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How access to addictive drugs affects the supply of substance abuse treatment: Evidence from Medicare Part D

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Abstract

This paper documents how substance abuse treatment (SAT) providers and services respond to increases in population-level opioid addiction. I do this by exploiting the implementation of Medicare Part D as an exogenous increase in the availability of prescription opioids. Starting in 2006, states with higher shares of the population eligible for Medicare Part D experienced increases in residential and hospital inpatient SAT facilities, beds dedicated to SAT, and SAT facilities offering medication-assisted treatment, relative to states with lower shares. These results suggest that the supply of SAT in the United States is capable of responding significantly to changes in demand.

KEYWORDS

addiction, medicare, opioids, prescription, rehabilitation, substance abuse

1 | INTRODUCTION

In 2005, the Congressional Budget Office noted that by improving access to prescription drugs, Medicare Part D had the potential to increase the incidence of adverse drug events (Zhang et al., 2009). These concerns appear to have been well-founded. Recent analysis has determined that Medicare Part D exacerbated the opioid epidemic by increasing access to prescription opioids, thereby driving people into treatment for opioid-use disorder (OUD; Powell et al., 2020). If this increase in addiction led to greater aggregate demand for substance abuse treatment (SAT), it is possible that Medicare Part D could have also induced the entry of new SAT providers to treat these individuals.[1] This is particularly important because SAT is perhaps the most effective available method of treating OUD, especially when conducted using medication-assisted treatment (MAT; National Academies of Sciences, Engineering, and Medicine, 2019). Given the high costs to society imposed by substance-use disorders (Caulkins et al., 2014), and the current shortage of MAT availability (Dick et al., 2015; Jones et al., 2015), it is policy-relevant to understand whether the supply of SAT providers, both public and private, has been responsive to changes in population-level opioid addiction rates. If not, then it is possible that further policy intervention may be necessary to bolster the supply of treatment providers and MAT in addition to previous and ongoing efforts.

Although the question of whether increases in opioid addiction cause increases in the supply of SAT is fundamental for understanding the role of policymakers in addressing the opioid crisis, there exists little to no research on this topic. Furthermore, assessing this relationship empirically is not straightforward since simple correlations may produce misleading conclusions. For example, high addiction rates may be the product of local economic downturns, which could independently cause closures or prevent openings of SAT clinics. It is also possible that people are most likely to seek treatment when their opioid supply is cut off, which could attenuate the correlation between increases in opioid access and demand for SAT. To address these challenges, I use a quasi-experimental approach to circumvent these methodological issues and identify the causal impact of population-wide addiction on treatment capacity.

Estimating the effects of Medicare Part D on the supply of SAT is an empirical challenge since the program was implemented simultaneously for all Medicare beneficiaries on Jan 1st, 2006. In order to circumvent this difficulty, I follow the approach taken by Alpert et al. (2015) and Powell et al. (2020) by comparing states with higher shares of the population aged 65+ to states with lower shares, before and after the program's introduction in 2006. The premise of this method is that states with more Medicare-eligible individuals should have greater Part D enrollment (and, therefore, opioid use), on average, than states with fewer eligible people. Indeed, empirical tests confirm that high-share states had significantly greater Part D enrollment counts than low-share states. I exploit data on the near-universe of specialty licensed SAT facilities in the United States taken from the National Survey of Substance Abuse Treatment Services (N-SSATS) to estimate how Medicare D has affected the supply of SAT providers and services. Estimates suggest that a 10% increase in the supply of prescription opioids due to Part D increased residential and hospital inpatient SAT facilties by approximately 2.5% and beds by approximately 2.3%, compared to averages before Part D began in 2006. I also find that residential/hospital inpatient client counts increased by a similar magnitude, which implies that little to no additional within-facility crowding has resulted from this increase in addiction. Additionally, Part D has increased the number of SAT facilities offering MAT for OUD by 10.4%, an effect which was nearly entirely driven by the adoption of naltrexone.

This paper contributes to several strands of literature. Primarily, it contributes to our understanding of the determinants of healthcare access. The majority of the work on this topic has focused on the geographic distribution of physicians and the influence of public incentives on said distribution (Bärnighausen & Bloom, 2009). On the other hand, very little research has focused on whether treatment availability responds to demand, particularly with respect to SAT. The evidence that does exist in this space centers around insurance expansions rather than changes in opioid availability. For example, Maclean et al. (2018) find that state-mandated private insurance coverage of SAT services reduces provider participation in certain (public) insurance markets. On the other hand, Hamersma and Maclean (2021) and Meinhofer and Witman (2018) find that public insurance expansions change the types of services available from SAT providers. However, the effects of changes in opioid availability are likely to differ from those of specifc insurance expansions if the newly addicted people are covered by a diversity of insurers or are uninsured. Furthermore, changes in opioid access could also affect other outcomes, such as employment rates, which may have independent impacts on health insurance status and, therefore, demand for treatment. Thus, it is difficult to project what the effect of increased addiction would be on the supply of SAT providers based solely on studies of insurance expansions. This paper also contributes to the literature on Medicare Part D's implications for supply-side actors (Blume-Kohout & Sood, 2013; Dranove et al., 2014, 2020; Hu et al., 2017).[2] Furthermore, it is the first paper to analyze Part D's effects on provider behavior that is unrelated to prescribing tendencies.

2 | BACKGROUND

2.1 | Medicare Part D and opioid diversion

Medicare Part D is an opt-in prescription drug insurance program for Medicare enrollees. Passed as part of the Medicare Modernization Act on December 8th, 2003, and implemented on January 1st, 2006, Part D was the largest expansion to the Medicare program since its inception in 1966. Before that, only certain non-prescription drugs were covered by Medicare Parts A and B, and enrollees had to have either their own supplemental drug coverage or pay out-of-pocket for prescription medication. This left approximately 25% of enrollees aged 65+ without prescription drug coverage as of 2003 (Safran et al., 2005). Take-up of Part D was rapid (Cubanski et al., 2019). Approximately 22 million people (51% of Medicare enrollees) opted-in after just the first year, which grew to about 43.5 million people (72% of Medicare enrollees) by 2018. Half-way through the first year of implementation, the fraction of seniors without prescription drug coverage had already dropped to around 10% (HHS, 2006). A wide body of research has examined how Part D decreased out-of-pockets costs and increased drug utilization among seniors (Duggan & Morton, 2010; Ketcham & Simon, 2008; Lichtenberg & Sun, 2007; Yin et al., 2008). While these studies typically assume that Medicare Part D's effects began in 2006, Alpert (2016) demonstrates that the program's announcment may have influenced utilization among the elderly in the years leading up to implementation (although this does not appear to have been an issue in the outcomes I study).

Medicare Part D has covered prescription opioids since its implementation in 2006 and appears to have increased uptake of the drug among enrollees. Powell et al. (2020) found that after Part D went into effect, people aged 66–71 experienced a 28% increase in opioid prescriptions relative to people aged 59–64. Furthermore, there is evidence that Medicare Part D also increased the prescription drug consumption of those below age 65. Alpert et al. (2015) find that non-elderly people in counties with higher shares of the population eligible for Medicare experienced larger increases in prescription drug consumption

after 2006 than non-elderly people in counties with lower shares of Medicare-eligible people. Powell et al. (2020) translate this design to that state level and find that states with greater shares of the population aged 65+ experienced larger increases in opioid distributions per capita after Part D was implemented. Lastly, and importantly, they find that a 10% increase in opioid disbursement caused by Part D increased opioid mortality by 7.1% and opioid SAT admissions by 9.6%. Counterintuitively, these effects were entirely driven by people aged <65. When taken in conjunction with the effects on opioid prescriptions for people aged 66+, Powell et al. (2020) conclude that a substantial portion of the opioids distributed through Part D were diverted away from their intended recipients and toward abuse. Given Part D's impacts on prescription opioid treatment admissions, it stands to reason that the policy may have increased aggregate demand for SAT, thereby encouraging entry among SAT providers.

2.2 | Substance abuse treatment capacity in the United States

The main platforms for delivering SAT in the United States are community-based specialized SAT facilities (NIDA, 2018). These facilities offer several types of programming, which can be separated into two major treatment settings: outpatient and inpatient. Outpatient treatment ranges from simple drug education and counseling once per week, to intensive programs that meet every day (SAMHSA, 1997). Inpatient treatment can be separated into two further categories: residential and hospital. Residential inpatients stay in facilities under 24-h supervision, the length of stay depending greatly on the individual. Hospital inpatients, on the other hand, usually require care for acute issues including severe overdoses, withdrawal, or complications from comorbidities. Stays in hopitals are typically shorter than stays in residential facilities. The majority of SAT clients are in outpatient treatment, representing about 90% of clients in treatment on March 31st, 2017 according to the N-SSATS. However, according to the Treatment Episode Data Set (TEDS), outpatients only make up about 60% of new SAT admissions, implying that outpatients have longer stints of treatment than residential and hospital inpatient clients. Finally, one of the most important differences for this study between residential/hospital inpatient and outpatient care is how patient capacity is measured. For residential/hospital inpatient treatment, capacity is mostly determined by the number of beds per facility dedicated to SAT patients and, to a lesser degree, staffing levels. For outpatient treatment, determing capacity is less clear since the maximum number of clients does not depend on beds. Unlike beds, staffing data are not regularly collected by the N-SSATS.[3]

An important component of modern SAT is the use of specialized medications to help people overcome addiction. Called MAT, three varieties have been approved by the United States Food and Drug Administration (FDA) to combat opioid-use disorders (SAMHSA, 2020a). Methadone, first approved by the FDA in 1947 and used for the treatment of addictions since the 1970s, is an opioid that is used to wean people off of stronger narcotics like heroin and prescription pain relievers (Rettig & Yarmolinsky, 1995). Buprenorphine is similar to methadone in that it is an opioid that produces weaker euphoric effects than traditional narcotics and in that it helps users move away from more dangerous substances. It was approved by the FDA for the treatment of opioid-use disorder in late 2002 (SAMHSA, 2020a). Lastly, naltrexone was approved by the FDA for treatment of opioid dependence in 1984 (Krupitsky et al., 2010). Unlike the other two MATs, naltrexone is not an opioid substitute. Instead, it binds to opioid receptors and blocks the euphoric effects of the drugs. The effectiveness of these medications at combatting opioid addiction is empirically well-established (National Academies of Sciences, Engineering, and Medicine, 2019). However, despite these clinical benefits, MATs have not yet been fully embraced by SAT providers. As of 2018, only 44% of providers offered at least one of them as part of their service according to the N-SSATS. However, this represents a 123% increase over the offer rate in 2002.

3 | DATA AND EMPIRICAL STRATEGY

3.1 | Specialty substance abuse treatment facility data

The N-SSATS is an annual survey of specialty SAT facilities that collects data on many of this study's outcomes. The sampling frame for the N-SSATS is called the Inventory of Behavioral Health Services (I-BHS), which includes a registry of the universe of SAT facilities known to the SAMHSA.[4] Data collection for the N-SSATS occurs between late March and early December each year, during which time surveys are sent to all facilities on the I-BHS. New facilities that are discovered by SAMHSA during this period (or reported by state substance abuse agencies) are also included in the N-SSATS and subsequently placed on the I-BHS for the following year. Facilities fill out a questionnaires of services they provide, counts of clients currently receiving treatment, and counts of beds dedicated to SAT clients (if applicable).[5] Since the N-SSATS is voluntary for facilities, there

is a certain amount of non-response each year. These response rates are recorded by state and year, and are nationally around 90% or above in each year during my sample period.

