugs into milligrams of morphine equivalents using data from the Center for Medicare and Medicaid Services (CMS, 2017). We included opioid shipments from the most used opioids, including oxycodone, hydromorphone, hydrocodone, codeine, morphine, fentanyl base, alefentanil, remifentanil, and sufentanil base. We excluded shipments of buprenorphine and methadone, both of which are frequently used for opioid use disorder treatment. The included opioids accounted for more than 97 percent of total opioid shipments, excluding buprenorphine and methadone. Shipments of several opioids consistently reported throughout 1997 to 2017 were missing in 2000. For these opioids, we imputed shipments in 2000 using a linear interpolation between 1999 and 2001.

Data on mortality are from the **Centers for Disease Control and Prevention mortality data (CDC, 1990-2018)**. As part of this project, we obtained access to restricted county information. We use these data to construct opioid mortality rates at the county-year level.

Drug deaths before 1999 were identified based on *International Classification of Diseases, 9th edition* underlying cause-of-death codes E850-E858, E950.0-E950.5, E9620, and E980.0-E980.5. Opioid deaths before 1999 were identified from underlying cause-of-death-codes E850.1-E850.2 and 305.5, as well as multiple-cause-of-death codes 965.00-965.09 (Fingerhut & Cox (1998). Deaths involving more than one opioid category are counted in both. Drug deaths after 1999 were identified based on *International Classification of Diseases, 10th edition* underlying cause-of-death codes X40–X44, X60–X64, X85, and Y10–Y14. Overdoses by category were identified by multiple-cause-of-death codes T40.1 (heroin), T40.2 (prescription opioids = natural and semisynthetic opioids), T40.3 (methadone), and T40.4 (fentanyl/tramadol = synthetic opioids other than methadone) (Hedegaard, Miniño, and Warner, 2018). Total opioid deaths also included code T40.6 (other/unspecified narcotics).

Not all coroners tested for opioids in all years. Thus, in some counties and years there are deaths attributable to a drug overdose but not to any particular drug. We adjust for this following a procedure of Ruhm (2018). Using the sample of all drug overdose deaths where a particular drug was specified, we estimated probit models for the probability of death from each drug type as a function of individual demographic characteristics and type of place (inpatient hospital, outpatient hospital, at home, or other), year, and day of the week of death. We used predictions from the probit models to assign probabilities of overdose death from each drug type for drug overdose deaths where drug types were unspecified.

To account for the change from ICD-9 codes (1990–1998) to ICD-10 codes (1999–2017), the following comparability ratios were applied to ICD-9 codes E850-E858, E950-E950.5, E9620, and E980.0-E980.5 (respectively) in the calculation of total drug deaths: 1.0365, 1.0013, 0.9870, and 1.0417 (Miniño, et al., 2002). Total opioid deaths were adjusted upward by about 20 percent (comparability ratio = 1.195) (Hoyert, et al., 2001). Deaths were age- and sex- adjusted to the US 2000 population using population data from the Surveillance, Epidemiology, and End Results (SEER) Program (NIH, 2021).

II. Trends in Opioid Use

The primary data source on individual use of opioids is the **Medical Expenditure Panel Study (MEPS) (AHRQ, 2021)**. MEPS has run continuously from 1996. Each year, a new panel of people is enrolled, consisting of roughly 30,000 people. We use panels enrolled in 1996 through 2015. MEPS follows individuals for 5 rounds of data collection, asking questions referring to a period of about 2½ years. Data are aggregated across respondent's survey rounds, such that data for each year denotes individuals who entered MEPS in that year and were followed through the next calendar year. For example, 1996 denotes individuals who entered MEPS in 1996 and were followed through 1997. Data are for the non-institutionalized population aged 15+, weighted using survey weights, and age- and sex-adjusted to the US 2000 population.

To measure opioid use, we employ information on medications taken. In each round, MEPS asks about medications the person received in a specific time-period (generally six months). These are generally coded by name (e.g., "OxyContin" or "Percocet"). We compiled the responses, looking for possible misspellings. For MEPS scripts where a national drug code (NDC) was available, we cross-validated the scripts we coded as opioids with a CDC list of prescription opioid NDCs which excluded cough formulations (CDC, 2018).

Figure A1 presents trends in the share of people with any opioid script, one opioid script, and more than one opioid script. There is a 28 percent increase in the share of people with a prescription for opioids between 1999-2000 and 2008-2009, which is large, but far below the quintupling of MMEs per capita in ARCOS data and opioid deaths. There is a larger increase in the share of people with 2 or more prescriptions. Addiction to opioids can occur in as little as 4 to 8 weeks (Sharma, et al., 2016). Thus, obtaining two or more script is indicative of the type of opioid use which may have indicated or have led to opioid addiction. A better measure of excessive use would be the milligrams of morphine equivalent over the course of the panel. However, MEPS data on the dosage of the prescription are missing 70 percent of the time.

Figure A2 shows that people with 2 or more prescriptions often have a very large number of prescriptions. The share of people with 10 or more prescriptions more than doubled between 1999 and 2011. Further information on opioids prescriptions comes from state **Prescription Drug Monitoring Programs (PDMPs)**. We obtained PDMP data from Massachusetts (Massachusetts Department of Public Health, 2000-2018), Kentucky (Kentucky Cabinet for Health and Family Services, 2006-2018), and California (State of California Department of Justice, 2009-2018). **Figure A3** uses data from Massachusetts to examine the increase in prescribing over time. The figure decomposes the change in MMEs per capita (shown in panel a) into the number of scripts per capita (panel b), the average MME/day of the average script (panel c), and the number of days supply of the average script (panel d). As scripts per capita grew in Massachusetts, the average scripts involved more days supply – also contributing to the larger increase in MMEs per capita.

One concern with the MEPS data is that respondents to MEPS may under-report illicit use of prescription opioids. To assess this, **Figure A4** compares the trends we obtain using self-reported MEPS data with trends in opioid prescribing from IMS Health's National Prescription

Audit (NPA) data (Volkow, 2014). The NPA data underlying these estimates are from a sample of 59,000 pharmacies which represent 88% of prescriptions in the US. The trend in opioid prescribing in MEPS is broadly consistent with the NPA data. MEPS data are about one-third lower than NPA data. The growth rates are relatively similar, however: 98 percent growth from 1997 to 2011 in NPA data vs. 89 percent growth in MEPS. The reasons for these differences may reflect underreporting of illegal use of opioids, such as prescription opioids obtained from pill mills.

Figure A5 shows opioid use by subgroups: by gender (panel a), by BA or not (panel b), urban/rural location (panel c) and labor force status (panel d). For the different subgroups, we focus on people who receive at least two opioid prescriptions over the course of the MEPS panel. The share of people receiving more than one opioid script is higher among females and is higher and grew more among people without college degrees, people living in rural areas, and people not in the labor force.

Figure A6 shows trends in the treatment of people initiating more than one script of opioids, anti-depressants, and/or anxiolytics in MEPS rounds 3 to 5, and the share of people using NSAIDs/other analgesics. In each case, the sample is people reporting pain and not any taking these prescriptions except for NSAIDs before round 2. Opioid use increased in this population by 60 percent from 2001 to 2009, while use of NSAIDs/other analgesics fell by 39 percent. Thus, the data show that prescription opioids appear to have substituted for NSAIDs/other analgesics.

The text notes that physicians observed that opioids did not control pain as well as had been thought. We show this in our MEPS data in **Figure A7**. The figure shows the change in pain by initial level of pain for different cohorts. The most important comparison is the 2009-11 cohort versus those cohorts before and after. The 2009-11 cohort was most likely to receive an opioid.

Thus, if opioids controlled pain well, pain should decline more for people in the 2009-11 cohorts relative to other cohorts.

The lines in Figure A7 are all downward sloping, as expected: people with high pain reports in the second round are more likely to report reductions in pain by round 4. However, the change in pain is similar for the different cohorts. Indeed, the cohort with the greatest reduction in pain is the 2013-15 cohort, the one after opioids had been significantly curtailed. Thus, the data show no evidence that more frequent opioid prescribing led to greater reductions in pain.

Figure A8 analyzes concentration of prescribing at the prescriber level using the PDMP data from the three states. Opioid prescribing is highly concentrated—particularly in Kentucky, the state with the highest rate of opioid prescriptions per capita. In 2011, the top 5% of prescribers wrote 58% of prescriptions for opioids in Kentucky, 40% of prescriptions for opioids in California, and 38% of prescriptions for schedule-II opioids in Massachusetts. Concentration of prescribing has been increasing over time, particularly as opioid supply has tightened in recent years.

III. Demand and Opioid Initiation: Survey Data

MEPS Data

To examine how demand-side variables relate to opioid use, we statistically relate measures of pain, despair, and isolation to the initiation of (legal) opioid medication. We start with the MEPS data. We estimate models relating opioid initiation to various factors in the period 2002-2010, after detailed health data were added but before major cutbacks in opioid prescribing took place.

We use two measures of pain. The first is the experience of pain. For this metric, we use the MEPS question about pain interfering with life in the past 4 weeks, which we summarize linearly on a scale from 0 (not at all) to 1 (extremely). Our regression results are similar if we use a dummy for moderate or more pain. Our second measure of pain is use whether respondents were diagnosed with any painful conditions as reported in round 1 or 2 of the survey, based on the list in Nahin, et al., (2019). Painful conditions include sickle cell anemia, headache (including migraine), nonspecific chest pain, rheumatoid arthritis and related disease, osteoarthritis, other nontraumatic joint disorders, spondylosis (including intervertebral disc disorders, other back problems), joint disorders and dislocations (trauma-related), all fractures, sprains and strains, and abdominal pain. We use MEPS Clinical Classification Codes (CCC) codes to identify these conditions.[1] We also only consider painful conditions diagnosed by round 1 or 2, from before we measure opioid prescription initiation, to reduce endogeneity of diagnosis of painful conditions to opioid-seeking behavior. Our prevalence of painful conditions using this measure is 74 percent of the level of Nahin.

The MEPS does not have a good measure of despair. However, the SF-12 has several questions about mental health. We use the depression question: "How much of the time during the past 4 weeks: Have you felt downhearted and depressed?" Possible answers are: none of the time; a little of the time; some of the time; most of the time; all of the time; and – in 2001 and 2002 – a good bit of the time. To keep the possible responses constant, we use data from 2003 on. We summarize the responses into a linear 0 to 1 scale. **Table A1** shows the mean pain score is 0.16, 25 percent of people have a painful condition, and the mean depression score is 0.21. The correlation between the three variables ranges from .11 (between depression and painful conditions) to .32 (between physical pain and depression scores).

To measure social isolation, we use the MEPS measures of labor force participation and marital status. We include a dummy for not employed – divided separately into those above and

[1] Nahin includes more conditions, but we are unable to use the additional painful conditions which rely on 4- and 5-digit ICD9 codes.

below age 62 – and two marital status dummies: one for being widowed/divorced, and a second for being never married.

As opioid use might affect measures of pain and social situation as well as be affected by them, we focus on the connection between these variables and the decision to initiate opioids. Thus, we consider adults who are opioid naïve as of round 2 of the survey – the first time the pain and depression measures are asked. We then relate opioid initiation by the end of the sample – either any use or heavy use – to pain and social conditions measured in round 2. On average, 12 percent of opioid naïve respondents begin opioid use over a two-year period and 4 percent begin heavy opioid use (2+ prescriptions).

Our regressions include demographic and other controls. Demographic controls include five-year age-sex cells, race and ethnicity, marital status, region of the country (4 dummy variables), whether the person lives in an MSA, 1-digit industry, and year fixed effects. We also include dummy variables for occupation (blue collar, white collar, service, and other). To proxy for the out-of-pocket cost of medications, we include dummies for source of health insurance coverage and prescription drug coverage and usual source of care (office, hospital, neither). Finally, we include three health behaviors: a dummy for whether the person currently smokes; whether they received a flu shot last year; and whether they always wear a seat belt. We interpret these as measures of integration with the medical system and attention paid to health messaging. It is also possible that health behaviors pick up differences in discount rates or outlook for the future, though our past research shows that health behaviors are generally not highly correlated in the way one would expect if they picked up a constant utility function parameter (Cutler and Glaeser, 2005).

Table A2 shows regression results for the initiation of two or more opioid scripts. The first column relates opioid initiation to pain and the demographic controls. The coefficient on pain is positive, statistically significant, and substantively large. An individual in extreme pain has a 15 percentage point higher probability of receiving an opioid prescription than an individual with no pain. This increase is larger than the 12 percent rate of opioid initiation in the population. We can use this coefficient to estimate how much changes in pain over time would affect the initiation of heavy opioid use. Using our coefficient estimate $\hat{\beta}$, we calculate $\Delta X \cdot \hat{\beta} / \Delta Y$, the change in heavy opioid initiation due to changes in pain. The denominator is the change in opioid initiation from the 2002 to 2009 panel. The lower panel of the table shows that this is -0.8 percent; pain is strongly associated with opioid initiation, but pain among the opioid naïve fell slightly over time.

