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ABSTRACT

Opioid abuse, as measured by deaths involving opioid analgesics and substance abuse treatment admissions, has increased dramatically since 1999, including a 20% increase in opioid-related mortality between 2005 and 2006. This paper examines whether the introduction of the Medicare Prescription Drug Benefit Program (Part D) in 2006 may have contributed to the increase in prescription drug abuse by expanding access to prescription drug benefits among the elderly. We test whether opioid abuse increased not only for the population directly affected by Part D (ages 65+) but also for younger ages. We compare growth in opioid prescriptions and abuse in states with relatively large ages 65+ population shares to states with smaller elderly population shares. Using data from the Drug Enforcement Agency's Automation of Reports and Consolidated Orders System (ARCOS), we find opioid distribution increased faster in states with a larger fraction of its population impacted by Part D. We also find that this relative increase in opioids resulted in increases in opioid-related substance abuse treatment admissions. Interestingly, these states experienced significant growth in opioid abuse among both the 65+ population and the under 65 population, though the latter was not directly impacted by the implementation of Medicare Part D. We also find that opioid-related mortality increased disproportionately in the high elderly share states, though this relationship is not statistically different from zero.

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I. Introduction

Drug overdose deaths have risen steadily for the past two decades, and by 2009 they became a leading cause of death from injuries in the United States, exceeding deaths from motor vehicle accidents (Paulozzi, 2012). Death from prescription opioids has been the primary driver behind this upward trend, at least since 1999 (Jones, Mack and Paulozzi, 2013). In 2010, prescription opioids alone were involved in over 16,500 overdose deaths, more than heroin and cocaine combined, more than quadrupling the number in 1999 (Volkow et al., 2014).

While many have noted the enormous rise in deaths in opioid analgesics over the past two decades, substantially less attention has been given to the driving factors behind it. A key driver behind the opioid overdose death epidemic is underlying substance abuse disorders, which is underscored by the fact that 82 percent of the prescription drug overdose deaths were identified as unintentional (Volkov et al., 2014). An expert panel of pain medicine doctors and public policy experts offered individual factors (being white, middle aged and living in rural areas), physician prescribing factors (inadequate provider education about proper dosing of specific opioids or risk factors for addiction), and clinical factors (substance abuse co-morbidity, prescribing of heavier analgesics for chronic pain etc.) as major contributors to the uptick (Webster et al., 2011). Independently, Paulozzi (2012) examined trends in key factors characteristic of those who died from opioid overdose, including growing incidence of patients with chronic pain, mental health problems, substance abuse problems and obesity.

Only one of these identified risk factors has experienced the same enormous growth rate as opioid deaths: the availability of opioid analgesics. Indeed, several earlier studies have already identified the very strong positive correlation between the rise in opioid availability and the rise in opioid-related deaths (Mueller et al., 2006; Paulozzi and Ryan, 2006; Paulozzi 2006) and this relationship does not appear to have attenuated in recent years (Volkov et al., 2013; Paulozzi, 2012).

The lack of attention on the role of insurance in the rise of opioid abuse is surprising in light of the tremendous expansion in health insurance coverage that occurred during the same period when overdose deaths rose. Since 1987 the Medicaid program has undergone a series of changes that have expanded eligibility, particularly among the elderly, pregnant women, and children. In just the first five years following the first set of expansions, between 1987 and 1992, the share of *nonelderly* population on Medicaid rose 40% (Cutler and Gruber, 1996). Take up rates among the elderly population who became newly eligible were even higher (Yelowitz, 2000). In 1997 there was the further creation of the Children Health Insurance Program, which also expanded public insurance among children in families with incomes between 100 and 300 percent of the federal poverty level (Lo Sasso and Buchmueller 2004; Hudson, Selden and Banthin, 2005), although with some evidence of crowding out among the previously privately insured (Gruber and Simon, 2008; Bronchetti, 2014). Then in 2006 Massachusetts implemented its near universal health insurance, which several authors suggest reduced the rate of the uninsured within the state by at least 50% (Kolstad and Kowalski, 2012; Gruber, 2011).

In terms of access to prescription drugs, the most significant insurance expansion was the January 2006 implementation of the Medicare Prescription Drug Benefit Program, commonly referred to as Part D, which provides voluntary outpatient prescription drug coverage to millions of Medicare beneficiaries. Prior to 2006, the vast majority of Medicare beneficiaries did not have access to outpatient prescription drug coverage, although some accessed coverage through retiree benefit plans, Medigap insurance, and other sources. Several studies have shown that passage of Medicare Part D did in fact increase access and utilization of prescription drugs among the elderly (Duggan and Morton, 2010; Zhang et al., 2009; Ketcham and Simon, 2008).

While the elderly have a relatively modest rate of unintentional opioid overdose deaths (Paulozzi, et al., 2011), they are the legitimate medical users of more opioid prescriptions than any other age group (Volkov et al., 2011). According to retail pharmacy data, individuals 60 years or older receive 1.9 opioid prescriptions per person while those between the ages of 40-59 (the age group with the highest opioid overdose mortality) receive only 1.1 opioid prescription per person. Moreover, multiple opioid prescriptions at the same time is fairly common, with one study showing that well over half of Medicare beneficiaries with an opioid prescription in 2010 holding concurrent prescriptions from multiple providers (Jena, Goldman and Karaca-Mandic, 2014).

Independently, it is also known that a substantial proportion of those who self-report nonmedical use of prescription drugs indicate that friends and relatives are an important source for the drugs they use, with national household data suggesting that nearly two-thirds of people who report nonmedical use of prescription drugs either get them or take them from a friend or relative (Jones et al., 2014). Thus, access through friends and relatives is an important channel for individuals to obtain opioids, and elderly relatives with multiple concurrent prescription opioids may be easy targets for interested family members.

A visual inspection of the data suggest that there was indeed a jump – even relative to trend – in the total distribution of opioid medications per capita between the years 2005 and 2006, the per capita substance abuse treatment admissions for opioids, and – most pronounced – the number of prescription overdose death per capita (see Figure 1). These time series trends are suggestive that there might in fact be an association between the introduction of Part D and opioid availability and abuse.

This paper takes advantage of a natural experiment that occurred with the implementation of Medicare Part D to assess the extent to which expanding insurance coverage for prescription drugs specifically has contributed to the harmful consequences of opioid abuse, in particular opioid treatment admissions and overdose deaths. We do this in several steps. First we confirm a positive association between the implementation of Medicare Part D and the distribution of prescription opioids. We construct a measure of opioid prescriptions using the seven most commonly abused opioid analgesics and converting the total grams distributed into morphine equivalent doses. We study the total amount of morphine equivalent doses of these drugs that are distributed to each state via the Drug Enforcement Agency's Automation of Reports and Consolidated Orders System (ARCOS).

To determine if prescription drug coverage influenced access, we study opioid prescriptions both pre- and post-implementation of Part D. The ARCOS data cover the period 2000-2010. We exploit differences across states in the proportion of the population ages 65+ prior to Part D implementation to assist in the causal identification of the effects of the expansion in prescription drug coverage. As Medicare enrollment has grown substantially throughout the period we examine, due to the aging baby boomers and growing disability rolls, we identify an instrument that can help us clearly differentiate the impact of expanding coverage related to prescription drug access versus the rising number of newly Medicare eligible. Furthermore, Part D enrollment among the eligible population was a choice and this choice may be independently related to factors predicting opioid use and abuse.

We use a fixed measure of the proportion of the state population 65 years and older ("the eligible elderly") in each state as of 2003, the year that the Medicare Modernization Act was passed. We interact this measure of eligible elderly with a time indicator equal to 1 after Part D implementation. This instrument is unrelated to individual choices to enroll in Part D and other factors such as health. It solely uses cross-section variation in eligibility interacted with the implementation of Part D. Our analysis independently controls for time and state fixed effects to account for national trends and fixed differences across states with different elderly shares.

We find a strong positive association between our instrument and the total amount of prescription opioids distributed in each state in total, and by various types of agencies that might be distributing the drug (e.g., hospitals and pharmacies). Once we demonstrate the reasonableness of our instrument as a proxy for opioid prescription medication expansion in Medicare, we estimate difference-in-difference and event history models to assess the impact of Part D coverage on opioid treatment admissions and overdose deaths.