This study uses the N-SSATS for three categories of outcomes: facility counts, residential and hospital inpatient bed counts, and aggregate client counts. The N-SSATS collects data at the facility level on the types of treatment setting (inpatient, outpatient, both) and varieties of MAT for OUD they offer (methadone, buprenorphine, and/or naltrexone), as well as whether the facility is an offically licensed opioid treatment program (OTP) by SAMHSA. The N-SSATS also collects data on the number of beds designated for SAT patients in both residential and hospital inpatient facilities. These data were made publicly available as exact counts at the facility level until 2007, but in subsequent survey years the counts were censored into bins to protect facility privacy. However, by request to SAMHSA, I have obtained access to aggregate data containing exact counts of residential and hospital inpatient beds at the state-year level through 2017.[6] Lastly, I use the N-SSATS client counts by treatment setting (outpatient or residential/hospital inpatient), which I obtained in state-year aggregates from the N-SSATS Annual Reports (SAMHSA, 2020b).[7] It is important to note that I cannot disaggregate these client data by age or by substances used at admission (opioids, alcohol, etc.). I use these counts of facilities, beds, and clients to construct rates per 100,000 people. I also divide these rates by state-year facility response rates (described above) in order to better-account for non-response.[8] The time period I use for most of my analysis is 2000–2018, starting when the N-SSATS eligibility criteria were finalized.[9]

Additionally, since it is possible that Medicare Part D increased the aggregate number of SAT clients, but not facilities or beds, I construct "utilization rates" of clients-per-facility and clients-per-bed to examine the extent to which this occurred. Higher utilization rates indicate that facilities became more crowded, on average.[10] I also construct a ratio of inpatient beds-per-facility to examine the degree to which increases in beds are being driven by new facility construction. For utilization rates of residential/hospital inpatient facilities and beds, I consider only facilities that report both client and bed counts in a given year, which I draw from SAMHSA's N-SSATS Annual Reports (SAMHSA, 2020b).[11] However, since no such counts are available for outpatient facilities in the Annual Reports or using the publicly-available N-SSATS data, I divide the total reported outpatient clients by the number of outpatient facilities to create outpatient utilization rates.

3.2 | Detailed substance abuse treatment admission, Medicare Part D enrollment, and prescription drug distribution data

The TEDS, also conducted by SAMHSA, provides detailed information on individual admissions to all specialized SAT facilities that receive public funding (SAMHSA, 2020c). While this only represents a fraction of the facilities reporting to the N-SSATS, the TEDS provides more detailed information about individual admissions such the individual's age and substances used. I categorize a patient as being admitted for prescription opioid abuse if they list any of the substances used as "non-prescription methadone" or "other opiates and synthetics," the latter of which includes prescription opioids. Additionally, I focus on admissions of patients aged 12–54, which is the population that was induced into SAT by Medicare Part D (Powell et al., 2020). I obtain data on Medicare Part D enrollment from the Center for Medicare & Medicaid Services (CMS) Statistical Supplements (years 2006-12) and CMS Program Statistics (2013-18). Enrollment counts are aggregated to state-year levels.

Lastly, I obtain data on prescription opioid distributions from US Drug Enforcement Administration Automated Reports and Consolidated Ordering System, years 2000–2017. As mandated by the Controlled Substance Act of 1970, these data track quantities of Schedule II, and select Schedule III and IV, substances as they are supplied from manufacturers to retail distributors. I follow Powell et al. (2020) in defining a measure of prescription opioid supply distributed to a state in a given year that consists of the total morphine equivalent doses (MEDs) of the following medications: fentanyl, hydrocodone, hydromorphone, meperidine, methadone, morphine, oxycodone, codeine, dihydrocodeine, levorphanol, oxymorphone, and tapentadol.[12]

3.3 | Data on buprenorphine licensing

Although the N-SSATS documents whether or not specialty SAT facilities administer MAT, it does not account for the many providers who operate out of non-specialty settings. In order to determine if Medicare Part D had an affect on the provision of buprenorphine across all treatment settings, I use data on the granting of Drug Addiction Treatment Act of 2000 waivers by SAMHSA, which first began in 2002. These waivers are given to doctors, nurse practitioners, or physician's assistants who meet certain qualifications to enable them to treat opioid patients with buprenorphine. Each waiver specifies the number of patients (30, 100, or 275) that the practitioner is allowed to treat at once. Appendix Figure A2 displays the cumulative number of waivers and DATA 2000 patient capacity granted by year since 2002. Since SAMHSA does not record the exit of providers

who had formerly been granted DATA 2000 waivers, I measure the stock of DATA 2000 waivers capacity in two ways: based on the number of waivers ever granted and based on the number of waivers granted to providers still practicing in 2020. The former of these measurements is somewhat of an overestimate of capacity (especially later in the sample period) and the latter is an underestimate (especially earlier in the sample period).

3.4 | Population and control variables

I use state-by-year population data from the Surveillance, Epidemiology, and End Results Program for weighting regressions and two control variables (natural log of the population and fraction of the population "white"; SEER, 2019). Additionally, I control for a number of time-varying state-level policies which have been shown to have affected access to SAT and/or provider behavior (MacLean et al., 2018; Maclean & Saloner, 2019; Meinhofer & Witman, 2018; Wen et al., 2017). Specifically, these are the Affordable Care Act (ACA) Medicaid expansions, Health Insurance Flexibility and Accountability (HIFA) waivers, and State SAT Parity Laws.[13] I also control for the implementation of Pain Clinic Laws, Must-Access Prescription Drug Monitoring Programs (PDMPs), and Medical Marijuana Laws, all of which are associated with reductions in opioid prescribing (Powell et al., 2018; Rutkow et al., 2015; Sacks et al., 2021). Lastly, I control for state unemployment rates over time using data from the Bureau of Labor Statistics.

3.5 | Empirical strategy

The main challenge in estimating the impact of a national policy like Medicare Part D is assigning treatment and control groups. I follow the approach utilized in Powell et al. (2020), which exploits the fact that after the program was implemented, states with higher percentages of the population eligible for Medicare also had higher percentages of people eligible for Medicare Part D. This research design amounts to a differences-in-differences approach, where the first "difference" compares states before/after 2006, and the second "difference" compares states with varying fractions of the population aged 65+.[14] I fix the cross-sectional variation in the fraction of population aged the 65+ to its 2003 values, the year Medicare Part D was passed, in order to avoid incorporating systematic migration resulting from the policy (Figure 1 summarizes this variation across states). Thus, the treatment effect is identified by comparing outcomes of interest across states by the share of their 2003 population aged 65+ (*elderly share)*, before and after 2006.

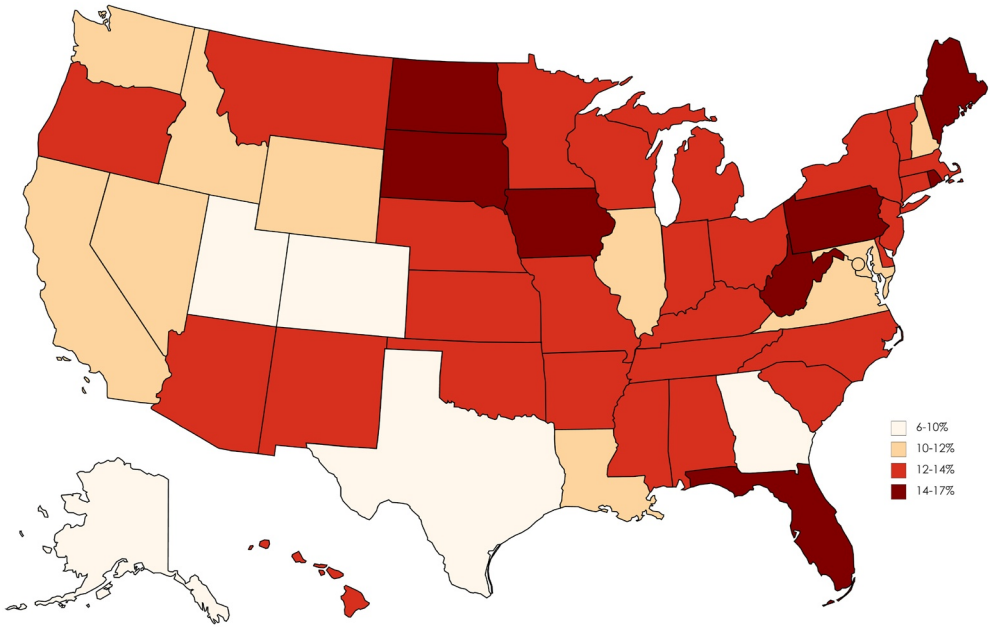

FIGURE 1 Fraction of population aged 65+ in 2003 (elderly share), by state

Below is the specification for the main differences-in-differences design:

$$y_{st} = \alpha + \gamma \left[\%aged \geq 65_{s,2003} \times Post_t \right] + X'_{st}\beta + \delta_s + \eta_t + \varepsilon_{st} \quad (1)$$

The variable y_{ist} stands in for the outcomes described above, all of which vary by state (s) and year (t). Regressions using admission, client, facility, or bed counts per 100,000 population are weighted using state population. Regressions using outcomes such as clients-per-bed, clients-per-facility, or beds-per-facility, are weighted by the outcome's denominator (e.g., regressions using beds-per-facility are weighted by state facility count). The treatment variable is as described in the previous paragraph, where $Post_t$ equals 1 in the years 2006+ and 0 otherwise. X'_{st} is a vector of control variables, added in alternate specifications. This may include a variety of policy indicators (ACA Medicaid Expansion, HIFA Waivers, State SAT Parity Laws, Strong PDMPs, Pain Clinic Laws, and Medical Marijuana Laws) and other time-varying controls (state unemployment rate, the natural log of the populaton, and fraction of population "white").[15] I also include state and year fixed effects which control for the independent effects of the fixed share of population aged 65+ and national effect of Medicare Part D, respectively. Standard errors are clustered at the state level. Given the regional differences in elderly share apparent in Figure 1 (e.g., older populations in the east and younger populations in the west), one may be concerned that the variable merely proxies for regional differences in outcomes trends. In order to address these concerns, I estimate alternate specifications in which I include region-by-year fixed effects in the regression. In these specifications, γ is identified only from variation driven by intra-regional differences in elderly share across states and the pre/post 2006 temporal variation. Since several of the outcomes I study are count variables (e.g., clients, facilities, and beds), I also estimate Poisson models in addition to the linear models.[16]

Additionally, I use an event study version of Equation (1) in which the effect of $\%aged \geq 65_{s,2003}$ is interacted with year fixed effects. This model is specified in Equation (2), where $T = \{t_0, \ldots, 2018 \backslash 2005\}$ and t_0 is either 2000 and 2002, depending on the outcome. I omit the year before Part D is implemented, 2005, as the baseline period.

$$y_{st} = \alpha + \sum_{t \in T} \gamma_t \left[\%aged \geq 65_{s,2003} \times \eta_t \right] + X'_{st}\beta + \delta_s + \eta_t + \varepsilon_{st} \quad (2)$$

4 | RESULTS

First, I provide evidence that Medicare Part D constituted an exogenous shock to aggregate demand for SAT through its effect on prescription opioid abuse. Then, I demonstrate the subsequent effects of the policy on the availability of SAT. Last, I provide instrumental variable estimates that contextualize the main results on the supply of SAT in terms of total prescription opioids distributed.

4.1 | Demand for substance abuse treatment

I replicate three key findings from Powell et al. (2020) and display the results in Figure 2. Panel A shows estimates from yearly cross-sectional regressions of elderly share of the percent of state population enrolled in Part D on elderly share. These coefficients show that, after Part D became effective in 2006, an additional percentage point of elderly share is associated with an approximately 0.4% point increase in Part D enrollment. This effect grew over time through 2018. Panel B shows that, beginning in 2006, increases in elderly share were associated with an increases in prescription opioid distributions to states. This effect grew through 2010 and then began to decline, a shift which coincides temporally with the decrease in prescription opioid abuse observed after the Oxycontin reformulation (Alpert et al., 2018). Panel C displays the effect of Part D on prescription opioid SAT admissions per 100,000 population. Similar to the trends in opioid distribution, after 2006 a 1% increase in elderly share caused an increase in admissions by about 20 per 100,000 population at its peak in 2011. After 2011, this differential begins to fall back to 2005 levels, which coincides with the reformulation as well. The parallel pre-treatment trends in opioid admissions through 2005 indicate that states with varying levels of elderly shares were experiencing similar trajectories of opioid abuse before Part D began.