The second column shows results for individuals with a painful condition. An individual with one of the eleven painful conditions has a 3.4 percentage point higher probability of receiving an opioid prescription than an individual without a painful condition. This is smaller than the initiation associated with pain, as one would suspect. The prevalence of painful conditions rose over time, and this explains 16 percent of the increase in heavy initiation.

The third column shows comparable results for depression. The coefficient is also positive and statistically significant, but roughly one-third the magnitude of the pain coefficient. Because both pain and depression are on a 0-1 scale, the smaller coefficient is an indication that the effect of depression is substantively smaller than that for pain. Depression also fell slightly between the 2002 and 2009 panel. Thus, changes in depression predict negative growth in opioid initiation over time. Results are similar using severe mental distress, as measured by a score of thirteen or more on the Kessler-6 index (not shown). Severe mental distress was associated with a statistically significant 3.2 percentage point higher probability of initiating 2+ opioids. However, trends in severe mental distress also fell in MEPS over the time period, as shown in **Table A5**. Thus, changes in mental distress in MEPS also predict a decline in opioid use.

The fourth column shows a mixed impact of social isolation. People who are widowed, separated, or divorced are more likely to initiate opioids, but people who are never married are less likely to initiate opioids. Working age people who are not employed are no more likely to initiate opioids than are those who are employed.

Columns (5) and (6) include all the categories of variables together, with a separate column for each measure of pain. The coefficient on physical pain and social isolation do not change greatly. Depression, in contrast, is not related to opioid initiation conditional on physical pain scores. All told, these variables explain at most 20 percent of the increase in heavy initiation of opioids.

Columns (7) and (8) models whether the individual initiates opioids at all (i.e., one or more scripts). The results are largely similar.

MIDUS Data

Because MEPS does not have good data on despair, we also utilize data from the **Midlife in the United States Survey (MIDUS) 1 to 3 (Brim, et al., 1995-1996; Ryff, et al., 2004-2006; and Ryff, et al., 2013-2014)**. MIDUS is a panel study of roughly 7,000 people interviewed three times: once in 1995-97, a second time in 2004-05, and a third time in 2013-15. The sampling in the MIDUS survey is somewhat unusual. One component of the sample is random, but another part is a twin sample. To maximize our observations, we use all observations. As a result, we do not use weights. However, we cluster the standard errors at the person level, since a person can have more than one observation in the sample.

We use the MIDUS data as a panel and consider whether an opioid-naïve person in one survey round (e.g., round 1 or round 2) becomes an opioid user by the next round (round 2 or round 3). We relate this to economic and health conditions as of the initial round.

A limitation to the MIDUS data is that it suffers from a great deal of attrition, roughly 30 percent. Other work has found that people who exit MIDUS have worse health and lower socioeconomic status (Radler and Ryff, 2010). Greater attrition for individuals in worse pain and in greater despair, and which is associated with opioid use, may bias our estimates towards the null. Thus, these results are suggestive but not definitive.

We use several variables to measure pain, negative affect, despair, and economic insecurity in MIDUS. The specific questions asked about in MIDUS are in **Table A3**. Within each category, we estimate a factor model and use the first principal component to measure possible demand for each category of variables. Summary statistics on the different measures are shown in **Table A1**. By definition, the measures of pain, affect, despair, and economic insecurity are standard normal. The largest correlations are among affect, despair, and economic insecurity, with all the correlations between 0.4 and 0.5.

Table A4 shows the factors that predict opioid initiation in the MIDUS. The first five columns show the relationship between the variables independently and opioid initiation. A one standard deviation increase in pain has the largest impact on opioid initiation; the magnitude is 15 percentage points. A one standard deviation change in despair increases opioid initiation by 3 percentage points, economic insecurity increases opioid initiation by 6 percentage points, and net negative affect raises it by 8 percentage points. Social isolation is not as important for opioid initiation; never married people initiate opioids less, and people who are not employed are no more likely to initiate opioids.

Column (6) shows the results with the variables entered together. The results of the multivariate regression are generally similar to the regressions with each variable included separately. The major distinction is that general despair is not related to opioid initiation, but economic insecurity is related to opioid initiation.

Overall, these results imply modest effects of changes in pain, affect, despair, and economic insecurity on opioid use. Including all variables together explains 24 percent of the increase in prescription pain reliever use; all of this effect is due to the rising prevalence of pain.

Trends in MEPS, BRFSS, and NHIS data

In **Tables A5-A6**, we present trends in our pain and despair measures in MEPS alongside a wide variety of additional metrics related to health, pain (physician and mental), and despair in that have been reported in the literature on pain and despair (Blanchflower and Oswald 2020; Case and Deaton 2020; and Nahin, et al., 2019). We use data from MEPS (AHRQ, 2021), BRFSS annual survey (CDC, 2021b), and National Health Interview Survey (NHIS) (Blewett, et al., 2019). We age- and sex-adjusted metrics in all surveys and years to the US 2000 population using population data from the NIH (NIH, 2021) and present changes over time in the metrics separately for all adults (**Table A5**) and all adults age 25+ without a college degree (**Table A6**). We focus on aggregate trends in pain and despair, as our goal is to compare changes in population prevalence of pain over time to changes in opioid death rates. However, we note that these aggregate trends in pain (which average across cohorts) may mask larger increases across cohorts, such as the high growth in cohort pain reported in Case, Deaton, and Stone (2020).

Trends were estimated in MEPS and NHIS by regressing each variable on year, and the cumulative percent change was estimated as the fitted change between the first and last year of our data over the fitted value in the initial year we observe. In the BRFSS, weighting methodology was changed in 2011, resulting in in some variables shifting in this year due to BRFSS better-capturing data from young people and racial and ethnic minorities post-2011.[2] Thus we use a different methodology to estimate a trend in BRFSS. We fit a regression of each BRFSS metric on year separately before and after 2011. Then, we estimate the trend as the weighted average trend over the time period and the cumulative percent change by extrapolating the estimated trend over the time period and dividing it by the fitted value in the initial year.

As has been shown in prior work, trends in many measures of health, pain, and despair have been worsening over time (Blanchflower and Oswald 2020; Case and Deaton 2020; IOM 2011; and Nahin, et al., 2019); though, estimated trends vary by metric and survey. On the topic of general health, more people report fair or poor physical health today than they did in the late 1990s in BRFSS and NHIS but not in the MEPS. In the BRFSS, people report more frequently having days with poor physical and mental health. In particular, the shares of people who report having poor physical for most (more than 20) or all 30 days in the past month (after age- and sex-adjustment) have risen by 85 percent and 41 percent. Limitations to people's activities due to poor physical, mental, or, emotional health have also been increasing in the BRFSS, but activity and physical functioning limitations have not increased in the MEPS.

By most measures, pain has risen. Musculoskeletal pain, comprised of any joint, back, or neck pain in the past 30 months, increased by 6 percent in the general adult population and by 10 percent for people without a college degree. Particularly severe forms of musculoskeletal pain—such as sciatica—increased by even more, rising by 20 percent in the general population and 34 percent among people without a college degree. However, trends in self-reported pain in MEPS

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[2] See "Can the 2010 BRFSS dataset be compared with the 2011 dataset?" at https://www.cdc.gov/surveillancepractice/reports/brfss/brfss_faqs.html

(shown in **Figure 3**) were relatively flat. Diagnosed pain increased the most of any pain measure, with the share of people diagnosed with at least two of the painful conditions defined in (Nahin, et al., 2019) rising by 220 percent between 1996 and 2015 in MEPS and cancer diagnoses growing by a third. On the other hand, injuries (shown in **Figure 3**) have fallen.

In contrast to pain, trends in mental or emotional problems and despair have mostly been flat or falling. The shares of people reporting spending some to all of their days depressed and a tendency towards depression (as measured by the PHQ-2) have fallen on the order of 20-30 percent in MEPS. Trends in the share of people dissatisfied with life have been flat or falling in BRFSS, as they also have been in the GALLUP polling data shown in **Figure 3**. The share of people reporting that their feelings interfere with their lives has also been flat or falling in the NHIS. There is one exception to this general upward trend. The share of people with a score of 13+ on the Kessler-6 index in the NHIS, indicating severe mental distress, rose by 23 percent in the general population and by 37 percent among people without a college degree since the late 1990s.

While trends in poor health, pain, and despair differ according to the survey and metric used, and many metrics have been rising over time, it is clear that no measure of poor health, pain, or despair has increased near as much as the more than fourfold increase in opioid deaths between the late 1990s and recent years. Even the measure of pain that grew the most—the share of people diagnosed with two or more painful conditions—grew by just over half as much. No measure of reported pain or despair has grown by even one-fifth as much as opioid deaths. Shifts in demand from higher rates of pain and despair were simply not large enough to explain the bulk of the rise in opioid deaths.

IV. Opioid Shipments and Mortality

Table 1 in the paper reports regression results showing the factors that influence where opioids were shipped and the mortality rate that followed from them. **Tables A7-A9** provide more detailed regression results. In these tables, we analyze the relationship between county level measures of pain and despair and three opioid-related outcomes: prescription opioid shipments from 1997 to 2010 (**Table A7**), prescription opioid deaths from 1990 to 2010 (**Table A8**), and illicit opioid deaths from 2008 through 2017 (**Table A9**). Opioid shipments and prescription opioid deaths are analyzed through 2010 as most deaths in that time period are due to use of legal opioids. Illicit opioid deaths are analyzed from 2008 through 2017, the last year for which we have data. In each case, data are at the county level.

The county-level pain and despair variables are standardized to be mean 0 and variance 1. Thus, the interpretation of the coefficients is the change in opioid shipments (or deaths) associated with a 1 standard deviation increase in each of the independent variables following the national increase in opioid shipments (or deaths) over the time-period being analyzed. All regressions control for county and year fixed effects and are weighted by county population in 2010.

Starting with **Table A7**, column 1 relates opioid shipments in the county to national opioid shipments interacted with the share of people in the county who received Social Security Disability Insurance (SSDI) in 1990, a marker of pain dating from before the opioid epidemic. Areas with one standard deviation more people on SSDI received 23 percent more opioids compared to an average county. This effect is statistically significant ($p<0.01$).

Columns 2 and 3 interact national opioid shipments and self-reported measures of pain, taken from the **2002-10 Behavioral Risk Factor Surveillance Surveys** (CDC, 2021a). Column 2 uses the question: "During the past 30 days, have you had any symptoms of pain, aching, or stiffness in or around a joint?" Possible responses were Yes, No, Don't know/Not sure, or Refused. Column 3 uses responses to a question about pain which made respondents activities difficult: "During the past 30 days, for about how many days did pain make it hard for you to do your usual activities, such as self-care, work, or recreation?" Possible responses are a range from 1-30 Days, None, Do Not Know/Not Sure, and Refused. We average both responses at the county level where counties are identified, generally large counties. Both pain metrics show a similar positive relationship with opioid shipments as the SSDI variable, though the results are less significant for the questions asked in smaller samples.

Columns 4 and 5 report the association between the interaction of national opioid shipments and despair or mental health impairment. To proxy for despair, we use the share of respondents in a county who were dissatisfied or very dissatisfied with life from the BRFSS question: "In general, how satisfied are you with your life?" Possible response are Very Satisfied, Satisfied, Dissatisfied, Very Dissatisfied, Don't Know/Not Sure, and Refused. Following Blanchflower and Oswald 2020, we also use the share of respondents who report all 30 days to the question: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" (possible responses were none, 1-30 days, don't know/not sure, and refused.) Prevalence of life dissatisfaction is positively related to opioid shipments, but not statistically significantly so. The share of people experiencing consistently poor mental health is a strong predictor of where opioid shipments went, with areas with a one standard deviation higher share of people with extremely poor mental health receiving 38 percent more opioid shipments than the average area.

Column 5 includes all the metrics available in the counties with data on both joint pain and life dissatisfaction. Only the extremely poor mental health variable remains significantly associated with opioid shipments in a positive direction, though the pain variables are still positively associated with opioid shipments. Opioid shipments predominantly went to areas with higher pain and poor mental health.

The last column uses an estimate of predicted pain and despair for all counties. To form these estimates, we used a two-step method. We started with a national sample that has pain (MEPS) and life satisfaction (BFSS). We use a LASSO technique to identify demographics and other independent variables that are also available at the county level to predict pain and despair. The variables considered include 10-year age-gender dummies, education (high-school, some college, and college graduate; interacted with age group and gender), employment status (interacted with age group and gender), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other), 2-digit occupation and industry dummies (also interacted with gender), whether the individual is obese, and region. County averages of these variables, drawn from SEER population data (NIH, 2021), the American Community Survey (U.S. Census Bureau, 2006-2010), and the CDC (CDC, 2004), were then used to impute prevalence of pain and despair at the county level. Files to replicate this procedure are provided in the online replication kit. **Tables A10** and **A11** show these results, along with how much the different factors contribute to urban-rural differences in the two metrics. County urban-rural status was drawn from the U.S. Census Bureau (U.S. Census Bureau, 2010b). We then imputed pain to all counties using county averages for the independent variables.