We find that states with larger elderly shares experienced higher growth in opioid prescriptions and substance abuse treatments. States with a 10% larger Medicare Part D per capita enrollment experienced 4% higher growth in per capita prescription opioid distribution and 8% higher growth in per capita substance abuse treatment admissions for opiates. We also find a positive association between our instrument and per capita opioid-related mortality, but we cannot reject that the mortality effect is statistically different from zero in our final specifications that include controls for prescription drug monitoring programs. Supplemental analyses in the TEDS data of the non-disabled, non-Medicare treatment admissions supports the hypothesis that Medicare expansion contributed to the rise in abuse in younger populations because of increased access through the elderly, not through direct access by the elderly who are part of SSDI. These findings suggest that a significant expansion of a public insurance program, like that which is occurring through the ACA's Medicaid expansion, can have important effects on access to and abuse of opioid medications.

The rest of the paper is organized as follows. In Section II we describe the data that we use to estimate our models. Section III describes our empirical approach and presents our main results. In Section IV we provide some additional findings from various sensitivity analyses we conducted to test the robustness and reasonableness of our findings. We close in Section V with a summary of our main findings and the policy implications.

II. Data

II.a. Outcome measures

We study the relationship between increased legal access to opioids and opioid-related outcomes by focusing on three measures at the state level: opioid distribution, opioid-related substance abuse treatment admissions, and opioid-related deaths. We discuss the sources for each of these outcomes in detail.

Information regarding the supply of prescribed opioids within the state is captured in the Drug Enforcement Administration's (DEA) Automation of Reports and Consolidated Orders System (ARCOS). The Controlled Substance Act of 1970 requires all manufacturers and distributors to report their transactions and deliveries of all Scheduled II-V substances to the Attorney General. ARCOS is the system that monitors and records the flows of these controlled substances as they move from manufacturers to retail distributors at the local level (down to the street address and zip code, although this level of disaggregation is not made publicly available). Thus, ARCOS can be used to identify the distribution of specific opioid medications that are prescribed for medicinal purposes. We construct a measure of the seven most commonly abused opioid analgesics (Paulozzi et al., 2011; Paulozzi and Ryan, 2006): fentanyl, hydrocodone, hydromorphone, meperidine, methadone, morphine, and oxycodone (as OxyContin as well as in other forms). Following prior work, we converted the total grams distributed per capita into morphine equivalent doses drawing on standard multipliers used in this literature (Paulozzi, Kilbourne and Desai, 2011). These were aggregated by state and year. Thus our total sales measure is the number of morphine-equivalent doses of the seven most commonly abused opioid analgesics.

We use the Treatment Episode Data Set (TEDS) to study substance abuse treatments. The TEDS treatment admission data are collected annually by state substance abuse agencies at the request of the Substance Abuse and Mental Health Service Administration (SAMHSA). They contain nearly the universe of substance abuse treatment admissions that occur within the United States, as all facilities that receive any government funding (federal block grant funding, state treatment dollars, or even insurance dollars from Medicaid, Medicare, or Tricare) are required to provide basic information. Only private facilities that treat non-publicly insured individuals and that receive no federal or state grant monies are excluded. The unit of observation is an admission, and information is retained on the primary, secondary, and tertiary substances reported at the time of the admission, as well as client demographics, expected source of payment, treatment setting, and treatment characteristics. Information is also collected on who referred the individual to treatment (the criminal justice system, a doctor or medical provider, an employer, a parent, or self). We use annual case-level data on admissions for the period 1992-2011. Our main analysis will use the 1998-2011 time period to narrow the time period closer to the implementation of Part D date, though we will also present results using data back to 1992.

We include two substance categories in our metric of opioid abuse: "non-prescription methadone" and "other opiates and synthetics." The latter category includes "buprenorphine, codeine, hydrocodone, hydromorphone, meperidine, morphine, opium, oxycodone, pentazocine, propoxyphene, tramadol, and any other drug with morphine-like effects." We include all admissions in which one of these drugs is included as primary, secondary, or tertiary substances.[1]

The TEDS data indicate whether treatment referral is from the criminal justice system. We use this variable to check whether systematic changes in enforcement, indicated by changes in referrals to treatment from the criminal justice system, affect our results. Finally, TEDS only provides age in broad categories: 12-15, 15-17, 18-20, 21-24, 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, 55+. Consequently, to study the impact of Part D on age groups not directly affected by its implementation, we study the age group 12-54. The 55+ age group includes both the indirect and direct effect.

Information on opioid overdose deaths comes from the National Vital Statistics System (NVSS), a census of deaths in the United States. We code deaths as related to prescription opioid pain relievers using the ICD-10 external cause of injury codes (X40-X44, X60-64, X85, or Y10-Y14) and drug identification codes (T40.2-T40.4), which indicate death by any opioid analgesic. We are not able to uniquely identify any specific opioid analgesic except for methadone (T40.3), and thus we group them all together. We follow the codes used by the CDC to categorize deaths of any intent (unintentional, suicide, homicide or undetermined). We then aggregate the data based on state of residence and year.

II.b. Independent Variables

[1] Our results do not change meaningfully if we only count primary substances.

Our primary variable of interest is per capita Medicare Part D enrollment. We use Part D enrollment number from the Centers for Medicare & Medicaid Services (CMS), aggregated by state and year. We use population data from the Census to construct per capita ratios. We also use age-specific population data from the Census to create our elderly share variable for our instrumental variable.

We do not have prescription drug coverage prior to Medicare Part D, similar to many papers studying the effects of Part D (e.g., Ketcham and Simon, 2008). Part D may impact access by providing prescription drug coverage to part of the population which would not have had any coverage otherwise or by providing more generous coverage to people who would have had coverage even in the absence of Part D. Given that our goal is to estimate the impact of Part D, we believe that both of these mechanisms are important components of the total effect.

In much of our analysis, we will also control for the adoption of prescription drug programs (PMPs) at the state level. Prescription drug monitoring programs are recommended by the CDC and ONDCP as a useful strategy for combatting prescription drug misuse and harms. The research evaluating these programs, however, is actually quite inconclusive in terms of their impact on opioid related harms (Brady et al., 2014; Paulozzi et al., 2011; Paulozzi & Stier, 2010). Nonetheless, there has been significant growth in the adoption of PMP programs across states during our sample period. According to data from LawAtlas, only 12% of states had authorized a prescription drug monitoring program in 2000, but by 2010 over 70% of states had authorized these programs. In particular, post 2005 there has been significant rise in the percent of states with PMPs requiring near real-time reporting (so updating of the data system at least once a week if not daily) as well as a rise in PMP's requiring those responsible for reporting to the PMP to proactively report suspicious behavior by patients, pharmacies, or even doctors.

These types of features of PMPs are expected to have a more significant impact at deterring improper prescription drug misuse than just poorly defined programs . We include state-varying controls for changes in proactive aspects of PMPs, based on data from LawAtlas.[2] We have information on PMP adoption by state starting in 1998. Prior to 1998, there is some evidence that PMPs were different in nature and did not require providing information to prescribers or pharmacists.

II.c. Descriptive statistics and trends

We include means for our outcomes and other variables in Table 1. There was substantial growth in our opioid measures, as shown in Figure 1, throughout our entire analysis period. Data on the sale of morphine equivalent doses of our seven problematic opioid analgesics clearly grew during this period, rising 129% from 2000 to 2005 and then again another 62% between 2005 and 2010. Opioid overdose deaths also show a significant rise on average across the states during the time period, more than doubling from 2000 to 2005 followed by a 45% rise from 2005 to 2010. Substance abuse treatment admissions also more than doubled between 2000 and 2005 and then doubled again from 2005 to 2010.

There appears to be a greater rise in opioid prescriptions and opioid deaths in the period preceding the implementation of Medicare Part D than in the period following Medicare Part D. Baseline differences account for some of those differences, but it is also true that during the same period Medicare Part D started expanding states more aggressively started adopting policies to combat prescription drug abuse.

[2] Data available at: http://lawatlas.org/query?dataset=corey-matt-pmp. Last accessed January 30, 2015.