Next, I demonstrate that Medicare Part D's effect on prescription opioid admissions increased SAT clients in aggregate rather than just crowding out other types of admissions. Figure 3 displays event study coefficients from estimating Equation (2) using outpatient and residential/hospital inpatient aggregate client counts per 100,000 population as the outcomes. Panels A and B demonstrated that, starting in 2006, a percentage point increase in elderly share is associated with increases in both categories of SAT clients after several years of parallel pre-treatment trends. Summing the treatment effects across event studies indicates

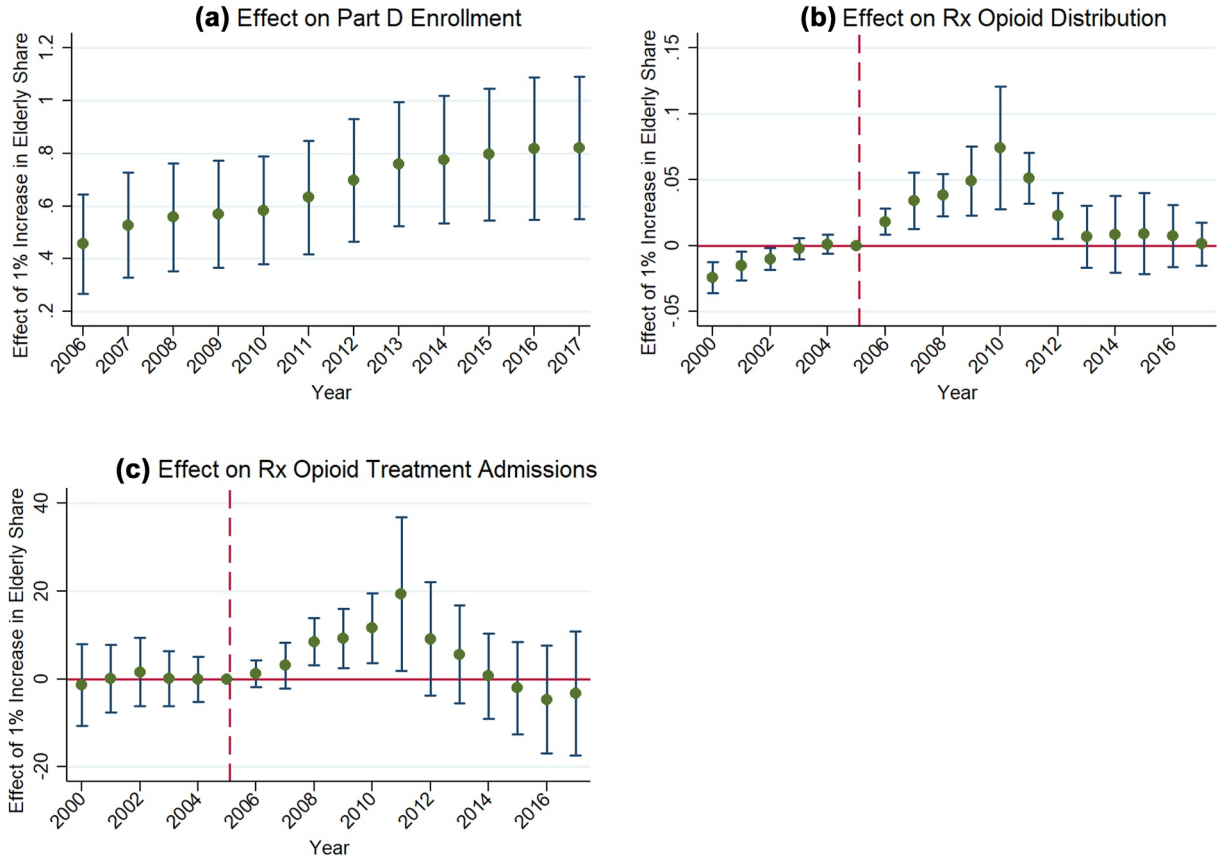

FIGURE 2 Event Studies of the Effects of Medicare Part D on Demand for substance abuse treatment (SAT). Panel A plots coefficients from yearly cross-sectional regressions between state-level elderly share and enrollment in Medicare Part D. Panel B plots event study coefficients of from estimating Equation (2) with opioids distributions per 100,000 population as the outcome. Panel C plots event study coefficients from estimating Equation (2) with SAT admissions for opioid use among individuals aged 12–54 per 100,000 population aged 12–54 as the outcome. Part D enrollment data from Center for Medicare & Medicaid Services (CMS), opioid distribution data from Automated Reports and Consolidated Ordering System (ARCOS), SAT admissions data from Treatment Episode Data Set (TEDS). Regressions producing Panels B and C include state and year fixed effects. Policy controls include Affordable Care Act (ACA) Medicaid Expansion, SAT Parity, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

increases in aggregate clients similar to the effects on prescription opioid admissions from Figure 2, Panel C, through 2011. However, unlike the estimates for only prescription opioid admissions, the relative increases in aggregate clients do not decline after 2011. These effects are summarized via differences-in-differences models by estimating Equation (1) with client counts as the outcomes with results displayed in Table 1. The preferred specification in column (3) indicates that a percentage point increase in elderly share is associated with a 2.5% increase in residential and hospital inpatient clients and a 3.6% increase in outpatient clients relative to the 2000–2005 pre-treatment means. These estimates are robust to excluding non-policy controls in column (2) and the exclusion of all controls in column (1). Additionally, the results are robust to inclusion of region-by-year fixed effects and use of Poisson model in columns (4) and (5), respectively.

4.2 | Residential/hospital inpatient and outpatient substance abuse treatment availability

In this section, I show how Medicare Part D affected the availability of SAT facilities and beds. Since client capacity at residential and hospital inpatient facilities is constrained by the number of open beds, as unlike outpatient facilities, I choose to split my analysis along these lines to allow for differing effects of Part D. I estimate event studies for residential and hospital inpatient facilities and beds per 100,000 population and display the results in Figure 4, Panels A and B. Both estimates show insignificant pre-period coefficients before Part D is introduced, after which states with higher shares of the population aged

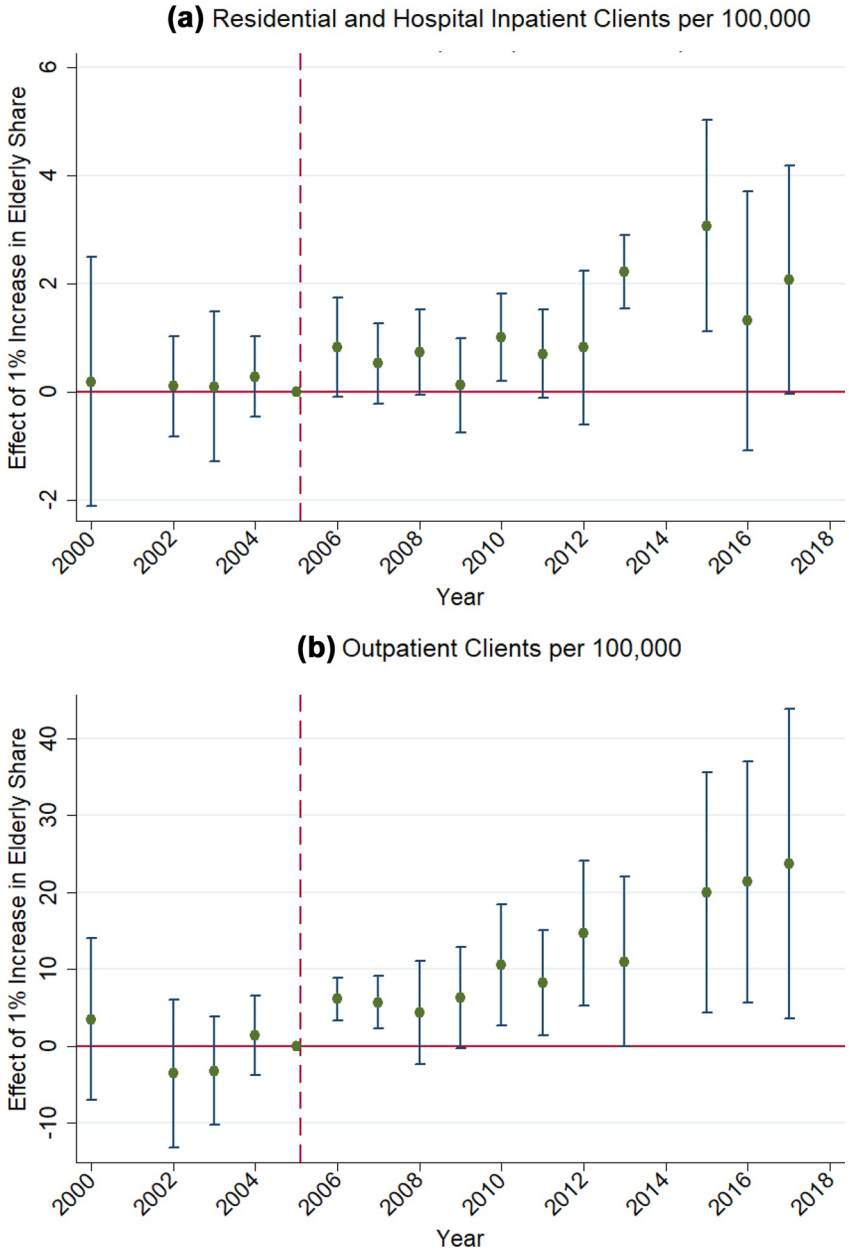

FIGURE 3 Event Studies of the Effects of Medicare Part D on Aggregate substance abuse treatment (SAT) Client Counts. Panels A and B are produced by estimating Equation (2) with residential and hospital inpatient or outpatient clients per 100,000 population as the outcomes. Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data taken from the National Survey of Substance Abuse Treatment Services (N-SSATS). Policy controls include Affordable Care Act (ACA) Medicaid Expansion, SAT Parity, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

65+ experience increases in facilities and beds relative to states with lower shares. Similar to the results for client counts, and contrasting with the results for opioid admissions, these effects on treatment availability do not contract again after 2011 and actually continue to increase slightly through 2018. I summarize these event study results by estimating Equation (1) with facility and beds counts per 100,000 population as the outcomes. The results are displayed in Table 2, Panels A and B. The preferred specification (column (3)) indicates that an additional percentage point of elderly share is associated with a 2.3% increase in residential and hospital inpatient facilities per 100,000 population and a 2.0% increase in beds per 100,000 population, relative to the 2000–2005 pre-treatment means. The results are also robust to exclusion of control variables, inclusion of region-by-year fixed effects, and use of Poisson models.

I also test whether, on average, the effects on bed capacity were driven by facilities altering their bed stocks or if they were entirely driven by changes in the number of facilities. I do this by estimating Equation (1) with the outcome being the state-level ratio of beds over residential and hospital inpatient facilities. Since a certain number of residential and hospital inpatient facilities fail to report bed and/or client data, these models are estimated on a sample of only facilities that report both pieces of information in a year. These estimates are displayed in Table 2, Panel C. Across all specifications, there are no statistically significant effects of elderly share on beds per facility. Looking at the preferred specification in column (3), the reported confidence interval allows me to rule out effects as small as an increase of 0.23 beds per facility at the 95% level. Exclusion of controls or inclusion of region-by-year fixed effects alter this estimate very little. Since the point estimate in Panel B, column

TABLE 1 Effect of medicare Part D on aggregate substance abuse treatment (SAT) client counts

	Clients per 100,000				Client Count
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Residential and Hospital Inpatients					
% Aged $65+_{2003}$ × Post	1.235**	0.998***	1.039***	1.427**	0.035***
	(0.466)	(0.349)	(0.300)	(0.557)	(0.012)
N	816	816	816	816	816
Mean of Outcome (2000-05)	40.994	40.994	40.994	40.994	2328.19
Panel B: Outpatients					
% Aged $65+_{2003}$ × Post	14.155*	13.162**	11.893**	12.128**	0.044**
	(7.552)	(6.102)	(5.146)	(5.849)	(0.018)
N	816	816	816	816	816
Mean of Outcome (2000-05)	344.277	344.277	344.277	344.277	19552.47
Policy Controls		X	X	X	X
Other Controls			X	X	X
Region × Year FEs				X	X
Model	Linear	Linear	Linear	Linear	Poisson

Note: Regressions produced by estimating Equation (1) with residential and hospital inpatient or outpatient clients (rates per 100,000 population or counts) as the outcomes. Outcome data taken from the N-SSATS. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions are weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

(3) is 0.877, this suggests that the majority of Part D's effect on the number of residential and hospital inpatient beds is due to an increase in the number facilities, as opposed to changing the number of beds per facility. I examine whether this increase in the availability of residential and hospital inpatient SAT services was commensurate with the increase in clients documented above. In order to determine whether facilities became more crowded with residential and hospital inpatient clients due to Part D, I estimate Equation (1) with utilization rates for facilities and beds as the outcomes and display the results in Appendix Table A3, Panel A. These estimates suggest any increase in utilization rates that may have occurred were small and the confidence interval in column (5) rules out effects on clients-per-bed greater than 1.7% of the pre-treatment mean at the 95% level.