Figure A9 shows a map of the predicted prevalence of pain and despair across counties, based on the two-step procedure. The maps are moderately correlated (ρ=0.30). Pain is higher in rural areas, especially in the South and Appalachia. Urban areas have less pain because urbanites are younger, weigh less, are better educated, are more likely to be in the labor force, and work in industries with lower levels of pain. Despair is higher in the urban Midwest and much lower in the rural west. Area education is highly correlated with both predicted pain (-0.61 correlation coefficient with percent college graduates) and predicted despair (-0.51 correlation coefficient). This is not just a function of the fact that we predict pain and despair at the county level. If we average the data on life satisfaction in the BRFSS from 2005-2010, for which 338 counties are identified, the correlation between average life satisfaction and the share of college graduates is -0.37. The high correlation between predicated pain and despair and education makes it difficult for cross-sectional regressions to distinguish between the impact of education and either predicted pain or despair on mortality. Consequently, we do not control for education levels in our regression utilizing the predicted data.

Column 7 of **Table A7** reports the association with the predicted measures of pain and despair interacted with national opioid shipments. As above, predicted pain and despair are converted to z-statistics. Areas with one standard deviation higher pain received 30 percent more opioid shipments relative to the average area ($p<0.01$), whereas areas with higher despair received 17 percent fewer opioid shipments ($p<0.01$). The coefficients on the predicted pain and despair measures are similar to those in column 5.

Table A8 repeats the analysis above with prescription opioid deaths as the dependent variable. Like for opioid shipments, the most important predictors of which areas experienced more opioid deaths as opioid shipments grew were areas with worse pain and mental health. Each of the coefficients on the interaction between pain/mental health and national opioid shipments are positive and statistically significant, whereas the coefficients on the interaction between life dissatisfaction and national opioid shipments are negative or not statistically significant.

Table A9 repeats the analysis above with illegal opioid deaths – largely heroin and fentanyl deaths – at the county-level as the dependent variable. We relate this to the national number of illegal opioid deaths interacted with measures of pain and despair. We also include an interaction between national illegal opioid deaths and oxycodone MME per capita shipments from 1997 to 2010 to examine how legal opioid usage is related to subsequent deaths from illegal opioids. As in the earlier tables, the coefficients are scaled to represent the impact of one standard deviation higher pain, despair, or opioid shipments.

Moving from column 1 to column 6, each of the metrics for pain, despair, and opioid shipments interacted with national illegal opioid deaths is positively associated with county-level illegal opioid deaths. The results for all of the metrics except the average days pain made usual activities difficult are highly statistically significant ($p<0.01$). In column 7, which includes all the metrics together, pain and oxycodone shipments are the most potent predictors of the rise in illegal opioid deaths. Areas with one standard deviation higher joint pain prevalence experienced 34 percent more illegal opioid deaths ($p<0.01$), and areas with one standard deviation higher oxycodone shipments experienced 50 percent more illegal opioid deaths compared to the average county ($p<0.01$). This latter finding is consistent with past work which has shown that the reformulation of OxyContin after 2010, which made it more difficult to abuse, was associated with substantial increases in heroin and other illegal drug overdose death rates (Alpert, Powell, and Pacula, 2018; Evans, Lieber, and Power, 2019; Powell and Pacula 2021).

Column 8 reports results for all counties using predicted pain and life dissatisfaction. The results are similar to those in the previous columns, but for illegal drug deaths, predicted life satisfaction is also a strong predictor of where illicit drug deaths increased. Areas with one standard deviation higher predicted life dissatisfaction experienced 25 percent more opioid deaths.

V. Comparison to Other Results

As noted in the paper, our conclusion that despair by itself has relatively little direct effect on opioid use is consistent with other studies that examine the impact of medium-term economic changes on opioid mortality. The one exception to this is Charles et al. (2019a). Charles et al. use data on changes in manufacturing employment linked to opioid deaths at the state level. They estimate models by OLS and also instrumenting for manufacturing employment change using a Bartik shift-share instrument. We obtained their replication kit, and downloaded data from the 2000 Census and 2014-2016 American Community Survey to replicate and extend their results (Charles, et al., 2019b; Ruggles, et al., 2021).

Their key regression equation is in the first column of **Table A12**. Using both OLS and IV methods, areas where manufacturing employment declined more are areas where opioid deaths increased more. The coefficient is large. The average change in the manufacturing employment share among prime age workers from 2000 to 2016 was -4.9 percentage points in the Current Population Survey. This implies that manufacturing decline can explain an increase in opioid deaths of 10.8 per 1,000 (-4.9 x -2.2). This is 71 percent of the observed change in opioid deaths over this time period, which was 15.2 per 1,000.

Since this finding is out of line with other studies, we explored it in more detail. We are extremely grateful to Charles et al. for making available their data and replication programs. **Table A12** shows the results of the replication and extension. The first column replicates their results from Table 5 column (4) nearly exactly. The second column modifies the regression of Charles et al. in a few ways. First, Charles, et al. do not include opioid overdose deaths from synthetic opioids (cause of death code T40.4) or unspecified narcotics (cause of death code T40.6); we add those.

In addition, we use the change in opioid deaths for all individuals aged 15 and older; we change the years to 1999-2001 and 2016-18; and we include all states, even those suppressed by CDC wonder (since we have the geocoded information). These changes do not affect the results materially. The third column switches to using data at the commuting zone level rather than the state level. As with all of our results, we age and sex adjust the CZ-level overdose death data. The IV estimate falls by a third at the commuting zone level. The fourth column includes the share of the population in 2000 in three age groups: 20-40, 40-60, and 60+. Charles et al. include these shares in their CZ analyses. Including the age adjustments reduces the IV coefficients by 43 percent, and the coefficient is no longer statistically significant at the 5 percent level.

The fifth column adds additional control suggested by Pierce and Schott (2021): median household income, the percent of the population that is a veteran, the percent of the prime age labor force that is foreign born, and the percent of the prime age labor force with a bachelor's degree, all from the year 2000. In this case, the IV coefficient is positive (greater manufacturing decline leads to fewer deaths), although not statistically significant. The last column further adjusts death rates for underreporting as outlined by Ruhm (2018) and in Appendix Section I. The coefficient is now positive and statistically significant at the 10 percent level.

Our conclusion is that the results of Charles et al. are very sensitive to the exact specification. Most importantly, including controls for the age distribution of the population or other population characteristics makes the results much smaller and generally not statistically significant. We thus believe that the evidence is not in favor of a large direct effect of economic changes on opioid mortality.

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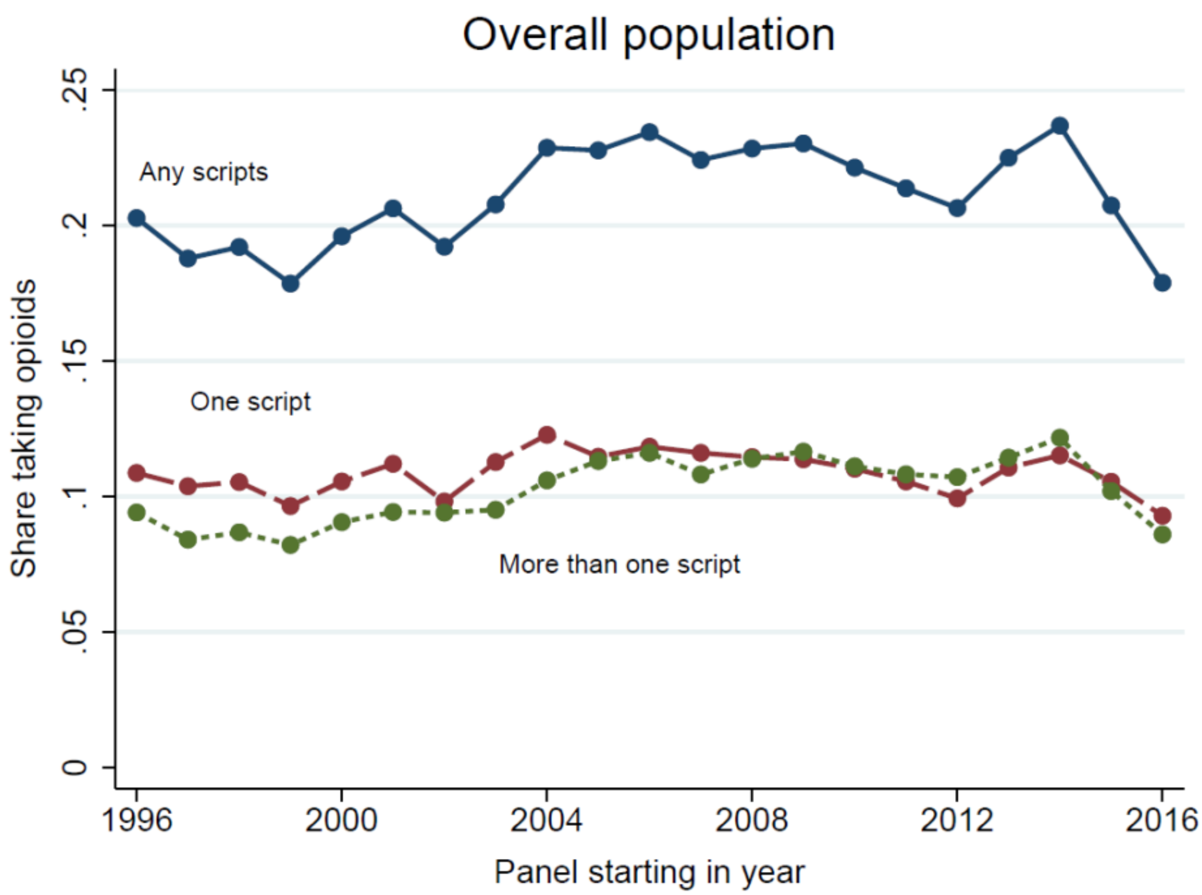
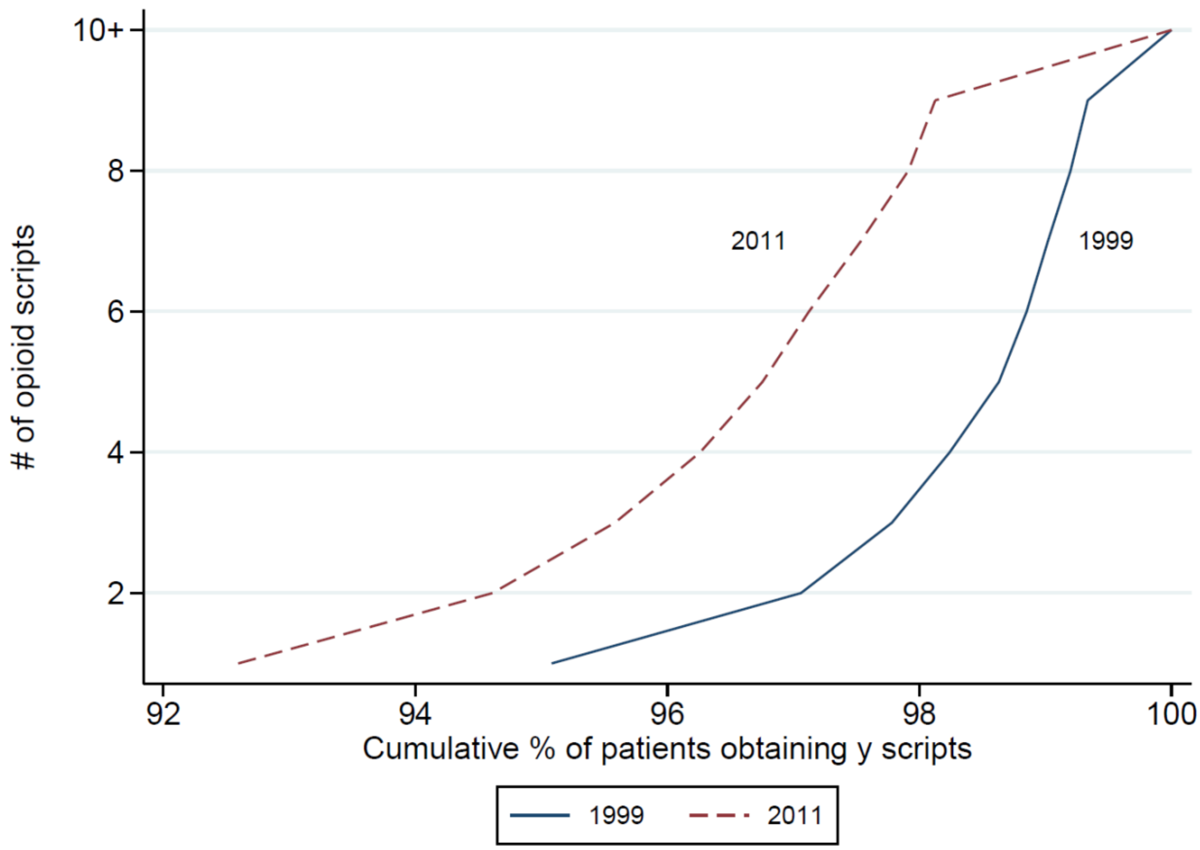
Figure A1: Use of Opioid Medications, 1996-2015