III. Empirical Framework

Our goal is to evaluate whether access to insurance coverage for prescription drugs used by the elderly (Medicare Part D) may have contributed to the rise in prescription opiate abuse ("OA") or overdose deaths ("OD"s). For this to have happened, insurance must first influence the sale of prescription opioids ("Rx"). We first examine the extent to which Part D coverage influenced the sale of specific opioids of abuse and then whether it impacted rates of overdose deaths and treatment admissions within the general population. The basis of our empirical strategy is to study changes in our measures of y_{it} = {Rx, OD, OA} based on implementation and uptake of Medicare Part D. We use the timing of Part D and differences in the eligible population across states for identification. We use a difference-in-differences strategy, which we implement by including state fixed effects and year fixed effects in our specifications. We estimate the specification:

$$y_{st} = \exp(\alpha_s + \gamma_t + X'_{st}\beta + \delta[\ln(\text{Part D enrollment per capita})_{st} \times 1(t \geq 2006)])\varepsilon_{st} \quad (1)$$

where y_{st} is a measure of opioid-related distribution, abuse, or mortality for state *s* in year *t*. X is a vector of time-varying covariates including the log of the share of the population ages 65+, other demographic variables, state-level economic variables, the private insurance rate, and PMP policy variables. We are primarily interested in the estimate of δ, which represents the differential change in the outcome experienced by states with a high per capita Part D enrollment relative to other states. This variable is set to zero before the implementation of Part D. We expect this estimate to be positive if Part D increased opioids access.

We use an exponential functional form to account for the skewness of the outcomes. While it is typical to use a log-linear specification in applied work, Silva and Tenreyro (2006) show that nonlinear least squares estimation of an exponential specification places less structure on the error term. A log-linear specification assumes that the error term is multiplicative in y, while equation (1) permits additive and multiplicative errors. Furthermore, we estimate equation (1) for opioid-related mortality at disaggregated age groups and, in some instances, there are zero opioid-related deaths in a state-year for an age group, making a logged dependent variable inappropriate. We estimate equation (1) using Poisson regression.[3] We will also show some corresponding log-linear estimates. In general, the log-linear estimates do not differ from the Poisson estimates in meaningful ways.

Our empirical strategy is to compare changes in outcomes pre- and post-Part D across states with different shares of individuals eligible for Part D. We control independently for the national impact of Part D and other secular trends through the inclusion of year fixed effects. Some variation in equation (1) originates from state-level changes in the fraction of the population 65+ after 2006 and different enrollment propensities. This variation is potentially problematic if we believe that there is systematic migration that is correlated with opioid abuse. For example, opioid abuse may be related to local economic downturns. If declining economic conditions also cause younger people to migrate out of the state (i.e., increasing the fraction of the population 65+), then this source of variation is confounded by omitted variables. Our specification includes the log of the elderly share as a separate control variable, which should alleviate some of these concerns. Furthermore, state-varying differences in health and economic conditions may predict Part D enrollment and independently correlate with opioid use and abuse.

[3] Related models such as negative binomial models require additional assumptions and are less robust than Poisson regression. See Chapter 18 of Wooldridge (2010) for more details.

To address these concerns, we estimate equation (1) using IV-Poisson, where our instrument is

$$1(t \geq 2006) \times \ln(\text{Fraction of Population 65+})_{s,2003}$$

In words, we fix the population share for each state in 2003. Consequently, identification originates solely from the introduction of Part D interacted with fixed state elderly shares in 2003. The instrumental variable strategy eliminates any identification originating from changes in the elderly share over time, allowing us to non-parametrically control for the independent effects of Part D (year fixed effects) and elderly share (state fixed effects). Medicare Part D was signed into law at the end of 2003 so we use the 2003 share because it is likely relatively free of any possible anticipation effects (see Alpert, 2014). Our results are not sensitive to this choice.

Furthermore, we are interested in isolating the impact of Medicare Part D on a population not directly impacted by the expansion of prescription drug coverage. However, the introduction of Part D increased coverage rates for the SSDI population, which includes those under 65. A further advantage of our approach is that we isolate the impact of Part D on states with high elderly share. This is potentially unrelated to the share of those under 65 enrolled in SSDI. We can test this more explicitly in the TEDS and we present evidence that our instrument is not correlated with SSDI share.

We weight all regressions by state population. Standard errors are adjusted for clustering at the state level.

IV. Results

IV.a. Graphical Evidence

Before we proceed to regression analysis, we show our trends graphically. We separate states into "above median" and "below median" based on the fraction of the population in 2003 that is

65 or older. We predict that states with a larger elderly share should experience larger changes in opioid abuse when Part D is implemented in 2006.

Figure 2 shows the trends in mortality. In the left panel, we graph per capita opioid-related mortality for ages 65+. Given the relatively low incidence at older ages, this graph is noisy. Before the implementation of Part D, the two groups of states look similar. Beginning in 2006, we observe higher per capita mortality in the "above median" states. The right panel present the equivalent trends for the under 65 population. Again, we do not observe systematic differences before 2006. After the implementation of 2006, per capita mortality is consistently higher in the "above median" states.

We also study the differential impact of Part D on opioid-related substance abuse treatment admissions. In Figure 3, we present the trends for the above and below median states. We only use states which report treatment admissions for every year 1992-2011, which includes 39 states (in our regression analysis, we use an unbalanced panel). In the left panel, we look only at treatment admissions for the 55+ age group. This group includes the 65+ age group which is directly affected by Part D but also includes ages 55-64 which were only impacted indirectly. Before 2006, the above median and below median states look very similar, with the exception of 2005 which suggests a possible anticipation effect. The gap widens beginning in 2006. In the right panel, we focus on ages 12-54. Again, we observe little evidence of pre-existing trends. Upon implementation of Medicare Part D, the above median states incur a relative increase in per capita substance abuse treatments, providing further evidence of an increase in opioid abuse in states with high elderly share resulting from Part D. This increase is occurring in the population not directly affected by Part D.

Overall, the graphical evidence is consistent across data sets and outcomes. We see little evidence of different pre-existing trends based on fixed elderly share. After the implementation of Medicare Part D, opioid abuses increase in the high elderly states relative to the low elderly states. Graphically, we observe relative increases for younger and older ages, implying that even those that did not directly gain access to prescription drug coverage were impacted by the additional access in the population.

IV.b. Regression Analysis

Prescriptions

We estimate equation (1) to compare growth in opioid prescriptions at the state-level based on Part D enrollment. In Table 2, we present the Poisson estimates, relating Part D enrollment to opioid distribution. We find a strong relationship between Part D enrollment and opioid prescription growth. We estimate that a 10% increase in Part D enrollment is associated with 3% growth in opioid distribution. We find similar effects if we focus on pharmacies (2.5% estimated growth) or hospitals (3.7% growth). We estimate much larger effects for distribution through practitioners, though these estimates are more imprecisely estimated.

Because of concerns that Part D enrollment and opioid use are both independently related to other confounding factors, we also estimate IV-Poisson models using fixed elderly share interacted with post-2006. We present these estimates in Table 3. We estimate slightly larger effects. We estimate that each 10% of additional enrollment in Part D is associated with an additional 4.3% growth in opioid distribution. The estimates are similar for pharmacies and hospitals. We, again, estimate especially large effects for practitioners, though we cannot reject a null effect.

Our identification strategy relies on the assumptions that state elderly share does not predict pre-existing trends. To test that assumption, we perform an event study, allowing the effect of the $\ln(\text{Fraction of Population 65+})_{s,2003}$ variable to have a different effect in each year. The results from this event study analysis are presented graphically in Figure 4. We normalize the estimated coefficients such that the coefficient in 2000 is equal to 0. We find no statistically significant relationship between elderly share and opioid distribution before 2006. Beginning in 2006, larger elderly share is associated with increased growth in opioid prescriptions. Elderly share is statistically significantly related to opioids in each year after Medicare Part D is implemented. Overall, we find little evidence that our estimates are driven by confounding trends.

Mortality

In Table 4 we show results from estimating equation (1) using the NVSS mortality data to measure the relative effect of Part D implementation on growth in opioid-related deaths. In Table 4, we find little evidence of a relationship between Part D enrollment and growth in opioid-related mortality. In fact, the estimates are negative for the full sample and the under-65 sample, suggesting that Part D enrollment is associated with lower mortality rates.