Next, I examine the impact of Medicare Part D on outpatient treatment facilities. Since outpatient clients do not take up beds, the only measure of outpatient treatment capacity available is the number of outpatient facilities per 100,000 population. I estimate Equation (2) using this outcome and display the lead and lag coefficients in Figure 5. None of the pre-period coefficients are significantly different from zero, though there is a slight downward trend leading up to implementation 2006. After Part D began, states with higher elderly shares experienced growth in the number of outpatient facilities over time. However, many of these coefficients are imprecisely estimated with large confidence intervals. I estimate Equation (1) for outpatient facilities and display the difference-in-difference estimates in Table 3. The treatment effect appears to be statistically insignificant using the linear models shown in columns (1)-(4) and only significant at the 10% level when using a Poisson model in column (5). However, although the point estimates for outpatient facilities are all statistically insignificant at the 95% level, the Poisson estimates are not significantly different than the Poisson estimates for residential and hospital inpatient facilities at even the 90% level.[17] Therefore, I cannot formally rule out the null hypothesis that the effects of Part D on residential/hospital inpatient and outpatient facilities are the same. Appendix Table A3, Panel B shows the results from estimating Equation (1) using outpatient utilization rates as the outcomes. These results suggest that Part D may have increased outpatient clients per-facility, although estimates are sensitive to the specification.

These effects on the supply of residential/hospital inpatient and outpatient SAT may explain some of the persistence in the effect of Part D on aggregate client counts as displayed in Figure 3. Previous evidence indicates that the opening of new SAT facilities in a given area results in a persistent increase in local treatment admissions (Swenson, 2015). Even if the effect on prescription opioid admissions began to decrease after 2011, the newly available treatment facilities resulting from Part D could have still been used by people with other conditions.

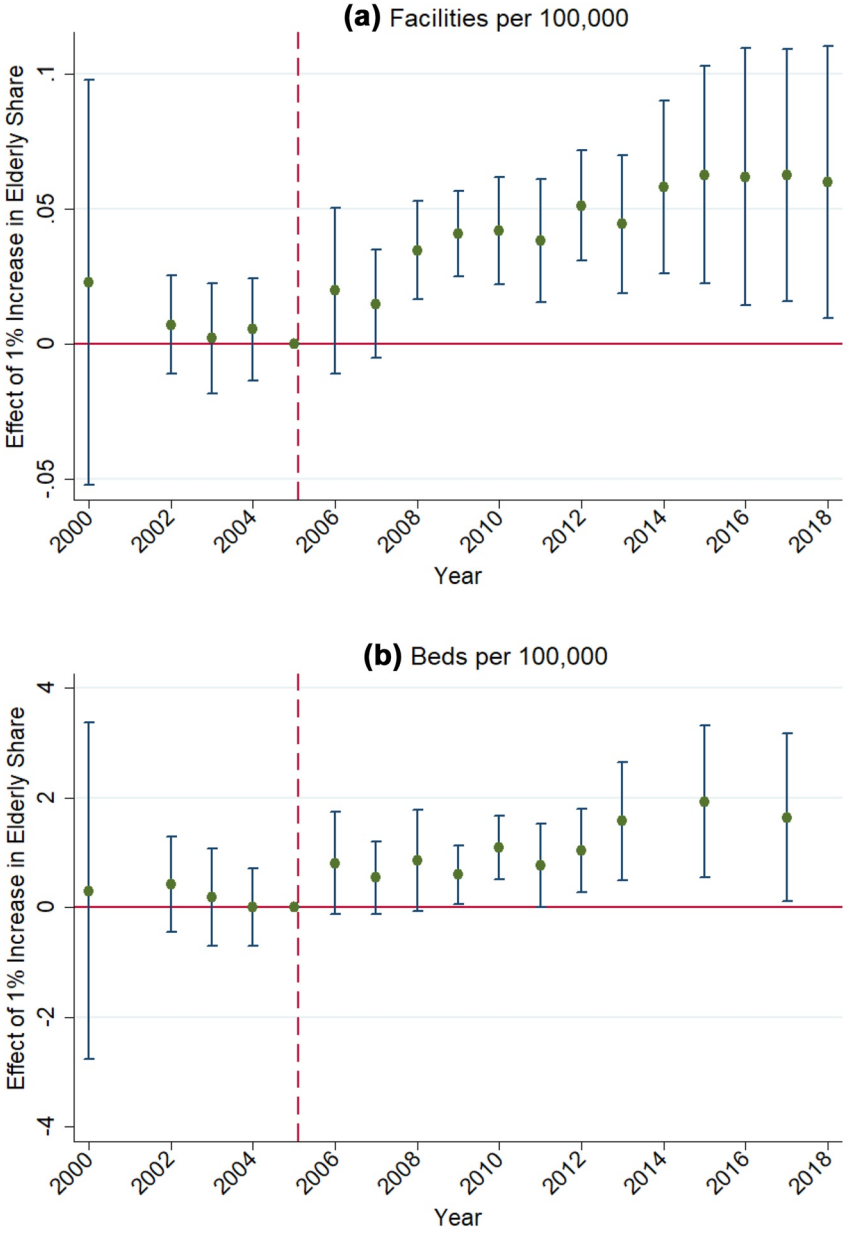

FIGURE 4 Event Studies of the Effects of Medicare Part D on Residential and Hospital Inpatient Facilities and Beds. Panels A and B are produced by estimating Equation (2) with residential and hospital inpatient facilities or beds per 100,000 population as the outcomes. Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data taken from the National Survey of Substance Abuse Treatment Services (N-SSATS). Policy controls include Affordable Care Act (ACA) Medicaid Expansion, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

4.3 | Medication-assisted treatment availability

Section 4.1 of this paper shows that Medicare Part D increased demand for SAT for OUD. Since the results in the previous section suggest that this increase in demand caused an expansion in residential and hospital inpatient SAT facilities and beds, it stands to reason that it may have also affected the number of providers offering MAT. To test this hypothesis, I analyze whether the introduction of Medicare Part D increased the number of specialty facilities offering at least one form of MAT for OUD. I begin the analysis period in 2002 since the N-SSATS did not track naltrexone offerings until that date. Additionally, bear in mind that since buprenorphine was not approved by the FDA to treat opioid-use disorder until late 2002, its offering was not tracked by the N-SSATS until 2003. Figure 6 contains the event study results from estimating Equation (2) with the outcome being the number of facilities per 100,000 population that offer at least one form of MAT. Between 2002 and 2005, outcomes trended similarly across states with varying elderly shares. Then, starting immediately in 2006, states with higher elderly shares experienced increases in facilities with MAT compared to states with lower elderly shares. This difference increased gradually throughout the sample period to its peak in 2018.

Next, I estimate differences-in-differences models using Equation (1) to summarize the relationship between elderly share and facilities with MAT for OUD, and display the results in Table 4, Panel A. I also estimate additional models examining whether Part D affected the number of facilities offering multiple forms of MAT, zero forms of MAT, or an OTP. Panel A,

TABLE 2 Effect of medicare Part D on residential and hospital inpatient treatment facilities and beds

	Facilities per 100,000				Facility Count
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel A: Facilities					
% Aged $65+_{2003}$ × Post	0.036**	0.031**	0.037***	0.043**	0.034***
	(0.014)	(0.012)	(0.011)	(0.017)	(0.010)
Mean of outcome (2000-05)	1.587	1.587	1.587	1.587	82.867
N	918	918	918	918	918
	Beds per 100,000				**Bed count**
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Panel B: Beds					
% Aged $65+_{2003}$ × Post	1.140**	0.921***	0.877***	1.300**	0.035***
	(0.518)	(0.338)	(0.282)	(0.554)	(0.011)
Mean of outcome (2000-05)	43.058	43.058	43.058	43.058	2445.379
N	765	765	765	765	765
	Beds per facility				
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	
Panel C: Beds per Facility					
% Aged $65+_{2003}$ × Post	0.043	0.042	−0.041	−0.066	
	(0.156)	(0.155)	(0.133)	(0.184)	
Mean of outcome (2000-05)	30.210	30.210	30.210	30.210	
95% confidence interval	[−0.271, 0.357]	[−0.269, 0.353]	[−0.308, 0.227]	[−0.437, 0.304]	
N	712	712	712	712	
Policy controls		X	X	X	X
Other controls			X	X	X
Region × Year FEs				X	X
Model	Linear	Linear	Linear	Linear	Poisson

Note: Regressions produced by estimating Equation (1). The outcomes in Panel A are the rate of residential and hospital inpatient facilities per 100,000 population or facility count. The outcomes in Panel B are the rate of residential and hospital inpatient beds per 100,000 population or bed count. The outcome in Panel C is the ratio of beds to residential and hospital inpatient facilities. Outcome data are taken from the N-SSATS in Panels A and B. Outcome data for Panel C taken from the N-SSATS Annual Reports (SAMHSA, 2020b), which do not include data on hospital inpatient clients or beds in 2013. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions in Panels A and B are weighted by population. Regressions in Panel C weighted by facility count. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

columns (1)-(3) indicate that elderly share is significantly related to the number facilities that provide MAT for OUD after 2006. These results are robust to the addition of controls and region-by-year fixed effects. According to the preferred specification in column (2), a percentage point increase in elderly share is associated with a 6.9% increase in facilities that offer MAT relative to the pre-treatment mean. Additionally, there are no statistically significant effects on facilities that offer no forms of MAT, or on facilities that offer at least two forms. There is also no significant impact on the number of facilities with accredited OTPs. These results suggest that the introduction of Medicare Part D, and the resulting shock to demand for opioid addiction treatment, played a role in moving the marginal facility to adopt MAT (either within existing facilities or within newly opening ones). Table 5 indicates the specific types of MATs that are driving this result by estimating Equation (1) with facilities offering nalterxone, buprenorphine, and/or methadone per 100,000 population as the outcomes. Panel B, columns (1)-(3) indicate that the effects on facilities offering MAT are nearly entirely driven by facilities newly offering naltrexone. These estimated treatment effects are very similar to those for facilities with MAT in Panel A. On the other hand, it appears that Part D did not have a significant effect on facilities offering buprenorphine or facilities offering methadone.This result is of note because naltrexone has been shown to be highly effective at improving treatment outcomes for opioid users.[18]

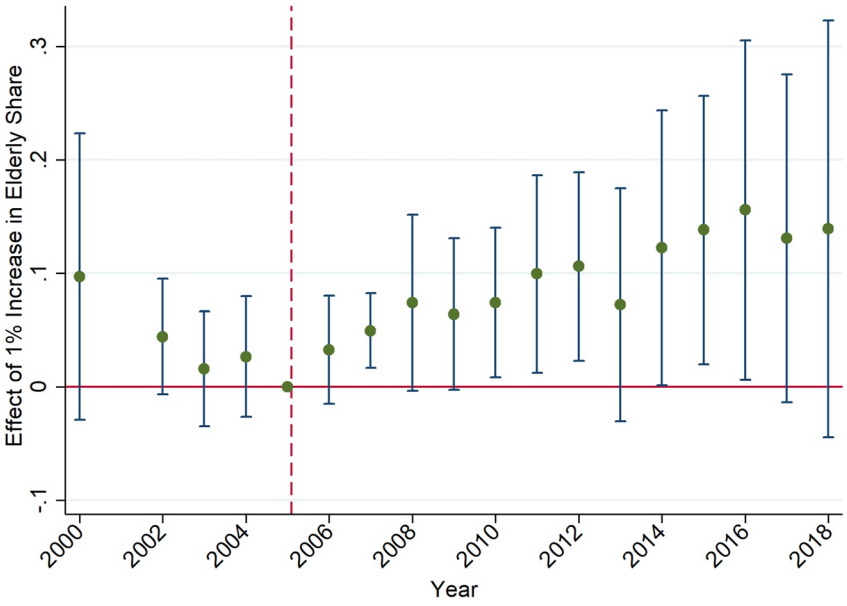

FIGURE 5 Event Study of the Effect of Medicare Part D on Outpatient Facilities per 100,000. Figure 5 plots the event study coefficients produced by estimating Equation (2) with outpatient facilities per 100,000 population as the outcome. Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data taken from the National Survey of Substance Abuse Treatment Services (N-SSATS). Policy controls include Affordable Care Act (ACA) Medicaid Expansion, substance abuse treatment (SAT) Parity, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