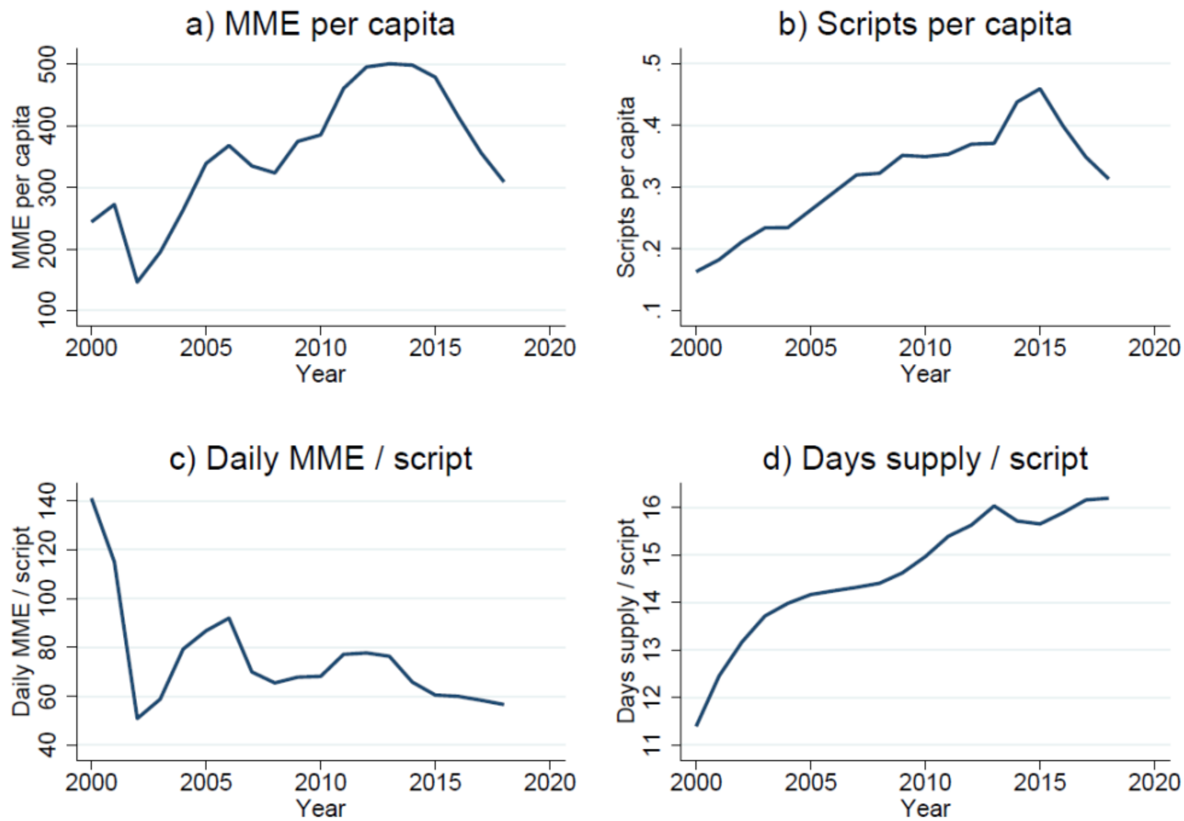
Notes: Data are from the Medical Expenditure Panel Study (MEPS), using waves 1996-2015. Each observation denotes a panel starting that year; for example, 1996 denotes individuals who entered MEPS in 1996 and were followed through 1997. Data are for the population aged 15+. All percentages are weighted using survey weights and are age and sex adjusted to the US 2000 population. Opioid use refers to a prescription report in any of the five rounds. Geographic location and labor force status are as of the first round of data collection.

Figure A2: Changes in the distribution of opioid prescribing to patients



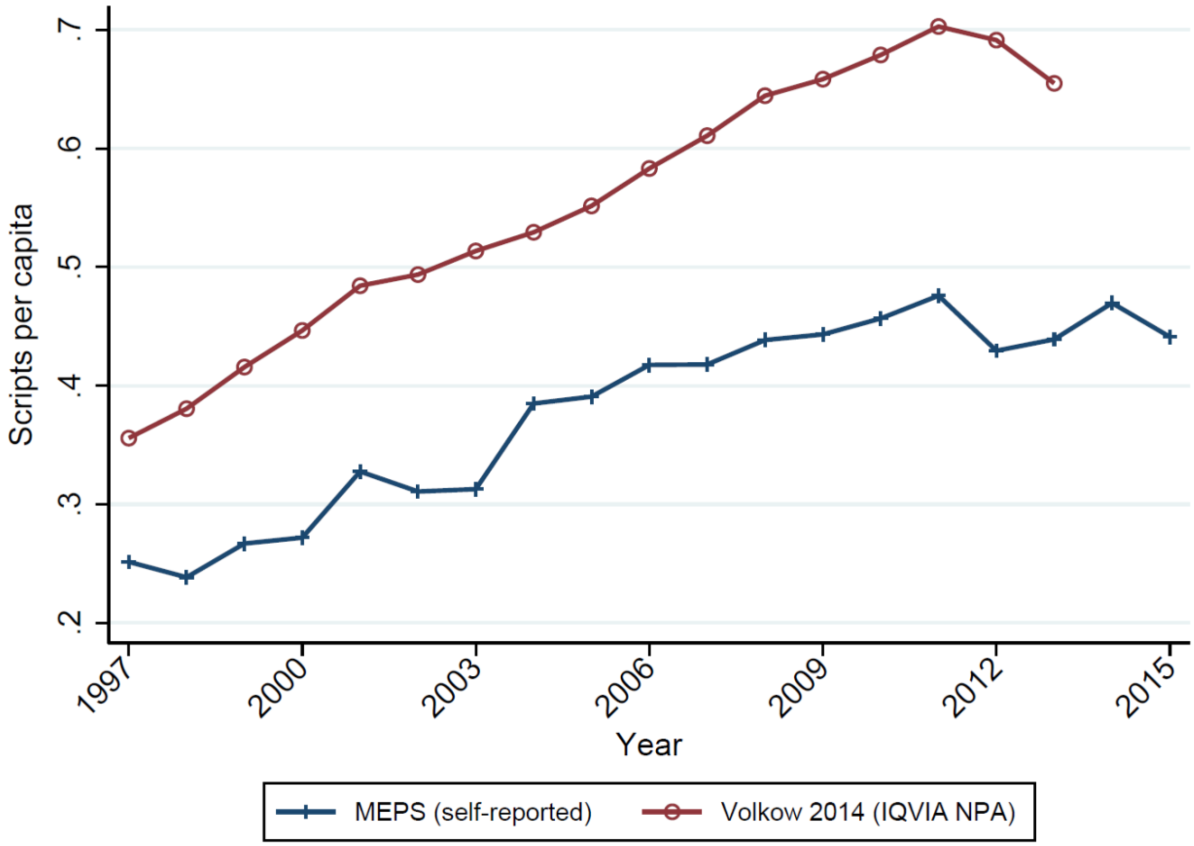
Notes: Data are from the Medical Expenditure Panel Study (MEPS). Each observation denotes a panel starting that year; for example, 1999 denotes individuals who entered MEPS in 1999. Data are for the population aged 15+. All percentages are weighted using survey weights and are age and sex adjusted to the US 2000 population.

Figure A3: Decomposition of changes in schedule-II MMEs per capita in Massachusetts



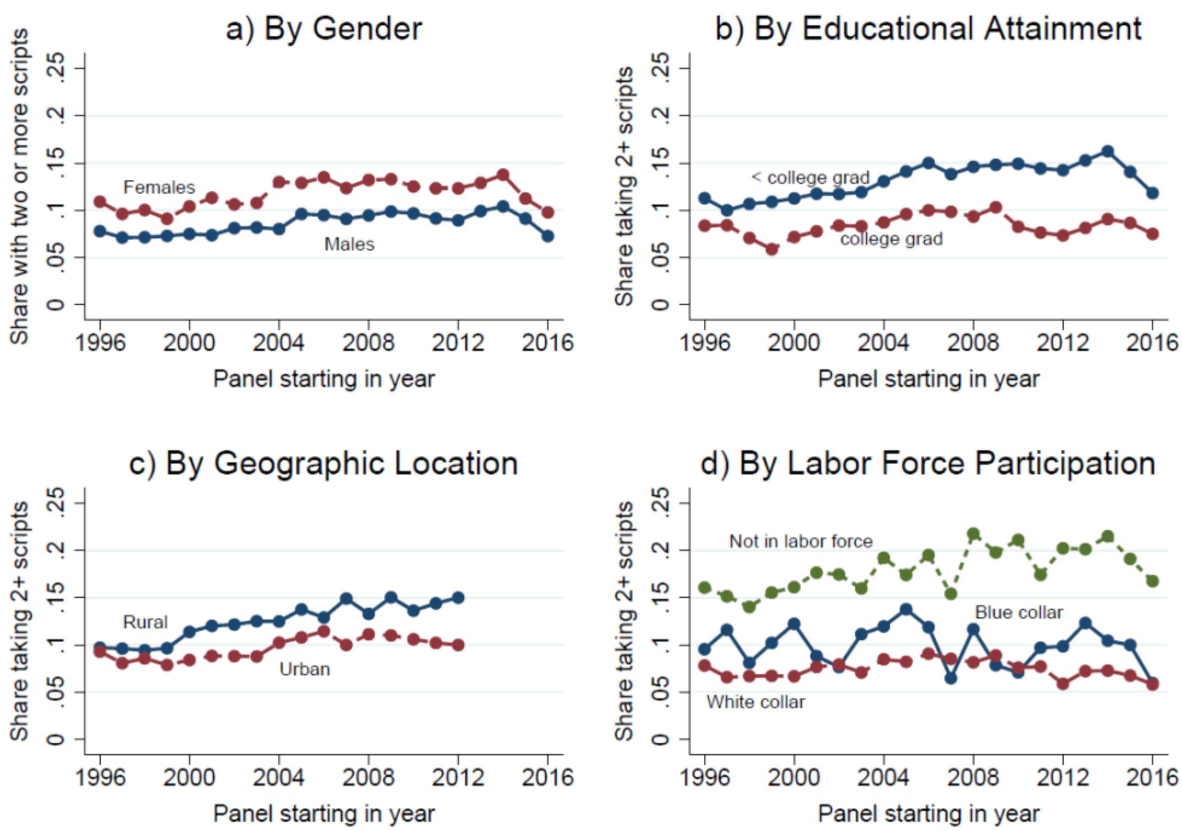
Note: Data are from the Massachusetts Prescription Monitoring Program (PMP) and include all schedule II opioid shipments. The DEA moved hydrocodone from a schedule-III to schedule-II drug in 2014, which explains the jump in schedule-II scripts per capita in 2014 (panel b). Scripts written by prescribers were bottom coded if the prescriber wrote between 1 and 5 scripts in any given year, and 2.5 scripts was imputed for these prescribers.