We present the corresponding IV-Poisson estimates in Table 5. We estimate that a 10% increase in Part D enrollment increase opioid-related mortality growth by 3.1%, though this estimate is not statistically significant from zero. With the exception of ages 50-59, we estimate a positive effect of Part D enrollment on mortality for all age groups. None of these estimates, however, are statistically significant. In the Appendix (see Appendix Table 1), we include unweighted IV-Poisson estimates and find similar results.

Opioid Abuse Treatment Admissions

Using TEDS, we estimate the differential effect of the implementation of Medicare Part D on treatment admissions for opioid abuse. We present both Poisson and IV-Poisson estimates of equation (1). Table 6 presents the Poisson estimates. We find little relationship between Part D enrollment and substance abuse treatment admission for pain relievers. We estimate a negative relationship for the full sample and for the 12-54 age group. We do not estimate a statistically significant relationship for any age group.

Table 7 includes the corresponding IV-Poisson estimates. We find strong evidence of a causal relationship between Part D enrollment and growth in substance abuse treatment admissions. We estimate that each 10% increase in Part D enrollment caused an 8.5% increase in substance abuse treatment growth. Our estimate for ages 12-54 is a similar magnitude. We focus on these ages given that they are not directly impacted by the introduction of Medicare Part D. We find statistically significant (at the 10% level) relationships of Part D enrollment on admissions for ages 12-20, 21-29, 30-39, 50-54, and 55+. These results suggest the introduction of Part D increased access of opioids to those not eligible for prescription drug coverage through Medicare.

In Table 8, we replicate Table 7 while excluding criminal justice referrals from the outcome variables. We find similar effects for all age groups. The similarity of the results whether we use all admissions or exclude criminal justice referrals suggests that changes in criminal justice activity related to opioid abuse are uncorrelated with the interaction of elderly share and the implementation of Part D.

The TEDS provides a longer pre-period than we use in Tables 7 and 8. We start our analysis in 1998 for two reasons. First, we wanted to use years close to the introduction of Part

D. Although there was little evidence of differential pre-existing trends (see Figure 3), there is concern that state-level differences in 1992 may drive our results if we include the full sample. Second, by starting at 1998, our PMP variables refer to the "third wave" of PMP implementation. To test the robustness of our results to excluding 1992-1997, we present equivalent results (we exclude the PMP policy variables from these regressions) for the full 1992-2011 sample in the Appendix (see Appendix Table A.2). The estimates are similar.

Above, we discussed the benefits of Poisson estimation techniques. In Appendix Table A.3, we provide log-linear instrumental variable estimates.   Because the log of treatments is undefined when the number of treatments is equal to zero, the sample size changes based on the number of cells with zero treatments. The results are similar to the corresponding estimates reported in Table 7, especially the full sample estimates and the ages 12-54 estimates.

Our estimates imply that states with higher elderly share experienced faster growth in opioid abuse due to the implementation of Part D even for ages not directly affected by the increase in prescription drug coverage. Individuals receiving Social Security Disability Insurance (SSDI) are also eligible for Part D coverage and experienced a shock when Medicare Part D was implemented. It is unlikely that the SSDI population is driving our results for the under 65 age group given that we study the differential effect based on variation in elderly share at the state-level. Even if the SSDI population itself was differentially impacted by Part D, we would not observe this effect in our analysis if it is uniform throughout the country or any differential state-level shocks were uncorrelated with elderly share.

We use the TEDS data to test this assumption more explicitly.   In the TEDS, we observe whether the expected primary payment source is Medicare. We also observe each individual's labor force participation, including "Retired, Disabled" as one option. We eliminate admissions in which the expected payment source is Medicare or the individual reports being retired/disabled. The remaining admissions should not include individuals on SSDI. We re-estimate equation (1) using only non-Medicare, non-Disabled admissions. We do this for all ages, the 12-54 age group, and the 55+ age group. Note that by excluding retired individuals from the 55+ age group, we are excluding a vast majority of older individuals.

We present these results in Table 9. The estimates are similar to our main TEDS results in Table 7 for all ages and the younger age group. The results are slightly different for the older age group though this is likely due to the exclusion of retired individuals (not people on SSDI). We conclude that our main results are not driven by SSDI.

IV.c. Other Insurance Expansions

Other major state-level health insurance expansions occurred at or around the same time as Medicare Part D. These expansions are not necessarily problematic for our empirical strategy unless elderly share predicts state-level health insurance expansions. To test whether other expansions are confounding our ability to isolate the differential impact of Part D, we exclude Massachusetts and Oregon. In 2006, Massachusetts implemented a major health insurance reform with large effects on the state insurance rate. In 2008, Oregon implemented a large Medicaid expansion.

Table 10 presents IV-Poisson estimates for our major outcomes, excluding Massachusetts and Oregon. The results are similar to our main estimates, suggesting that we are not conflating the effects of other major insurance expansions with the differential impacts of Medicare Part D.

V. Discussion and Conclusion

In 2013 16,235 overdose deaths were caused by opioid pain relievers alone (CDC, 2015). The new role or prescription opioids as the leading cause of injury death, causing more deaths than motor vehicle traffic crashes for people 25 to 64 years of age, has raised considerable alarm and concern among public health officials and policy makers alike. While many strategies have been offered to try to counteract the tide, explanations for why the rise has occurred in the first place have been slower to come. This paper attempts to move the thinking forward by examining one potential driver: expanding insurance coverage.

We find that one particular insurance expansion that focuses exclusively on expansion of prescription drug benefits, i.e. Medicare Part D, has indeed been a significant contributor to the rise in opioid sales and opioid treatment admissions since its implementation in 2006. Instrumental variable techniques help us identify a rise in prescription drug distribution and treatment episodes in states with a larger share of the Medicare aged population post implementation of Medicare Part D. Importantly, however, we find that abuse, as indicated by treatment admissions, rises more for the non-elderly (and in the case of the treatment data), non-disabled population. In other words, we find evidence of diversion from those with legitimate medical need (i.e. the Medicare population) to other individuals. We estimate that an additional 10% increase in Medicare Part D enrollment is associated with a 4% increase in opioid prescriptions in the state, and an 8% increase in opioid treatment admissions. The larger impact on treatment admission is likely due to the much smaller base of potential users; there are at most tens of thousands of individuals misusing opioids in a given state, while there are billions of opioids being distributed for medical purposes.

We also see positive associations with mortality, although the results are not statistically significant. This may be due in part to the relative short panel in which we are examining what is still a somewhat rare event. Supplemental analyses (not presented here) examining the relationship over a longer time period (1990-2014) do suggest a statistically significant relationship, although we cannot be certain that this is real or simply caused by a much longer pre-treatment period. Graphically, we can see a clear break in opioid-related mortality trends post-2006 between states with a large share of elderly population from states with a low share of elderly population particularly for the nonelderly population, which is the population most affected in the treatment population.

The finding that insurance expansions, and in particular expansion of prescription benefits for the elderly, has contributed to the rise in prescription drug abuse and mortality among the nonelderly has important implications for understanding what we might expect of this trend in the future. There are a number of provisions of the Affordable Care Act that explicitly expand insurance to the previously uninsured, by offering dependent care coverage, promoting Medicaid eligibility expansions, and supporting state and federal insurance exchanges. It is possible that as the ACA expands insurance coverage, we see an exasperation of the growing trend in opioid misuse and mortality. Our evidence presented here suggests that there is clear leakage from the medical market to those seeking to misuse the substance, as we find the strongest impacts in terms of abuse on those under the age of 65 and not disabled. However, it is also possible that private insurance-based mechanisms to reduce the risk of diversion, such as lock-in programs and, are more effective than those administered through Medicare. Future research should further explore the relative effectiveness of alternative tools, both insurance-based and state or federal policy based, in light of the growing expansion in coverage.