TABLE 3 Effect of medicare Part D on outpatient treatment facilities

	Facilities per 100,000				Facility Count
Outcome	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
% Aged $65+_{2003}$ × Post	0.061	0.047	0.058	0.097	0.031*
	(0.044)	(0.034)	(0.38)	(0.058)	(0.016)
Mean of outcome (2000-05)	3.935	3.935	3.935	3.935	223.483
N	918	918	918	918	918
Policy controls		X	X	X	X
Other controls			X	X	X
Region × Year FEs				X	X
Model	Linear	Linear	Linear	Linear	Poisson

Note: Regressions produced by estimating Equation (1) with outpatient facilities per 100,000 population as the outcome. Outcome data taken from the N-SSATS. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions are weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

As an alternative measure of buprenorphine availability, I also estimate the effects of Part D on state-level DATA 2000 buprenorphine patient capacity. Appendix Figure A3 shows the event study results from estimating Equation (2) using as the outcome the total number of bupreorphine clients per 100,000 population ever granted under DATA 2000 by state. The sample period begins in 2002, which is the first year that SAMHSA began granting DATA 2000 waivers. Through 2005, states with high and low elderly shares trended closely. Starting in 2006, states with higher elderly shares began to see increases in capacity relative states with lower elderly shares, though these differences remained statistically insignificant throughout much of the post-treatment period. Starting in 2016, when SAMHSA began granting waivers that permitted a patient capacity of 250, the effect of having a higher elderly share become much more pronounced. However, the results from the differences-in-differences models displayed in Appendix Table A4, column (4) indicate that these results are not robust to controlling for region-by-year trends in DATA 2000 client waivers. Estimating Equation (1) using clients allowable under DATA 2000 as the outcome, but restricted to professionals who are still practicing in 2020, returns smaller coefficients that are less statistically significant. In

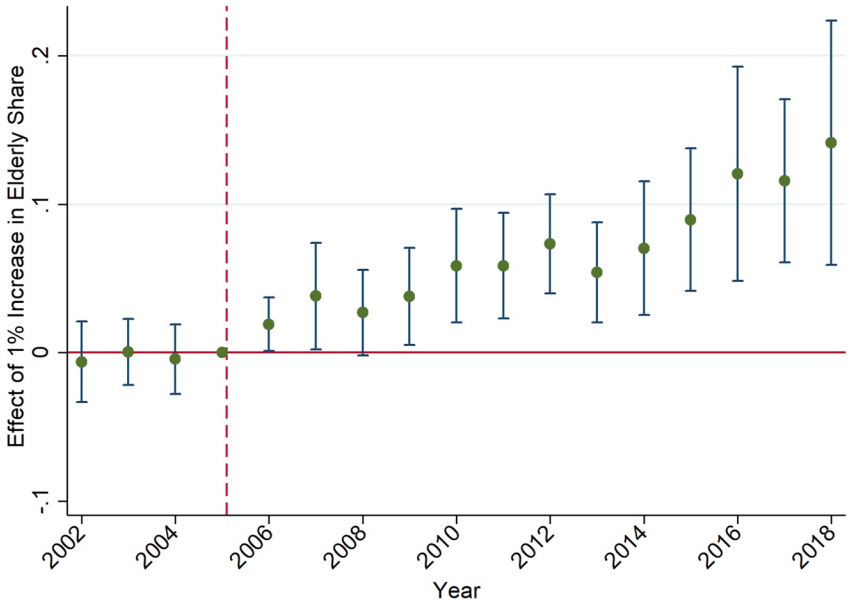

FIGURE 6 Event Study of the Effect of Medicare Part D on Facilities Offering at Least One Form of medication-assisted treatment (MAT) for OUD per 100,000. Figure 6 plots the event study coefficients produced by estimating Equation (2) with facilities offering at least one form of MAT per 100,000 population as the outcome. Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data taken from the National Survey of Substance Abuse Treatment Services (N-SSATS). Policy controls include Affordable Care Act (ACA) Medicaid Expansion, substance abuse treatment (SAT) Parity, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

TABLE 4 Effect of medicare Part D on the number of facilities per 100,000 offering MATs or opioid treatment programs (OTPs)

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	**≥1 MAT**	**≥1 MAT**	**≥1 MAT**	**0 MAT**	**≥2 MAT**	**OTP**
% Aged $65+_{2003}$ × Post	0.081**	0.068***	0.053**	0.028	0.022	0.006
	(0.036)	(0.020)	(0.022)	(0.041)	(0.016)	(0.008)
Mean of outcome (2002-05)	0.984	0.984	0.984	3.757	0.239	0.381
N	867	867	867	867	867	867
Policy controls		X	X	X	X	X
Other controls		X	X	X	X	X
Region × Year FEs			X			
Model	Linear	Linear	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcomes are the numbers of facilities per 100,000 population with: at least one form of MAT for OUD, zero forms of MAT, at least two forms of MAT, or that offer a OTP. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions weighted by population. Standard errors clustered at the state level.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

sum, there is some evidence that Medicare Part D may have increased the number of buprenorphine clients allowable under DATA 2000, but results are sensitive to the specification.

4.4 | Effects on facilities by ownership status

Previous work has documented that the effects of health policies on SAT providers can vary by ownership status (i.e., public, non-profit, and for-profit; Hamersma & Maclean, 2021; Maclean et al., 2018). Therefore, there is also reason to believe that Medicare Part D and its subsequent effect on opioid addiction could have had varying effects on the supply of SAT according to the ownership statuses of facilities. This analysis will shed light on the degree to which the public versus the private sector is driving the observed effects on providers. Table 6 displays the results of estimating Equation (1) using facilities per 100,000

TABLE 5 Effect of medicare Part D on the number of facilities per 100,000 offering specific MATs

	(1)	(2)	(3)	(4)	(5)
Outcome	**Naltrexone**	**Naltrexone**	**Naltrexone**	**Buprenorphine**	**Methadone**
% Aged $65+_{2003}$ × Post	0.072**	0.061***	0.052**	0.025	0.008
	(0.028)	(0.018)	(0.019)	(0.018)	(0.010)
Mean of outcome	0.579	0.579	0.579	0.336	0.427
N	867	867	867	816	918
Policy controls		X	X	X	X
Other controls		X	X	X	X
Region × Year FEs			X		
Model	Linear	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcomes are the numbers of facilities per 100,000 population that offer nalterxone, buprenorphine, or methadone. Outcome data taken from the N-SSATS. Estimates use a sample period beginning in 2002 for columns (1)-(3), 2003 for column (4), and 2000 for column (5). Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE 6 Effect of medicare Part D on substance abuse treatment (SAT) facilities by ownership status

	For-Profit Ownership	Non-Profit Ownership	Public Ownership
Ownership status	**(1)**	**(2)**	**(3)**
Panel A: Residential and Hospital Inpatient Facilities			
% Aged $65+_{2003}$ × Post	0.006	0.018	0.013**
	(0.008)	(0.013)	(0.006)
Mean of outcome (2000-05)	0.225	1.157	0.206
N	918	918	918
Panel B: Outpatient Facilities			
% Aged $65+_{2003}$ × Post	0.004	0.027	0.027**
	(0.025)	(0.024)	(0.011)
Mean of outcome (2000-05)	1.149	2.193	0.593
N	918	918	918
Panel C: Facilities Offering ≥ 1 MAT			
% Aged $65+_{2003}$ × Post	0.015	0.051***	0.002
	(0.010)	(0.019)	(0.005)
Mean of outcome (2002-05)	0.331	0.481	0.172
N	867	867	867
Policy controls	X	X	X
Other controls	X	X	X
Model	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcomes in Panel A are for-profit, non-profit, or government-run facilities that accept residential and/or hospital inpatient clients. The outcomes in Panel B are similar but for facilities that accept outpatients. The outcomes in Panel C are for facilities that offer at least one form of MAT. Outcome data taken from the N-SSATS. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Regressions are weighted by state population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

population by treatment environment and ownership status. Panel A shows that only publicly-owned residential and hospital inpatient facilities were significantly increased by Part D, although the coefficients for each type of privately-owned facility are positive and relatively large. Panel B shows a similar pattern for outpatient facilities. Panel C examines Part D's effects on facilities offering MAT by ownership type and shows that the vast majority of the effect is concentrated among non-profit facilities. Estimates suggest that a percentage point increase in elderly share after 2006 is associated with 0.051 more non-profit private facilities offering MAT per 100,000 population. In sum, these results suggest that both private and public facilities increases treatment capacity in response to demand. However, it is difficult to specify precisely the mechanism by which these increases work. For example, the significant increase in private non-profit facilities offering MAT could be due to market-based forces or due to mediating government policies which have encouraged MAT adoption.

4.5 | Scaling the effects of Part D by its impact on prescription opioid distribution

I argue that Part D increased the supply of SAT by expanding the availability of prescription opioids. This section uses a two-stage least squares (2SLS) approach to rescale the effect of Part D on SAT provides to be in terms of quantity of medication distributed. Table 7, columns (1) and (3) show the results of "naive" regressions of the outcomes of interest on MEDs of prescription opioids distributed per capita. Columns (2) and (4) show the 2SLS results from instrumenting for prescription opioid distribution with Medicare Part D. Translating the 2SLS results into percentage terms: a 10% increase in MEDs per capita is associated with increases in residential/inpatient facilities per 100,000 population by 2.6%, in beds per 100,000 by 2.3%, in outpatient facilities per 100,000 by 1.6% (at 10% significance), and in facilities with MAT per 100,000 by 8.6%, all relative to the pre-treatment means.[19] All of these effects are larger than the "naive" ordinary least squares (OLS) estimates in columns (1) and (3). This disparity either suggests that there are downward biases inherent to the OLS models or that there are alternative channels through which Part D positively affects the availability of SAT.

4.6 | Robustness checks

4.6.1 | Leave-one-out tests

The research design used in this paper weighs a state's contribution to the treatment effect as being proportionate to its elderly share. Therefore, states with particularly large or small values of elderly share have the potential to drive a substantial portion of the treatment effects. I test directly for this possibility by re-estimating Equation (1) with the main outcomes of interest while systematically removing one state at a time. I display point estimates and 95% confidence intervals from these regressions in Appendix Figure A4 for the following outcomes: residential and hospital inpatient facilities, beds, outpatient facilities, and facilities with at least one form of MAT for opioid-use disorder, per 100,000 population. The only states whose exclusions meaningfully impact the point estimates are Florida and Texas.[20] Furthermore, in only one instance among the former three outcomes (residential and hospital inpatient beds) is there a case in which the exclusion of a state (Texas) from the sample renders the treatment effect statistically insignificant at the 5% level. In Panels A and D, on the other hand, estimates are robust to the removal of any one state. Estimates in Panel C are statistically insignificant at the 5% level in almost all cases.

4.6.2 | Are these effects driven by other Medicare Policies?