Figure A4: Trends in Opioid Scripts Per Capita in the US in MEPS vs. IMS Health and IQVIA National Prescription Audit



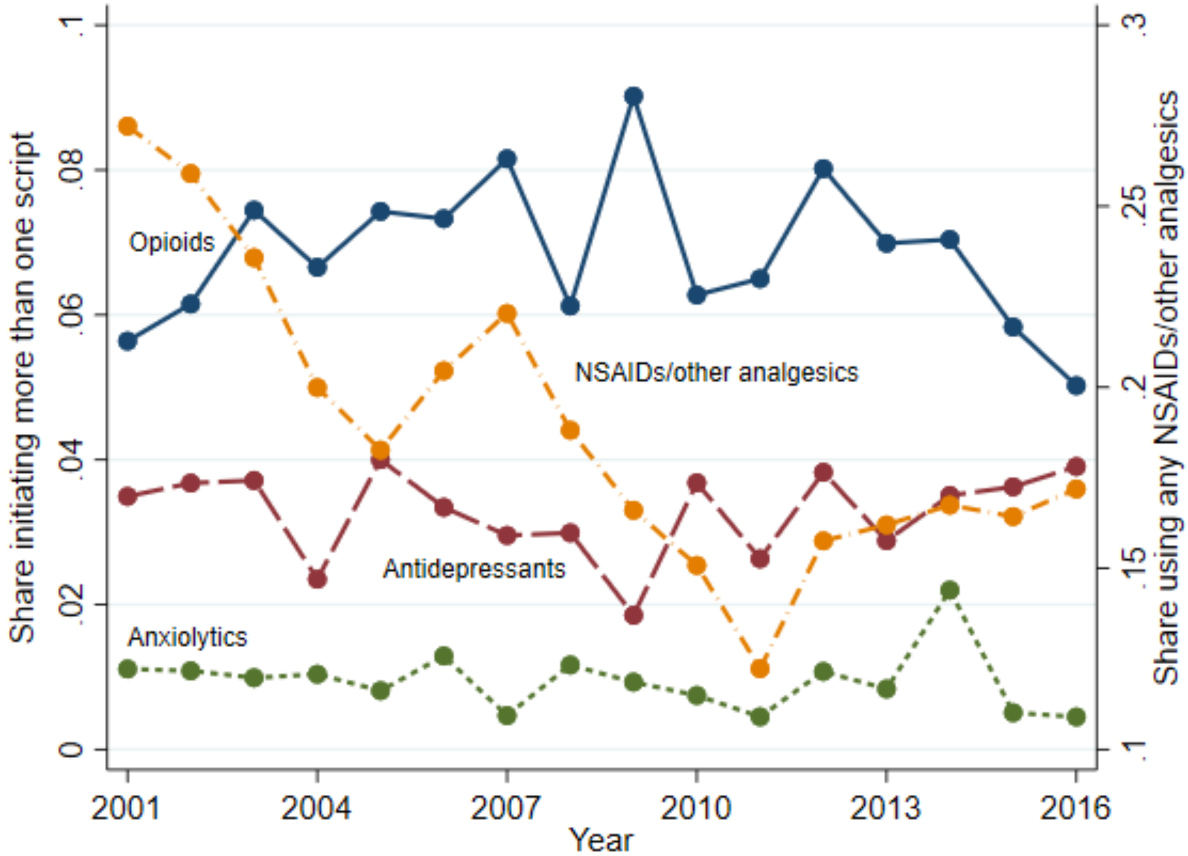
Notes: for MEPS data, each observation denotes a panel starting that year; for example, 1997 denotes individuals who entered MEPS in 1997. Data are for the population aged 15+. All percentages are weighted using survey weights and are age and sex adjusted to the US 2000 population. IQVIA data are presented as totals and are not age and sex adjusted.

Figure A5: Use of Opioid Medications, 1996-2015



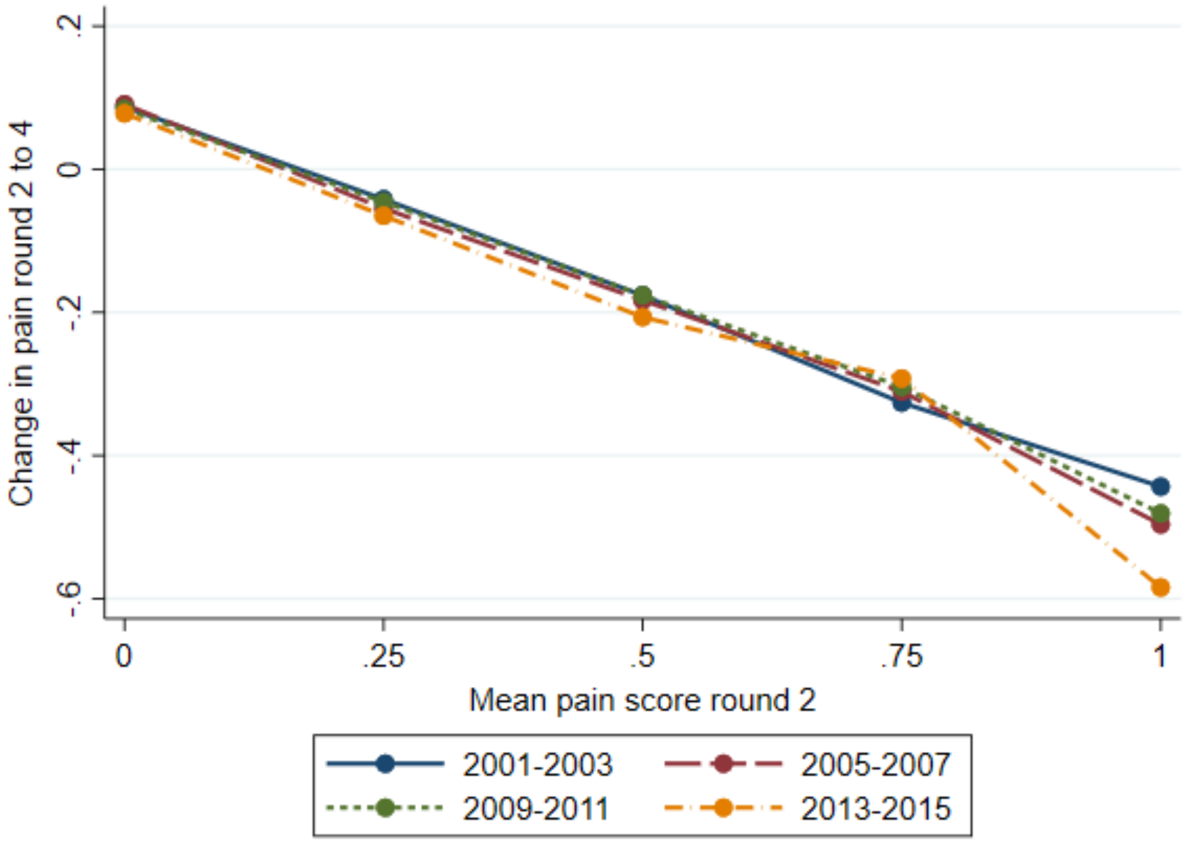
Notes: Data are from the Medical Expenditure Panel Study (MEPS), using waves 1996-2015. Each observation denotes a panel starting that year; for example, 1996 denotes individuals who entered MEPS in 1996 and were followed through 1997. Data are for the population aged 15+. All percentages are weighted using survey weights and are age and sex adjusted to the US 2000 population. Geographic location and labor force status are as of the first round of data collection.

Figure A6: Trends in Treatment of Pain over Time



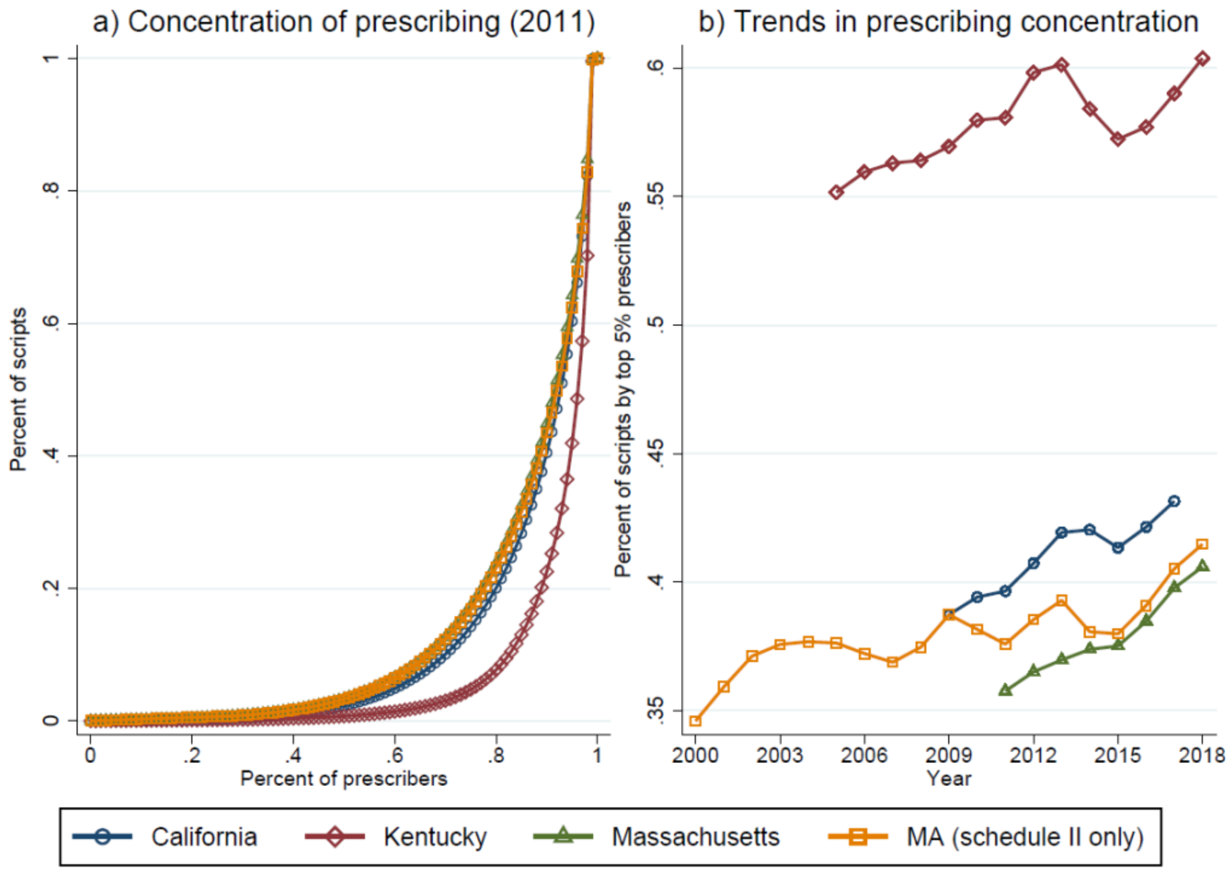
Notes: Data are from the MEPS. The sample is people in round 2 of each survey who reported pain but were not receiving opioids, anxiolytics, and antidepressants. Subsequent use is tracked through round 5, roughly 2 years later. Data are weighted with survey weights and adjusted to the year 2000 population by age and sex.

Figure A7: Trends in Pain Relief for People Who Report Pain, 2001-2015



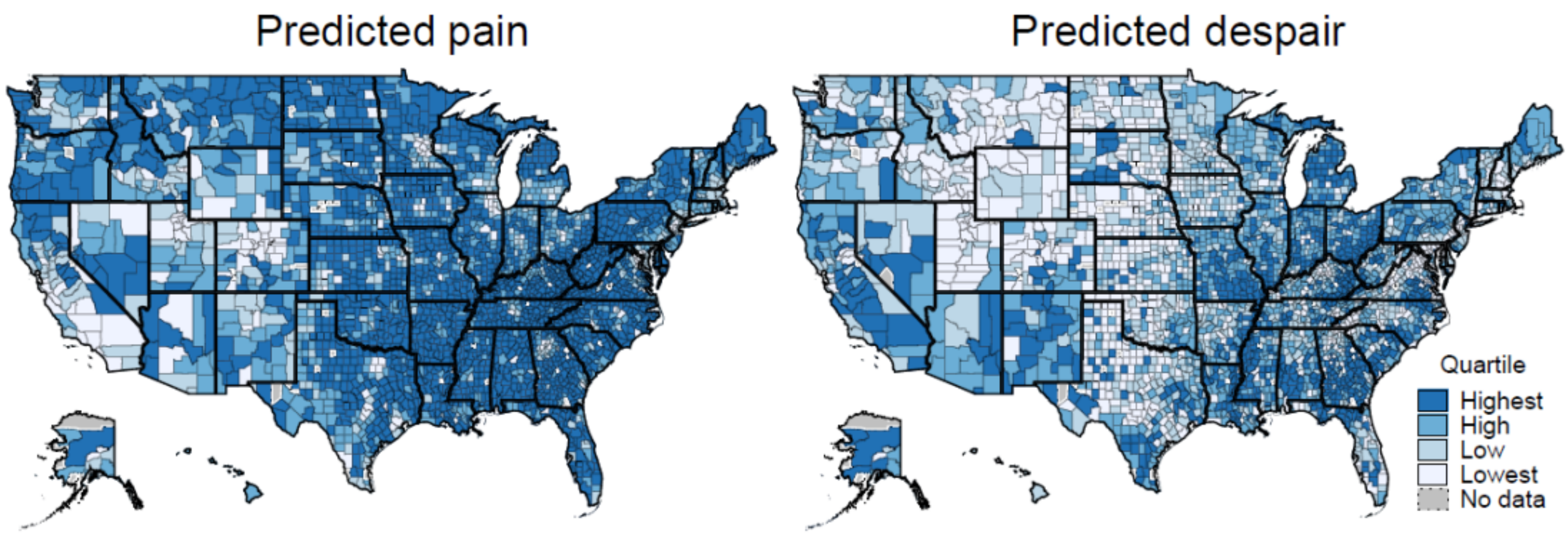
Note: The figure shows the change in pain assessment from round 2 to round 4 of the MEPS, roughly one year apart. The sample is everyone in round 2 who is not taking opioids. Data are weighted with survey weights and adjusted to the year 2000 population by age and sex.