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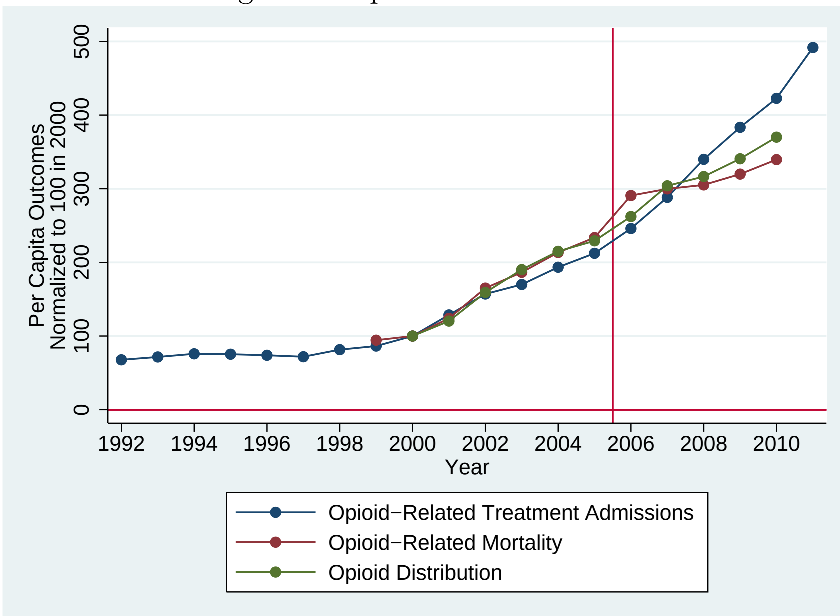
Figures

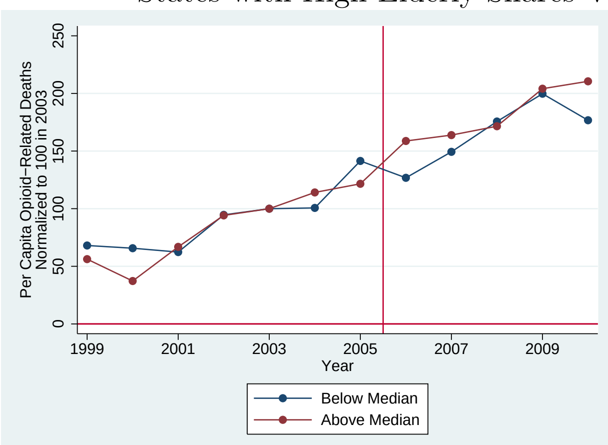
Figure 1: Opioid Use and Abuse



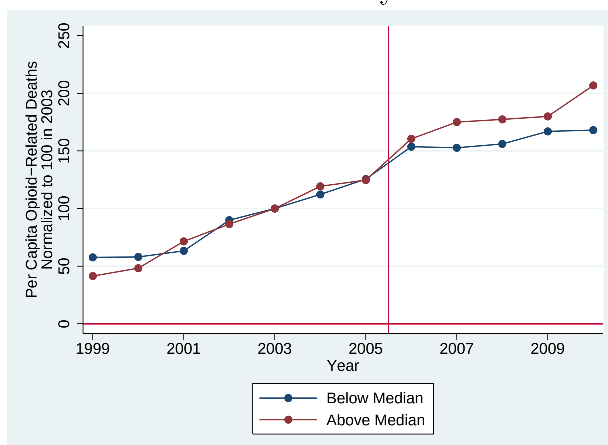
Notes: We use ARCOS data to generate per capita opioid distribution, NVSS to create per capita opioid-related mortality, and TEDS to calculate per capita substance abuse treatments for opiates. We normalize each time series to 100 in 2000. The ARCOS time series spans 2000-2011; NVSS 1999-2010; TEDS 1992-2011.

Figure 2: Opioid-Related Mortality

States with High Elderly Shares Versus States with Low Elderly Shares



Ages 65+



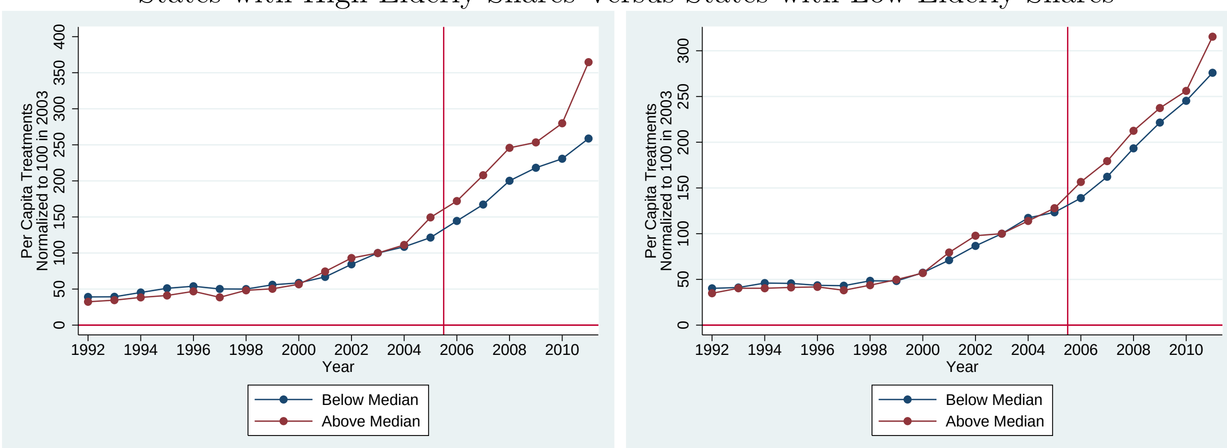
Under 65

Source: National Vital Statistics System

Notes: "Above Median" and "Below Median" refer to the elderly share of the population in 2003.

Figure 3: Opioid-Related Substance Abuse Treatments

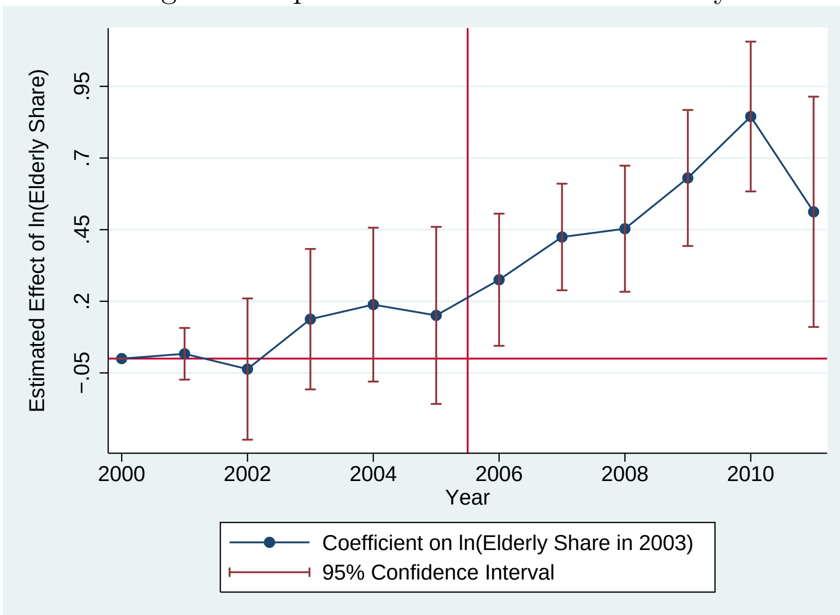
States with High Elderly Shares Versus States with Low Elderly Shares



Ages 55+ Ages 12-54

Source: Treatment Episode Data Set
Notes: "Above Median" and "Below Median" refer to the elderly share of the population in 2003. We only use states which report data in each year 1992-2011 (39 states).

Figure 4: Opioid Distribution: Event Study



Notes: We estimate equation (1) but allow the effect of ln(Elderly Share in 2003) to vary by year, normalizing the coefficient for 2000 to 0.