Medicare Part D reduces the cost of obtaining prescription opioids. However, Medicare Part D can also pay for certain prescription MATs (HHS, 2016).[21] Therefore, one concern may be that the effects of Part D on the availability of SAT are not driven by the policy's effect on prescription opioids, but instead by the effects of other Part D provisions. I show that this mechanism is unlikely. Appendix Table A5 contains the results of estimating the effect of Part D on the number of Medicare admissions and facilities that accept Medicare per 100,000 population. Column (1), which uses as the outcome the number of SAT admissions per 100,000 that report having non-Medicaid public insurance (i.e., Medicare, Civilian Health and Medical Program of the Uniformed Services, etc.), shows an insignificant effect of elderly share.[22] Columns (2)-(4) show the effects of Part D on the number of various types of facilities that accept Medicare. None of these effects are statistically significant, and the point estimates are all smaller than the effects on each type of facility as estimated in Sections 4.2 and 4.3. Furthermore, since Medicare acceptance rates are substantial and remain relatively unchanged across the sample period (about 37% of all facilities in

TABLE 7 Effect of opioid distribution on substance abuse treatment (SAT) availability: Instrumenting for opioid distribution with medicare Part D

	Facilities per 100,000		Beds per 100,000	
Outcome	**(1)**	**(2)**	**(3)**	**(4)**
Panel A: Residential and Hospital Inpatient Facilities				
MEDs per capita	0.273**	1.038***	10.105**	24.975***
	(0.116)	(0.260)	(4.550)	(7.183)
F-statistic	–	40.81	–	62.28
Mean of outcome (2000-05)	1.587	1.587	43.058	43.058
N	867	867	765	765
	Facilities per 100,000			
Outcome	**(1)**	**(2)**		
Panel B: Outpatient Facilities				
MEDs per capita	0.385	1.627*		
	(0.312)	(0.883)		
F-statistic	–	40.81		
Mean of outcome (2000-05)	3.935	3.935		
N	867	867		
	Facilities per 100,000			
Outcome	**(1)**	**(2)**		
Panel C: Facilities Offering ≥ 1 MAT				
MEDs per capita	0.179	2.178***		
	(0.206)	(0.533)		
F-statistic	–	32.54		
Mean of outcome (2002-05)	0.984	0.984		
N	816	816		
Policy controls	X	X	X	X
Other controls	X	X	X	X
Estimator	OLS	2SLS	OLS	2SLS

Note: Regressions produced by estimating Equation (1). The outcomes in Panel A are residential and hospital inpatient facilities/beds per 100,000 population. The outcomes in Panel B are outpatient facilities per 100,000 population. The outcomes in Panel C are facilities that offer at least one form of MAT per 100,000 population. F-Statistic refers to value associated with excluded instrument. Outcome data taken from the N-SSATS. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Regressions are weighted by state population. Standard errors clustered at the state level.

Abbreviation: OLS, ordinary least squares.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

both 2000 and 2018), low participation rates are not inducing power issues in these analysis. These results indicate that other Medicare Part D provisions are not likely to be driving the main results.

4.6.3 | Alternative data: County Business Patterns

An alternative source of data on SAT facilities is the County Business Patterns (CBP). These data, collected by the United States Census Bureau, contain yearly information on establishments extracted from their Business Register. The Businesss Register, in turn, is a database of all single and multi-establishment employer companies that are known to the Census Bureau. The strength of the CBP for this project's purposes, when compared to the N-SSATS, is that they should contain a more complete count of private SAT establishments since they are not similarly subject to non-response from participants. However, the CBP also comes with at least two drawbacks. The main drawback is that they exclude most establishments reporting government

employees. This is particularly challenging for my analysis, since my estimates by ownership status indicate that a large share of the effects on residential/hospital inpatient and outpatient facilities are driven by publicly-owned facilities. The second drawback is that the North American Industry Classification System (NAICS) codes used to identify both outpatient SAT facilities (621,420) residential SAT facilities (623,220) group together substance abuse and mental health facilities. Although many specialty mental health facilities also run programs for substance-use disorder, as of 2017 about 44% of mental health facilities did not offer SAT (SAMHSA, 2018a). Furthermore, SAMHSA estimates the existence of approximately 15,000 SAT facilities and 13,000 mental health facilities that same year. This implies that the share of mental health facilities without SAT within each NAICS code is non-trivial (SAMHSA, 2018b). Both of these drawbacks suggest that estimates using the CBP may differ meaningfully from estimates using the N-SSATS.

Appendix Figure A5, Panels A and B display the event study coefficients from estimating Equation (2) with outpatient and residential/hospital inpatient facilities as the outcomes, respecitively. These graphs display patterns that are qualitatively similar to the estimates using the N-SSATS but the confidence intervals tend to be wider. Furthermore, each graph displays the treatment effects estimated using Equation (1) along with the CBP. Although point estimates are similar in magnitude to the N-SSATS estimates, the are statistically insignificant at conventional levels.

5 | CONCLUSION AND DISCUSSION

Despite the best efforts of policy makers and public health initatives, opioid mortality reached an all-time high in 2020. Since the number of people suffering from opioid use disorders is increasing every day, policymakers need to be able to assess how well the U.S. healthcare system has fared at expanding treatment supply to meet demand. In order to estimate this directly, I exploit the introduction of Medicare Part D as an exogenous increase in the availability of prescription of opioids and addiction. Using the N-SSATS, I find that a 10% increase in MEDs, induced by Part D, resulted in a 2.6% increase in the number of residential/inpatient SAT facilities and a 2.3% increase in the number of beds. Furthermore, I find that a 10% increase in MEDs resulted in an 8.4% increase in the number of SAT facilities offering at least one form of MAT.

The effects I estimate incorporate not only the profit-driven responses to demand of private sector actors, but also the mediating effects of any government policy implemented in response to the increase in opioid addiction. Therefore, my results can be viewed as the capability of SAT providers (which includes public sector actors) to respond to population-wide changes in opioid addiction rates. These results are encouraging in that they show that the supply of SAT expanded to meet the increase in need. Furthermore, this effect is particularly pronounced for facilities offering MAT, which is especially important for treating opioid-used disorder. I also find that the increases in residential/hospital inpatient facilities, and possibly outpatient facilities, were driven in large part by increases public facilities. This implies that the government has played a significant role in addressing the shock to addiction induced by Medicare Part D. Therefore, policymakers may consider continung and expanding the policies that have supported the provision of SAT over the past 15 years in order to combat the new wave of the opioid addiction in the post-COVID era.

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CONFLICT OF INTEREST

The author declares no conflict of interest.

ETHICS STATEMENT

Not applicable.

PATIENT CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The N-SSATS data that support some of the findings of this study are made openly available by the SAMHSA at https://www.datafiles.samhsa.gov/dataset/national-survey-substance-abuse-treatment-services-2020-n-ssats-2020-ds0001. The N-SSATS data on residential and hospital inpatient beds that support some of the findings of this study are available from the SAMHSA upon request sent to cbhsqrequest@samhsa.hhs.gov. The N-SSATS data on client counts by treatment setting and data on facility response rates that support some of the findings of this study are made openly available within N-SSATS Annual Reports at https://www.samhsa.gov/data/data-we-collect/n-ssats-national-survey-substance-abuse-treatment-services. The TEDS data on SAT admissions that support some of the findings of this study are made openly available by the SAMHSA at https://www.samhsa.gov/data/data-we-collect/teds-treatment-episode-data-set. Data on Medicare Part D enrollment that support some of the findings of this study are made openly available in the CMS Statistical Supplements (years 2006-12), found here: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/Archives/MMSS/2013, as well as CMS Program Statistics (years 2013-18), found here: https://data.cms.gov/summary-statistics-on-beneficiary-enrollment/medicare-and-medicaid-reports/medicare-part-d-enrollment. Data on prescription opioid distributions that support some of the findings in this study are made openly available in the DEA's ARCOS, and can be found here: https://www.deadiversion.usdoj.gov/arcos/index.html. The DATA 2000 waiver data on buprenorphine licensing that support some of the findings in this study were obtained from the SAMHSA by request sent to foia@samhsa.hhs.gov. The data on population counts are openly available from SEER, available at: https://www.nber.org/research/data/survey-epidemiology-and-end-results-seer-us-state-and-county-population-data-age-race-sex-hispanic. The data on unemployment rates are openly available from the BLS at: https://www.bls.gov/lau/data.htm. Lastly, the data from the CBP are also openly available from the BLS at: https://www.census.gov/programs-surveys/cbp.html.

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ENDNOTES

[1] Gowrisankaran and Town (1997) model hospital profits to scale positively with the number of "sick" patients in a community. Their model predicts that an increase in these patients can induce hospital entry. I use this framework as motivation for my analysis of opioid addiction, acknowleding that differences exist between specialty SAT facilities and hospitals.

[2] Dranove et al. (2020), Dranove et al. (2014), and Blume-Kohout and Sood (2013) are primarily concerned with the policy's effects on prescription drug R&D. Hu et al. (2017) examines Part D's effects on the number of prescriptions made per physician visit.

[3] The N-SSATS only collected detailed staffing data in a special supplement in 2016.

[4] SAMHSA defines a SAT facility as an entity, public or private, that provides substance abuse treatment (SAMHSA, 2020b).

[5] The reference date for residential and hospital inpatient beds and client counts was October 1 until the 2002 survey, when it changed to March 30/31. For outpatient clients, the reference period is/was the month before those dates.

[6] N-SSATS stopped collecting bed counts in even years after 2013, meaning that counts for 2014, 2016, and 2018 are unavailable for analysis. Additionally, some observations show implausibly large counts of beds for individual state-years. I have confirmed with SAMHSA that at least some of these temporary spikes can be attributed to individual facilities in these states, which suggests that the data were reported erroneously. I discuss my method for dealing with such outliers in Appendix A.

[7] As with the counts of inpatient beds, client counts ceased being collected during even years after 2013. The one exception to this is in 2016, when client counts were collected for that year alone. Inpatient client counts were also subject to apparent misreporting in certain state-years, similar to the misreporting for bed counts (as discussed in footnote 7). I discuss my method for dealing with such outliers in Appendix A.

[8] Separate response rates are not available by type of facility. However, this will not introduce bias as long as the difference between the pooled facility response rate and the response rates by facility type are uncorrelated with the treatment variable. Additionally, I show that there is no significant correlation between Medicare Part D and the pooled response rate in Appendix Table A2.

[9] I explain the evolution of the N-SSATS eligiblity criteria in further detail in Appendix B.

[10] Note that it is common for clients-per-bed to be greater than 100% because clients can occupy beds that are not designated for SAT. For example, in 2017 about 10% of residential and 20% of hospital inpatient facilities had utilization rates greater than 100% (SAMHSA, 2020b).

[11] After 2012, these counts are only reported every odd year. The 2013 data are excluded because the report censors several state cells for hospital inpatients due to small sample sizes.

[12] MED conversion executed according to the conversion factors published by CMS here: https://www.cms.gov/Medicare/Prescription-Drug-Coverage/PrescriptionDrugCovContra/Downloads/Opioid-Morphine-EQ-Conversion-Factors-March-2015.pdf.

[13] I use the same implementation dates as are listed in the above studies.

[14] This approach does not take into account people qualified for Medicare via Social Security Disability Insurance (SSDI) who would have gained access to Medicare Part D. However, many who had received SSDI for 24 consecutive months were also eligible for Medicaid, which has its own prescription drug benefit.

[15] Since these controls vary by time, I want to confirm that none of them are related to the treatment variable. Additionally, since I divide all of my N-SSATS outcomes by the survey response rate, I also need to verify that the response rate is not related to treatment either. I show the results of estimating Equation (1) (excluding $X'_{st}\beta$ from all specifications) using the control variables and response rate as the outcomes in Appendix Table A2.

[16] Poisson models assume effects that are in proportion to the outcome means, which is a plausible alternative to the linearity assumption in linear regression.

[17] I compare effect sizes using Poisson models since the estimates for γ can be interpreted as percent increases relative to their respective means.

[18] Evidence from clinical trials of extended release Naltrxone have been shown that application during treatment of OUD can increase treatment retention by 75%–78% and reduce relapse rates 94% (Comer et al., 2006; Krupitsky et al., 2011).

[19] Table 7 also shows the F-statistics on elderly share for the corresponding first stage regressions for each 2SLS estimate.

[20] Possible reasons for this include the relatively extreme levels of elderly share in Florida (high) and Texas (high) and their large populations. Indeed, re-estimating the leave-one-out tests without population weights mutes the impact of excluding either of these states. Furthermore, this phenomenon is also present in the mortality estimates in Powell et al. (2020) to a milder degree.

[21] These include some forms of buprenorphone and naltrexone, though not methadone when prescribed as a MAT (Congressional Research Service, 2020).

[22] The reduced number of observations is due to certain state-years not reporting health insurance status of clients.