Figure A8: Concentration of Opioid Prescribing in California, Kentucky, and Massachusetts



Note: data are from state prescription drug monitoring programs. These include the Massachusetts PMP, the Kentucky All Schedule Prescription Electronic Reporting (KASPER) prescription monitoring system, and the California Controlled Substance Utilization Review and Evaluation System (CURES). Data were available for schedule-II opioids in Massachusetts starting in 2000, all opioids in Massachusetts starting in 2011, all opioids in Kentucky starting in 2005, and all opioids in California starting in 2009. To restrict the set of opioids to strong opioids, we restricted the Kentucky and California PDMP data to scripts written for codeine, hydrocodone, hydromorphone, meperidine, morphine, oxycodone, opium, oxymorphone, tapentadol, and fentanyl. The Massachusetts data reflect all opioids (or all schedule-II) opioids, excluding buprenorphine and cough formulations and elixirs or combination products containing opioids and antitussives, decongestants, antihistamines, or expectorants.

Figure A9: Pain and Despair at the County Level



Notes: The figure shows predicted pain and despair at the county level. Pain is based on responses to the MEPS question on how pain interferes with life, using data from 2002 to 2010. Data on county averages for the covariates in the regression are used to form a predicted pain measure for each county. Despair is based on a BRFSS question on life satisfaction, using data from 2005 to 2007. County averages are again used to predict despair in all counties.

Table A1: Summary Measures of Pain, Depression, and Despair

	N	Mean	Correlation Matrix			
MEPS			Pain	Painful condition	Depression	
Pain report	61,180	0.163	1.000			
Painful condition	61,180	0.256	0.305	1.000		
Depression	61,180	0.207	0.315	0.106	1.000	
Widowed	61,180	0.038	0.067	0.044	0.074	
Divorced/separated	61,180	0.131	0.077	0.055	0.023	
Never married	61,180	0.266	-0.104	-0.082	0.022	
Not employed (among age < 62)	52,231	0.205	0.095	-0.007	0.113	
MIDUS			Pain	Negative Affect	Despair	Economic insecurity
Pain	4,914	0.002	1.000			
Negative affect	4,914	-0.008	0.355	1.000		
Despair	4,914	-0.013	0.215	0.489	1.000	
Economic insecurity	4,914	0.002	0.201	0.435	0.419	1.000
Widowed, separated, or divorced	4,914	0.220	0.061	0.100	0.085	0.116
Never married	4,914	0.074	-0.023	0.083	0.055	0.068
Not employed (among age < 62)	3,126	0.223	0.044	0.071	0.053	0.100

Notes: Factor scores for pain, negative affect, despair, and economic insecurity in the MIDUS are mean 0 and variance 1.

Table A2: Impact of Pain, Mental Health, and Social Isolation on Initiation of Opioids, MEPS Data.

	2+ opioids						Any opioids	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Physical pain								
Physical pain score	0.100***				0.100***		0.152***	
	(0.005)				(0.005)		(0.009)	
Has painful condition		0.034***				0.032***		0.056***
		(0.002)				(0.002)		(0.004)
Depression			0.031***		0.000	0.023***	0.004	0.039***
			(0.004)		(0.005)	(0.004)	(0.008)	(0.007)
Social isolation								
Widowed				0.011***	0.009**	0.009**	0.014**	0.013*
				(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Divorced/Separated				0.009	0.008	0.007	0.012	0.011
				(0.006)	(0.006)	(0.006)	(0.010)	(0.010)
Never Married				-0.002	-0.002	-0.004	-0.011*	-0.013**
				(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
NILF; age < 62				0.030***	0.025***	0.028***	0.012	0.017
				(0.006)	(0.006)	(0.006)	(0.014)	(0.014)
NILF; age 62+				0.023**	0.017*	0.021**	0.011	0.018
				(0.007)	(0.007)	(0.007)	(0.015)	(0.015)
Occupation (rel. to white collar)								
Blue collar				0.003	0.002	0.003	0.010	0.012*
				(0.004)	(0.004)	(0.004)	(0.006)	(0.006)
Service/other				-0.004	-0.005	-0.004	0.001	0.003
				(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
Change 2002 to 2009	0.007	0.007	0.007	0.007	0.007	0.007	0.015	0.015
Implied % of total ↑	-0.8%	15.5%	-0.1%	6.1%	4.2%	20.1%	-2.9%	10.7%
Unadjusted mean	0.038	0.038	0.038	0.038	0.038	0.038	0.118	0.118
R-squared	0.028	0.020	0.015	0.015	0.029	0.022	0.031	0.026
N	61,180	61,180	61,180	61,180	61,180	61,180	61,180	61,180

Note: Data are from the MEPS 2002-2010 cohorts. The regressions for physician and mental pain account for MEPS design features and control for five-year age-sex cells, race and ethnicity, marital status, region, whether lives in an MSA, education, health and prescription drug insurance status, usual source of health care, health behaviors (whether received flu shot in last year, smoking status, and whether always wears a seat belt while in a car), and year fixed effects. Columns 3-6 additionally control for condensed industry codes. The sample for each of the initiation regressions was all adults not reporting opioids in the first two waves of MEPS, age 18 to 77. The sample for the continuation regressions was adults already reporting opioids during or before the first two waves.
Standard errors are reported in parentheses. ***(**)* indicates statistically significant at the 1%(5%)10% level.

Table A3: Description of MIDUS Data

Pain

Reverse-coded mean of 6-items that ask "How often did you experience the following symptoms in the past 30 days?" (each included as separate variable) (1=almost every day, 2=several times a week, 3=once a week, 4=several times a month, 5=once a month, 6=not at all)

a. Headaches
b. Back aches/pain
c. Joint aches/pain

Positive and negative affect

Reverse-coded mean of 6-items that ask "during the past 30 days, how much of the time did you feel?" (answers: 1=all the time, 2=most of the time, 3=some of the time, 4=a little time, 5=none of the time)

1) Positive affect – (a) cheerful? (b) in good spirits? (c) extremely happy? (d) calm and peaceful? (e) satisfied? (f) full of life?
2) Negative affect – (a) so sad that nothing could cheer you up? (b) nervous? (c) restless or fidgety? (d) hopeless? (e) that everything was an effort? (f) worthless?

Despair

Each scale represents the sum of 3 items; positive items were reverse-coded so higher values represent higher social well-being. Please indicate how strongly you agree or disagree… (answers: 1 strongly agree, 2 somewhat agree, 3 a little agree, 4 don't know, 5 a little disagree, 6 somewhat disagree, 7 strongly disagree).

1) Meaningfulness of society – (a) The world is too complex for me; (b) I cannot make sense of what's going on in the world; (c) I find it easy to predict what will happen next in society.
2) Social integration – (a) I don't feel I belong to anything I'd call a community; (b) I feel close to other people in my community; (c) My community is a source of comfort.
3) Acceptance of others – (a) People who do a favor expect nothing in return; (b) people do not care about other people's problems; (c) I believe that people are kind.
4) Social contribution – (a) I have something valuable to give to the world; (b) my daily activities do not create anything worthwhile for my community; (c) I have nothing to contribute to society.
5) Social actualization – (a) The world is becoming a better place for everyone; (b) society has stopped making progress; (c) society isn't improving for people like me.
6) Generativity

Reverse-coded weighted mean of 6-items. To what extent does each of the following statements describe you? (answers: 1=a lot, 2=some, 3=a little, 4=not at all)

a. Others would say you that have made unique contributions to society
b. You have important skills that you can pass along to others
c. Many people come to you for advice
d. You feel that other people need you
e. You have a good influence on the lives of many people
f. You like to teach things to people

7) Life satisfaction
Using a scale from 0 to 10 where 0 means "the worst possible life overall" and 10 means "the best possible life overall," how would you rate your life overall these days?
8) Disappointed by achievements
Please indicate how strongly you agree or disagree with each of the following… In many ways, I feel disappointed about my achievements in life? (answers: 1=strongly agree, 2=somewhat agree, 3=a little agree, 4=don't know, 5=a little disagree, 6=somewhat disagree, 7=strongly disagree)
9) Perceived social contribution
Using a scale of 0 to 10 where 0 means "the worst possible contribution to the welfare and well-being of other people" and 10 means "the best possible contribution to the welfare and well-being of other people," how would you rate your contribution to the welfare and well-being of other people these days? Take into account all that you do, in terms of time, money, or concern, on your job, and for your family, friends, and the community.

Economic Insecurity
1) Self-rated financial situation
Using a scale from 0 to 10 where 0 means "the worst possible financial situation" and 10 means "the best possible financial situation", how would you rate your financial situation these days?
2) Self-rated control over financial situation
Using a 0 to 10 scale where 0 means "no control at all" and 10 means "very much control," how would you rate the amount of control you have over your financial situation these days?
3) Enough money to meet needs?
In general, would you say you (and your family living with you) have… (1=more money than you need, 2=just enough money, 3=not enough money)
4) Difficult to pay bills?
How difficult is it for you (and your family) to pay your monthly bills? (1=very difficult, 2=somewhat difficult, 3=not very difficult, 4=not at all difficult)
5) Self-rated work situation
Please think of the work situation you are in now, whether part-time or full-time, paid or unpaid, at home or at a job. Using a scale from 0 to 10 where 0 means "the worst possible work situation" and 10 means "the best possible work situation," how would you rate your work situation these days?
6) Self-rated control over work situation
Using a 0 to 10 scale where 0 means "no control at all" and 10 means "very much control," how would you rate the amount of control you have over your work situation these days?

Table A4: Impact of Pain, Mental Health, Despair, and Economic Insecurity on Prescriptions for Pain, MIDUS Data

	Taking Prescription Pain Reliever in Next Wave					
	(1)	(2)	(3)	(4)	(5)	(6)
Pain	0.151***					0.128***
	(0.010)					(0.011)
Negative affect		0.085***				0.041***
		(0.009)				(0.011)
Despair			0.032***			-0.019*
			(0.008)			(0.009)
Economic insecurity				0.058***		0.030***
				(0.008)		(0.008)
Social isolation						
Widowed, separated, or divorced					0.033	0.012
					(0.018)	(0.017)
Never married					-0.065**	-0.079***
					(0.023)	(0.022)
NILF; age<62					0.015	0.004
					(0.023)	(0.022)
Employment (rel. to white collar)						
Blue collar					0.040	0.029
					(0.022)	(0.022)
Other					0.024	-0.003
					(0.025)	(0.024)
NILF; age 62+					0.018	0.013
					(0.029)	(0.028)
Change wave 2 to 3	0.098	0.098	0.098	0.098	0.098	0.098
Implied % of total ↑	34.8%	-4.9%	-5.1%	-11.1%	-1.1%	23.6%
Unadjusted mean	0.279	0.279	0.279	0.279	0.279	0.279
R-squared	0.109	0.082	0.065	0.074	0.067	0.121
N	4,914	4,914	4,914	4,914	4,914	4,914

Notes: There were three MIDUS waves that occurred approximately 10 years apart (1995 to 1997, 2004 to 2005, and 2013 to 2015). Pain and despair scores were used to predict prescriptions for pain for subsequent waves. All regressions controlled for five-year age-sex cells, race and ethnicity, marital status, education, wave fixed effects, and missing occupation (not shown). Standard errors were clustered on individuals and are reported in parentheses. ***(**)* indicates statistically significant at the 1%(5%)10% level.