Tables

Table 1: Summary Statistics

Variable	Mean	Standard Deviation
Substance Abuse Treatment per 100,000	49.19	49.22
Deaths per 100,000	3.75	2.58
Morphine Equivalent Doses per 100,000	1,411,359	669,103
Unemployment Rate	5.95	2.19
% Private Insurance	68.58	6.71
% 65+	12.65	1.88
PMP Prescriber	0.32	0.47
PMP Proactive Requirement	0.05	0.22
PMP Real Time	0.13	0.34

Table 2: Opioid Distribution

	Poisson Estimates			
Dependent Variable:	Opioids (Morphine Equivalent)			
Source:	All	Pharmacy	Hospitals	Practitioners
ln(Part D per capita)	0.298***	0.249***	0.369***	1.154*
	(0.073)	(0.063)	(0.105)	(0.595)
PMP Prescriber	0.064***	0.058***	-0.002	0.350***
	(0.020)	(0.021)	(0.018)	(0.064)
PMP Proactive	0.037**	-0.004	0.028	-0.053
	(0.019)	(0.020)	(0.045)	(0.284)
PMP Real Time	-0.097***	-0.064***	0.011	-1.074***
	(0.029)	(0.021)	(0.021)	(0.202)
ln(% White)	-0.194	-0.328	6.157**	-9.745
	(1.098)	(1.063)	(3.006)	(6.366)
ln(% Black)	0.015	0.048	-0.082	-1.727
	(0.213)	(0.220)	(0.266)	(1.627)
ln(Unemployment Rate)	0.132**	0.197***	-0.034	1.437***
	(0.065)	(0.066)	(0.058)	(0.421)
ln(Median Income)	-0.431*	0.088	-0.484	2.87
	(0.238)	(0.319)	(0.492)	(3.319)
log(% Private Insurance)	0.229	-0.019	0.101	8.197***
	(0.252)	(0.221)	(0.232)	(2.206)
N	612	612	612	612

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Substances in ARCOS data converted to morphine-equivalent.

Table 3: Opioid Distribution

	IV-Poisson Estimates			
Dependent Variable:	Opioids (Morphine Equivalent)			
Source:	All	Pharmacy	Hospitals	Practitioners
ln(Part D per capita)	0.432***	0.424***	0.466***	1.015
	(0.070)	(0.066)	(0.146)	(0.974)
PMP Prescriber	0.055**	0.047*	-0.009	0.354***
	(0.022)	(0.025)	(0.019)	(0.068)
PMP Proactive	0.039*	-0.002	0.028	-0.047
	(0.021)	(0.023)	(0.046)	(0.292)
PMP Real Time	-0.096***	-0.062***	0.012	-1.078***
	(0.030)	(0.021)	(0.021)	(0.212)
ln(% White)	-0.706	-1.013	5.860**	-9.668
	(1.213)	(1.216)	(2.958)	(6.273)
ln(% Black)	-0.01	0.015	-0.108	-1.719
	(0.219)	(0.236)	(0.276)	(1.610)
ln(Unemployment Rate)	0.109	0.167**	-0.051	1.451***
	(0.069)	(0.073)	(0.051)	(0.416)
ln(Median Income)	-0.406*	0.11	-0.467	2.773
	(0.246)	(0.346)	(0.496)	(3.267)
log(% Private Insurance)	0.223	-0.027	0.1	8.246***
	(0.252)	(0.217)	(0.230)	(2.330)
N	612	612	612	612

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Substances in ARCOS data converted to morphine-equivalent.

Table 4: Opioid-Related Mortality

	Poisson Estimates								
Dependent Variable:	Opioid-Related Deaths								
ln(Part D per capita)	-0.128	-0.085	0.098	-0.064	-0.094	-0.062	-0.346	0.134	-0.157
	(0.267)	(0.238)	(0.216)	(0.248)	(0.281)	(0.319)	(0.211)	(0.348)	(0.357)
PMP Prescriber	-0.131**	-0.134***	-0.063	-0.158**	-0.169***	-0.148***	-0.079*	-0.049	-0.153**
	(0.051)	(0.050)	(0.076)	(0.070)	(0.054)	(0.050)	(0.046)	(0.062)	(0.061)
PMP Proactive	-0.255	-0.271	-0.299	-0.213	-0.354*	-0.252	-0.206	-0.179	-0.158
	(0.184)	(0.181)	(0.247)	(0.222)	(0.184)	(0.153)	(0.183)	(0.403)	(0.186)
PMP Real Time	-0.037	-0.036	0.213	-0.021	-0.062	-0.068	-0.057	0.106	-0.102
	(0.075)	(0.074)	(0.149)	(0.122)	(0.073)	(0.082)	(0.049)	(0.069)	(0.080)
ln(% White)	6.078*	5.835	-16.851***	2.609	11.700**	7.084*	5.803*	4.397	3.645
	(3.497)	(3.584)	(6.174)	(4.598)	(5.393)	(4.193)	(3.348)	(4.147)	(4.413)
ln(% Black)	2.327***	2.448***	0.114	1.397*	3.287***	2.205**	2.544***	2.075***	0.508
	(0.688)	(0.720)	(0.961)	(0.717)	(0.979)	(0.886)	(0.532)	(0.775)	(0.583)
ln(Unemployment Rate)	0.632***	0.629***	-0.011	0.806**	0.822***	0.801***	0.119	0.213	0.16
	(0.210)	(0.203)	(0.387)	(0.319)	(0.236)	(0.233)	(0.170)	(0.310)	(0.250)
ln(Median Income)	1.667	1.592	-0.986	2.207	2.292	2.225	-0.809	2.453	3.365**
	(1.876)	(1.822)	(2.170)	(2.992)	(1.855)	(2.176)	(1.293)	(2.163)	(1.420)
log(% Private Insurance)	-1.488***	-1.610***	-1.377*	-1.499**	-2.444***	-1.124**	-1.411**	1.497	0.136
	(0.420)	(0.402)	(0.801)	(0.731)	(0.635)	(0.484)	(0.648)	(0.942)	(0.925)
Ages	All	Ages 0-64	Ages 10-19	Ages 20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-64	Ages 65+
N	612	612	612	612	612	612	612	612	612

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 5: Opioid-Related Mortality

	IV-Poisson Estimates								
Dependent Variable:	Opioid-Related Deaths								
ln(Part D per capita)	0.31	0.346	0.061	0.512	0.379	0.521	-0.15	0.388	0.095
	(0.349)	(0.316)	(0.286)	(0.357)	(0.408)	(0.459)	(0.291)	(0.483)	(0.402)
PMP Prescriber	-0.157***	-0.159***	-0.06	-0.187***	-0.199***	-0.185***	-0.09	-0.059	-0.165***
	(0.058)	(0.057)	(0.077)	(0.071)	(0.068)	(0.054)	(0.057)	(0.073)	(0.051)
PMP Proactive	-0.267	-0.283	-0.298	-0.238	-0.373**	-0.266*	-0.207	-0.176	-0.154
	(0.182)	(0.180)	(0.247)	(0.231)	(0.175)	(0.152)	(0.181)	(0.404)	(0.184)
PMP Real Time	-0.027	-0.026	0.212	-0.007	-0.055	-0.057	-0.054	0.111*	-0.096
	(0.071)	(0.070)	(0.149)	(0.118)	(0.069)	(0.077)	(0.048)	(0.065)	(0.079)
ln(% White)	5.076	4.774	-16.721***	0.38	10.289*	5.829	5.394	3.687	3.138
	(3.755)	(3.899)	(6.488)	(5.372)	(5.382)	(4.566)	(3.441)	(4.527)	(4.347)
ln(% Black)	2.315***	2.469***	0.108	1.559**	3.288***	2.219**	2.522***	2.066***	0.47
	(0.713)	(0.751)	(0.951)	(0.731)	(1.000)	(0.934)	(0.548)	(0.774)	(0.601)
ln(Unemployment Rate)	0.561***	0.554***	-0.003	0.683***	0.745***	0.703***	0.103	0.177	0.121
	(0.161)	(0.156)	(0.399)	(0.243)	(0.200)	(0.175)	(0.153)	(0.285)	(0.241)
ln(Median Income)	1.767	1.678	-0.999	2.25	2.358	2.349	-0.693	2.478	3.418**
	(2.024)	(1.948)	(2.182)	(3.089)	(1.984)	(2.346)	(1.436)	(2.194)	(1.508)
log(% Private Insurance)	-1.461***	-1.607***	-1.374*	-1.605**	-2.380***	-1.108**	-1.401**	1.45	0.095
	(0.436)	(0.404)	(0.794)	(0.711)	(0.657)	(0.513)	(0.644)	(0.910)	(0.916)
Ages	All	Ages 0-64	Ages 10-19	Ages20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-64	Ages 65+
N	612	612	612	612	612	612	612	612	612