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APPENDIX A: CORRECTING FOR MISREPORTING

As discussed in Section 3.1, the N-SSATS data on bed and client counts provided by SAMHSA in state-year aggregates contain several implausibly large observations. Correspondence with SAMHSA has confirmed that these anomalies are driven by single facilities that are misreporting bed and client counts in these individual years. However, since I cannot observe these counts at the facility level, I adopt the following procedure for correcting for outliers using these state-level aggregates. First, I define a state-year observation as an outlier when it is at least two times greater than the values in both adjacent years. I then replace the bed/client counts driving the outlier with a linear interpoliation using the client/bed counts in these adjacent years. I provide a list of outliers selected by this criterion, adjacent year values, and result from linear interpolation in Appendix Table A1. Note that the interpolation results are not exact averages of the adjacent years. This is because I interpolate between the underlying counts (of beds, clients) instead of the rates per 100,000 population. For example, an outlier for inpatient clients may be driven entirely by a state-year observation of residential clients, as opposed to hospital clients. In this case I would interpolate only the count of residential clients, then proceed to construct the total inpatient client rate per 100,000.

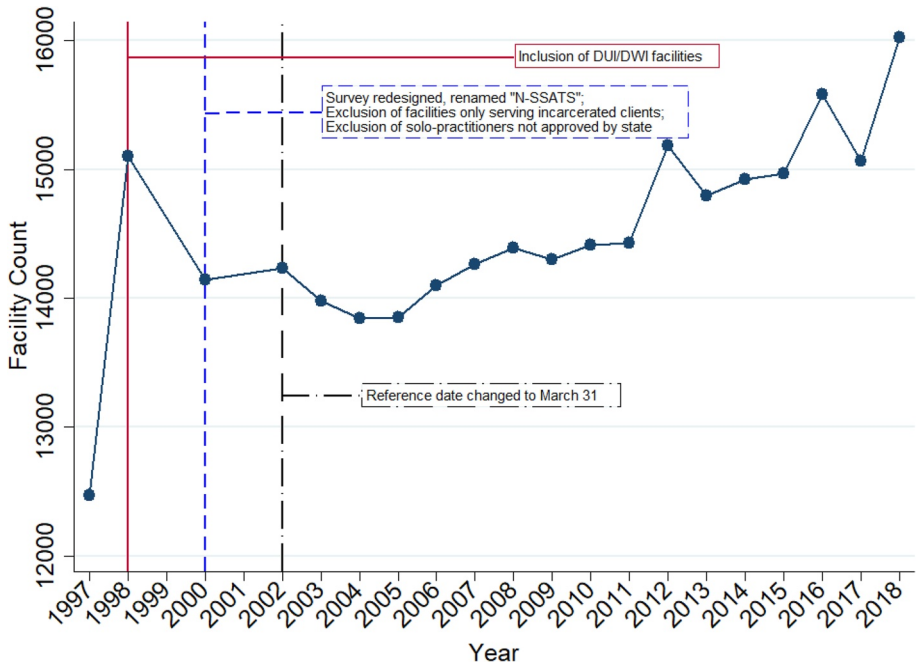

FIGURE A1 National substance abuse treatment (SAT) Facility Count Over Time - National Survey of Substance Abuse Treatment Services (N-SSATS)/Uniform Facility Data Set (UFDS). This graph plots the total number of specialty SAT facilities over time. Facility counts are produced by totaling N-SSATS/UFDS respondents by year. Yearly counts are divided by yearly response rate to produce final values

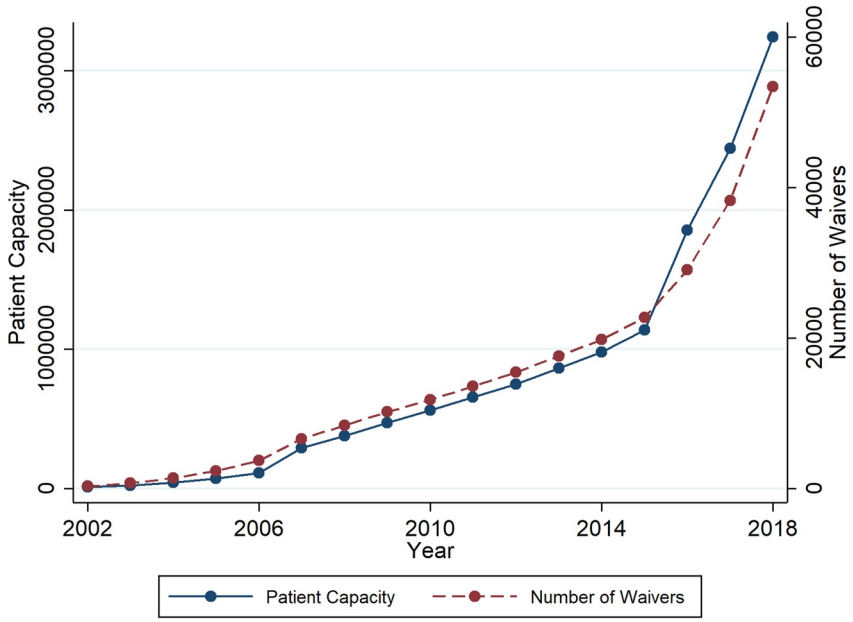

FIGURE A2 Cumulative DATA 2000 Waivers and Patient Capacity Granted to Specialty and Non-specialty Providers. The red dots display the cumulative number of DATA 2000 waivers granted to providers up to and including that year. The blue dots display the cumulative number of patients providers have been granted to treat via DATA 2000 waivers. A year's total DATA 2000 patient capacity granted as of year t can be calculated through the following formula: $CAPACITY_t = 30 \times N30_t + 100 \times N100_t + 275 \times N275_t$ where $N30_t$, $N100_t$, $N275_t$ represent the number of waivers granted for each patient limit as of year t

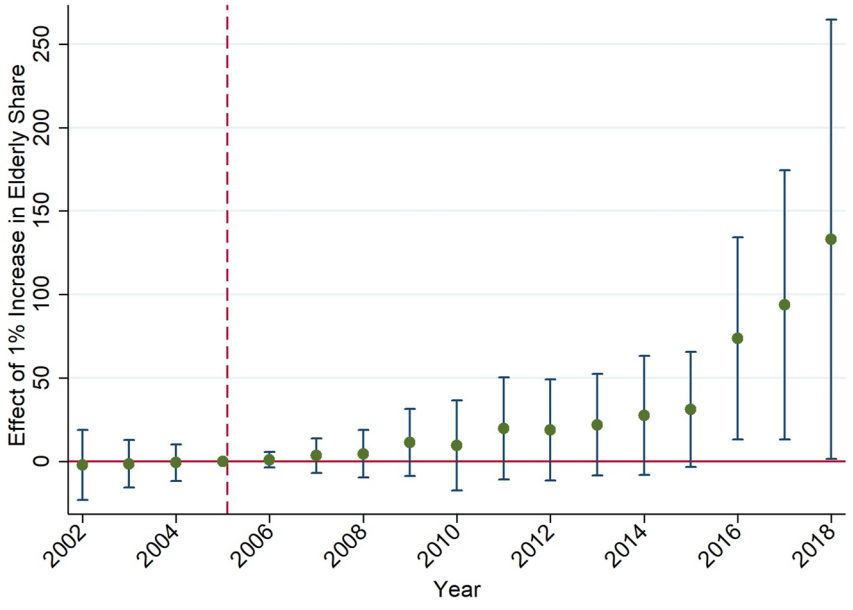

FIGURE A3 Event Study of the Effect of Medicare Part D on DATA 2000 Patient Capacity per 100,000. Figure A3 plots the event study coefficients produced by estimating Equation (2) with the cumulative amount of DATA 2000 patient treatment capacity per 100,000 population as the outcome. Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data received by request from Substance Abuse and Mental Health Services Administration (SAMHSA). Policy controls include Affordable Care Act (ACA) Medicaid Expansion, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals are clustered at the state level

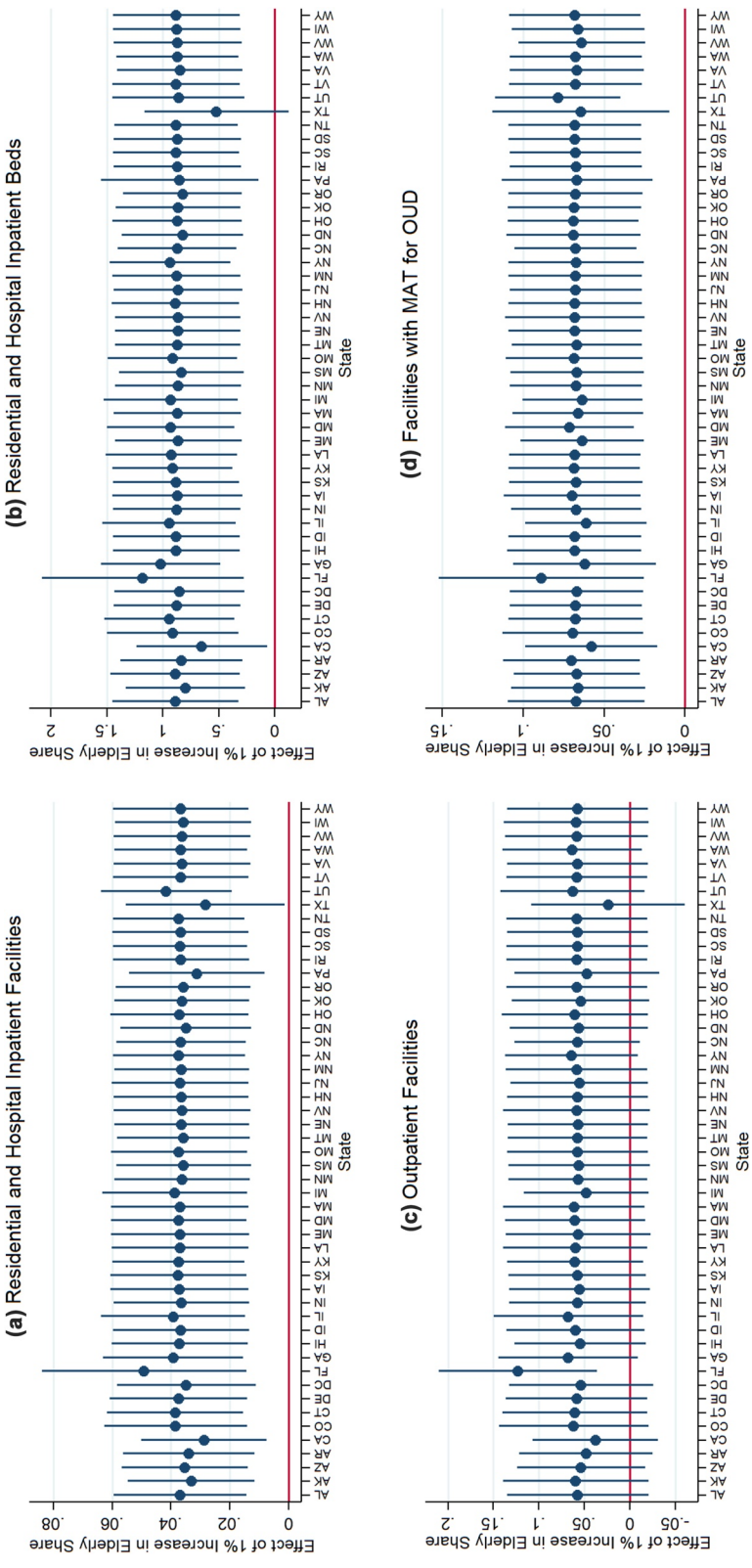

FIGURE A4 Leave-One-Out Tests. Panels A-D contain the results of re-estimating Equation (1) for each of the following outcomes, while sequentially removing one state a time: residential and hospital inpatient facilities, residential and hospital inpatient beds, outpatient facilities, and facilities with medication-assisted treatment (MAT) for OUD, per 100,000 population. Outcome data taken from the National Survey of Substance Abuse Treatment Services (N-SSATS). Each point estimate is the coefficient on the share of the population aged 65+. 95% percent confidence intervals are cluster-robust at the state level