Table A5: Trends in poor health, pain, and despair, all adults

	Initial	Last year	Trend coef.	p-value	% change (tot.)
Self-reported physical/mental health					
Fair/poor self-reported health (NHIS) (1997-2019)	0.11	0.13	0.0004	0.09	7.7%
Fair/poor self-reported health (BRFSS) (1999-2019)	0.15	0.17	0.0009	--	12.5%
Fair/poor self-reported health (MEPS) (1996-2016)	0.14	0.13	-0.0001	0.70	-1.2%
Fair/poor mental health (MEPS) (1996-2016)	0.07	0.07	0.0004	0.02	12.9%
Activity limitations					
Limited in activities because of physical, mental, or emotional problems (BRFSS) (2001-2016)	0.15	0.19	0.0013		8.4%
Limitation to work/housework/school (MEPS) (1996-2016)	0.10	0.09	-0.0002	0.54	-3.4%
Limitation to physical functioning (MEPS) (1996-2016)	0.13	0.12	-0.0004	0.17	-6.8%
Days with poor physical/mental health					
Most days poor physical health (BRFSS) (1999-2019)	0.07	0.08	0.0006	--	14.9%
All days poor physical health (BRFSS) (1999-2019)	0.05	0.06	0.0003	--	10.5%
Most days poor mental health (BRFSS) (1999-2019)	0.08	0.14	0.0023	--	85.0%
All days poor mental health (BRFSS) (1999-2019)	0.04	0.06	0.0008	--	40.8%
Muskuloskeletal pain					
Any musculoskeletal (neck, back, or joint pain) (NHIS) (2002-2018)	0.42	0.44	0.0015	<0.01	5.6%
Any joint pain (NHIS) (2002-2018)	0.30	0.53	0.0090	0.21	61.4%
Joint pain lasting 3 months (NHIS) (2002-2018)	0.25	0.27	0.0016	<0.01	10.4%
Back pain past 3 months (NHIS) (1997-2018)	0.28	0.28	0.0004	0.30	2.8%
Neck pain past 3 months (NHIS) (1997-2018)	0.14	0.15	0.0003	0.26	3.7%
Any neck, facial, or sciatic pain (NHIS) (1997-2018)	0.21	0.21	0.0005	0.07	5.2%
Sciatic pain (NHIS) (1997-2018)	0.08	0.09	0.0008	<0.01	19.9%
Facial pain (NHIS) (1997-2018)	0.04	0.05	0.0001	0.32	6.1%
Any joint pain past year (MEPS) (2000-2016)	0.32	0.34	-0.0002	0.84	-0.8%

Self-reported pain					
Moderate or more pain (MEPS) (2000-2016)	0.21	0.18	-0.0013	0.01	-9.5%
Quite a bit or extreme pain (MEPS) (2000-2016)	0.10	0.10	<0.0001	0.99	0.0%
Diagnosed pain					
Any diagnosed painful condition (MEPS) (1996-2015)	0.27	0.31	0.0027	<0.01	19.6%
2+ diagnosed painful conditions (MEPS) (1996-2015)	0.01	0.02	0.0006	<0.01	220.0%
Cancer diagnosis (MEPS) (1996-2016)	0.04	0.05	0.0006	0.01	31.4%
Injuries					
ER visit due to injury (MEPS) (1996-2016)	0.10	0.07	-0.0012	<0.01	-23.7%
ER visit due to workplace injury (MEPS) (1996-2016)	0.02	0.01	-0.0006	<0.01	-51.0%
Mental distress					
Severe mental distress (13+ on Kessler-6) (NHIS) (1997-2018)	0.03	0.04	0.0003	0.01	23.1%
Severe mental distress (13+ on Kessler-6) (MEPS) (2004-2016)	0.05	0.04	-0.0013	<0.01	-27.0%
Feelings interfered with life					
Feelings interfered some or a lot (NHIS) (1997-2018)	0.33	0.30	-0.0014	0.04	-8.3%
Feelings interfered a lot (NHIS) (1997-2018)	0.11	0.10	-0.0003	0.43	-4.6%
Depression					
Feel depressed some to all days (MEPS) (2003-2016)	0.25	0.19	-0.0048	<0.01	-23.9%
Feel depressed most or all days (MEPS) (2003-2016)	0.07	0.05	-0.0010	<0.01	-19.6%
Tendency towards depression (3+ on PHQ-2) (MEPS) (2004-2016)	0.10	0.07	-0.0021	<0.01	-25.6%
Life dissatisfaction					
Somewhat or very dissatisfied with life (BRFSS) (2005-2017)	0.05	0.05	-0.0006	--	-10.7%
Very dissatisfied with life (BRFSS) (2005-17)	0.01	0.01	-0.0002	--	-20.9%

Note: All variables were age- and sex-adjusted to the US 2000 population. Trend coefficients were from a regression of each variable on year (rescaled with 0 as the initial year). Robust p-values are reported for the trend. The last column reports the fitted total cumulative % change over the time-period.

Table A6: Trends in poor health, pain, and despair, adults 25+ without a college degree

	Initial	Last Year	Trend coef.	p-value	% change (tot)
Self-reported physical/mental health					
Fair/poor self-reported health (NHIS) (1997-2019)	0.15	0.18	0.0012	<0.01	17.7%
Fair/poor self-reported health (BRFSS) (1999-2019)	0.18	0.21	0.0014	--	14.6%
Fair/poor self-reported health (MEPS) (1996-2016)	0.18	0.19	0.0006	0.04	7.0%
Fair/poor mental health (MEPS) (1996-2016)	0.08	0.10	0.0007	0.01	17.6%
Activity limitations					
Limited in activities because of physical, mental, or emotional problems (BRFSS) (2001-2016)	0.16	0.21	0.0018	--	9.4%
Limitation to work/housework/school (MEPS) (1996-2016)	0.13	0.14	0.0003	0.39	5.3%
Limitation to physical functioning (MEPS) (1996-2016)	0.17	0.17	-0.0002	0.67	-2.1%
Days with poor physical/mental health					
Most days poor physical health (BRFSS) (1999-2019)	0.08	0.10	0.0009	--	17.5%
All days poor physical health (BRFSS) (1999-2019)	0.06	0.08	0.0006	--	15.3%
Most days poor mental health (BRFSS) (1999-2019)	0.09	0.15	0.0029		67.8%
All days poor mental health (BRFSS) (1999-2019)	0.05	0.08	0.0012		48.2%
Muskuloskeletal pain					
Any muskuloskeletal (neck, back, or joint pain) (NHIS) (2002-2018)	0.47	0.51	0.0029	<0.01	9.9%
Any joint pain (NHIS) (2002-2018)	0.34	0.55	0.0086	0.14	48.3%
Joint pain lasting 3 months (NHIS) (2002-2018)	0.29	0.33	0.0027	<0.01	15.0%
Back pain past 3 months (NHIS) (1997-2018)	0.31	0.34	0.0018	<0.01	12.9%
Neck pain past 3 months (NHIS) (1997-2018)	0.16	0.18	0.0008	<0.01	10.1%
Any neck, facial, or sciatic pain (NHIS) (1997-2018)	0.24	0.26	0.0014	<0.01	13.0%
Sciatic pain (NHIS) (1997-2018)	0.11	0.13	0.0017	<0.01	34.1%
Facial pain (NHIS) (1997-2018)	0.05	0.05	0.0002	0.11	9.8%
Any joint pain past year (MEPS) (2000-2016)	0.37	0.39	0.0004	0.58	1.9%

Self-reported pain					
Moderate or more pain (MEPS) (2000-2016)	0.27	0.25	-0.0008	0.14	-4.8%
Quite a bit or extreme pain (MEPS) (2000-2016)	0.14	0.14	0.0004	0.20	5.1%
Diagnosed pain					
Any diagnosed painful condition (MEPS) (1996-2015)	0.29	0.35	0.0033	<0.01	21.5%
2+ diagnosed painful conditions (MEPS) (1996-2015)	0.01	0.02	0.0007	<0.01	217.8%
Cancer diagnosis (MEPS) (1996-2016)	0.04	0.05	0.0007	0.01	30.5%
Injuries					
ER visit due to injury (MEPS) (1996-2016)	0.09	0.08	-0.0006	0.02	-12.6%
ER visit due to workplace injury (MEPS) (1996-2016)	0.03	0.02	-0.0006	<0.01	-44.2%
Mental distress					
Severe mental distress (13+ on Kessler-6) (NHIS) (1997-2018)	0.04	0.05	0.0006	<0.01	37.6%
Severe mental distress (13+ on Kessler-6) (MEPS) (2004-2016)	0.07	0.05	-0.0016	<0.01	-25.1%
Feelings interfered with life					
Feelings interfered some or a lot (NHIS) (1997-2018)	0.36	0.33	-0.0007	0.37	-3.9%
Feelings interfered a lot (NHIS) (1997-2018)	0.12	0.13	0.0003	0.48	4.2%
Depression					
Feel depressed some to all days (MEPS) (2003-2016)	0.29	0.22	-0.0051	<0.01	-22.0%
Feel depressed most or all days (MEPS) (2003-2016)	0.08	0.06	-0.0014	<0.01	-21.0%
Tendency towards depression (3+ on PHQ-2) (MEPS) (2004-2016)	0.12	0.10	-0.0024	<0.01	-22.9%
Life dissatisfaction					
Somewhat or very dissatisfied with life (BRFSS) (2005-2017)	0.06	0.06	-0.0006	--	-9.2%
Very dissatisfied with life (BRFSS) (2005-17)	0.01	0.01	-0.0004	--	-26.7%

Note: All variables were age- and sex-adjusted to the US 2000 population. Trend coefficients were from a regression of each variable on year (rescaled with 0 as the initial year). Robust p-values are reported for the trend. The last column reports the fitted total cumulative % change over the time-period.

Table A7: Impact of national opioid shipments interacted with pain and despair on county-year opioid shipments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interaction between national opioid shipments and							
Pain							
% of labor force claiming DI (1990)	86.10***					55.90	
	(10.73)					(41.86)	
Joint pain prevalence		65.83**				38.83	
		(31.26)				(32.22)	
Avg. days pain made usual activities difficult			51.17*				
			(28.95)				
Despair							
Share dissatisfied/very dissatisfied w/ life				33.98		-70.94**	
				(28.26)		(29.63)	
% reporting all days with poor mental health					140.86***	149.03***	
					(28.27)	(36.38)	
Imputed pain and despair							
Predicted pain							106.23***
							(17.42)
Predicted life dissatisfaction							-58.56***
							(15.65)
Unadjusted mean	368.575	373.675	341.920	373.675	373.675	373.675	368.575
R-squared	0.750	0.713	0.759	0.707	0.738	0.747	0.758
N	42,966	4,634	910	4,634	4,634	4,634	42,966

The sample is all counties from 1997-2010. The dependent variable is county-year MMEs per capita. Variables for predicted pain and predicted despair were standardized to mean 0 and variance 1. National opioid shipments (per adult) included shipments of oxycodone, hydrocodone, hydromorphone, codeine, morphine, and fentanyl base and were scaled by the change in shipments between 1997 and 2010 in Figure 2. Thus, the co-efficients represent the impact of one standard deviation higher pain (or despair) times the change in national opioid shipments which occurred over the time period. Counties were weighted by total population. All regressions control for county and year fixed effects. Standard errors were clustered at the county-level and are reported in parentheses. ***(**)* denote p<0.01(p<0.05)p<0.10.

Table A8: Impact of drug-shipments interacted with pain and despair on county and year prescription opioid death rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Interaction between national opioid shipments and							
Pain							
% of labor force claiming DI (1990)	2.48***					1.11*	
	(0.22)					(0.60)	
Joint pain prevalence		1.02***				0.61**	
		(0.26)				(0.28)	
Avg. days pain made usual activities difficult			1.11***				
			(0.29)				
Despair							
Share dissatisfied/very dissatisfied w/ life				0.70**		-0.49	
				(0.28)		(0.33)	
% reporting all days with poor mental health					1.58***	1.27***	
					(0.34)	(0.38)	
Imputed pain and despair							
Predicted pain							2.12***
							(0.23)
Predicted life dissatisfaction							-0.56***
							(0.18)
Unadjusted mean	3.596	3.533	3.124	3.533	3.533	3.533	3.596
R-squared	0.302	0.408	0.420	0.396	0.431	0.448	0.284
N	36,824	3,968	776	3,968	3,968	3,968	36,824

The sample is counties from 1997-2010, including all counties with data available on each metric. The dependent variable is county-year age- and sex-adjusted prescription opioid death rate, imputing for drug overdose deaths with unspecified causes following Ruhm (2017). To facilitate comparison, variables for predicted pain and predicted despair were standardized to mean 0 and variance 1. National opioid shipments (per adult) included shipments of oxycodone, hydrocodone, hydromorphone, codeine, morphine, and fentanyl base and were scaled by the change in shipments between 1997 and 2010 in Figure 2. The co-efficients represent the impact of one standard deviation higher pain (or despair) times the change in national opioid shipments which occurred over the period. Counties were weighted by total population. All regressions control for county and year fixed effects. Standard errors were clustered at the county-level and are reported in parentheses. ***(**)* denote p<0.01(p<0.05)p<0.10.

Table A9: Impact of national heroin + fentanyl deaths interacted with local shipments, pain, and despair on county and year heroin + fentanyl death rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Interaction between national illegal opioid deaths and								
Pain								
% of labor force claiming DI (1990)	1.65***						3.02*	
	(0.50)						(1.57)	
Joint pain prevalence		5.01***					3.01***	
		(1.01)					(1.00)	
Avg. days pain made usual activities difficult			2.58					
			(1.86)					
Despair								
Share dissatisfied/very dissatisfied w/ life				3.34***			1.32	
				(1.09)			(1.08)	
% reporting all days with poor mental health					4.11***		-0.09	
					(0.98)		(1.04)	
Opioid shipments								
Oxycodone MME per capita, 1997-2010						6.22***	4.47***	5.95***
						(0.95)	(1.11)	(0.91)
Imputed pain and despair								
Predicted pain								1.89***
								(0.54)
Predicted life dissatisfaction								2.08***
								(0.74)
Unadjusted mean	8.37	8.86	8.33	8.86	8.86	8.37	8.86	8.37
R-squared	0.413	0.542	0.514	0.514	0.523	0.483	0.607	0.502
N	33,759	3,641	715	3,641	3,641	33,759	3,641	33,759

The sample is counties from 2008 to 2017. The dependent variable is county-year age- and sex-adjusted illegal opioid death rates. Note, the average # days pain made activities difficult was asked in the fewest number of counties. To facilitate comparison, were standardized to mean 0 and variance 1. National illegal drug deaths were scaled by the change in shipments between 2008 and 2018. The co-efficients represent the impact of one standard deviation higher pain, despair, or oxycodone shipments times the change in national illegal opioid deaths which occurred over the period. Counties were weighted by total population in 2005. All regressions control for county and year fixed effects. Standard errors were clustered at the county-level and are reported in parentheses. ***(**)* denote $p<0.01$($p<0.05$)$p<0.10$.