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 6: Opioid-Related Substance Abuse Treatment Admissions

	Poisson Estimates							
Dependent Variable:	Opioid-Related Substance Abuse Treatments							
ln(Part D per capita)	-0.047	-0.028	0.155	0.171	-0.037	-0.084	-0.012	-0.117
	(0.177)	(0.174)	(0.348)	(0.296)	(0.161)	(0.187)	(0.115)	(0.175)
PMP Prescriber	0.037	0.031	0.143**	0.103*	0.016	-0.013	0.03	0.048
	(0.070)	(0.071)	(0.066)	(0.059)	(0.078)	(0.090)	(0.072)	(0.073)
PMP Proactive	0.01	0.015	-0.058	-0.062	0.016	0.09	0.081	-0.012
	(0.143)	(0.141)	(0.182)	(0.152)	(0.120)	(0.118)	(0.107)	(0.120)
PMP Real Time	-0.044	-0.053	0.033	-0.048	-0.051	-0.056	-0.034	0.036
	(0.098)	(0.096)	(0.108)	(0.121)	(0.087)	(0.087)	(0.069)	(0.100)
ln(% White)	0.184	-0.276	-19.718***	-13.149**	5.844	2.378	5.740*	2.703
	(4.092)	(3.974)	(6.715)	(5.849)	(3.841)	(3.703)	(3.486)	(3.503)
ln(% Black)	0.668	0.6	-1.776**	-0.767	0.880*	1.099**	1.703***	1.548***
	(0.702)	(0.683)	(0.876)	(0.858)	(0.531)	(0.471)	(0.570)	(0.591)
ln(Unemployment Rate)	0.696***	0.699***	0.933***	0.758***	0.578***	0.402*	0.340*	0.269
	(0.188)	(0.186)	(0.315)	(0.214)	(0.182)	(0.221)	(0.180)	(0.214)
ln(Median Income)	1.128	1.137	1.673	0.844	0.655	1.637**	0.849	0.628
	(0.986)	(0.985)	(2.321)	(1.773)	(0.869)	(0.813)	(0.901)	(0.916)
log(% Private Insurance)	-2.881***	-2.912***	-0.991	-2.841***	-3.012***	-2.002**	-2.868***	-2.126**
	(0.949)	(0.969)	(1.256)	(1.078)	(0.891)	(0.840)	(0.820)	(0.832)
Ages	All	Ages 12-54	Ages 12-20	Ages 21-29	Ages 30-39	Ages 40-49	Ages 50-54	Ages 55+
N	688	688	688	688	688	688	688	688

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 7: Opioid-Related Substance Abuse Treatment Admissions

	IV-Poisson Estimates							
Dependent Variable:	Opioid-Related Substance Abuse Treatments							
ln(Part D per capita)	0.846***	0.820***	0.878*	0.800**	0.807**	0.563	0.534**	0.752*
	(0.303)	(0.287)	(0.456)	(0.330)	(0.377)	(0.343)	(0.271)	(0.387)
PMP Prescriber	-0.019	-0.023	0.098	0.07	-0.038	-0.054	-0.001	0.005
	(0.083)	(0.083)	(0.073)	(0.065)	(0.091)	(0.100)	(0.074)	(0.081)
PMP Proactive	0.03	0.03	-0.041	-0.054	0.023	0.094	0.091	0.013
	(0.157)	(0.155)	(0.191)	(0.160)	(0.131)	(0.129)	(0.112)	(0.133)
PMP Real Time	-0.04	-0.046	0.045	-0.034	-0.047	-0.055	-0.028	0.042
	(0.105)	(0.101)	(0.112)	(0.119)	(0.093)	(0.092)	(0.073)	(0.110)
ln(% White)	-3.486	-3.706	-22.774***	-16.238***	2.476	0.341	4.271	0.473
	(4.431)	(4.258)	(6.674)	(5.765)	(4.289)	(3.963)	(3.880)	(4.117)
ln(% Black)	0.321	0.294	-2.084**	-1.011	0.62	0.892*	1.529**	1.255*
	(0.769)	(0.739)	(0.931)	(0.912)	(0.591)	(0.488)	(0.631)	(0.671)
ln(Unemployment Rate)	0.631***	0.634***	0.870***	0.709***	0.508**	0.356	0.322*	0.272
	(0.203)	(0.201)	(0.330)	(0.225)	(0.200)	(0.222)	(0.182)	(0.209)
ln(Median Income)	1.242	1.22	1.835	0.847	0.714	1.735**	1.047	1.038
	(1.171)	(1.138)	(2.503)	(1.868)	(0.998)	(0.874)	(0.922)	(1.019)
log(% Private Insurance)	-2.725***	-2.805***	-0.947	-2.820**	-2.849***	-1.877**	-2.748***	-1.915**
	(1.007)	(1.031)	(1.297)	(1.109)	(0.948)	(0.918)	(0.867)	(0.963)
Ages	All	Ages 12-54	Ages 12-20	Ages 21-29	Ages 30-39	Ages 40-49	Ages 50-54	Ages 55+
N	688	688	688	688	688	688	688	688

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 8: Opioid-Related Substance Abuse Treatment Admissions: Non-Criminal Justice Referrals Only

	IV-Poisson Estimates							
Dependent Variable:	Opioid-Related Substance Abuse Treatments (Excluding Criminal Justice)							
ln(Part D per capita)	0.700***	0.666***	0.238	0.508*	0.831***	0.503*	0.509**	0.532*
	(0.255)	(0.248)	(0.506)	(0.296)	(0.259)	(0.295)	(0.236)	(0.296)
PMP Prescriber	-0.001	0.002	0.081	0.113	-0.015	-0.057	-0.002	-0.031
	(0.087)	(0.089)	(0.082)	(0.077)	(0.093)	(0.094)	(0.089)	(0.101)
PMP Proactive	0.046	0.04	-0.065	-0.021	0.032	0.094	0.098	0.055
	(0.130)	(0.131)	(0.169)	(0.149)	(0.117)	(0.107)	(0.097)	(0.103)
PMP Real Time	-0.088	-0.083	-0.076	-0.086	-0.049	-0.087	-0.057	-0.074
	(0.095)	(0.096)	(0.111)	(0.107)	(0.095)	(0.094)	(0.079)	(0.087)
ln(% White)	-4.979	-4.579	-16.964***	-12.502***	-1.829	-0.22	1.706	-0.138
	(3.143)	(3.150)	(6.317)	(4.804)	(3.027)	(2.064)	(1.904)	(2.590)
ln(% Black)	-0.058	-0.017	-0.997*	-0.491	0.124	0.400**	0.368	0.292
	(0.268)	(0.272)	(0.521)	(0.373)	(0.228)	(0.199)	(0.285)	(0.229)
ln(Unemployment Rate)	0.227	0.231	0.288	0.244	0.218	0.127	0.147	0.071
	(0.217)	(0.222)	(0.296)	(0.254)	(0.214)	(0.212)	(0.177)	(0.200)
ln(Median Income)	-0.287	-0.331	-0.551	-1.377	-0.61	0.84	0.812	0.374
	(0.949)	(0.952)	(1.669)	(1.422)	(0.864)	(0.720)	(0.812)	(0.794)
log(% Private Insurance)	-1.892**	-1.964**	-1.5	-2.143**	-1.981**	-1.355*	-2.041***	-1.221*
	(0.841)	(0.877)	(1.135)	(1.049)	(0.796)	(0.759)	(0.739)	(0.727)
Ages	All	Ages 12-54	Ages 12-20	Ages 21-29	Ages 30-39	Ages 40-49	Ages 50-54	Ages 55+
N	688	688	688	688	688	688	688	688

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 9: Opioid-Related Substance Abuse Treatment Admissions: Excluding Admissions with Medicare Payments and Disabled/Retired Individuals

	IV-Poisson Estimates		
Dependent Variable:	Opioid-Related Substance Abuse Treatments		
ln(Part D per capita)	0.747**	0.763**	0.023
	(0.337)	(0.338)	(0.450)
Ages	All	Ages 12-54	Ages 55+
N	688	688	688