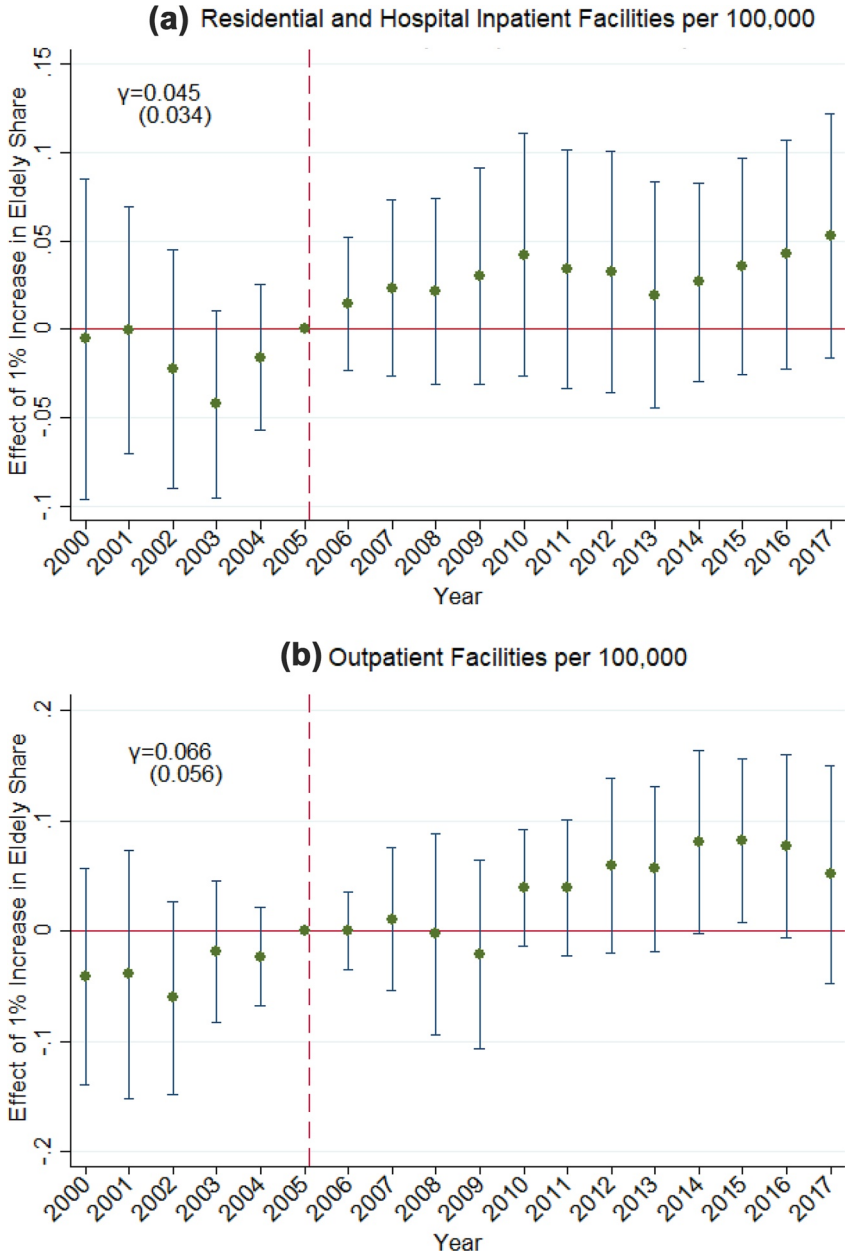

FIGURE A5 Event Studies Using the County Business Patterns (CBP). The graphs in Panels A and B are produced by estimating Equation (2) with residential and hospital inpatient facilities or beds per 100,000 population as the outcomes. Point estimates and standard errors from differences-in_differences models obtained by estimating Equation (1). Vertical dashed line separates pre- and post-treatment event study coefficients. Outcome data taken from the CBP 2000–2017. Policy controls include Affordable Care Act (ACA) Medicaid Expansion, Health Insurance Flexibility and Accountability (HIFA) Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong Prescription Drug Monitoring Program (PDMP) dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. All regressions are weighted by state populations. 95% confidence intervals and standard errors are clustered at the state level

TABLE A1 Correcting for Misreporting

State	Year	Outlier	Adjacent Year (left)	Adjacent Year (right)	Interpolation
Panel A: Residential and Hospital Inpatient Clients per 100,000					
Arkansas	2015	98.062	29.215	23.288	27.658
Delaware	2015	448.508	33.391	23.281	25.223
Rhode Island	2009	394.184	38.894	42.073	37.337
Rhode Island	2015	571.215	36.333	32.920	37.654
South Carolina	2015	39.320	19.607	17.253	19.437
Washington	2015	101.249	34.309	34.719	34.270
Panel B: Outpatient Clients per 100,000					
Montana	2011	1020.747	302.392	460.645	377.107

TABLE A1 (Continued)

State	Year	Outlier	Adjacent Year (left)	Adjacent Year (right)	Interpolation
Panel C: Residential and Hospital Inpatient Beds per 100,000					
Rhode Island	2015	571.215	38.921	36.224	39.770
Washington	2015	86.770	38.703	40.872	39.253

Note: This table displays outliers in the bed and client data according to the criterion laid-out in the Appendix. It also shows the corrected values for the outliers, calculated by linearly interpolating between the bed and clients counts for the state-year observations adjacent to the outlier, then using the interpolated count to construct the final rate per 100,000.

TABLE A2 Impact of Part D on Controls and N-SSATS Response Rates

	Policy Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	ACA medicaid expansions	HIFA waivers	SAT Parity laws	Medical marijuana laws	Pain clinic laws	Strong PDMPs
Panel A: State Policies						
% Aged $65+_{2003}$ × Post	−0.016	0.005	−0.037	0.013	0.010	0.003
	(0.035)	(0.010)	(0.039)	(0.024)	(0.055)	(0.023)
Mean of outcome (2000-05)	0.000	0.037	0.055	0.048	0.000	0.000
95% confidence interval	[−0.085, 0.054]	[−0.015, 0.025]	[−0.115, 0.042]	[−0.034, 0.061]	[−0.100, 0.120]	[−0.044, 0.050]
N	969	969	969	969	969	969
	UI rate	ln (Population)	% White	N-SSATS response rate		
Outcome	(1)	(2)	(3)	(4)		
Panel B: Other Controls and N-SSATS Response Rate						
% Aged $65+_{2003}$ × Post	0.073	−0.009	0.001	0.001		
	(0.092)	(0.010)	(0.001)	(0.001)		
Mean of outcome (2000-05)	5.209	16.005	0.811	0.953		
95% confidence interval	[−0.112, 0.257]	[−0.029, 0.011]	[−0.000, 0.002]	[−0.002, 0.004]		
N	969	969	969	969		
Model	Linear	Linear	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1) with each control variable as the outcome. Each specification includes state and year fixed effects. Linear regressions are weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A3 Effect of Medicare Part D on SAT Facility Utilization Rates

	Clients-per-Facility			Clients-per-Bed		
Outcome	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Residential and Hospital Inpatient						
% Aged $65+_{2003}$ × Post	0.200	0.179	0.118	0.005	0.007*	0.008
	(0.208)	(0.151)	(0.229)	(0.005)	(0.004)	(0.006)
Mean of outcome (2000-05)	27.244	27.244	27.244	0.906	0.906	0.906
95% confidence interval	[−0.217, 0.618]	[−0.125, 0.482]	[−0.342, 0.577]	[−0.004, 0.015]	[−0.001, 0.015]	[−0.005, 0.020]
N	714	714	714	714	714	714

(Continues)

TABLE A3 (Continued)

Outcome	Clients-per-Facility (1)	(2)	(3)			
Panel B: Outpatient						
% Aged $65+_{2003}$ × Post	3.064*	2.192**	0.874			
	(1.599)	(1.035)	(0.908)			
Mean of outcome (2000-05)	87.591	87.591	87.591			
95% confidence interval	[−0.148, 6.277]	[0.113, 4.271]	[−0.950, 2.698]			
N	816	816	816			
Policy controls		X	X		X	X
Other controls		X	X		X	X
Region × Year FEs			X			X
Model	Linear	Linear	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcome in Panel A, columns (1)-(3) is the ratio of residential and hospital inpatient clients to facilities of the same type. The outcome in Panel A, columns (4)-(6) is the ratio of residential and hospital inpatient clients to beds. The outcome in Panel B, columns (1)-(3) is the ratio of outpatient clients to outpatient facilities. Outcome data taken from N-SSATS and the N-SSATS Annual Reports (SAMHSA, 2020b). The models producing Panel A restrict the sample only to facilities that report both client and bed counts in the same year. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions are weighted by the outcomes' denominators. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A4 Effect of Medicare Part D on Cumulative DATA 2000 Patient Capacity

Outcome	Patient Capacity per 100,000 (1)	(2)	(3)	(4)
Panel A: DATA 2000 Waivers Ever Granted				
% Aged $65+_{2003}$ × Post	54.461**	50.207**	31.835**	18.048
	(26.547)	(20.162)	(15.799)	(11.430)
Mean of outcome (2002-05)	43.011	43.011	43.011	43.011
N	867	867	867	867
Panel B: DATA 2000 Waivers Granted to Practitioners Operating in 2020				
% Aged $65+_{2003}$ × Post	26.989*	24.262**	15.026*	6.844
	(14.921)	(9.732)	(8.898)	(6.330)
Mean of outcome (2002-05)	13.463	13.463	13.463	13.463
N	867	867	867	867
Policy controls		X	X	X
Other controls			X	X
Region × Year FEs				X
Model	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcome in Panel A is the cumulative amount of DATA 2000 capacity granted to providers in a given state, per 100,000 population. The outcome in Panel B is the cumulative amount of DATA 2000 capacity granted to providers in a given state who are stillp practicing, per 100,000 population. Outcome data taken from the N-SSATS Annual Reports. Panel B uses a sample period beginning in 2002 for columns (1)-(3), 2003 for column (4), and 2000 for column (5). Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

TABLE A5 Effect of Medicare Part D on Medicare Admissions and Acceptance at SAT Facilities

	Admissions per 100,000	Residential/Hospital Inpatient Facilities per 100,000	Outpatient Facilities per 100,000	Facilities with MAT per 100,000
Outcome	**(1)**	**(2)**	**(3)**	**(4)**
% Aged $65+_{2003} \times$ Post	2.675	0.008	0.003	0.021
	(1.934)	(0.005)	(0.014)	(0.019)
Mean of outcome (2000-05)	24.078	0.475	1.492	0.458
N	898	918	918	918
Policy controls	X	X	X	X
Other controls	X	X	X	X
Model	Linear	Linear	Linear	Linear

Note: Regressions produced by estimating Equation (1). The outcome in column (1) is the number of SAT admissions per 100,000 population, where each admission reports having public insurance that is not Medicaid (i.e., Medicare, Civilian Health and Medical Program of the Uniformed Services, etc.). Column (1) outcome data are taken from the TEDS. The outcomes in columns (2)-(4) are the numbers of residential/hospital inpatient facilities, outpatient facilities, and facilities with MAT per 100,000 that accept Medicare. Columns (2)-(4) outcome data are taken from the N-SSATS. Each specification includes state and year fixed effects. Policy controls include ACA Medicaid Expansion, SAT Parity, HIFA Waiver, Pain Clinic Regulation, Medical Marijuana, and Strong PDMP dummies. Other controls include state unemployment rates, natural log of the population, and percent of the population white. Linear regressions are weighted by population. Standard errors clustered at the state level.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

APPENDIX B: CHANGES TO N-SSATS ELIGIBILITY CRITERIA

Prior to a survey re-design in 2000, the N-SSATS was known as the Uniform Facility Data Set (UFDS). Like the N-SSATS, the goal of the UFDS was to survey the universe of SAT facilities in the United States. Unlike the N-SSATS, however, its sample design was altered with each wave as SAMHSA changed their criteria for which facilities were considered eligible. Appendix Figure A1 plots SAMHSA's known universe of SAT facilities eligible for the N-SSATS/UFDS between 1997 and 2018. Counts were constructed by dividing the surveys' final sample size each year by the corresponding response rate (the survey underwent re-designs in 1999 and 2001). The large swings in facility counts from 1997 to 2000 reflect the concurrent changes in eligibility criteria and it was not until 2002 that the survey design was finalized with the change in reference date.