Table A10: Importance of variables for predicting pain (MEPS) and share of each variable in explaining urban-rural differences in pain (counties)

	β (z-score)	% of urban-rural difference
Age		
25 to 34	0.0054	-1.53%
35 to 44	0.0200	-1.87%
45 to 54	0.0335	2.52%
55 to 64	0.0351	7.72%
65 to 74	0.0353	9.54%
75 to 84	0.0364	5.15%
85 +	0.0260	2.50%
% of urban-rural difference explained by age		*24.03%*
Female	0.0162	-1.06%
Female x Age 25 to 34	-0.0026	0.52%
Female x Age 35 to 44	-0.0031	0.26%
Female x Age 45 to 54	-0.0044	-0.11%
Female x Age 55 to 64	-0.0039	-0.52%
Female x Age 65 to 74	-0.0049	-0.89%
Female x Age 85 +	0.0008	0.04%
% of urban-rural difference explained by age-gender		*-1.76%*
Education (rel. to HS grad)		
Some college	-0.0066	1.45%
College graduate	-0.0114	12.73%
Some college x Female	-0.0019	0.20%
College grad x Female	0.0015	-1.41%
College grad x Female x Age 25 to 34	-0.0012	0.13%
College grad x Age 35 to 44	-0.0025	1.48%
College grad x Female x Age 35 to 44	-0.0037	0.30%
College grad x Age 45 to 64	-0.0086	4.68%
College grad x Age 65 +	-0.0117	2.33%
College grad x Female x Age 65 +	0.0012	-0.01%
% of urban-rural difference explained by education-age-gender		*21.89%*
Not in labor force	0.0389	19.63%
Not in labor force x Female	-0.0160	-1.12%
Not in labor force x Age 25 to 44	-0.0154	-0.65%
Not in labor force x Age 45 to 54	-0.0085	-1.75%

Not in labor force x Age 55 to 64	0.0023	0.81%
Not in labor force x Age 65 to 75	0.0172	7.74%
Not in labor force x Age 75 +	0.0199	4.33%
% of urban-rural difference explained by labor force-age-gender		*28.99%*
Race/ethnicity (rel. to Non-Hispanic White)		
Non-Hispanic Black	0.0013	-0.61%
Hispanic	-0.0076	8.92%
Non-Hispanic Other	0.0031	-1.58%
% of urban-rural difference explained by race-ethnicity		*6.73%*
Occupation (rel. to management, business, and financial)		
Professional and related	-0.0007	0.49%
Service	0.0036	-0.36%
Sales	0.0030	-0.94%
Office	0.0032	-0.83%
Farming, fishing, and forestry	0.0014	0.42%
Construction, extraction, maintenance, and repair	0.0038	0.96%
Production, transportation, and materials moving	0.0035	1.66%
Professional x Female	0.0039	-1.04%
Service x Female	0.0052	0.18%
Sales x Female	0.0021	-0.30%
Office x Female	-0.0011	0.13%
Farming x Female	-0.0011	-0.09%
Construction x Female	0.0004	0.02%
Production x Female	0.0020	0.58%
% of urban-rural difference explained by occupation-gender		*0.89%*
Industry (rel. to agriculture, forestry, and hunting)		
Mining	-0.0000	-0.05%
Construction	-0.0019	-0.23%
Manufacturing	-0.0043	-1.80%
Wholesale and retail trade	-0.0036	0.60%
Transportation, warehousing, and utilities	-0.0028	0.02%
Information	-0.0013	0.40%
Finance, insurance, real estate, and rental/leasing	-0.0034	1.71%
Professional, scientific, and administrative waste mgt.	-0.0022	1.41%
Educational services, health care, and social assistance	0.0000	0.01%
Public administration	-0.0014	0.04%
Other services	-0.0010	0.11%

Mining x Female	0.0001	0.00%
Construction x Female	-0.0016	0.05%
Manufacturing x Female	-0.0011	-0.37%
Wholesale and retail trade x Female	-0.0028	0.16%
Transportation x Female	-0.0006	0.05%
Information x Female	-0.0011	0.22%
Financial x Female	-0.0031	0.93%
Professional x Female	-0.0023	1.00%
Educational services, etc. x Female	-0.0067	0.23%
Arts, entertainment, etc. x Female	-0.0028	0.30%
Public administration x Female	-0.0038	0.00%
Other services x Female	-0.0019	0.26%
% of urban-rural difference explained by industry-gender		*5.04%*
Obese (BMI > 30)	0.0152	4.86%
Obese x Female	0.0129	5.20%
% of urban-rural difference explained by obesity-gender		*10.06%*
Census Region (rel. to Northeast)		
Midwest	-0.0012	-1.12%
South	0.0020	3.06%
West	-0.0012	2.20%
% of urban-rural difference explained by region		*4.14%*

To predict pain, we estimated a linear LASSO model in MEPS (2001 to 2010) to predict self-reported pain as a function of 10-year age-gender dummies, education (high-school, some college, and college graduate; interacted with age group and gender), employment status (interacted with age group and gender), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other), 2-digit occupation and industry dummies (also interacted with gender), whether obese, and region. Pain was from an SF-12 question about how much pain interferes with an individual's normal work, with possible answers "not at all; a little bit; moderately; quite a bit; and extremely". We scaled these responses from 0 = "not at all" to 1 = "extremely". Variables selected by LASSO and their standardized impact on pain are presented in column 2. Column 3 reports the results of a decomposition of differences in pain between urban and rural areas. To compute the shares of each variable in explaining differences in pain between urban and rural areas, we multiplied the average difference in these characteristics for urban vs. rural counties by their coefficients on pain and then divided by the difference in predicted pain.

Table A11: Importance of variables for predicting despair (BRFFS) and share of each variable in explaining urban-rural differences in despair (counties)

	β (z-score)	% of urban-rural difference
Age		
25 to 34	0.0044	-0.88%
35 to 44	0.0048	-0.28%
45 to 54	0.0090	0.41%
55 to 64	-0.0020	-0.34%
65 to 74	-0.0062	-1.05%
75 to 84	-0.0037	-0.36%
85 +	-0.0012	-0.10%
% of urban-rural difference explained by age		*0.91%*
Female	-0.0004	0.02%
Female x Age 25 to 34	-0.0007	0.13%
Female x Age 45 to 54	-0.0056	-0.07%
Female x Age 55 to 64	0.0001	0.02%
Female x Age 65 to 74	0.0014	0.14%
Female x Age 75 to 84	-0.0023	-0.10%
Female x Age 85 +	-0.0025	-0.11%
% of urban-rural difference explained by age-gender		*0.01%*
Education (rel. to HS grad)		
Some college	-0.0096	1.27%
College graduate	-0.0286	21.37%
Some college x Female	-0.0004	0.03%
College grad x Female	-0.0057	2.58%
College grad x Female x Age 25 to 34	-0.0002	-0.01%
College grad x Age 35 to 44	0.0026	-1.05%
College grad x Female x Age 35 to 44	-0.0004	0.01%
College grad x Age 45 to 64	0.0031	-1.09%
College grad x Female x Age 45 to 64	0.0011	-0.09%
College grad x Age 65 +	0.0003	-0.07%
College grad x Female x Age 65 +	0.0030	-0.02%
% of urban-rural difference explained by education-age-gender		*22.94%*
Not in labor force		
Not in labor force x Female	-0.0103	-0.47%
Not in labor force x Age 20 to 24	0.0027	-0.18%

Not in labor force x Age 25 to 44	0.0180	0.38%
Not in labor force x Age 45 to 54	0.0243	3.10%
Not in labor force x Age 55 to 64	0.0142	2.86%
Not in labor force x Age 65 to 75	0.0062	1.22%
Not in labor force x Age 75 +	0.0079	0.94%
% of urban-rural difference explained by labor force-age-gender		*7.85%*
Race/ethnicity (rel. to Non-Hispanic White)		
Non-Hispanic Black	0.0025	-1.16%
Hispanic	0.0020	-2.94%
% of urban-rural difference explained by race/ethnicity		*-4.10%*
Marital status (rel. to married)		
Separated + divorced	0.0288	1.47%
Separated + divorced x Female	0.0040	0.32%
Separated + divorced x Age 20 to 34	0.0005	0.03%
Separated + divorced x Female x Age 20 to 34	0.0062	0.30%
Separated + divorced x Age 25 to 34	-0.0001	0.00%
Separated + divorced x Female x Age 45 to 54	0.0034	0.05%
Separated + divorced x Age 55 to 64	0.0038	-0.10%
Separated + divorced x Age 65 +	0.0034	-0.01%
Separated + divorced x Female x Age 65 +	0.0014	-0.05%
Widowed	-0.0013	0.05%
Widowed x Female	0.0224	3.01%
Widowed x Age 20 to 34	0.0032	0.03%
Widowed x Female x Age 20 to 34	-0.0028	-0.02%
Widowed x Age 35 to 44	-0.0016	-0.04%
Widowed x Female x Age 35 to 44	0.0025	0.04%
Widowed x Age 45 to 54	0.0040	0.10%
Widowed x Female x Age 45 to 54	-0.0012	-0.02%
Widowed x Age 55 to 64	0.0015	0.07%
Widowed x Female x Age 65 +	0.0010	0.04%
Single	-0.0040	-0.43%
Single x Female	0.0140	-7.35%
Single x Age 20 to 34	0.0028	-1.30%
Single x Female x Age 20 to 34	0.0095	-5.47%
Single x Age 35 to 44	0.0110	-2.24%
Single x Female x Age 35 to 44	-0.0015	0.25%
Single x Age 45 to 54	0.0087	-1.01%
Single x Female x Age 45 to 54	-0.0014	0.15%

Single x Age 55 to 64	0.0056	-0.33%
Single x Female x Age 55 to 64	-0.0012	0.07%
Single x Age 65 +	0.0053	-0.12%
Single x Female x Age 65 +	-0.0035	0.13%
% of urban-rural difference explained by marital status-age-gender		*-12.40%*
Census region (rel. to West)		
Midwest	0.0014	-1.49%
South	0.0032	-1.20%
West	-0.0023	90.98%
% of urban-rural difference explained by region		*88.30%*

To predict despair, we estimated a linear LASSO model in BRFSS to predict self-reported despair as a function of 10-year age-gender dummies, education (high-school, some college, and college graduate; interacted with age group and gender), employment status (interacted with age group and gender), race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, and non-Hispanic other), marital status, and region. Despair was from a question that asks "In general, how satisfied are you with your life?", with possible answers "very satisfied; satisfied; dissatisfied; and very dissatisfied". We scaled these responses from 0 = "very satisfied" to 1 = "very dissatisfied". Variables selected by LASSO and their standardized impact on pain are presented in column 2. Column 3 reports the results of a decomposition of differences in despair between urban and rural areas. To compute the shares of each variable in explaining differences in despair between urban and rural areas, we multiplied the average difference in these characteristics for urban vs. rural counties by their coefficients on despair and then divided by the difference in predicted despair.

Table A12: Replication of Charles, et al. (2019) and sensitivity of the impact of manufacturing decline on opioid deaths.

	(1)	(2)	(3)	(4)	(5)	(6)
<u>OLS</u>						
Change Manuf. Share of Pop. 2000-16	-2.32**	-2.01**	-1.80***	-0.89***	-0.12	0.09
	(1.00)	(0.78)	(0.40)	(0.33)	(0.36)	(0.36)
R-squared	0.139	0.182	0.066	0.332	0.419	0.444
<u>IV</u>						
Change Manuf. Share of Pop. 2000-16	-2.21*	-2.15**	-1.42***	-0.81*	0.61	0.96*
	(1.15)	(0.89)	(0.53)	(0.43)	(0.52)	(0.57)
R-squared	0.138	0.181	0.063	0.332	0.412	0.434
Unadjusted mean	0.094	0.080	0.152	0.152	0.152	0.166
Geographic level	State	State	CZ	CZ	CZ	CZ
Controls	None	None	None	Age	Age + Characteristics	Age + Characteristics
N	45	51	741	741	741	741

Notes: Geographic areas are weighted by their prime age labor force population in 2000. Robust standard errors are reported in parentheses. The IV specification instruments for the change in manufacturing share of population following the shift-share procedure in Charles, et al., 2019.