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: PMP laws, ln(% White), ln(% Black), ln(Unemployment Rate), ln(Median Income), ln(% Private Insurance), state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table 10: Excluding Massachusetts and Oregon

	IV-Poisson Estimates				
Dependent Variable:	Treatments		Deaths		Opioids
ln(Part D per capita)	0.750**	0.738***	0.316	0.35	0.408***
	(0.301)	(0.283)	(0.349)	(0.316)	(0.071)
Ages	All	Ages 12-54	All	Ages 0-64	
Data Set	TEDS	TEDS	NVSS	NVSS	ARCOS
N	660	660	588	588	588

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: PMP laws, ln(% White), ln(% Black), ln(Unemployment Rate), ln(Median Income), ln(% Private Insurance), state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Appendix

Table A1: Mortality Estimates, Unweighted

	IV-Poisson Estimates (Unweighted)								
Dependent Variable:	Opioid-Related Deaths								
ln(Part D per capita)	0.157	0.18	-0.095	0.125	0.428	0.279	-0.091	0.527	0.015
	(0.254)	(0.235)	(0.276)	(0.179)	(0.335)	(0.274)	(0.248)	(0.407)	(0.335)
PMP Prescriber	-0.1	-0.101	-0.015	-0.049	-0.189	-0.125	-0.053	-0.013	-0.132
	(0.091)	(0.091)	(0.077)	(0.092)	(0.116)	(0.097)	(0.082)	(0.107)	(0.085)
PMP Proactive	-0.148	-0.153	-0.264	-0.191	-0.178	-0.142	-0.067	-0.072	-0.136
	(0.149)	(0.149)	(0.204)	(0.177)	(0.154)	(0.135)	(0.154)	(0.297)	(0.163)
PMP Real Time	-0.048	-0.046	0.069	-0.074	-0.047	-0.039	-0.113**	0.074	-0.075
	(0.050)	(0.050)	(0.104)	(0.066)	(0.072)	(0.070)	(0.052)	(0.067)	(0.080)
ln(% White)	0.521	0.4	-9.803**	-0.985	3.2	0.286	-0.02	-0.076	-1.511
	(2.685)	(2.765)	(4.969)	(4.511)	(2.779)	(2.973)	(2.526)	(3.276)	(2.923)
ln(% Black)	0.699	0.721	-0.119	0.397	0.685	0.721	1.150***	0.534	0.122
	(0.462)	(0.486)	(0.610)	(0.476)	(0.647)	(0.511)	(0.399)	(0.547)	(0.371)
ln(Unemployment Rate)	0.291**	0.290**	0.068	0.360**	0.335**	0.406***	0.069	0.064	0.086
	(0.129)	(0.130)	(0.295)	(0.181)	(0.170)	(0.131)	(0.135)	(0.226)	(0.223)
ln(Median Income)	0.132	0.082	-1.111	0.683	0.329	0.278	-0.929	1.01	2.059
	(1.100)	(1.089)	(1.622)	(1.544)	(1.221)	(1.140)	(1.070)	(1.389)	(1.284)
log(% Private Insurance)	-1.492***	-1.535***	-1.178	-1.309*	-1.791***	-1.306**	-1.928***	0.458	-0.589
	(0.465)	(0.482)	(0.893)	(0.693)	(0.634)	(0.576)	(0.545)	(0.747)	(0.691)
Ages	All	Ages 0-64	Ages 10-19	Ages20-29	Ages 30-39	Ages 40-49	Ages 50-59	Ages 60-64	Ages 65+
N	612	612	612	612	612	612	612	612	612

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population).

Table A2: Opioid-Related Substance Abuse Treatment Admissions: 1992-2011

	IV-Poisson Estimates							
Dependent Variable:	Opioid-Related Substance Abuse Treatments							
ln(Part D per capita)	0.858**	0.862**	0.759	0.740*	0.878**	0.57	0.588	0.443
	(0.393)	(0.378)	(0.516)	(0.432)	(0.447)	(0.477)	(0.370)	(0.408)
ln(% White)	0.522	0.629	-13.523***	-5.558***	4.527	3.086	4.21	-0.427
	(2.998)	(3.031)	(4.816)	(2.141)	(3.287)	(3.318)	(3.416)	(3.127)
ln(% Black)	0.726	0.705	-1.637**	-0.202	0.878**	1.184**	1.489***	1.453**
	(0.552)	(0.539)	(0.636)	(0.562)	(0.406)	(0.550)	(0.532)	(0.644)
ln(Unemployment Rate)	0.509**	0.508**	0.897***	0.741***	0.339	0.219	0.234	0.184
	(0.228)	(0.222)	(0.320)	(0.209)	(0.244)	(0.234)	(0.224)	(0.248)
ln(Median Income)	1.347	1.387	1.785	0.677	1.169	1.912***	0.99	0.315
	(0.927)	(0.936)	(2.322)	(1.894)	(0.725)	(0.707)	(0.727)	(0.721)
log(% Private Insurance)	-2.544**	-2.505**	-0.706	-2.282*	-2.443***	-2.169***	-2.811***	-3.300***
	(1.001)	(1.023)	(1.344)	(1.326)	(0.887)	(0.756)	(0.824)	(0.719)
Ages	All	Ages 12-54	Ages 12-20	Ages 21-29	Ages 30-39	Ages 40-49	Ages 50-54	Ages 55+
N	973	973	973	973	973	973	973	973

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.

Table A3: Opioid-Related Substance Abuse Treatment Admissions: Log-linear Specification

	IV Log-Linear							
Dependent Variable:	Opioid-Related Substance Abuse Treatments (Excluding Criminal Justice)							
ln(Part D per capita)	0.782**	0.732**	0.742	0.432*	0.726**	0.526	0.578*	0.489
	(0.319)	(0.300)	(0.522)	(0.261)	(0.338)	(0.402)	(0.306)	(0.363)
PMP Prescriber	-0.045	-0.051	0.086	0.071	-0.061	-0.071	-0.027	-0.059
	(0.099)	(0.101)	(0.075)	(0.076)	(0.112)	(0.121)	(0.117)	(0.125)
PMP Proactive	0.198	0.194	0.025	0.143	0.207	0.235*	0.223*	0.175
	(0.172)	(0.178)	(0.247)	(0.221)	(0.181)	(0.142)	(0.136)	(0.117)
PMP Real Time	-0.069	-0.067	0.054	-0.025	-0.073	-0.089	-0.108	-0.123
	(0.091)	(0.090)	(0.133)	(0.107)	(0.087)	(0.089)	(0.089)	(0.107)
ln(% White)	-1.224	-1.171	-8.092**	-2.578	0.442	0.51	1.754	0.21
	(2.020)	(1.943)	(3.555)	(2.141)	(2.182)	(1.838)	(1.796)	(1.854)
ln(% Black)	0.555*	0.614*	0.042	0.428	0.623*	0.532*	0.464	0.326
	(0.331)	(0.351)	(0.558)	(0.372)	(0.348)	(0.311)	(0.407)	(0.364)
ln(Unemployment Rate)	0.277	0.267	0.530**	0.267	0.294	0.231	0.21	0.226
	(0.173)	(0.174)	(0.226)	(0.180)	(0.191)	(0.215)	(0.204)	(0.230)
ln(Median Income)	-0.497	-0.522	-0.58	-1.634	-0.385	0.59	0.853	0.571
	(0.945)	(0.949)	(1.462)	(1.210)	(1.111)	(1.053)	(1.158)	(1.251)
log(% Private Insurance)	-0.859	-1.009	0.805	-0.222	-1.311	-0.969	-1.454	-0.427
	(0.898)	(0.912)	(1.202)	(0.920)	(0.870)	(0.881)	(1.028)	(0.925)
Ages	All	Ages 12-54	Ages 12-20	Ages 21-29	Ages 30-39	Ages 40-49	Ages 50-54	Ages 55+
N	688	688	683	688	687	688	688	678

Notes: ***Significance 1%, ** Significance 5%, * Significance 10%. Standard errors in parentheses adjusted for clustering at state level. All regressions weighted by population. Controls also included but not shown: state fixed effects, year fixed effects, ln(Fraction 65+), and ln(population). Population refers to size of population for the relevant age group.